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REAL-TIME LEARNING ANALYTICS FOR FACE-TO-FACE LESSONS

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Abstract

Even though the use of digital technology and e-learning has grown over the years, most of the time spent in schools around the world is still in face-to-face lessons. Traditional classroom teaching encounters fundamental constraints like the difficulty faced by one educator to track the understanding of a group of learners. Numerous tools exist to help educators but they are mostly detached from the actual teaching and learning materials, and hence necessitate a breaking away from the flow of the lesson to collect, visualize and understand the data collected. In this paper, we present a real-time learning analytics system that can provide both educators and learners with a real-time view of the data collected from learners' interaction with a mobile-optimized lesson embedded in a learning management system and accessible via mobile phones or computers. Data collection and visualization is automated and achieved with no friction to the flow of the lesson. The educator could use the data to keep track of individual students' responses, as well as moderate the pace of the whole class. Action research was done on a total of four classes of students to test the benefits of using the real-time learning analytics system. Quantitative sentiment feedback was collected and the number of targeted interventions by the

educators was recorded. Targeted interventions are defined as moments when the educator spot a learning gap or misconception and intervene immediately to address the issue. Both categories of data captured showed positive results for the use of real-time learning analytics in the classroom. The system has the potential to be used in any domain as it is domain-neutral and built on open-source technology. Usage of the system does not require much technical know-how, and the lessons created can be easily exported into any major Learning Management Systems (LMSs).

Keywords

Real-Time, Learning Analytics, Data Visualization, Classroom Teaching, Face-To-Face Lessons

1. Introduction

Learning analytics has garnered much attention from educators and schools alike with its potential to offer previously unobtainable insights to students' learning. Feedback or analytics performed on learners' data can be roughly categorized into three types: summative, delayed and real-time. Most feedback or analytics fall into the first two categories because the analysis results are not immediately fed back to teachers or students at the point of teaching or learning. One reason is that in practice, as the measurement or collection of data is performed via active human intervention e.g. actual marking of test scripts and/or entering of marks into a spreadsheet, immediate feedback and intervention based on the data would be impossible.

This problem is made worse by the fact that face-to-face lessons still comprise the majority of the time spent by both learners and educators in schools around the world. Most, if not all, classrooms do not have a one-to-one ratio between learners and educators (World Bank, 2020). Without the aid of digital tools, it would be humanly impossible for educators to gather the data from all the students in the class and analyze them in real-time.

In this paper, we propose a domain-neutral real-time analytics system that was built on open-source technology that can be used by non-tech-savvy educators easily in their classroom teaching to capture and visualize learners' interaction automatically in real-time. The system comprises a student app where learners' interactions with the app are captured and pushed to the cloud, and the data is fed back into a tutor app in real-time. The tutoring app has numerous data visualizations that educators can use to analyze learners' responses.

2. Literature Review

One definition of learning analytics is the measurement, collection, analysis and reporting of data about learners and their context for understanding and optimizing learning and environments in which it occurs. One of the main drivers behind learning analytics is the ability to collect and analyze traces of information learners leave behind to improve learning. With the usage of the internet and consequently e-learning being increasingly a normal way of life for digital natives (Lai & Lee, 2019), learners leave behind more and more traces of such information for learning analytics to capture. Acknowledging that equipping youths with technical know-how empowers them in multiple aspects (Ohagwu, 2020), it is recommended that educators leverage learning analytics to further enhance the teaching and learning process.

Strategies to embark on learning analytics could span from predictive modelling and patterns discovery (Romero & Ventura, 2007), to simple descriptive statistics and data visualization (Duval, 2011). Data visualization on learners' data is a comparatively low-cost entry into the realm of learning analytics to improve teaching and learning. One reason for the popularity of data visualization is its ease of understanding by non-analytical background administrators and educators. Visualization is a powerful means to influence decision-making as humans are predominantly visual (Keller et al., 1994), even more so when we are considering using learning analytics on a real-time basis.

Many educational institutions use learning management systems (LMSs) such as Blackboard and Moodle to manage users' access and act as online repositories for course materials. LMSs empower the institutions by making large-scale educational data collection relatively seamless. However, most LMSs do not have the capabilities to do data reporting and visualization in real-time in a user-friendly manner, leaning instead towards providing a centralized database for delayed and summative analytics.

