Research on the Multidimensional Educational Review Strategy Based on MOOCs Integrated by the Multidimensional Learning Theory

Li Ming, Zhang Ju, Zhang jingzhong, Chen Lian

***Abstract*—Through a detailed analysis of the theoretical basis for MOOCs in terms of educational learning theories, this paper attempts at finding the corresponding relationship between the theories and MOOCs, which not only theoretically explains the reasons why MOOCs exceed all the previous education models, but also empirically proves it with voluminous facts and data. The author conducts this research in the hope of enlightening the online education platform of other types. Besides, this paper provides the model framework and strategy to multidimensional educational review based on MOOCs. The model and strategy are applicable not only to MOOCs, the large-scale online education, but also to various online education platforms.**

***Index Terms*—MOOCs, educational review strategy, multidimensional learning theory .**

I. Introduction

MOOCs (Massive Online Open Courses) gained its inspiration from ML (Mastery Learning) Theory put forward by Bloom in 1968 [1], and is combined with other effective education and learning theories to conduct innovation and practice of brand-new teaching models and teaching techniques. In 1984, Bloom pointed out that there are three education models: 1) lecture-based classroom education model; 2) ML-based classroom education model; and 3) face-to-face small-classroom elite education model. Bloom thought that, if ML teaching method is applied to the traditional classroom education, the standard deviation of students' test score distribution can be improved by 1 sigma. If small-classroom elite personalized teaching method is also adopted based on the ML teaching method, the standard deviation of students' test score distribution can be improved by 2 sigma. Bloom called it 2 Sigma Problem [2].

As is shown in Fig.1, Fig.2, Fig.3, Fig.1 shows students' test score distribution under the traditional classroom teaching model, which is in line with Gaussian distribution rules. With the median as the threshold, half of students have failed to master knowledge taught in class well. Fig.2 shows students' test score distribution under the Mastery Learning teaching model[3]. Compared with the traditional teaching model, the standard deviation is increased by 1 sigma. MOOCs can be regarded as a second kind of teaching model, which is represented by Coursera, Udacity and Edx, all of which adopt advanced scientific methods to enable students to master their acquired knowledge well. Fig.3 shows students' test score distribution model under face-to-face small-classroom elite teaching model. Compared with the first method, the standard deviation is increased by 2 sigma. With the median as the threshold, more than 98% of students have mastered the knowledge taught in class well. However, it is impossible to provide every learner with the face-to-face education conditions. In face of the problem, MOOCs education models represented by Coursera, Udacity and Edx are attempting to make the test score distribution curve under the second model to get close to or even exceed that under the third model through advanced techniques.

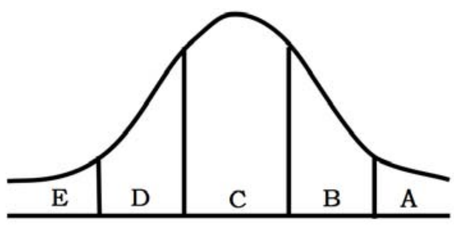

Fig. 1 lecture-based model

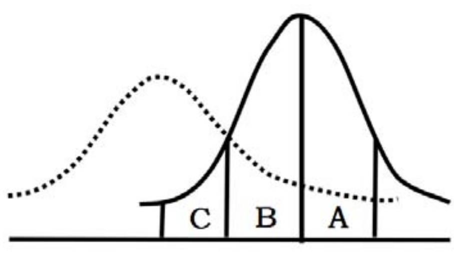

Fig. 2 ML-based model

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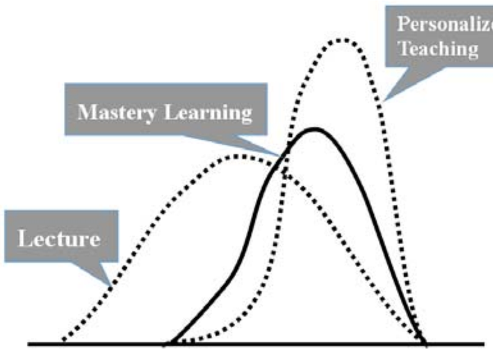

Fig. 3 Comparement about three models

II. MOOCs BASED ON THE INTEGRATION OF VARIOUS LEARNING THEORIES

Then, how should MOOCs get close to, realize or even exceed the small-classroom elite personalized education? This requires MOOCs to constantly explore and implement in the following five aspects through artificial intelligence, machine learning and data mining. The five aspects are in fact the learning theoretical basis for the huge success of MOOCS. MOOCs have done quite well in some of the five aspects, which is also the reason why MOOCs can attract leaners of various age groups, learning levels, fields, countries and backgrounds, while in some aspects more exploration efforts are expected of MOOCs.

