Adaptive Recommender System for an Intelligent Classroom Teaching Model

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Abstract—The development of information technology has facilitated the use of intelligent classroom models supported by information technology to improve the college students' comprehensive quality and ability. However, the existing models are too sophisticated to be applied to the actual teaching process, and ignore the individualized teaching characteristics of students. Therefore, an intelligent classroom model with adaptive learning resource recommendation is proposed. First, the entire teaching process was divided into three stages which were used to combine teachers' teaching and students' learning. Second, the key problems of the learning resources recommendation system were studied and a learning resource recommendation based on Teaching Resources-Latent Dirichlet Allocation (TR-LDA) is proposed. It used an improving structure model of three layers (documents, theme, and words). The proposed intelligent classroom model was verified in practical teaching. The results show that the new model with adaptive learning resources recommendation can help to improve students' learning efficiency. The relevant conclusions can be used as a reference for exploring the use of information technology to improve the quality of undergraduate professional course teaching.

Keywords—Intelligent classroom, learning resource recommendation, Dirichlet, university education

1 Introduction

With the expansion of the higher education admissions, the education division and some scholars believed that the quality of the undergraduate education has to be improved. Opinions on deepening undergraduate education reform jointly issued by the Ministry of Education, the National Development and Reform Commission and the Ministry of Finance (2013) pointed out that, "at present, higher education is not fully adapted to the needs of economic and social development, and there is still a big gap between the quality of cultivation and the international advanced level". High-quality undergraduates have made considerable contributions to scientific research innovation and economic development. A survey showed that more than 58% of scientific research projects involved undergraduate students [1]. Education authorities and some scholars have pointed out that large gap exists between innovation ability of undergraduate and the construction demand of an innovative country. Improving the teaching quality of undergraduate specialized courses has become an important issue concerned by education authorities and scholars.

The development of information technology based on network information technology has facilitated the wide use of intelligent information technology such as artificial intelligence [2] big data, Internet of things [3], cloud computing and mobile Internet in classroom teaching. This utilization brings profound transformation to college teaching. From multimedia teaching software, learning management system, online interactive learning platform to smart education cloud platform, information technology is promoting the development of classroom teaching reform in depth with its irreplaceable advantages [4]. Intelligent classroom, which is a new mode of classroom teaching, emerges at the historic moment, facilitates the deeper integration of information technology and classroom teaching, and provides new ideas for the reform of college course teaching.

The learning environment created by intelligent classroom fully integrates teaching resources into the learning environment, records the learning process and has flexibility, practicality and interactivity [5]. However, the current classroom still uses hardware as the means to share resources and push the teaching contents and does not apply intelligent information technology such as big data in the teaching design by the individualized adaptive teaching [6]. Developing a new approach that integrates individualized and adaptive teaching strategies; introducing it in the intelligent classroom model; and applying the model to learn, promote individualized learning initiative, and improve the teaching quality of the undergraduate course are interesting tasks.

2 State of the Art

Intelligent classroom and smart learning are new major directions in the development of education informatization at present. The education informatization in university are the objective trend of development from idea to practice, from macroscopic to concrete, and from implementation to classroom teaching.

Under the information age, intelligent classroom has gradually emerged. It is found that the study of the intelligent classroom is mainly reflected in two aspects after the investigation and study of foreign literature. The first aspect is to study the construction of learning models related to learning activities, and to explore the individualization, autonomy and diversity of students' learning methods. Rachida AJhoun and Benkiran believed that learners can conduct personalized and autonomous learning at their own pace and can selectively learn knowledge [7][8].

Liu Bangqi argued that intelligent classroom is constructed on the basis of constructivism theory, and uses the thinking mode of "Internet +"and the new generation of information technology, such as Internet of things, big data, and cloud computing; intelligent and efficient classroom is applied in the entire process (i.e., before, during, and after class) [9] [10]. Tang Yewei sorted out the different application levels of the integration of intelligence classroom and teaching, and summarized them as translational, integration point-targeted, revolutionary learning, and wisdom applications; the construction method of intelligent classroom was proposed with the aim of changing the teaching model [11]. The current study attempts to decompose and analyze various elements in the learning process of intelligent classroom, and designs a learning mode based on intelligent classroom to promote the integration of technology and learning in intelligent classroom.