To circumvent the difficulties present in current LMSs in furnishing real-time analytics, Choi et al. (2018) deferred to using clickers and free cloud services, as a low-cost solution to obtaining real-time data instead of relying on an LMS. However, this approach neglects the benefits and affordances that LMS offers. That is why Poon et al. (2017) proposed using visualization techniques to mine for information based on log data from LMSs. Nonetheless, the suggested approach still offered only delayed analytics at best.

The challenge in providing real-time analytics to educators is compounded by the fact that students have, in many formal and informal studies, expressed that they prefer face-to-face lessons as compared to online lessons (Keis et al., 2017). With data collection even harder in the physical world than in the digital realm, real-time analytics becomes a luxury, if not a myth, in face-to-face lessons. We will present our solution for bridging face-to-face lessons with real-time analytics in the next section.

3. An EXSERLAN System

The real-time analytics system proposed is titled EXSERLAN (Extensible Seamless Real-time Learning Analytics). It consists of two main components: the student app, and the tutor app.

3.1 Student App

The student app is built using an open-source technology called Adapt Learning (<https://www.adaptlearning.org/>). Adapt Learning provides both a framework, as well as a graphical Adapt Learning Authoring Tool, to create mobile-optimized, interactive lessons that are responsive to devices' screen sizes (Figure 1). Leveraging on the open-source nature of the technology, the team created plugins that can be used to extend the capability of the system (hence the use of the term "Extensible" in the system's name). These plugins include a Multiple-Choice Question (MCQ) plugin, a Short-Answer-Question (SAQ) plugin, as well as a free-response text input plugin. In particular, the MCQ plugin allows for educators to issue "Red-Orange-Green" questions, also known in pedagogy as the "Traffic Light Tool". Adapt Learning allows for the use of both content delivery components, as well as the assessment plugins listed above. The customized plugins created are linked to a cloud database, so learners' interaction can be saved for retrieval.

At the same time, the student app created thus can be exported as a SCORM package to be embedded into any major LMSs. The LMS used by the educational institution where the authors helm from is BlackBoard, and so these student apps are placed into BlackBoard, where they have to sign in to access. The advantage of putting the lesson in an LMS is that the LMS already captures the names of the students, which the student app can extract and push to the cloud database along with the interaction data.

Q1A

What does the M stand for in MOHICANS?

Mobile-Engaging

Mobile-Effective

Mobile-Enhanced

Submit Show feedback

Q1B

What does the O stand for in MOHICANS?

Off-the-shelf

Ordinary

Other means

Correct answer Show feedback

Q2

What subject would you consider a good fit to implement mobile learning?

Submit



Figure 1: An Example of the Student App Incorporating both Assessment (In This Case an MCQ) as well as Content Delivery (In This Case, A Video) Components

3.2 Tutor App

To use the learners' data stored in the cloud database, a customized tutor app was developed using open-source web technology. The tutoring app can thus be used on both desktop browsers as well as on web browsers found on mobile devices. The tutoring app has various data visualizations; spanning common ones like bar charts and pie charts, as well as customized ones used to track individual students' progress (see Figure 2).

