Promoting Student Completion in a MOOC on Information Theory

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***Abstract*—Massive Open Online Courses (MOOCs) have become an option for convenient access to education opportunities. However, the low completion rates remain a major challenge for MOOC teachers and providers. Meanwhile, very little has been known about learner experience in MOOC on Information Theory; which is a fundamental field of interest in engineering. This work-in-progress aims at promoting student completion rate in a MOOC on Information Theory by identifying effective strategies for individualized MOOC learning. In particular, the research-to-practice study takes place in a MOOC designed and taught by the third author. We established a learning experience model by extended an existing framework in the MOOC literature. We validated our model with empirical learning data collected from our own MOOC. We identified variables that predict student learning outcomes and completion. Our model enables us to further develop an Individualized Learning Path System that generates and selects the most suitable learning path for individual students.**

Keywords—Massive Open Online Course (MOOC); information theory; learner experience modelling; individualized learning path system; learning analytic with empirical data.

I. Motivation and Background

A growing emphasis is being placed on Massive Open Online Courses (MOOCs) which have successfully created global connectivity to support online learning [1]. At the end of 2016, MOOC has taken over 6,000 courses from more than 700 universities, which grows in an exponential trend [2]. So far, MOOC platforms such as Coursera and edX have become major options for people to explore their higher education [3]. Almost all MOOCs support lecture videos, quizzes, assignments, and discussion forums, but also face a salient challenge—large enrollments, but very low completion rate. Meanwhile very little has been known about learner experience in MOOC on Information Theory; which is a fundamental field of interest in engineering.

Our work extended from the adaptive educational system (AES) proposed by Brinton *et al.* that consists of four modules: inputs, user modelling, path generation, and path selection [4]. Inputs refers to parameters that the AES collects, such as assessment points, viewing behaviour, and annotations [5]. These parameters can be used to estimate future learning outcomes of users in a course. User modelling maps the inputs to update the user model (UM) of a specific user. Typical user modeling involves the following two processes [6]: (1) *Path Generation* which specifies each of the learning paths a user may follow and (2) *Path Selection* which compares the UM to each learning path and select the most suitable individualized learning path for each specific user. Brinton *et al.* applied the user modelling technique to the context of MOOC learning, in particular, they provided individualized MOOC contents based on behavioral data collected from learners.

The purpose of this work-in-progress is to promote student completion rate in a MOOC on Information Theory by identifying effective strategies for individualized MOOC learning. In order to promote student completion in our MOOC, we constructed a learning experience model based on our course context and proposed an individualized learning path system by extending the AES framework.

In the rest of this paper, we will present the design of our teaching and learning context in Section II. We have established a learner experience model applied it to the learning data collected from the MOOC for Information Theory; our method and model will be presented in Section III. Based on our analysis and findings provided in Section IV, we can propose an individualized learning path system that aims to promote student completion in MOOC on Information Theory; the outline of our design will be provided in Section IV.

II. The Current Study

A. Teaching and Learning Context

Our research-to-practice study takes place in a MOOC on Information Theory designed and taught by the third author [7]. The course was launched in Coursera in January 2014. The study involved learning data collected from N = 10,953 participants.

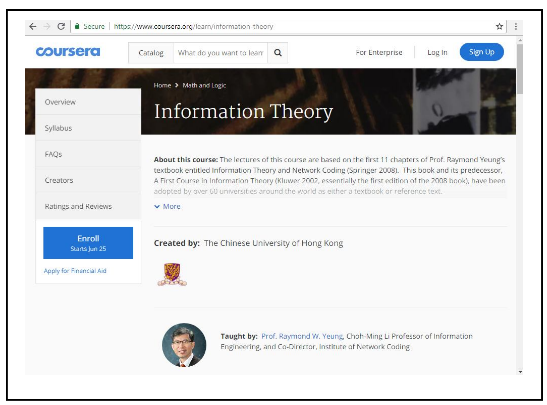

Fig. 1. Screen captured from our MOOC.

