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Shady Shehata and Jennifer Pei-Ling Tan

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Introduction

Practitioners spearhead a significant portion of learning analytics, relying on implementation and experimentation rather than on traditional academic research. Both approaches help to improve the state of the art. The LAK conference has created a practitioner track for submissions, which first ran in 2015 as an alternative to the researcher track.

The primary goal of the practitioner track is to share thoughts and findings that stem from learning analytics project implementations. While both large and small implementations are considered, all practitioner track submissions are required to relate to initiatives that are designed for large-scale and/or long-term use (as opposed to research-focused initiatives). Other guidelines include:

- *Lessons learned – implementation*: After going through the learning analytics implementation process, what factors have surfaced that affect the success of the project?
- *Lessons learned – outcomes*: What were the stated measures of success of the project? Have they been met during the implementation? Did other unexpected results appear after a certain amount of time?
- *Innovative new tools/techniques*: Share newly developed tools or approaches to learning analytics that have been implemented at an institution. Reviewers will look for unique characteristics and at how deployment has influenced development.
- *Application of standards*: A project making use of data/analytics standards and illustrating the benefits of such an approach.
- *Collaboration and sharing*: How are groups of institutions/practitioners partnering to solve shared problems in the learning analytics space?
- *Solving a new problem*: Traditional analytic approaches tackle questions like "Did the student master this topic?" or "Will this student pass that class?" Has the submission tried to answer a novel question in the learning analytics space?

Papers accepted in 2017 fell into two categories. Both types of paper are included in these proceedings.

- **Practitioner Presentation:** Presentation sessions are designed to focus on deployment of a single learning analytics tool or initiative. Topics can range from single implementations of learning analytics tools / initiatives up to the deployment of cross functional systems or larger projects that have been rolled out at scale.

- **Technology Showcase:** The Technology Showcase event is designed to enable practitioners to demonstrate new and emerging learning analytics technologies that they are piloting or deploying.

Shady Shehata, D2L Corporation, Canada
Jennifer Pei-Ling Tan, National Institute of Education, Singapore

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MAP: Multimodal Assessment Platform for Interactive Communication Competency

Saad M. Khan
Educational Testing Service
skhan002@ets.org

David Suendermann-Oeft
Educational Testing Service
suendermann-oeft@ets.org

Keelan Evanini
Educational Testing Service
kevanini@ets.org

David M. Williamson
Educational Testing Service
dmwilliamson@ets.org

Scott Paris
Educational Testing Service
sparis@ets.org

Yao Qian
Educational Testing Service
yqian@ets.org

Yuchi Huang
Educational Testing Service
yhuang001@ets.org

Phillip Bosch
University of Notre Dame
pbosch1@nd.edu

Sidney D'Mello
University of Notre Dame
sdmello@nd.edu

Anastassia Loukina
Educational Testing Service
aloukina@ets.org

 In: Shehata, S. & Tan, J.P-L (Eds) (2017). Practitioner Track Proceedings of the 7th International Learning Analytics & Knowledge Conference (LAK'17). Simon Fraser University, Vancouver, Canada (13–17 March): SoLAR.

Lawrence Davis
Educational Testing Service
ldavis@ets.org

ABSTRACT: In this paper, we describe a prototype system for automated, interactive human communication assessment. The system is able to process multimodal data captured in a variety of human-human and human-computer interactions. These data can be analyzed along many dimensions of verbal and non-verbal communication competencies including speech delivery, language use, social affect and engagement. The system also integrates speech and face recognition-based biometric capabilities and has design elements to enable ranking and indexing of large collections of assessment content.

Keywords: Multimodal Analytics, Interactive Communication Assessment, English Language Learning and Assessment, Biometrics, Learning Systems

1 INTRODUCTION

Assessment of English language communication competence is difficult because of the complex skills that underlie the competence and the technical difficulties of measuring dynamic speaking behaviors. Current large-scale assessments of non-native English speaking proficiency (such as TOEFL iBT[1] and Pearson Test of English Academic[2]) typically contain brief test questions and prompts that elicit monologues from the test taker. Since they do not elicit interactive conversations from the test taker or measure non-verbal communication, these assessments are incomplete evaluations of human communication skills. These tools do not capture the patterns of speech and behavior that are critical to effective human interactions (Pentland 2008). Other assessments (such as IELTS[3]) assess interactive speech by using one-on-one interviews with human examiners. However, this approach is difficult to standardize due to subjective aspects of individual interviewers.

In recent years some exciting work has been done to create learning/training systems that combine virtual agent, multimodal analyses of user behaviors, and dialogue management (Devault et al. 2014, Hoque et al. 2013). A key feature of these systems is the ability to perform real-time tracking of both verbal and non-verbal behavior to create immersive simulation experiences. However, these tools are not designed to create holistic assessments of conversational English communication skills and have not been validated for assessments of speaking proficiency of non-native English speakers.

In this paper we present the Multimodal Assessment Platform (MAP); a system that can analyze audio-visual data from non-native English speakers engaged in interactive conversations with other humans or

[1] http://www.ets.org/toefl

[2] http://pearsonpte.com/

[3] http://www.ielts.org

automated agents as well as structured prompt questions and response scenarios. The system captures and analyzes data in authentic settings using rich audio-visual interfaces. MAP provides data about subjects along three dimensions of speech and non-verbal behavior: Delivery, Language Use, and Social Engagement. In addition, the system includes a Biometric Security functionality for identity verification based on facial recognition and speech-based speaker identification. MAP has the potential to be a useful tool to better gauge interactive English communication ability in a variety of domains including university admissions offices, workforce hiring non-native speakers and English language learning systems. In the following we provide details of the MAP system starting with a brief description of the service-oriented architecture underlying the back-end core.

2 TECHNICAL APPROACH

The MAP front-end user interface is designed to review, and verify analytical results as well as to demonstrate system functionality. The interface can be used to (a) play back processed audio-visual data, (b) annotate processed data with automatically scored metrics and behavioral events, and (c) view score reports and summary statistics. Figure 1 below shows the user interface when browsing the assessment results from the processing of a test video. The interface has a tabbed structure that allows users to easily browse through the details of each of the three assessment categories: Delivery, Language Use and Social Engagement. In addition, the Security tab displays results from speech biometrics and face recognition. Finally, the Dashboard tab provides an overview of performance results from each of the three constructs of interactive communication assessment and biometric authentication using color codes: threshold (yellow), above threshold (green) and below threshold (red). The threshold values are configurable by the system administrator and can be determined empirically. A customized version of the interface can be used to identify classification errors in analytics and provide data to improve and refine the underlying algorithms.

The MAP back-end has been designed using a service-oriented architecture that can accept processing job requests submitted over the web. The core consists of a multimodal data processing framework analyzing audio and visual data for automated detection of verbal and non-verbal communication. Computer vision, speech, and natural language processing algorithms, are utilized to extract low-level visual features including facial action units, head orientation, silhouette contours, and acoustic features

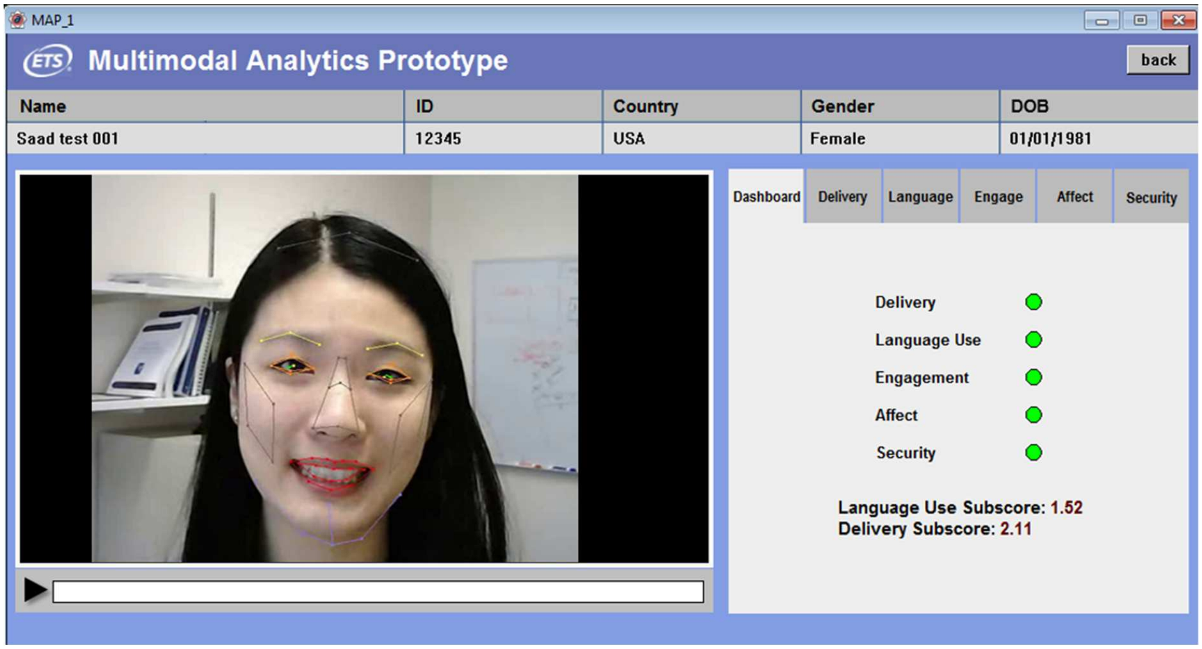

Figure 1: Front-end interface of the system | Users can click on tabs to obtain detailed assessment results on biometrics security, social affect, delivery, and language use. The dashboard tab shows a bird's eye view of the analysis results with color codes for threshold (yellow), above threshold (green) and below threshold (red)

such as Mel-frequency cepstral coefficients (MFCCs); mid-level features such as speaking rate and word tokens; and higher level behavioral classifications including facial expression/affect, prosody and vocabulary richness, among others. This core multimodal data processing framework is composed of four functional modules corresponding to the three aspects of interactive communication delivery, language use and engagement, plus biometrics used for speaker identification. In the following subsections we provide technical details of these functional modules.

2.1 Delivery and Language Use

In order to provide information about the speaker's English speaking ability, MAP provides feedback about two different aspects of the speaker's responses captured in the interactive conversation: delivery and language use. Delivery encompasses fluency and pronunciation whereas language use consists of grammar and vocabulary. While these two aspects of speaking proficiency are often correlated in a given non-native speaker's English, they represent different types of skills that are learned and taught in different ways. This is reflected by the fact that standardized assessments of English speaking proficiency often incorporate separate rubrics for delivery and language use.

We use SpeechRater (Zechner et al. 2009), a state-of-the-art automated speech scoring engine designed to process non-native spontaneous speech, to extract a wide variety of features that measure different aspects of the spoken response to prompt questions. These include fluency features such as number of words per second, rate of silent pauses, repetitions and repairs, pronunciation and vocabulary features such as number of distinct lexical types, word-level acoustic model likelihood amongst others (see (Loukina et al. 2015) for further detail).

2.2 Social Engagement

We developed models to detect two different aspects of student engagement (Fredricks et al. 2004) from video data: behavioral and affective. The behavioral engagement model detects whether students appear to be paying attention and putting forth discretionary effort, on-task behaviors, and participation. We used 3D facial feature tracking (ref) to detect students' faces and extract head yaw (side to side angle) in consecutive 10-second windows in the video stream. We considered the proportion of video frames within the windows in which the face could be detected as an indicator of engagement, based on the intuition that failure to register the face for prolonged periods might suggest disengagement from the interface.

The affective engagement model observes affective and emotional states such as enthusiasm, energy, lethargy, sadness, or distress. It utilizes facial expressions to infer engagement. The model utilizes facial expressions to infer engagement. We applied supervised machine learning methods to facial features extracted from 21 participants in the publically available SEMAINE database (McKeown et al. 2012) of dyadic human interactions. These features included head pose (yaw, pitch, and roll), head position in 3 dimensions, eye gaze direction, and 17 facial action units (AUs) (Ekman and Friesen 1978). We experimented with logistic regression, support vector machines, and multi-layer perceptron classifiers using Weka, a machine learning toolkit. Cross-validation was done by repeatedly (50 iterations) selecting a random 67% of SEMAINE participants for training data and the rest as testing data. Synthetic minority oversampling (SMOTE) was applied to the training data in order to create 400% more examples of engagement so as to bias the model toward predicting the minority class of engagement. A logistic regression classifier produced the best results, with an area under the receiver-operating characteristic curve (AUC) = .612 (chance level = .500).

2.3 Security Biometrics

To enhance security and user identity authentication for validity of the interactive communication competency assessments, we developed voice biometrics (i.e., speaker recognition) and face recognition functionality into the MAP system. Our approach for voice speaker recognition it to utilize i-vectors a compact representation of a speech utterance in a low-dimensional subspace based upon factor analysis. Speech utterances are first converted to a sequence of acoustic feature vectors, and their dynamic counterparts. These are fed into a Gaussian Mixture model to compute a match score between the target and the test speaker (or imposter). A detailed review of a preliminary voice biometrics study can be found in (Qian et al. 2016).

Our face recognition consists of four stages: face detection, face alignment, feature extraction and classification (or verification). Face detection, the first step, identifies a bounding box around the human face in the query image. This is followed by automated face alignment process that uses the face bounding box and localizes accurate positions of various facial feature points in a predefined template. For face detection, we utilized the mature OpenCV detection algorithm based on Haar cascades [10]; for face alignment, we will employ the method of Kazemi et al. 2014 using an ensemble of regression trees. Aligned face images are used as input for feature extraction and identity verification using a Deep-Convolutional Neural Network (D-CNN) approach (Parkhi et al. 2015).

3 CONCLUSION AND DISCUSSION

In this paper we have presented MAP: Multimodal Assessments Platform a system for the assessment of interactive English communication ability from multimodal data. The system is designed to evaluate performance along a number of dimensions that underlie the construct including speaking fluency, language use, social affect and behavioral engagement. Additionally, for user authentication our system has multimodal biometrics functionality including voice-based speaker identification and facial recognition. The system is designed using a service-oriented architecture and can be used for large scale batch processing.

The MAP system is currently a prototype and has not yet been deployed with end users. One of our potential end users are university admissions offices interested in better understanding interactive English communication ability of non-native students. To that end we are working University of Rochester to capture pilot user data. "Through both our own research and testimonials of staff, students, and alumni, Rochester has long understood and prioritized face-to-face interaction in the admission process. Admission interviews make an important difference in how much we know about an applicant and how much they know about us. We continue to welcome this partnership with ETS in their evaluations." – Jon Burdick, Vice Provost and Dean of College Admission, University of Rochester.

In the future we plan to incorporate avatar-based fully autonomous dialogic interactions and real-time processing of multimodal data. A key area of focus is the fusion of features extracted from multiple modalities for improved accuracy of the assessment constructs as well as better performance on biometric identification. Finally, we believe functionalities developed in this system may also find application in areas such as workforce staffing and healthcare where interactive, conversational communication skills are highly valued.

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Crossing the Chasm to Big Data: Early Detection of At-Risk Students in a Cluster Computing Environment

Eitel J.M. Lauría
School of Computer Science & Mathematics
Marist College
Eitel.Lauria@marist.edu

Edward Presutti
Information Technology
Marist College

Mathew Sokoloff
Information Technology
Marist College

Michael Guarino
Information Technology
Marist College

ABSTRACT: This work describes the ongoing redesign of the early detection framework originally developed at Marist College as part of the Open Academic Analytics Initiative, a multi-year EDUCAUSE/NGLC research grant funded by the Gates Foundation and focused on impacting the student retention rates. The early detection framework uses machine learning to identify at early stages of the semester the student population who are potentially at academic risk. The paper specifically tackles the migration of the early detection framework from a single node architecture to a big data, cluster computing architecture using Apache Hadoop and Spark.

Keywords: Learning Analytics, Early Detection, Open Source, Big Data, Cluster computing, Machine Learning, ETL, Apache Hadoop, Apache Spark

1 SUMMARY OF DEPLOYMENT

The early detection framework in its new big data cluster computing implementation has been successfully tested using Marist College data. A pilot of the cluster computing implementation was completed throughout 2016 at North Carolina State University. The presentation includes preliminary results on predictive performance. The framework was chosen in late 2015 as a key component of the

UK's national analytics infrastructure provided by Jisc[4], and several pilots are currently being rolled out at UK institutions.

2 FULL DESCRIPTION

Marist College has pioneered the discipline of learning analytics starting with the Open Academic Analytics Initiative (OAAI) in 2011 (Lauria, 2011; Lauría et al, 2012; Jayaprakash et al, 2014). The original design of the early detection framework developed as part of the OAAI used a single-node architecture (software running on a single workstation) that collected data from various sources and condensed them into a single data set (the unit of analysis) where each record depicted a student taking a course in a given semester. Four sources of data were considered: student records (including demographic and academic data), course data, student interactions with the LMS, and gradebook data (collected by the LMS). Each record in the resulting unit of analysis was labeled with the student grade in the course. The grade was recoded to a binary value based on a threshold grade (typically a letter grade C for undergraduate students); students with a C or more were considered in good standing (binary code 0), whereas student with a course grade below a C where considered at risk (binary code 1). This framed the problem as a binary classification. Classifiers were trained and tested using several supervised learning algorithms (decision trees, naïve Bayes, support vector machines and logistic regression). The trained models were subsequently used to provide forecasts on student performance a few weeks into the semester. The software platform used to implement the ETL and predictive analysis stages was Pentaho, a well-known open source suite. Although this platform has worked well for most of the work we have completed, we are aware of some of its limitations:

- A single node architecture can have problems of scale when considering much larger data sets.
- Adding new sources of structured and unstructured data could also lead to an off-scale increase of input data processing that could easily overwhelm the single-node architecture.

2.1 Enter Cluster Computing Architecture

The early detection framework has been recently migrated (Lauría et al, 2016) to a cluster computing architecture based on Apache Hadoop (see Fig. 1). Since the new platform selected is horizontally scalable as data volumes increase, no platform change is required. Data is stored in Hadoop's distributed file system (HDFS) and several software tools of the Hadoop ecosystem are used to implement the data integration (ETL) stage. The predictive modeling stage has been implemented using Apache Spark, using Hadoop's Yarn as the resource manager that interacts with Spark. The following paragraphs place

[4] JISC (Joint Information Systems Committee) is a UK non-profit organization that provides higher education digital services and solutions for deployment at national scale

emphasis on the design decisions made by the development team when tackling a big data platform in constant evolution.

2.1.1 Migrating the ETL Stage to a Cluster Computing Architecture.

To support the ETL process, data was exported to a MySQL database from two primary systems that contained student information. This implementation was originally constructed to provide a convenient mechanism for supporting the single node implementation. Further it was initially believed that by using an intermediate store for the exported data, queries could be executed that closely mimicked the original ETL process and the source data could be better manipulated through standard SQL mechanisms.

– The first step in the migration process was to extract the originally SQL code that was used in the Pentaho implementation and convert it to run in a "big data" distributed environment.

– One of the most significant migration decisions was determining which technologies should be used to facilitate the implementation. The decision was made to use Hadoop Hive, Sqoop and Oozie. Hive was selected as it provided a SQL-like environment that encompassed the core expertise of the team. Sqoop was chosen given its well-aligned interface with the existing mySQL databases. Finally, Oozie was selected for its simplicity and the fact that a web based GUI (Hue) was available that provided a convenient path to implementation.

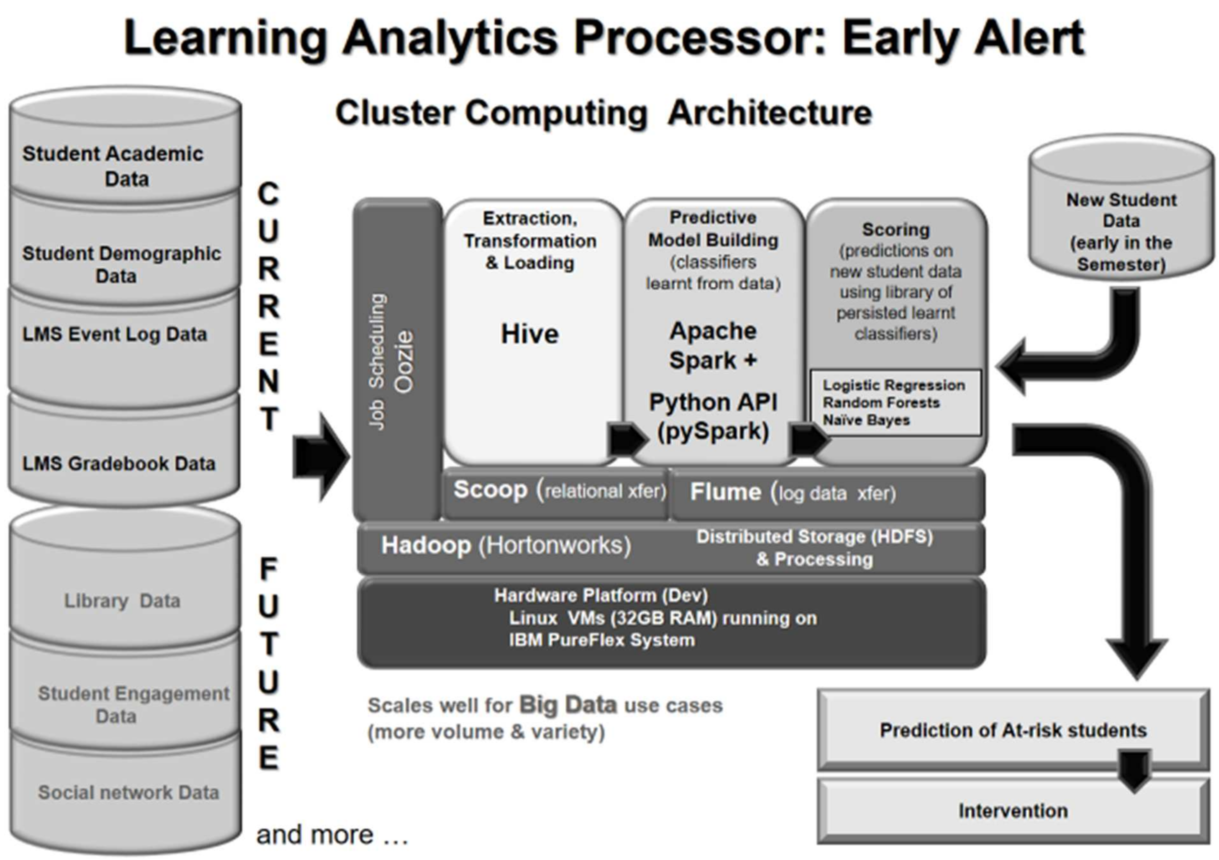

Figure 1: Learning Analytics Processor (Early Detection Framework)

2.1.2 Migrating the Predictive Modeling Stage to a Cluster Computing Architecture.

Apache Spark was selected given its speed in a cluster computing environment (10x to 100x in machine learning tasks when compared to MapReduce-based libraries), and the fact that it is an open source platform. Finally, there was a comparatively rich set of resources (algorithms) available within the API and supplemental libraries.

One of the major issues in converting to the Spark environment was the inherent lack of built-in functionality as compared to single node implementations. The first step in the process was to identify the missing functionality and recreate it in the Spark implementation. Two examples of custom implementations were resampling and imputation.

Marist chose to implement the Spark ML pipeline + the Python API (pySpark) for the predictive modeling process. This technology significantly reduced the amount of code needed to implement the model and allowed the development team at Marist to more efficiently recognize the impact of multiple preprocessing techniques and make adjustments accordingly. The API has an elegant implementation which results in better code readability, easier debugging and better knowledge transfer.

2.2 Crossing the Chasm to Big Data - Lessons Learned

2.2.1 Migrating the ETL Stage to Big Data Platform.

HQL is not SQL: In the initial stages of the project, there was a false assumption that the efficiencies that are achieved by more traditional SQL engines would translate into the same type of efficiencies when deployed in the Hadoop environment. This was not necessarily the case and in the example of the implementation of views this was demonstrated quite dramatically. What was discovered is that using cascading views to produce the final units of analysis was significantly slower than generating intermediate tables that could then be used as part of a join at a later time. This was due in part to the fact the Hive Query language was being translated into MapReduce code that did not distribute well across execution nodes.

