Learning Analytics to Improve the Effectiveness of Continuous Assessment

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Abstract. In recent years, university courses have gone through many changes in terms of teaching and assessment methods. The introduction of continuous assessment is one of such changes, encouraging students to carefully plan and spread their efforts over the whole duration of the course. However, this assessment method can imply problems such as task overload, which complicate the elaboration of effective work plans by students. Ultimately, a poor work plan will likely lead to underwhelming performance by the student. This paper describes a work in progress on how learning analytics can be used in order to help students improve their performance in a continuous assessment setting. Some outlines for the objectives to be fulfilled by future work are provided as well.

Keywords: Learning analytics · Learning management systems · E-assessment · Assessment methods.

1 Introduction

Over the last decade, the educational field has been heavily influenced by the evolution and progressive popularization of learning technologies. This led to the birth of several different disciplines with the objective of supporting and enhancing the learning process. *Learning analytics* (LA) is one of such disciplines, being the result of applying data analytics techniques to the educational environment [1]. At the same time, new teaching and assessment methods have gained great popularity during recent years, *continuous assessment* being among the most important ones.

This document proposes the use of learning analytics techniques in order to improve students' performance in a continuous assessment setting. The paper starts with a brief overview on learning analytics and dashboards, as well as modern teaching and assessment methods which are used in higher education institutions. Afterwards, an application of learning analytics is proposed with the objective of evaluating and mitigating the interferences of concurrent courses under continuous assessment. Finally, some guidelines are provided to further explore this line of work in the future.

2 Learning analytics and dashboards

Learning analytics is commonly defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [2]. It has acquired great interest among the research community in recent years, being the main topic in a steadily increasing number of publications up to this day [3]. Some examples of applications that this discipline has are:

- *Student classification.* By using clustering techniques, a big number of students can be divided in several groups depending on one or more observed characteristics. For example, this has been used to identify different learning strategies used by students and establish a relationship with their performance in the course [4].
- *Prediction models.* Learning analytics can provide the ability to predict certain events using models trained with past data. The most popular prediction goals are dropout rate [5] and student performance [6, 7].
- *Resource recommendation.* Tools based on LA have been developed in order to provide personalized recommendations of academic literature and other resources to students. Their way of working is similar to that of general resource recommenders that are present in many web platforms. There exist many algorithms to find appropriate recommendations, based on elements such as search history of the user [8] or what other users with a similar profile found useful in the past [9].

As e-learning features became more present in educational scenarios, the solutions provided by learning analytics grew more sophisticated and effective. Particularly, the now generalized use of *learning management systems* (LMS) vastly facilitates the collection of student data for the purpose of analysis. In its most basic definition, a LMS is "a software application that automates the administration, tracking and reporting of training events" [10].

The main element responsible for the visualization of analysis results and indicators is the *learning dashboard*. This tool is often embedded into the LMS, although it can also be a standalone utility. The goal of a learning dashboard is to "capture and visualize traces of learning activities, in order to promote awareness, reflection and sense-making, and to enable learners to define goals and track progress toward these goals" [11].

Members of the LA research community have developed their own learning dashboards as part of their work, implementing some unique functionalities. These features may be directed to students [12], instructors [13] or other figures such as the student adviser [14].

A properly designed dashboard is often necessary to convey the results of data analysis in education to the target audience. Easily comprehensible tables and graphs are normally the most effective way to display the desired information.

3 Teaching and assessment methods

As stated earlier, the influence of new technologies was the source of numerous changes observed in teaching and assessment methods during recent years. This led to events such as the quick rise in popularity of massive open online courses (MOOCs), as well as deep transformations in higher education institutions.

Many university courses nowadays implement some form of *blended learning*, an education program that combines traditional in-classroom teaching with the delivery of online resources and activities to the student [15]. This implies that learning happens both inside and outside the classroom, in such a way that student progress can be appropriately tracked. In a blended learning setting, the student has some flexibility to control their pace, learning strategy and the time and place at which learning occurs; while also preserving the regular supervision by an instructor.