The second aspect is the promotion of learning by the technical means of intelligent classroom. Rania Albalawi believed that learning on mobile terminals with physical interaction interfaces will help children's overall development and social skills [12]. Kristopher Scott argued that the types of classroom teaching, such as terminal ,can enhance students' learning process, and record students' performance in the teaching activities, these methods can also be used to introduce personalized learning resources and support real-time group collaboration and earning resource sharing between students and teachers [13][14].Lin Liyao developed "mobile" intelligent terminal applications, on the basis of the intelligent terminal electronic schoolbag "smart classroom system" to provide highly efficient "teaching "and "learning" modes for teachers and students [15].

The literature analysis indicates that the application of intelligent classroom as a new media technology in teaching has gradually attracted the attention of researchers at home and abroad. Many researchers have put forward the model framework of intelligent classroom application from the theoretical level to provide theoretical guidance for practical work. However, the studies on intelligence classroom all over the world are still relatively weak, and most of them on intelligence classroom is at the level of model construction or application of new media equipment. The above-mentioned model also separates teachers' teaching from students' learning, which is not conducive to the integration of teaching and learning. In addition, only few models can provide individual learners with learning resources depending on their learning situation and interest.

Emerging technologies can play a positive role and have a profound impact on the application of education and teaching only when they are effectively combined with advanced educational concepts, teaching methods and teaching models. Therefore, a practical teaching intelligent classroom model that integrates teaching and learning need to be studied and built, and an adaptive learning recommendation algorithm need to be designed for the model to realize the personalized needs of learners.

The rest of the paper is organized as follows. Section 3 introduces of the design process of practical intelligence class model, the proposed learning resources recommendation algorithm basic on teaching resources-latent Dirichlet allocation (TR-LDA), and the implementation method of the model and its algorithm. Section 4 introduces the verification of the intelligent classroom model based on adaptive learning resource recommendation in practical teaching. Section 5 elaborates the conclusions of this study.

3 Methodology

3.1 Practical model design of intelligent classroom

The aforementioned analysis indicates that the principle of the ideal "8+8" classroom model comprise eight steps of teacher's "teaching" and eight steps of the students' "learning". The eight steps of "teaching" are learning statistics, resource distribution, teaching design, project import, new task, earnest reviews, personalized push, and checking of students' papers. The eight steps of "learning" are preview and homework, class discussion, sharing, cooperation, exploration, in-class test, ascension consolidation, homework completion, and summary reflection. However, this model is too complex to be applied in the actual classroom teaching. The five traditional "5+4" teaching model is composed of five steps of teachers' "teaching" and four steps of students' "learning" The five steps of "teaching" are lesson preparation, teaching, question asking, homework assignment and homework correction. The four steps of "learning" are preview, listening to lectures, answering questions, and completing homework. This model is too simple. Thus, we adopt a compromise method and integrate teacher' teaching and student' learning. The "ten stages with two supports and one center" model (as shown in Fig.1) is abstracted as a practical model for implementing the intelligence classroom. The two supports refer to the before and after. The purpose of doing well before and after class is to support the actual class. A center is to point to in the course and highlight the central position in the course. The ten stages refer to the three stages of resource push, preview communication and assessment positioning before class the four stages of group discussion, teacher and student study, effect diagnosis and summary analysis during class; and the three stages of digestion and consolidation, homework self-test, and reflection refining after class. A closed circuit is formed before, during, and after class. The specific operation of the model is shown as follows.