A. Repetitive Learning

Repetitive Learning was put forward by Bloom, the founder of MOOCs, who was inspired by ML. With the help of the immediate feedback of the review tool, learners can improve their study and their final test score through repetitively submitting homework. Lots of experiments have proved the positive role of Repetitive Learning in the improvement of test scores. (See [5] in Fig. 4) Karpicke and Grimalidi discovered that university students of liberal arts can memorize more English vocabulary through Repetitive Learning. In the courses of a long learning period, students can improve their test scores by 50% through Repetitive Learning[6].

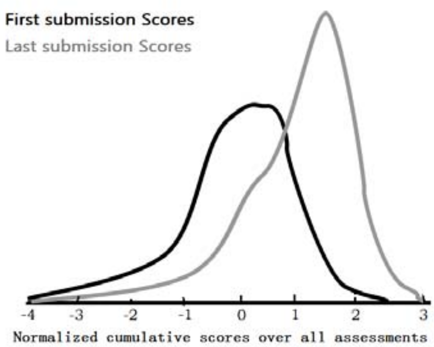

Fig. 4 the positive role of Repetitive Learning

There are two corrective feedbacks: 1) give different guidance according to different answers given by learners; 2) just give the feedback about whether their answers are right or wrong. Based on the study of Roediger and Butler in 2011, it was found that, even without specific guidance, the second feedback model can also generate effective learning effects through repetitive exercises. Of course, specific guidance immediately given to their students can lead to better learning effects. (See [7] in Fig. 5)

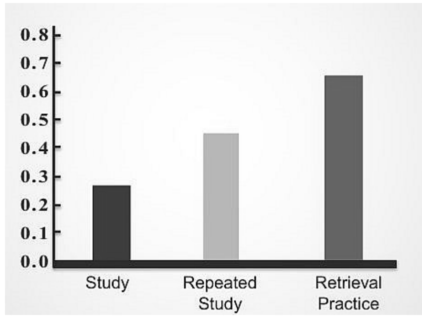

Fig. 5 Comparing of study, repeated study and retrieval practice

B. Mastery Learning

Mastery Learning (ML) was put forward by Bloom in 1986. Its basic idea is that: learners should master the current knowledge points before learning the next. This forms a sharp contrast with the traditional learning style. Due to limits of the teaching method, the traditional classroom education cannot ensure every student to master the knowledge points[3]. Under the classroom teaching model, when a teacher put forward one question, some students are thinking about the question, while some are absent-minded. Only a small number of students can immediately make a feedback. At the moment, the teacher thinks that he/she can go on teaching the next knowledge point in view of the correct feedback. However, in fact, some students have failed to master the knowledge.

Under the classroom education model, if learners fail to do well in homework or tests, they would obtain a low score and then go on with the next knowledge point. In this way, learners might have not yet laid a solid foundation for themselves to learn the next concept. The feedback of their learning effect is usually obtained several weeks after learning the knowledge. However, it has been a long time after the learner learned the concept. If they obtain a low score and fail to master the previous knowledge, they would seldom review the knowledge and master the knowledge point according to the feedback[5]. Under the MOOCs model, students must answer the questions imbedded in the teaching video; otherwise, it would be impossible for them to enter in the learning of the next knowledge point. After students give the answer, the system will immediately give feedback to guide students until they master the knowledge point.

C. Personalized Learning

Personalized Learning is a reflection of behaviorist learning theory. In terms of behaviorist learning theory, Programmed Instruction of Skinner emphasizes the principle of small steps. In other words, learning content should be decomposed into several small units and students can learn it according to their own progress (free arrangement of time and energy). In 1968, Bloom pointed out the necessary to provide different learning flows for learners of different abilities so as to meet personalized demands [1]. MOOCs can meet learners' personalized learning demands to the maximum degree. MOOCs are usually divided into short

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videos of 10 to 15 minutes. The advantage of doing so is that: knowledge in the video carefully; some students maybe have had a better grasp of knowledge in this video (based on ML theory, these students have the better transition to the next video, learn new knowledge points); some students will be inspired from the video section, and even can do a deeper exploration and scientific research. This pattern is not "one size fits all" model of education to provide students with the greatest degree of personalized arrangements.

D. *Collaborative Learning*

Online forum provides a learning community for leaners, through which learners can form an online and offline collaborative learning relationship. The collaboration form can help learners of the same interest better learn the course and rekindle their research interest in the field that the course belongs to.

Koller found that the average time for her learners to obtain an answer from the forum from the question put forward is 22 minutes. The speed obviously exceeds the average speed of her students in Stanford University[4]. Some research findings even found that the online discussion method can obtain even better learning effects compared with face-to-facediscussion.

