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Learning Analytics Pilot with Coach2 - Searching for Effective Mirroring

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Abstract. Coach2 project investigated usability and effectiveness of Learning Analytics in a group of Bachelor courses in the area of Computer Science. An advanced architecture was developed and implemented, including a standalone Learning Record Store for data storage and easy access to miscellaneous data, Machine Learning techniques for determining relevant predictors, and a dashboard for informing learners. The overall approach was based on mirroring, the idea that learners see themselves operating in the context of their peers. The results were informative in terms of pro's and con's regarding the design and approach. The treatment showed tendencies, but finding statistical significant results turned out difficult. This paper reports on the Coach2 project.

Keywords: Learning Analytics · Usability and effectiveness · Higher education · Mirroring

1 Introduction

Learning analytics concerns the process by which data generated by learners during learning activities is used to inform and advice learners about their behaviour with the goal to help them improve their learning and achieve better learning outcomes. Initial results on the potential of Learning Analytics have been reported [2,4,5,7], but it is also evident that Learning Analytics is still a challenge and in search of the appropriate procedures and techniques (cf. [6]).

As many higher education institutions, the University of Amsterdam (UvA) is interested in understanding and using Learning Analytics. Within that context the Coach2 project was formulated [1]. The overall goal of the project was to investigate the *usability* and *effectiveness* of Learning Analytics as an instrument to improve learning within the context of typical and regular ongoing courses. Additional foci included the wish to use only data generated within an actual course, and that the feedback towards learners should focus on mirroring (the

idea to show a learner’s specific behaviour in the context of the behaviour of his or her peers). It was also deemed important to stay within the scope of the tools and Learning Management System (LMS) currently used during these courses, and learn about the potential and limitation thereof. Hence, a strong emphasis on working with data available from using Blackboard (the dominant LMS at the UvA), and the need to work with the technical infrastructure regarding tooling and educational software as currently deployed.

Figure 1 depicts the idea of the approach taken. Learners use educational tools and by doing so they generate data. This data is obtained and stored. Next, this data is processed, particularly using machine learning techniques to discover correlations and potentially predictors of successful learner behaviour. Finally, learning behaviour data are displayed in an informative way to the learner.

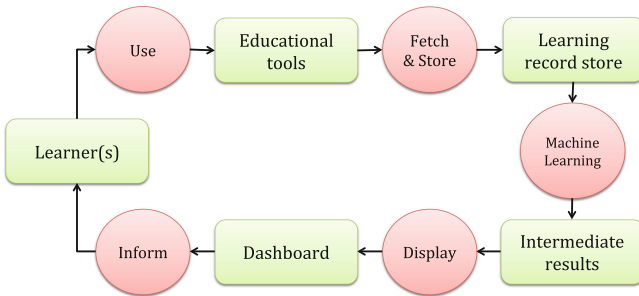


Fig. 1. Data containers and their high level activities implementing Learner Analytics.

For the technical realisation and the evaluation studies, three courses were selected from a bachelor programme on computer science. Each course had over 80 participants, and used a variety of tools and educational activities. Two of the courses worked with Blackboard; the third one did not. Using an informed consent, the learners were given the choice to participate in the evaluation study or decline. Next, the participating learners were randomly divided into two conditions, one with and one without a dashboard. In other words, a group with and a group without Learning Analytics. The teachers of the courses were informed about the study, and agreed to have their learners participate. However, the teachers were left outside the evaluation study. Hence, keeping them ignorant and thereby preventing unwanted effects because of their potential interferences.

2 Architecture and Technical Context

The Coach2 pilot architecture is shown in Fig. 2. The Coach2 pilot used a central Learning Record Store (LRS) as the secure web enabled location to capture and query the learners digital traces.¹ The protocol applied was xAPI. The LRS

¹ <https://github.com/Aperreo-Learning-Analytics-Initiative/Larissa>.