Creating an intermediate store had limited use: Ultimately, the data that is stored in HDFS is delimited in nature and is represented as a flat structure. There was no advantage in taking the flat output structure generated during the export processes, storing it in an intermediate SQL repository, only to ultimately convert it back into a flat structure.

In summary, it is important to note that one should be acutely aware that the data being processed by Hive in the distributed environment is best thought of from the standpoint of a flat structure rather than a relational database although the data manipulation language resembles SQL.

2.2.2 Lessons Learned During Model Implementation.

The choice of the Python API was convenient given the flexibility and widespread use of Python as a programming platform. But Apache Spark was initially implemented in Scala, and therefore all new releases of the platform become available first in the Scala. For example, after choosing the rather new Spark ML Pipeline, the development team had to deal with the issue that there was no pySpark implementation of predictive model persistence to disk, a basic requirement of the early detection framework. The persistence issue was not immediately identified due to implementation assumptions that were made during the development process: as earlier versions of Spark and MLLIB (the older machine learning API) supported persistence through Python, the development team assumed that the new version of Spark and the ML pipeline would maintain this functionality. A workaround had to be developed that took considerable amount of time and effort. The disk persistence issue has since been resolved with the release of recent updates of both Spark and ML pipeline. The take away is that prior to migration a careful evaluation of the language, libraries and technology selections needs to be undertaken, especially considering the staggering rate of change in these technologies.

2.3 Outcomes

Table 1 reports the predictive performance outcomes of tests run using the cluster computing implementation of the early detection framework using Marist data and NCSU data.

Table 1: Predictive performance outcomes at Marist College and NCSU.

Phase II: Cluster Computing	Accuracy	Recall	FP Rate
Marist			
– **3 semesters, 25K records each**	86%	87%	14%
North Carolina State University			
– **3 semesters, 160K records each**	81%	77%	18%
– **3 semesters, online, 85K recs each**	80%	82%	19%

In each institution two semesters of data were used to train the model and one semester for testing purposes. Using Marist data, the models achieved recall values of 87% with 13% of false positives. Using NCSU data, and a slightly different set of predictors given the data availability, the models attained 77% of recall and 18% of false positives. The models were retrained using a subset of the NCSU data (only online courses), and for that scenario the recall reached 82%, with a similar percentage of false alarms (19%).

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Evolving a Process Model for Learning Analytics Implementation

Adam Cooper
Tribal Group
Sheffield
adam.cooper@tribalgroup.com

ABSTRACT: The subject of this contribution is the lessons learned from applying and adapting the Cross Industry Standard Process for Data Mining (CRISP-DM) process model to guide data science activities for learning analytics. It makes connections with the complexity of institutional change processes and summarizes an adapted form of CRISP-DM which better matches the need for data science activities to accommodate emerging institutional objectives and stakeholder engagement. This is done in the context of institutions which are taking the first steps towards adoption in practice.

Keywords: Process model; implementation; data science; crisp-dm; business objectives

1 BACKGROUND AND CONTEXT

This contribution is concerned with implementation of learning analytics as a tool for student support – typically focusing on retention, progression, or academic attainment – in post-compulsory education settings. It outlines the lessons learned from applying and adapting a process model to guide data science activities in this scenario, a model which we will instantiate across multiple implementations in the coming years. So far, we have worked with five UK Universities and one Further Education college using the CRISP-DM inspired process model. Each of these institutions is participating in the Jisc Effective Learning Analytics project[5] and is piloting a learning analytics solution for institutional adoption.

1.1 The Adoption Process

Adopting learning analytics in universities and colleges is known to be a multi-level challenge, requiring navigation through a set of activities which coordinate change in management, power structures, culture, professional practice, technology acceptance, data literacy, technical infrastructure, etc (Arnold, Lonn, & Pistilli, 2014). It has been argued that the institutional context in which learning analytics is adopted is characteristically a complex adaptive system, and high-level process models have been proposed to guide learning analytics adopters in managing change in such systems. The Rapid Outcome Mapping Approach (ROMA) is one example (Ferguson et al., 2014). ROMA accommodates the inherent reactive nature of complex adaptive systems by focusing on ideas such as iteration and social process to illuminate the way forward; it is the antithesis of implementation being a process of specifying a solution followed by its construction.

[5] Jisc Effective Learning Analytics: https://www.jisc.ac.uk/rd/projects/effective-learning-analytics.

Whereas ROMA deals with strategy and policy, it is mute in respect of the practical implementation work. The presentation will focus on one such counterpart to a strategy-oriented process model; an inner process model which is concerned with way the data science activities are conducted. In particular, it will consider experience in adopting and adapting the Cross Industry Standard Process for Data Mining, CRISP-DM, (Chapman et al., 2000) for use in Universities and Colleges at the stage of commencing their first pilot implementations of learning analytics. CRISP-DM shares with the ROMA model an emphasis on iterative refinement, but neglects socially-mediated mechanism.

1.2 Context of the Process Model Deployment

The particular context of these first pilot implementations is the Jisc Effective Learning Analytics project[6]. Jisc, a UK charitable organization with a mission to support the effective utilization of ICT for education and research, has identified institutions with an appropriate level of organizational and technical readiness and provides/funds the software tools, data wrangling, and predictive model development for their first pilot. Our role is as a provider of data wrangling and predictive model development, and a dashboard to surface the predictions and interface with an intervention management system.

The six institutions with which we have applied CRISP-DM have different missions, scale, and problems:

- One is an established research-oriented institution, with a focus on higher levels of attainment, and some research interests in learning analytics.
- One is a small institution that only recently acquired University status, with a focus on improving retention through a focused central initiative.
- One is a small Further Education college.
- Three are mid-scale institutions, with interest in helping personal tutors to guide students in respect of both persistence and progression.

1.3 CRISP-DM in Outline

The Cross Industry Standard Model for Data Mining was published in 2000, as the culmination of a series of collaborations and projects involving data mining practitioners from multiple industries. As the introduction to the CRISP-DM states:

> CRISP-DM has not been built in a theoretical, academic manner working from technical principles… CRISP-DM succeeds because it is soundly based on the practical, real-world experience of how people conduct data mining projects.

[6] Jisc Effective Learning Analytics: https://www.jisc.ac.uk/rd/projects/effective-learning-analytics.

The CRISP-DM is a process model comprises two parts: a reference model (Figure 1) and a user guide which breaks down the likely tasks within the stages of the reference model. It is a process model insomuch as it describes stereotype stages of activity, tasks, and broad patterns of progress, which are always to be contextualized to the application domain, analytical problem type, and technical tool-chain.

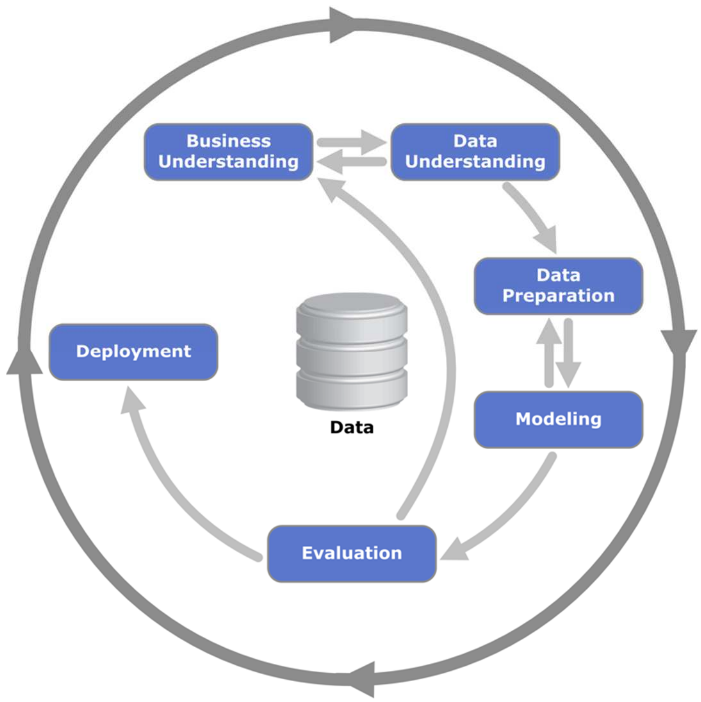

Figure 1: CRISP-DM reference model[7]

The reader is encouraged to consult the CRISP-DM document [2] for a description of the reference model.

2 ADOPTING AND ADAPTING CRISP-DM

Given our role is as a provider of data wrangling and predictive model development, and a dashboard, CRISP-DM is a natural fit to our services within a wider adoption process. A similar factorization is likely to be applicable where a center of expertise within an institution articulates with other units.

Our use of the process model fulfils a number of aims:

- It provides a framework for data science work which is organized and repeatable, and so is efficient, cost-effective, and quality-enhanced.

[7] Image by Kenneth Jensen [CC BY-SA 3.0 (http://creativecommons.org/licenses/by-sa/3.0)], via Wikimedia Commons.

- It provides a point of reference and a vocabulary to communicate process and progress with diverse stakeholders within Tribal, Jisc, and academic institutions.
- It helps to promote and legitimize two pillars of our approach to learning analytics adoption:
    - That adoption should be an iterative discovery-oriented approach; and
    - That predictive model development should always be grounded in the objectives and requirements of the student support framework/systems (soft sense of "systems").

Our initial attempts set out with the expectation that we would be able to directly apply CRISP-DM, with appropriate contextualization to the application domain of learning analytics. While it was possible to broadly follow the approach, some stakeholders expressed the view that they were not yet ready to respond to the questions we posed, while others gave responses which indirectly revealed a mismatch between our intention and their readiness.

Reflecting on the feedback, we concluded that CRISP-DM presumes a degree of stability in the context of application, i.e. that the subject of "business understanding" has relatively good definition and that the lessons learned from deployment are largely data/analytics centered rather than being oriented towards practice or culture. In essence, while we understood that the institutional adoption process is a complex affair, we had failed to account for the strength of interaction with pilot implementation. The depth and focus of the interactions between client stakeholders and data science experts is, in the first instance, more limited than CRISP-DM assumes. We have observed two broad issues which limit the extent of engagement in isolation from having something real to show stakeholders:

- Inexperience with learning analytics limits the extent of meaningful dialogue. In particular, while stakeholders are familiar with the appearance of dashboards and management reports, and recognize the potential of data to improve education, predictive methods are a novelty.
- Project objectives and requirements are initially only clear at a high level of description, with the detail requiring stakeholder participation for its definition.

It is in relation to these aspects which we have re-imagined the way the CRISP-DM reference model is realized for our learning analytics projects. For the first iteration, at least, this is less inwards-looking and more oriented to the adoption context:

- Business Understanding – focus on understanding the drivers which led to learning analytics being identified, the nature of the stakeholder groups who will be instrumental to success (who will use the analytics results and how), and on the local meaning of concepts such as progression and success. At this stage we do not attempt to solicit sufficient detail for deployable predictive models.

- Data Understanding – focus on core datasets which capture the academic structure, student progress, and attainment. In addition to being the bedrock of meaningful analytics, infidelity between the reality as perceived by institutional stakeholders and the basic content of the dashboard will undermine the engagement which is required to make progress.

- Data preparation – is initially a light-weight selection of attributes and outcomes which are relevant to the drivers. Since detailed objectives/requirements are not yet defined, this is quite generic.

- Modelling – simple logistic regression and shallow decision trees are built, not as models for deployment, but to support discussion with the more analytically-literate stakeholders. This helps to make our process more transparent and trusted. It also provides an opportunity to develop in key stakeholders a better understanding of data science, as an underpinning to clarification of data science objectives in subsequent iterations. A standard un-optimized model is created for demonstration purposes.

- Evaluation – is about data mining evaluation in CRISP-DM and is omitted as there are no models to evaluate.

- Deployment – the dashboard is implemented with historical data driving visualizations of historical trends/patterns and only the generic model feeding demonstration-level predictions on current students. The aim is to provide something which is locally-contextualized and sufficiently real that stakeholders can be critically engaged in dialogue to surface information on: how the dashboard and learning analytics results are likely to be used in practice; the requirements/objectives which can be translated to data mining objectives, including an understanding of the appropriate precision/recall tradeoff; the kind of facts which users feel will help them to correctly translate predictions to action.

3 CONCLUDING REMARKS

CRISP-DM is an attractive process model to guide iterative data science activities, providing a common vocabulary and the basis of repeatable implementation patterns which have been found to be useful across a variety of industries. It does not, however, address the process of socio-technical change which is central to the initial adoption of learning analytics. Our experience is that there are some questions which fall within the scope of CRISP-DM, which we would like to gain answers for as pre-requisites to building appropriate predictive models, but for which initial adopters are typically unable to provide answers in the first instance. We have made progress by taking the initial data science steps to provide the basis for demonstrable dashboards and statistical results as a platform for posing these pre-requisite questions, and to facilitate pre-pilot stakeholder activities, while doing so in a way which is consistent with later use of CRISP-DM.

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Knowing the Score: Deploying a Risk Score Model in Excelsior's Student Success Center

Lisa Daniels
Analytics and Decision Support
Excelsior College
ldaniels@excelsior.edu

Glenn Braddock
Student Success Center
Excelsior College
gbraddock@excelsior.edu

ABSTRACT: An ambitious initiative is underway at Excelsior College to guide the delivery of coaching services to at-risk students through predictive analytics and technology. The Student Success Center (SSC) prioritizes students for support within a caseload management and communications platform based on a set of attrition risk score models and an engagement model. The presenters will discuss successes and lessons learned during the first year of SSC operations, preliminary intervention results, and next steps.

Keywords: Predictive Analytics, Risk Score, Student Success, Coaching, Caseload Management, At Risk Student

1 DEPLOYMENT

Attrition risk modeling allows Coaches in the Student Success Center (SSC) to manage large caseloads and to prioritize at-risk students for outreach and support. A coaching platform increases the effectiveness of outreach to working adult students by allowing for multi-channel communications by phone, email, text messaging, and a mobile application.

2 IMPLEMENTATION DETAILS

Excelsior College is a distance learning institution with more than 35,000 enrolled students. Its mission is to provide educational opportunities to adult learners with an emphasis on those traditionally underserved in higher education. The mean age of an Excelsior student is 37, 75% of its students are employed full time, and about 45% are military members or veterans. Most students enroll with significant transfer credit. Students complete their degrees with credit from a variety of sources including Excelsior online courses and examinations, coursework from other institutions, and military and professional training and experience.

Prior to the launch of the SSC, at-risk students at Excelsior were defined by discrete factors such as academic probation status and lack of academic engagement. Academic Advisors distributed across

Excelsior's five schools were charged with outreach to students in these categories in addition to other responsibilities for transfer credit evaluation and on-demand academic advising and degree planning. Due to large caseloads and the complex role of the Academic Advisor, the capacity to serve at-risk students varied across the College.

With the launch of the SSC in the fall of 2015, outreach to at-risk students became the responsibility of coaching specialists in a centralized unit. Success Coaches support students to overcome academic and non-academic challenges. They work with students on issues such as time management, managing multiple commitments, study skills, facing personal obstacles, and navigating learning resources. By offering coaching services to assist adults with integrating higher education into their busy lives, the SSC delivers interventions targeted directly at some of the main causes of student attrition.

The prioritization of students for outreach by the SSC is now based on ranked predicted risk and engagement. The goal is to focus outreach on students who are both at risk and likely to engage with coaching in order to maximize efficiency and impact. Excelsior's Analytics unit has produced a set of sixteen attrition risk models which generate risk scores for each enrolled student. Scores are updated daily. A student's risk score is an indication of the student's likelihood of engaging in credit activity six to twelve months in the future. In cooperation with our coaching capacity building provider we have also produced an engagement model based on data collected during the SSC's first few months of operation. By applying both risk and engagement modeling, students are prioritized for support from highest to lowest in these categories: high risk and high engagement (most likely to engage with coaching), high risk and low engagement, low risk and high engagement, and low risk and low engagement.

Each of Excelsior's Student Success Coaches has a roster with an "intensive" tier of approximately 175 students and a larger "base" tier. Students in the intensive tier are higher risk and more likely to engage per the models. They receive outreach by email and phone. They are invited to have meetings with their coaches and to download a customized mobile application. Once a student adopts coaching, the Coach and student decide together on the frequency, focus, and communication channels for future meetings.

Students in the base tier receive emails making them aware of the option for coaching and inviting them to sign up for the mobile application. Through the mobile application, students on coaching rosters have access to self-directed content designed to promote student progress and success. They can also request coaching sessions and exchange messages with their coaches through the application. Besides receiving these benefits of the mobile application, students in the base tier are monitored for intensive support.

3 CHARACTERISTISTICS OF RISK MODELS

To accommodate Excelsior's degree mix and continuous enrollment model, a set of sixteen models were developed using a random forest methodology. Excelsior's student population includes associate, bachelors, and masters' students; associate degree students make up more than half of the population. Undergraduate students typically enter the college with substantial transfer credit. Models begin with an 'at entry' model (model 0) and follow for each month of enrollment; students who have been enrolled for 15 months or more (model 15) are scored using the final model. The total number of students in historical data enrolled at 16 or more months begins to decrease to levels insufficient for monthly modeling.

Based on test data, by the end of the second month of enrollment (model 2) the specificity and AUROC of the models is typically above .90 and sensitivity is between .85 and .90. By the second month of enrollment the proportion of students missed (false negative) by the process is about 5% or less. At the time of this writing the correlation of the risk scores generated by these models with subsequent outcome has not yet been tested.

The factors of greatest predictive value vary based on the length of enrollment. Factors important early on include, among others, the number of credits accepted in transfer, number of student system logins, and student age. In later models data associated with student academic progress (such as grades and pace) become more prominent and the accuracy of the models increases. After about six months' indicators of potential financial difficulty join the prominent predictors of attrition.

4 INTERVENTION RESULTS

Preliminary data suggest that the analytics-driven outreach and coaching provided by the SSC is having a positive impact on student credit-taking activity and on course outcomes. 4,006 students were offered intensive coaching between June 1 and October 31, 2016, the first five months that the models were in production. Three course terms were available during this period. Results are shown in the following table.

Table 1f: Course registrations and outcomes.

	Adopted coaching	Did not adopt coaching
Number of students	1,451	2,555
Percentage of students registered for a course	52%	35%
Total number of course registrations	1,697	2,052
Percentage of registrations with C or better grades	71%	63%

Due to its flexible programs designed for working adults, Excelsior students can be enrolled in degree programs without making academic progress for long periods of time. While this flexibility is convenient for students, data show that students who earn credit early in their enrollment and at a consistent pace are more likely to be retained and to complete their degrees. Thus, the early data showing increased credit activity and better outcomes for coached students are encouraging indicators of the effectiveness of the risk score model and intervention by the SSC.

5 LESSONS LEARNED

- Guiding well-designed interventions with predictive analytics can lead to improved student outcomes.
- Multiple models should be considered because the impact of predictors can change through the student enrollment cycle.
- Close collaboration between academic programs, student services, IT, and data science is essential for successful development and implementation of student success interventions guided by analytics.
- Communication and data exchange with third party vendors may take significantly more time and resources than anticipated.
- Institutions should consider their resources and student populations before committing to a project of this magnitude. It is of value to institutions like Excelsior College serving large and heterogeneous populations with limited resources.

6 NEXT STEPS

Excelsior's Analytics and Decision Support unit will test the performance of the risk scores on data gathered since implementation. We will also continue to refine the predictive models over time as additional data is collected and tested for predictive value. Potential improvements to the models, particularly those early in the enrollment cycle, are expected through the addition of data collected through the Diagnostic Assessment and Achievement of College Skills (DAACS; www.daacs.net) framework currently under development. Excelsior College has received a multimillion-dollar grant from the US Department of Education, Fund for the Improvement of Postsecondary Education, first in the World (FITY) program to develop this assessment framework. DAACS is an open-source assessment tool, which will provide students detailed information and feedback on their preparation for college level work, and can assist colleges and universities in targeting resources and services to students based on their academic and non-academic skills. The Student Success Center has also begun to offer coaching based on referrals from advisors and faculty to complement the risk score method of populating coaching rosters.

From the Trenches: Factors That Affected Learning Analytics Success with an Institution-Wide Implementation

Jennifer Heath
University of Wollongong
jheath@uow.edu.au

David Fulcher
University of Wollongong
dfulcher@uow.edu.au

ABSTRACT: The implementation process of Learning Analytics (LA) capabilities at the University of Wollongong (UOW) has been undertaken using an ambitious institution wide approach and many factors impacted success. Engaging the academic community, organization of work structures and engaging with students are considered here. 'Top-down' and 'bottom-up' approaches offered a hybrid, pragmatic change management strategy for the implementation of learning analytics capabilities for teaching staff and students. This work has been informed by technology innovations and technology enabled learning (TEL) complexes proposed in earlier international research. The success of this project relied on multi-discipline institution wide collaboration.

Keywords: Learning Analytics, Technology Enhanced Learning, Change Management

1 INTRODUCTION

Background information about the drivers for LA adoption are well covered in the literature (Ferguson, 2012; Jackling & Natoli, 2011; Siemens & Long, 2011). Actioning LA insights to aid in student experience and retention are also argued in recent literature (Colvin et al., 2016; Lonn, Aguilar, & Teasley, 2013; Mandinach & Jackson, 2012; Wilson, 2009). The multidisciplinary nature of the field necessitates an approach that considers a range of perspectives when working towards an institution-wide implementation of LA. Key aspects of the adoption of LA go beyond technology and are, as adapted from Scanlon et al. (2013), academics, students, pedagogy, student support, governance and technology (Heath & Leinonen, 2016). Initial work began at UOW in quarter 3 of 2013 on three fronts; technology foundations, governance operation and a survey to students about LA. These aspects align with what has been proposed in the literature to increase adoption of LA (Arnold, Lonn, & Pistilli, 2014; Baer, 2013).

At the University of Wollongong it was agreed that use of LA would focus on the near real-time delivery of insights to support key teaching and learning activities to enable personalization and optimization of students learning opportunities. Large first year transition units of study have been of particular interest. The next section focuses on some of the "softer" dimensions for this scope of work with the goal of enhancing student experience rather than concentrating on technology dimensions and measuring learning, which are well addressed elsewhere (Johnson et al., 2016; Rienties, Toetenel, & Bryan, 2015; You, 2016).

2 ENGAGING THE ACADEMIC COMMUNITY

Effective engagement with faculty academic colleagues has been crucial to the sustainability of the LA initiatives at UOW. A wide range of matters have benefited from the collaboration and insights provided by subject coordinators who volunteered to be early adopters of LA. These matters include: adjustments to pedagogy, enhancements to online learning sites (Moodle), adoption of governance requirements, refinement of analytics deliverables to teachers and, importantly, clarification of the approaches to be taken to provision of support to individual students when LA suggest they may be facing challenges with their studies.

A number of changes to academic work practices occurred as a result of the adoption of LA. For example, students not engaging with key online learning resources were identified and sent targeted messages encouraging them to turn their attention to using these online resources. Student interaction patterns were then subsequently monitored to ensure the identified students engaged with the key learning opportunities as a result of the nudge provided by the targeted messages sent earlier. Another example of changes to academic work practices involved changes to attendance taking procedures. Previous methods of taking attendance such as spreadsheets and paper-based approaches where replaced with functionality provided directly in the Learning Management System (LMS) to capture face-to-face classroom attendance. This afforded mutually beneficial outcomes for both the academic community and learning analytics implementation team. Firstly, process efficiencies were realized by not having to keep track of multiple spreadsheets and paper rolls and consolidate these overtime as the academic session unfolded. Secondly, the data flowed through to the data warehouse that enabled insights to be gained from class attendance patterns within each participating unit of study. Students in turn benefited as this information was often used as the basis for student outreach at points in the academic session before any assessment tasks had been completed, which would previously be the point at which performance problems were made evident to students. Establishing this change to academic work practices for attendance taking also provided the learning analytics implementation team with compelling exemplars to encourage change for other academics. It also provided a solid foundation for a solution to scale across the institution.

