Learning Analytics And Formative Assessments
In Blended Learning Of Mathematics And Statistics

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Abstract. Learning analytics seeks to enhance the learning process through systematic measurements of learning related data, and informing learners and teachers of the results of these measurements, so as to support the control of the learning process. Learning analytics has various sources of information, two main types being intentional and learner activity related metadata. This contribution provides a practical application of Buckinghan Shum and Deakin Crick's theoretical framework of dispositional learning analytics [1]: an infrastructure that combines learning dispositions data with data extracted from computer based, formative assessments. In a large introductory statistics course based on the principles of blended learning, combining face-to-face problem-based learning sessions with technology enhanced education, we demonstrate that students learning choices profit from providing students with feedback based on learning analytics, so as to optimize individual learning choices. This study is based on a project financed by SURffoundation as part of the Dutch Learning Analytics program..

Introduction

The prime data source for most learning analytic applications is data generated by learner activities, such as learner participation in continuous, formative assessments. That information is frequently supplemented by background data retrieved from learning management systems and other concern systems, as for example accounts of prior education. A combination with intentionally collected data, such as self-report data stemming from student responses to surveys, is however the exception rather than the rule. In their theoretical contribution to LAK2012 [1], see also the 2013 LASI Workshop [2], Buckinghan Shum and Deakin Crick propose the dispositional learning analytics infrastructure that combines learning activity generated data with learning dispositions, values and attitudes measured through self-report surveys and fed back to students and teachers through visual analytics. Their proposal considers for example spider diagrams to provide learners inside in their learning dispositions, values and attitudes.

In our empirical contribution focusing on large scale education in introductory math and statistics, we aim to provi-

de a practical application of such an infrastructure based on combining learning and learner data. In collecting learner data, we opted to use a wide range of well validated self-report surveys firmly rooted in current educational research, including learning styles, learning motivation and engagement, and learning emotions. Learner data were reported to both students and teachers using visual analytics similar to those described in [1], so instead of focusing on technology to feedback learner data, we will focus here on the crucial role of the richness of the profile of learner dispositions, values and attitudes.

Our second data source is rooted in the instructional method of test-directed learning, and brings about the second focus of this empirical study: to demonstrate the crucial role of data derived from computer-based formative assessments in designing effective learning analytic infrastructures. This paper extends our earlier study [3].

1. Formative Assessment

The classic function of testing is that of taking an aptitude test. After completion of the learning process, we expect stu-

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dents to demonstrate mastery of the subject. According to test tradition, feedback resulting from such classic tests is no more than a grade, and that feedback becomes available only after finishing all learning.

The alternative form of assessment, formative assessment, has an entirely different function: that of informing student and teacher. The information should help better shape the teaching and learning and is especially useful when it becomes available during or prior to the learning. Diagnostic testing is an example of this, just as is practice testing. Because here the feedback that tests yield for learning constitutes the main function, it is crucial that this information is readily available, preferably even directly. At this point digital testing comes on the scene: it is unthinkable to get feedback from formative assessments in time without using computers.

2. Learning Analytics

The broad goal of learning analytics is to apply the outcomes of analysing data gathered by monitoring and measuring the learning process, as feedback to assist directing that same learning process. Several alternative operationalizations are possible to support this. In [4], six objectives are distinguished: predicting learner performance and modelling learners, suggesting relevant learning resources, increasing reflection and awareness, enhancing social learning environments, detecting undesirable learner behaviours, and detecting affects of learners. In the following sections describing our approach, we will demonstrate that the combination of self-report learner data with learning data from test-directed instruction allows to contribute to at least five of these objectives of applying learning analytics. Only social interaction is restricted to learners being able to assess their individual learning profiles in terms of a comparison of their own strong and weak characteristics relative to the position of other students.

These profiles are based on both learner behaviour, including all undesirable aspects of it, and learner characteristics: the dispositions, attitudes and values. Learner profiles are used to model different types of learners, and to predict learner performance for each individual student. Since our instructional format is of student-centred type, with the student, and not the teacher, steering the learning process, it is crucial to feedback all this information to learners themselves as to make them fully aware of how to optimize their individual learning trajectories.

3. Case Study: Mathematics and Statistics

Our empirical contribution focuses on freshmen education in quantitative methods (mathematics and statistics) of the business & economics school at Maastricht University. This education is directed at a large and diverse group of stu-

dents, which benefits the research design. The population of students studied here consists of two cohorts of freshmen: 2011/2012 and 2012/2013, containing 1,800 students who in some way participated in school activities (have been active in the digital learning environment *BlackBoard*). Besides *BlackBoard*, two different digital learning environments for technology-enhanced learning and practicing were utilized: *MyStatLab* and *MyMathLab*.

