When students can choose easy, medium, or hard homework problems

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When Students Can Choose Easy, Medium, Or Hard Homework Problems

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Abstract. We investigate student-chosen, multi-level homework in our Integrated Learning Environment for Mechanics [1] built using the LON-CAPA [2] open-source learning system. Multi-level refers to problems categorized as easy, medium, and hard. Problem levels were determined a priori based on the knowledge needed to solve them [3]. We analyze these problems using three measures: time-per-problem, LON-CAPA difficulty, and item difficulty measured by item response theory. Our analysis of student behavior in this environment suggests that time-per-problem is strongly dependent on problem category, unlike either score-based measures. We also found trends in student choice of problems, overall effort, and efficiency across the student population. Allowing students choice in problem solving seems to improve their motivation; 70% of students worked additional problems for which no credit was given.

Keywords: Introductory Physics, Problem Solving, Online Homework
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INTRODUCTION

Problem classifications such as easy, medium, and hard are widely used in physics textbooks and curricular materials. Such classifications are typically based on instructors’ opinion with little research-based justification. In our Integrated Learning Environment for Mechanics (ILEM), we are investigating quantitative measures that justify such classifications, as well as students’ behavior when allowed to choose from a collection of pre-categorized problems. This research will be used to enhance our categorization and the pedagogical effectiveness of ILEM.

In this article, we investigate problem characteristics and student performance using multiple assessment techniques. We aim to measure properties of our categories and to understand how students use the system.

BACKGROUND

We implemented student-chosen multi-level homework during a reformed off-semester introductory mechanics course in Spring 2011 (8.011) for students who had failed or not completed introductory mechanics (8.01). Student-chosen homework was offered only in the first part of the course, targeting basic knowledge and solving single-concept problems; the latter part of the course emphasized developing strategic knowledge necessary to identify physical principles in multi-concept problems. Student-chosen homework problems were organized in easy, medium, and hard categories using the Taxonomy of Introductory Physics Problems [3] that categorizes problems based on cognitive processes and knowledge required. Our problems involved similar cognitive processes, but different declarative and procedural knowledge (Table 1 has characteristics and examples).

Each homework assignment in ILEM featured an average of six problems from each category weighted by points: easy=1pt, medium=2pts, and hard=3pts. Students were required to accumulate at least 15 pts with no restrictions regarding the types or order of problems solved. Students were allowed 7 attempts to solve each problem and it was always possible to accumulate 15 points while working within only two of the categories. A total of five assignments were given along with a wiki-based online text to introduce the relevant material. The ILEM homework was due before students came to class and was meant to establish their basic knowledge of the physical concepts and their understanding of the introductory text. After class, students had to complete Mastering Physics [4] problems and written problem sets. The course was taught in a SCALE-UP [5] format with ~18 students per section using our Modeling Applied to Problem Solving pedagogy [6, 7]. Classes emphasized students solving problems in pairs at the board.

DATA ANALYSIS AND RESULTS

Our homework has two unique features: problems are classified according to cognitive processes and knowl-
Table 1. The cognitive processes and the knowledge (both declarative and procedural) targeted by easy, medium, and hard problems. For more detailed definitions of the cognitive processes and knowledge types see ref. [3].