In the years since LA was introduced at UOW there have been many opportunities for staff to exchange ideas regarding the use of LA and guide necessary ongoing development, similar to the 'bricolage' aspect outlined by Scanlon et al. (2013) when considering Technology Enhanced Learning (TEL) complexes. Small communities of practice amongst UOW teaching staff have guided the effective development of LA deliverables for staff with a 'right information at the right time' philosophy adopted. This experience reinforces the importance of community building, with support and training proposed and well-argued by Ferguson et al. (2014). Initially the volume of analytics deliverables provided at UOW was too much for the staff to meaningfully process during busy teaching sessions and over time more succinct, targeted analytics are now 'pushed out' to teaching staff 'just-in-time' for key decision points throughout the academic session.

Diffusion of LA innovation has proceeded in an unstructured manner with various academic staff adopting the use of LA and influencing their peers at UOW in a manner similar to innovation adoption described in the literature (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2004; Orlikowski, 1996; Rogers, 2003; Venkatesh, Morris, Davis, & Davis, 2003; Weick & Quinn, 1999). Mid way through the academic session the focus of LA moves from student support to reflection on the continuous improvement of teaching and learning aspects of the use of LA – these are beyond the scope of the discussion here.

The vast amount of possible actions from insights identified from the use of LA exceeds what can be reasonably resourced and difficult decisions need to be made regarding the best organizational approach such as 'top-down' or 'bottom-up' as outlined by Buerck (2014). The scope of work at UOW attempts to achieve a balance between providing benefits to students, through outreach, and the effective use of resources (Harrison, Villano, Lynch, & Chen, 2016). The student experience at UOW has been enhanced through the shared vision of the Deputy Vice-Chancellor Academic and the academic staff engaged in teaching students. An institution-wide framework for LA has been established whilst also offering an opt-in model for academic staff. This has enabled a simultaneous top-down and bottom-up approach to increase buy-in from the UOW academic community. While this has reduced the hurdles for take-up of LA by academics, acting on insights still requires collaborative efforts from a variety of people. The next section outlines what has worked for UOW in addressing the key aspects of this broader organizational change management.

3 ORGANIZATION OF WORK STRUCTURES

The governance framework adopted to support LA at UOW requires some action to be taken, such as contacting a student or adjusting an approach to teaching, if LA indicates less than optimum learning and teaching is taking place. Without this clear requirement for action, ethical dilemmas (Slade & Prinsloo, 2013) may have arisen with the slow, well documented and analyzed decline of an individual students learning experience. As Slade & Prinsloo noted "higher education cannot afford to not use data" (Slade & Prinsloo, 2013, p. 12) and the governance framework adopted from the start at UOW covers the six principles they propose.

Traditionally students would self-refer to the student support services available at UOW. Now, with the introduction of LA it has been possible to reach out to students well before the point at which they might usually self-refer for academic and / or welfare support. In mid-2015 the student support team was merged with the business analysis and learning analytics team to enable proactive, data information support provision. The academic staff responsible for the teaching of subjects that have adopted learning analytics remain key decision makers about the provision of support to students. There are a number of options available to these academics including; contacting the students themselves, referral to another member of the faculty, or referral to a member of the Student Support and Education Analytics team (specifically a Student Support Adviser). The importance of trust amongst LA stakeholders, as suggested by Greller and Drachsler (2012), was very clear in the establishment of the data informed referral processes at UOW. Interestingly, the student support staff needed to 'trust' that LA could provide useful insights. Once the LA procedures were in place the students flagged were often already 'on the radar' of the support staff and this tended to engender some trust in the data-driven insights as they confirmed (on some occasions) the view of the support staff.

One of the benefits of having the analytics staff working in the same team as the Student Support Advisers is the capacity to be agile and move quickly from capture of initial LA insights in the first weeks of session through to student support action taken before unintended setbacks are experienced by students, such as incurring a financial debt for a unit of study they have no intention of completing.

4 ENGAGING WITH STUDENTS

A key part of the implementation of LA at UOW also involves the delivery of analytics directly to students. Providing such information to students gives them a greater awareness of their learning context. To this end, a survey was designed asking students what types of functionality they would like to see from LA. In this way students have been engaged as collaborators above and beyond their engagement as recipients of interventions, which aligns with the argument put forth by Kruse and Pongsajapan (2012) to make LA more student-centric. The results of the survey showed the majority of students would like to see a comparison of their own performance to other students (Heath & Fulcher, 2016).

Consequently, a student dashboard was designed and deployed within the Learning Management System (LMS) that provides a visual summary of student assessment marks and interactions compared to their peers, which can be powerful in showing a student where they stand in relation to others in the same cohort (Govaerts, Verbert, Duval, & Pardo, 2012; Wise, 2014). The student dashboard was implemented institution-wide, displayed in a collapsed view be default at the top of each site with the LMS.

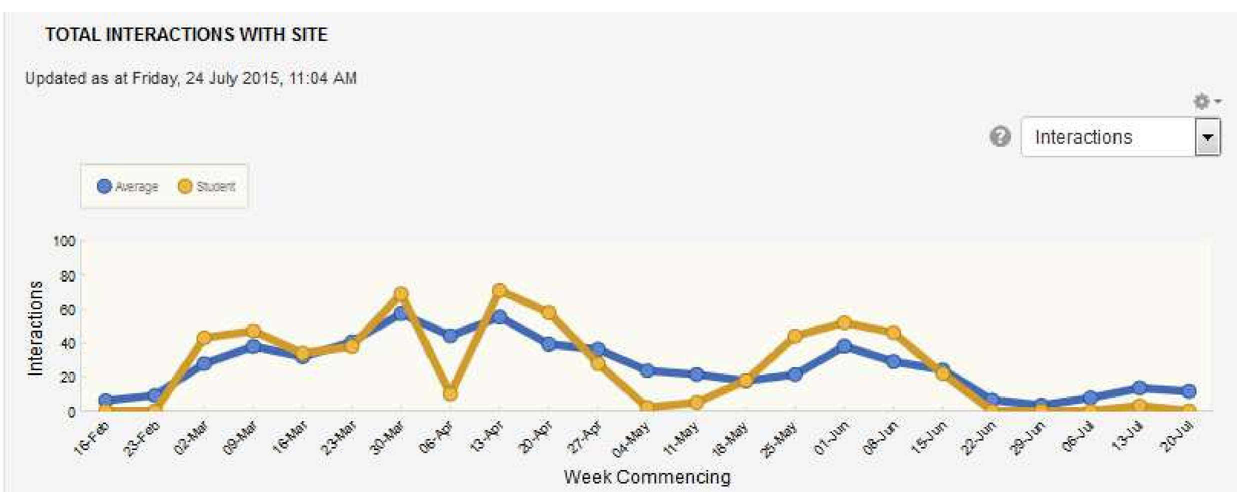

Figure 2: Sample student dashboard (interactions chart)

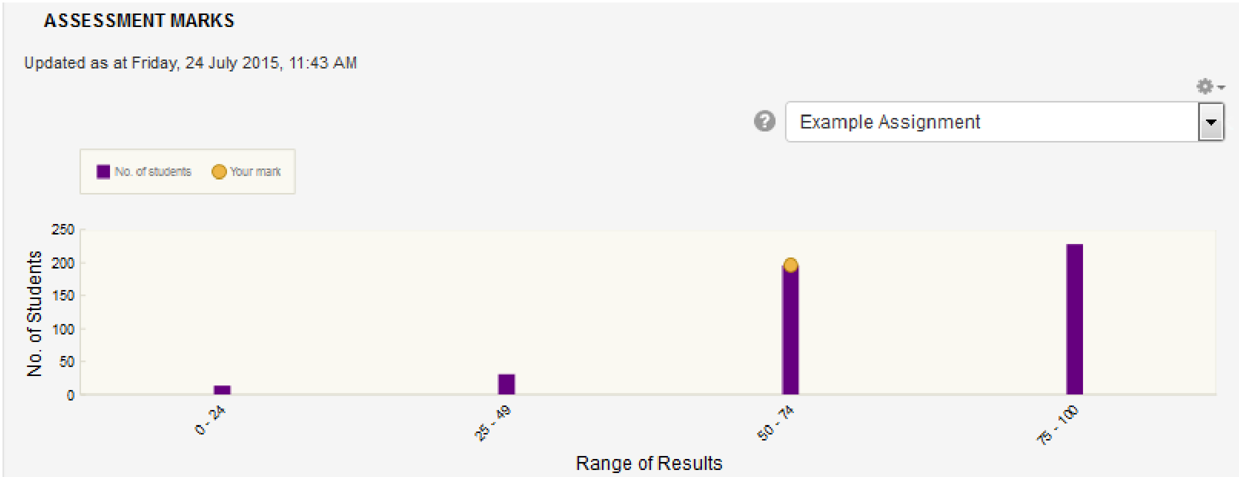

Figure 3: Sample student dashboard (assessments chart)

Teachers are able to hide the student dashboard for their particular site, as there may be concerns about the potential for detriment to be caused for the student through misunderstanding and a sense of added pressure about their performance. Where students may have previously compared assessment marks amongst themselves, this information is now available from the student dashboard. In this way a student is able to conduct a more accurate comparison to peers based on actual data instead of anecdotal evidence gleaned from one another. The information provided in the student dashboard increases student agency, an important aspect of LA as discussed by Slade and Prinsloo (2013), by supporting students' development and use of self-regulatory skills such as goal-setting and reflection.

When the student support staff engage with students as a result of a LA referral the communications avoid starting with a recount of '… the LA system indicates …' as literature from the United States indicated this was an unsuccessful approach (Arnold & Pistilli, 2012). Rather, the student support staff rely on their professional skills that enable connection with students in a meaningful way within a usually short amount of time. Anecdotal evidence from early LA adopters speaks to the strength of this human driven approach with students commenting 'thanks for noticing' and 'thanks for contacting me. Here is my situation …'. Thus LA insights have triggered the well-honed professional practice of UOW student academic and welfare support staff. In many instances the academic teacher elects to use a technology based approach to connecting with the flagged students and there is clear evidence through Learning Management System (LMS) utilization data that a brief, personalized message to students can guide their navigation through online learning materials.

5 CONCLUSION

After going through the LA implementation process at UOW, the key factors that have impacted success center on change management and organizational work structures. LA is more than the underlying technology alone, and so the approach at UOW has been informed from a number of TEL complexes to try and maximize uptake. A variety of change management approaches are required to increase adoption of LA initiatives at UOW. A unique hybrid of 'top-down' approaches, focused on aspects such as technology design and governance structures, have been combined with 'bottom-up' approaches, such as early academic adopters. All of this has been informed by a LA strategy derived from student perspectives on LA. As the focus of LA at UOW is on the provision of near real-time insights, there is a limited window of opportunity at the start of the academic session where enough data exists to generate insights, but also early enough to act on before issues escalate further for students. It has therefore been important to adjust existing work structures to bring together analytics and student support expertise so that insights generated from LA can be actioned in a timely manner. This has been further complimented by planning and integration of LA-driven student outreach into core teaching and learning processes.

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Supporting Classroom Instruction with Data Visualization

Chia Pei Xian
Ministry of Education
chia_pei_xian@moe.gov.sg

Thong Chee Hing
Ministry of Education
thong_chee_hing@moe.gov.sg

Qiu Yiru
Ministry of Education

Kang Eng Hiok Zachary Dexter
Raffles Institution

ABSTRACT: This paper elaborates on our understanding of data visualization and efforts to empower teachers by providing information to support just-in-time instruction in the context of an inquiry-based lesson with a game on identifying the names and formulae of ionic compounds (wRiteFormula). It highlights the process of identifying the data teachers need to gauge student learning and determining how to visualize the data appropriately. It also describes the efforts taken to ensure a high degree of accuracy in the data visualization, and usability and customizability for teachers. It concludes with suggestions on how teachers can use the visualized data in class.

Keywords: data, visualization, teachers, classroom, instruction, accuracy, customizability

1 INTRODUCTION

Data visualization has been described by Few (2013) as “the graphical display of abstract information for two purposes: sense-making (also called data analysis) and communication,” and by Assam, Evergreen, Germuth, and Kistler (2013) as “a process that (a) is based on qualitative or quantitative data and (b) results in an image that is representative of the raw data, which is (c) readable by viewers and supports exploration, examination, and communication of the data (adapted from Kosara, 2007).”

In both definitions, raw, non-visual data is processed to create an image that can be used and communicated more easily than the original raw data. This may seem like a self-evident definition, especially with the increasing pervasiveness of visualizations like infographics, and may seem easy to do – a few steps are all it takes to select a set of data and create a graph in a spreadsheet programme. But the full process is more complex; much thoughtful consideration is required to identify the necessary data, determine how to collect, organize, and visualize the data, and ensure that the output is valid and accurate. And finally, from the end-users’ perspective, the real test of a successful visualization is whether it empowers them to explore, examine, make sense of, communicate and easily utilize the information therein.

In this project, the end-users were teachers, and data visualization was introduced to enhance an existing content management system (CMS) from an earlier project. The earlier project involved the development of wRiteFormula, a tile-matching game to motivate and help students learn ionic compound nomenclature. To play wRiteFormula, students freely select cations and anions to form a binary ionic compound, and then identify the correct chemical formula and name of the compound. Figure 1 shows an example for the compound potassium sulfide, K_2S. The combinations were limited to binary ionic compounds in order to build students' foundational knowledge of ionic compound nomenclature. The game has a customised feedback system, and an accompanying CMS that allows teachers to access records of game moves made by students (Chia & Sivaram, 2016; Thong, Chia, & Kang, 2015). In a typical lesson, students play the game, have a group discussion to compare observations made during the game, and then a class discussion facilitated by the teacher to deduce the relevant nomenclature rules encountered (Thong, Qiu, & Chia, 2016).

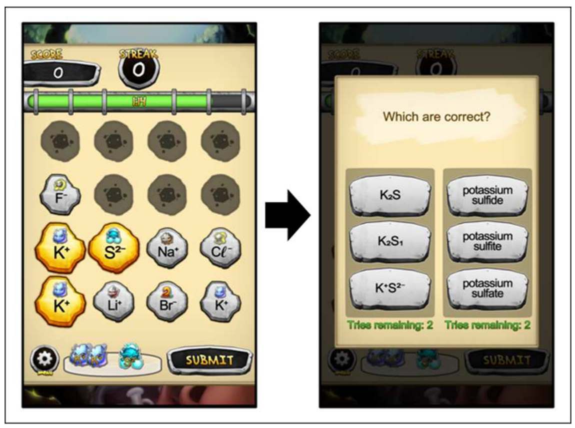


Figure 1: Screenshots of typical in-game screens

Feedback from teachers during the first project revealed that they had difficulty locating and interpreting information presented in the CMS data tables. For instance, they could not easily determine how well their class was performing from the Class Summary table (Figure 2), and much effort was required to determine the frequency of a type of mistake from the Class Errors Analysis table (Figure 3).

Player List			Class Games Analysis					
	Idx No.	Username	Games Played	Highest Score	Highest Streak	Mastery Level	Level (Exp)	Highest Compound (Score)

Figure 2: Class Summary table headings

Count	Game Mode	Index No.	Name	Game Time (+8 GMT)	(Dissoc. Ion) Selected Cations	(Dissoc. Ion) Selected Anions	Symbol Recognition Error	MCQ Formula Errors	Synthesis / MCQ Formula Feedback	MCQ Name Errors	MCQ Name Error Feedback

Figure 3: Class errors analysis table headings

2 WRITEFORMULA DATA VISUALIZATION JOURNEY

To empower teachers to make sense of the CMS information and support just-in-time instructional decisions backed by the information about students' performance, the team (more than half of whom were teachers) decided to incorporate data visualization into the CMS. The key work to be done was identifying useful information about student performance to support classroom instruction more effectively, and identifying, reorganising, and analysing the game moves to obtain the desired information. Since the wRiteFormula game data is quantitative, the team's working definition of data visualization was: Data visualization is the graphical display of quantitative data that is representative of the data, and readable and usable by teachers (adapted from Assam et al., 2013; Few, 2013; Kosara, 2007).

The first step was to identify and articulate what constituted essential information about student learning. The discussion started with the teachers listing questions that were important to them, then determining which questions were essential to answering the overarching question of whether students had learnt ionic compound nomenclature. Next, the team identified the data needed to answer the essential questions, and discussed how to present that information to make it usable by teachers (Figure 4).

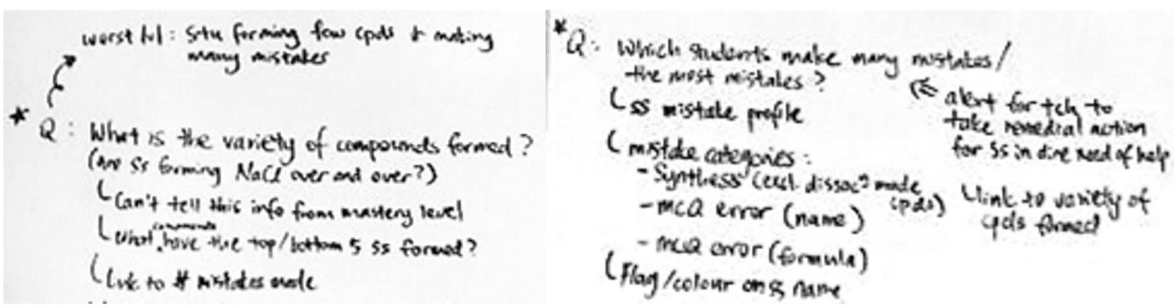


Figure 4: Example of notes from a preliminary discussion

In some instances, combinations of data from the game moves were needed to answer one question. For example, to determine students' proficiency in identifying the chemical names and formulae of compounds, the team concluded that the information about students' game mastery level would need to be supplemented by other indicators like the percentage of correct answers, the streak of correct answers, and the variety of compounds formed. This information was eventually presented on the Class Summary page (Figure 5) as a pie chart to illustrate the proportion of students at each game mastery level block, and an accompanying table (the Alert System) that aggregated the three indicators and sorted students into three bands: exceeding expectations; meeting expectations; approaching expectations.

The Alert System was created to display and help teachers monitor students' level of mastery of ionic compound nomenclature. When discussing the criteria for the Alert System indicators, the team agreed that customizability was necessary as different schools, classes and teachers would have different standards, and those standards might change over time. Thus the Alert System criteria was made adjustable, and the percentiles of 54,000 game moves for each indicator (obtained from the first project) were used to guide the choice of the default values. Figure 6 shows the Alert System's default values (Example 1) and the effect of lowering the default values (Example 2).

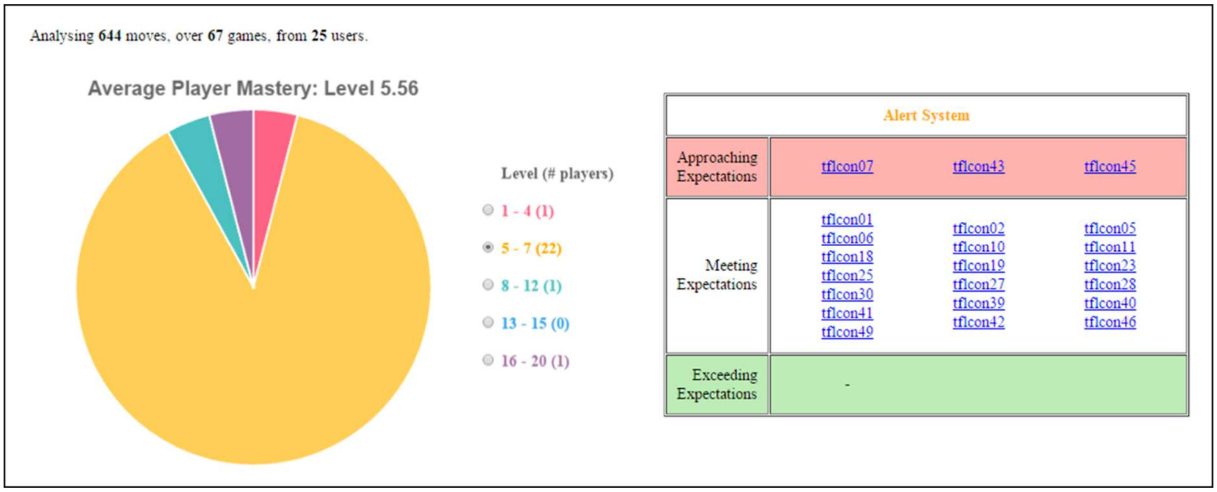


Figure 5: Sample class summary page

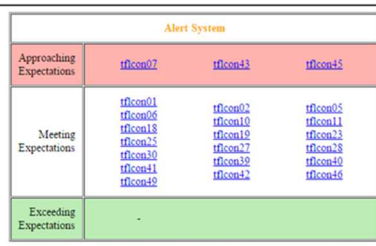
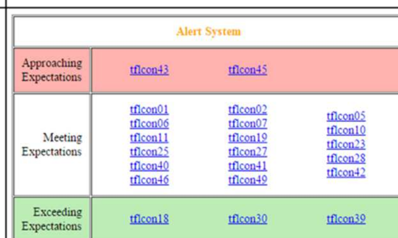
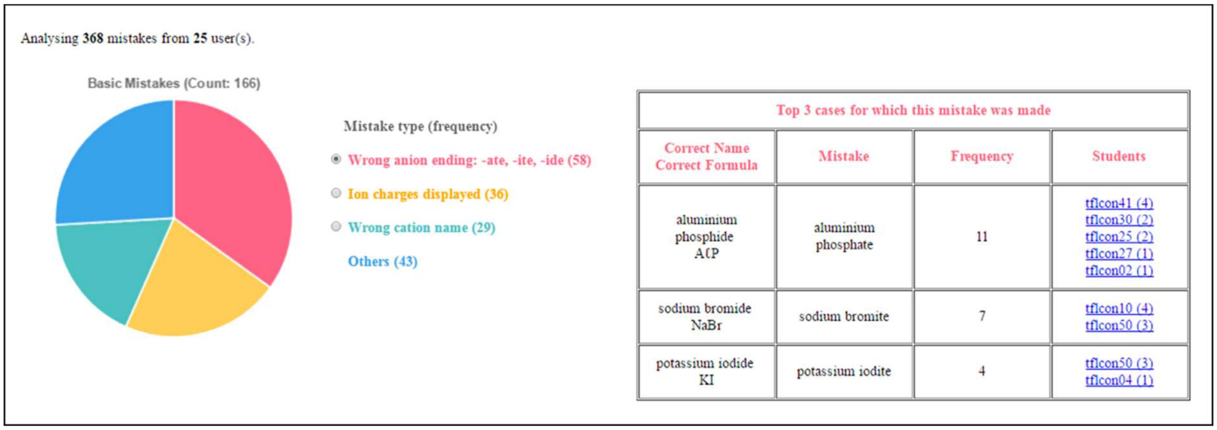
Example	**1 (Default)**		**2 (Adjusted)**	
Alert System				
Criteria to Use	**Boundary Conditions**		**Boundary Conditions**	
	Lower Boundary	**Lower Boundary**	**Lower Boundary**	**Upper Boundary**
☑ Variety of Compounds Formed	≥ **4** Categories of Compounds	≥ **6** Categories of Compounds	≥ **2** Categories of Compounds	≥ **4** Categories of Compounds
	≥ **1** Compound(s) per Category		≥ **1** Compound(s) per Category	
☑ Percentage of Correct MCQs	> **75** %	> **85** %	> **50** %	> **75** %
☑ Maximum Streak	≥ **2**	≥ **6**	≥ **2**	≥ **4**

Figure 6: Example of the effect of a change in the alert system criteria

To allow teachers to make sense of students' common mistakes quickly, the team explored how to present information on the frequency of mistakes made meaningfully. After much discussion, the team grouped the seventeen types of mistakes into four major categories. The mistakes in each category were presented as a pie chart to indicate the proportion of each mistake at a glance, with an accompanying table to provide further details for each of the top three types of mistakes in that category (Figure 7).