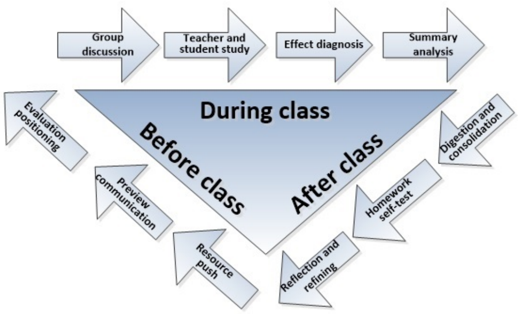

Fig. 1. "Ten stages with two supports and one center" model

Before-class support is based on the adaptive learning resources recommendation: The before-class support is divided into three stages: resource push, preview communication, and evaluation positioning. This support, which is the first step of each teaching cycle, is intended to prepare for the class, lay a good foundation and divide students into groups among three stages, resource push is particularly critical. This stage of resource push recommends resource with adaptive technology by intelligent data depending on students' past learning situations, interests, and habits, in combination with the rich media of learning resource database constructed by teachers. This stage aims to meet the demand of students' learning ability based on preview, improve the efficiency of preview, and achieve the result of students' aptitude. The proposed resource recommendation algorithm for the proposed model will be discussed later. In the stage of preview communication, the content pushed by resources is used for targeted preview. Problems encountered in the process of preview are communicated through real-time interactive technology, non-real-time technology of text or voice messages for students to interact with one another, teacher-student interaction, and human-computer interaction. Discussion and exchange of some contents and key knowledge points can also be conducted to deepen understanding and achieve strong preview effect. After preview communication, positioning is needed to preview the evaluation effect. Evaluation orientation can group students into four to six according to the different degrees knowledge.

Center focused on studying and learning of teacher-student in class: The four stages during class, are group discussions, teacher and student study, effect diagnosis, and summary analysis. With the support and preparation before class, students mainly communicate with teachers on problems that are difficult for them, those they do not understand, and those that they fail to reach consensus. The teacher also studies and discusses with students through before-class test communication and the situation reflected by classmates to solve the problems that confuse students and those that they do not understand. This stage focuses on the study of teachers and students. This stage of group discussion intends to distinguish students who have mastered the knowledge points well from those who have not mastered the knowledge points firmly. The knowledge points are clearly by excellent students to help poor students to achieve the purpose of common progress. In this process, if no understanding is obtained within the group and consensus is not reached, then the problem can be pushed to the group for discussion and communication. In the stage of teacher and student study, students provide feedback through group discussion, and the teacher determines the relatively topics, key, and difficult topics based on the class group feedback and explains them accordingly. Students who have topics in the course can interrupt the teacher and ask the teacher to study the topic together. Effect diagnosis is also carried out during class. The teacher pushes the classroom diagnosis questions to students through the intelligent class support system. Students finish the questions within the prescribed timeline through smart terminals (e.g. mobile phones and tablets), submit and complete the diagnosis, and obtain the diagnosis results in real time. Diagnostic statistics are displayed on the teacher's large screen, from which the learning effect can be visibly observed. Summary analysis is aimed at the first three stages of before class and the first three stages of during class. This stage determines students' learning situation, summarizes the learning effect and analyzes the existing problems and solutions to these problems. The entire process of during class is recorded by the data acquisition module of the intelligent classroom system and transmitted to the system in real time. In this way, teachers and students can analyze the learning process after class.

After-class support centered on reflection and refining: After-class support is divided into three stages: digestion and consolidation, homework self-test, and reflection and refining. After learning in class, students should have a basic grasp of all knowledge points and a certain understanding of the content of the course. However, the grasp of the learning content is insufficiently strong in some cased. The ability of using the knowledge to analyze specific problems needs to be improved, which requires another support in the course through this stage. In the stage of digestion and consolidation, we should digest the knowledge learned and the enlightenment gained from group discussion and communication, and absorb the knowledge the teachers interpreted in class to make it a part of our knowledge system. We should also re-learn the doubtful knowledge points through micro-video to deepen our memory and consolidate our knowledge. The homework self-test stage is not only an objective evaluation of the previous knowledge but also an exploratory analysis of related practical problems. In this process, the teacher corrects the students' subjective homework through the intelligent classroom system and provides timely guidance to form a system for automatically correcting the objective questions. The online teacher corrects the subjective questions by human and machine cooperation. This system of after-class homework correction and guidance process timely guides students in using the knowledge learned to analyze practical problems. Reflective refining stage is the last stage of a complete teaching process and is the core of after class. The learner reviews and summarizes the entire learning process; summarizes and refines the key problems, learning experience, and gains in the learning process; forms a unique learning method and path; and records it in his or her own way and language.