The diversity of the student population derives mainly from its very international composition: only 23% took Dutch high school, whereas all others were educated in international high school systems. The largest group, 45% of the freshmen, were educated according to the German Abitur system. High school systems in Europe differ strongly, most particularly in the teaching of mathematics and statistics. In that European palette the Netherlands occupies a rather unique position, both in choice of subjects (one of the few European systems with substantial focus on statistics) and the chosen pedagogical approach. But even beyond the Dutch position, there exist large differences, such as between the Anglo-Saxon and German-oriented high school systems.

Therefore it is crucial that the first course offered to these students is flexible and allows for individual learning paths. To some extent, this is realized in offering optional, developmental summer courses, but for the main part, this diversity issue needs to be solved in the program itself. The digital environments for test-directed learning play an important role in this.

4. Technology-Enhanced Learning

The two technology-enhanced *MyLabs*, *MyStatLab* (MSL) and *MyMathLab* (MML), are generic digital learning environments, developed by the publisher Pearson, for learning statistics and mathematics. It adapts to the specific choice of a textbook from Pearson. Although *MyLabs* can be used as a learning environment in the broad sense of the word (it contains, among others, a digital version of the textbook), it is primarily an environment for test-directed learning and practicing. Each step in the learning process is initiated by submitting a question. Students are encouraged to (try to) answer the question. If they do not master (completely), the student can either ask for help to step by step solve the problem (Help Me Solve This), or ask for a fully worked example to show (View an Example). Next, a new version of the problem loads (parameter based) to allow the student to demonstrate their newly acquired mastery.

In the investigated courses, students work an average 35.7 hours in MML and 23.6 hours in MSL, 30% to 40% of the available time of 80 hours for learning in both topics. In this study, we use two different indicators for the intensity of use of thye *MyLabs*:

1) #hours, the number of hours a student spent practicing in both *MyLab* environments, and
2) #TestScore, the average score for the practice questions, all chapters aggregated, again for both topics.

5. Educational Practice

The educational system in which students learn mathematics and statistics is best described as a 'blended system'. The main component is 'face-to-face': problem-based learning (PBL), in small groups (14 students), coached by a content expert tutor. Participation in these tutor groups is required, as for all courses based on the Maastricht PBL system. Optional is the online component of the blend: the use of the two test-directed learning environments.

The reason for having this component optional is at one hand that this best fits the Maastricht educational model, which is student-directed and places the responsibility for making educational choices primarily with the student, and at the other hand, the circumstance that not all students will benefit equally from using these environments: due to the diversity in prior knowledge, it is supposed to have less added value for students at the high end.

However, the use of technology-enhanced environments is stimulated by making bonus points available for good performance in the quizzes. Quizzes are taken every two weeks and consist of items that are drawn from item pools very similar to the item pools applied in the two digital practice platforms. We chose for this particular constellation, since it stimulates students with little prior knowledge to make intensive use of the test platforms. They realize that they fall behind other students in writing the exam, and need to achieve a good bonus score both to compensate, and to support their learning. The most direct way to do so is to frequently practice in the MML and MSL environments.

The student-directed characteristic of the instructional model requires first and foremost adequate information for students so that they are able to monitor their study progress and their topic mastery in absolute and relative sense. That provision of relevant information starts the first day of the course when students take two entry tests for mathematics and statistics, so as to make their positions clear. Feedback from entry tests provide the first signals of the importance of using the test platforms.

Next, the digital MML and MSL-environments take over the monitor function: students can at any time see their progress in preparing the next quiz, get feedback on the performance in the already taken quizzes and on the conduct of the practice sessions. The same information is also available for the teachers. Although the primary responsibility for directing the learning process is with the student, the tutor acts complementary to that self-steering, especially in situations where the tutor considers that a more intense use of digital learning environments is desirable, given the position of the student concerned. In this way, the application of learning analytics shapes the instructional situation.