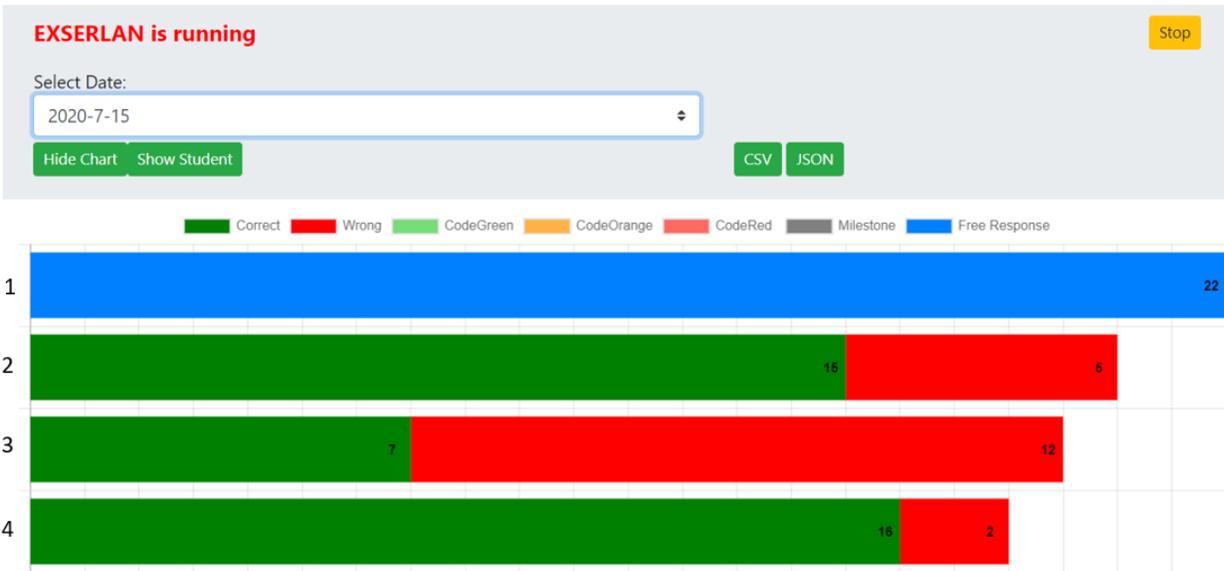


Figure 2: *The Tutor App View in Real-Time as Students Interact with the Student App*

4. Research Methodology

The sample for this study was collected before and after the implementation of the said technology. The sample included four Year 1 Polytechnic classes from the School of Information Technology, amounting to 74 students in total. The behaviour of the students in a Digital Business module they were taking was observed for the sake of this research.

To evaluate the use and effectiveness of real-time analytics in class, a before-and-after design was taken for the research methodology. Students first attended class as usual; where the educator goes through tutorial questions and answers while the students check back with their answers. Thereafter, the first survey was implemented. In the following week's lesson, students attended class while using the EXSERLAN student app. At this point, no real-time intervention was taken by the educator as the educator did not look at the tutor app. Thereafter, the second survey was implemented. At the next lesson, students attended class using the student app and the educator also looked at the tutor app so he or she could administer real-time intervention, where students' doubts and mistakes were clarified on the spot. Thereafter, the third and last survey was implemented.

Quantitative data was collected via an anonymous response on an online survey platform. To capture the key measuring factors for this study, 3 questions were asked:

1. On a scale of 1 to 10, how would you rate the level of **engagement** you experienced in the class?
2. On a scale of 1 to 10, how would you rate the level of **effectiveness** of the class in helping you understand the topic for the week?
3. On a scale of 1 to 10, how would you rate the level of **helpfulness** the educator was to you, in terms of clarifying your doubts, providing thorough explanations of the lesson contents etc?

Students were also allowed to provide qualitative response optionally. Not all students responded to the survey, and the total number of responses for each survey is as follow:

Total Number of Responses per Survey		
Pre-Implementation		
63	63	63
Count of Helpfulness	Count of Engagement	Count of Effectiveness
No Real-Time Intervention		
59	59	59
Count of Helpfulness	Count of Engagement	Count of Effectiveness
Real-Time Intervention		
59	59	59
Count of Helpfulness	Count of Engagement	Count of Effectiveness

Figure 3: Number of Respondents for Surveys

While the usual method for evaluation is to look at the average score of each question asked, a more stringent (or accurate) way of evaluating the score for the questions is to adopt the Net Promoter Score (NPS) calculation method. The NPS is a customer loyalty metric developed in 2003 by management consultant Fred Reichheld of Bain & Company in collaboration with the company Satmetrix (Reichheld, 2003). Although the NPS approach is highly used to compare satisfaction with brands, it can also be used here to tackle satisfaction related concerns.

Depending on the score that is given to the Net Promoter question, three categories of people can be distinguished:

- Promoters = respondents giving a 9 or 10 score
- Passives = respondents giving a 7 or 8 score
- Detractors = respondents giving a 0 to 6 score

Lastly, quantitative data in the form of the number of interventions were needed (e.g. when learners got any question wrong, or they indicated they needed help via the Traffic Light tool), and the number of interventions given by the educators was recorded.

5. Findings and Discussions

For each of the metrics, the average score was calculated. All 3 metrics received an average score of 7 at pre-implementation phase, an average score of 8 at no real-time intervention phase and an even much better score of 9 at the real-time intervention phase (Figure 4). A quick conclusion tells us that real-time intervention does help with face-to-face classes where students find effectiveness, engagement and helpfulness at class. However, one might argue the significant differences among the scores; hence NPS calculation is employed to further ascertain the impact of real-time analytics application during class.