B. Assessment Criteria and Completion Rate

The assessment scheme contains two items:

- Item One: Assignment (95%)
- Item Two: Participation (5%)

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Assessment item one consist of weekly assignments. One assignment is issued per week, with a total number of fifteen assignments throughout the whole semester. Only the scores from the twelve best attempts will be included in the overall assessment. Assessment item two is contributed from students' online participation. Students are encouraged to raise self-initiated questions about the lectures in the MOOC discussion forum. Students can earn 1 score for each post or comment made before the deadline, up to a maximum of 5 scores.

The student will pass (complete) the course if the final score is higher than 70%. The current completion rate of this course is only around 0.137%. Our completion rate is low when compare to that of other MOOCs. The average completion rate of MOOCs was reported to be 6.5% [8]. But it has also been found to be less than 5% [9].

C. Research Questions

We ask the following two research questions in the context of massive online learning in Information Theory:

(RQ1) What can we know about students' learning behavior in MOOCs on Information Theory?

(RQ2) How can we promote student completion using the dynamic learner data collected from the MOOC platform?

III. METHOD

A. Participants

The data of our current study were collected from N = 10,953 students who enrolled in our MOOC on Information Theory during the spring semester of 2014.

B. Measures

We construct a Learner Experience Model (LXM) that includes the predictor variables and an outcome variable and collected their measurement values from the MOOC.

TABLE I. LEARNER EXPERIENCE MODEL

Variable Type	Variable	Measurement Item
Predictors	Geographical Background	(1) Timezone of the learner
	Quiz	(2) num. of completed quizzes (with non-zero marks)
	Learning Behavior	(3) num. of downloaded lectures (4) num. of viewed lectures
	Online Social Behavior	(5) reputation points (6) num. of threads viewed (7) num. of forums viewed (8) num. of up-votes given (9) num. of down-votes given (10) num. of tags added (11) num. of posts made (12) num. of views (13) num. of votes in threads (14) num. of votes in posts (15) num. of votes in comments
Oucome	Completion	Course final scores (passed / failed)

As shown in table one, our predictors include: the user's location, number of lectures viewed, number of lectures downloaded, number of quizzes completed, and various variables indicating the learners activities in the discussion forums. Our outcome variable is individual student's final score calculated from the assessment scheme described in Section II.B.

IV. PRELIMINARY FINDINGS

A. Prediction of MOOC Students' Performance

We performed linear regression analyses to examine the relationship between the predictor variables and the outcome variable (table II).

TABLE II. INITIAL LINEAR REGRESSION ANALYSES

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.01742956	0.06106799	0.28541229	0.77533369
(1) timezone	0.02351034	0.020163326	1.16599515	0.24364183
(2) num. of completed(>0 mark) quiz	3.28044693	0.861369186	3.8084099	0.00014063
(3) lecture view counts	0.00158225	0.000465396	3.3998022	0.00067676
(4) lecture download counts	0.00089814	0.00046314	1.93924063	0.05249773
(5) forum reputation points	5.11756373	0.304188547	16.8236568	1.0034E-62
(6) num of view threads	-0.11424	0.014491667	-7.8831484	3.4956E-15
(7) num of view forum	0.34700917	0.014822087	23.4116273	2.566E-118
(8) num of giving upvote	0.1206625	0.123060148	0.98051642	0.32685296
(9) num of giving downvote	-5.687857	0.39914665	-14.250043	1.1471E-45
(10) num of adding tags	-0.2629807	0.524439214	-0.5014513	0.61606365
(11) total num of posts under all his threads	1.20540195	0.099266623	12.143074	1.0286E-33
(12) num of views of all his threads	-0.0002393	0.009430533	-0.0253763	0.9797553
(13) num of votes of all his threads	1.07317202	0.389206431	2.75733373	0.00583715
(14) num of votes of all his posts	-4.5299499	0.279650203	-16.198629	2.4561E-58
(15) num of votes of all his comments	-0.1535105	0.369369196	-0.4156017	0.67770964

Our results are provided in table II above. High *p*-values reflect that a number of variables do not have significant relationship with the outcome. We therefore remove these variables from our model: (1) timezone, (8) num. of up-vote given by the learner, (10) num. of tags added by learner, (12) num. of views of all threads provided by the learner; and (15) num. of votes in comments. We then obtained a refined model and performed linear regression analyses based on the new model (table III).

