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Innovative personalized teaching in language education supported by generative adversarial networks

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Abstract The study proposes a personalized teaching content generation and adaptation method based on generative adversarial network in language education reform in response to the problems in language education, and designs a language learner portrait model. By introducing the self-attention mechanism of Gaussian deviation as a generator, student portrait features are collected to ensure personalized teaching content generation. In addition, the feature vectors of learner portraits and learning resources are extracted using normalization to improve the adaptability of teaching content. The designed reform method is applied to language teaching in a city experimental school to evaluate the application effect of the method in this paper.The FID and IS values of the PB-ESGAN model converge to 9.35 and 7.81, respectively, before iterating for 100 rounds, and the authenticity and diversity of the language teaching content is more generated is improved. In addition, the F1 values of the model in the teaching resource recommendation fitness experiment are improved by 18.33% to 42.08% compared with the comparison algorithm, which can provide reliable teaching resources for students. At the end of teaching, the language ability of students in class 2 is significantly improved compared with class 1, with a difference of 6.27 points between the two language test scores. Students' satisfaction with the teaching content recommended by the model of this paper is as high as 4.76 points, which demonstrates the accuracy and variety of the language teaching content generated by the model of this paper.

Index Terms Generative Adversarial Network, Self-attention Mechanism, Normalization, Language Education, Teaching Content Generation

I. Introduction

“Digital resources” is a combination of computer technology, communication technology and multimedia technology, the sum of information resources released, accessed and utilized in digital form [1]. With the continuous development of science and technology, computers into the society of the public life, the Internet has been highly popularized, students can through the computer, cell phone learning resources for language learning, digital resources are changing the way of thinking and learning, but also to the traditional teaching to provide a new reform opportunities and challenges [2]-[6]. Digital resources can transform abstract textual information into vivid images, sound, animation, video, etc., stimulate students' visual and auditory senses, stimulate students' interest in learning languages, thus realizing the excellent transformation of teaching and learning, achieving the purpose of allowing students to learn independently and think independently, and comprehensively improving students' comprehensive ability in languages [7]-[11].

Presetting and generation are the elements of teaching that language teachers must pay attention to, and effective presetting and wonderful generation are the goals that teachers have been trying to achieve, and the correct handling of the relationship between the two is one of the necessary skills for teachers [12], [13]. At this stage, there are various ways to introduce digital resources into language teaching, for example, the more common E-learning courseware, microclass videos, PPT courseware and so on [14], [15]. These teaching methods involve pictures, text, sound, animation, video, etc., which can transform the traditional “static classroom” to a new type of “dynamic classroom” and create a more vivid and interactive language classroom for students [16]-[19]. However, in the face of fragmented and superficial massive educational information, how to generate teaching content that can fully meet students' learning needs and abilities is worth focusing on [20]. The development of the technological era requires us to improve the level of language teaching with a deep perspective, and the use of deep learning algorithms can transform and reconstruct meaning-associated knowledge, and provide students with teaching content with high-level learning objectives by emphasizing a holistic approach to the organization of learning content [21]-[23]. Therefore, it is of great significance to explore the method of personalized teaching content generation and adaptation in the intelligent education environment.

In this paper, student process data are collected to construct a learner portrait model from the dimensions of basic information and behavioral characteristics. Based on the learner portrait, a class of personalized content generation and adaptation framework for language education based on generative adversarial networks is developed. By introducing local modeling, the situation of dispersed attention distribution in the training process of self-attention mechanism is solved. At the same time, the objective function of minimum penalty is introduced, which makes the decoder efficiently utilize the learner model context information to enrich the generated content of language teaching text. In addition, a sigmoid function with scaling and offset parameters is added to process the teaching resource data for normalization, which improves the adaptability of language teaching resource recommendation. The method is applied to an experimental school, and the role of the method in language education reform is evaluated in terms of teaching effectiveness and student satisfaction.

II. A preliminary study of language education reform

With the advancement of educational reform and the updating of educational concepts, language education has been generally emphasized and recognized by educators. However, in the practice of language education at the compulsory education stage, especially in junior high schools, language education is often caught in dilemmas and embarrassments, such as vague objectives, lack of competence and simple methods.

II. A.Purpose of the survey

Questionnaire survey method and interview method were used to grasp the situation of middle school students' subjective initiative in learning, and to investigate the status of middle school students' interest in language reading, their sense of questioning, classroom discussion, and their ability to read on their own. To better understand the teacher's dominance in teaching, the interviews mainly focused on the teacher's teaching objectives and teaching methods. From the students and teachers to analyze the problems and causes of language education, to facilitate from the practical point of view, to mobilize students' subjective initiative, play an important role in the teacher's leadership.

II. B.Subjects of the survey

Language teachers and students in grades 7, 8 and 9 of a city experimental school were chosen as survey respondents. The school has a long history of operation, strong teachers, and the overall quality of students is generally high. Coupled with the fact that the author had interned in this experimental school, the students and teachers can have an in-depth understanding of the students and teachers of this school as a sample survey sample, and strive to ensure the reasonableness of the data in the distinction.

II. C.Survey methodology

Questionnaire method: 508 questionnaires were distributed to the students, of which 175 were distributed to the seventh grade, 164 to the eighth grade, and 169 to the ninth grade, and 508 valid questionnaires were retrieved, and after sifting out some invalid questionnaires, the valid questionnaires amounted to 500 in total.

Interview method: for the middle school teachers' language teaching situation, interviews were conducted with language teachers of different ages, totaling 20.

Observation method: go into the classroom and observe the language classroom teaching to understand the actual situation of the front-line teachers in carrying out language education.

By analyzing the data of this survey, it is not difficult to find out that there are a lot of problems in junior middle school language education, both from the perspective of teachers and students.

II. D.Analysis of problems in language education reforms

This section analyzes the results of the survey on the problems of language education reform, and in order to quantify the strengths and weaknesses of the problems, the survey was analyzed using a five-point Richter scale.

The results of the questionnaire survey on language teaching problems are shown in Figure 1. Indicators 1-4 in the figure represent, in order, teaching goal orientation, learning motivation, teaching mode, and teaching content. It can be seen from the figure that students at all grades in the school gave low ratings to teaching goal orientation, learning motivation, teaching mode, and teaching content in language education. Students' ratings for each indicator did not vary much across grades, with ratings for instructional content being the most problematic in the eyes of students at all grades. Taking the results of the survey of seventh grade students as an example, the ratings of teaching goal orientation, learning motivation, teaching mode and teaching content in language education are 2.62, 2.69, 2.39, 2.16 respectively. Classroom observation and interviews have revealed the following reasons: there is no unified planning of the teaching goals and programs during the language teaching process, and the goals of the curriculum are mostly located in the mastery of knowledge and the lack of practical exercises. Exercise. Most of the students did not develop good habits of language learning, they were distracted by books and seldom expressed their opinions in class. Some students accept knowledge passively and their basic knowledge is weak. In addition, teachers take the lecture method as the main teaching method, and methods such as subject research and cooperative learning are less frequent. Some students reported less interaction with teachers in class, low rate of being asked questions, and students were easily distracted and did not actively think about problems. Some teachers have little understanding of the syllabus teaching content requirements. Teachers take a great deal of initiative in choosing the teaching content and select the content of the textbooks differently. The use of teaching materials is liberalized, and there is a gap between the teaching content and the actual needs of students.