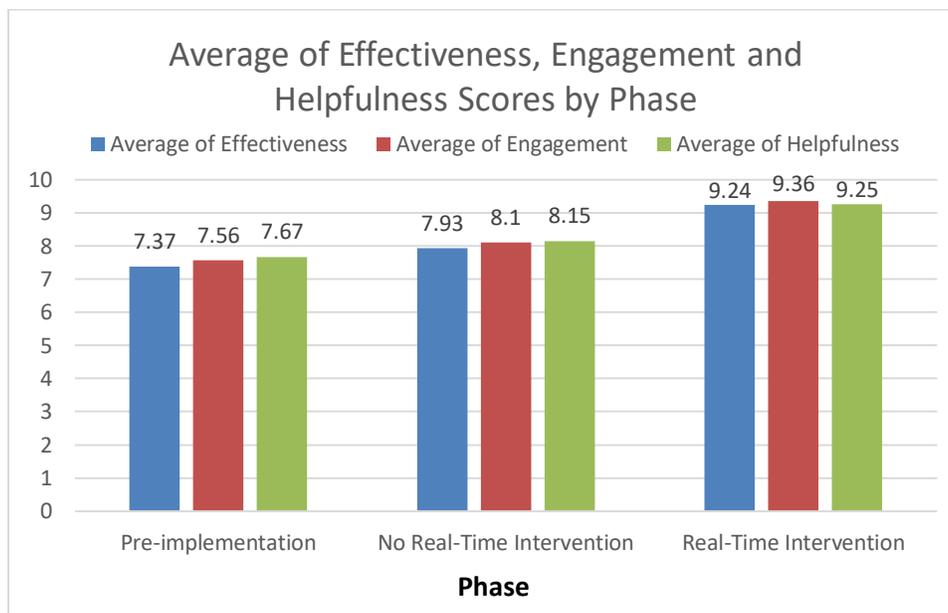


Figure 4: *Average of the Effectiveness, Engagement and Helpfulness Survey*

The NPS calculation results amplified the impact of the use of real-time analytics in class with a high NPS of 80% and above as shown in the chart below. When real-time analytics was used, but with no intervention, the NPS result showed a much lower score of 20%, that is to say, 60% more students gave a rating of 9 or 10 at the final phase (Figure 5).

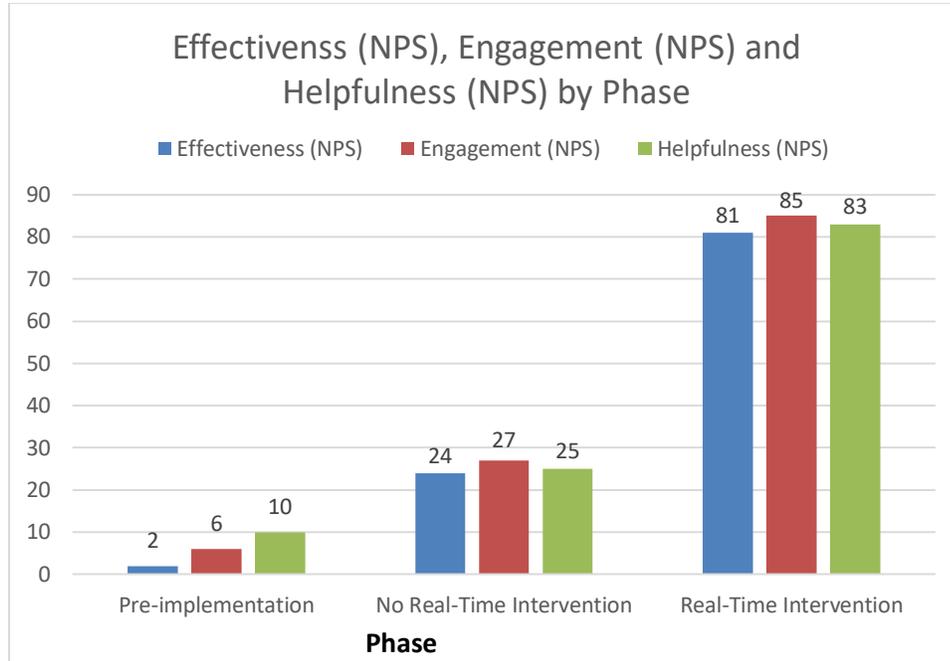


Figure 5: *NPS of the Effectiveness, Engagement and Helpfulness Survey*

In Table 1, we noted that the number of interventions that the educator could take that was targeted at learning gaps of learners during class was a paltry 6%, as only students called upon or more vocal would have their needs addressed. Armed with a real-time view, the educator could capture 79% of the learning gaps and address them immediately to the whole class.