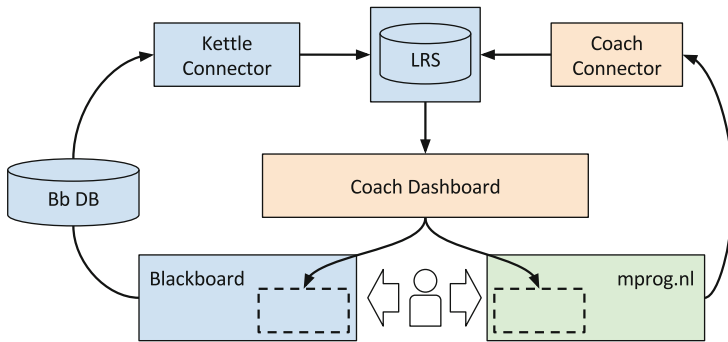


Fig. 2. Blue boxes denote institution-wide infrastructure, including the Learning Record Store, the Blackboard learning environment and its database, and the Kettle connector that exports Blackboard data to the LRS. Yellow boxes denote pilot-wide infrastructure maintained by the Coach2 project to use in the evaluation studies, including the Coach dashboard that was integrated into the learning environments and a Coach connector that provided an API for external sources to send events to, which would be exported to the Learning Record Store. The green box denotes the website of one of the courses that was used as their learning environment instead of Blackboard. (Color figure online)

was implemented by UvA ICT-Services. The motivation for this was to build indigenous expertise to understand in great detail the inner workings of the approach. The LRS was stress tested by Jmeter² an open source Java application and found to scale to 4 million records on one virtual machine. For the pilot the scalability was acceptable, however, greater usage would require improving the internal mechanisms for responding to querying. One of the significant lessons learned was that some xAPI queries are more expensive in resources such as CPU time than others. One approach to limit the impact is to define a specific set of queries that are allowable thus avoiding unnecessary resource consumption.

Filling the LRS with data was achieved by added an Extract Transform Load layer, which allows to pull in data from various systems and then convert to xAPI statements and pump events into the LRS (for details see Github³).

3 Dashboard and Data Processing

The developed DashBoard (DB) is shown in Fig. 3. It was presented inside the LMS for each of the three courses. By selecting specific study behaviour values on the left side, the probability of the values of study outcome metrics are updated on the right side. The hypothesis was that the DB enables learners to explore and reflect upon statistical relations between current study behaviour and future result, based on experiences of learners in the past. By visualising

² <https://github.com/Apereio-Learning-Analytics-Initiative/LRSLoadTest>.

³ <http://c-f-k.github.io/bb-kettle-lrs-tutorial/>.

how the learner’s study behaviour compares to that of peers, as well as whether that study behaviour correlates to study outcome in the past, it was expected that the DB provides an actionable tool for reflection.

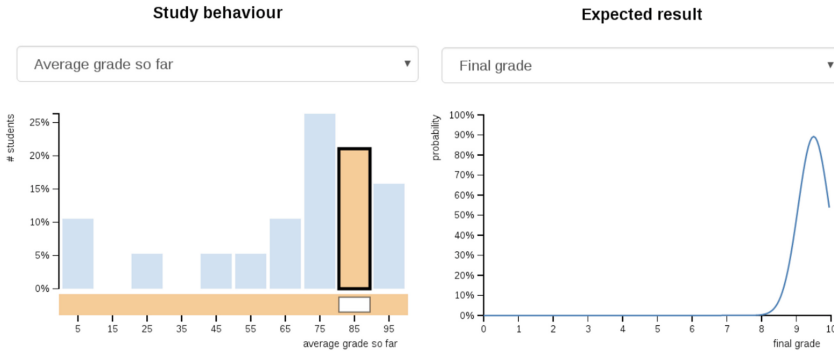


Fig. 3. Dashboard interface. The *barplot visualisation* (LHS) is used to visualize the values of a metric of study behaviour. The x-axis denotes the bin values and the y axis denotes the percentage of learners that have a value that falls into that bin for the specific metric. A bin can be selected (orange) by clicking on it, or by sliding the bar underneath the barplot to the desired bin. The bin in which the viewing learner is placed is selected at the beginning. The *bell curve visualisation* (RHS) is used to visualize the probability of each value of a metric of study result, given a selected value of a metric of study behaviour in the barplot. In other words, how likely it is that a certain end result is achieved based on the current state of behaviour. When a different bin is selected in the barplot, this curve is updated. The data is represented by mean and variance parameters. (Color figure online)

The study behaviour and expected results were approximated by quantitative metrics (Table 1), including (i) Input metrics (used to represent the current state of behaviour, e.g. time on task), (ii) Output metrics (represent the end result, e.g. exam grade), and (iii) In/Out metrics (can be used to represent either, e.g. running average grade). The DB provided insight in how certain values of an input metric related to certain values of an output metric. In the evaluation studies, depending on the course, a subset of the metrics (Table 1) were used.