By summarizing and analyzing the survey on the questionnaires of school students and language teachers in a city experimental school, it is found that there are some problems in the teaching of junior high school language courses at present, which are mainly reflected in the following aspects:

(1) Unclear positioning of teaching objectives.

(2) Low motivation of students in language learning.

(3) Single teaching mode and method.

(4) There is a gap between teaching content and students' development needs.

In response to the above students' dissatisfaction with the teaching content in language education, the following section will adopt the deep learning technology, which is currently hot in research, to build a personalized teaching content generation and adaptation method for language education.

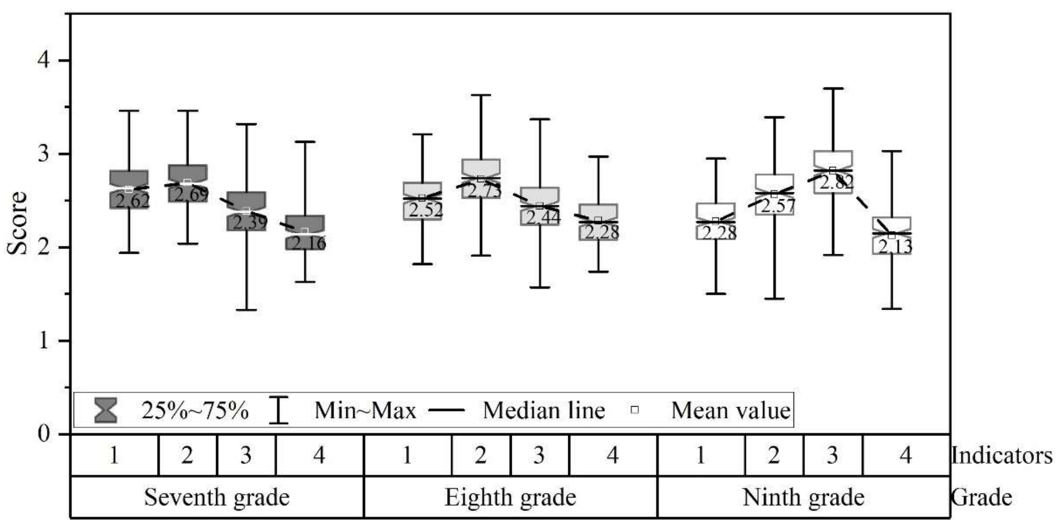

Figure 1: The results of the questionnaire survey of Chinese teaching problems

III. Language learner profiling modeling

III. A. Process dataset mining

The source of the learner process dataset collected in this paper is an online teaching and learning platform, packaged in classes, with the following files included in each class folder: grade trend folder, assessment score statistics, assessment activity statistics, classroom interaction grade level statistics, student classroom performance statistics, student classroom interaction statistics, and language knowledge point mastery statistics. Each class folder stores a grade trend folder, which includes data from the grade trend statistics for each student within this class.

The study combed through the raw data set, and the raw student processual data were more complete and could present better structured characteristics. The process data generated by the students is stored in a SQL database for data processing and access.

III. B. Learner Profile Construction Process

Process guidance is needed for learner portrait construction based on process data, and this study proposes a process framework for learner portrait construction based on process data as shown in Figure 2. The process of learner portrait construction based on processual data includes five key stages:

(1) Portrait construction goal and demand determination: the goal and seek analysis play a guiding role in the whole process of portrait construction and ensure the application value of the portrait.

(2) Data collection and pre-processing: data collection and pre-processing are the basis of learner portrait construction, which determines the effectiveness of learner portraits.

(3) Portrait construction and analysis: Portrait construction and analysis is the process of mining the information embedded in process data. The dimensions are determined by the goals of the learner portrait model construction, and the process data are labeled according to the dimensional requirements and stored in the portrait label library.

(4) Portrait output and visualization: The learner portrait model needs visualization technology to present learner characteristics, and then form individual learner portraits and learner group portraits.

(5) Application and updating of portraits: Learner portraits are constructed based on the process data generated by learners' learning, and should ultimately be used in education and teaching practice and correspond to the goals of portrait construction.

