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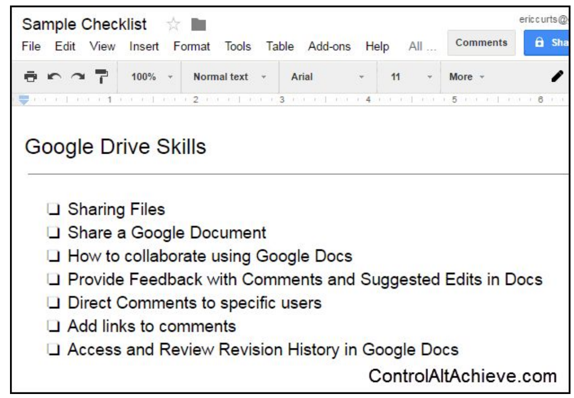

Category

- ✓ Data-Driven Course Design
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Title

The importance of iterative course design: using learning analytics to evaluate and revise difficult problems in a Biochemistry MOOC

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Abstract

Problem sets are important tools for formative assessment of learning. MITx Biology is a subgroup of the MITx Digital Learning Lab that develops MOOCs (as well as other digital resources) in collaboration with faculty in the Department of Biology for residential and global learners. Our problem sets are designed according to well-established pedagogical guidelines, evaluated based on learner performance, and revised to maximize their effectiveness towards facilitating learning. Here we describe our use of learning analytics to assess and revise difficult problems that learners struggled to answer correctly from the first course run of a Biochemistry MOOC.

Introduction

Assessments (problem sets) are important for facilitating active learning (Bell & Cowie, 2001) and are a major component of the learning experiences we develop in our MOOCs. We apply educational frameworks such as backwards design (McTighe & Thomas, 2003) and Bloom's Taxonomy (Krathwohl, 2002), and utilize established learning strategies such as activating prior knowledge (Ambrose et al, 2010), instructional scaffolding (testing one or a few steps at time per problem; Reiser, 2004, Jumaat & Tasir, 2014), and retrieval practices (Baker & Weidman, 2015) in the design of our problem sets.

An integral step of our design process is the analysis of learner performance and answer submissions across all problem sets at the completion of a course run. We use these data to evaluate the quality of our problem sets (appropriate difficulty level of problems; detecting errors or ambiguity in problem design) and identify common learner errors. Based on our findings, we revise our problem sets and course materials for the next course run.

We present our use of learning analytics data (readily available through edX insights) to assess and revise the design of 44 problems that learners struggled to answer correctly from the first course run of 7.05x, our Biochemistry MOOC, as an example of how we approach iterative, data-driven course design.

Results

Problem Set Name	# of Problems	% Average Correct Answer Submissions	# of Flagged Problems
Buffers and Amino Acids	33	83.7	8
Protein Purification	37	79.8	10
Protein Structure and Folding	45	81.6	10
Hemoglobin	29	79.5	7
Enzymes	40	84	8
Membranes and Signal Transduction	42	89.7	1

Table 1. 7.05x Problem Sets Overview

From our learning analytics, we provide an overview of learner performance by reporting the number of problems and the percent average correct answer submissions per problem for each problem set (**Table 1**). We analyzed the percent of correct answer submissions for all problems within the problem sets and flagged 44 problems that had percent answer submissions values below 70% (also summarized in **Table 1**). We chose below 70% as our limit because the majority (~75%) of problems per problem set had percent answer submissions above 70%. The flagged problems represented ~25% of the problems per problem set (with the exception of the final problem set). We further analyzed the answer submissions of these flagged problems, and assigned error categories (coding, wording, or learner) based on our interpretation of why learners performed poorly; when applicable, we assigned multiple error categories per problem. We assigned coding and wording error to problems with incorrect code guiding automatic grading or unclear exposition/answer options for novices (based on beta testing and forum queries), respectively. We assigned learner error to problems where learners made incorrect answer submissions despite having the correct code and (as far as we can discern) clear exposition.

We identified one coding error, seven wording errors, and 37 learner errors. We further subcategorized learner errors based on our interpretation of learner mistakes; when applicable, we assigned multiple subcategories per learner error. Ranked by frequency, we observed thirteen instances where learners struggled to correctly proceed through multiple steps to solve flagged problems, nine where learners made incorrect computation, seven where learners needed to answer prior problems correctly to solve flagged problems, five where learners failed to synthesize multiple concepts to correctly solve flagged problems, five where learners used surface level reasoning, and four where learners disregarded clear instructions.

We are revising flagged problems in response to the category and subcategory of identified errors. For problems with coding and wording errors, we will correct our code and reword the exposition/answer options to be unambiguous for all learners. For problems requiring multiple steps, we plan to provide more scaffolding so learners have multiple opportunities to check their reasoning and work towards the correct answer. For problems with incorrect computation, we plan to increase the number of attempts, relax the stringency of accepted answers, and provide more scaffolding. For problems requiring a prior correct answer, we plan to eliminate their dependency on answering previous problems correctly. For complex problems that require synthesis of multiple concepts, we plan to divide these problems to provide more scaffolding, similar to problems requiring multiple steps. For problems that require deeper understanding, we plan to provide hints to activate learners' prior knowledge. Finally, for problems where learners did not follow instructions, we plan to make our instructions even clearer by bolding crucial details, adding hints, increasing attempts, and (when applicable) relaxing the stringency of accepted answers.

The second course run of 7.05x is scheduled to start June 2019, and once it is completed, we will repeat this process of evaluating our problem set learning analytics to scan for difficult problems and assess whether the revisions documented here from the first course run have improved learner performance on these flagged problems.

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