Would Linked MOOC Courseware Enhance Information Search?

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***Abstract*—The revolution of online learning brings great opportunities to millions of learners. However, the size of the learner population and the heterogeneity of the learners' backgrounds make conventional one-size-fits-all pedagogies inappropriate. We propose a conceptual model – educational resource linking with the goal of satisfying various learning needs by building a rich platform integrating abundant and open online resources. With this model, resources could be organized around a shared curriculum, and materials on the same topic are cross-linked for recommendation. This idea may improve the efficiency in utilizing and digesting scattered knowledge. As a first step, we conducted a case study using crowd-sourcing techniques, and found that learners, especially novices, can search learning materials faster without sacrificing accuracy, when using an interface with linked learning resources, as compared to a traditional, monolithic one.**

Keywords–MOOC, educational content organization, RecSys

I. Introduction and Related Work

Massive Open Online Courses (MOOCs) bring great opportunities to millions of learners around the world by allowing them to take courses from top universities without the need for physical presence [1]. However, the openness of these platforms has also created some challenges – the sheer size of the learner body and the heterogeneity of their background (e.g., demographics, enrollment motivation) make it very difficult to meet everyone's learning needs [2, 3, 4]. Specifically, today's MOOC courseware typically consists of several high-quality resources that vary in types (e.g., videos, slides, textbooks, discussion forum), course level (e.g., college courses, graduate level courses), etc. As illustrated on the left-hand side of Figure 1, these resources are accessible to learners as disjoint entities. Although materials under this scenario can potentially meet learners' diverse needs, a learner interested in a specific topic may not be able to easily look up relevant resources, such as from slides to textbook sections, or from introductory materials to advanced ones, to broaden his/her learning or to overcome confusion.

We hypothesize that *organizing the various educational resources into a form that will enable the learner to navigate efficiently from one type of resource to another will promote better learning*[1]. Depending on learners' backgrounds, they can easily select supporting resources to fulfill their needs. Based on the hypothesis, we introduce the framework, *educational resource linking* – the process of organizing learning materials scattered around online learning platforms into an easily accessible structure. This framework is illustrated on the right-hand side of Figure 1. Conceptually, one can visualize the linked courseware as a tree, where the trunk corresponds to lecture topics (red nodes) that the instructor has chosen to organize the material, and the branches correspond to various resource segments (blue and green nodes) that are associated with the lecture topics. This notion is similar to a proposal called LinkedUp [5] – an attempt at creating, utilizing, and organizing open Web data for education, as well as building an active research community. Our work, however, focuses on scalable (i.e., automatic) solutions for implementation and evaluation using human language technologies and crowd-sourcing techniques.

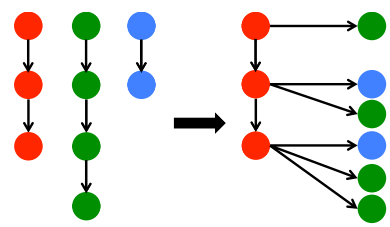

Figure 1. Schematics of the transformation of several independent educational resources to a linked structure. Each color illustrates one type of education resource.

We believe this model could benefit learning in two aspects. First, because resources are organized around a unified structure, learners can better store and retrieve the courseware, which is a crucial factor differentiating experts from novices [6], as well as allowing meaningful learning [7]. Second, the linkage can offer the domain model (i.e., the comprehensive and networked learning materials) upon which recommendation systems (RecSys) [8, 9, 10] are built. RecSys provides learners guidance on course materials, facilitates navigation through relevant and complementary topics, offers learners the freedom of exploring information they need, and realizes personalization [10].

To validate our hypothesis, this paper explores usefulness of linked content on learners with a case study. We choose three typical types of resources around an existing MOOC and demonstrate how to build a system implementing the linking model. Similar to [11], we evaluate the impact of the system on learners through information search. Crowd-sourcing techniques are applied to recruit experimental subjects for comparative study. Such techniques have been proven effective and efficient in assessing RecSys [12]. In our case, linking is accomplished manually by experts. Once the hypothesis is validated, we will proceed to automate the process in our future research for scalability.

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II. Experimental Setup and Results

A. The Course Material and The Access Interface

We focus our investigation on resources for a single MOOC – Stat2.1x: *Introduction to Statistics,* offered by UC Berkeley on edX in 2013. This course is chosen because it comes with three resource types common to many MOOCs – lecture videos, slides, and (electronic) textbook. Therefore, our results may be more generalizable to other courses. Stat2.1x contains 31 lectures totaling 7 hours of video, and 157 pages of slides. The suggested textbook contains 77 sections, providing independent support to the lecture material.