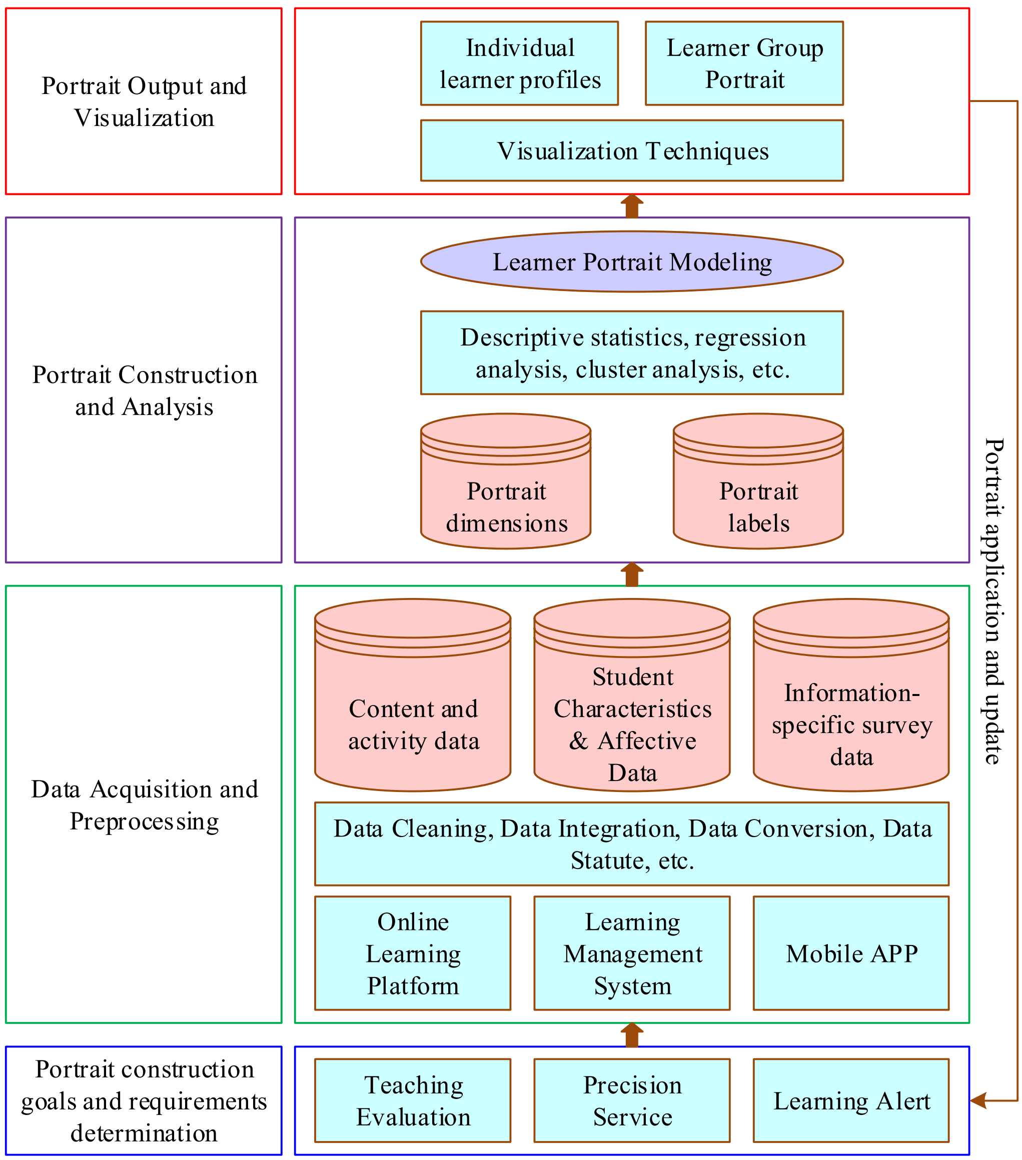

Figure 2: The process framework of the learner portrait based on procedural data

III. C. Learner Profile Modeling

This study establishes a learner portrait model with four dimensions: basic information, behavioral characteristics, style preferences, and outcome evaluation through previous mature models and process dataset features.

(1) The basic information dimension is extracted from information-specific survey data, which contains information related to learners' demographics and serves as a locative evaluation of learners.

(2) Behavioral characteristics dimension is extracted from the learner characteristics and emotion data. Learner behavioral characteristics refer to the learning behaviors generated in the process of interacting with the environment, and contain a collection of all the performances of the learner in the learning process.

(3) The style preference dimension is extracted from the learner characteristics and emotion data as well as the teaching content and activity data, which contains the learners' style tendency and willingness preference in the learning process.

(4) The outcome evaluation dimension is extracted from the survey data of specific information as well as the data of teaching content and activities, and the evaluation of learners' learning outcomes is the most direct way to measure their learning effectiveness.

III. D. Results of Student Portrait Generation

This experimental environment is used as follows:

Hardware environment: CPU: INTEL(R) CORE(TM) I7-11800H @ 2.30GHZ, Graphics card: NVIDIA GeForce RTX 3060, Memory: 32GB.

Software Environment: Operating System: Windows 11 64-bit, Development Language: Python 3.8, Programming Tool: PyCharm2022.3.

The data for this experiment use the process data of the students processed above. 100 students from the above school were selected based on the correlation between each eigenvalue and academic performance. Through the base model K-means clustering algorithm [24] for centroid selection of multiple algorithmic experiments, it was finally found that when the clustering algorithm in accordance with the K = 4 clustering, the most significant differences in the characteristics of the student clusters were obtained, Cluster1, 2, 3, 4 a total of 4 clusters, three-dimensional clustering results are shown in Figure 3.

Self-disciplined learner type students: corresponding to Cluster1, this type of students have good language scores, actively study and strictly demand themselves during school, the number of extracurricular books read and the number of classroom interactions are much higher than the other two types of students. They also have strong self-discipline and strictly control the time they spend on the Internet.

Internet Learning Students: corresponding to Cluster2, these students, whose language scores are slightly lower than those of Cluster1, read a certain amount of extracurricular books, but they lack the initiative and are not willing to participate in classroom interactions. They spend a long time on the Internet, but most of the time is spent on learning behaviors such as consulting materials.

Lack of planning students: corresponding to Cluster3, this type of students have medium language scores, and at the same time, do not actively read extracurricular books or participate in classroom interactions after joining the school. They do not have high academic requirements and do not think about life planning.

Students to be improved: corresponding to Cluster4, these students have the worst language scores and have a weak foundation. They basically do not read books outside the classroom, and also do not participate in classroom interaction. They are addicted to Internet entertainment and lack motivation and self-discipline.