6. Impact of Technology-Enhanced Learning

To explore the role of technology-enhanced learning, we investigated the relationship between the intensity of use of the two technology-enhanced platforms and academic performance. Two indicators measure academic performance: the exam containing a mathematics and statistics part (MathExam and StatExam) and three quizzes for both sub-topics, summed into a MathQuiz and StatQuiz score. Before examining the relationship between practice and performance, we corrected for differences in prior knowledge, in two ways: by the level of prior mathematics education, and by the student score in the math entry test. What prior education is concerned: high school systems distinguish a basic level preparing for the social sciences and an advanced level preparing for sciences. An indicator variable is used for math at advanced level (MathAdv) (which is true for one third of the students), with basic level of math prior schooling being the reference group. Moreover, the level of prior math knowledge is determined by the day-one entry or diagnostic test, of which the score is labelled as EntryTest, focusing on the mastery of basic algebraic skills.

One of the most straightforward ways to investigate the role of technology-enhanced learning on achievement is to use regression analyses in which performance variables are explained by prior knowledge and data on intensity of using the practice tests. These regressions indicate that prior knowledge, both as type of prior schooling and as score in the entry test, explains part of performance differences. But the most important predictor of course performance is the level that students gain in the test platforms. The number of different tests students need to acquire that level, or the time they need to practice to acquire that level, has a corrective effect, what is intuitive: knowledge achieved through testing helps, but if a student needs a lot of time or effort to reach that level, this signals more problematic learning. An alternative demonstration of the impact of using the test environments is obtained by dividing the population of students into students with high and low mastery in the entry test and high and low level of intensity of using the test platforms, and comparing exam scores and pass/fail outcomes. The fit resulting from these prediction models is very high. For example, in a median split on performance in the math platform, 92% of the students with the better practice performance do pass, against 59% in the students with lower practice performance.

6.1. Learning Analytics: Demographic Characteristics

Having demonstrated that on average students benefit from the opportunity of technology-enhanced learning, the ques-

tion arises whether this is equally true for all students. This question asks for learning analytics applications using data from other sources than the learning environments to identify specific student groups most in need for these practice environments. In this section of our empirical study, we follow [1], [5] to investigate individual differences in the intensity of using digital learning tools. As a first step, we make use of data from the regular student administration such as whether or not Dutch high school, whether or not advanced prior math schooling, gender, nationality and entry test score. Students with advanced prior schooling are better at math, without incurring more need to practice. They are not better at statistics, which corresponds to the fact that in programs at advanced level, the focus is not on statistics but abstract math. Dutch students make considerably less use of both test environments and hence achieve a slightly lower score, benefiting from a smoother transition than international students, but relying just somewhat too much on that. Students with a high entry test score do better in mathematics and a little better in statistics in the test environments, without the need to exercise more. Finally, there are modest gender effects, the strongest in the intensity of exercising: female students are more active than male students.

6.2. Learning Analytics: Cultural Differences

The remaining data from the student records of administrative systems regard the nationality of students. Because cultural differences in education has been given an increasingly important role, and because the Maastricht student population makes it very suitable through its strong international composition, the nationality data are converted into so-called national culture dimensions, based on the framework of Hofstede [6]. In that framework, there are a number of cultural dimensions that refer to values that are strongly nationally determined. In this study we use six of these dimensions: Power Distance, Individualism versus Collectivism, Masculinity versus Femininity, Uncertainty Avoidance, Long-Term vs. Short-Term Orientation and Indulgence vs. Restraint. Scores for each of these national dimensions are assigned to the individual students. Correlating these scores with the four indicators of practice tests intensity result in several significant effects, all in line with Hofstede's framework. The most significant effects are for students from a masculine culture, where mutual competition is an important driver in education, for students from a culture that value long-term over short-term and, somewhat in relation thereto, cultures that value sobriety rather than enjoyment. In this, masculinity and hedonism have a stronger impact on the intensity of exercising, than on the proceeds of exercising, in contrast to long-term orientation, that has about equal impact on both aspects. Uncertainty avoidance contributes, as expected, to practicing, albeit to a lesser extent and again primarily toward intensity of exercising rather than its outcome. The roles of power dis-

tance and individualism play a less salient role in learning, as expected.

6.3. Learning Analytics: learning styles

Although the effects are smaller in size, learning data based on the learning style model of Vermunt [7] exhibit a characteristic role. Vermunt's model distinguishes learning strategies (deep, step-wise, and concrete ways of processing learning topics), and regulation strategies (self, external, and lack of regulation of learning). Deep-learning students demonstrate no strong relationship with test directed learning: they exercise slightly less, but achieve a slightly better score. That is certainly not true for the stepwise learning students. Especially for these students the availability of practice tests seems to be meaningful: they practice more often and longer than other students and achieve, especially for statistics, a better score than the other students. These patterns repeat themselves in the learning regulation variables that characterize the two ways of learning: self-regulation being characteristic for deep learning, external regulation as a feature for stepwise learning. Indeed, the students whose learning behavior has to be externally regulated, are those who benefit most from the test environments: both in intensity and performance they surpass the other students. A notable (but weak) pattern is finally visible in learning behaviour lacking regulation: these students tend to practice more often and longer than the other students but achieve in both subtopics lower performance levels. Apparently, even the structure of the two test environments is incapable to compensate the of lack of regulation for these student.

