Analyzing K-12 Blended MOOC Learning Behaviors

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ABSTRACT

We investigate student learning behaviors in a Massive Open Online Course with in-person components. Our goal is to improve the design of the course through learning analytics. The programming language taught, App Inventor, is a drag-and-drop language to create Android applications. We visualize and quantify student behaviors such as automatic and manual saving of code, video sections viewed, and the various forms of knowledge required to understand the course material. It appears students are less likely to go from course material that teaches procedures to other material that teaches procedures than we would expect, and rarely review previous topics covered in the course. We also find students tend to save marginally less at the beginning and end of sessions. However, since the data set is small, our conclusions are limited.

Author Keywords

Blended MOOCs; App Inventor; learning analytics; learning design; resource usage; knowledge type.

CCS Concepts

•Applied computing → E-learning; •Social and professional topics → Computational thinking; K-12 education;

INTRODUCTION

It is difficult for instructors to monitor student progress or provide feedback in Massive Open Online Courses (MOOCs) to the extent possible in physical classrooms [8] [1]. Instructor feedback can be essential to introductory programming classes because programming is hands-on and difficult to learn and teach [1] [5]. Programming used to be considered a specialized skill set. Therefore, much of the knowledge regarding how to teach programming is targeted towards post-secondary education. Now, however, programming is considered more mainstream [4]. In the absence of level-specific knowledge, teaching programming to K-12 students in an online setting is particularly challenging. To address this issue, some MOOCs have in-person components. These are called blended MOOCs [3]. This structure allows for students to be largely independent yet still receive some instructor feedback and monitoring.

However, the mixture of online and in-person content adds noise to the data as we are unsure what students were told in person (ex. "Skip unit 5").

We focus on a blended MOOC taught by the Hong Kong University of Science and Technology in 2018¹. The in-person portion of the course consists of workshops for students. The course teaches K-12 students App Inventor, a drag and drop programming language to create Android Applications, and computational thinking. Computational thinking is the set of problem-solving methods used to express problems and their solutions in ways that computers can execute [7]. The App Inventor programming is done on a separate server.

Our research questions are: What patterns of learning do students exhibit in a blended MOOC environment? How do students progress throughout the course and within individual problems? What difficulties do students have with the online course material (resources)? What habits and skills should they develop to improve their studies in such an environment?

We answer these questions by quantifying and visualizing behaviors such as automatic and manual saving of code, video sections viewed, and student interactions with different types of resources, which we categorize by the "forms" of knowledge required to understand the material (knowledge types). From these data, we infer how students work and whether that matches the design of the course (learning design). By investigating resource usage patterns and knowledge types, we try to understand how students interact with different types of course material.

Students are not required to follow the course from start to finish, which we call the intended course trajectory. Yet, we find students do. We examine this adherence to the intended course trajectory in combination with resource knowledge types. Finally, reviewing course material has been shown to be an effective learning technique, so we look at whether students review materials [6].

COURSE CONTEXT

The course uses the Open edX platform, which we use to collect clickstream data. User code is extracted from the App Inventor Server. User code is automatically saved every five minutes if the code has changed from the previous save state. Students may also manually save at any time. As a result, we only see changes from one save state to another, rather than

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¹https://learn.familylearning.hk/courses/course-v1:HKUST+appinv2+2019_Q4_R1/about

every change a student makes. We take this as evidence that the save data is noisy.

The data is derived from approximately 300 students, only about 100 of whom interact with both the edX course and the App Inventor Server. For questions pertaining to user code, we only use data from those 100 students with both server and course activity. Otherwise, we use the data from all 300 students. It appears the only difference between these cohorts is that students with both course and server activity tend to have more daily interaction with resources.

The data are separated into clickstream data (logs of how users interact with the course material) and code save states, which are tied to a user and time of occurrence. We define a user save state as the characteristics of a user's code at any given save point. Note, for clickstream data, we cannot know if students use these resources or if they are accidental clicks. We are also unable to say if the user is actively engaged with a resource or if they are idle.

Clickstream data allows us to track how students interact with each resource in the edX course. The edX data do not provide all the information necessary to see an accurate progression of students learning. So, we ran a web scraper to obtain the order that resources appear within the course, accurate resource names and all possible URLs for every resource.

Each resource is categorized based on a revised Bloom's taxonomy [2] by learning design experts according to what types of knowledge are required to understand the material. *Factual* knowledge is the basic information necessary to understand a topic (ex. vocabulary). *Conceptual* knowledge refers to the interrelationships among facts and how they function within larger structures. *Procedural* knowledge consists of methods, algorithms and skills used to solve problems, and the criteria for when it is appropriate to use them. A resource can have multiple knowledge types.

