LAViEW: Learning Analytics Dashboard Towards Evidence-based Education

Rwitajit Majumdar[1], Arzu Akçapınar[1], Gökhan Akçapınar[1,2], Brendan Flanagan[1], Hiroaki Ogata[1]
Kyoto University[1], Hacettepe University[2]
{majumdar.rwitajit.4a, ogata.hiroaki.3e} @kyoto-u.ac.jp

ABSTRACT: Learning analytics dashboards (LAD) have supported prior finds that visualizing learning behavior helps students to reflect on their learning. We developed LAViEW, a LAD that can be easily integrated with different learning environments through LTI. In this paper, we focus on the context of eBook-based learning and present an overview of the indicators of engagement that LAView visualizes. Its integrated email widget enables the teacher to directly send personalized feedbacks to selected cohorts of students, clustered by their engagement scores. These interventions and dashboard interactions are further tracked to extract evidence of learning.

Keywords: BookRoll, LAViEW, Student Engagement, Visual Analytics, Intervention widgets

1 INTRODUCTION

One of the key issues in this data driven era in education is to find evidence of learning from analyzing the log data itself. It would have impact in designing ways to increase the students' engagement, especially for at-risk students who have low motivation to the course. In today's technology enhanced learning scenario we can collect learning logs of students and analyze them. A learning analytics dashboard (LAD) assists easier and useful interpretation by different stakeholders based on the visualized information. Learners can view the different indicators presented in dashboards, triggering them to reflect and examine their learning behavior and learning outcomes (Durall, E. and Gros, B. 2014). The teacher can use LAD to get a pulse of the class and analyze if there is any problem. Typically, we envision that the learning analytics system developer would visualize various indicators based on the data that a particular system gathers and the features that are extracted from them. Then a teacher can identify a problem based on the defined indicators. For example, in our context BookRoll is an e-book reader and an issue of low engagement may be indicated in terms percentage completion of content. The teacher sets the level of indicators to identify any problem. For instance, a completion lower than 60% may be considered low engagement for that content.

Currently none of the LADs capture this preference of the teachers to relate problems and indicators and assist them to plan interventions directly from the dashboard. This paper presents LAViEW (Learning Analytics Visualizations & Evidence Widgets), a LAD that supports the users to analyze learning logs and gather evidence of learning. Figure 1 gives sample visualizations in the current version of the LAViEW dashboard. Readers can access the system at live.let.media.kyoto-u.ac.jp/analysis to explore the features with anonymized dataset.

Figure 1: Sample information and visualizations in LAViEW Dashboard.

1.1 Our LA Framework

We developed our dashboard based on our earlier proposed framework (Flanagan B., and Ogata H., 2017). This framework helps us to collect anonymous learning logs of students. For example, teachers can use a LMS to coordinate a course and upload reading content in BookRoll linked to the LMS. While students use BookRoll for browsing course material, their reading behaviors can be anonymously logged. The eBook system in our context assists instructors to support students' in-class learning activities. It has features to highlight important and difficult to understand text. Students can add memos or bookmark important pages. Learning Logs of eBook reading is recorded in Learning Record Store (LRS) as an eXperience API (xAPI) statements. Next, the analytics engine helps to analyze the log data and extract features and recording in MySQL database. This processed data is visualized in the dashboard. All these processes work in real-time. The framework applies two-way anonymization to the student data. In the logs, students are represented by UUID to ensure their privacy. However, when user logins to the system via LTI, based on their roles, s/he can see the converted student ids. The framework is also very flexible to connect to any other behavior sensors which has LTI.

This first version of LAViEW was deployed in October 2017 across 3 universities which used BookRoll, the digital textbook reader, as the learning behavior sensor. In Kyoto university as of 1 February 2019, the LA system had collected 795401 logs about student's reading behavior. The other novelty in the current implementation is the inclusion of a learning evidence extraction system, the evidence portal that captures the interactions of the dashboard users while they monitor learning, analyzing problems, implementing solutions based on the learning widgets in the dashboard and reflecting on the results. The current updated version will be deployed even at school level across several districts in the country from the next school term.