TABLE III. LINEAR REGRESSION ANALYSES BASED ON THE REFINED LEARNER EXPERIENCE MODEL

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.07908798	0.031202402	2.53467611	0.01126895
(2) num. of completed(>0 mark) quiz	3.2706712	0.860709033	3.79997314	0.0001455
(3) lecture view counts	0.00157741	0.00046531	3.39001052	0.00070137
(4) lecture download counts	0.00092903	0.000462612	2.00822351	0.04464408
(5) forum reputation points	5.08185574	0.242144086	20.9869083	6.6041E-96
(6) num of view threads	-0.1144012	0.014443843	-7.9204155	2.5964E-15
(7) num of view forum	0.34906481	0.014652346	23.8231347	2.425E-122
(9) num of giving downvote	-5.6984246	0.30720515	-18.549248	1.1882E-75
(11) total num of posts under all his threads	1.20237692	0.060706599	19.8063626	8.28E-86
(13) num of votes of all his threads	1.09685701	0.334321472	3.28084525	0.0010382
(14) num of votes of all his posts	-4.5405262	0.274816796	-16.522011	1.3766E-60

From the results (table III) we know that (2) num. of completed quizzes (with non-zero marks), (5) forum reputation points, (7) num. of view forum, (11) total num. of posts under all his threads, and (13) num. of votes of all his threads all have significant positive correlation with the course performance. Meanwhile, (9) num. of giving down-vote and (14) num. of votes of all his posts have significant negative correlation with the course completion.

B. Other Observations

We list a number of observations made from the current analyses below.

1. The predictor variable (5) forum reputation points has the most significant positive correlation with the course grade: Based on the grading criteria, Participation part only consist of 5% of the final

course grade. Each post or comment before the deadline grants 1 point and the maximum score for the Participation part are 5 points. However, the input (5) forum reputation points are based on all kinds of user behaviours in discussion forum, whose coverage is much broader than the 5% Participation part. From this perspective, we know that the learner is likely to get higher grades if he or she does well in various kinds of activities in discussion forum.

2. The input (2) num. of completed (> 0 mark) quiz also has significant correlation with the course grade: Although quizzes are not counted into final grades, it seems that the learners are likely to get higher grades if they voluntarily complete more quizzes.
3. The inputs (11) total num. of posts under all his threads, (13) num. of votes of all his threads, and (7) num. of view forum also has some positive correlation with the course grade: Firstly, if the thread are popular and attracts many posts, the user who put forward this thread would get higher grades. Secondly, if the thread gets many votes and supports from other users, the user who put forward this thread would get higher grades. Lastly, if the user view the forum more frequently, he is likely to get higher grades.
4. The input (9) num. of giving downvote has significant negative correlation with the course grade: Users who are likely to give downvote and negative feedbacks on posts by other users would get lower grades.
5. The input (14) num. of votes of all his posts also has significant negative correlation with the course grade: If the post is popular and gets many votes, the user who posted the post is likely to get lower grades. This conclusion seems to be contradictory compared with (13) which has positive correlation with the course grade. Actually, (13) and (14) are logically self-consistent. In the discussion forum, there are three hierarchical layers-threads, posts, and comments. Specifically, a user put forward a thread which is a valuable topic giving other users an opportunity to post some posts which are related to this thread; and users can also make comments under each post. (13) is positively correlated with the course grade, because the establisher explored an valuable topic which inspired other users a lot; and (14) is negatively correlated with the course grade, because the user posted funny but not academically valuable comments which received many votes from other users. From this perspective, we could infer that compared with the posts getting supports from other users, the exploration of some valuable topic would help much more in the final grade.
6. Surprisingly, the inputs (3) lecture view counts and (4) lecture download counts are not correlated with the course grade: This result is contrary to common sense but actually make sense. Some student roughly watched the lecture video without understanding about course material; and some students download lecture materials but did not carefully digest them. In MOOC, there is no face-to-face interaction between the user and the instructor, and thus the user's self-control is likely to decline.

