Study on Personalized Course Generation Based on Layered Recommendation Algorithm

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Abstract

The paper introduces the concept of a layered recommendation system (LRS) based on multi-dimensional feature vectors to implement personalized course generation model and algorithms. In this work, we present a personalized course generation algorithm based on the multi-dimensional feature vectors (PCG-LRS) and hybrid applications by content-based recommendations and collaborative filtering recommendation algorithm to generate personalized curriculums. Based on this algorithm, we introduce the teaching outline as the basis of the initial generated course and the final learning goals. The knowledge base of the courses can be constructed from the teaching outline. The initial personalized knowledge models of students are generated by pre-tests. These personalized knowledge models are the base of personalized course generation. This algorithm not only helps teachers to develop the overall curriculum teaching plan and to generate the curriculum automatically, but also meets the learning requirements of each individual student with different knowledge and abilities. Additionally, the layered recommendation algorithm recommends content within a large-scale knowledge base repository and resource base implement at different levels. The personalized recommendation algorithm is divided into a number of steps, which achieves an effective dimensionality reduction, reduces the amount of computation, and improves the courses generated algorithm.

Keywords: layered recommendation system, Personalized learning, Recommendation algorithms, Course generation

1. Introduction

The existing course generation method is to proceed from the students' interest, hobby, browsing behavior for the students in personalized recommendation of learning resources [1-2], or to find suitable learning resources for students learning goals for the students, and the application of sequencing technologies to generate course. However, in the actual teaching, before the network learner is learning a course, in the course of learning plan, learning goal is required by the field of professional teacher according to the teaching characteristics of the course itself, the degree of difficulty, teaching objects (students) of the initial level and learning objective and other features to design and develop [3-4]. In the learning process, because the difference between learners, such as different initial levels, learning ability, learning time difference different arrangements, different learning stages have different local learning plan, learning objectives, need in the whole learning process for different students set up the course content different [5].

Combined with the analysis of learner initial personality characteristics, puts forward Personalized Course Generation based on Layered Recommendation System (PCG-LRS), to

achieve Learners personalized learning course content is generated in the preparation stages of learning.

2. Personalized Course Generation Model based on Layered Recommendation Algorithm

The aims of the course of users (students) are to participate in a pre-test learning activity before learning a course in the system [6-7]. System implementation of explicit and implicit to collect personal information of users, assessing the personality characteristics of their knowledge, ability and target characteristics. Enable personalized recommendation algorithm based on user, formed to adapt to the target of curriculum concept map and the learning object resources, and according to the structure of the concept map, presented to the network course of learner structured [8-9]. The process is shown in Figure 1 in the whole system.
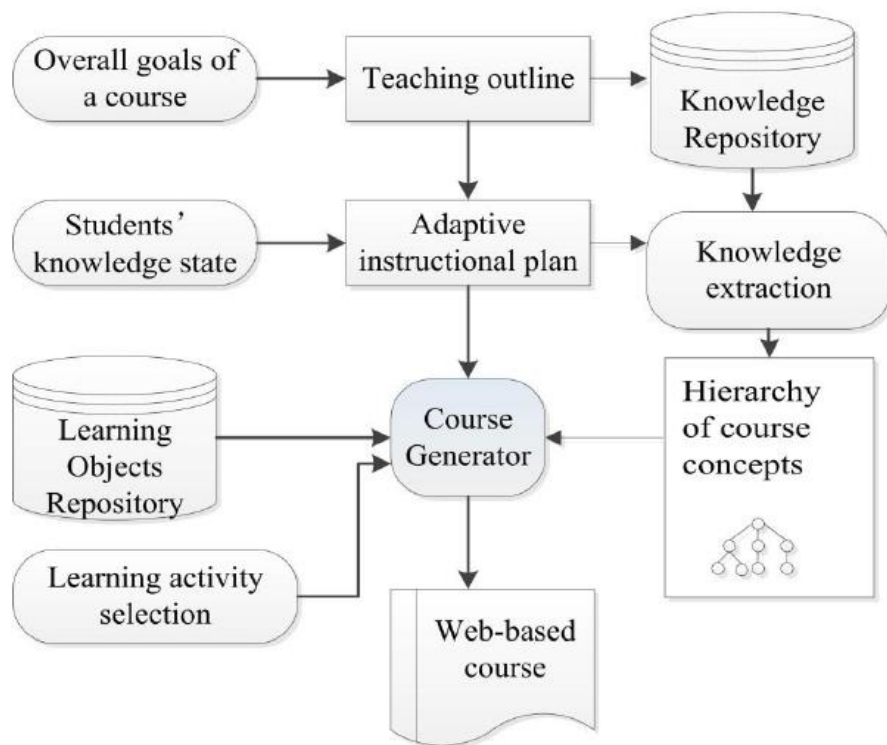