<table>
<thead>
<tr>
<th>Difficulty</th>
<th>Cognitive Processes</th>
<th>Declarative Knowledge</th>
<th>Mental Procedures</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Easy</td>
<td>recall, execution,</td>
<td>definitions,</td>
<td>single rules and</td>
<td>evaluate definitions, identify</td>
</tr>
<tr>
<td></td>
<td>representation,</td>
<td>vocabulary terms,</td>
<td>basic algorithms</td>
<td>appropriate systems, perform</td>
</tr>
<tr>
<td></td>
<td>ranking,</td>
<td>basic facts,</td>
<td></td>
<td>simple calculations, match</td>
</tr>
<tr>
<td></td>
<td>analyzing errors</td>
<td>simple time</td>
<td></td>
<td>basic graphs with verbal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>sequences</td>
<td></td>
<td>descriptions, match</td>
</tr>
<tr>
<td>Medium</td>
<td>same as Easy +</td>
<td>complex facts and</td>
<td>complex algorithms</td>
<td>choose an appropriate problem</td>
</tr>
<tr>
<td></td>
<td>integration</td>
<td>time sequences</td>
<td>and tactics</td>
<td>solving strategy, perform</td>
</tr>
<tr>
<td>Hard</td>
<td>same as Easy +</td>
<td>more complex facts</td>
<td>complex procedures</td>
<td>evaluate solutions, match</td>
</tr>
<tr>
<td></td>
<td>integration</td>
<td>and time sequences,</td>
<td></td>
<td>complex diagrams with verbal</td>
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<td></td>
<td>principles</td>
<td></td>
<td>descriptions, match</td>
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<td></td>
<td></td>
<td>and generalizations</td>
<td></td>
<td>problems with their</td>
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<td></td>
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<td></td>
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<td>strategies, perform</td>
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<td>multi-step and limiting</td>
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<td></td>
<td></td>
<td></td>
<td>case calculations, multiple</td>
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<td></td>
<td></td>
<td>object scenarios</td>
</tr>
</tbody>
</table>

edge required and students choose which problems to solve. These features raise the following questions:

- How do our qualitative problem categories compare with performance-based measures of difficulty?
- How much time do students spend on the different types of problems and with what efficiency?
- What seems to guide students’ choice as to which and how many problems to do?

Three assessment techniques have been used to address these questions: LON-CAPA difficulty $Di f f_{LC}$, item difficulty using item response theory ($Di f f_{IRT}$), and time measures describing both problems and students. All submissions in LON-CAPA are logged with a time stamp, a score (right or wrong), and the number of attempts, allowing performance-based and time-based measurements for problems and students. A total of $N = 63$ students interacted with $M = 99$ questions embedded in our multi-level homework in ILEM.

LON-CAPA estimates problem difficulty using methods similar to classical test theory, defining the difficulty as the fraction of submissions that are incorrect, $D i f f_{LC} = I n c o r r e c t / T o t a l$ ($D i f f_{LC} = 0$ if all submissions are correct and $D i f f_{LC} = 1$ if all submissions are incorrect). $D i f f_{LC}$ is based only on those students who attempted a given problem and so may be biased towards students with either high or low average skill.

IRT allows for a skill-based assessment of problem difficulty, where the probability that a student of a given skill level would answer each problem correctly is fit using logistic models. For these calculations, a matrix of student responses for each problem is dichotomized into correct/incorrect (or no response). In the IRT analysis presented here, we consider only the first submission to a problem; little variation was found between levels when applying IRT to the seventh submission. We provide results from a simple Rasch model [8] using the open source package in $R$ known as $l t m$. Since our course was relatively small, problem discriminations could not be performed; details regarding IRT and our implementation can be found in ref. [9].

Time-based measures are calculated using time stamps associated with the first view and subsequent submissions of a problem. We define the time-per-problem ($τ_{p r o b l e m}$) as the average time students spend on a particular problem (times for multiple attempts are accumulated), irrespective of whether the problem was answered correctly. We define the time-per-submission ($τ_{s u b m i s s i o n}$) as the average time of individual answer submissions on a certain problem, again, irrespective of whether the submission was correct. In all our time-based calculations, we exclude submission times longer than 30 minutes to account for idle students; this cutoff removes ≈ 4% of the total number of submissions.

**Distinguishing Easy, Medium, And Hard**

We first examine the differences among our easy, medium, and hard categories of problems with respect to student performance and time spent. In Fig. 1, two types of problem difficulty ($Di f f_{LC}$ and $Di f f_{IRT}$), time-per-problem ($τ_{p r o b l e m}$), and time-per-submission ($τ_{s u b m i s s i o n}$) are plotted for each easy, medium, and hard problem category. Within each measure, our primary interest is the relative position of the plotted quantities.

