Assessing Adaptive Learning Gain and its Relation to Task Difficulty

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Abstract

In web based adaptive learning, the notion of task difficulty analysis is recognized as influential in studies of student learning outcomes. This paper examines the relationships between operational measures of learning performance in goal related tasks and goal oriented tasks in a web based adaptive learning environment. Data from 403 students in an undergraduate Electrical DC Machines course is used to identify task-related temporal dynamics analysis. The Kolmogorov and Smirnov (K-S) statistic is used to identify the correlation between goal related and goal oriented task performance in both training and testing phases. While recent work has shown the efficacy of classifying knowledge levels as a part of efficient knowledge modeling, this work advances the analysis of adaptation through goodness of fit (GoF) and null hypothesis testing. It is noticed that participants performing the medium task have more control in the testing phase than in the training phase. Furthermore, this presents a novel way of learning gain estimation in an adaptive learning environment, through K-S statistics. Overall, the evidence supports the view that in the adaptive learning process a significant difference is observed between goal oriented and goal related learning, predominantly in the training phase.

Keywords: Adaptive learning; Learning assessment model; Kolmogorov–Smirnov test; Learning gains.

1. Introduction

Adaptive learning systems are designed to support users in accomplishing their learning tasks through web application or mobile learning environments. Accordingly, students learning task (in difficulty level) have recognized as an important factor in web based learning technology design [1]. Recently, many adaptive web based learning applications feature the type of learning task and its relation to the task goal as a focal point in adaptive learning assessment [2]. The potential learning gain depends on the learning outcomes and the efficiency of the technology solution, including aspects of goal oriented tasks and goal related tasks [2]. Many studies have focused on a specific characteristic of adaptive learning assessment, with the task as an independent variable to explain associated learning outcomes through goal related tasks and goal oriented tasks [3]. Learning gain assessment and its relation to work tasks is a current area of discourse in the educational testing community. Mieke et al. [4] explains the contribution of learner characteristics in the development of computer-based adaptive learning environments. Many studies have addressed the efficacy of classifying knowledge levels as a part of efficient knowledge modeling with task complexity or difficulty [5][6][7]. Moreover, in recent years there is a heightened awareness of the potential benefits of adaptive learning technologies. However, most adaptive learning approaches have failed to realize this promise due to no specific mechanism for measuring cognitive effort and learning gain. The relationships between the learners’ performance and task difficulty with goal related and goal oriented task in both training and testing phase of web based adaptive learning have not been studied extensively. This was the purpose of this study.

2. Related Literature

Estimating students’ learning gains in web-based adaptive applications became one of the most important issues with students’ knowledge modeling [3]. Many studies have focused on understanding learning tasks related to learning gains [8][9]. A method of leaning gain associated within the adaptive learning process can be called the adaptive learning gain (ALG).

ALG can be defined as the performance discrepancy between goal oriented and goal related tasks in the adaptive learning process. Examples of adaptive learning tools developed so far, are: ALEKS[18] uses adaptive questioning to adopt students background knowledge; Cognitive Tutor [11] offers adaptive math for high school students with traditional textbook offerings; dreamBox [19] offers individualized paths for personalized learning; and, eSpindle [10] is useful in vocabulary and spelling coaching. Education companies (e.g., McGraw-Hill Education, Pearson, PrepMe etc.) are promoting adaptive learning at all education levels.

The above brief overview of literature highlights adaptive learning in web based learning technology. Work in other fields tends to emphasize the objective view of task complexity, or the integration of subjective and objective perspectives [18][11]. Aroyo et al., raised the issue of semantic interoperability of educational contents on the Web. They considered the integration of learning.
standards, Semantic Web, and adaptive technologies to meet the requirements of learners [11].

This paper focuses on the relationships between task difficulty (easy, medium and hard) and ALG in training and testing phases. It also explores the significance of ALG from the goal related task to the goal oriented task with a goodness of fit test.

3. Adaptive Learning and Gain (ALG) Computation

Adaptive learning makes content dynamic and interactive. It places the student at the center of his or her individual learning experience. The platform monitors how the student interacts with the system and learns, leveraging the large quantity of data generated by a student’s online interactions. Goal related instruction assesses learner activities and interactions. Goal assessment and needs assessment are keys to performance assessment and identifying instructional problems.

In an adaptive learning process, a combination of needs assessment, goal analysis and performance assessment helps identify an instructional problem. Needs assessment includes six types of needs; normative, comparative, felt, expressed, anticipated, critical incidents. Goal analysis identifies aims, establishes the goals and sub-goals, refines goals, and prioritizes goals. Performance assessment determines when a training program, or an alternative intervention would be appropriate [3].

A. Learning gain in classical learning

In classical learning technology assessment, the learning gain score is computed for each student. When a student scores higher on the post-test than the pre-test, the learning gain is considered positive. If a student scores lower on the post-test than the pre-test then the learning gain is negative. In classical assessment the gain effect (learning outcome) is computed from the average gain scores for the class. The formula for learning gain is:

\[
\text{Positive gain: } \frac{(\text{Post-assessment} - \text{Pre-assessment})}{(100\% - \text{Pre-assessment})}
\]  

Pre-assessment is the percent correct on pre-unit assessment and post-assessment is the percent correct on the post unit assessment. For example, a student having a pre-assessment of 45% and post-assessment of 70% will have a learning gain score of 0.45. The student gained 0.45 (or 45%) of the possible percentage points from pre to post assessment. In the dynamic adaptive learning environment, the same technique is not possible. However, the learning outcome or the effect of learning gain assessment is more appropriate.