The introduction of blended learning spawned several different teaching models that combine both brick-and-mortar and online learning. One of the most popular is the *flipped classroom* model, which is defined as "an educational technique that consists of two parts: interactive group learning activities inside the classroom, and direct computer-based individual instruction outside the classroom" [16]. This implies that lectures are delivered to the student online, while in-class sessions consist of group-based problem solving. Hence the term "flipped": what traditionally happened at home is done in the classroom, and vice versa.

Alongside teaching methods, there have been some recent developments in assessment methods as well. *Continuous assessment* is now very common in many Spanish universities as encouraged by the Bologna process [17], a statement that can be extended to any European educational institution that adheres to said process. Previously, with the traditional assessment method, students needed to pass a single final exam in order to complete the corresponding course. Continuous assessment, on the other hand, establishes a series of tasks and exams that are spread throughout the duration of the course, each one of them contributing to a greater or lesser degree towards the final grade. This requires students to carefully plan their efforts during the entire course.

A course under the continuous assessment method normally contains a series of *formative* and *summative* tasks. The former are low-risk activities that are meant to follow the students' progress with no impact over their final grade, while the purpose of the latter is evaluating their knowledge through an activity or exam that counts towards the final grade [18]. The balance between both kinds of tasks is decided by the instructor of the course.

4 Current work: supporting continuous assessment with learning analytics

4.1 Objectives

The purpose of this work is providing solutions to improve the effectiveness of continuous assessment using learning analytics techniques. This is a long-term project of increasing complexity.

The first specific objective of this line of work is studying the interferences between courses under continuous assessment that are carried out at the same time. In a university setting, a student is often enrolled in many courses at the same time, which may mean that at some point of the semester they must take on a large number of tasks belonging to different subjects in a short period of time. In said circumstance, the student has to adopt a certain strategy: it is their decision whether to split their attention evenly among all subjects, or prioritize some over others. Looking at their final performance, the magnitude of the interferences can be determined, as well as the students' chosen preferences.

This study will focus on students during their *first semester* at university. Since they are not familiar with the continuous assessment used at university, they are more likely to have a harder time planning their efforts due to inexperience, possibly accentuating the effects of interferences.

The following data is available, corresponding to first year students from University of Vigo's Telecommunications Engineering School:

- Anonymized *grades* from *one subject*, including all of the summative tasks performed throughout the course.
- The *dates* on which summative tasks take place, corresponding to *all concurrent subjects*, along with the *weight* of each task — that is, how much they contribute towards the final grade.

Since grade data is anonymized, it is not possible to perform an effective study targeting individual students. Instead, the analysis will be performed in a *group-wise* manner: as there are too many enrolled students, they are split into several smaller groups, each one of them having weekly in-classroom sessions at a different time and day of the week.

Analysis tasks on the previously mentioned data will aim to provide an answer to the following questions:

- *Do interferences between subjects under continuous assessment really exists? If so, how important are they? In other words, evaluate the correlation between performance — grades — and the existence of summative tasks from other subjects.*
- *Are there relevant performance differences between groups in the same course? If so, do this differences correlate with the day of the week on which in-classroom sessions take place?*
- *Do students prioritize some subjects or tasks over others? If so, does it hold a correlation with the weight of each task?*

- *Does any pattern exist regarding students that drop continuous assessment?*

The conclusions obtained from this study will be used as feedback for both instructors and students towards future courses, namely:

- Teachers from concurrent subjects could coordinate their schedules better, in such a way that task combinations that are observed to be very difficult to handle for students can be minimized or avoided altogether.
- Students will have valuable information that will allow them to improve their effort planning throughout the duration of the entire course.

4.2 Visualization

In addition to the previously described study, an interactive online tool will be developed in order to help instructors track the progress of their students in a course where continuous assessment is applied. This tool will be designed as an add-on to the e-assessment platform BeA (Blended e-Assessment) [19], which is used in selected courses belonging to Telecommunications Engineering at University of Vigo.

The BeA platform contains a wide variety of functionalities with the purpose of designing and evaluating exams, as well as providing a communication method between students and instructors for revision requests on said exams. This platform is in active development: new features that were added over time include automatic assessment of multiple choice type exams and, as shown in Fig. 1, graphical representations that facilitate tracking a student's performance and compare it to that of their peers [20].