METHODS

Aggregated Saves

We aggregate code save states to visualize how often students save code throughout sessions. We define a session as a set of resource interactions surrounded by no interactions for at least δ amount of time. We examine code save states on the App Inventor Server across all sessions. By definition, a session on the App Inventor Server must end and start with a save. Therefore, we ignore the first and last save in every session. We run this process for all sessions with δ values between 1 and 40 minutes. We look at this time range because 80% of all saves are within 40 minutes of another save. Sessions longer than 40 minutes appear to be less representative of the data. For each run, we calculate the percentage of the number of times each student saves at every point in a session out of the total number of saves each student makes in that session. We then take the median percentage of saves at each point across all sessions and students.

Resource Reviews

We classify a review as a transition from a resource that appears later in the course to a resource that occurs earlier in

the course. For example, a review could be a transition from resource 9 to resource 2. We can say any pair of resources (n_i, n_j) is a review if and only if $j < i$. We call n_i the origin resource and n_j the destination resource.

To track whether students review resources, we look at clickstream data excluding the App Inventor Server page and the homepage. We attempt to filter out accidental clicks and students quickly reviewing a resource but then realizing it is not relevant. We do this by only including reviews in which a student spends at least three minutes on the destination resource. We define the time spent on a resource as the time spent between subsequent clicks in a clickstream log.

Knowledge Type Transitions

We quantify the likelihood a student will transition from one resource knowledge type to another within a session, where the session threshold is two hours.

One transition can include multiple knowledge type transitions. For example, if the user moves from a resource which contains factual and procedural knowledge to a resource which contains conceptual and procedural knowledge, that would be considered a transition from factual to conceptual, factual to procedural, procedural to conceptual, and procedural to procedural.

Since the distribution of resource transition knowledge types is unequal, we look at the percentage of transitions from each knowledge type to all three knowledge types in comparison to the percentage of resources that contain each knowledge type.

Also, since knowledge types are often followed by the same knowledge types in the intended course trajectory, we consider the distribution of repeated knowledge type transitions in the context of the intended course trajectory.

Video Fast Forwards and Rewinds

We aggregate clickstream data by video within the course to see whether students are reviewing or skipping sections of videos. We look at the clickstream event *seek_video* which represents when a user fast forwards or rewinds a video.

A *seek_video* event contains two time fields: the time that the *seek_video* event occurred within the video and the time in the video moved to. We use this to determine whether a user has fast forwarded or rewound. We will refer to fast forwards as forward seeks and rewinds as backward seeks.

Prior to every *seek_video* event a *play_video* event occurs, which represents when the user plays the video. Every *play_video* includes the time within the video that the video starts from. Note, in about 6.8% of *seek_video* events, the time within the video that the event occurs is earlier than the time in the *play_video* event before it. These data are invalid because a *play_video* event always precedes a *seek_video* event. For this reason, we take this as evidence that the clickstream data is noisy.

RESULTS

Aggregated Saves

Based on the data shown in Figure 1, it appears students save slightly less towards the beginning and end of a session. To

Figure 1. Distribution of Saves at Different Points in a Session: we determine the percentage of the number of times each student saves at every point within a session out of the total number of saves each student makes. We do this for sessions with δ values between 1 and 40 minutes. We then take the median percentage of saves at each point within the sessions across all students. The x-axis shows how far through a session a save occurs. The y-axis shows the percentage of total saves made at each point within the session. We see students tend to save slightly less at the beginning and end of sessions.

support this observation, we run Kruskal-Wallis tests on the beginning and middle, middle and end, and beginning and end sections of the aggregated distribution. We classify the beginning section to be saves that occur within the first 10% of sessions, the middle section to be saves that occur between 45% and 55% of the way through sessions, and the end section to be saves that occur in the last 10% of sessions. We also compare medians to estimate the effect size. According to Table 4, there is a small but statistically significant difference in the number of saves throughout a session. Therefore, it is possible students save slightly more in the middle of a session than at the beginning and end.

Resource Reviews

As shown in Table 1, there is little evidence to suggest students review resources. Many of the reviews that do occur make sense in context of the course. For example, “*Component Property*” contains knowledge directly related to “*Label component*” (highlighted in Table 1).