Collaborative Learning is a form of relevance learning. Relevance learning theory emphasizes that learning is not just the establishment of the binding between stimulation and reaction after the absorption of the conception of "binding" in behaviorist learning theories, but the relevance (binding) between individuals and knowledge, individuals and individuals. It aims to form a knowledge network through learning. Relevance learning theory emphasizes the interaction learning based on social network media, focusing on the independence, self-control and spontaneity of learning.

E. *Active Learning*

Active Learning reflects the cognitivist learning theory. The theory emphasizes the utilization of various media resources and that instructors should act as a pioneering organizer for students' learning. It also attaches importance to students' learning motive and encourages students to conduct "Learning by Discovery." The traditional classroom education model tends to fill students' knowledge gap, but what is needed currently is to stimulate students' creativity, imagination and ability to solve problems. Many experiments have suggested that, with active interaction, the attendance and participation rate and the learning enthusiasm of students will be greatly increased. (See [8] in Fig. 6) MOOCs can stimulate not only learners' wish of independent learning, but also leaners' enthusiasm to further their study and head towards lifelong learning.

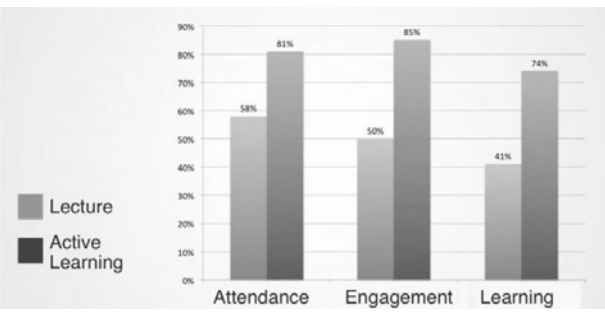

Fig. 6 the effect of active interaction

All the above five aspects cannot be achieved through traditional course teaching. Even the online education model centered on videos cannot achieved the above five aspects; even if it achieves, it cannot reach the depth of MOOCs.

III. MULTI-DIMENSIONAL EDUCATIONAL REVIEW STRATEGY BASED ON MOOCS

MOOCs not only exceeds various education forms, such as classroom education, distance education, network education and open education, but also gets ride of the shackles of the traditional educational review model. The traditional education mainly evaluates students' learning results. The most representative review method of the traditional education model is the standardized exam. Based on the big data, MOOCs can conduct more comprehensive review of learners' learning process and learning results.

A. *Educational Review form based on MOOCs*

At present, MOOCs mainly have two review methods, namely automatic review and peer review.

Automatic Review

Automatic review can provide immediate feedback for learners to help with their study. Currently, automatic review can handle multiple choice, gap filling, simple questions, mathematical or mathematical expressions, financial models and physical models, and programming work [4].

Peer Review

In fact, there are many questions, such as mathematical process of proof and project design, beyond the automatic review. Under the circumstance, peer review becomes a feasible method. However, peer review must also be accurate and reliable. Some experiments suggest there is high relevance between the correct results of peer review and teachers' review. This can provide a vigorous support for the reliability and accuracy of peer review [9]. PM Sadler, E Good also obtained the similar positive results in [10]. Fig.7also gives the association graph between peer review and teachers' review[10].

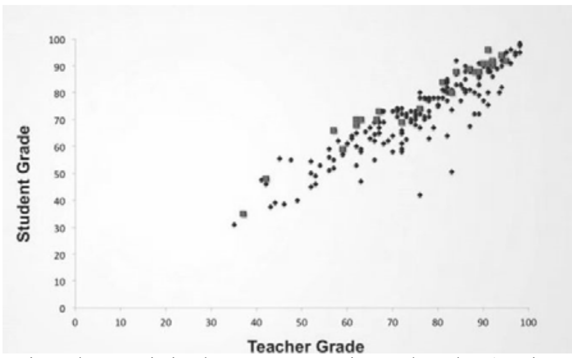

Fig. 7 the association between peer review and teachers' review

Peer review can not only play a positive role in evaluating learners' learning quality, but can also improve the evaluators' self-learning ability and learn their self-learning strengths and weaknesses and their professional techniques and self-thinking ability. From the above experiment (Fig. 5),

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it can be seen that peer review is more reliable, accurate and feasible within the experiment scope. However, the evaluators of the peer review all come from the same university (the level and field of evaluators and learners are similar) and the evaluators have undergone training. Under the practical online education model, evaluators are from various regions and fields. They are randomly chosen, and their choices are relied on their own interests and temporary willing. Their level is uneven. It is even more impossible to conduct training before the review.

B. Multi-dimensional education Review models and strategies based on MOOCs

How should peer review be implemented? Up to now, there have not yet been literatures putting forward stable review mechanism. Some researchers attempted to connect review with individual test scores through the reward mechanism. However, evidences showed that such reward opportunity will make review unreasonable.