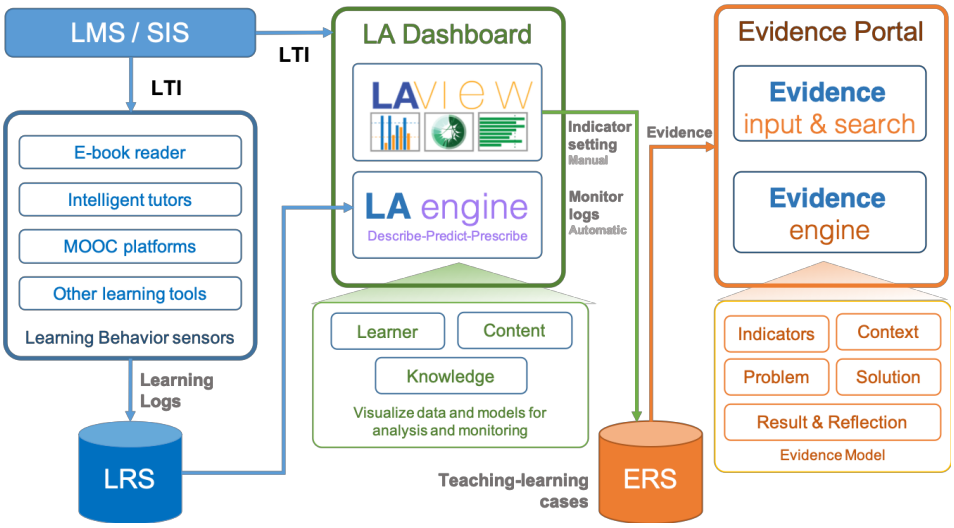

Figure 2: LEAF framework and the LA Dashboard.

2 LAVIEW: LEARNING ANALYTICS DASHBOARD

Our dashboard LAViEW (Learning Analytics Visualizations & Evidence Widgets) can be added as an external tool in LMS and accessed by both teachers and students. LAViEW automatically handles the role from the LTI and displays different panels of graphs based on customized views. When the user login to the system, they need to select the content and the period of time they want to analyze from Context Selector panel (see Fig 1 as reference). According to the user's selection the data in every panel is updated. We created an Overview panel which gives aggregated statistics about selected course. In this section both teachers and students can see average statistics of the class on the bottom and selected student's record on the top. Overview information is split into four groups of information, each group having specific color which is also used in the title of the graphs which belong to that group. The current dashboard provides information regarding *Learners & Content, Engagement, Learning Traces and Learning Outcome*. User gets the number of students and pages of the ebook in the selected course. For engagement we visualize indicators such as time spend on eBook, completion percentage of the content, average engagement rating of the class or selected student, and total number of interactions that students made. Learning Traces are the interactions that the students do with the BookRoll content to create annotations like yellow and red marker highlights, memos written or bookmark put. The learning trace section gives the count and the content related to each trace. For Learning Outcome, we link the performance scores gathered in the LMS and the knowledge points based on our content-knowledge (Flanagan, B., Majumdar, R., Akçapınar, G., Wang, J. and Ogata, H. 2018).

The dashboard contained charts with information on display or as pop ups on click interactions. To assist users, we added an overlay panel to every graph which gives explanation about each graph to the users. Additionally, such an implementation also helps to track usage of graphs and collect data for researching regarding visual approaches in LAD in terms of effectiveness, efficiency or other criteria that pertain to learning (Klerkx, J., Verbert, K. and Duval, E. 2014). The opensource implementation of LAViEW APIs also makes it easy to add novel visualizations and widgets to the dashboard. Thus, it has the potential to visualize collected data from multiple data sources that are connected through LTI.

In this paper we consider the teacher as our primary user and conceptualize the following user goals for the LAViEW. (1) monitoring a class of students, (2) provide feedback and intervention through dashboard, (3) increase engagement of students.

3 SUPPORTING ACTIONABLE ANALYTICS WITH LAVIEW: ILLUSTRATION OF AN INTERVENTION FOR LOW ENGAGEMENT

3.1 Purpose

Increasing students' engagement is one of the important features to increase students' success. However; especially at-risk students who are disengaging from coursework, it is difficult to identify students' engagement in large class sizes (Field, J., Lewkow, N., Burns, S. and Gebhardt, K. 2018). For this reason, using computers, to 'observe' students 'in situ', that is, while students are occupied in learning activities is an appropriate way to measure the engagement. Systems like dashboards with potential to visualize large amounts of data about students' behavior, is being harnessed to improve learning interactions and to personalize the learning experience (Liu, M. 2015). We enable teachers to identify at-risk students based on their engagement score and integrated intervention widget of emailing that helps to send clear guidance on how to improve personalized for different cohorts of students.

3.2 Design

According the student's usage of BookRoll, we created 9 indicators to define their engagement. An aggregated value is computed as an Engagement Score. That Engagement Score is visualized in three Engagement Graphs as shown in Fig. 3. The first one (Fig 3a.) visualizes the breakdown of the Engagement Score showing parameters value of each of the nine indicators. The number in the center (43) is the overall engagement score. To see the value of each indicator you can hover on each segment on the donut graph. Leaderboard (Fig. 3b.) is a table that users can see engagement score of the all students in the class and their ranking among other students. Weekly Engagement graph (Fig. 3c) visualizes the engagement score computed across the activity in that week. It can be used to compare individual's weekly engagement with average class engagement by comparing the point values in that week. Further looking at the lines gives a temporal trend. Green line shows the average score of the class and red line shows the student's score.