3.2 Learning resource recommendation algorithm

Model design of TR-LAD learning resource recommendation algorithm: Resource recommendation algorithm has collaborative filtering method [16], association rule method [17], and preference mining method of browsing [18]. Meanwhile, latent Dirichlet allocation (LDA) model was first put forward by Blei [19]. LDA is a structure model of three layers and is based on probability as a condition, including documents, theme, and words. LAD is also based on correlation of words and documentation, modeled by means of document and excavated by the potential themes. LDA has brought convenience in investigation using Weibo and other social networks [20] and gradually became a major means of research. The process of proposed TR-LAD learning resource recommendation is shown in Fig. 2.

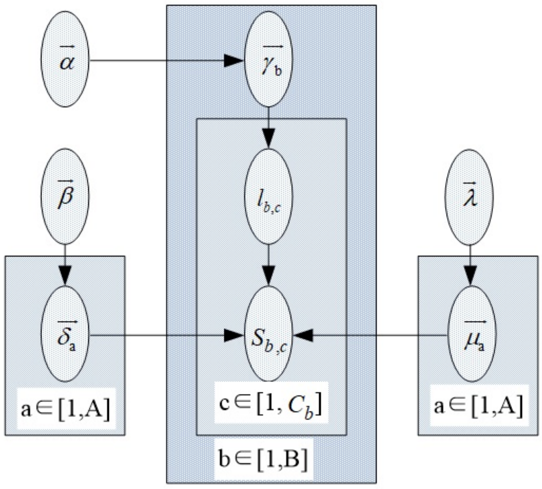

Fig. 2. Process diagram of TR–LDA learning resource recommendation

We assume B learning resource banks (different resource banks established by different teachers) and a learning resource category in a teaching system. Then, the generation process of TR-LDA learning resource recommendation model is described as follows:

- $\vec{\lambda}$ is a Dirichlet [21] prior parameter, and the distribution of learning resources in user reading category a is selected from the Dirichlet prior distribution of $\vec{\lambda}$, and $\vec{\mu}_a$ is a v-dimensional vector (V is the total number of learning resources).
- $\vec{\alpha}$ is the Dirichlet prior parameter, and the distribution of categories in the b-th learning resource base is $\vec{\gamma}_b$ and K-dimension vector (K is the total number of categories) selected from the Dirichlet prior distribution of $\vec{\alpha}$.
- $l_{b,c}$ selects the category of the c resource in the b learning resource base on the premise of selecting the b learning resource base.
- $\vec{\beta}$ is a Dirichlet prior parameter. The Dirichlet prior distribution of $\vec{\beta}$ is randomly selected to choose the distribution $\vec{\delta}_a$ of resources in browse resource category a, which is a V-dimensional vector (V is the total number of learning resources).
- $s_{b,c}$ represents the c learning resource in the b learning resource database (learning resource C_b). $\vec{\lambda}$, $\vec{\alpha}$, and $\vec{\beta}$ are prior parameters given accordance with practical experience. In accordance with the TR-LDA model, the joint probability distribution of all variables in Fig.2 is (1)

$$P(\vec{s_c},\vec{l_b},\vec{\gamma_b},\underline{\delta},\underline{u}\mid\vec{\lambda},\vec{\alpha},\vec{\beta})=\prod_{c=1}^{c_b} P(s_{b,c}\mid\overrightarrow{\delta_{l_{b,c}}},\overrightarrow{u_{l_{b,c}}})$$
$$P(l_{b,c},\vec{\gamma_b})P(\vec{\gamma_b}\mid\vec{\alpha})P(\underline{\delta}\mid\vec{\beta})P(\underline{u}\mid\vec{\lambda}) \quad (1)$$