We first build a search module to access these resources for our study. Upon receiving a query, the search module retrieves the results and shows them to the user. The left panel of Figure 2 illustrates how the results are presented to the user in *baseline* condition, i.e., the conventional way of delivering materials where each type of courseware is shown monolithically. By clicking the icon, the corresponding content will appear in a call-out box *independently*. In contrast, the right panel of Figure 2 illustrates the *linked* interface. It is powered by our linking model. In this case, materials that are linked are enclosed in a sequence of red rectangular boxes, which corresponds to the trunk, i.e., the lecture videos. Clicking on the box causes the associated segments to appear on the same call-out box for the learner to peruse at will.

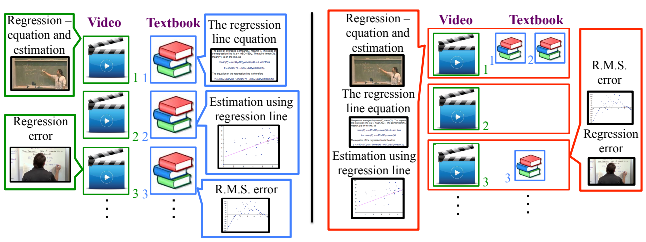

Figure 2. An example of the *baseline* and *linked* interface used in our experiment.

To create the *linked* interface, we first delineate each type of learning resources into segments, such that these learning units are large enough to be self-contained, and yet small enough to enable learners to browse effectively. These segments are subsequently organized into a proper curriculum. Finally, relevant topic vignettes from each type of resource must then be linked, as shown in Figure 2.[2]

B. The Experiment and Subjects

The question we seek to answer is whether the *linked* interface will results in better learning outcomes than the *baseline*. However, learning is a combination of mental processes such as attention, memory, problem solving, thinking, etc.; it may be too elusive to ascertain in one set of experiments. We thus adopted a specific set of learning-related activities – educational content navigation, as a proxy for learning, similar to [11]. Better content navigation may bring additional benefits to learning, such as helping struggling learners to find high quality and immediate remediation [13]. Thus, we focus on testing educational content navigation, leaving out for the moment more psycho-educational effects on learning.

To evaluate learners' performance in content navigation, we design a learning scenario – "information search," where a learner in our experiment is given a question, and asked to retrieve a learning segment (in videos, slides, or textbook) that can be used to solve the given question. This scenario attempts to emulate a situation where the learner is trying to review educational content and/or searching for useful information for problem solving. In this study, four questions are sampled from the problem set in Stat2.1x. We conduct a comparative study and measure learners' performances in this scenario by computing the task completion time and the accuracy of the retrieved segment. By analyzing the difference in performance using each interface, we seek to provide evidence that our proposed model benefits learners in navigating across educational contents.

We have chosen to apply crowd-sourcing techniques to recruit online workers on Amazon Mechanical Turk (AMT) as subjects for our experiments. Ideally, one may want the subject pool to be learners who are actually taking the course, so that one can measure directly the usefulness of the linked resources. However, performing a live experiment in an actual MOOC can be expensive, time-consuming, and disruptive. In contrast, taking advantage of the abundant online labor pool is a good strategy to ensure that our study is scalable [12, 14]; these micropayment workers have shown similar performance to that of experts in completing tasks when suitable quality controls are adopted. Besides, we can easily access AMT workers with a variety of backgrounds. The diverse demographics of online workers are good approximations to the ones of online learners. Specifically, 151 AMT workers participated in our experiments. Table I summarizes these subjects' background – whether or not they have at least a college degree, have taken MOOCs previously, or have had exposure to statistics.

TABLE I. A BREAKDOWN OF SUBJECTS FOR THEIR BACKGROUND

≥ Bachelor	≤ Some college	MOOCs	No MOOCs	Statistics	No Statistics
67	84	40	111	86	65

C. Experimental Results

Table II summarizes the learner performances. There are two performance metrics: average searching time (in seconds) and accuracy of task completion (in percent). To compute the task accuracy, we compare each user response to the ground truth, which is defined as the most frequently selected learning segments in each resource – video, slides, and textbook, by all learners. For this measure, we also include, in brackets, the number of tasks as an indication of the scale of the experiment. In addition to reporting the two absolute performance measures, we also give the *p*-values for significance test of the improvement made by the *linked* interface. We adopt a one-tailed, two-sample t-test for search time, and one-tailed binomial proportion test for accuracy.