It is necessary to give multi-dimensional peer review strategies and models. First, various data related to learners' learning behaviors should be collected and analyzed to help with the establishment of the review capability model. Every visit, every assignment and every quiz post might be object for data mining and index for review. Apart from review indexes, review dimensions should also be considered in the review system so as to provide the most comprehensive reference. The review dimensions can be divided into the following three types:

1) Learners' dimensions: including learners' statistical information (can be obtained from users' registration information), active degree, whether they are new users, etc.

2) Courses' dimensions: including courses' property information, popularity, average points, whether they are new courses, etc.

3) Time's dimensions: including seasons, whether workdays or weekends, whether daytime or evenings, etc.

Through review indexes and review dimensions, learners' learning interests, learning demands, learning level, learning methods and various characteristics can be obtained to provide support for the establishment of various review models. In the following part, four models are given to form review strategies:

Establish the consistency test model:

The courses learned by evaluators and learners are the same. Through collecting the learning data, users' behaviors and interest models are established based on the training set. Then the consistency test is conducted of the evaluators' interest models and course models waiting to be reviewed. The neighborhood algorithm is employed to conduct similarity calculation. The high similarity proves the high consistency. This suggests that evaluators have intense interest in the research field of the course. In this way, evaluators can try their best to provide the accurate review.

Establish the reliability test model:

The consistency test of the previous review and the accuracy review given by teachers (courses provide teachers' accuracy review) and the average review of the peer review (courses do not provide teachers' accuracy review) prove to be of high consistency. This suggests that the review quality of evaluators is high and reliable. (1) and (2) in the above models are applicable to the massive review. When the review questions arouse extensive interests, some spontaneous and active learners on the internet take an active part in the review. Two models can be employed to ensure the accuracy of the review. Since there are great differences between the prediction accuracy and the users' satisfaction degree, the high prediction accuracy does not stand for the high users' satisfaction degree. Apart from (1) and (2) strategies, other review strategies should be designed. (3) and (4) in the models below are suitable for small-scale review.

Establish the learners' question answering ability review model:

1) Trace every learner's ability to answer questions through the learning algorithm and trace the number, frequency, field, course and reception degree (namely users' satisfaction degree) of every learner to answer other learners to give the comprehensive indexes of learners' ability to answer question in their learning field;

2) Employ users' label data and label out learners' ability in various fields and courses through the swarm intelligence. This is not a quantitative model form. The model can make learners generally learn evaluators' ability in various fields and courses and assist learners in applying for review through the label cloud. (Conduct visualized weighting of characters. The more times they appear, the bigger their character size is; the few times they appear, the smaller their character size is. This can help people directly and conveniently find rules in the data.)

Establish the recommendation model for learners' review questions :

1) Calculation recommendation (recommend evaluators to learner)

Work out the recommended ranking according to the comprehensive indexes through the Personal Rank algorithm. Learners can put forward review requirements of other learners through combining the label cloud and the recommended ranking. (Can put forward the review request to more than one evaluator and conduct comprehensive review);

2) Calculation recommendation (recommend evaluators to learner)

I) If learners who rank in the top list in certain course or field put forward the review request in other courses or fields, they should gain the priority to be recommended.

II) If the learner (X) once reviewed the learner (Y) in the other courses or fields and was accepted (namely high satisfaction degree), and if (X) puts forward the review application in the fields or courses that (Y) is familiar with, (Y) must immediately give feedbacks and review, and conduct restrictions according to the reward and punishment mechanism in the review system.

IV. Conclusion

As a brand-new education type, MOOCs have been adopted by many countries for their education, but it does not mean that every teaching institution and teaching field has the condition, financial resource, strength and necessity to implement it, but they can refer to, adopt and implement some functions of MOOCs based on their original online education model. Proceeding from the perspective, this paper gives a detailed analysis of various education and learning theories supporting MOOCs and finds out the corresponding relationship between these theories and MOOCs in the hope of enlightening the online education platform of other types. Besides, multi-dimensional education review model frameworks and strategies based on MOOCs are given in this paper. More specific implementation steps will be covered in the follow-up paper. The above review algorithms, models and strategies are applicable to the large-scale online education like MOOCs and various online education platforms. What is different is that MOOCs conduct an analysis of the big data of the current education, and big data is known for its huge quantity, quick generation and diversity. If all the above review algorithms, models and strategies are transformed to online education platforms of other scales, data scales and model scales can be simplified correspondingly.

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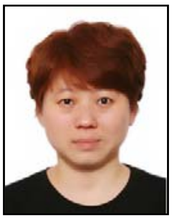

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