The probability distribution of t when each learning resource is initialized is shown as (2)

$$P(s_{b,c}=\mathrm{t}\mid\vec{\gamma_b},\underline{\delta},\underline{u})=\sum_{a=1}^{A} P(s_{b,c}=\mathrm{t}\mid\vec{\delta_a},\vec{u_a})P(l_{b,c}=a\mid\vec{\gamma_b})$$
$$=\sum_{a=1}^{A} P(s_{b,c}=\mathrm{t}\mid\vec{\delta_a})P(s_{b,c}=\mathrm{t}\mid\vec{u_a})P(l_{b,c}=a\mid\vec{\gamma_b}) \quad (2)$$

The formula above finds the product of the probability of browsing resource c under category a and the probability of collecting resource c under category a multiplied by the probability of category an appearing in the resource pool. Considering that resources under the following two special circumstances have high probability to become recommended objects, only one item with a non-zero probability is taken at this time:

- A learning resource has a high probability of being browsed but has never been bookmarked, that is, $P(s_{b,c}=\mathrm{t}\mid\vec{u_a}) = 0$.
- The probability of collecting a learning resource is relatively high in the past, but was never browsed again, that is, $(s_{b,c}=\mathrm{t}\mid\vec{\delta_a}) = 0$; Thus, the likelihood function of teaching resources in the entire learning resource database can be obtained as (3)

$$P(s=\mathrm{t}\mid\underline{\gamma},\underline{\delta},\underline{u})=\prod_{b=1}^{B} P(\vec{s}\mid\vec{\gamma},\underline{\delta},\underline{u})=\prod_{b=1}^{B}\prod_{c=1}^{c_b} P(s_{b,c}\mid\vec{\gamma},\underline{\delta},\underline{u}) \quad (3)$$

Learning resource recommendation algorithm and analysis: The proposed TR-LDA model is applied in the learning resource recommendation system of intelligent classroom to determine the potential learning resources that students are interested in. Through the analysis and derivation of the model above, the algorithm of this model can be designed depending on the generation process of TR-LDA model. The pseudo-code description is shown in Table 1.

Table 1. Algorithm of TR-LDA model

Input: datasets of reading history; parameters $\vec{\lambda}, \vec{\alpha}$ and $\vec{\beta}$.
Output: recommended teaching resources.
1: Calculate the total number of teaching resource C_b.
2: Calculate the total number of categories A.
3: Calculate the total number of teaching resource bases B.
4: Sample a teaching resource base b randomly.
5: Initialize an array G［n］for storing teaching resources.
6: For a = 1 to A do
7: Sample distribution $\overrightarrow{\mu_a}$ ~Dirichlet ($\vec{\lambda}$) .
8: Sample distribution $\vec{\delta_a}$ ~Dirichlet ($\vec{\beta}$) .
9: End for
10: For b = 1 To B do
11: Sample distribution $\overrightarrow{\gamma_b}$ ~Dirichlet ($\vec{\alpha}$) .
12: For c = 1 To C_b do
13: Sample category $l_{b,c}$ according to $\overrightarrow{\gamma_b}$.
14: Sample resource $s_{b,c}$ according to $\overrightarrow{\delta_{l_{b,c}}}$ & $\overrightarrow{u_{l_{b,c}}}$.
15: Put $s_{b,c}$ into G.
16: End for
17: End for
18: Return G.

According to the above-mentioned description of the algorithm, some variables in the execution of the algorithm are obtained by Gibbs sampling [22], and the probability calculation is carried out. The recommended learning resources are stored in the array G [n], and finally G is returned. The algorithm analysis indicates that the time required for the completion of execution of the first part for loop is O (A), and the time required for the completion of nested execution of the second part for loop is O (B$\cdot C_b$) ＜O (B·n) ≤O (n^2), where n = max {C_b|b∈［1，B］}.Thus, the time complexity of TR-LDA algorithm is less than O (n^2).