When the dashboard was requested for viewing by a learner, he or she also selected an input metric to examine. The value history of that metric was transformed into the aggregated data necessary for the visualisation. For each aggregated value, the system calculated predicted aggregated values on each output metric. The metric’s value history items were filtered to only contain data from learners of the same (and current) cohort of the viewing learner.

The data was divided into equally sized bins, with a fixed number of bins defined for the metric. The bins span from the lowest to the highest aggregated value. These steps resulted in an array of frequency bins where each bin denoted a range of metric values (e.g. average grade) and its frequency denoted the number of learners for which the metric value fell into that bin.

Table 1. Available metrics

Metric	Type	Based on data
Average grade	In/Out	Intermediate grades from assignments and/or tests
Final grade	Output	Final course grade, based on exams and coursework
Pass rate	Output	Final course grade and the passing threshold
Blackboard activity	Input	The number of individual clicks in blackboard
Attendance	Input	Who was present at which lecture
Time spent on video	Input	Number of seconds spent playing an instructional video
Time spent on course site	Input	Estimate number of seconds in non-idle state on the site. This is based on time between user actions and tab focus
Time submitted before deadline	Input	Number of seconds between the submission time and the assignments deadline
Time before first attempt	Input	Number of seconds between the availability of the programming assignment and the first compilation of an attempt

4 Evaluation Study

For each of the three courses data for the relevant variables (Table 1) were collected, and the following issues evaluated:

- Impact of the DB on the performance of learners, i.e. impact of the DB on the obtained grades. Evaluate if the percentage of successful learners was higher in the group which utilized the DB.
- Predictive value of the first achieved grades of each learner with regard to their entire performance during a course.
- The predictive value of cumulative grades of each learner obtained during a course (to predict learner performance at exams and of the entire course).
- Time spent on the LMS of a course, click behaviour, hand-in time of assignments before a deadline, watch time of videos and website paths were evaluated (if applicable) based on their correlation with the academic success/performance of learners during a course.

Correlations in data were found using the WEKA⁴ visualization and correlation matrix functionality. The most notable (and surprising) result was that on average the learners in a DB condition had a (statistically significant) higher chance

⁴ <https://weka.wikispaces.com>.

of successfully graduating for a course (79% of the learners with a DB passed and 67% of the learners without DB passed).

For one of the courses, more than half of the learners with no DB failed to pass the course, while 68% of the learners who used the DB passed the course. On average, learners which on average scored low (below 4.5) for the first assignment of a course, also had a higher chance at scoring a low grade for the entire course. Learners with a high or average grade for their first assignment had similar results for their end grade as well. However, only for one course this result was statistically significant. The cumulative grades showed high potential as predictors as well, but this was dependent on the course and the amount of grades taken into consideration.

Time spent on the course LMS, click behaviour, hand-in time of assignments before a deadline, watch time of videos all had low correlations with the performance of learners (correlations were evaluated for each course if available).

5 Conclusion and Discussion

We have implemented and evaluated a Learning Analytics instrument, within the context of three bachelor courses in higher education. The instrument has the technical potential to scale and be applied to a much larger set of courses. However, the impact it has on learners and their behaviour is still unclear. The obtained results are preliminary, and further analysis is required.

On average, the learners in groups with DB seem to have better overall performance compared to the learners in groups without DB. However, it is unclear why and which aspects of the DB caused this influence on the performance of the learners, or if there were other confounding factors. The grade for the first assignment in each course can be considered relevant for predicting the performance of each learner during the entire course. Moreover, as further information of this sort accumulates (data related to cognitive behaviour), the predicted power quickly increases. Finally, there seem to be no significant correlations between learner activity in the LMS (e.g. click behaviour in Blackboard) and the expected output performance.

In further research we plan to include personal characteristics and motivation using the MSLQ questionnaire [3], as well as demographic data, and investigate how these can help to increase the accuracy of the prediction power of our Learning Analytics instrument and become a reliable and relevant tool for learners.

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