Figure 1. Course Automatic Generation System Implementation Process

3. Conceptual Model of Personalized Course Generation

3.1. User Model

User model is to reflect the real information and computing ability, while limiting the user modeling method is selecting in a certain extent. Common user model representations are: theme representation, keyword list notation, representation method based on neural network, representation method based on Ontology and the representation method based on vector space model.

In this system, first, the user model is to collect related knowledge level learning ability and of assessment learners before a course. In this paper, experts design a set of pretest

questions, the test project that contains the preparation knowledge required courses. Learners participate in pre-school testing, system achieves data collection, analysis and to calculate assess knowledge level and learning capabilities. To generate knowledge matrix Q and ability matrix B. In this paper, the user model is using representation method based on the vector space. At the same time, as the personalized recommendation algorithm in course development process is personalized learning object recommendation, it is based on the learn characteristics of the learner, so in the user model is not interested in a node. But learning characteristic of node, the different characteristics of the study, such as the concept of master degree, learning ability, goal, described in detail below:

Set a course knowledge structure diagram concept is $C = (c_1, c_{2,...,}c_n)$

Corresponding to each concept c_i, respectively, to define the corresponding feature vector (s_i, b_i, o_i), where s_i indicates the concept of c_i learners learning score in the learning process. b_i represents the concept c_i of learner's learning capability assessment. o_i represents the concept of k_i learners learning objective.

It is based on this, we get the student personality characteristics vectors as follows:

Knowledge Vector: $C = (c_1, c_2, ..., c_n)$

Knowledge score vector: $S = (s_1, s_2, ..., s_n)$

Ability vector: $B = (b_1, b_2, ..., b_n)$

Target vector: $O = (o_1, o_2, ..., o_n)$

Therefore, this paper represents the learners to learn the concept c_i characteristics (c_i, s_i, b_i, o_i) by four-tuple form. Personalized Learning Profile (PLP) used n-dimensional feature vector was expressed as: $PLP = (C, W, B, O) = ((c_1, s_1, b_1, o_1), (c_2, s_{2,}b_2, o_2), ...(c_n, s_n, b_n, o_n))$

3.2. The Learning Object Model

In implementation process of the personalized recommendation algorithm, learning object model and the characteristics of the user knowledge are mutual restraint.

This paper created an index of resource and concept, to show a learning object in collection of resource. Let course knowledge structure diagram concept set was $C = (c_1, c_2, ..., c_n)$, Collection of all learning objects in resources repository were $R = (r_1, r_2, ..., r_m)$ .Then The correlation coefficient between i -th learning object r_i and k -th concept c_k were calculated as follows:

$$V_{ik} = tf_{ik} \times \log \frac{M}{df_k} = tf_{ik} \times IDF \qquad (1)$$

Which, V_{ik} denotes k -th concept right at i -th value of learning objects. tf_{ik} represents concept k frequency of appearance in learning objects i . M represents the total number of Learning Object in the courses. df_k represents concept k frequency of appearance in the courses.

4. Recommendation Algorithm based on Knowledge Structure and the Personalized Feature of Knowledge

4.1. Course Knowledge Structure Generation Algorithm for Goal-oriented and Initial Personality Characteristics

This section algorithm is divided into a plurality of records for the teacher's teaching plan according to the format, each record is represented as a separate document, and the concept of knowledge is as characteristic keywords.