Top 3 cases for which this mistake was made			
Correct Name Correct Formula	Mistake	Frequency	Students
aluminium phosphide AℓP	aluminium phosphate	11	tflcon41 (4) tflcon30 (2) tflcon25 (2) tflcon27 (1) tflcon02 (1)
sodium bromide NaBr	sodium bromite	7	tflcon10 (4) tflcon50 (3)
potassium iodide KI	potassium iodite	4	tflcon50 (3) tflcon04 (1)

Figure 7: Sample class errors analysis page

An underlying consideration throughout the project was the validity and accuracy of the data visualization. To ensure all game moves were accounted for, and that the graphical image was representative of the raw data, a range of games was played to cover commonly expected scenarios, and the data generated from those games was analysed through a variety of manual and automated methods. The output of the different methods of analysis was compared to verify the accuracy of each method, and ultimately, of the CMS.

3 TEACHING AND LEARNING WITH WRITEFORMULA DATA VISUALIZATION

While the CMS was being developed, the team concurrently discussed how the data visualization would impact teaching and learning. In the earlier project, the team had adapted the discovery-learning approach from Wirtz, Kaufmann, and Hawley (2006) to incorporate the use of wRiteFormula (Thong, Qiu, & Chia, 2016). In this project, the team reviewed the earlier lesson design, and looked at which sections of the lesson that could be strengthened by the use of data visualization. For example, during the class discussion phase of the lesson, teachers could refer to the Class Errors Analysis page (Figure 7) to identify common mistakes, decide which examples to use for the classroom discussion, or which students to call on to respond to questions. After a lesson, teachers could review the Class Summary page (Figure 5) to identify which students might need more support in the subsequent lesson.

4 CONCLUSION

Having teachers participate actively in the project was critical in creating a reliable and relevant educational resource with just enough features and options for teachers to make just-in-time instructional decisions supported by information about students' performance. Along the way, the team acquired a greater understanding of proficiency profiling through the work on the criteria and mechanisms of the customizable Alert System. While the team's data literacy has definitely improved as a result of all the discussions, other teachers who wish to use wRiteFormula may not be as proficient, thus the team will include a data literacy component in workshops to train teachers who intend to adopt the use of wRiteFormula for learning and teaching.

At the time of writing, the development work has just been completed, and the team is in the process of deploying wRiteFormula to local schools. The team is excited about the prospect of making wRiteFormula available to more students. However, due to funding constraints, and lack of manpower and experience in managing and supporting large scale adoption of this innovation, the team hopes to work with others who can assist in the scaling up effort.

5 ACKNOWLEDGEMENTS

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Playing with Student Data: The Learning Analytics Report Card (LARC)

Jeremy Knox
Centre for Research in Digital Education
The University of Edinburgh
jeremy.knox@ed.ac.uk

ABSTRACT: While the field of Learning Analytics continues to develop, examples of student-focused projects have been in short supply. This paper will describe the design and implementation of the Learning Analytics Report Card (or LARC), an experimental project undertaken at the University of Edinburgh. The LARC involved postgraduate students as research partners and active participants in their own data analysis, and used data-to-text methods to generate a written textual report. The LARC allowed students to 'play' with their own data; choosing *what* to include or exclude, and *when* to generate the report. This paper will summarise key findings from the project.

Keywords: LARC, LMS, Moodle, data-to-text, student-focused, digital education, critical data studies.

1 INTRODUCTION

The Learning Analytics Report Card (LARC) was a small-scale pilot project undertaken at the Centre for Research in Digital Education at the University of Edinburgh. This paper will outline the development and implementation of the project, the main features of the LARC, as well as an analysis of student responses. The central question underpinning the project was: How can students and university teaching teams develop critical and participatory approaches to educational data analysis? The two principal aims were, firstly, to develop a means of capturing LMS data and creating a textual report from the results, as well as providing students with the capacity to choose what kind of data is used, and when the report is generated. Secondly, the project aimed to promote a critical understanding of data analysis in education amongst students. Student involvement in the project was incorporated at all stages of the project. The design, development, and testing phases of the LARC were informed by formal student representation, and this was motivated by a general concern for ethical practices in data collection.

2 THE LEARNING ANALYTICS REPORT CARD (LARC)

The LARC functioned by capturing student's course-related activity data within an institutional LMS (Moodle), and presenting a summary of an individual's academic progress in the form of a textual report. However, rather than manifesting exclusively through hidden and inaccessible institutional data aggregation and analysis, the LARC offered students an opportunity to 'play' with their data; to choose what is included or excluded, and when the report is generated – hence the acronym 'LARC'. This facility for choice, although limited, was intended to explore the capacity for participation while still retaining the 'reporting' function of learning analytics. The LARC interface consisted of a web form, accessible only through the institutionally protected login, which provided various options for generating the report (see fig 1).

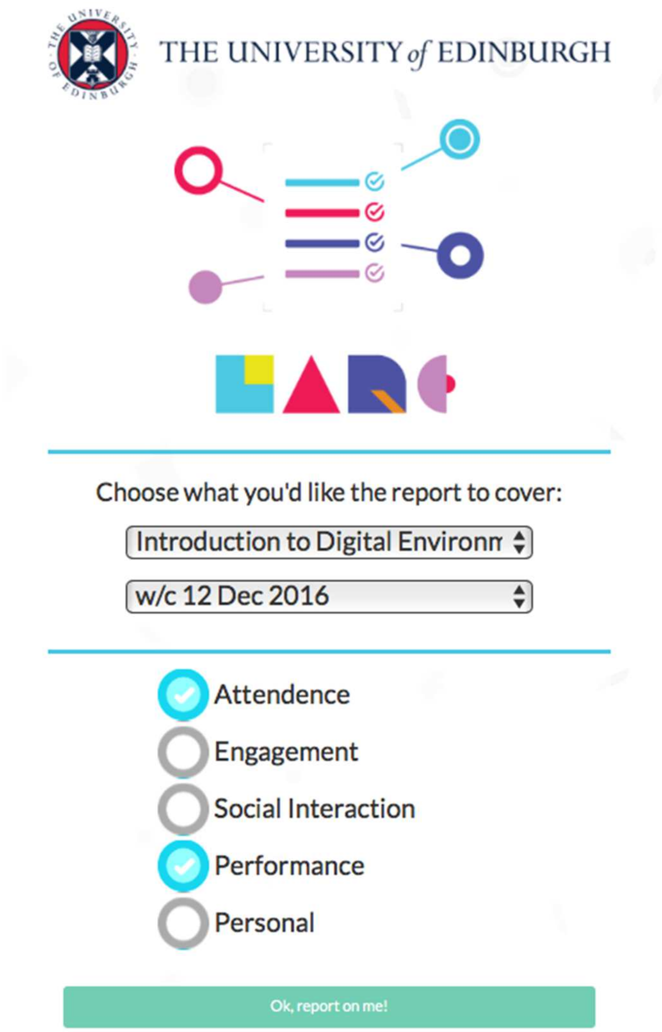

Figure 1: The LARC web form interface

Drop down boxes at the top of the interface allowed users to select a course from which to generate the report, and importantly, the specific week from which to view activity (see fig 1). This choice of *when* to generate the report was considered a crucial part of learner agency within the project, and students were encouraged to take charge of the process and activate the LARC whenever they desired.

Student choice related to the content of the report, and thus the kind of data that the LARC would capture and analyse, was facilitated through the selection of report themes: 'attendance', 'engagement', 'social interaction', 'performance', and 'personal' (see fig 1). These were intended to suggest different perspectives on course activity, and allowed students to select one or more to generate the report, and thus tailor their subsequent result towards particular aspects of their course interactions. Basic data was gathered from specific areas of the LMS for each report theme: 'attendance' from date and time of login; 'engagement' from frequency of interaction with course resources; 'social interaction' from discussion forum module data; 'performance' from aggregating the other theme data and comparing it to the student group; and 'personal' from interactions with profile information and introductory course tasks.

Algorithmic calculations and data-to-text processes (see Isard and Knox 2016) were developed to present this data in the form of a 'report card', consisting of a number of automatically generated sentences that corresponded to the report themes selected by the student (see fig 2).

Figure 2: An example of anonymised report from the LARC showing a number of sentences produced from selected report themes

Following student feedback and a further stage of development, the LARC reports were amended to include sample data, improved individual comparisons, and sentiment analysis of forum posts (see fig 3).

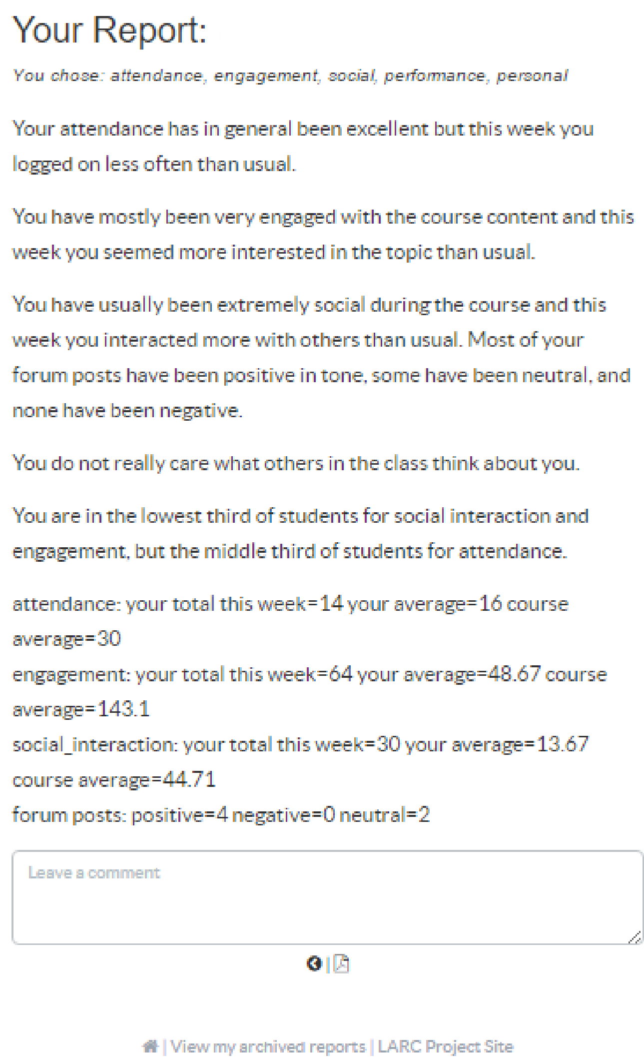

Figure 3: An example of the second stage LARC report showing sample data, improved individual comparisons, and sentiment analysis of forum posts

A facility for students to add comments was provided underneath each report (see figs 3 and 4), and was intended to expand the scope for interactivity in the LARC. Comments encouraged students to reflect, not only on their activity within the course, but also to critically discuss the efficacy of the generated report, the kind of language used, and experience of participating in decision-making (and the lack of it) concerning the analytics process itself. Through facilitating choice in the report themes, learners had the ability to reflect on what an 'active', 'engaged' or 'valued' student might be, and to recognise how the automated algorithmic processes of data analytics might interpret their online activity, and make decisions behind the scenes to which they were not party (see student feedback section below). All generated reports were archived and available to individual students, and any report could be downloaded and shared if desired.

3 IMPLEMENTATION

The LARC was piloted on three option courses within the MSc in Digital Education offered by the University of Edinburgh; a fully-online postgraduate programme. Over three 12 week semesters, 75 students participated. In the first semester, 208 reports were generated, 26 of which were accompanied with student comments. Data from the second semester is currently being analyzed for presentation at LAK17. Rather than operating independently from the courses in question, the LARC was aligned with already existing course themes (including learning theory, online presence, and digital research methods), and introduced as a provocation for critical reflection on the data analysis in higher education.

4 ANALYSIS

Although limited due to the small-scale nature of the initial pilot, data from the LARC project offers some productive insights into how student participation in Learning Analytics might be explored.

Figure 4 shows the dates and times when LARC reports were generated during the first semester of the pilot study. Given that new LARC reports were available at the beginning of each week, this type of analysis could reveal the time of the week at which students decided to view their latest report, and thus when they were motivated to reflect on the previous week's activity.

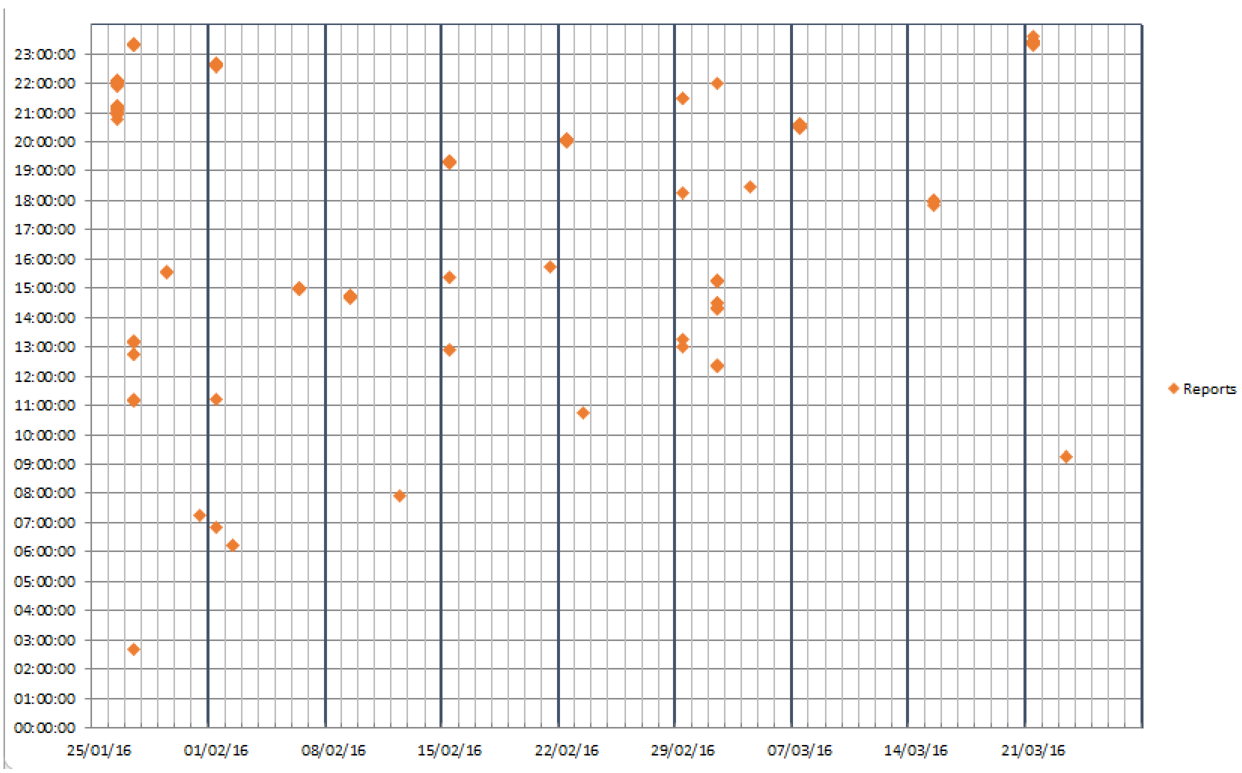

Figure 4: A graph showing the date and times when LARC reports were generated during the first semester of the pilot

Figure 5 shows which archived reports were accessed when LARC reports were generated. This kind of analysis could be used to determine the extent of student interest in reflecting on the sequence of their activities and performance throughout a course. A larger number of archived reports accessed might indicate that a student is concerned their overall course progress, and trying to understand their current performance in the context of the course as a whole. Accessing specific weeks from the archive might indicate a concern with particular topics within the course, and could be mapped onto course themes.

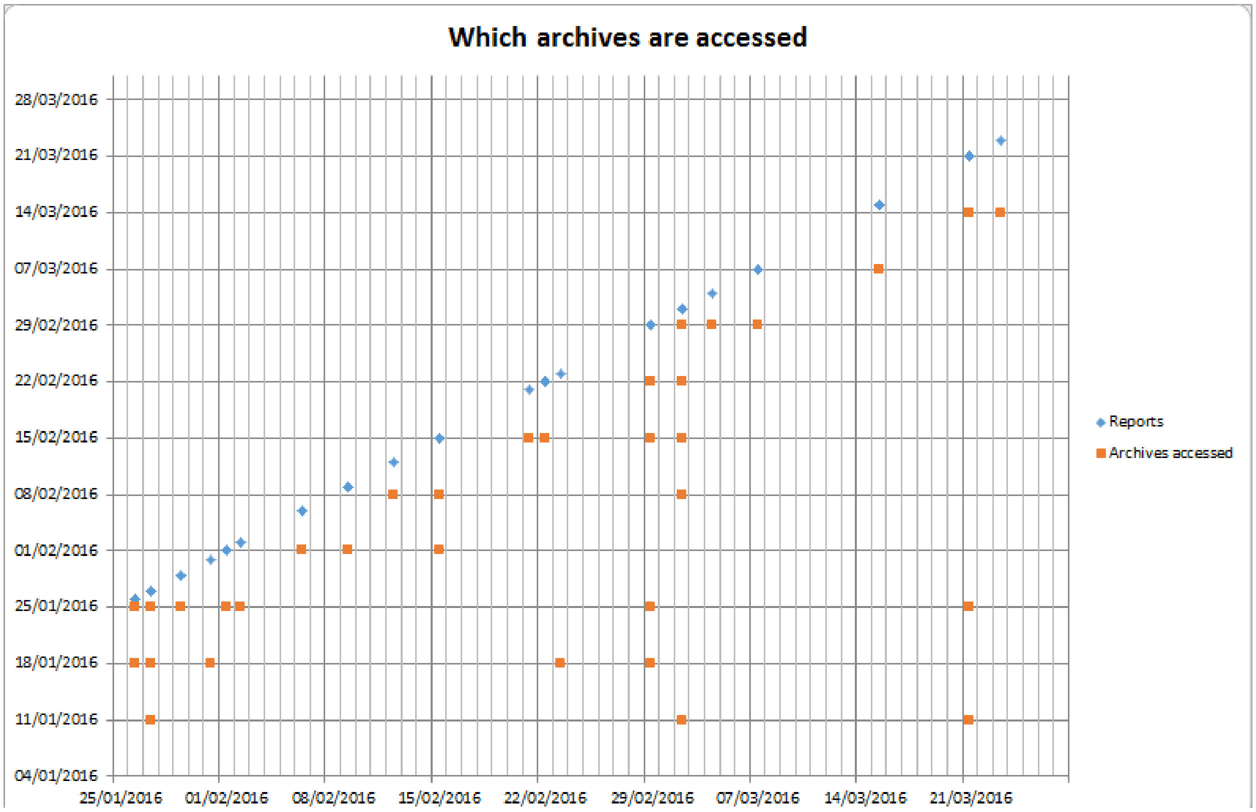

Figure 5: A graph showing which archived reports were accessed when LARC reports were generated

5 STUDENT FEEDBACK

Although limited at this stage, student feedback offers ways of working towards an understanding of whether the LARC was able to foster a critical awareness of data analysis in education amongst students (project aim 2). Comments revealed themes of ethics, privacy and surveillance, pedagogical relationships, and trust (see Knox 2017 for a fuller discussion). On the whole, a concern for the accuracy of the analytics, and the experience of receiving automated feedback was apparent. This was perhaps due to the novelty of the activity, as expressed by one participant: "to have "computerised" (through human generated algorithms of course) feedback is a newish experience!" Nevertheless, an awareness of the entanglement of social and technical concerns is expressed in this comment, showing an awareness of the complex issue of agency in data analytics. Critical views were also expressed, one participant commenting:

> it cannot account for the time I might have been engaging informally with the course (thinking about my dissertation topic, dipping into the course textbook, the level of interest demonstrated in the first assignment).

This highlights concerns about the ability of data analysis to capture the full range of learning activities, suggested by this student to involve a range of spaces and times outside of direct interaction with the LMS. This is mirrored in a comment from another participant:

> it is possible for a student to be not fully engaged with the course content but still engaged with reading material from other related sources… How would the tutor know this from analytics only?

Another comment highlights the hidden and inaccessible aspects of analytics, and suggests a concern for privacy: "should students be made aware of how analytics are functioning and how they might feel as though they are being 'watched'. Or does this only add to the creation of a surveillance culture?" This suggests the need to develop ethical awareness in educational data analytics.

Elsewhere, another participant revealed a distrust of the LARC reports, stating: 'I need to observe the results over a period of time before I can gain more confidence in the information it's providing.' This suggests an importance given to relationship building in educational activity, and calls into question the transactional functions that automated systems tend to supply.

Further research of student perspectives, I suggest, will offer important ways of understanding the development and implementation of analytics, and will provide crucial insights about how to use data analysis *with* students, as active participants in the emerging field of Learning Analytics.

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SURF Learning Analytics Experiment: Hands-on Experience for Dutch Higher Education

Jocelyn Manderveld
SURFnet
jocelyn.manderveld@surfnet.nl

Marieke de Wit
SURFnet
Marieke.dewit@surfnet.nl

Herman van Dompseler
SURFnet
Herman.vandompseler@surfnet.nl

ABSTRACT: In 2016 SURFnet started the Learning Analytics Experiment for Dutch institutes for higher education to gain hands-on experience with learning analytics. With this experiment, SURFnet demonstrates the possibilities of learning analytics in education. By carrying out this experiment, educational institutions can answer the following questions: Is learning analytics really so complicated? How does learning analytics fit into an educational infrastructure? How do you collect data? How do you visualise data? In this paper we present the set-up of the Learning Analytics Experiment, the learning analytics architecture and infrastructure used and the institutes who participate in the experiment as well as the first results of the experiment.

Keywords Hands-on, experiment, online student activities, xAPI, learning record store, visualization

1 INTRODUCTION

Learning analytics is often viewed as a complicated process by educational institutions. Frequently asked questions include: How do I use learning analytics? How can I use the data indirectly provided by students during online learning in order to provide targeted feedback? This raises other questions: Is learning analytics secure? What about the students' privacy?

In 2016 SURFnet started the Learning Analytics Experiment for Dutch institutes for higher education to gain hands-on experience with the above-mentioned aspects of learning analytics. With this experiment, SURFnet wishes to demonstrate the possibilities of learning analytics and to show how learning analytics can link to educational processes and provide insight into student activities.

SURFnet is the Dutch NREN (National research and education network) representing all Dutch institutes for higher education and research. SURFnet's mission is to boost the quality of education and research through the support, innovation, development and operation of an advanced, reliable and interconnected ICT infrastructure, enabling the potential of ICT to be harnessed to its full extent. One of the innovation topics, which SURFnet is addressing, is Learning Analytics. This is done in a multi-year innovation program in which all institutes for higher education can participate.

In this paper we present the set-up of the Learning Analytics experiment, the learning analytics architecture and infrastructure used for this experiment and the institutes who participate in the experiment as well as the first results of the experiment.

2 LEARNING ANALYTICS EXPERIMENT: SET-UP

Learning analytics offers the possibility of supporting students in their learning on the basis of educational data. In addition, it offers teachers and educational developers a new and practical source of information alongside their own observations and evaluations, namely data about student behaviour and learning needs.

Learning analytics can provide teachers with real-time information about the quality of the learning material and the course curriculum. Learning analytics can also provide insight into online study behaviour both for students and teachers.

With the experiment, SURFnet provides insight into student activities. It measures which online activities students actually perform. In the experiment, the focus is not on making predictions with data, but on making improvements to education. We will measure and display the data, and educational institutions participating in the experiment can decide for themselves whether they will make any changes to aspects of education based on the displayed data.

By carrying out this experiment, educational institutions can answer the following questions: Is learning analytics really so complicated? How does learning analytics fit into an educational infrastructure? How do you collect data? How do you visualise data? How do you obtain permission from students?

Furthermore, the process of collecting data becomes more transparent. The experiment will show which questions are used to obtain the data and how this data is analysed and visualised.

2.1 Experimental Approach

As previously explained, we are focusing on collecting data and generating reports. Collecting data and generating reports consists of the four steps shown in the figure below.

