AN EARLY ALERT FEEDBACK SYSTEM IN LEARNING

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ABSTRACT

The fields of teaching and learning are evolving as a result of new techniques like blended-, online-, and exploratory learning being implemented. Lecturers need to ensure successful teaching and also create an environment in which students can learn effectively. Two important factors that a lecturer can control to enhance learning are instruction and feedback. A learning analytics system was developed for the latter, utilizing mathematical programming models, which enables a lecturer to provide real-time progress feedback to students at regular intervals during the course of a program. This paper highlights flaws identified in some existing feedback scenarios, discusses the development of an electronic feedback system, and explains how its implementation can keep students informed on their progress from an early stage of instruction and present them with actionable targets for reaching their ultimate goal.

KEYWORDS

Data envelopment analysis; early alert feedback system; mathematical modelling; student ranking

1. INTRODUCTION

The parties involved in a teaching and learning environment are the lecturers, who must establish an optimal learning setting, and the students who must participate and learn. Although the common perception among students is that their main responsibility is partaking in lectures, they still feel that lecturers have to provide guidance and motivation for them to achieve success (Geçer, 2013). In order to enhance learning, lecturers must adopt effective instruction- and subsequent feedback methods that jointly creates an ideal environment for learning. They supplement their teaching regimes with examples, topical case studies relating to new work, and in-depth class discussions. The pace at which technology is advancing enables lecturers to adapt their teaching and assessment techniques (Landau, et al., 2014) by augmenting them with the use of learning management systems (LMSs) (Sin & Muthu, 2015). Different forms of LMSs are used to aid the learning process and are readily accepted by students. Most LMSs have analytic capabilities which can provide useful feedback statistics regarding students' use of certain fields in the LMS (Siemens, 2011). Together with effective teaching, feedback plays an equally important role in enhancing the learning environment (Hattie, 2005).

With all the challenges lecturers face (Brühwiler, 2011), the role of the lecturer has indeed shifted from explicit teaching to facilitating and trying to create an environment in which students accept responsibility for their own learning progress (Ozel, 2015). Additionally, with the incorporation of novel teaching methods like blended learning and online facilitation, many new systems are being implemented to aid in the teaching and learning processes (Reyes, 2015) but methods in student feedback are still lacking. Feedback can be defined as information that is provided about a person's progress in his/her efforts towards reaching a specific goal (Wiggins, 2012). Analytical methods used to process student data need to adapt so as to ensure effective-, learning enhancing feedback. The use of a hierarchy structure to provide feedback can assist students in understanding improvable factors which determine their academic success (Barker & Garvin-Doxas, 2004). For feedback to be helpful to students, it needs to be target/goal-referenced, demonstrable and obvious, actionable, user-friendly or manageable, timely, dynamic, and consistent (Wiggins, 2012).

The changing face of education has highlighted flaws in existing teaching and learning environments relating to feedback, which can be addressed by the development and implementation of novel learning analytics systems. Section 2 will outline some of the shortcomings identified in previous research. In section

3, the development of a learning analytics system in the form of an early alert feedback system as solution to the identified shortfalls, will be discussed. This is followed by section 4, which will evaluate the developed system according to the criteria for effective feedback. The paper will conclude with some closing statements and plans for future work.

2. LEARNING INHIBITING SHORTFALLS IDENTIFIED IN FEEDBACK

Studies by Bond, et al. (2000) have shown that while feedback is hard to record, feedback frequency is mostly low. Although lecturers realize the value that feedback provides, the associated administrative tasks can be so time consuming that even if they wanted to provide early or frequent feedback, it can be an almost impossible task. Hattie and Timperley (2007) found in their research, that there are three important issues that should be addressed by a feedback model. It must provide a student with information on completed tasks that helps him/her understand what the goal is, how to progress to that goal, and which activities to perform to reach the goal. Students need to understand how they are progressing toward their end-goal, and to get directions on how to attain that goal (Wiggins, 2012). Lecturers use different ways to provide students with information on their progress, many of them unofficial.