The whole algorithm is the representation of knowledge base of concept map and vector space model of learning object. The system knowledge base is a concept map of constraint relations concepts. With a tuple is represented as $Knowledge\ Domain = \{C, R\}$, where, C is a concept set, R is the set of constraint relations concepts. Let $\|C\| = N$, Using different keywords expressed as $C = (c_1, c_2, ..., c_n)$. The teacher's teaching plan is submitted by the document, it is divided into M document. Denoted as $D = (d_1, d_2, ..., d_M)$, it was as shown in algorithm1

Algorithm1 PCG-LRS-Layer1 $(D, C^{'}, R^{'})$

Comments: D is the document set which designed by teacher in a defined format. $C^{'}$ & $R^{'}$ compound to knowledge domain for a special subject domain.

Output: $KD^{'} = \{C^{'}, R^{'}\}$

1. Input D, separate D to D= $(d_1, d_2, ..., d_M)$

2. For each i=1 to M do
      For each j=1 to N do;
      c_{ij} =the number of c_j in d_i

      dc_i =the number of c_j in the document D

      $tc_j = c_{ij} / dc_i$

      $id_{cj} = \log M / dc_i$

3. End for

4. For each c_j do (j=1 to N);

$$Dc_j = \sum_{k=1}^{M} w_{kj}$$

   If Dc_j >d then $C^{'} = C^{'} + c_j$

5. End for

6. For each $< c_i, c_j > \in R$ do

7. End for

8. Return $KD^{'} = \{C^{'}, R^{'}\}$

4.2. Personalized Knowledge Structure Generation Algorithm based on the Personalized Characteristics of Knowledge

Algorithm 1 obtains the whole knowledge domain $KD^{'} = \{C^{'}, R^{'}\}$. This section generated adaptive knowledge structure according to the learner's individual characteristics.

Let concept set of course knowledge structure and Knowledge Domain were $C^{'} = (c_1, c_2, ..., c_n)$. According to the definition, the concept of metadata for: (id, difficulty coefficient, duration, the concept and type), which, the difficulty coefficient was used to measure the concept learning difficulty. The duration was used to weigh the length of the concept of learning. The type parameter is used to weigh the concept learning goals. The user model defines the goal is for the user characteristics and the concept and characteristics of resources are from different angles to do adaptive matching. It was as shown in algorithm 2

Algorithm 2 PCG-LRS-Layer2 ($KD^{'} = \{C^{'}, R^{'}\}, (C^{u}, S^{u}, B^{u}, O^{u})$)

Comments: $C^{'}$ and $R^{'}$ are the knowledge domains for a special subject domain which are generated from the whole knowledge base from algorithm 1.

$(C^{u}, S^{u}, B^{u}, O^{u})$ is the local feature vector of a special user u in a special moment of the learning process. There C^{u} is the concept character of user u; S^{u} is the knowledge character of user u; B^{u} is the ability character of user u; O^{u} is the learning goal character of user u.

Input: ($KD^{'} = \{C^{'}, R^{'}\}, (C^{u}, S^{u}, B^{u}, O^{u})$)

Output: $KD^{u} = \{C^{u}, R^{u}\}$

1. Generated all the topological sort list of k-concept of the set $C^{'}$ according to the relation set $R^{'}$

2. For each sequence C_i do

   $C_i^{'} = \varnothing$

   For each $c_j \in C_i$

        If $s_j < 0.6$ or $(0.6 \leq s_j < 0.8)$ & $(o_j = 2)$ or $(0.8 \leq s_j < 1)$ & $(o_j = 3)$

            $C_i^{'} = C_i^{'} + c_j$

3. For each possible learning sequence $C_i^{'}$ do

   Collect the ability character of user u: $B^{u} = (b_1^{u}, b_2^{u}, ..., b_{p_i}^{u})$

   The difficulty parameter of $C_i^{'}$ is $dif^{u} = (dif_1^{u}, dif_2^{u}, ..., dif_{p_i}^{u})$

   $$Dis_i = \cos(B^{u}, dif^{u}) = \frac{B^{u} \cdot dif^{u}}{\|B^{u}\| \times \|dif^{u}\|} = \frac{\sum_{i=1}^{p} b_i^{u} dif_i^{u}}{\sqrt{\sum_{i=1}^{p} b_i^{u}} \sqrt{\sum_{i=1}^{p} dif_i^{u}}}$$