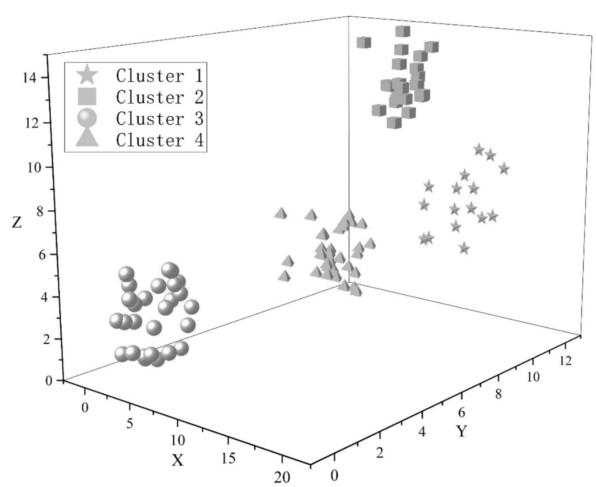

Figure 3: Three-dimensional clustering results

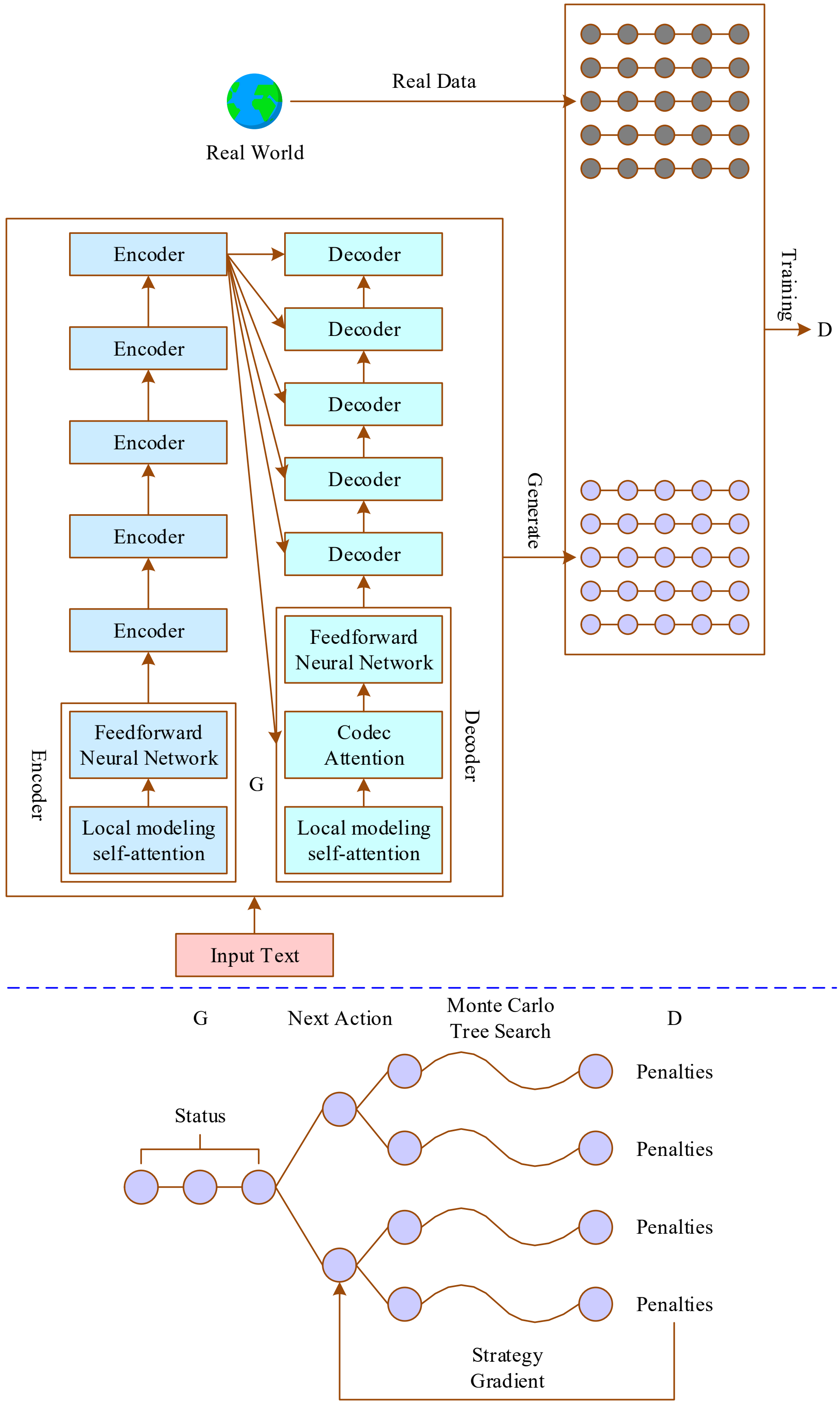

Figure 4: Complete architecture of the PB-ESGAN model

IV. Penalty Minimization Reinforcement Sequence GAN-based Instructional Content Generation Model

IV. A. Modeling Framework for Instructional Content Generation

For the task of personalized teaching content generation in language education reform, this study designs a new Penalty-Based Minimization Enhanced Sequence Generation Adversarial Network Algorithm (PB-ESGAN), which improves the feature extraction of the model with the diversification of language teaching content.

Figure 4 depicts the complete architecture of the PB-ESGAN model, and the whole framework mainly consists of two opposing learning objectives: generator learning and discriminator learning. The generator is based on language learner profiles and aims to generate personalized teaching content that meets the styles of different language learners. Specifically, it aims to minimize the proposed penalty-based objectives. On the contrary, the discriminator is conditioned by the language education pedagogical objectives and aims to provide better pedagogical content while conforming to the language education syllabus. The discriminator can be viewed as a dynamic goal since it is updated in synchronization with the generator.

IV. B. Sequence Generation Adversarial Networks

The detailed procedure of the Sequence Generation Adversarial Network (SeqGAN) algorithm [25] can be described as follows: first a dataset of real sequences is given and this dataset is used to train a generator G_θ with parameter θ which is used to generate a sequence:

$$y_{l:T} = (y_1, y_2, \cdots y_t, \cdots\cdots y_T), y_T \in Y \tag{1}$$

where Y represents the lexicon used to generate the sequence units. Combined with the concept of reinforcement learning it can be interpreted that at a certain point t, the sequence $(y_1, y_2, \cdots y_{t-1})$ that has now been generated is the state and the next word y_t action that is planned to be output.

The model used for the discriminator is Convolutional Neural Network (CNN), which performs discriminative classification for the whole sequence rather than the unfinished sequence. The idea of the algorithm is as follows: the original dataset text sequence is denoted as $x_1, x_2, \cdots, x_T$, and the target generated teaching content text sequence is denoted as $y_1, y_2, \cdots, y_T$, after which the source and target data matrices are constructed separately as follows:

$$X_{1:T} = x_1; x_2; \cdots; x_T \tag{2}$$

vs:

$$Y_{1:T} = y_1; y_2; \cdots; y_T \tag{3}$$

where x_t, $y_t \in R^k$ are k-dimensional word embeddings and the semicolon is the splicing operator. For source matrix $X_{1:T}$, kernel $\omega_j \in R^{l \times k}$ performs a convolution operation on a window of size 1 words and generates a series of feature mappings:

$$c_{ij} = \rho\left(\omega_j \otimes X_{i:i+l-1} + b\right) \tag{4}$$

where the $\otimes$ operator is the sum obtained by adding the yields of all elements, b represents the deviation term, and ρ represents the nonlinear activation function. In order to obtain the final function with respect to kernel ω_j, the maximum time pooling operation is utilized on the function graph:

$$\tilde{c}_j = \max\left\{c_{j1}, \cdots, c_{jT-l+1}\right\} \tag{5}$$

The target generated content representation c_y is extracted from the target matrix $Y_{1:T}$. Finally, the probability that the instructional content text is authentic can be calculated as:

$$p = \sigma\left(V\left[c_x; c_y\right]\right) \tag{6}$$

where V is the transformation matrix that transforms the juxtaposition of c_x and c_y into a two-dimensional embedding, and σ is a logarithmic function.

At a certain moment t, the generator can be represented as $G_\theta\left(y_t \mid y_{1:t-1}\right)$, and the goal of the strategy is to maximize the reward from the initial state s_0 to the time when the complete sequence has been generated. The sequence between moments t and T is to be realized with a Monte Carlo tree search, which is set to G_ϕ:

$$\left\{y_{1:T}^1, y_{1:T}^2, \ldots, y_{1:T}^N\right\} = MC^{G_\phi}\left(y_{1t-1}; N\right) \tag{7}$$

$\left\{y_{1:T}^1, y_{1:T}^2, \ldots, y_{1:T}^N\right\}$ represents the N possible sequences generated during the search process, and the discriminant probabilities of all sequences are then averaged to find the value function of the entire sequence:

$$\begin{aligned} & Q_{D_\phi}^{G_o}\left(y_t = y_T, s = y_{1:T-1}\right) \\ & = \begin{cases} D_\phi\left(y_{1:T}\right), & t = T \\ \frac{1}{N}\sum_{n-1}^{N} D_\phi\left(y_{1:T}^n\right), y_{1:T}^n \in MC^{G_\phi}\left(y_{1:-1}; N\right) & t < T \end{cases} \end{aligned} \tag{8}$$

The principle of the discriminator uses a logistic regression-like approach to compute the logarithmic function of the loss and minimize it:

$$\min_\phi - E_{y\sim pdata(x)}\left[\log D_\phi(Y)\right] - E_{y\sim G_e}\left[\log\left(1 - D_\phi(Y)\right)\right] \tag{9}$$

The basic idea of the policy gradient used in the algorithm is to set the feedback parameter to the reward value, increasing the chance of occurrence of behaviors that get a larger reward and decreasing the chance of occurrence of behaviors that get a smaller reward, so that obtaining the reward allows the gradient to be trained, thus updating the parameters.

IV. C. Modeling content generation based on self-attention mechanism

In the process of personalized instructional content generation, the process of generating each content can be regarded as a series of operations taken according to the strategy specified by the generator, which defines the strategy and generates the target content based on the source data. In the improved algorithmic model of this study, the codec structure with self-attention is used as the generator and local modeling expressed in the form of Gaussian deviation [26] is introduced.