B. Learning gain in adaptive learning

By its nature, adaptive learning assesses a student's present schema and learning status and differentiates from one’s next states of learning in some terms related to learning gain. In both pre- and post-tests, two types of tasks are given to students to assess their learning gain effect. An exploratory and non-parametric goodness of fit test can be used to compare two samples of scores in a goal related task and a goal oriented task. The K–S test is used to test whether two underlying one-dimensional probability distributions differ [14],[15]. The K–S statistic is:

\[
D_{n,n'} = \sup \left| F_1(x) - F_2(x') \right|
\]  

where \( F_1 \) and \( F_2 \) are the empirical distribution functions of the first and the second sample respectively. The null hypothesis is rejected at level of \( \alpha \) if

\[
D_{n,n'} > \alpha(n)\sqrt{\frac{n+n'}{nn'}}.
\]  

It is notable that, the two-sample test checks whether the two data samples come from the same distribution or not. If the goal related and goal oriented task outcomes are from the same distribution in pre-test (or post-test), there is no gap. Hence, learning gain affects learning outcome. This phenomenon is empirical evidence of ALG. The K-S statistic is a nonparametric test used in a goodness of fit test [11]. Recently a two-dimensional K-S test was proposed by Lopes et al. [26]. Multi-dimensional K-S statistics for goodness of fit were proposed [27] which can be applied in a student’s ability assessment with multiple attributes [28]. This is illustrated with adaptive learning datasets.

4. Results

The dataset was obtained from the UCI machine learning repository [3] which was originally from a doctoral thesis. This dataset contains students' knowledge states within the Electrical DC Machines course. The knowledge level of a student was classified as: very low, low, middle, or high. Of 403 participants, there were 50 very low, 129 low, 122 middle and 130 high. Input values were: the study time for goal object materials (STG); the number of repetitions of a user for goal object materials (SCG); the study time for goal object materials (STG); the study time for related objects with goal object (LPR); the exam performance of a user for goal objects (PEG); and, the knowledge level of a user (UNS). The participants’ knowledge levels were classified by the researchers using an intuitive knowledge classifier (a hybrid ML technique of k-NN and meta-heuristic exploring methods), k-nearest neighbor algorithm. More details on how the participant data was collected and evaluated by the user modeling server are explained in a previous study [3].

The online dataset was used from a machine learning repository [3]. It included six learning attributes in both pre-test and post-test. These were: (a) study time for goal object materials (STG), (b) the number of repetitions of a user for goal object materials (SCG), (c) study time of a
We performed with bi-variate bag plots (Fig.2a and Fig.2b) to see more detailed differences in goal oriented and goal related tasks. The smaller inner circle, the larger bag sizes (the median distribution) and fewer outliers indicated the positive learning gains in the testing phase (post-test). To signify more on-task performance in the training and testing phase, we compared the exam performance for related objects with the exam performance for goal objects. Box plots in figure 3 shows the differences. The similar percentile in post-test or the testing phase indicates participant adaptive gains after the pre-test.

The relationship between task difficulties and ALG is illustrated in Figure 4. Both training and testing phases are considered in the ALG computation. The gain is shown by the gap between CDF of goal oriented task versus goal related task. Table 1 summarizes the gain value through K. Participant adaptability is tested by the goodness of fit test, H. Finally the p-value signifies the task difficulty versus ALG effects.

<table>
<thead>
<tr>
<th>Knowledge Level</th>
<th>H (Training)</th>
<th>P (Training)</th>
<th>K (Training)</th>
<th>H (Testing)</th>
<th>P (Testing)</th>
<th>K (Testing)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>2.0240e-16</td>
<td>0.7460</td>
<td>1.0945e-16</td>
<td>0.9487</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>3.7519e-34</td>
<td>0.9205</td>
<td>0.0853</td>
<td>0.2941</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>3.1212e-36</td>
<td>0.9759</td>
<td>4.7771e-10</td>
<td>0.6739</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vary Low</td>
<td>5.7358e-10</td>
<td>0.9167</td>
<td>1.1223e-07</td>
<td>0.7692</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5. Conclusion
This research has focused on the relationships between operational measures of ALG with task difficulty as an independent variable in the context of web based adaptive learning technology design. Task complexity (easy, medium or hard) was found to affect the relative importance of the ALG effect in learning outcomes, and affect students’ judgments of task difficulty. Comparison of our findings with those of Kahraman [3] suggests that the relationships between the task difficulty and learning gain were not trivial. Our analysis of correlational relationships indicates that the students’ perceptions of medium task complexity do not only reflect the inherent complexity of the task, but also signify good test design. We suggest that the K-S test can be a good choice for identifying students’ perceptions of task difficulty, which may also depend on individual factors such as one’s experience (novice or expert), domain knowledge, verbal ability, other cognitive abilities, and motivation. We contend that understanding a student’s subjective assessment of learning gain requires knowledge of the objective task complexity and the student’s individual characteristics. Only then we can attempt to explain the relationships between the student’s ALG and the relationship with task difficulty. Figure 5 depicts the discussed relationships.
The learning gain estimation in an adaptive learning context is a new and challenging research issue. This pilot study presents K-S statistics, bi-variate bag plots, and box plots as important tools to illustrate ALG and the positive or negative learning effects. Due to the exploratory and non-parametric nature of these data analytics, the learning gain assessment is robust and would be useful in future adaptive learning technology design. A future study will be conducted with larger datasets and experiments. Furthermore, adaptive mobile learning technologies and intelligent tutoring systems can be re-designed with these analytics.

6. References