Du Toit (2015) developed a computer program, benchMark, which assisted lecturers in calculating the participation levels of students, taking into consideration the activities in which they were required to participate. The program calculates average marks for each class activity (class attendance, practical assignments, etc.) that a lecturer in a specific module expects the students to participate in. An overall participation mark is then calculated as the sum of these averages, each multiplied by a weight representing that activity's importance. If, for example, the averages of two activities were 35% and 45%, then the participation can be calculated as $50\% \times 35 + 50\% \times 45$, meaning they are equally important, or $40\% \times 35 + 60\% \times 45$, meaning the ratio of importance is 40:60 for activity_1:activity_2, with a total of 100%. To write the equation in a general form for an example of 4 activities, let w_1 denote the weight level of activity 1, likewise $w_2, w_3,$ and w_4 the weights for activities 2, 3, and 4 respectively. Subsequently, let s_1 denote the average (of all marks achieved) for activity 1, and $s_2,\ s_3,$ and s_4 the averages for activities 2, 3, and 4 respectively. The overall participation mark, p, is then calculated according to the following equation:

$$p = s_1w_1 + s_2w_2 + s_3w_3 + s_4w_4 \qquad (1)$$

The program orders the activities according to importance and constrains the weights to be in multiples of 5. It empirically calculates a set of participation marks for each student, using all of the different weight combinations allowed by the model. Feedback is provided in the form of spreadsheets wherein students are identified by means of their student numbers. It shows their activity averages, the minimum participation mark, and their ranking in relation to the rest of the class. The program has the unique capability of performing these calculations as frequently as required by the lecturer, who will have access to the maximum-, minimum-, and average participation marks as well as other useful statistical information. The benchMark system enables lecturers to present students with regular updates on their progress in the form of participation marks (Du Toit, 2015).

In a pilot study, it was found that the students were very satisfied with the feedback frequency and most of them wanted the system to be implemented in all of their programs. Table 1 presents a short summary on some statistical insights gained from this study.

Table 1. Summarizing statistics of student responses on the benchMark system

Question	% of 25 students agree
The frequency of feedback is acceptable.	96%
The marks system should be implemented in all of my modules.	88%

The benchMark system presented timely, goal-referenced, and dynamic feedback to students. Issues that were however identified included concerns regarding privacy (personalization), ease of use of the system (user-friendliness), and the lack of actionable goals that will help in creating a future perspective (demonstrable).

Section 2 summarized the operation of an existing feedback system that has been implemented in actual teaching/learning environments and identified areas in which improvement is required. Section 3 will discuss the development of the early alert feedback system which uses the optimizing attributes of mathematical models to perform its calculations.

3. DEVELOPMENT OF AN EARLY ALERT FEEDBACK SYSTEM

The positive response elicited by benchMark (Du Toit, 2015), justifies its use as a steady foundation for development of a two stage early alert feedback system. In the first stage, an NLP model was formulated and solved for each student in order to eliminate the repetitive nature of benchMark:

$$\begin{array}{lll} maximize/minimize & p_\alpha = \sum_{j=1}^{n} s_{\alpha j} w_j & (2) \\ subject\ to & \sum_{j=1}^{n} w_j = 1 & (3) \\ & w_j \ mod\ k = 0 & (4) \\ & l < w_j \leq u & (5) \\ & w_j \geq w_{j+1}, \quad j < n & (6) \\ & 0 \leq s_{\alpha j} \leq 1 & (7) \\ & l, u \geq 0 & (8) \end{array}$$

where p is the participation mark, s_i is the student average for activity i, w_i is the weight assigned to activity i, (4) ensures that w_i is a multiple of k, l is the lower limit for all the weights, u is the upper limit for all the weights, n is the number of activities used, and $i = 1, \ldots, n$. Minimizing the model yields a minimum participation mark and its corresponding weights, and maximizing the model yields a maximum participation mark and its corresponding weights. An average participation mark is determined from the results, according to which a student ranking is created. The model is therefore solved twice per student before the average participation marks are calculated. Applying an existing student data set, the student ranking obtained by solving the NLP model was compared to that resulting from benchMark, by calculating the Spearman's rank order correlation coefficient (Puth, 2015). This coefficient was calculated for the two sets of rank values and resulted in a value of ρ=0.99, which shows that there is a very strong positive association between the rankings resulting from benchMark and the NLP. This model represents an adaptation of the benchMark program but is optimized in terms of the number of calculations, and follows a consistent process.