The local modeling scheme is designed as a learnable Gaussian deviation G as in Eq:

$$G_{i,j} = -\frac{\left(j - P_i\right)^2}{2\sigma_i^2}, \sigma_i = \frac{D_i}{2} \tag{10}$$

$$\begin{bmatrix} P_i \\ D_i \end{bmatrix} = I \cdot sigmoid\left(\begin{bmatrix} P_i \\ z_i \end{bmatrix}\right) \tag{11}$$

where P_i and D_i represent the center and size of the local range that needs to get more attention, respectively.

The query pair P_i is computed using the query corresponding to the target word i:

$$P_i = U_P^T \tanh\left(W_P Q_i\right) \tag{12}$$

Select the Query-Specific Window method to calculate the window size D_i:

$$z_i = U_d^T \tanh\left(W_p Q_i\right) \tag{13}$$

Finally, a Gaussian bias is introduced into the original attention distribution to achieve a correction so that a locally reinforced weight distribution can be obtained as:

$$ATT\left(Q, K\right) = soft\max\left(energy + G\right) \tag{14}$$

IV. D. Penalty-based objective function

By changing the loss function to avoid the generative network in order to get a higher reward score, and keep generating duplicate content, forcing the generative network to leave the “safe” samples, so as to generate more diversified content. In this study, the concept of objective function in SentiGAN [27] is chosen, and the specific structure is as follows:

A generator G_i is trained to generate a sequence at any time point t:

$$X_{1:t} = \{X_1, X_2, \ldots, X_t\} \tag{15}$$

where X_t represents a vector in a given dictionary C. $G_i\left(X_{t+1} \mid S_t; \theta_g^i\right)$ represents the probability of selecting a $t+1$ th lexicon based on the previously generated words, $S_t = \{X_1, X_2, \ldots, X_t\}$. Define the penalty-based loss function in this study as:

$$L(X) = G_i\left(X_{t+1} \mid S_t; \theta_g^i\right) \cdot V_{D_i}^{G_i}\left(S_t, X_{t+1}\right) \tag{16}$$

where $V_{D_i}^{G_i}\left(S_t, X_{t+1}\right)$ is the penalty term of sequence $X_{1:t+1}$, computed with the discriminator. Finally, the goal of the i rd generator is to minimize the overall penalty term:

$$\begin{aligned} J_{G_t}\left(\theta_g^i\right) &= E_{X \sim p_{p_i}}[L(X)] \\ &= \sum_{t=0}^{t=|X|-1} G_i\left(X_{t+1} \mid S_t; \theta_g^i\right) \cdot V_{D_i}^{G_i}\left(S_t, X_{t+1}\right) \end{aligned} \tag{17}$$

In this study, we choose to use Monte Carlo search combined with roll-out strategy to complete the sampling of the remaining $X-t$ unknown content. In summary, the penalty function of the i nd generator can be expressed as follows:

$$V_{D_i}^{G_i}\left(S_{t-1}, X_t\right) = \begin{cases} \dfrac{1}{N}\displaystyle\sum_{n-1}^{N}\left(1 - D_i\left(X_{1:i}^n; \theta_d\right)\right) & t < |X| \\ 1 - D_i\left(X_{1:i}; \theta_d\right) & t = |X| \end{cases} \tag{18}$$

The objective functions of the three models are compared to the Generative Adversarial Networks, Sequential Generative Adversarial Networks and the algorithmic model of this study:

$$J_G(X) = \begin{cases} E_{X \sim p_g\left[-\log\left(D(X\theta_d)\right)\right]} & GAN \\ E_{X \sim p_g\left[-\log\left(G(X|:_t)D(X:\theta_d)\right)\right]} & SeqGAN \\ E_{X \sim p_g\left[G(X|;\theta_t))(X)\right]} & OurModel \end{cases} \tag{19}$$

IV. E. Simulation results of language teaching content generation

The combination of GAN and natural language processing models can generate coherent dialogues, articles and other text contents. In this section, the traditional GAN model and the PB-ESGAN model of this paper are selected for the simulation comparison experiment of personalized language teaching content generation. The simulation process through the random initialization of the generator and discriminator, iterative training, content generation test, comprehensive verification of the model generation ability and stability, to determine that it can guarantee the generation efficiency and scalability. The evaluation indexes are FID and IS, the lower the value of FID, the closer the generated content is to the students' needs, and the higher the value of IS, the higher the diversity of the generated content.

During multiple iterations of GAN training, the FID and IS metrics of each cycle were recorded and analyzed to track the gradual improvement of the model-generated content. The FID and IS training results of the two models are shown in Figure 5. The results in the figure show that as the number of iterations increases, the FID metrics of the two models decrease significantly and the IS metrics keep increasing, which indicates that the authenticity and diversity of the model-generated content of the two groups are continuously optimized during the training process. Comparison shows that the PB-ESGAN model in this paper converges faster than the traditional GAN model in the training process of FID and IS metrics, and both metrics can complete convergence before 100 rounds of iterations, while the traditional GAN model needs 120 rounds of iterations or even longer to converge. In addition, for the convergence values of FID and IS metrics, this paper's model also achieves better results, with FID and IS convergence values of 9.35 and 7.81, respectively.The training results validate that this paper's model generates significantly higher authenticity and diversity of content for language personalized teaching, indicating that it can achieve the goal of high-quality content generation in language education reform applications.

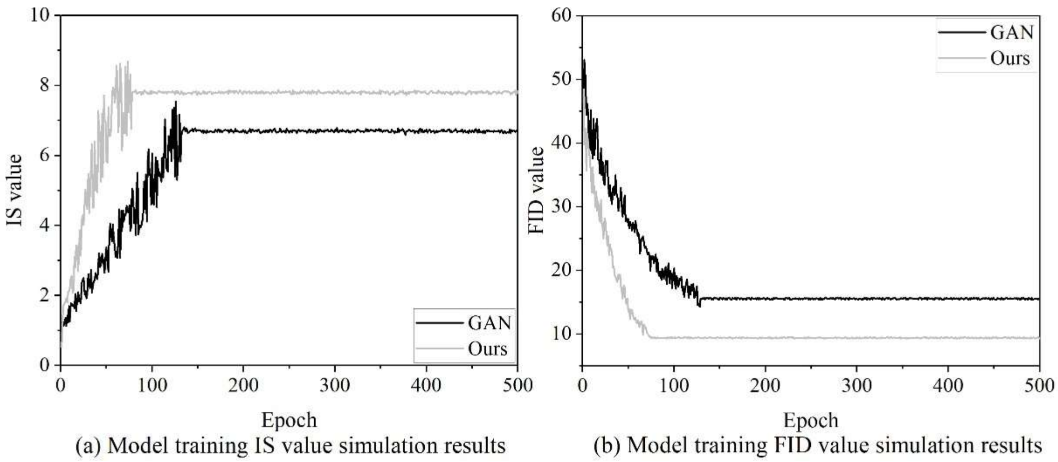

Figure 5: Two model FID and IS value training results

Generative testing of different categories of language teaching content using a generator trained to the desired effect. The language teaching contents include, reading teaching, writing teaching, language learning, ancient poetry learning, and comprehensive ability. The generated teaching contents were evaluated by automation in terms of authenticity and diversity, and the simulation results of the generated contents for language teaching are shown in Fig. 6. The results in the figure show that the generator used in this paper exhibits high content quality and diversity in the generation of specific teaching content, which verifies the superiority of the PB-ESGAN model in language teaching reform. Especially in the ancient poetry learning content generation, the low FID value (11.54) indicates that the generated content's is close to the authentic teaching content. The IS value reaches 4.14, reflecting a high diversity of generated content. In addition, the FID in the generation of other categories of instructional content such as reading instruction ranged from 12.57 to 14, and the IS ranged from 5.19 to 5.69, which showed the adaptability and stability of the PB-ESGAN model generator in multiple categories of instructional content.