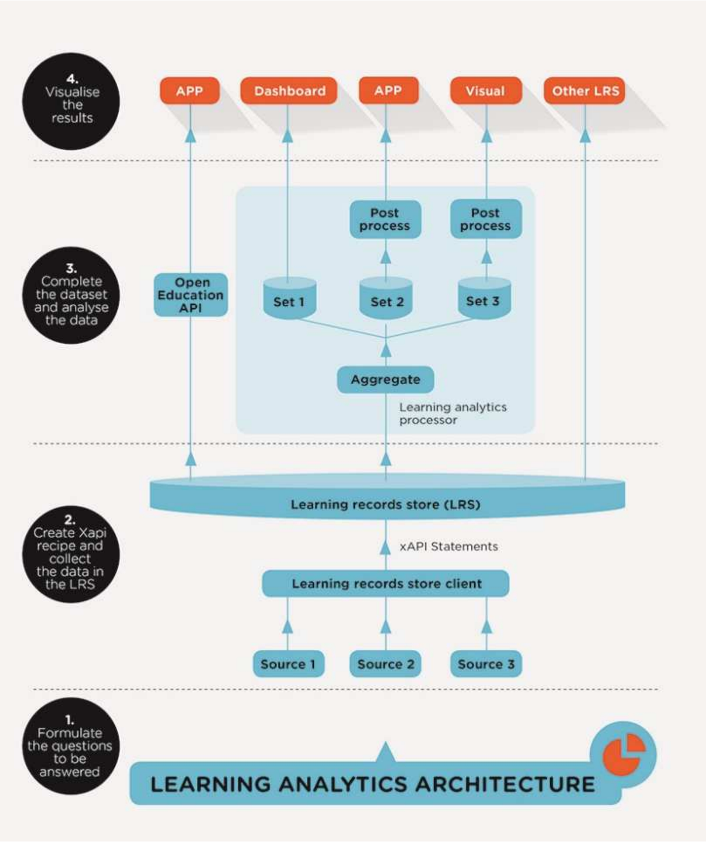

Figure 1: Learning analytics architecture and learning analytics process | In the figure, the four steps are linked to the learning analytics architecture

Step 1: Formulate the questions to be answered

It is important to first consider which data needs to be collected. In other words: Which questions can we answer with the data?

Teachers and educational developers can determine these questions, potentially in collaboration with management.

SURFnet has formulated five questions for this experiment while working in collaboration with educational institutions:

- Has the student submitted the assignments and when were they submitted?
- When does the student carry out learning activities?
- Does the student monitor their own progress?
- How often does the student take interim tests during the course?

- Which materials are frequently used?

Step 2: Create Xapi recipe and collect the data in the LRS

xAPI recipes will be created for the educational questions listed above. This is the second step

To be able to collect data, the xAPI recipes need to be linked to the applications used by students. When they are linked, data can be collected, analysed and organised. Data collection is performed in the Learning Record Store.

Step 3: Complete the dataset and analyse the data

After collecting the data in the Learning Record Store, the organisation and analysis of the data is carried out in the Learning Analytics Processor.

Step 4: Visualise the results

The data report will be shown on a webpage where the teacher and student can view and evaluate the visualisation for one of the educational questions. The teacher can then decide whether to give feedback to the students based on the visualisations. The process of providing feedback is not part of this experiment.

3 LEARNING ANALYTICS ARCHITECTURE & INFRASTRUCTURE

In order to facilitate the above described learning analytics process, SURFnet has developed a learning analytics architecture and built a learning analytics infrastructure. This infrastructure shows how the different layers within a learning analytics system – input, data storage, business and presentation – are connected.

The technical architecture (see figure below) of the infrastructure can be divided into four layers:

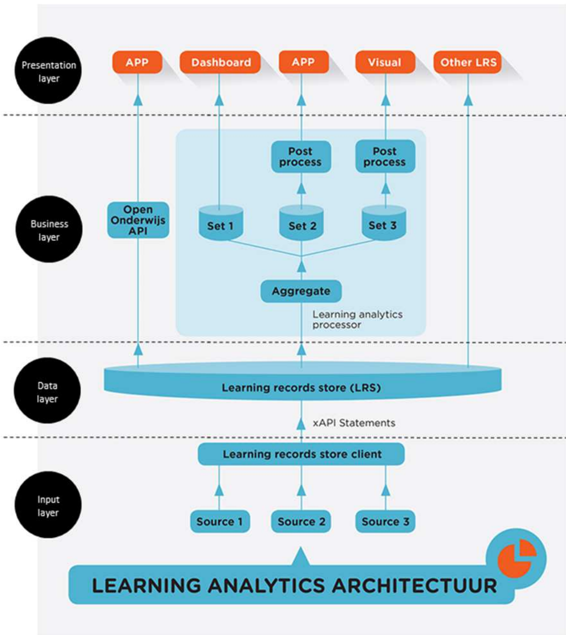

Figure 2: Technical architecture with the four layers

1. The presentation layer, which provides the visualisation.

The visualisations are visual presentations of the results of the Learning Analytics Experiment, which are intended to provide teachers and students insights into study behaviour. These visualisations are displayed on a dashboard.

2. The business layer, which provides the functionality for the experiment.

This is the Learning Analytics Processor, which aggregates, organises, analyses and customises data from the Learning Record Store for different users in the presentation layer.

3. The data layer – the centre of the architecture.

The most important component is the Learning Record Store, which is for storing student activities carried out in the various online learning environments used by students.

4. The input layer

To which various sources (environments) are connected that provide the LRS with the activities.

The features of the architecture for the Learning Analytics Experiment are:

- The components are vendor independent, and use open standards.
- The architecture is separate from the different kind of online learning environments and sources that are used within the institutions.

3.1 The Process: Capture

The input layer ensures that data is collected in the LRS. Student activities originate from different sources and reach the LRS in a uniform manner through the LRS client developed by SURFnet.

Three main functionalities are used in this process:

1. Tracking the student. Since student activities are distributed across various sources, it is important to clearly identify the student at each source.
2. It should be easy for the teacher to collect the student activities. This is achieved by removing the complexity of the xAPI from the source and monitoring the activities with simple javascript code via the LRS client.
3. The javascript code at the source is translated to xAPI statements used as input for the LRS. These xAPI statements record the type of student activity according to a defined xAPI recipe.

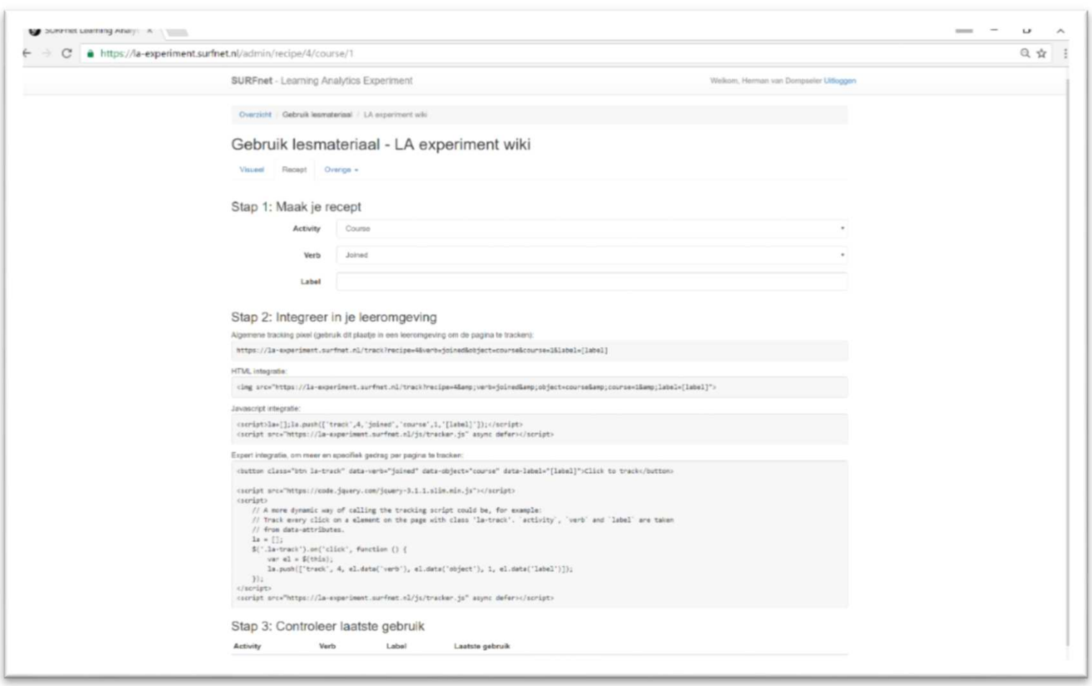

Figure 3: Creating xAPI recipes

3.2 The Process: Report

Collecting data results in a huge amount of student activities in the LRS. In the Learning Analytics Processor, statements from a particular student are aggregated in a dataset, which then serves as input for the visualisation of the data. Different datasets are prepared for different visualisations.

Datasets are stored in a uniform format, which allows post processing to occur in order to prepare data for visualisation. Simple visualisations require zero or very little post processing. For other visualisations, it may be necessary to interpret the data and organise it correctly prior to visualising it.

The Learning Analytics Experiment focuses on visualisations of the questions asked by teachers. Visualisations can be easily interpreted by teachers, so they can determine any steps that need to be taken.

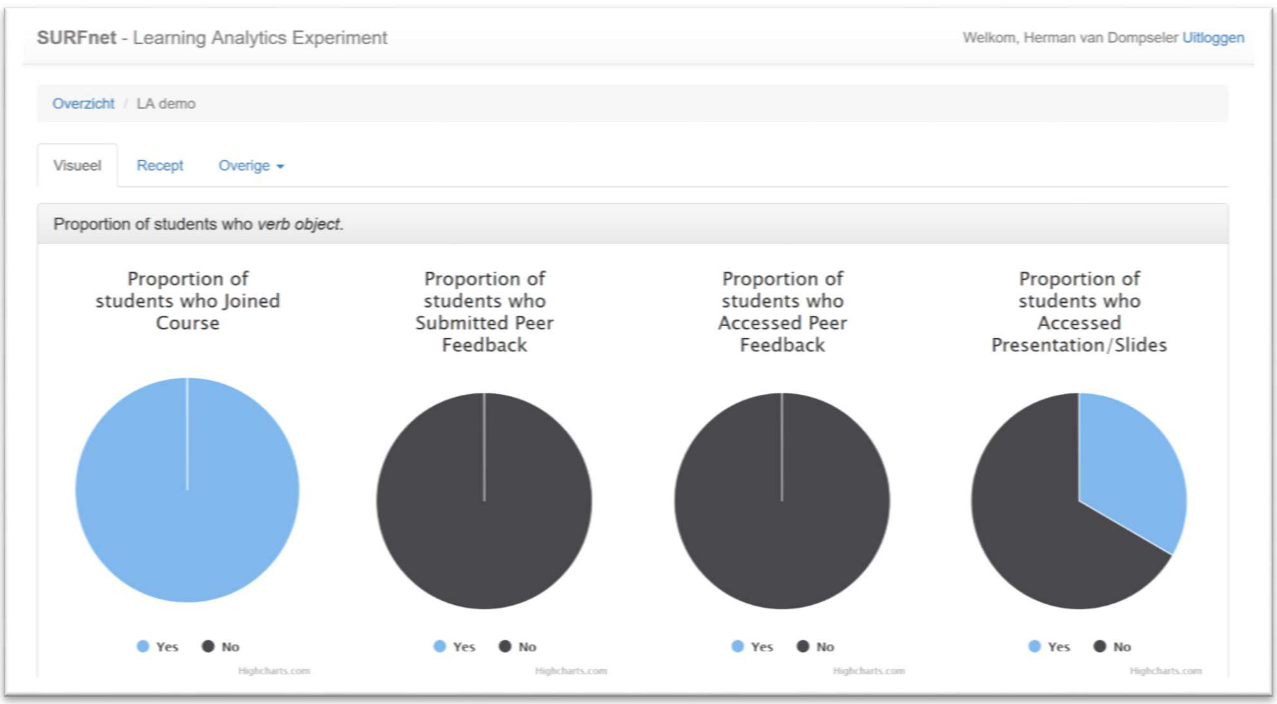

Figure 4: Example of visualisation

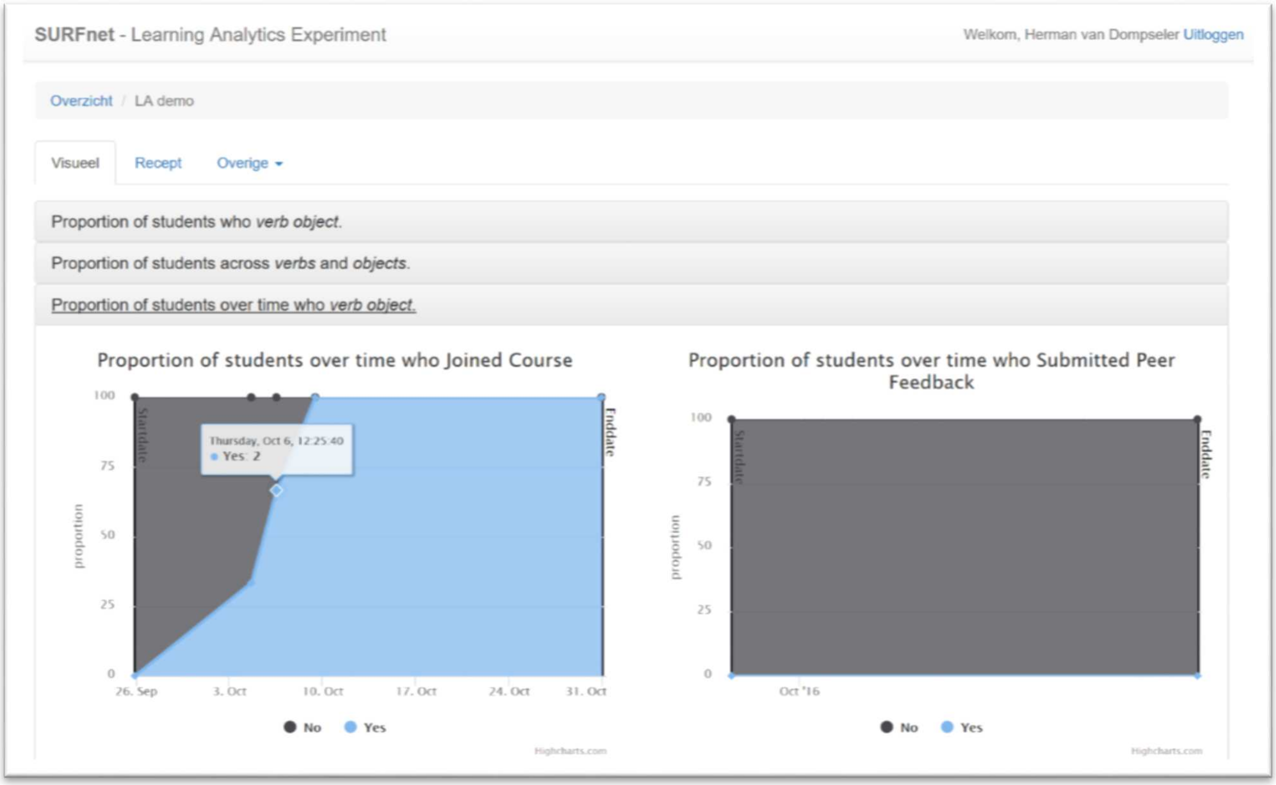

Figure 5: Example of visualisation

4 THE EXPERIMENT IN PRACTICE

Since the launch of the learning analytics experiment, 3 institutes of higher participated in the experiment and used the learning infrastructure in daily educational practice. In the last couple of months over 500 students and 5 teachers worked with the learning analytics infrastructure. With this experiment, students and teachers are able to follow the learning process, near real-time. What's also interesting is that all the participating institutes use various learning management systems, such as Blackboard, N@tschool & Mentorix.

At this moment we are collecting and evaluating the results of this experiment. But what we have learned till now is that as long as you connect the use of learning analytics with the educational process, teachers and students are having a lot of advantage, by looking at the students' data on study activities. We also learned that it was easy for teachers to get started with learning analytics. The infrastructure is running in the SURFnet Cloud, so there is no "burden" implementation and technical issues. Creation of the xAPI recipes was fairly easy for teachers by using our developed tool. One last thing we want to mention is. We asked all the privacy officers of the involved institutes if they agreed that some of their teachers and students participate in the learning analytics experiment. They all agreed, because SURFnet made clear rules and regulations of the use of the students' data.

For 2017 it is the ambition of SURFnet together with the Dutch institutes for higher education, to improve the learning analytics infrastructure and to offer more institutes, teachers and students the possibility to work with the infrastructure. We work together on creating evidence, guidelines and tools for effective use of learning analytics.

Community Building Around a Shared History: Rebooting Academic Reporting Tools at the University of Michigan

August E. Evrard
Departments of Physics and Astronomy
University of Michigan
evrard@umich.edu

Chris Teplovs
Digital Innovation Greenhouse
University of Michigan
cteplovs@umich.edu

ABSTRACT: In spring 2016, the central student government, faculty senate and provost at the University of Michigan agreed to release student evaluations of teaching (SET) back to active students. Coincidentally, a dashboard service known as Academic Reporting Tools, which had served visual summaries of historical course information to faculty and staff since 2006, was being rebooted as part of a campus-wide Digital Innovation Greenhouse initiative. We describe development of the rebooted service, known as ART 2.0, including rollout of a CourseProfile tool offering SET summaries (and more) and our ongoing efforts to build a sustainable community of practice around curricular information.

Keywords: Knowledge engine, dashboard, visualization, curricular data, student evaluations of teaching

1 UNIVERSITIES AS INSTRUMENTED CURRICULAR ECOSYSTEMS

Like all universities of significant size, the curricular environment at the University of Michigan (U-M) is a complex ecosystem driven by a shared mission to develop ``leaders and citizens who will challenge the present and enrich the future[8].'' And like its natural counterparts, that ecosystem is being increasingly instrumented with digital sensors built into the internet services used by students, staff and faculty. While data acquisition grows apace, higher education institutions' abilities to analyze, summarize and internalize its myriad features struggle to keep up.

At Michigan, the Digital Innovation Greenhouse (DIG)[9] is a new organization designed to cultivate and responsibly grow projects that seek to drive positive innovations in this deeply sensed academic

[8] http://www.accreditation.umich.edu/mission/

[9] http://www.ai.umich.edu/digital-innovation-greenhouse

ecosystem. With 19 colleges and professional schools, the U-M's Ann Arbor campus is one of the largest higher education institutions in the US. The scale poses the challenge of how to inform students, staff and advisers, and faculty of the multitude of rich educational opportunities offered within the ecosystem.

For many good reasons, residential learning at Michigan is rooted in tradition. Students take classes taught by instructors and receive final letter grades. They speak with advisers to help steer their academic careers, declare subject majors and minors, and graduate with a set of academic credentials. Informing the campus community about the historical structure of these interactions is the core purpose of Academic Reporting Tools (ART).

Begun in 2006 in the College of Literature, Science and the Arts (LSA), ART has provided faculty and staff with a dashboard service (*sensu* Verbert et al., 2013) offering tailored visual summaries of enrollment and grades for courses and pairs of courses as well as relationships between course grades and pre-college standardized test measures.

Funded by a grant from the Office of the Provost, ART is undergoing a reboot within DIG. Key goals of the new project, known as ART 2.0, are to: i) develop new information services for students, and ii) expand the service to a campus-wide scope.

As ART 2.0 was ramping up, negotiations between U-M's Central Student Government, Senate Advisory Committee on University Affairs, and the Provost were being held to secure release of student evaluations of teaching (SET) back to students on campus (see, for example, Alderman et al., 2012). Committees recommended revisions to the existing survey instrument as well as best practices around release of SET data. As a result, a new set of eight questions will be used across campus for SET starting Fall 2016, summaries of which are being made available to students via the ART 2.0 service.

2 COMMUNITY BUILDING AND COURSEPROFILE TOOL ROLLOUT

The authors of this report are the faculty team lead and lead developer, respectively, for the ART 2.0 project. Even before the latter was hired, the former began to assemble a steering team whose 15 members include representatives from six of the colleges with a significant undergraduate component, the University Library, Office of Student Life, and the Information Technology Services division. Input from this team has been essential in navigating the complex social and political landscape associated with curricular information access.

In summer 2015, the steering team began working with a group of DIG developers to design a course-focused tool from refactored ART 1.0 elements. After a small-scale pilot during Fall term, a beta service, called CourseProfile, was released to students in mid-March 2016, timed to assist with the course selection process for Fall 2016 term.

CourseProfile serves historic information on courses arranged effectively as a set of cards, one for each course, containing a course description along with the following dynamic content:

- Student evaluation of teaching summaries for this course (details below);
- A list of recent (non-graduate student) instructors;
- Demographics of students who have taken the course: by academic level, college affiliation, and subsequent major;
- Lists of other courses commonly taken by students who took this course, arranged chronologically by pre-, co-, and post-enrollment. Active links allow navigation to other course cards.

The beta release focuses on undergraduate courses and information on past instructors, demographics and co-enrollment is based on behavior over the previous five years.

Of the eight new SET questions, three are closely aligned with the following Likert-scale questions in the existing SET instrument:

1. I learned a lot from this course.
2. I had a strong desire to take this course.
3. The workload for this course was [Very Heavy ... Very Light].

The CourseProfile tool offers visual summaries of the fractions of students who responded positively (SA, A) to the first two and the fraction who responded Very Heavy or Heavy to the third, as long as the total number of respondents is greater than 30 (see Figure 1). The fraction of enrolled students who responded is also provided.

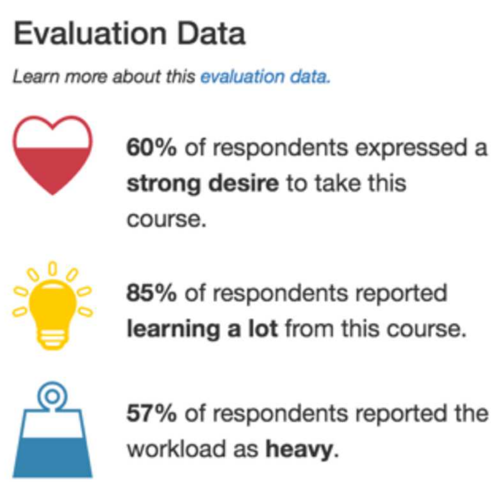

Figure 1: Example of the visual summaries of five-year averaged student evaluations of teaching for a large introductory science course under laptop or tablet conditions, these icons are displayed in the upper-right screen portion. The same set of icons is used across all courses for which data are available, with the fill level and bold font providing details for a particular course. The link in blue

directs students to a cautionary statement requested by the Faculty Senate. Planning is underway to extend this design to include responses to all eight SET questions

The release of CourseProfile was publicized to students through an article in a student-run newspaper[10], and via presentations to student government groups and LSA advisers. Links to the CourseProfile course entries were added to the administrative registration system and to the LSA course guide in early March 2016.

Within a month after its release, CourseProfile was used by more than 4000 U-M students, or roughly 20% of the student population eligible to register for fall classes. Figure 2 shows the number of sessions served per day as reported by Google Analytics. Dates of local peak usage can be traced to student recommendations of CourseProfile: a 29 March e-mail from Central Student Government and a 7 April posting to a student group Facebook page.

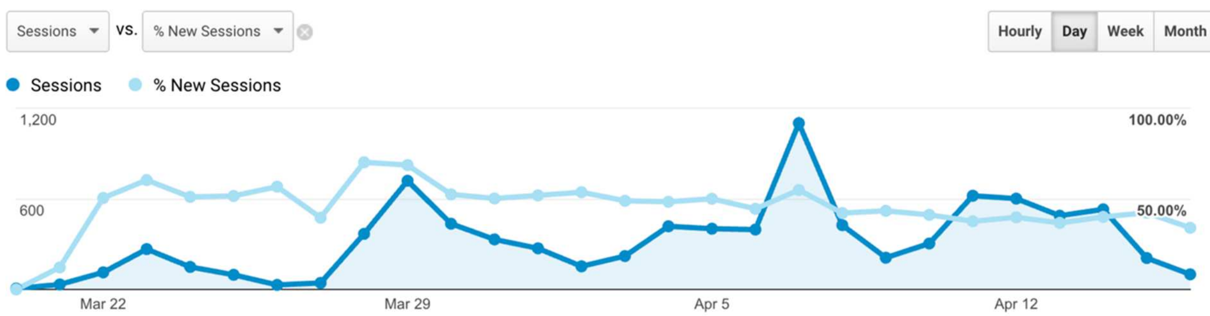

Figure 2: The number of CourseProfile sessions per day (bold and shaded, left axis) and an estimate of new user fraction (light, right axis) for the four-week interval shown (Google Analytics)

The demographics of students who used the service was balanced in gender but somewhat imbalanced in academic level, biased toward senior students. By academic major, the user base reflected with wide scope of Michigan's educational reach, from engineering to business to information. Still, "LSA Undeclared" was the most frequent major.