Somewhat to our surprise, both measures of problem difficulty show little difference across the categories, especially between medium and hard. The $Di f f_{LC}$ (top plot in Fig. 1) has small variation between easy, medium, and hard categories: ≈ 58% of all answers submitted to
easy problems are correct vs. \( \sim 48\% \) for both medium and hard problems. It is important to consider student-choice when analyzing \( \text{Diff}_{\text{LC}} \) because hard problems were typically done by the better students, leading to values that may differ from the case where all students attempted a given problem. IRT analysis confirmed the \( \text{Diff}_{\text{LC}} \) measures by giving similar results: medium and hard problems have \( \text{Diff}_{\text{IRT}} \sim -0.1 \) whereas the easy problems have \( \text{Diff}_{\text{IRT}} \sim -0.6 \). On first try, average students answer medium and hard problems correctly \( \sim 52\% \) of the time vs. \( \sim 65\% \) easy problems. IRT takes into account student skill level when determining problem difficulty, so our medium and hard problems are roughly equal in difficulty as judged by the probability of students answering them correctly.

In contrast, the bottom plot in Fig. 1 shows significant differences in both the time-per-problem (\( \tau_{\text{problen}} \)) and the time-per-submission (\( \tau_{\text{submission}} \)) across the three problem categories. These measures show that the more complex the problem’s procedural and declarative knowledge (as displayed in Table 1), the more time needed for a student to solve the problem and the more time needed for each submission.

**Student Choice Behavior**

We now look at student behavior in selecting problems. Of the total number of problems attempted by our class, \( 45\% \) were easy, \( 35\% \) were medium, and \( 20\% \) were hard, yielding \( 26\% \), \( 40\% \), and \( 34\% \) of the total points earned respectively. In order to better understand student behavior, we binned students in categories based on exam performance (weekly quizzes and final), and analyzed additional parameters related to their effort, strategy, efficiency, and motivation.

We define four groups of students, expressing their total exams grade as z-scores (standard deviations from the mean, e.g. a student with a z-score of \( +1.5 \) has grade that is \( 1.5 \) standard deviations above the average of the class). These four groups, labeled A (the best performing), B, C, and D (the worst performing) have the following ranges:

- A (\( 1.0 < \text{z-score} \leq 2.0 \), 11 students)
- B (\( 0.0 < \text{z-score} \leq 1.0 \), 16 students)
- C (\( -1.0 < \text{z-score} \leq 0.0 \), 26 students)
- D (\( -2.0 < \text{z-score} \leq -1.0 \), 10 students)

Fig. 2 provides measurements of effort for students in each of the four groups: their total number of attempts (right or wrong) for each problem category and the total time spent working problems in each category. The most striking feature in Fig. 2 is that both the total number of attempts and the total time spent working problems in each category rise from group D to group B, peaking with group B. Group A behaves differently, where a larger fraction of attempts and time is spent on hard problems, but total time and total attempts are down with respect to other groups. Group A appears to be able to exceed the required number of points with less total effort, confounding the general belief that A students work harder. This perceived low effort may reflect that LONCAPA assignments were straightforward and prepara-
Efficiency (points/minute) and efficiency (total points earned per minute), averaged within the four z-score groups. Horizontal error bars represent standard error of the z-score within each bin and vertical error bars represent standard errors of the quantities plotted on the y-axes.

Conclusions

We categorized problems based on the types of declarative and procedural knowledge involved as easy, medium, and hard (all were single-concept problems involving similar cognitive processes). We offered students choice in the type of problems they solved and discovered that time-per-problem and time-per-submission are strongly dependent on the easy, medium, and hard categories, whereas LON-CAPA difficulty and IRT item difficulty are less dependent. Furthermore, we found that allowing students choice in problem solving leads to the following patterns of behavior:

- D, C, and B students spent progressively more total time solving problems whereas A students satisfied requirements with effort comparable to D students.
- 70% of students earned extra points on assignments (consistent with previous findings on flexible versus traditional homework [10]).
- All students (regardless of z-score) have comparable efficiencies in solving problems.

In the future, it will be interesting to consider the effect of the contexts [11], the students’ self-awareness, epistemological beliefs [12], and familiarity (experience) [13] with their problem-solving behavior.

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