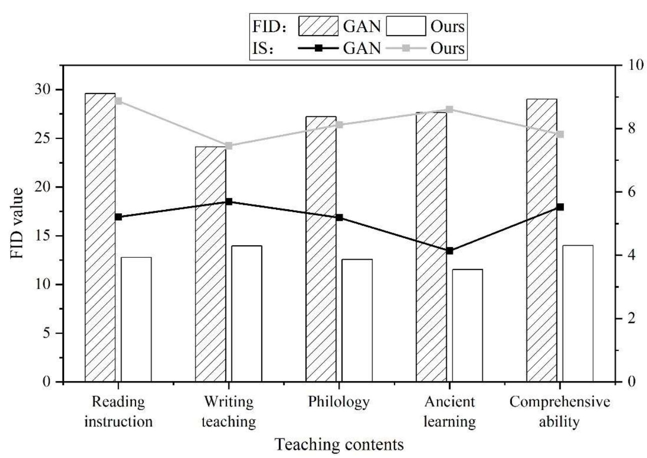

Figure 6: Language teaching generates content simulation results

V. Research on teaching adaptation methods based on the recommendation of online learning resources

V. A. Model framework for recommending language teaching resources

In this section, a personalized push and match method for online teaching resources based on the PB-ESGAN model is proposed for the study of personalized teaching content suitability in language education.

The framework of the online learning resource recommendation model based on PB-ESGAN is shown in Fig. 7. First, the raw data are input into the feature extraction layer to extract all the user feature vectors and all the online learning resource feature vectors, and then the user feature vectors are input into the generator model respectively, so that the generator model generates the feature vectors of the online learning resources that may be of interest to these users. Taking user u and user u interested in e-learning resource i as an example, using $q'u$ to represent the eigenvector of the e-learning resource that user u may be interested in generated by the generator, splicing the eigenvector p_u of user u with the eigenvector q_u' of the e-learning resource that user u may be interested in generated by the generator, recording the vector obtained by this splicing as v_f, the eigenvector p_u of user u and the eigenvector q_i of e-learning resource i as splicing, and denoting the vector obtained by splicing as v_r, then:

$$v_f = \begin{bmatrix} p_u \\ q' \end{bmatrix} \tag{20}$$

$$v_r = \begin{bmatrix} p_u \\ q_i \end{bmatrix} \tag{21}$$

Inputting v_f and v_r into the discriminator model, respectively, eventually yields the predicted value of the output of the discriminator model. It can be defined as:

$$\hat{y}_{ui} = f\left(p_u, q_i \mid \Theta f\right) \tag{22}$$

where Θf represents the parameters of the model.

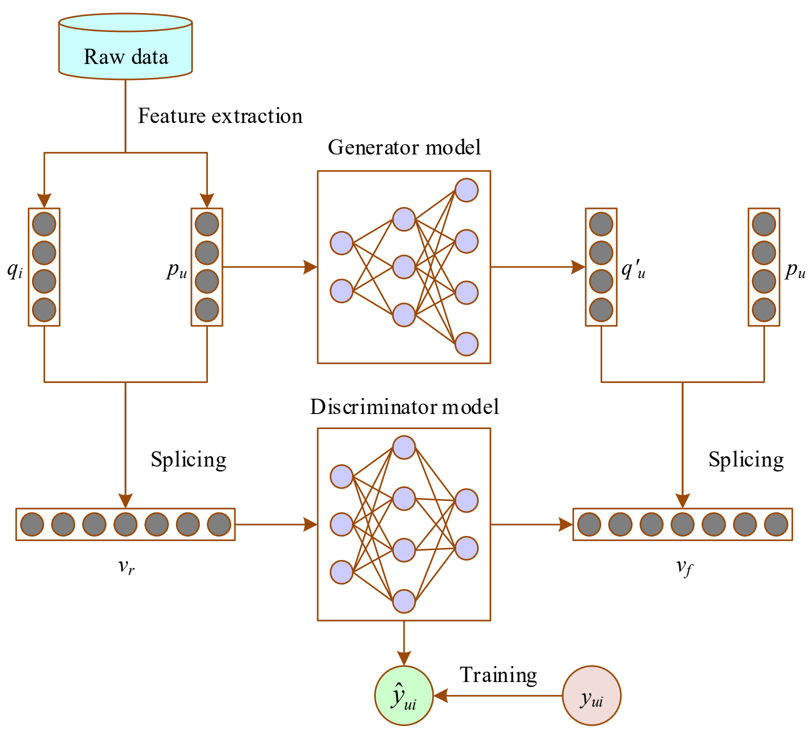

Figure 7: PB-ESGAN based E-learning recommendation model framework

V. B. Feature Extraction Layer

The main work carried out in the feature extraction layer is to extract the features of learners and online learning resources, so as to obtain the feature vector of each learner and online learning resource. In this paper, normalization is used to achieve feature extraction, because after the data has been normalized, the optimization process of the optimal solution during training will obviously become smoother, and it is easier to converge to the optimal solution correctly.

The normalization process [28] employs a sigmoid function with scaling and offset parameters to normalize the features, and adjust the scaling and offset parameters to make the distribution of values of different learners or features of the online learning resources as wide as possible after the normalization process. For example, for a value of x before normalization, it becomes $\frac{1}{1+e^{-ax+b}}$ after normalization, where a and b are the scaling offset parameters. The special treatment of timestamps is to sort the learning resources interacted with by the same user according to the chronological order of the timestamps, where each learning resource appears only once in the sorted sequence of learning resources for a user. For example, if user A has interacted with learning resource A,C,A,B,D in chronological order, then, for user 4, the learning resources he has interacted with are sorted as A,C,B,D, and learning resources A,B,C,D have their features 1, 3, 2, and 4, respectively, from the behavior of user 4. The feature represents that the learning resource accessed by the user is the first one accessed by that user. After counting all the access records of the users, the features of the learning resources obtained from the counting are averaged once to get the final temporal features of the learning resources f_t^i.