Table 1: *Quantitative Results Gathered Using EXSERLAN Student App*

No real-time view			Real-time view		
Interventions required	Targeted Interventions were given	Proportion captured	Interventions required	Interventions were given	Proportion captured
263	16	6%	370	293	79%

6. Limitations and Conclusion

The EXSERLAN system allowed the capture and visualization of learners’ data with no friction to the flow of the lesson. Learners were more on-task and felt that the face-to-face lessons were effective and helpful to their learning when they could have their learning gaps addressed in real-time. Educators appreciated the real-time system for providing them with

immediate insights so that they can narrow the students' learning gap in a class by following their learning pace.

One limitation to the system could be that it would not be suitable for large group lectures, where it would disrupt the lesson too much for the educator to address the learning needs of too many students. In this case, the EXSERLAN system could be used for aggregated feedback instead of checks on the individual level. The educator could also reach out to the key students who require more interventions after the lesson.

As the learners involved in this study were taking a largely theoretical module while being part of this experiment, more research could be done to ascertain the efficacy of real-time learning analytics when applied to other more hands-on modules. Nevertheless, the results obtained proved that the EXSERLAN system developed assisted educators greatly to gather data from all the students in the class and analyze them in real-time. Being domain neutral meant that the system has the potential to reach out to other educators regardless of their tech-savviness in vastly different fields of teaching and learning.

REFERENCES

- Choi, S.P.M., Lam, S.S., Li, K.C. and Wong, B.T.M. (2018). "Learning analytics at low cost: at-risk student prediction with clicker data and systematic proactive interventions", *Journal of Educational Technology and Society*, Vol. 21 No. 2, pp. 273-290.
- Duval, E. 2011. Attention please! Learning analytics for visualization and recommendation. In *Proceedings of LAK11: 1st International Conference on Learning Analytics and Knowledge*. ACM, 9-17. <https://doi.org/10.1145/2090116.2090118>
- Duval, E. and Verbert, K. (2012). Learning Analytics, eled 8. Retrieved from <https://eeced.campussource.de/archive/8/3336>
- Keis, O., Grab, C., Schneider, A. and Öchsner, W. (2017). Online or face-to-face instruction? A qualitative study on the electrocardiogram course at the University of Ulm to examine why students choose a particular format. *BMC Medical Education*, 17:194. <https://doi.org/10.1186/s12909-017-1053-6>
- Keller, P.R., Keller, M.M., Markel, S., Mallinckrodt, A.J., and McKay, S. (1994). Visual cues: Practical Data Visualization. *Computers in Physics* 8, 297. <https://doi.org/10.1063/1.4823299>

- Lai, Y. L., & Lee, J., (2019). Trend of Internet Usage and Learning Style of Digital Natives. PUPIL: International Journal of Teaching, Education and Learning, 3(2), 94-102. <https://doi.org/10.20319/pijtel.2019.32.94102>
- Ohagwu, O. M. (2020). Technical Training: A Pathway to Youth Empowerment. MATTER: International Journal of Science and Technology, 6(1),101-112. <https://doi.org/10.20319/mijst.2020.61.101112>
- Poon, K.M., Kong, S.C., Yau, T.S.H., Wong, M. and Ling, M.H. (2017). A learning analytics for monitoring students participation online: Visualizing navigational patterns on learning management system, blended learning. New Challenges and Innovative Practices, Vol. 10309, pp. 166-176. https://doi.org/10.1007/978-3-319-59360-9_15
- Reichheld, Frederick F. (December 2003). "One Number You Need to Grow". Harvard Business Review.
- Romero, C. and Ventura, S. 2007. Educational data mining: A survey from 1995 to 2005. Expert Systems with Applications 33, 1, 135-146. <https://doi.org/10.1016/j.eswa.2006.04.005>
- The World Bank. (18 Jan 2020). Pupil-teacher ratio, tertiary. Retrieved from <https://data.worldbank.org/indicator/SE.TER.ENRL.TC.ZS>