V. Discussions

A. *Understanding Students' Learning Behavior in MOOC on Information Theory*

We have obtained a number of observations from our empirical data collected from the MOOC platform. In particular, our statistical analyses show that: (1) number of online quizzes completed, (2) forum reputation, and (3) total number of posts made predict students' course completion significantly. It is also found that (1) number of down vote given and (2) total number of votes made have significant negative relationships with MOOC completion.

B. *Promoting Student Completion Rate in MOOC on Information Theory*

Based on the empirical findings, we are able to propose an individualized learning path (ILP) system to promote the MOOC completion rate. The procedure is briefly presented below.

1) Construct the Learner Experience Model: The first step is to construct a learner experience model (LXM) from the MOOC learning data using the way described in Section IV.A. Given that the size of MOOC data is usually large, comprehensive machine learning tools can be applied.

2) Segmentize the study period into sub-intervals: The entire study period is segmentize into an arbitrary number of sub-intervals. Figure 2 illustraes the scenario when the entire study period (a term) is divided into 4 sub-intervals. Sub-models are built based on the learning data collected within each of the sub-intervals. Based on the sub-model, threashold values of the predictor variables for course completion (i.e. having a course final score higher than 70 out of 100) can be obtained.

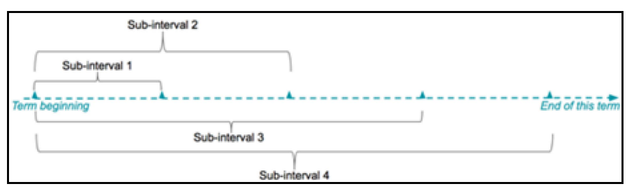

Fig. 2. MOOC study period and sub-intervals (N = 4).

3) Construction of Individualized Learning Path: Based on the learning analytic results obtained from each of the sub-interval, together with the LXM that have been constructed in Step 1, an individualized learning path (ILP) can be derived and revised.

Our idea inherits that from [4]. For predictor variables within the LXM where the learner obtains a value lower than the threshold (i.e. minimum value of the predictor variable that can lead to an outcome variable higher than the passing scores; or 70 out of 100 scores in our MOOC), the ILP will be automatically revised to recommend the corresponding additional learning materials and/or learning behaviours in a way that the learner's low performance can be mitigated. This is depicted in figure 3 below.

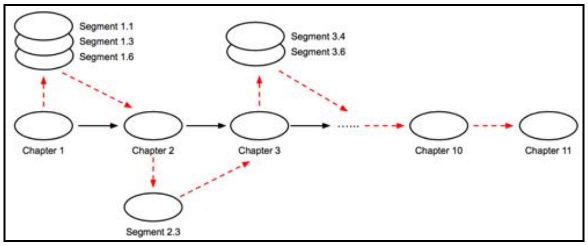

Fig. 3. Individualized learning path construction based on learning analytics within sub-intervals.

Using the LXM, we can get the predicted final course grade of each user, and identify the input parameters that the user did not do well in. For input parameters where the user gets score lower than the standard limit, the ILPS would automatically provide related additional materials which aim at improving the user's performance in these input parameters.

VI. Conclusion

In this work-in-progress, we have collected empirical data from an MOOC in Information Theory provided by our third author. We established a learning experience model by extended an existing framework in the MOOC literature. We have identified significant predictive relationship between a number of metrics for online learning behavior and MOOC completion. Our preliminary findings enable us to further propose an Individualized Learning Path System that generates and selects the most suitable learning path for individual students. We will continue our on-going work and hope this work-in-progress paper can engender further discussions in this area.

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