After obtaining all the above features, using p_u to denote the feature vector of the learner u and q_i to denote the feature vector of the online learning resource i, then:

$$p_u = \left[f_1^u, f_2^u, f_3^u, f_4^u, f_5^u, f_6^u, f_7^u \right] \tag{23}$$

$$q_i = \left[f_{t^i}, f_1^l, f_2^t, f_3^t \right] \tag{24}$$

V. C. Generator Model

Using z_n to denote the output of layer n of the deep neural network, this generator model can be defined as follows:

$$\begin{gathered} z_1 = \phi_1(p_u) = [p_u] \\ \phi_2(z_1) = a_2\left(W_2^T z_1 + b_2\right) \\ \cdots\cdots \\ \phi_L(z_{L-1}) = a_L\left(W_L^T z_{L-1} + b_L\right) \\ q_u' = \sigma\left(h^T \phi_L(z_{L-1})\right) \end{gathered} \tag{25}$$

where L denotes the number of layers of the deep neural network, W_x denotes the weight matrix of layer x of the deep neural network, b_x denotes the bias vector of layer x of the deep neural network, and a_x denotes the activation function of layer x of the deep neural network.

Define the process in the generator model as:

$$G_{out} = G_\theta(p_u) \tag{26}$$

where G_{out} is the output of the generator model and θ is the parameter in the generator model.

V. D. Discriminator Modeling

Using z_n to denote the output of layer n of the deep neural network when input v_r to the discriminator model and z_n' to denote the output of layer n of the deep neural network when input v_f to the discriminator model, this discriminator model can be defined as follows:

$$\begin{gathered}
z_1 = \phi_1(v_r) = [v_r] \\
z_1' = \phi_1'(v_f) = [v_r] \\
\phi_2(z_1) = a_2\left(W_2^T z_1 + b_2\right) \\
\phi_2'(z_1') = a_2\left(W_2^T z_1' + b_2\right) \\
\cdots \\
\phi_L(z_{L-1}) = a_L\left(W_L^T z_{L-1} + b_L\right) \\
\phi_L'(z'_{L-1}) = a_L\left(W_L^T z'_{L-1} + b_L\right) \\
\hat{y} = \sigma\left(h^T \phi_L(z_{L-1})\right) \\
y' = \sigma\left(h^T \phi_L'(z'_{L-1})\right)
\end{gathered} \tag{27}$$

where W_x denotes the weight matrix of layer x of the deep neural network, b_x denotes the bias vector of layer x of the deep neural network, a_x denotes the activation function of layer x of the deep neural network, $\hat{y}$ denotes the output of the discriminator model when input v_r to the discriminator model, and $\hat{y}'$ denotes the output of the discriminator model when input v_f to the discriminator model.

For ease of writing later, we define the process in the discriminator model as:

$$D_{out} = D_\varphi(v) \tag{28}$$

where L denotes the number of layers of the deep neural network, D_{out} is the output of the discriminator model, v denotes vector v_r or vector v_f, and φ is a parameter in the discriminator model.

V. E. Analysis of the suitability of language teaching resource recommendations

In order to validate the effectiveness of a language learning resource adaptation recommendation method based on generative adversarial networks, the study used a crawler program to crawl the language courses and user-related data in an online learning website. After cleaning, the dataset includes 4464 course-related learning resource profiles and 1656 users with learning records.

The training of this experimental model is built on top of the TensorFlow open-source framework, and two sets of key features are obtained by in-depth feature extraction of learner information and course information through neural networks, and transferred into the fully connected layer. In order to verify the performance of the personalized resource adaptation algorithm in this paper, when the number of recommendations is 5, 10, 15, 20, 25 and 30, respectively, the SVD (Singular ValueDecomposition), CF (Collaborative filtration), LSTM (Long Short-TermMemory), LSTM (Long Short- TermMemory) and the four methods in this paper are compared in terms of checking accuracy, recall and F1 value.

The check accuracy, recall and F1 values of different recommendation algorithms are shown in Fig. 8. When the number of recommended learning resources is small, SVD, collaborative filtering method, LSTM method and this paper's method have high recommendation accuracy rate. As the number of recommendations increases, the recommendation precision of each algorithm starts to decrease while the recall rate starts to increase. The analysis of F1 value shows that the magnitude of change in F1 value is smoother than precision rate and recall rate. The check accuracy rate, recall rate and F1 value of this paper's algorithms are greater than the comparison algorithms for different number of recommendations, where the F1 value is increased by 18.33% to 42.08% compared to the comparison algorithms. The personalized recommendation performance of teaching resources is used to further grasp the content appropriateness in language teaching. The results illustrate that the adaptation method based on generative adversarial network in this paper can provide learners with accurate teaching resources.

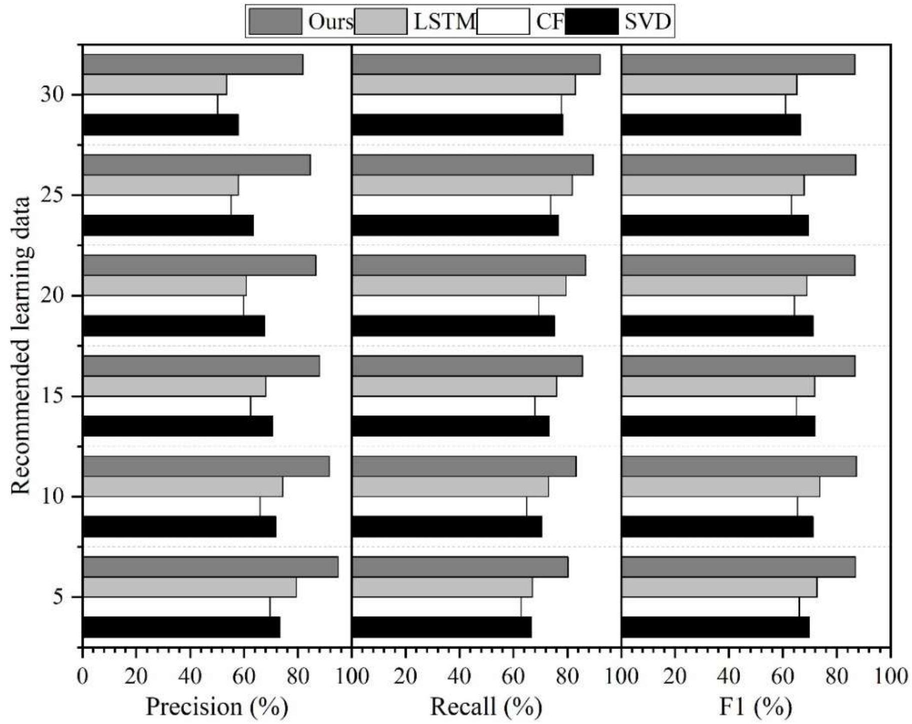

Figure 8: The precision, recall rate and F1 value of different algorithms

VI. Analysis of the effectiveness of reform methods based on teaching cases

VI. A. Assessment of teaching effectiveness at the language learning level

In order to verify the actual effectiveness of the methodology proposed in this paper in improving students' language learning, the teaching of language in eighth grade classes 1 and 2 of the pilot school mentioned above was the object of the study. These two classes have 50 students each, with similar average scores on the most recent test, and are taught by the same language teacher. During this experiment, it was hypothesized that a personalized instructional content generation and resource adaptation system based on the PB-ESGAN model would improve students' average language proficiency.