A follow-up survey distributed to students who had used CourseProfile resulted in 260 responses. A high degree of satisfaction was reported; nearly 90% will use the service again or recommend it to a friend. Responses to the narrative question, **How did CourseProfile help you make choices about courses?** offer insight into the utility perceived by students.

- *It greatly helped me in determining how heavy the workload of a class would be and whether I would be comparatively prepared to take a certain course.*

[10] michigandaily.com/section/news/art-20-gives-students-more-information-about-courses

- *Helped me schedule my courses to see when they would fit together semester-wise (F vs W) but I also enjoyed seeing the professors (after looking each up separately online).*
- *I needed to find a really easy 3-credit class, since I'm taking 6 classes next semester and I don't want to die. The evaluation responses made that easy.*

Asked **What other information could make CourseProfile more useful for your future course planning?** the respondents often cited historical grade distributions, more details on workload, and additional information about instructors.

- *Individual ratings for the instructors. Still relied most heavily on RateMyProfessor because obviously which instructor is teaching that semester makes a big difference in the course.*

As agreed by the key campus community stakeholders cited above, CourseProfile will present this level of detail in a Winter 2017 release. To protect professors during their formative years as teachers, the agreement provides protection in the form of redacted data to newly-hired instructors. Department chairs will have authority to withhold SET information for senior faculty under particularly unusual circumstances such as serious illness.

Several students expressed an opinion that the simple summary views of Figure 1 were insufficiently nuanced, and some expressed the desire to see the entire set of answers to each question. Many mentioned more information about instructors, and the ART 2.0 team is planning a November 2016 release of InstructorInfo, a new tool that summarizes the teaching history of a particular instructor.

2.1 Community Building Challenges

Following recommendations of the policy committee convened by the U-M Provost, the SET summaries are available only to students and are not currently available to staff, advisers, or faculty. This situation leaves many people unsatisfied, particularly advisers who effectively have access to the information via the screens of their advisees. Managing change for this type of widespread initiative is hard, and the ART 2.0 team is making regular presentations on campus and engaging with student and faculty groups to build a sustainable community of practice around academic information at Michigan. Active engagement of our diverse community is both in line with DIG's guiding principles[11] and a productive way forward in the complex socio-technical ecosystem that surrounds the use of academic analytics in higher education.

3 PROJECT EVOLUTION

When charting their curricular paths, students consult a variety of on- and off-campus information sources about courses, instructors and majors. ART's original purpose was to provide faculty and staff with simple

[11] http://ai.umich.edu/about-ai/digital-innovation-greenhouse/dig-guiding-principles/

ways to view structure within the complex learning ecosystem that is U-M, and ART 2.0 expands that access to our students.

When ART 2.0 was rebooted, the project's stated mission was "*to support curricular decisions with evidence you understand and trust."* As the project evolves, we seek to enhance that mission by emphasizing opportunities for *exploring* and *discovering*. For example, each year brings over a hundred new courses to the U-M campus but there is no simple way to identify them. Considering the enormous power of Big Data, how should we leverage public data to more clearly link academic majors to subsequent career trajectories?

Finally, we note that analytic tools such as ART 2.0 can act as boundary objects (Star & Griesemer, 1989) to facilitate ongoing engagement with groups of student government representatives, faculty groups, and university administrators.

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Implementation of Adaptive Learning for Automotive Examination Preparation at the British Columbia Institute of Technology Using Brightspace LeaP

Stephen Michaud
D2L Corporation
stephen.michaud@d2l.com

Lawrence Potyondi
British Columbia Institute of Technology
lawrence_potyondi@bcit.ca

ABSTRACT: Lawrence Potyondi at the British Columbia Institute of Technology (BCIT) took the 10 week "Automotive Service Technician IP Refresher" course and rebuilt it using Brightspace LeaP, an adaptive learning tool. With hundreds of content items and thousands of questions for use with LeaP, each module guided students through the course with LeaP paths to prepare them for the Automotive Service Technician Inter-Provincial (IP) examination and/or the respected ITA level exams. The pilot program involved 53 students and results will be available at the end of the pilot (December 31, 2016).

Keywords: Adaptive Learning; Brightspace LeaP; BCIT; Automotive; Trades; Pilot; Implementation; Lessons Learned

1 SUMMARY

The Brightspace LeaP implementation at British Columbia Institute of Technology (BCIT) provided learnings that will apply to any school looking to implement adaptive learning: Finding, curating, and planning the content, questions and learning outcomes needed to successfully fuel an adaptive learning product is no small challenge. The learnings around publisher-vendor-institution partnerships as well as content and module sizing were invaluable. Despite these challenges, the results of the pilot were more than encouraging enough to dive back in and figure out how to address the issues.

2 BRIGHTSPACE LEAP IMPLEMENTAITION AT BCIT

2.1 Introduction

Lawrence Potyondi at British Columbia Institute of Technology (BCIT) took the 10 week "Automotive Service Technician IP Refresher" course and rebuilt it using Brightspace LeaP, an adaptive learning tool. AUTO 0100 refreshes theoretical knowledge of the trade in preparation for the Automotive Service Technician Inter-Provincial (IP) examination and/or the respected ITA level exam. The students in this pilot course are mainly 18 – 30 whose main goal is to pass the inter-provincial examination and/or the respected ITA level exams.

The course consists of content from Pearson and Nelson. BCIT, working with D2L was able to secure permission from Nelson and Pearson to take the eBook form of 2 textbooks (Erjavec – Automotive Technology 3rd Canadian Edition and Halderman – Advanced Automotive Electricity and Electronics) and break them down into section sized html documents. A very large question library consisting of question banks provided by both Pearson and Nelson was also created. Around the content and questions, Lawrence also built a comprehensive, module by module set of learning objectives aligned to the 2015 ITA Automotive Service Technician program outline that would lead to successfully passing the Automotive Service Technician Inter-Provincial (IP) examination and/or the respected level exams.

2.2 Initial Implementation

BCIT and D2L's first iteration of implementation with Lawrence consisted mainly of ensuring the content, questions, and learning objectives were in place, as well as the mechanics of deploying Brightspace LeaP LTI tool to BCIT's Brightspace instance. What became apparent soon after the implementation engagement was completed was that Lawrence and BCIT were not left with the information and resources to succeed. In attempting to build a rich adaptive course in Brightspace with LeaP the following roadblocks were hit:

- The number of questions in the question library of the course were nearly unmanageable within LeaP
- The main sources of content for the course were protected behind user level authentication
- Being the richest and most complicated implementations of Brightspace LeaP to date, it exposed some issues and weaknesses that needed to be addressed.

2.3 Implementation Re-Visited

One of the first and most challenging roadblocks was the three-way negotiation of digital content rights and access. For LeaP to be most effective, content needs to be sized in such a way that each document viewed will inform the student on one or two learning objectives at the most. These smaller chunks of content allow the adaptive algorithms the flexibility they need to be able to adjust the students' path through the learning objectives as the learning engine learns.

For the pilot, Nelson and Pearson were willing to allow BCIT to take the EPUB version of their textbook and break it down into many HTML documents, one for each section. Though acceptable for the pilot, in the longer term, it will be necessary to negotiate better access to DRM protected content. Brightspace LeaP was built under the assumption that content would either be publicly accessible (Open Educational Resources – OER) or protected and served from the Learning Management System (LMS). Through implementations like the one with BCIT, it has become evident that the trend is towards publishers hosting content and providing secure access methods (like Learning Tool Interoperability – LTI) to their customers.

For the Electude simulations, there were a number of technological and access barriers that could have been overcome with effort but for the pilot, it was deemed too prohibitive. The implementation engagement was considered successful when the Nelson and Pearson textbook, the numerous questions banks, and learning objectives were all prepared and ready to be ingested into LeaP.

In contrast to the difficulties in getting enough smaller chunks of content, an embarrassment of riches was the issue with questions. The publisher question banks from Nelson and Pearson were designed to be imported into the LMS and Brightspace and LeaP were both ready to leverage them. As such, there were over 5,000 questions in the pilot course. The shear number of questions available overwhelmed the review workflows within LeaP. To enable LeaP to better search and provide Lawrence with the information he needed to review the alignment of questions to learning objectives, the implementation team wrote a custom script to title all the questions with a prefix indicating the related textbook and the chapter within the textbook. The prefix allowed Lawrence to quickly identify any misaligned questions.

2.4 Lessons Learned

One of the major learnings of this pilot was that having the content, questions, and learning objectives ready was not the end of the implementation. As Lawrence and the staff at BCIT struggled to create their own learning paths with LeaP, it became apparent to all that the initial implementation engagement was not sufficient to ensure success. Adaptive learning in general; and LeaP specifically, are new technologies and concepts. And the scale of the AUTO 0100 course with the large amount of content and questions pushed the organizational and usability of LeaP to its edges. Here are just some of the things we learned in doing the AUTO 0100 implementation:

- Content and questions need to be organized and subdivided for easier manipulation inside and outside of LeaP
- The semantic algorithms do a good first pass of determining what content and questions are relevant for what learning objectives but each LeaP does need to be fine tuned
- Without good naming conventions and organization, it is hard to manually adjust content within LeaP
- Limitations in how LeaP imports questions and content from the LMS require that everything be well organized up front before the first LeaP is created in a course
- Guidance from a person with deep understanding of how the algorithms work within LeaP is required when training people who will be creating learning paths with LeaP.

2.5 Outcomes

With the pilot now complete, we are now gathering both the subjective and quantitative feedback from both students and instructors. The Automotive Service Technician Inter-Provincial (IP) examination that these students were preparing for is not administered by BCIT so we are collecting the results from the students on a voluntary basis. We will use these results as well as the test results from LeaP to perform some analysis. This cohort of 58 students will be compared with previous cohorts in order to determine what (if any) impact LeaP had on their performance in the course and on the exam.

The anecdotal results from the pilot are very encouraging with the first deployment of the tool, the day before a final exam resulted in 15/16 students being successful with a significant increase in marks above the expected average. A more in-depth analysis of the results looking at effectiveness, efficiency and perceived helpfulness of LeaP should be available in time for the presentation of this paper at LAK'17.

3 CONCLUSTION

The aim of the pilot was to test the capabilities of adaptive learning and observe if there was a perceived and/or measurable improvement in the learning experience. In both cases, the LeaP enhanced "Automotive Service Technician IP Refresher" course met and exceeded expectations. The experience was not without its troubles and lessons learned:

1. There needs to be implementation support around organizing content and designing a LeaP learning path.

2. Adaptive Learning requires content be presented in a flexible manner. In order to accomplish this, there needs to be better institution-vendor-publisher relations, preferably relations and agreements that are already in place.

3. Brightspace LeaP has been designed to use as much content as it can to build adaptive paths. When presented with an abundance of content and questions, there is a need for more organizational tools and structure.

4. LeaP was also designed with OER and custom content in mind but more and more, it has become evident that digital rights managed (DRM) content is a very important source. It will be necessary for D2L (vendor) and publishers to find the best way for institutions to use the DRM content while maintaining rights protection.

Exiting the pilot, the desire on the part of BCIT is to expand the offering to the entire automotive program, requiring that progress be made on the lessons learned. At the same time, D2L and BCIT will look for opportunities to use the pilot data and future courses to perform more scientific study into the effectiveness and efficiency gains delivered by adaptive learning in general and LeaP specifically when combined with such a content rich environment provided by BCIT's automotive program.

Connectivist Learning Using SuiteC - Create, Connect, Collaborate, Compete!

Sandeep Markondiah Jayaprakash
University of California
sandeep.jayaprakash@berkeley.edu

John M. Scott
University of California
jmscott212@berkeley.edu

Paul Kerschen
University of California

ABSTRACT: The turn in learning sciences towards more sociocultural-oriented theories of development has spurred our interest in creating SuiteC. SuiteC comprises three interrelated LTI based applications that privilege peer-to-peer collaboration, connectivism, discourse, content sharing and elements of gamification over more didactic, instructor-centered pedagogies. The apps include: 1) Asset Library for sharing, discussing, liking student-generated content; 2) Whiteboards for remixing Assets in the Library through individual/collaborative multimodal composing; and 3) Engagement Index with course leaderboards for tracking, visualizing and awarding points for social participation. We will discuss the tools design, initial pilots findings and visualize student engagement trends in collaborative environments.

Keywords: learning analytics, social networks, connectivist learning theory, gamification, visualizations, student engagement, interoperability, pedagogy, leaderboard, content curation

1 SUMMARY OF DEPLOYMENT WITH END USERS

The SuiteC software was rewritten in Node.js and follows a multi-tenant architecture. It is built on widely accepted industry standards such as Learning Tools Interoperability (LTI) and the emerging Experience API (xAPI) and IMS Caliper specification. The multi-tenant architecture has enabled UC Berkeley to host separate deployments of SuiteC for its own instance of Canvas and UC Online's since Fall 2015, with Stanford now running a pilot during the 2016-17 academic year. Over a relatively brief period, SuiteC has been adopted in over 250 courses, serving several thousands of students. Several other Canvas institutions are exploring SuiteC integration.

2 INTRODUCTION

The SuiteC project is an ongoing partnership among the University of California Office of the President (UCOP), University of California at Berkeley (UCB) faculty, and UCB's Educational Technology Services (ETS) team to develop a set of online tools designed to increase and track student engagement. Representing the merger of two visions by a pair of key faculty partners, Prof. Greg Niemeyer and Prof.

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Glynda Hull, SuiteC enables students to contribute, discuss, and remix a wide variety of course-relevant content in new ways. The tools include a digital asset library, an online interactive whiteboard, and a leaderboard for measuring student engagement.

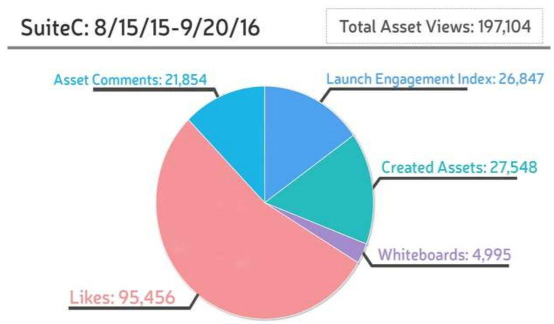

Figure 1: SuiteC usage statistics

Funding to design and build the first version of the tools was provided by the UCOP's Innovative Learning Technology Initiative for a course taught by Prof. Niemeyer called "Data Cultures." When Prof. Hull received additional funding for her Education 140 course, working with graduate researcher John Scott, she decided to invest in and complement the tools that had already been developed for Data Cultures rather than create a separate project. The entire suite of tools was then branded as "Collabosphere" later renamed "SuiteC".

ETS continues to enhance tool functionality, improve the user experience, and evaluate the on-going teaching and learning requirements. Since Fall 2015, SuiteC has been incorporated with multiple courses at UCB and the offerings at UC Online, and is now being piloted by Stanford University. Figure 1 shows the usage statistics of SuiteC tools since its deployment.

3 CONNECTIVIST LEARNING THEORY, GAMIFICATION AND SOCIAL NETWORKS

A key feature of connectivist learning theory is that much learning can happen across peer networks that take place online (Seimens 2005). Here, a teacher will guide students to information and answer key questions as needed, in order to support students learning and sharing on their own. Students are also encouraged to seek out information on their own online and express what they find. On the other hand, gamification includes using elements of game elements and game-design techniques in non-game contexts to engage people and solve problems. Probably it would not be an exaggeration to say that for connectivist learning theory the social network is a key element of the learning process, while for gamification the network is rather a supporting drive to reach higher motivational levels (Biro 2014).

SuiteC tools blends the aspects of connectivism, social networks and gamification to provide an enhanced pedagogical experience. While the Whiteboards and Asset library enable students and instructors to share, discuss and remix the content. The Engagement Index tool is designed to provide strong social community based performance evaluation and feedback, thereby catering to a diverse learner in a single environment.

4 SUITEC TOOLS AND CAPABILITIES

The SuiteC tools are LTI standards compliant and the tools have been integrated with the Canvas LMS The tools give the ability to capture the essence of the social interactions within the collaborative learning environments, which can be used to improve learning design in such environments.

4.1 Asset Library

Goal: Create and Share Content.

The Asset Library is an interactive repository for an entire class that stores the links, images, and content contributed and created by the students. Once content is added via the tool's upload system or via a browser plug-in, all students in the class can engage with the assets and each other by discussing, commenting on, and liking the items. The tool is designed to allow students to share relevant information and ideas from outside of the curriculum and allows them to help shape the course. The assets can be sorted and filtered by keywords, people, hashtags and assignments.

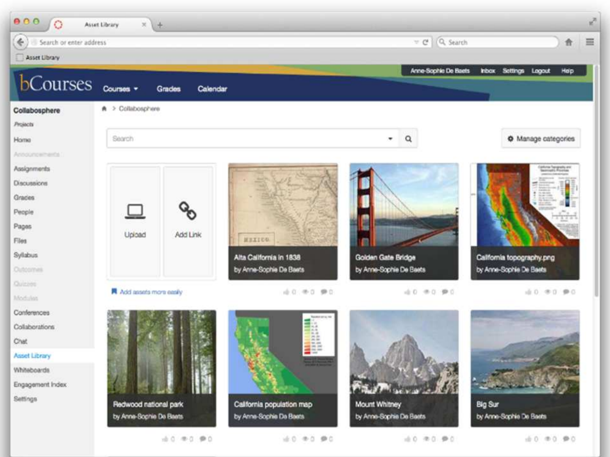

Figure 2: SuiteC asset library

4.2 Whiteboards

Goal: Collaborative Remixing and Concept Mapping.

The Whiteboards tool allows students to work with items from the Asset Library by organizing and re-mixing the contributions of their classmates to find new meaning and understanding. It provides a real-time collaborating ability and messaging for the students. The possibilities with Whiteboards are nearly endless. For example, students can use the tool to create mindmaps, collaborative brainstorms, prepare for individual/group presentations, compare and contrast ideas, and more. Once re-mixing is finished, the result can be contributed back to the Asset Library for further student engagement.

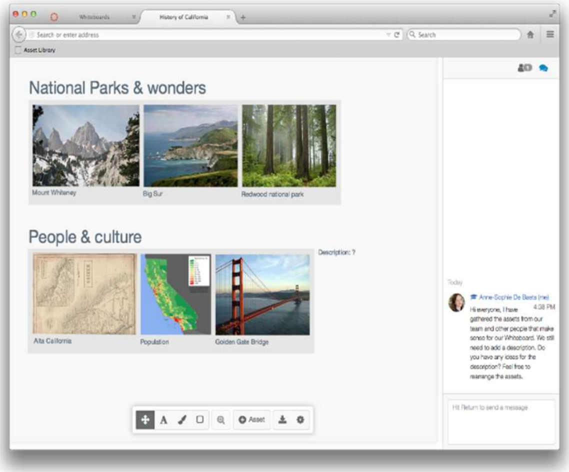

Figure 3: SuiteC whiteboards

4.3 Engagement Index

Goal: Track Student Engagement.

The Engagement Index marries student engagement tracking and gamification by providing a leaderboard for student engagement in the course. By using the Asset Library, Whiteboards tool and other native LMS tools, students can earn engagement points and compare themselves with the other students in the class. The points allocated for the nature of engagement is configurable. The leaderboard consists on the sum total engagement points earned in comparison to the peers (Figure 4).

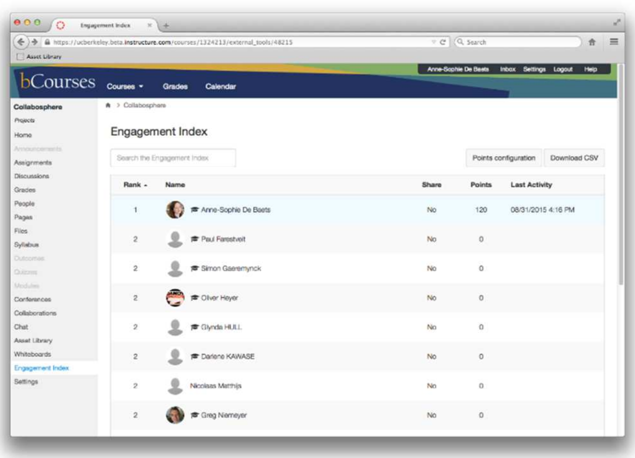

Figure 4: SuiteC engagement index leaderboard

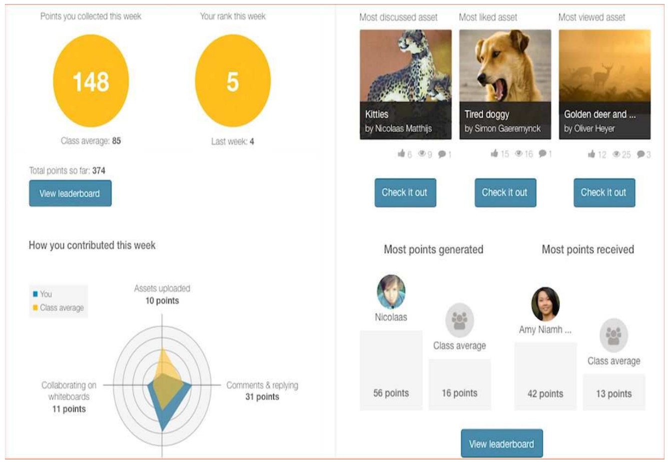

Figure 5: SuiteC weekly engagement reports

4.4 Weekly Engagement Reports

The competencies leaderboard along with visualizations of individual student participation are used to create a unique learner profile. These profiles provide detailed feedback to students and instructors for efficiently and effectively communicating student accomplishments, collaboration roles, and skills developed. The visuals like bullseye radar gives a summarized view of the student's participation on multiple criteria benchmarked against the class average performance (Figure 5). The profile also contains top trends like the most discussed assets, points for the week, ranking, class averages, most points generated etc. to motivate students' participation.

5 VISUALIZING STUDENT ENGAGEMENT IN COLLABORATIVE ENVIRONMENT

Drawing from a social learning analytics toolkit and an assemblage approach, we will present the preliminary findings from SuiteC implementation in two online learning courses, visualizing patterns and trends in social participation in relation to SuiteC features and the pedagogical orientations of the courses.