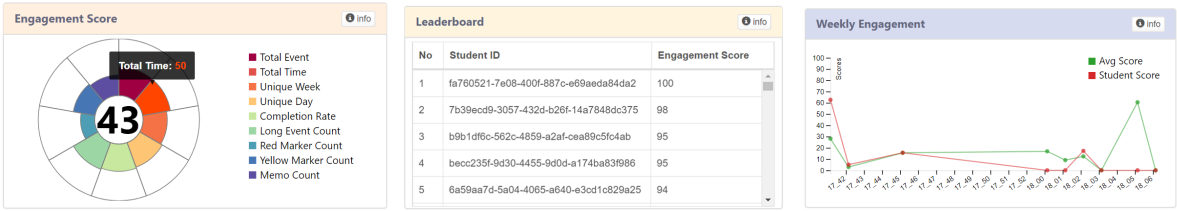

Figure 3: a. Engagement Score b. Leaderboard c. Weekly Engagement

3.3 Email Intervention Widget

Based on the engagement score LAViEW also affords the teacher to plan intervention such as sending emails (see Fig4. For the currently implemented version of sending email). The system automatically clusters 3 different cohorts of students, *Good*, *OK* and *At-risk*. Teacher can select the

students in that cohort and send them a personalized email. Then after a chosen period of time, the teacher can receive a report regarding the indicators to assess the result of the intervention. The interface is presented in Figure 4 and workflow of the instructor is presented in Figure 5..

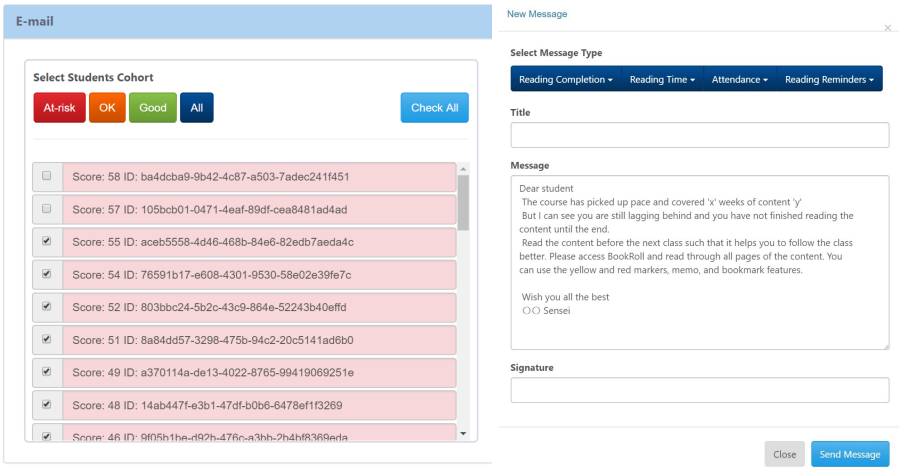

Figure 4: Email widget in LAViEW

3.4 Extracting evidence from teaching-learning practice

We propose an evidence portal (Majumdar, R., Akçapınar, A., Akçapınar, G., Flanagan, B. and Ogata, H. 2018.) which would have the provision to record all the information that is part of the above workflow. It records the criteria of the classification of students from the learner model, the teacher can input additional details of the context, the description of the indicators of the problem, the solution plan of intervention regarding this case and its result. The ERS stores this as a single record along with the automatically linked context from the LMS and the search parameters of the LAViEW. We call each record as a teaching-learning case (TLC). Context anonymized dataset in the LRS can be used to retrieve the whole case details during evidence search. We give a sample xAPI data that would be stored in the ERS corresponding to the email sending activity in Figure 6.