For class 2, the strategy proposed in this paper was deployed, which included resources of various media types such as PPT, text, video, and audio. These resources were pushed to the students in class 2 for pre-study and review according to their course progress and language learning style. For Class 1, the strategy in this paper was not deployed, but only all the course materials were uploaded to the e-platform and students were verbally informed by the teacher to do the pre-reading on their own.

Two months after the implementation of the language education reform strategy, the language proficiency of students in Class 1 and Class 2 was assessed. The assessment indicators mainly include engagement, interaction, and concentration. Among them, engagement was mainly measured by calculating the number of monthly visits to the resource library and the average length of study for each student. Second, the degree of interaction is mainly measured by the number of online interactions and the number of classroom interactions. Third, attentiveness was mainly measured by the number of times the content was viewed and the average score on the final quiz.

After 2 months of language instruction, the results of the language proficiency assessment of students in Class 1 and Class 2 are shown in Table 1. As can be seen from the table, Class 2's participation, interaction, and concentration were significantly improved with the use of this paper's method.The final quiz scores of the students in Class 2 increased significantly from 75.69 to 84.71 compared to the previous test, while Class 1's scores did not show any significant improvement compared to the previous test. It can be concluded that the method of personalized content generation and adaptation in language education in this paper has a more significant effect on the improvement of students' language proficiency.

Table 1: The results of the language ability of the two students

Group		Class one		Class two	
		Pre-test	Post-test	Pre-test	Post-test
Participation	Resource access times	7	8	6	59
	Resource access time	417	535	442	4325
Interaction degree	Online interaction times(min)	13	16	15	82
	Offline interaction times	21	26	22	64
Concentration	The number of subjects of teaching	11	14	13	45
	Test score	76.21	78.44	75.69	84.71

VI. B. Language Reform Classroom Satisfaction Survey

At the end of the course, a questionnaire survey was conducted through Questionstar, focusing on students' experiences, perceptions and attitudes towards the use of self-directed learning task sheets. A total of 50 questionnaires were distributed and 50 questionnaires were returned with a recovery rate of 100%. Among them, there were 50 valid questionnaires and 0 invalid questionnaires, with an effective rate of 100%. The results of the satisfaction of the language classroom under the method of this paper were analyzed from the four dimensions of learning tasks, learning resources, learning process and teaching content.

Figure 9 shows the results of students' satisfaction with the language classroom under this paper's method. It can be seen that students' satisfaction with the learning tasks is the lowest among the four dimensions, with an average satisfaction score of only 4.13. Data analysis reveals that students who are able to complete all the learning tasks are usually those who have better academic performance and learning ability in general. In the process of completing the tasks, most of the students would encounter problems that prevented them from completing some of the tasks, while a few students could only complete a small number of tasks. And the satisfaction score of teaching content is the highest at 4.76, which indicates that the PB-ESGAN model in this paper can provide personalized teaching content according to different learner profiles. The generated language teaching content is accurate, clear and meets students' needs. In addition, the learning resource satisfaction and learning process satisfaction scores are 4.64 and 4.39 respectively, indicating that the teaching resources recommended by the model in this paper are targeted, do not require students to waste a lot of time on finding resources, and are sufficient to support students' independent learning. The way used in teaching, which requires more than one person to work together to complete the way can be brainstorming, and at the same time cultivate students' team spirit and sense of cooperation, so that every student is involved in language learning.

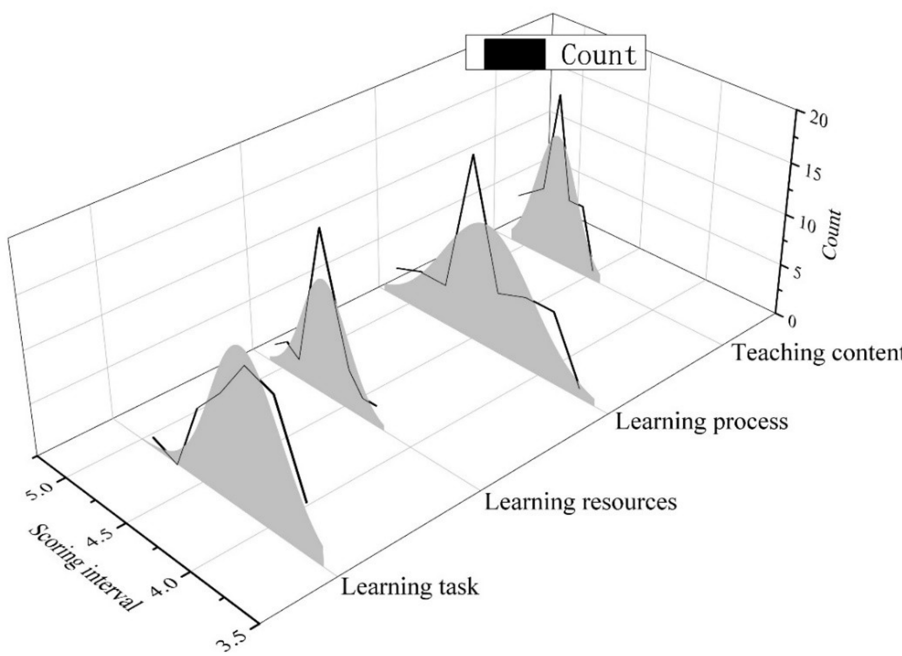

Figure 9: The students' satisfaction survey results in this article

VII. Conclusion

The article conducts a field visit and questionnaire survey on language education reform in a city experimental school, and proposes a generative adversarial network method for personalized teaching content generation and adaptation in language education based on the survey results. The method takes learner profiles and teaching objectives as inputs, and automatically generates diversified teaching text content that meets students' individualized needs. In addition, based on the dynamic learning situation of students, the difficulty level of the teaching content is adjusted in real time to realize accurate recommendation and matching of teaching resources. The technology is practiced in the above experimental schools to verify its effectiveness in language education reform. The results of the study are as follows:

The portraits of language learners constructed in the study are categorized into: self-disciplined learner type, online learner type, lack of planning and to be improved type. This paper's model FID and IS index training convergence speed is faster than the traditional GAN model, in the iteration 100 rounds before the two indicators can complete the convergence, in different types of language teaching content generation in the FID value and IS value were between 11~14 and 4~6 respectively. Moreover, the checking rate, recall rate and F1 value of the model's language teaching resources recommendation are better than those of the comparison algorithms, demonstrating the superior adaptability of teaching resources recommendation. At the end of teaching, the test scores of students in class 2 increased from 75.69 to 84.71, which is significantly higher than that of class 1. Under the model intervention in this paper, the satisfaction of students in class 2 for learning tasks, learning resources, learning process and teaching content ranged from 4.13 to 4.76 points, with a higher overall satisfaction.

Compared with traditional deep learning algorithms, the teaching content generation and adaptation method designed in this paper can effectively improve the scientific and richness of teaching content generation, have higher accuracy of resource recommendation, and meet the personalized needs of students at different learning stages and learning styles. In the future, the recommendation algorithm can be further optimized to improve the accuracy of the recommendation system, increase the variety of teaching resources, and conduct in-depth research on the learning styles of different subject areas.

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