5.1 Studying Gamification Effects and Student Engagement Using Time Series Plots

The graph in Figure 6 (Niemeyer et al, 2015) gives an insight into a time series analysis on the student's engagement and their interactions within the SuiteC tools within a Data Arts course. The x-axis represents the timeline and the y-axis represents the engagement points. A line graph shows the variation in engagement points for each student at various time intervals. The minimum requirement for the engagement points was set to 1500 points. The instructors can select individual student line graphs to compare and benchmark performance. The line graphs highlighted show different types of student engagement behaviors and effects of gamification of the learning process. The types include:

1. Consistent regular performers who pace themselves
2. Competitors striving for top position on the leaderboard

3. Sudden bursts of heightened engagement to be in contention on leaderboards or make up for minimum points (1500)

4. Lurkers who are constantly falling short

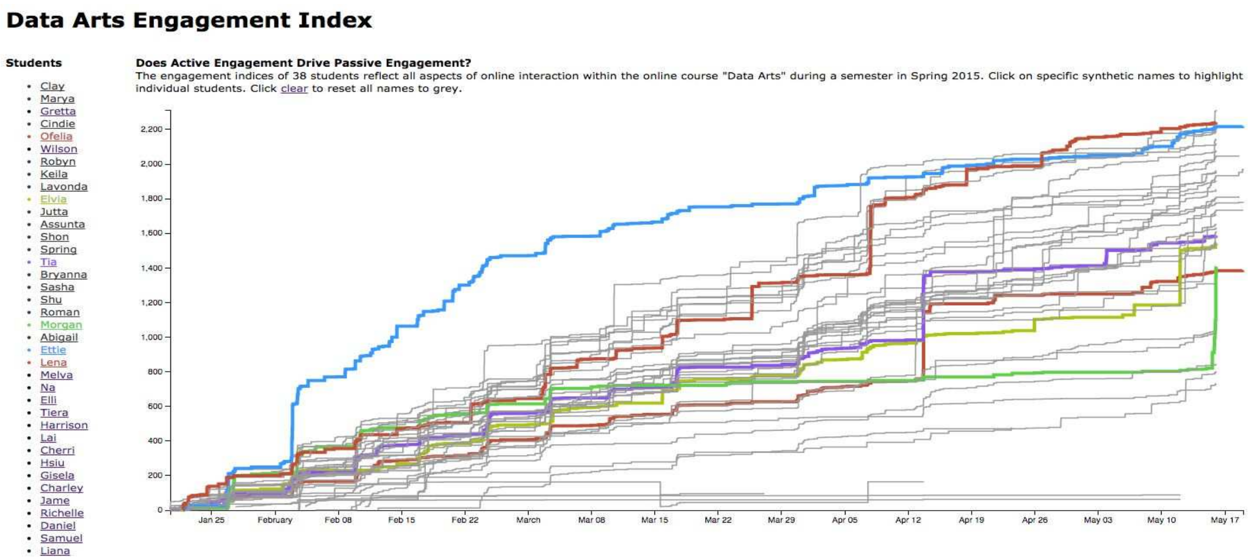

Figure 6: Student engagement patterns over time

The following quote by one of the participants' sums the user experience in SuiteC.

> "The engagement index is a smart way to monitor how everyone is participating in the class. It provides a rough idea of who is participating the most and who is lacking in those discussions. The only problem with it, like every other ranking system, it promote competence that can be helpful for students at first, but once they aim for the highest score in the rankings, it becomes more about doing whatever they can to get to that score. In some ways, it reminds me of Freire's "banking model," where students work towards a prize. Even so, I believe that itself is a motivation that (with the optimum amount) can be helpful to one's learning as it promotes participation in class."

5.2 Social Network Graphs

The social network graphs are an intuitive way to visualize how students are interacting with each other. The nodes in the graph represent the students while the edges of the graphs depict the interaction between them. The interactions are color-coded based on number of interactions between the student and their peers as shown in the Figure 7 (Niemeyer et al., 2015). The visuals can be used to identify students with weaker peer interactions and intervene with them accordingly to improve their engagement. Some of the pedagogical strategies might include pairing such students with groups with stronger team dynamic, encouraging more participation, asset recommendations etc.

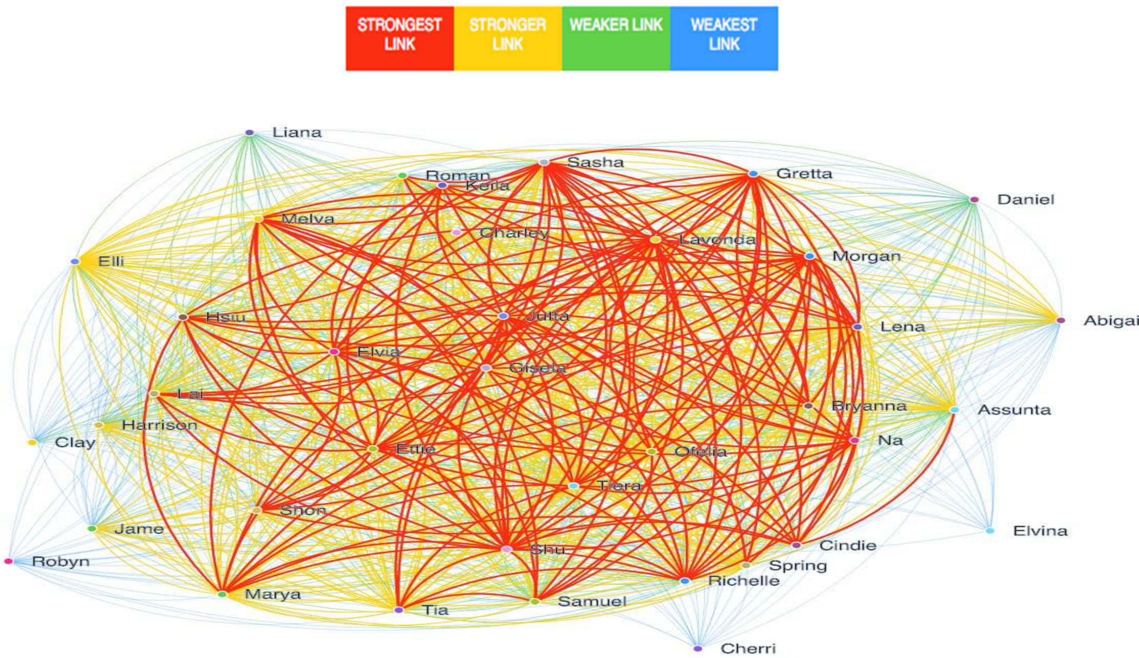

Figure 7: Social network analysis of student interactions

6 FUTURE RESEARCH

The research on the pedagogical strategies that can have a significant impact in a social connectivist environment is still in its infancy. These preliminary findings provide insight into the nature of social participation in dynamic collaborative environments as well as inform the next round of development on SuiteC tools, currently being funded by a National Science Foundation grant. The goal for this next round will be the design of an "Impact Studio," a social engagement dashboard that will provide students with rich feedback on their participation, including more sophisticated social network visualizations and content/user recommendations. These new features aim to improve inclusivity, collaboration, learning and pedagogy in the environment through greater metacognitive awareness of learner activity. Continued adherence to xAPI and Caliper standards ensures data are systematically organized and analyzed. Join us in exploring software demos, course examples, and preliminary findings from the social learning software SuiteC.

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Are We Losing Sight of the Trees for the Forest? A Case for Localized Longitudinal Analytics

Alan J. Hackbarth
Wisconsin Center for Educational Research
ajhackbarth@wisc.edu

ABSTRACT: The Learning Analytics community has always advocated a multi- disciplinary approach as the field evolves, with a special emphasis on including of practitioners and stakeholders in education – higher education institutions, MOOCs, policy makers, administrators, K-12 institutions, teachers, and students. While significant strides have been made on the "analytic" side of the equation, the "learning" side of learning analytics, with all the acknowledged complexity, is proving to be the more challenging side of the proposition. Assumptions about teachers – more specifically what they believe about teaching and learning that would drive their interest in analytics – is conspicuously absent from the LA literature. In this paper I identify and discuss teacher dispositions and objectives that would drive the adoption of learning analytics in their practices and suggest what those learning analytics should tell them.

Keywords: Learning analytics, teachers, disposition, instruction, objectives, assessments

1 INTRODUCTION

From the first recognition of an opportunity to co-opt analytical practices used in business and some branches of science (i.e., biology, climate) and fit them to the field of education and the study of learning, leaders of the Learning Analytics (LA) community have consistently advocated a multi-disciplinary approach (Suthers & Verbert, 2013.) Over the relatively short evolution of the field, this has come to be understood to mean a search for a synthesis of theories, products, and procedures from research that takes place in multiple disciplines; examples include academic analytics, action research, educational data mining, multimodal interaction, recommender systems, intelligent tutoring systems, social network analysis, business intelligence, interactive learning systems, and personal learning environments (Bilkstein, 2013; Chatti, Dykoff, Schroeder, & Thüs, 2012; Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012; Greller & Drachsler (2012). The inclusion of practitioners and stakeholders in education – higher education institutions, MOOCs, policy makers, administrators, K-12 institutions, teachers, and students (Chatti, Dykoff, Schroeder, & Thüs, 2012) - has also been an emphasis of the learning analytics community (Suthers & Verbert, 2013). The conceptual and technical advances in such areas as automated methods of monitoring, discovery, adaptation, prediction, structure discovery, relation mining, distillation of "big" learning data into visualizations for interpretation, assessment analytics, and knowledge modeling (Baker & Siemens, 2014; Ellis, 2013; Suthers & Verbert, 2013) in a short period of time have been remarkable. In short, the community is making substantial strides on the "analytic" side of the equation. The "learning" side of learning analytics, with all the acknowledged complexity, is proving to be the more challenging side of the proposition. That's not to say that some of the goals of some of the stakeholders in learning environments aren't being met; for example, refinements in techniques for analysis of large and diverse academic datasets have been used to inform university and department decision making, predict student "at risk" performance, and discovery of patterns that contribute to high level hypotheses and theories about learning (Baker & Siemens, 2014; Chatti, Dykoff, Schroeder, & Thüs, 2012.)

But as Clow points out, "The promise of learning analytics is the empowerment of teachers and students to understand the wealth of data that relates to their learning" (Clow, 2013.) This in turn is grounded in what Greller and Drachsler (2012) identified as the "soft" dimensions of LA – "assumptions made about humans or society in general." But assumptions about teachers – more specifically what they believe about teaching and learning that would drive their interest in analytics – is conspicuously absent from the LA literature, despite Suther's and Verbert's (2013) call for multivocality, including the voices of educators (assumed to include "teachers") in the discussion. In the remainder of this paper I will identify and discuss teacher dispositions and objectives that would drive the adoption of learning analytics in their practices and suggest what those learning analytics should tell them. Dyckhoff et al (2012) suggest "Teachers should have access to Learning Analytics tools (e.g., provided via dashboards) that can be integrated into a VLE or other learning environments" so that "…users could easily analyze and interpret available data based on individual interests." I argue that realizing an accurate description of teachers' dispositions and the challenges they face can contribute to the development of such tools.

2 TEACHER DISPOSITIONS

2.1 Toward Instructional Design

Any teacher who is engaged in instruction is teaching to objectives; at the end of a unit of instruction there are certain things – concepts, declarative knowledge, procedures, etc. – that they want their students to know (i.e., to have obtained some prescribed level of mastery at that point in time.) In their conception of "backward design", Wiggins and McTighe (2005) delineate a process of three broadly defined steps that begin with the declaration of a lesson's learning objectives followed by the means of assessment for each objective. Only after those two elements are determined does the teacher develop lesson activities. In plain terms, teachers ask, "What do I want the students to know?" and "How will I know they know it?" and "What will I do and what will they do so that they know it?" The answers to the first and last question are concrete; objectives and activities are easily described. The second question – "How will I know they know?" is less certain. At best, all we can ever do as teachers is make inferences about what students know, and those inferences primarily evolve from the assessments we give them. But there nearly always questions about the validity and reliability of the formative and summative assessments that teachers use to infer learning has occurred. The conclusions are only as good as the quality of the data that can be derived from the environment. That is not to say that teachers, particularly as they gain experience in management aspects of learning environments, do not develop fairly accurate intuitions about the learning trajectories of individual students. Such intuition is reinforced by the amount of interaction a teacher has with a student and the opportunities a teacher has to examine and reflect upon student produced artifacts. For example, as a high school mathematics instructor I gave daily assignments and spent hours reviewing and notating the work of individual students, a practice I have continued as an education and psychology professor. In short I was analyzing student learning; all teachers do, often in non- systematic ways. Analytical tools developed by LA researchers need to reinforce the natural intuitions of teachers. And they need to show the ability to enhance those intuitions by supporting reflection. I will suggest how this might happen later in the paper.

2.2 Toward Other Teachers' Student Performance

A second disposition that LA researchers need to understand about teachers is that they aren't really concerned about the performance of other teachers' students. First, because they generally don't have the time to be, and second, because they recognize that the combination of themselves and the students who populate their learning environment is unique. They are like no other teacher; their understanding and their value of their discipline is like no other teachers. They recognize that each of their students have unique learning trajectories and know that they should work with each student at her/his level of mastery. Learning Analytic tools need provide feedback that help teachers identify that state, in much the same way that doctors use instruments and tests to determine the health of a patient.

2.3 Toward Research on Successful Learners

Finally, researchers need to understand that teachers don't care too much about what the most successful learners in a discipline do to be successful. They simply don't equate research results from "out there somewhere" with the performance of their own students. It is more important they, and their learners, know what success looks like in the discipline. They know that there is often more than one path to acquiring knowledge and, while some paths are more efficient than others, not all of their learners have access to those best paths for various reasons that aren't related to instruction. Yes, it is a valuable attribute of learning analytics that they may reveal the patterns of successful students, particularly when those patterns can influence an improvement in instructional design. But teachers are professionals who have an obligation to understand multiple paths to understanding, and learning analytics should help teachers recognize on what path students are and where on that path they are.

These observations about teachers and the value they would place on learning analytics is not a criticism of "big data" analytics, which serve important functions in the education discipline. But they do not directly address the prosaic realities of a teachers job – to identify what students should know, make inferences about if and how well they know it, and decide what learning activities they can (or cannot) do to master the specified knowledge. This requires a localized, longitudinal analytic tool. In the next section I describe what such a tool entails.

3 LOCALIZED LONGITUDINAL ANALYTICS

3.1 Localized – Grounded by Objectives

Earlier in the paper I explained that teachers' goals in a learning environment are guided by objectives.

Most disciplines have a scope and sequence of learning objectives (or standards and sub- standards) that articulate what and when concepts should be taught. This in turn influences curriculum, and most educators understand curriculum to be cyclical. By this I mean that concepts are introduced and developed to a certain degree early in a curriculum and then revisited, elaborated, and expanded upon later in the curriculum, usually in cycles that can be as short as weeks or as long as a year or more. The point is that the selection of instructional activities and assessment items are guided by objectives which can be qualified in writing and quantified. Imagine, for example, a sixth grade mathematics teacher; during each class period s/he has a certain objective(s) to complete. It is likely that the teacher will give an assignment for the purpose of practice, but also formative assessment. It is also possible that individual elements of that assignment can be qualified according to the objectives for that lesson, and can also be quantified during the evaluation of the assignment. As this process continues day in and day out, objectives will get tagged to elements of assignments (i.e., student produced artifacts) multiple times, and eventually a profile of a student's performance with respect to an objective could be created. Now suppose that, as time passes, each time the teacher creates a lesson and corresponding assessment that targets a particular objective, s/he receives a list of students that have struggled in the past with that particular objective. S/he may have known that intuitively, but the sheet serves as an empirical "nudge" that the teacher may want to pay particular attention to these students. This is not too much unlike predictor analytics such as Purdue's Signals (Arnold, 2010) and it actually describes some of the functionality of a standards-based gradebook that my teachers and I developed fifteen years ago when I was a middle school principal. The gradebook was developed in FileMaker Pro, a database program which gave us the ability to query data in flexible and imaginative ways. In addition to identifying the objectives that students struggled with, we also used the tool, in conjunction with standardized test results, to identify gaps in coverage – objectives that we were not addressing adequately in our delivery of instruction.

3.2 Longitudinal

To extend my K-12 example a bit further, imagine that all the teachers in the school kept the same type of assessment data for each subject and that they had a consistent objective annotation protocol. This could mean that an eighth grade teacher would have access to longitudinal data related to every objective s/he teaches for each student since the student had been in the system. This data might be reported to the teacher automatically in the manner described above, or the teacher might query the database for information about a single student performance related to a single objective, or any number of students' performance related to any number of objectives. Or s/he might query the database to discover when last an objective was covered, or in what context it was covered, or how many times it has been covered. A classroom teacher would find *this* kind of learning analytic functionality useful. This is not to say that it would not be challenging to build such a system with respect to a number of factors that have been discussed in the LA literature – ethical issues of privacy and technical issues such as data portability, for example – but some of these issues share some similarities with the maintenance of e- portfolios and transcripts and others are just technical issues to be solved.

3.3 Accessible

Finally, as noted earlier, learning analytics tools for teachers have to elaborate on teachers' intuitions and do so with little more effort. In other words, the tool needs to be easy to use, it needs to stimulate their curiosity about students and learning, and it needs to satisfy their curiosity. Basically the tool needs to distill queried data into visualizations from which teachers can identify interesting patterns or data points that either push them to explore further, or provide insight into student learning, or answer their questions about the same. The tool needs to include a configurable dashboard application that will allow teachers to see multiple representations of certain data points (for example, to compare the work patterns of differently performing students) and to see multiple aggregations of the same data.

4 SUMMARY

A great deal of discovery and development has occurred on the "analytics" side of the learning analytics landscape in fields that include educational data mining, multimodal interaction, recommender systems, intelligent tutoring systems, social network analysis, business intelligence, interactive learning systems, and personal learning environments. Much less has been accomplished toward the goal of putting useful learning analytic tools in the hands of classroom teachers, and one significant reason is the lack of understanding of the disposition of classroom teachers. While remarkable progress has been made with respect to many technical and conceptual problems that have a tendency to dominate the landscape, we as a community need focus a little more attention on connecting the power and promise of these breakthroughs to people who teach. Despite the proliferation of technology in the classroom and greater access to colleagues and opportunities for collaborative professional development, teaching is still very much a personal practice. Teachers develop personal intuitions about the learning that is taking place in their classrooms, and learning analytic tools need to reinforce and extend that intuition. Teachers understand that the configuration of teacher and students in their learning environment is unique, and while they accept that there are general best practices for mastering their domain content, they also recognize that unique factors constrain some of their students. Learning analytics must be easily configurable to the local contexts in which they are used, and that can be accomplished with a tool that allows teachers to annotate with respect to the objectives they are teaching to. The tool must also be flexible enough to facilitate imaginative queries so that teachers can access and interpret data relative to their own context. And tools must display data using visualizations that facilitate discovery and reflection by teachers.

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Developing a Strategy for the Implementation of Learning Analytics at the University of Strathclyde

Ainsley Hainey
University of Strathclyde
ainsley.hainey@strath.ac.uk

Howard Ramsay
University of Strathclyde

Brian Green
University of Strathclyde

Helyn Gould
University of Strathclyde

Scott Walker
University of Strathclyde

Michael Aherne
University of Strathclyde

ABSTRACT: Higher education institutions urgently require strategies for the use of emergent technologies such as learning analytics. The University of Strathclyde achieved this through an exploratory piloting structure and process. A Learning Analytics Strategy Group oversaw the use of learning analytics in five diverse classes across all four faculties, capturing evidence of impact on learning, teaching and student success. This evidence, combined with a wide range of literature, was used to develop the institutional strategy. Components of the strategy document, in addition to the keys to success and lessons learned from this approach, will be discussed.

Keywords: Strategy, Implementation, Pilot Projects, Keys to Success, Lessons Learned

1 BACKGROUND

The University of Strathclyde was founded in 1796, when Professor John Anderson, a professor of natural philosophy and a leading figure in the Scottish enlightenment, left a bequest to set up a place of useful learning that would allow the working women and men of Glasgow to improve their situation. Today, our collective vision for Strathclyde is as a leading international technological university, inspired by its founding mission as 'the place of useful learning', that makes a positive difference to the lives of its students, to society and to the world.

Learning Analytics is an emerging discipline that develops from, and can be facilitated by, the increasing use of technology in learning and teaching. The potential sources of relevant data are wide ranging and include: management information at institutional level, student records, virtual learning environment (VLE) usage, and library access. The list of potential data sources is extensive and growing as IT systems develop and institutional data expands with a corresponding increase in technical and computing capacity and infrastructure.

This presentation will discuss the University of Strathclyde's journey of discovery with learning analytics and how it developed its strategy for implementing learning analytics, in line with the current University Strategic Plan and University Vision, and will discuss keys to success and lessons learned.

2 THE CATALYST

For some years, localised areas of the Institution such as the Business School, had started to examine the potential use of educational data which subsequently became available after the successful implementation of a University wide project to unify and create a single Learning Management System (LMS) for the Institution. The University had also partnered with MOOC provider FutureLearn, which was using the large amount of quantitative data available from a growing number of MOOCs, to reveal useful insights into the usage of video and behaviour of learners. In addition to the developments in these projects, centrally and at Senior Management level, understanding of the potential of learning analytics was growing rapidly. The OU's recent review of emerging and innovative pedagogy reinforced the potentially high impact of learning analytics on student learning and engagement (Open University, 2014). This view was supported by studies published by Jisc (2014) and NMC (2013) which highlighted the significant potential of learning analytics. Strathclyde had recently invested in various technology based projects, such as Strathclyde's system for academic management information was much improved through the work of the Institution's Strategy and Policy Directorate and the SunBIRD system (Strathclyde University Business Intelligence Reports and Dashboards - a system based on QlikView), and through the previously mentioned unified LMS project to introduce Myplace (a Moodle-based LMS). These needed to be developed to provide greater feedback to staff (course leaders, teaching staff and course support teams). Thus the vision for using learning analytics for enhancing the student experience was fostered.

3 LEARNING ANALYTICS STRATEGY GROUP

In order to examine and develop this vision, a Learning Analytics Strategy Group was established. The group consisted of two Deputy Associate Principals (DAP) for Teaching & Learning, and the Director, Deputy Director, and a Learning Enhancement Manager from Education Enhancement, which supports learning and teaching projects in the institution. A Project Officer was appointed to the Group to carry out the operational aspects of the project. The Group's remit was to research learning analytics, sector developments, develop a project plan, and provide senior level oversight to the project to feed into the development of a robust institutional strategy. In essence, they were steering and providing oversight to the activities used to capture the evidence which would inform the resultant strategy document. This group's responsibilities included:

- Overseeing the development of a strategy for the implementation of learning analytics at the University of Strathclyde
- Scoping current data sources and analysis tools existing within the University
- Researching the learning analytics field to identifying examples of effective use of learning analytics in the sector
- Designating data into three 'data levels' and formalising how each data level is used in the Institution
- Submitting an internal resource bid for project funding
- Participating in a Learning Analytics Readiness Assessment undertaken by Blackboard on behalf of Jisc
- Networking with other Institutions currently implementing or scoping learning analytics, such as the UK Open University and Jisc
- Identifying five pilot classes, one from each of the Institution's four faculties in addition to a class provided by the Organisational and Staff Development Unit (OSDU), to implement a learning analytics approach to provide proof of concept evidence to inform the finalised learning analytics strategy
- Establishment of a Learning Analytics Steering Group of key stakeholders to oversee the progress of the project and function as the Institution's on-going oversight of the use and development of learning analytics
- Recruiting a Project Officer, and supporting and steering the Officer in the management of the five pilot projects and the development of a learning analytics strategy
- Providing regular project updates to faculty, strategic learning and teaching committees and senior management
- Overseeing the mapping of how learning analytics can position itself to support, improve and provide evidence for key strategic documents produced by the University such as the University Strategic Plan 2015-2020, Scottish Funding Council Outcome Agreements, and Quality Assurance Agency for Scotland's Enhancement Led Institutional Review

4 DEVELOPING THE STRATEGY

The strategy was developed by the Project Officer, Deputy Director and Learning Enhancement Manager from Education Enhancement, with oversight and guidance provided by the DAPs Teaching & Learning for the University. The responsibilities of the Learning Analytics Strategy Group, and the research, analysis, and conclusions resulting from these activities, provided the information and evidence for shaping the resultant strategy document. This included the data level models, information provided in the Jisc/Blackboard Learning Analytics Readiness Assessment, the results, conclusions and recommendations based on the five pilot classes, the mapping of learning analytics to key strategic documents, and the initial vision of the impact learning analytics could provide to improve to our student body. The components of the final strategy document will be discussed in the presentation.

5 KEYS TO SUCCESS AND LESSONS LEARNED

The most notable success to date can be attributed to be the guidance, support and enthusiasm from senior levels of the University, and the DAPs in particular. These colleagues grasped the potential that implementing learning analytics could have in addressing improvement areas for the University such as student experience, curriculum flexibility, assessment, feedback, retention, operational excellence, and staff development. Their oversight has been a key driver in ensuring the success of the project.