Knowledge Type Transitions

In Table 2, we see that transitions made by students (student transitions) from factual to factual knowledge types occur 34% of the time, while only 19% of all transitions contain factual knowledge, a ratio of about $\frac{5}{3}$. We see about the same ratio for conceptual to conceptual transitions. Yet, for procedural to procedural transitions, we see a ratio of about $\frac{14}{13}$. In addition, according to Table 3, procedural resources follow other procedural resources about 13% more than factual resources follow factual resources and about 20% more than conceptual resources follow conceptual resources. Therefore, we would expect a procedural to procedural transition to be as, if not more, likely to occur than a factual to factual or a conceptual to conceptual transition.

Figure 2. Video Fast Forwards and Rewinds: this figure shows the distribution of fast forwards (forwards seeks) and rewinds (backwards seeks) per video. The x-axis shows the percentage of each type of seek within a video and the y-axis shows the frequency at which that percentage occurs.

Video Fast Forwards and Rewinds

As indicated by Figure 2, backward seeks typically make up 40% or less of seeks within a video, with 0% being the mode. In contrast, most forward seeks make up 60% or more of the seeks within a video, with 100% being the mode. It appears that in comparison to forwards seeks, students rarely seek backwards. One possibility is that these forward seeks are representative of students skipping content. Another possibility is that students might watch a video once, then come back to it at a later time and fast forward to the relevant content.

CONCLUSION AND FUTURE WORK

In order to improve distance learning, we must understand students’ learning patterns. Our investigation focused on patterns in how students solve computational problems. In essence, we attempted to infer students’ computational thinking processes.

We find that students are less likely to go from a resource with procedural knowledge to one with procedural knowledge than we would expect, appear to not review resources often and fast forward videos more often than rewind. In addition, we see students tend to save slightly less at the beginning and end of sessions.

However, our data set is small, and thus our interpretations are limited. It would be best to run this analysis with data from multiple runs of the course. In addition, some of the clickstream data is corrupt such as some of the *seek_video* events. In fact, we do not know if any clicks in the clickstream were accidental, if the students attempted to learn from the resources, or if the users were idle after a click. Further, the App Inventor Server only collects data in five-minute intervals, which may or may not be often enough to accurately track how students save code. We also only know what students do, not what they are thinking. One solution to this could be to include a survey at the end of certain resources that asks questions such as “*What did you find hard about this problem?*”. In addition, we do not know what the students were told during the in-person portions of the course, which adds noise to the data. We also arbitrarily defined the threshold for a transition to be

Origin Resource	Destination Resource	Count
Waste Data And Statistics	Background Information	2
Using Emulator	Code2App Student Advanced Workshop Mar 2	2
Label Component	Component Property	2
App Inventor Project and Starting HelloWorld Project	Syllabus	2
Homework 1	Non-visible TextToSpeech Component	3
Background Information	Code2App Student Advanced Workshop Mar 2	3
Homework 2	Homework 1	3

Table 1. Resource Reviews: this shows what resources students review. The “Origin Resource” column shows the origin resource, the “Destination Resource” column shows the destination resource, and the “Count” column shows the amount of times each review occurred. It appears students do not review resources often. The highlighted row is an example of a review which makes sense in context of the course.

Origin Type	Destination Type		
	Factual	Conceptual	Procedural
All	19%	16%	65%
Factual	34%	13%	52%
Conceptual	16%	26%	58%
Procedural	15%	14%	71%

Table 2. Knowledge Type Transitions: The row named “All” shows the percentage of student transitions that contain a certain knowledge type. The other rows show the percentage of student transitions that go from an origin resource with a knowledge type to a destination resource with some knowledge type out of the total number of transitions that include the knowledge type of the origin resource.

Factual	Conceptual	Procedural
62%	70%	83%

Table 3. Knowledge Type Repeats: this shows the percentage of transitions in the intended course trajectory that go from one knowledge type to the same knowledge type out of all transitions containing that knowledge type.

Comparison	Change in % Saves	p-value
Beginning vs. Middle	-1%	< 0.001
Middle vs. End	2%	< 0.001
Beginning vs. End	1%	< 0.001

Table 4. Kruskal Wallis Tests: we perform Kruskal-Wallis tests to compare the beginning, middle and end sections of the aggregated saves. The “Comparison” column shows the two sections being compared. The “Change in % Saves” column shows the difference in medians between the two sections. The “p-value” column shows the p-value of the Kruskal-Wallis test between the two sections.

considered a review to be three minutes. In future work, we will explore different review thresholds. Additionally, we only considered transitions in sessions with δ values of two hours when analyzing knowledge type transitions. In future work, we will analyze knowledge type transitions in sessions with different δ values. In addition, to better understand student habits, we will determine whether there are certain periods of time when students save code more frequently, relative to their time zones. Lastly, we will attempt to infer whether video fast forwards are representative of students skipping content or reviewing it by checking if they have viewed the video before.

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