A feedback system should provide students with information on personalized (user-friendly) actions towards reaching a goal (actionable). In the second stage of the feedback system, the activity averages for each student are used to perform an output oriented data envelopment analysis (DEA) which determines an efficiency score for each student based on performance (Kao & Lin, 2008), and divides them into classes of equal efficiency:

$$\begin{array}{lll} E_k = & Maximize \sum_{j=1}^{n} s_{kj} w_j & (9) \\ subject\ to & \sum_{j=1}^{n} s_{ij} w_j \leq 1, \ i = 1, \ldots, m & (10) \\ & w_j \geq \varepsilon > 0, \qquad j = 1, \ldots, n & (11) \end{array}$$

where E_k represents the efficiency score for student k, s_{ij} is the average of student i in activity j, w_j is the weight for activity j, n is the number of students to be considered, m is the number of activities, and ε is a small number. This class-ranking is used for solving the dual formulation of the outputs-only DEA (in (12) to (14)) to present each student with personalized targets to reach in each of the activities to improve his/her position on the class-ranking.

$$\begin{array}{lll} E_k = & Minimize \sum_{i=1}^{m} \lambda_i - \varepsilon \sum_{j=1}^{n} q_j & (12) \\ subject\ to & \sum_{i=1}^{m} s_{ij} \lambda_i - q_j = s_{kj}, \ j = 1, \ldots, n & (13) \\ & \lambda_{ji}, q_j \geq 0, \qquad i = 1, \ldots, m; \ j = 1, \ldots, n & (14) \end{array}$$

where E_k represents the composite index for student k, s_{ij} is the average of student i in activity j, w_j is the weight for activity j, n is the number of students to be evaluated, m is the number of activities, ε is a small positive number, q_j is the change in activity j, let $\theta = \sum_{i=1}^{n} \lambda_i$, then $(s_{kj} + q_j)/\theta$ is the target for activity j, and $j = 1, \ldots, m$. The model successfully calculates personalized improvement targets for each activity, indicating how much each student needs to improve in each activity, to progress to a level of higher efficiency.

The two-stage early alert feedback system successfully addresses most of the concerns lacking from existing feedback systems. It consistently incorporates an optimized method for calculating participation marks and provides personalized, actionable improvement targets that demonstrate to students how they can improve.

4. RESULTS

Wiggins (2012) presented seven criteria for effective feedback according to which the success of the developed system will be evaluated (Table 2).

Table 2. Criteria and evaluation of the developed system

Criteria	Evaluation
Target/goal-referenced	The system provides students with feedback directly related to activities needed to reach their goal.
Demonstrable, obvious	Students are presented with tangible results related to each sub goal (activity).
Actionable	The DEA model provides targets that show students how to improve in each activity.
User-friendly	A certain amount of explanation from the lecturer is needed for students to effectively understand the feedback.
Timely	The system can calculate feedback information as often as required by the lecturer.
Dynamic	Every time feedback is provided in real-time, all previous sets of marks are included. This means that students can see how they are progressing by comparing their latest results with all those previously calculated.
Consistent	The marks are consistently calculated by solving the same optimized models for all students.

One of the most important advantages the developed system presents to lecturers, is that the mathematical models are consistent. This means that whenever an activity has been completed, the marks can be imported into the database and a new set of feedback statistics can be calculated automatically.

5. CONCLUSIONS

This paper discussed the need and development of an early alert feedback system that regularly provides students with information on their ultimate goal, how the goal can be achieved, which activities to perform to reach that goal, and which is easy to use. A two-stage early alert feedback system was developed that implements an NLP to consistently calculate an average participation mark for each student and that uses a class-ranking method to calculate personalized improvement targets for each student in each activity. The system was evaluated according to the seven attributes of successful feedback presented by Wiggins (2012).

To efficiently address remaining concerns regarding student privacy as well as user-friendliness, the system is to be implemented in an electronic dashboard that will allow individual students private access to solely their own marks and statistics. Also, for very large student numbers, a specialized solver is required to implement the dual formulation of the outputs-only DEA because of an exponential increase in decision variables. Therefore an improved model for activity target calculation is currently being developed.

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