6.4. Learning Analytics: (Mal)Adaptive Thoughts & Behaviours

Recent Anglo-Saxon literature on academic achievement and dropout assigns an increasingly dominant role to the theoretical model of Andrew Martin: the 'Motivation and Engagement Wheel' [8]. That model includes both behaviours and thoughts or cognitions that play a role in learning. Both are then divided into adaptive and mal-adaptive or obstructive forms. As a result, the four quadrants are: adaptive behaviour and adaptive thoughts (the 'boosters'), mal-adaptive behaviour (the 'guzzlers') and obstructive thoughts (the 'mufflers'). In Figure 1, two panels depict the relationships of adaptive and mal-adaptive thoughts and behaviours with the usage data.

The first panel documents adaptive thoughts Self-belief, Value of school and Learning focus, and adaptive behaviours Planning, Study management and Perseverance. All adaptive thoughts and all adaptive behaviours have a positive impact on the willingness of students to use the test environments, where the effect of the adaptive behaviour dominates that of cognitions. The mal-adaptive variables show a less uniform
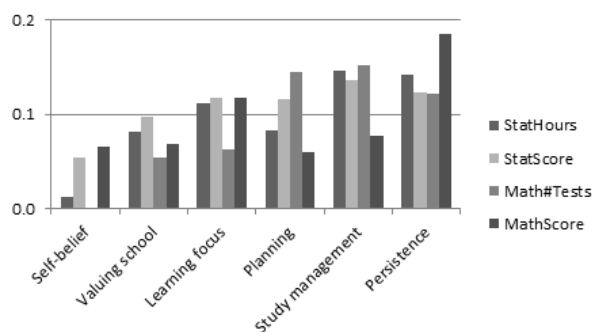
Fig. 1. Role of (mal)adaptive thoughts and behaviours.

picture. Because gender effects play a prominent role here, the dummy variable female/male is added to the four data of use intensity in the panel. From these additional correlations we conclude that mal-adaptivity manifests itself differently in female and male students: for female students primarily in the form of limiting thoughts, especially fear and uncertainty, in male students primarily as mal-adaptive behaviours: self-handicapping and disengagement. That difference has a significant impact on learning. Mal-adaptive behaviours negatively impact the use of the test environments: all the correlations, both for use intensity and performance, are negative. The effect of inhibiting mind, however, is different: uncertainty and anxiety have a stimulating effect on the use of the test environments rather than an inhibitory effect. Combination of both effects provides a partial explanation for the observed gender effects in the use of the test environments.

6.5. Learning Analytics: Learning Emotions

Also of relatively recent date is research on the role of emotions in learning. Leading in this research is Pekrun's control-value theory of learning emotions [9]. That theory indicates that emotions that arise when learning are influenced by the feeling to be 'in control' and something worthwhile to do. Pekrun's model distinguishes several emotions, and for this study we selected emotions that contribute most strongly to student success or failure: the negative emotions of Anxiety, Boredom and Hopelessness, the positive emotion Enjoyment. Emotions are context-specific measured, for example, Anxiety is defined in the context of learning mathematics. Learning emotions are typically measured in the middle of the course, unlike all other instruments that are taken in the beginning of the course. Correlations can thus not be interpreted within a cause-effect framework, as we can do for most other variables. The most obvious association is that of mutual influence: emotions will impact the use of the test environments, but conversely experience gained in practicing, and ideally the performance in practicing, will also determine learning emotions. Associations we find all have predicted directions: negative emotions demonstrate negative relationships to the use of the test environments, positive emotion and feeling in control, demonstrate positive relationships. It is striking that
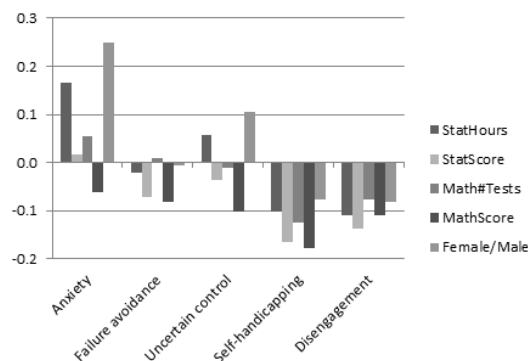
performance in the test environment, especially for mathematics, is much stronger associated with learning emotions than the intensity of practicing in the test environments.