[2] We first automatically segment the textbook into sections, and slides into pages. We then recruit two researchers to manually align the video transcription to the deck of slides from the same lecture, and segment the video into vignettes, where each vignette corresponds to one aligned page of slides. The aligned vignettes are then linked to the slides accordingly. For each page of slides, the same two researchers also label the most relevant textbook section, and we link the labeled segment to the slide page. If there is a disagreement, the two researchers discuss until consensus is reached.

The significance level is defined to be α = 0.05. Finally, we filter out spammers and outliers for reliable experimental analysis, here, among each group of learners. This is done by discarding results from subjects who spend abnormal amounts of time (above 95th percentile or below the 5th percentile of spent time).

TABLE II. LEARNERS PERFORMANCE ON 'INFORMATION SEARCH' TASKS USING 'BASELINE' OR 'LINKED' INTERFACE.

Learner background	Time consumed: Seconds			Task accuracy: % of correct tasks (# tasks)		
	Baseline	Linked	P-value	Baseline	Linked	P-value
≥ Bachelor	306	284	0.162	52 (96)	65 (98)	**0.032**
≤ Some college	322	257	**0.006**	66 (98)	55 (96)	0.942
MOOCs	277	286	0.633	70 (40)	63 (34)	0.744
No MOOCs	323	267	**0.004**	55 (154)	59 (160)	0.212
Statistics	294	268	0.101	60 (120)	61 (120)	0.448
No Statistics	346	276	**0.012**	57 (74)	58 (74)	0.435
Overall	315	271	**0.006**	58 (194)	60 (194)	0.379

Focusing first on the last row of Table II, we see that the overall performance suggests that the averaged search time using the linked interface is 14% less than using the baseline interface (cf. 315 *vs.* 271), and this improvement is statistically significant. In contrast, there is no significant difference in task accuracy for using the two interfaces. Looking over the top six rows of Table II for the individual results of the three demographic groups described earlier, we observe that the linked interface reduces search time in five of the six cases. However, the difference is statistically significant only for novice learners – those who are less educated, less experienced with MOOC, or less familiar with the subject materials. In all but one case, including all results involving novices, the speed improvement is accomplished without sacrifice of search accuracy.

The fact that the linked interface yields better performance for novice subjects is perhaps not surprising. Because of the lack of preparedness of these subjects – less education, less experience with MOOC, and less familiarity with the subject matter, they may not possess the broad perspective to explore the various resources on their own. By organizing the learning resources in a *linked* interface, we can potentially help novices navigate through the knowledge space more effectively, which could lead to improved knowledge acquisition. This is consistent with previous work that shows "guidance" is particularly crucial for learners who are likely to struggle [15].

Our results indicate that linking has little impact on task accuracy in most cases. This could be due to the fact that the difference between the two interfaces is about how the materials are presented, rather than the information itself. Therefore, learners can always find the correct learning segments with sufficient time and persistence.

III. Summary and Future Work

This paper describes the first step in our effort to provide students with diverse backgrounds the ability to enhance their learning through a linked interface. Before building such an interface automatically to achieve scalability, as well as investigating a variety of resources or psycho-educational effects thoroughly, we conducted a case study to explore whether such an interface would improve a specific learning task in a controlled condition. Our result suggests that learners, especially novices, can search for desired information faster with the *linked* interface than in the context of a *baseline* where learning resources are presented monolithically. Simultaneously, no sacrifice in accuracy is observed. The result provides evidence that the linked interface, which is an embodiment of the proposed linking model, is beneficial in educational content navigation. We believe our linking model is well suited to MOOC, in which there is a high demand for providing multiple alternatives of resource presentation in order to accommodate the diverse backgrounds of learners. It is the novice learners who will need the most help and who stand the most to benefit [15].

Future work for our research will follow several directions. First, we plan to refine our experimental procedure, expand our repertoire of learning metrics, explore other educational resources (e.g., discussion forum), as well as conduct similar experiments on other MOOCs to further validate our results. Second, we will investigate how a system can be built to realize the model automatically, without the need for expert labeling, An automatic method such as understanding the education contents with text mining [16] is crucial for the system to be scalable and practical.

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