4 Result Analysis and Discussion

Theoretically, we believe that cloud computing, big data, and new generation of information technology (e.g. Artificial Intelligence) in combination with the recommendation algorithm of adaptive learning resources can be used to build a highly efficient of teaching process before, during and after class This model can improve the students' academic performance and cultivate a large number of intelligent students. An experiment, which was supported by the platform that was designed by our project group, was conducted to demonstrate the practicability and effectiveness of the proposed model .The platform centered at students on the basis of adaptive learning resource recommendation , and the management information system course was introduced to 50 students of information management and information systems .These students were randomly divided into the experimental (supported by intelligent classroom) and normal group (traditional course), of 25 people each. The two groups of students had no significant difference in cognitive ability. Each group was further divided into students of weak foundation (0-40 points) and students of good foundation (50-90 points) depending on the test results before the experiment. During the 3-month learning process, all students in the experimental and normal groups were tested after the experiment of knowledge points. The comparison results are shown in Table 2.

Table 2. Comparison results for experimental and normal groups

Group	Experimental group		Normal group	
Student	***Students of weak foundation***	***Students of good foundation***	***Students of weak foundation***	***Students of weak foundation***
Score before experiment	35	56	34	57
Score after experiment	69	70	56	68
Extracurricular learning time (minutes)	3840	3360	4380	4260
Number of communicating questions with classmates	23	18	11	9
Number of communicating questions with teachers	7	6	4	3

The data in Table 2 shows that the grade improvement effect is most evident for students of weak foundation in the experimental group. Specifically, the score before experimental test is 35, which increases to 69 after the experimental test. By contrast, the score of students of good foundation in this group only slightly increase from 56 to 70. Students of good foundation in the experimental and normal groups show no significant difference in learning result. The reason is that students of weak foundation completely follow the recommended path and learning resources by the system. By contrast, students of good foundation have strong autonomy and do not follow the recommended path and learning resources by the system. The intelligent classroom model based on the learning resource recommendation algorithm is effective for the intervention and guidance of students of weak foundation. Regardless whether students have good or weak foundation, the intelligent model shortens students' learning time, and improves learning effect .Given the recommendation of teaching resources, students do not have to spend much time to find relevant learning materials and can receive targeted exercises, thereby greatly improving their learning efficiency. Using this model, students in the experimental group have raised a large number of questions and have considerable communication with one another and with teachers. Therefore, using this model facilitates communication, promotes the interaction between teachers and students and among students, and improves academic performance.

The above-mentioned analysis shows that the use of the "ten stages with two supports and one center" model can improve the academic performance of college students, (i.e., students of weak foundation), reduce the extracurricular learning time of students, improve the learning efficiency of students, and promote the interaction and communication between teachers and students and among students. The teaching effect of this model is evident.

5 Conclusion

Emerging technologies and advanced education concepts and teaching methods and modes aim to improve the quality of college students' learning by using the new science and technology of undergraduates' ability to effectively train. On the basic of existing models of the intelligent classroom and in-depth study, the "ten stages with two supports and one center" model with learning resources recommendation algorithm based on TR-LDA is proposed and verified. From the results, the following conclusions are drawn:

- The proposed intelligent classroom model integrated teachers' teaching and students' learning. This model provided convenience for communication, promoted the interaction among students, and achieved good teaching results.
- The learning resource recommendation algorithm can effectively improve students' learning efficiency. With this algorithm, students did not have to spend much time to find for relevant learning materials. The analysis of data indicated that the intelligent classroom model based on learning resource recommendation algorithm is instructive for the intervention and guidance of students with weak foundation.

The emergence of new generation of information technology has continuously evolved the learning styles. Intelligent classroom has become a barometer of the reform of classroom teaching. However, studies on intelligent classroom still are limited. Developing deep thinking and innovation ability in intelligent and mining and analyzing learners' emotional attitude are interesting topics and will be focus of the follow-up research.

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