Conclusions

The intensive use of technology-enhanced environments makes a major difference for academic performance. But in a student-centred curriculum it is not sufficient when teachers are convinced of the benefits that test-based learning in digital learning environments entails. Students regulate their own learning process, making themselves choices on how intensively they will exercise and therefore, are the ones who need to become convinced of the usefulness of these digital tools. In this, learning analytics can play an important role: it provides a multitude of information that the student can use to adapt the personal learning environment as much as possible to the own strengths and weaknesses. For example, in our experiment the students were informed about their personal learning dispositions, attitudes and values, together with information on how learning in general interferes with choices they can make in composing their learning blend. At the same time: the multitude of information available from learning analytics is also the problem: that information requires individual processing. Some information is more important for one student than the other, requiring a personal selection of information to take place. Learning analytics deployed within a system of student-centred education thus has its own challenges.

The aim of this contribution extends beyond demonstrating the practical importance of Buckingham Shum and Deakin Crick's dispositional learning analytics infrastructure. Additionally, this research provides many clues as to what individualized information feedback could look alike. In the learning blend described in this case study, the face-to-face component PBL constitutes the main instructional method. The digital component is intended as a supplementary learning tool, primarily for students for whom the transition from secondary to university education entails above average hurdles. Part of these problems are of cognitive type: e.g. international students who never received statistics education as part of their high school mathematics program, or other

freshmen who might have been educated in certain topics, without achieving required proficiency levels. For these kind of cognitive deficiencies, the technology-enhanced environments proved to be an effective tool to supplement PBL. But this applies not only to adjustment problems resulting from knowledge backlogs. Students encounter several types of adjustment problems where the digital tools appear to be functional. The above addressed learning dispositions are a good example: student-centred education presupposes in fact deep, self-regulated learning, where many students have little experience in this, and feel on more familiar ground with stepwise, externally regulated learning. As the analyses demonstrate: the digital test environments help in this transformation. It also makes clear that the test environments are instrumental for students with non-adaptive cognitions about learning mathematics and statistics, such as anxiety. An outcome that is intuitive: the individual practice sessions with computerized feedback will for some students be a safer learning environment than the PBL tutorial group sessions. Finally, the learning analytics outcomes make also clear where the limits of the potentials of digital practice are: for students with non-adaptive behaviours and negative learning emotions. If learning involves boredom and provokes self-handicapping, even the challenges of test-based learning will fall short.

Acknowledgements

References

1. Buckingham Shum S., Deakin Crick R. Learning Dispositions and Transferable Competencies: Pedagogy, Modelling and Learning Analytics. // In: Proceedings LAK2012: 2nd International Conference on Learning Analytics & Knowledge. – ACM Press: New York, 2012. – Pp. 92-101.

2. LASI Dispositional Learning Analytics Workshop, 2013. – <Learningemergence.net/events/lasi-dla.wkshp>, accessed 2013.

3. Tempelaar D. T., Cuypers H., Van de Vrie E. M., Heck A., Van der Kooij H. Formative Assessment and Learning Analytics. // In: Proceedings LAK2013: 3rd International Conference on Learning Analytics & Knowledge, 2013. – ACM Press: New York, 2013. – Pp. 205-209.

4. Verbert K., Manouselis N., Drachsler H., Duval E. Dataset-Driven Research to Support Learning and Knowledge Analytics. – *Educational Technology & Society* 15(3) (2012) 133-148.

5. Whitmer J., Fernandes K., Allen W. R. Analytics in Progress: Technology Use, Student Characteristics, and Student Achievement. – *EDUCAUSE Review Online* 7 (2012).

6. Hofstede G., Hofstede G. J., Minkov M. Cultures and organizations: Software of the mind. Revised and expanded third edition. – Maidenhead: McGraw-Hill, 2010.

7. Vermunt J. D. Leerstijlen en sturen van leerprocessen in het Hoger Onderwijs. – Amsterdam/Lisse: Swets & Zeitlinger, 1996.

8. Martin A. J. Examining a multidimensional model of student motivation and engagement using a construct validation approach. – *British Journal of Educational Psychology* 77 (2007) 413-440.

9. Pekrun R. The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. – *Educational Psychology Review* 18 (2006) 315-34.