4. End for

5. Average the Dis vector: $Dis = \frac{1}{k} \sum_{i=1}^{k} Dis_k$

6. Select the closest to the average Dis from $Dis_i (1 \leq i \leq k)$, $C^{u} = \{c_1^{u}, c_2^{u}, ..., c_p^{u}\}$

7. For each $<c_i, c_j> \in R^{i}$

8. End for

9. Return $KD^{u} = \{C^{u}, R^{u}\}$

4.3. Learning Objects Generation Algorithm based on the User Personality Characteristics

Application algorithm1 has been adapted to course concept of the teacher teaching plan $KD^{'} = \{C^{'}, R^{'})$ .Algorithm2 recommended to adapted to personalized knowledge domain $KD^{u} = \{C^{u}, R^{u}\}$ of the learner individual character. The course was supported by a series of conceptual learning objects. So this section used relationship between concepts and learning objects. Further recommendations to adapt learning object set with the KD^{u}, and generates structured course. It was as shown in algorithm3

Algorithm3 PCG-LRS-Layer3 $(KD^{u} = \{C^{u}, R^{u}\}, (C^{u}, S^{u}, B^{u}, O^{u}), R^{u'})$

Input：$KD^{u} = \{C^{u}, R^{u}\}$

Output：$R^{u'}$

1. For each $r_i \in R$, $i = 1$ to m, do

If $\sum_{j=1}^{p} V_{ip_j} > 1$ then $r_i \in R^{u}$, marked as r_i^{u}

2. End for;

3. Create the relation matrix of R^{u} and $C^{u}, R - C^{u}$

4. For i=1 to m
    Dele=True;
    For j=1 to p , do
   End for

5. End for

5. Experimental Analysis and Results

This paper uses a university network education of personalized learning platform to test and verify the proposed algorithm.

In order to test the feasibility of layered recommendation algorithm, professional teacher education network of computer science and technology are building knowledge Domain in the system. System construction in the field of 100 subjects 849 points of knowledge, to build the knowledge base. In order to unify the representation, unit independent of all teachers and experts are called concept. The second step, by teachers and teaching assistants to the construction of 2441 Learning Object, to construct the corresponding learning resource.

In the experiment, we choose computer science undergraduate education in "data structure" as the experiment course. The teacher made a teaching plan according to the requirements of the document A. At the same time, we chose 100 computer professional degree education network education students, before learning "Data structure" course, first as a pretest, before the tests include learning the course of data structure knowledge. Including basic concepts of discrete mathematics, basic knowledge of C programming language, such as mastery. According to the 100 students on the pretest process, collection, establish the student archives.

According to the PCG-LRS algorithm, needing to layer implementation, respectively to achieve personality for 100 students of course, and it also needs the provisions of the teachers'

teaching plan learning objectives. 16 professional teachers are given different teaching plans, through algorithm1 to complete the course generation for teachers, teachers' course feedback are generated by their expected course distance. Through the double evaluation of domain knowledge and learning resource, and each knowledge point (concept) were evaluated each learning object. Eventually arrive at the average absolute deviation, in order to determine the accuracy of the algorithm1.

Choosing a course and 100 students are to learn this course by course, student feedback system is generated with a desired course distance. Through the double evaluation domain knowledge and learning resource. Each concept and each learning object were evaluated respectively. Eventually arrive at the average absolute deviation, in order to determine the accuracy of the algorithm 2-3.

5.1. Set Different Threshold d , the Effectiveness of Course Knowledge Domain is Generated

In the algorithm1, according to the teaching plan documents, to recommend concept of subset associated with teaching plan document from Knowledge Base. The concept of subset is in accordance with the teaching objectives and requirements of teachers, to measure the effectiveness of algorithm important standard. In this experiment, the different value as weight, detection of teacher satisfaction for their results, and then to determine a threshold d in the algorithm 1.

The experimental methods are as follows:

First, for all the concept of the knowledge base for teaching document D weights to define an average weight Avg_d .

$$Avg_d = \sum_{i=1}^{M} \sum_{j=1}^{M} w_{ij}$$

(2)

Then taken $d = Avg_d; d = 1.5 Avg_d; d = 2 Avg_d; d = 3 Avg_d$, for teachers proposed Teaching programs D, Application algorithm3-1 to generate different course knowledge domain $KD_1^{'}, KD_2^{'}, KD_3^{'}, KD_4^{'}$.The application of this method for 16 teachers put forward to teaching plan for their teaching subjects, respectively used different threshold to generate knowledge domain of different course. The results are feedback to the 16 teachers, please they were evaluated with knowledge domain of different course.