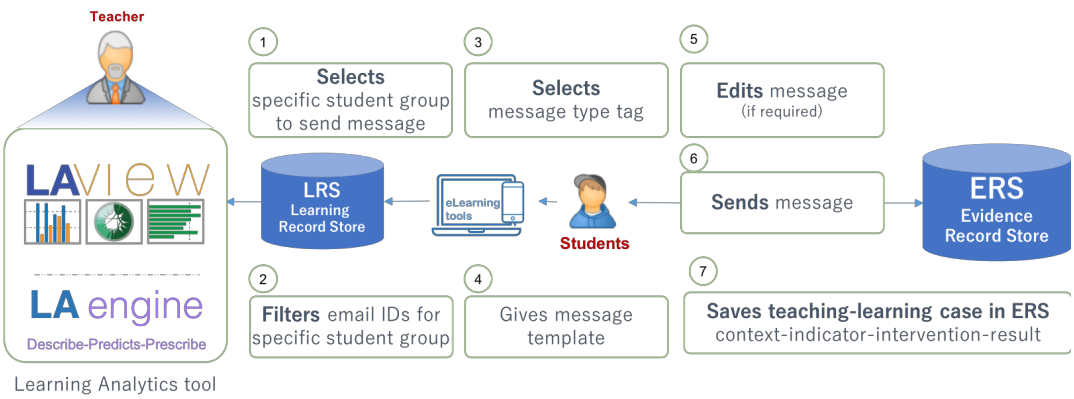

Figure 5: Workflow for intervention

xAPI Statement

```
{"version": "1.0.0",
"actor":{
"objectType": "Agent",
"account": "User account",
"homePage":
"LAViEW Dashboard",
},
"verb":{"id": Planning},
"object":{
"objectType": "Activity",
"id":" {#URI#}",
"definition": "Contents Name",
"description": "Contents ID",
"extensions":{
"course_detail": "Course Detail",
"content_name": "Content Name",
"indicator":
"Visualization Name",
"problem_class":
"Low engagement"
"problem_description":
"Low Percentage Completion."
"solution_class":
"E-mail Intervention",
"solution_description":
"Solution description",
"reflect_description":
"Reflection description",
}},
"result":{ "extensions":{
"result": "Result description",
"report_link": "Result link",
"rating" : "Rating",
"timestamp": "Timestamp",
}
```

Figure 6: Sample structure of the xAPI log of Teaching-Learning Case in the ERS.

Our approach to commence an evidence-based practice in education supported by technology starts with systematically gathering indicators of learning in a specific scenario and then analyzing visualized indicators in the analytics dashboard to identify problems (Ogata, H. et.al. 2018). Teacher can design intervention to mitigate it and then monitor its effectiveness. We believe technology can help to capture this process and reflect on the effectiveness of the practice as evidence. Conceptualizing such an evidence analytics system in education would push the boundaries of existing learning analytics infrastructures towards a technology-enhanced and evidence-based education and learning.

ACKNOWLEDGEMENT

This research was partly supported by JSPS Grant-in-Aid for Scientific Research (S) Grant Number 16H06304, Research Activity Start-up Grant Number 18H05746 and NEDO Special Innovation Program on AI and Big Data 18102059-0.

REFERENCES

Durall, E. and Gros, B. (2014). Learning Analytics as a Metacognitive Tool. *Procs. of the 6th Int. Conf. on Computer Supported Education - Volume 1*, Portugal, 2014, 380–384.

Flanagan, B. and Ogata, H. (2017). Integration of Learning Analytics Research and Production Systems While Protecting Privacy. *Procs. of the 25th Int. Conf. on Computers in Education*, pp.333-338,

Flanagan, B., Majumdar, R., Akçapınar, G., Wang, J. and Ogata, H. (2019). Knowledge Map Creation for Modeling Learning Behaviors in Digital Learning Environments. Companion Procs. of 9th LAK.

Klerkx, J., Verbert, K. and Duval, E. (2014). Enhancing Learning with Visualization Techniques. *Handbook of Research on Educational Communications and Technology*, J. M. Spector, M. D. Merrill, J. Elen, and M. J. Bishop, Eds. New York, NY: Springer New York, 2014, pp. 791–807.

Field, J., Lewkow, N., Burns, S. and Gebhardt, K. (2018). A Generalized Classifier to Identify Online Learning Tool Disengagement at Scale. *Procs. of the 8th LAK*, New York, NY, USA, 2018, pp. 61–70.

Liu, M. (2015). Using Particle Swarm Optimization Approach for Student Engagement Measurement. I*nternational Journal of Learning, Teaching and Educational Research*, vol. 11, no. 1, Apr. 2015.

Majumdar, R., Akçapınar, A., Akçapınar, G., Flanagan, B. and Ogata, H. (2018). Learning Analytics Dashboard Widgets to Author Teaching-Learning Cases for Evidence-based Education, Companion Procs. of 9th LAK.

Ogata, H., Majumdar, R., Akçapınar, G., Hasnine, M.N. and Flanagan, B. (2018). Beyond Learning Analytics: Framework for Technology-Enhanced Evidence-Based Education and Learning, Proceedings of the 26th Int. Conf. on Computers in Education, pp. 486-489, 2018.11.26.