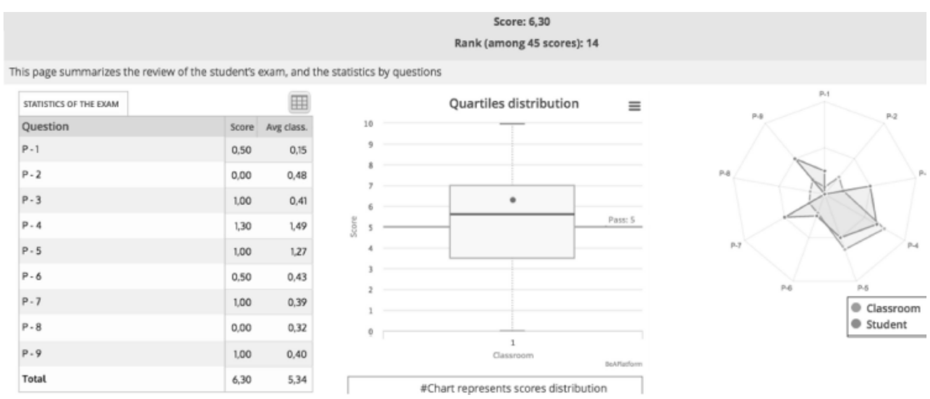

Fig. 1. Performance comparison between a student and their peers.

The new add-on will include a calendar-like widget displaying the schedule of tasks and exams of concurrent subjects, in such a way that time periods with a high load of work for students are easily identifiable. Additionally, real-time information about students' progress will be provided, focusing on the different groups in one subject. This information includes:

- Evolution of grades over time.
- Comparison between groups.
- Tracking of dropout rate.

5 Conclusion and future work

The described work in progress attempts to provide a useful application to address a common problem that students face in current Spanish universities: the need to handle many concurrent subjects under continuous assessment. The proposed solutions will be tested in first year courses belonging to University of Vigo's Telecommunications Engineering School, and the obtained results will be analyzed and documented later on.

As a long-term line of work, there are more objectives to be met in the future. The first one of them would be the *individualization* of the features described above. That is, instead of targeting an entire group of students, provide detailed analytics for single students, allowing for more specific analysis and advice. As this would imply working with non-anonymized data, students need to provide explicit permission in order to use their personal data for this purpose.

If individual analysis is achieved, then it could be possible to add the *difficulty* of tasks as a factor that could influence students' decisions in a continuous assessment setting. However, unlike the date or weight of a certain task, its difficulty is subjective. Even if the instructor can provide an estimation of how difficult a task is, each individual student may find it harder or easier depending on personal factors such as preference of previous knowledge. Directly obtaining the students' opinion would be a way of circumventing this issue. In any case, it is clear that effectively using task difficulty as input data is more challenging than utilizing the data types previously discussed.

One feature of the e-assessment platform BeA allows teachers to directly assign seats in the classroom for each student. This is shown in Fig. 2, where the seats, arranged by rows and columns, are represented by colored circles. Seats that have already been assigned to a student are represented by a picture of said student. On the other hand, seats that are free and available to be assigned are represented by green circles, and gray circles mean that the seat cannot be assigned due to a problem unrelated to the course, such as it being broken.

The seat assignment system is currently used for in-classroom exams, giving each student a predetermined spot in order to speed up the preparation time. However, this idea could be extended to regular instruction in a flipped classroom environment, where students are divided in groups for problem-solving activities. With a process of analysis of the strengths and weaknesses of each student, they could be strategically arranged for in-classroom sessions. This way, students in groups could cover each others' weaknesses, making it possible for them to more effectively learn from each other.

Fig. 2. BeA widget that allows editing the seat distribution of students in a classroom (platform available in Spanish).

Another goal that will be pursued is adding xAPI compatibility in order to improve the *interoperability* of the developed tools. xAPI is a specification for learning technologies that makes it possible to trace learning experiences of any kind in the form of subject-verb-object statements[1], storing them in a learning record store (LRS). One of the advantages of using this specification is that any compatible tool should be able to read records stored in this format, allowing for easy data exchange between different entities. By defining a xAPI profile for data recorded in the scope on this project, the information could be fed to other tools, such as an independent LMS.

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