Definition of Mean Error (ME) is to measure the course knowledge domain generation algorithm accuracy. The ME is through calculation algorithm to generate the course domain knowledge and teaching plan to desire course knowledge. ME is more small, quality of recommendation is more high. The calculation process of ME are as follows:

$$ME = \frac{\sum_{c \in C} \gamma_c}{|C| + |Incre|}$$

(3)

C is a concept set of algorithm generating; $|C|$ is size of the concept set; $Incre$ is added to the concept set for teacher generating. $|Incre|$ represents the size of the concept set of teachers complementary. γ_c represents concept evaluation of domain knowledge for generation of teacher.

According to the evaluation of 16 teachers on the concept of course domain, calculate Mean Error in different threshold, it was as shown in Table 1.

Table 1. Affecting the Accuracy of the Threshold d of the Algorithm

d syllabus	Avg_d	$1.5Avg_d$	$2Avg_d$	$2.5Avg_d$	$3Avg_d$	$3.5Avg_d$
D_1	0.52	0.63	0.89	0.87	0.78	0.6
D_2	0.37	0.58	0.78	0.85	0.81	0.59
D_3	0.42	0.61	0.85	0.83	0.78	0.71
D_4	0.42	0.52	0.87	0.84	0.79	0.56
D_5	0.39	0.59	0.79	0.8	0.71	0.61
D_6	0.49	0.52	0.76	0.86	0.72	0.63
D_7	0.47	0.63	0.86	0.81	0.76	0.62
D_8	0.46	0.69	0.82	0.78	0.75	0.68
D_9	0.51	0.7	0.81	0.82	0.74	0.64
D_{10}	0.47	0.59	0.83	0.89	0.74	0.63
D_{11}	0.5	0.58	0.79	0.85	0.86	0.69
D_{12}	0.43	0.56	0.75	0.83	0.78	0.65
D_{13}	0.38	0.51	0.78	0.85	0.71	0.63
D_{14}	0.35	0.49	0.79	0.87	0.69	0.69
D_{15}	0.29	0.45	0.69	0.85	0.75	0.63
D_{16}	0.43	0.59	0.82	0.86	0.69	0.68
Average ME	0.4312	0.577	0.805	0.8412	0.7537	0.64

The experimental results are shown in Figure 2, when the threshold is taken as the average weight, teachers for their overall satisfaction are only 43%. And when the threshold increases as the average weight of 1.5 times, 2 times, 2.5 times, course knowledge domain of teacher to generate satisfaction increased. And when the threshold to continue to increase, average weight 3 times, 3.5 times, satisfaction course knowledge generated is decline. Thus, according to the results of this experiment. Threshold in this paper is $d = 2.5Avg_d$.
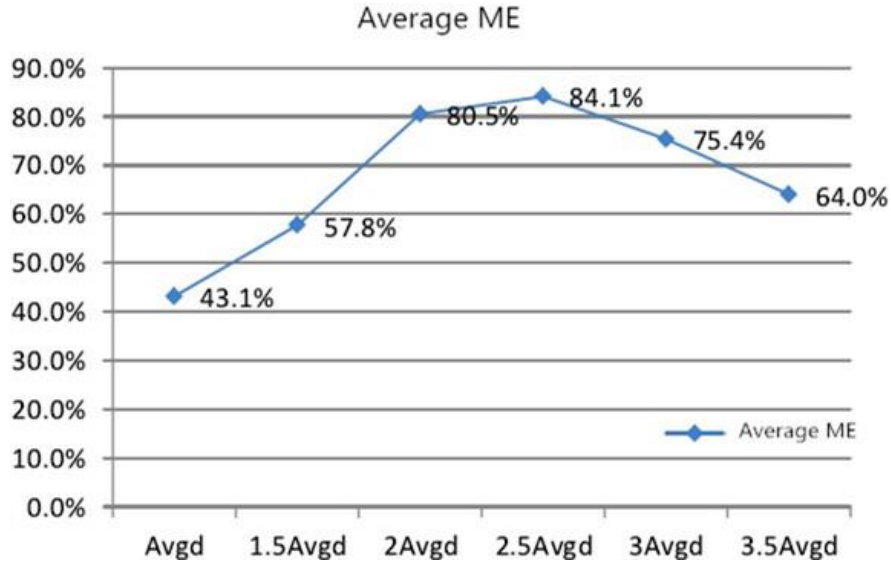
Figure 2. Affecting the Accuracy of the Threshold d **of the Algorithm**

5.2 Several Different Difficulty Difference Function Value Comparison

In the algorithm2, because learning content cannot be too difficult or too easy, therefore, the algorithm needs to measure the difficulty coefficient difference of user's ability vector and concept subsets of concept generation. This difference calculation method plays a key role in the whole algorithm, it is crucial to the algorithm the accuracy of recommendation. And in the measure of fitness, theoretically distance is minimum, the average difficulty of concept set and the users' ability are closest. However, in practice, some students want to challenge with the difficulty of knowledge easier to arouse the students' interest and morale. But it should not be too difficult, too difficult content will make students lose confidence, but easy to middle school. Therefore, choose a slightly is higher than the minimum distance of the difficulty, which is more appropriate. How to choose a suitable value, it is the main goal of the experiments.

The experimental designed in several different ways to solve the deviation of the corresponding concept vectors capacity between the subsets, and by taking the minimum value to close to the different values of the minimum. To find the most suitable offset value with the concept of sub-strings, in order to improve the adaptability and accuracy of the recommended course.

Specifically, the deviation with the following different methods to achieve capacity vector and the concept of subset difficulty:

Method1: the definition of Absolute Ability Error (AAE) measures Error of user ability and string difficulty, defined as follows:

$$AAE = \frac{1}{n} \sum_{i=1}^{p} (b_i^u - dif_i^u)^2 \qquad (4)$$

The next two methods are based on the following definitions: Absoulte Difficulty degree (ADif) and Absolute Easy degree (AEasy)**:**

$$ADif = \sum_{\substack{i=1 \\ b_i^u > dif_i^u}}^{p} |b_i^u - dif_i^u| \qquad (5)$$

$$AEasy = \sum_{\substack{i=1 \\ b_i^u > dif_i^u}}^{p} | b_i^u - dif_i^u | \qquad (6)$$

Method two: use relatively difficult strategy, to provide concept substring beyond their ability difficulty of the user, Specific strategy: $ADif - AEasy \geq A$, Absolute difficulty degree is big than absolutely easy degree

Method three: use relatively easy strategy, to provide concept substring below their ability difficulty of the user. Specific strategy: $AEasy - ADif \geq A$, Absolute difficulty degree is small than absolutely easy degree

Method four: Apply the cosine vector to compute distance of user ability vector and the difficulty vector of the each subset in the concept. As follows:

$$Dis_i = \cos(B^u, dif^u) = \frac{B^u \cdot Dif^u}{\|B^u\| \times \|Dif^u\|} = \frac{\sum_{i=1}^{p} b_i^u dif_i^u}{\sqrt{\sum_{i=1}^{p} b_i^u} \sqrt{\sum_{i=1}^{p} dif_i^u}} \qquad (7)$$

Theoretically, the average value of all concepts and user capacity vector are average level of the distance, however, in practical applications there may be deviation, so the experiment to calculate the user u and the average distance of all conceptual sequence set:

$$Dis = \frac{1}{k} \sum_{i=1}^{k} Dis_k \qquad (8)$$

Because the algorithm2 is on the user (student) personalized course character generation, so this experiment has 100 students participate. The students were randomly divided into 4 groups, each group has 25 students, for students with different groups were using different methods. Through the student's actual feedback to obtain each course recommended average accuracy.

To this end, we define the Mean Difficulty-Easy Error (MDEE), MDEE is calculated as follows

$$MDEE = \frac{\sum_{c \in C^u} (\gamma_{dif_c} + \gamma_{easy_c})}{|C^u|} \qquad (9)$$

Which, C^u represents the algorithm for the user u to generate personalized course concepts set. $|C^u|$ represents the size of the collection concept. γ_{dif_c} indicates difficulty evaluation of the concept c for user u. γ_{easy_c} indicates easy evaluation of the concept c for user u. Obviously, strategy values of MDEE is smaller, the error is smaller, the strategy is better. According to different strategy of each student to generate the evaluation data of concept subset and count each strategy Mean Difficulty-Easy Error result. It was as shown in table2. As the data shows, similarity strategy of method4 of Mean Difficulty-Easy Error is the most minimum.

Four groups of students were the result of statistic data of different feedback strategies are Comparing. It is as shown in Figure 3 from the statistical results, each student feedback analysis results that the method4 is most similar strategy and is suitable for student recommendation strategy.

Table 2. The First Group Feedback Data Statistics

| Method \ Group1	Method1 Least ABE	Method2 Difficult strategy	Method3 Easy strategy	Method4 Most similarity
S1	0.55	0.76	0.54	0.41
S2	0.47	0.84	0.31	0.32
S3	0.51	0.79	0.32	0.37
S4	0.56	0.72	0.34	0.34
S5	0.39	0.75	0.36	0.31
S6	0.68	0.59	0.42	0.42
S7	0.45	0.63	0.52	0.28
S8	0.62	0.68	0.38	0.34
S9	0.56	0.71	0.35	0.45
S10	0.41	0.63	0.32	0.52
S11	0.51	0.56	0.48	0.55
S12	0.68	0.75	0.53	0.42
S13	0.53	0.55	0.33	0.47
S14	0.45	0.68	0.51	0.51
S 15	0.52	0.66	0.54	0.35
S16	0.54	0.56	0.46	0.44
S17	0.42	0.86	0.41	0.25
S 18	0.35	0.71	0.32	0.52
S19	0.67	0.71	0.42	0.34
S20	0.58	0.89	0.33	0.35
S21	0.35	0.7	0.36	0.42
S22	0.56	0.76	0.31	0.32
S23	0.63	0.71	0.51	0.32
S24	0.53	0.71	0.45	0.32
S25	0.61	0.78	0.51	0.56
Mean of MDEE	0.525	0.703	0.413	0.396
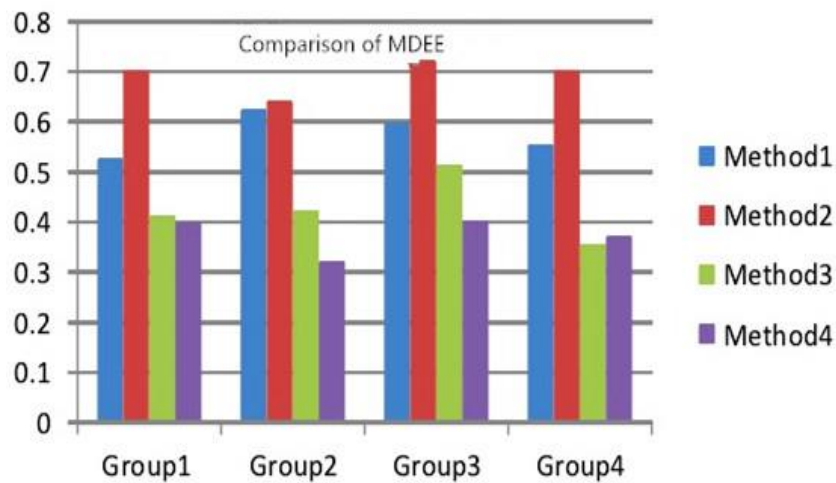
Figure 3. For Different Methods of Different Group Students to Generate Course Evaluation Data Comparing

6. Conclusion

This paper mainly studies courses automatic generation and personalized learning in large-scale formal learning the network education environment. Proposed Personalized Course Generation Model based on Layered recommendation algorithm. Separating the course domain knowledge and learning objects, the personalized needs of layered will be teaching objective and student learning process to achieve. Proposed a formal learning program for teaching teachers to develop programs to automatically generate efficient algorithm. To solve professional teachers needs to build teaching online course in large-scale network learning. Proposed personalized knowledge generation algorithm based on user knowledge structure characteristics. On the basis of the teaching programs generated knowledge domain, and further to generate personalized knowledge domain for the user. The experimental data proves that automatic generation algorithm of teachers' course and Hierarchical Personalized Course generated for the students' recommendation algorithm have high accuracy and scalability.

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