A second factor contributing to success has been the team approach adopted, both in terms of the Strategy Group but also with the Steering Group. The Steering Group includes DAPs, academics, education managers, the project officer, a systems developer, University Librarian, a Business Intelligence Analyst from within the Strategy and Policy Directorate who manages the SUnBIRD system and, critically, the Student's Association Vice President Education, an elected student responsible for representing the study body on academic matters. This allows the Institution, along with other means, to ensure that Strathclyde students have a voice in determining the direction and implementation of the project.

Engaged staff was another key factor – the pilot classes were chosen to represent each faculty and OSDU, for their diversity, but also for their class leads. These faculty members were willing to dedicate time to ensure the pilot classes could run successfully, but also provide crucial feedback which helped shape the resultant strategy.

Another key to the success of the project was the principle that the student was kept at the heart of the project. Although the data analysis and the emerging technology is innovative and exciting, it was more important to have the focus of the project, and ultimately the strategy, on the impact that it would have for each individual Strathclyde student.

Any lessons learned? In this area, with the correct engagement from senior levels, and the involvement of expert professional colleagues, teaching faculty and our students, it is possible to achieve a desired outcome by dedicating relatively small resource. However, it is critical to have clear oversight and support from senior management supporting an effective team working together to achieve the outcome.

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Piloting Learning Analytics to Support Differentiated Learning through LearningANTS

Edna Chan
School of Mathematics and Science
Singapore Polytechnic
edna_chan@sp.edu.sg

Say-Beng Lai
School of Mathematics and Science
Singapore Polytechnic

May Lim
School of Mathematics and Science
Singapore Polytechnic

Ying-Ying Soh
School of Mathematics and Science
Singapore Polytechnic

Ah-Choo Tan-Yeoh
School of Mathematics and Science
Singapore Polytechnic

ABSTRACT: Students at Singapore Polytechnic (SP) have diverse mathematical aptitude. Academically-weak students need much hand-holding while academically-strong students may get bored if not inspired. It remains a challenge for any teacher to meet individual student's learning needs. SP piloted LearningANTS, a learning analytics system that supports differentiated learning, in a mathematics module in semester one of the 2016-17 academic year. Research at SP demonstrates that differentiated learning was supported and students using LearningANTS performed better when compared to those in traditional tutorial settings. Learning points gathered will be used to fine-tune the system for the next deployment which will benefit about 1,500 students.

Keywords: learning analytics, differentiated learning, teaching and learning

1 DEPLOYMENT

LearningANTS, a learning analytics system that supports differentiated learning, was deployed to replace the traditional tutorial in a bridging mathematics module. Students were encouraged to log into the system to practise online tutorial questions whenever each topic was covered in lecture, and use the system during tutorial for learning. The system diagnoses students' learning and recommends individualised learning schedules. Teachers are able to monitor both class' and individual students' performances to offer more effective help.

2 MOTIVATION

The School of Mathematics and Science at Singapore Polytechnic (SP) offers mathematics to all students in the institution. One of the challenges teachers face is to meet the diverse learning needs of students who come with varied mathematics aptitudes. On the one hand, we have students whose foundation in mathematics is very weak – some may not have taken any mathematics for two years prior to joining SP even if they enrolled in SP to pursue an engineering diploma[12] which requires good grounding in mathematics. On the other hand, we see mathematically strong students who are ever so ready to embark on advanced mathematics when they join the institution.

Our research question for this study: Could learning analytics support differentiated learning, and thus improve teaching and learning?

3 APPROACH

"Differentiated learning or instruction is a philosophy for effective teaching that involves providing students with different avenues to acquiring content; and to developing teaching materials and assessment measures so that all students within a classroom can learn effectively, regardless of differences in ability". (Tomlinson, 2001)

Halls (2002) explains that differentiated instruction facilitates the approach to "teaching and learning for students of differentiating abilities in the same class. The intent is to maximise each student's growth and individual success by meeting each student where he or she is… rather than expecting students to modify themselves for the curriculum."

While differentiated learning could be applied in terms of Content (what students learn), Process (how students learn) and Product (the end result of student learning), LearningANTS focused on differentiation in Content.

[12] Diplomas are 3-year post-secondary programmes offered by polytechnics in Singapore with the aim of training professionals to support the technological and economic development of Singapore. Polytechnic graduates could either join the industry or further their studies in a university upon graduation. For more information, refer to https://www.moe.gov.sg/education/post-secondary#universities

LearningANTS[13] is the product of a research collaboration between SP and its industry partner 3ELogic. The system was designed to leverage analytics to support differentiated learning. LearningANTS was deployed in a bridging mathematics module in semester one of the 2016-17 academic year where about 300 students were registered in the module. This bridging mathematics module is predominantly taken by students who are weak in mathematics, many of which may not have taken any mathematics for two years prior to enrolling at SP.

To study how LearningANTS supports differentiated learning, control and experimental groups were set up to compare the effectiveness of the system against traditional tutorials in the module. Immediately after lectures were delivered, a pre-test was administered. While the control group then continued with a traditional tutorial, the experimental group used LearningANTS as their tutorial. A post-test was then administered at the end of the semester.

For the experimental group using LearningANTS, learning topics were adaptively released to students based on a teacher-defined teaching plan. There were altogether up to four difficulty levels of learning achievement in LearningANTS – Beginner, Advanced Beginner, Competent, and Expert for each topic. Students' progression through the difficulty levels for each topic were dependent on their own ability. LearningANTS diagnosed students' learning and generated individualised learning schedules for each student following the teacher-defined learning plan.

Data collected of students' learning is automatically tracked and presented in a simple way to help students monitor their own learning. Students could review all the questions that they have attempted, and communicate with their teachers via a feedback feature in the system if they needed help with the questions. At the same time, teachers could monitor the learning progress of their class through the system. This facilitated the face-to-face tutorial sessions as teachers could then offer more targeted help to the class, for example, by going over questions with which a majority of the students had trouble, as well as diving down to help an individual student who was struggling to progress in the system.

4 FINDINGS

When the system was deployed during the pilot to the experimental group, we saw a utilization rate of 93.8%, or 153 students out of a total of 163 students who were invited to use the system. For the students who used the system, the system diagnosed and recommended additional learning topics to 111 students. This additional recommended learning corresponded to 437 lessons covering 20 different topics. Students attempted and leveled up at least one difficulty level for 98% of the 437 recommended lessons.

[13] The research on LearningANTS was funded under the Public-Private Co-Innovation Partnership funding scheme from October 2014 – Apr 2015, and October 2015 - present. Many features in LearningANTS were shaped by the findings of an empathy study that had been carried out with targeted users before system development.

We compared the average improvement between pre- and post-test for both the experimental group (153 students) and the control group (138 students) by setting up a hypothesis test (two-sample t-test) as follows:

$$\mathrm{H}_0 : \mu_{Experimental\ group} - \mu_{Control\ group} = 0$$
$$\mathrm{H}_1 : \mu_{Experimental\ group} - \mu_{Control\ group} > 0$$

Table 1: Comparison of results between experimental and control groups.

	Experimental	*Control*
Mean	7.58496732	4.579710145
Variance	155.8348383	134.3038189
Observations	153	138
Hypothesized Mean Difference	0	
df	289	
t Stat	2.1294372	
P(T<=t) one-tail	0.017031597	
t Critical one-tail	1.650143229	
P(T<=t) two-tail	0.034063193	
t Critical two-tail	1.968206436	

As shown in Table 1 above, the p-value of the test at 1.7% is less than 5% ($p < 0.05$), so we rejected the null hypothesis. Hence, there is significant evidence to suggest that the mean mark of the experimental group is more than the mean mark of the control group.

5 BENEFITS AND CHALLENGES

The benefits of learning analytics are manifold. With learning data automatically tracked, data can be visualised and analysed to gain insights into students' performance. In LearningANTS, this can be carried out at the class-, student-, topic-, concept-, and even question-level.

When the study was conducted, teachers were able to identify struggling students quickly. It was found that a good 25% of the students could not clear even the Beginner level. And only 40% achieved Advanced Beginner level or higher. Because solutions were provided for each question and Beginner level questions were supposedly simple, the fact that 25% attempted the questions but could not clear this level was surprising. It suggested that students not only lacked understanding of pre-requisite concepts identified by the system, teachers also learned that students had difficulty in understanding the step-by-step solutions provided in the system which teachers had initially thought were good enough and clear. This insight certainly narrowed down the areas in the module that needed to be further enhanced to better support the mathematically weaker students.

A good 7% of students achieved at least Competent level. Students who were mathematically more advanced did not have to be slowed down by their classmates in learning. They were able to self-regulate their own learning and progress to attempt more challenging questions to stretch their understanding of the topics. Expert level questions remained difficult for students. To address this steep learning curve, scaffolds such as hints could be added to the questions in the future.

Despite the benefits and affordances of learning analytics, some teachers found it a challenge to adopt learning analytics. One challenge shared was the lack of time due to a tight curriculum that prevented teachers from fully embracing learning analytics. To mitigate this challenge, we feel it is important to integrate learning analytics into the teaching and learning process. When it is part of the process, then the adoption will come naturally.

Another challenge surfaced was the lack of guidance in using analytics. For teachers new to analytics, training will need to be provided. Moving forward, the team will look at use cases to guide teachers more prescriptively on how learning analytics can be adopted to improve teaching and learning both within and without the classroom.

6 CONCLUSION

Through this study, we saw how learning analytics supported differentiated learning. Both students and teachers were able to leverage data to better monitor students' learning. From the data gathered, insights could be gained to further enhance module delivery as well as the design of LearningANTS to better support teaching and learning. Lessons learned from the study will fine-tune future roll-outs of the system to facilitate learning analytics and differentiated learning.

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Data-Supported Learning Design: A Customer Care Training Example

Tanya Dorey-Elias
Thompson Rivers University
telias@tru.ca

ABSTRACT: While working for a customer care company in 2011, the instructional design team was engaged to improve employee performance that was not meeting performance expectations. The company was at risk of losing a high-profile account with our largest client, putting thousands of jobs at risk. Our solution integrated current learning theory, work-related performance data, and learning/ training data from customer care centers to create a data-supported, scenario-based curriculum map. The instructional design team then developed and implemented scenario-based training (SBT) at five work sites in three countries. As a result, learning and performance outcomes improved dramatically.

Keywords: data-supported learning design, performance improvements, scenario-based training, outcome-based learning

1 INTRODUCTION

While working for a customer care company in 2011, the instructional design team was engaged to improve employee performance for an account not meeting performance expectations. Only 25 % of key metrics, including customer satisfaction, were being met at a time when the goal was meet at 75 %. The team undertook an ambitious plan to redesign the new hire curriculum using a data-supported approach to learning design and created what became known internally as Scenario-Based Training (SBT).

The SBT approach combined call volume data stored in the client's CRM, quality evaluations and a series of task analyses to identify the most critical elements and appropriate sequencing of those elements for training. The information gleaned from this was then joined with innovative learning theory to develop of a 26-day data-supported curriculum map and eventually to roll out of a completely new training approach.

1.1 Related Research

Combining early work related to data-informed learning design and learning analytics and several new learning theories formed a strong theoretical framework for this project. Armellini & Aiyegbayo (2010) and MacLean & Scott (2011) suggested the use of a data-informed approach to learning design. Elias (2011) proposed a model for learning analytics that aligns well with this project, seen in Figure 1.

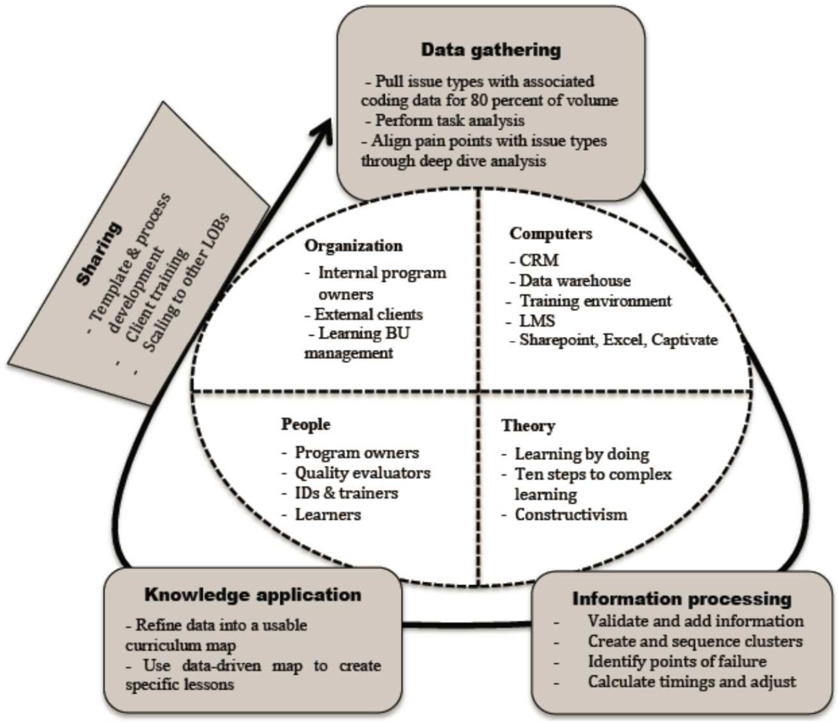

Figure 4: Learning analytics model (Elias, 2011) as applied to learning design

This project also drew heavily on two learning theories aligned with empirical learning research (NRC, 2000). Schank's (1999) Learning by Doing, and Ten Steps to Complex Learning (Kirschner & van Merriënboer, 2008) recognize the importance of context in learning.

Since then, Lockyer and Dawson (2013) have discussed the alignment of learning analytics and learning design and Rienties & Toetenel (2016) have "identified "the importance of learning design in predicting and understanding… performance of students," (p.333).

2 PROJECT DESCRIPTION

As in a typical learning design undertaking, the first step was to decide what the trainees needed to learn. Rather than relying on anecdotal feedback of trainers, focus groups with general questions and a review of the training curriculum, the instructional design team went straight to the data.

2.1 Data-Supported Curriculum Map Development

From a list of close to 400,000 customer interactions gathered over the previous six months, the team was able to pull accurate data related to the reason for calling down to the fourth level issue code (Figure 2).

Issue Code 1 (Program name)	Issue Code 2 (Sub-program)	Issue Code 3 (Customer Issue)	Issue Code 4 (Resolution)	Volume	Cummulative Volume	Cummulative percentage
Home Service	Tier 1 support	Balance Inquiry	Provide Balance	11452	11452	2.9%
Home Service	Tier 1 support	Payment Confirmation	Payment Confirmation	11311	22763	5.8%
Home Service	Tier 1 support	Payment Inquiry	Provide Payment options	11254	34017	8.6%
Home Service	Tier 1 support	Payment confirmation	Upgrade existing service	11118	45135	11.4%
Home Service	Tier 1 support	Add additional services	Add outlets and wire plan	11051	56186	14.2%
Home Service	Tier 1 support	Promotions	Add another LOB	10885	67071	17.0%
Home Service	Tier 1 support	Cancel/Reschedule change of	Reschedule change of service	10845	77916	19.7%
Home Service	Tier 1 support	Billing inquiry	View online and provide due date	10725	88641	22.4%
Home Service	Tier 1 support	Billing inquiry	Explain packages, taxes and fees	10492	99133	25.1%
Home Service	Tier 1 support	Billing inquiry	Explain proration and one-time charges on	8854	107988	27.3%
Home Service	Tier 1 support	Customer rolling off promotion	Educate and offer a new package	8774	116762	29.5%

Figure 5: Sample of issue codes pulled from client CRM

Using a Pareto chart, 59 scenarios accounted for 80 % of the volume handled by staff were identified. These are the scenarios that served as the starting point of our curriculum map (Figure 3).

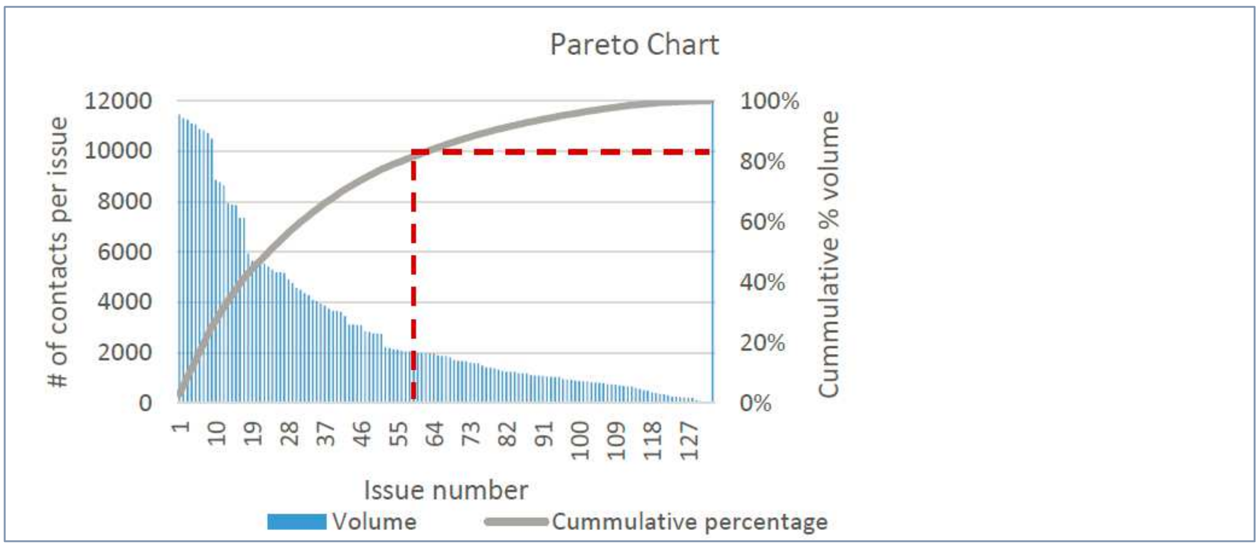

Figure 3: Pareto chart of call volumes by issue type

The instructional design team then documented the steps required to resolve each issue type, identifying the tools and systems required as well as any relevant regional variation to process or customer information (Figure 4) which allowed us to better understand the relationship between tasks. For example, "checking the billing ledger" was a task that was repeated in many scenarios so it could be introduced in a short learning "breakout session," a trainer-facilitated targeted discussion or practice session of 10 to 30 minutes in length, in the first scenario it was required and then practiced in subsequent scenarios.

Call Driver	Resolution	Task/Learning Opportunity (Per Process Document [?])	Related Tool/Resource	Market Variation - Process (Y/N)	Market Variation - Information (Y/N)
Credit issues	Correct previous adjusment	Check the notes on the customer's account.	Billing Tool/ CRM	Y	N
Credit issues	Correct previous adjusment	Check the billing ledger or the Exact View of the Bill.	Billing Tool/ CRM	Y	N
Credit issues	Correct previous adjusment	Review and correct previously apply credits	Billing Tool/ CRM/ Knowledge base	Y	Y
Credit issues	Correct previous adjusment	Process the appropriate credit	Billing Tool/ CRM/ Knowledge base	Y	Y

Figure 4: Example of task analysis completed for each of 59 scenarios

The next step was to sequence the scenarios from the simplest to the most complex and integrate additional learning breakout sessions at specific points of failure that had been identified during a recent quality assurance analysis. We also developed a formula to calculate the length of each lesson that took into account the target call length on the program, the number and length of breakout sessions and a coaching debrief session (Figure 5).

Scenario	Scenario-Specific Skills and Tasks	Knowledge of Product & Service		Non-scenario specific		# Scenario-Specific	# Non-Scenario-Specific	Total Timing (onshore)	Total Timing (offshore)
Frozen screen	Check connections	Advanced and alternate connections	30.00	Reinforce to customer how loose cables impact picture	15.00	1.00	1.00	85.00	100.00
No picture	Verify types of connection	Sales	45.00	Reasoning/ structured approach	20.00	1.00	1.00	105.00	120.00
Known video issue	Test the box	Common video problems	30.00	Test a repair	15.00	2.00	2.00	100.00	130.00
On demand	Use on demand tool			Leave out jargon	30.00	1.00	2.00	70.00	100.00
Missing channels	Check status Educate reps on how to close work order to enable access	PPV Premium channels	70.00	How additional products can be used as a solution	20.00	2.00	1.00	145.00	160.00
Outages	Set expecatations with respect to an outage					1.00	0.00	40.00	40.00

Figure 5: Example of draft data-supported curriculum map

2.2 Curriculum Map Validation

During validation, the instructional design team sometimes disagreed with our business partners. Sometimes, they felt that employees "needed" to know something, for example a legacy tool. Upon further inquiry however, they could only identify 1-2 rare opportunities when it would be used. In this case, the data helped to identify and challenge historical beliefs about what needed to be included in the training.

For upcoming business changes however, the data needed to be supplemented by human expertise. New products, and their resulting support issues, were not included in historical data. Other issue types, including misrouted calls and transfers were excluded from the data reviewed because of how they were coded but did need to be trained. The program experts provided business insight that the data lacked.

By the end of the validation process the team had a well-crafted, data-supported curriculum map that took only a few weeks to create.

2.3 Implementation

Using the data-supported curriculum map, content for each scenario was assigned and developed. A modular development approach to the scenario and skill training helped support portability of much of the training between businesses (an example can be shared during the presentation).

Many training tools and processes needed to be rewritten including the previous assessment tools. The instructional design team settled on an approach that combined use of scenario-based multiple choice questions and performance-based assessment (Figure 6). In another project the instructional design team correlated assessment scores to performance metrics to improve our assessment tools.

Assessment Type	Assessment Name	Number	Approx. Timing	Pass Criteria	Measurement Tool
Knowledge Check	Gate	9	Every 2 days	85% on > 7	MC questions tied to key failure points
Tollgate	Mid-term mock call	1	Middle of training	60%	Modified quality form (focus on key criteria)
Tollgate	Live call certification	1	Days 2 & 3 of transition	80%	Modified quality form (focus on key criteria)

Figure 6: Scenario-based assessment strategy

After six months of design and development, we ran a pilot with five classes that was followed by a full scale implementation.

3 RESULTS

Trainees using the SBT training outperformed trainees who attended the legacy training as seen in the pilot comparisons. Fairly consistently two interesting trends emerged (Figure 7).

- Trainees who attended SBT training showed slightly better performance in their first 30 days, but also continued to improve at a faster rate than those who completed the legacy training from 31-60 days (Red arrows).
- Trainees who attended a class taught by a trainer who had already taught one or more SBT class performed better than trainees whose trainer was teaching SBT for the first time (Orange arrow).

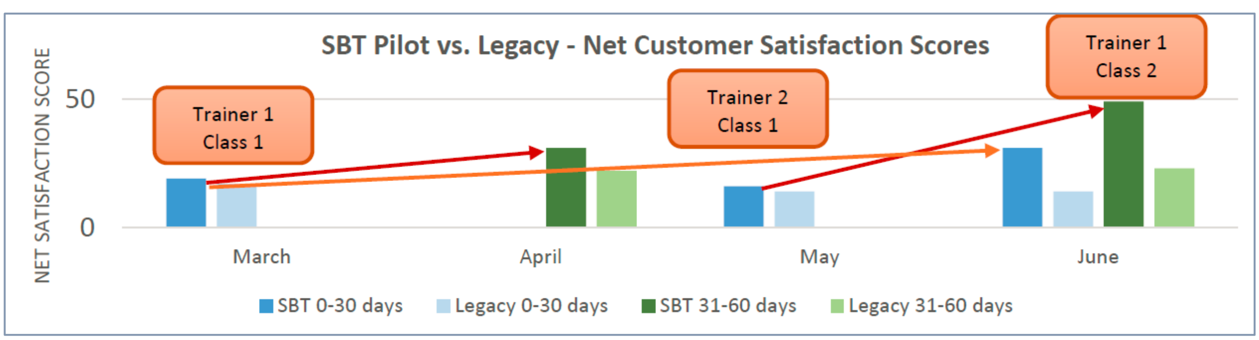

Figure 7: Faster rate of performance improvement in the first 60 days

Based on the positive early pilot results, a full scale roll out of the new training began and similar performance improvements were seen program wide. Net customer satisfaction scores more than doubled. Repeat caller rates dropped by over two points (Figure 8).

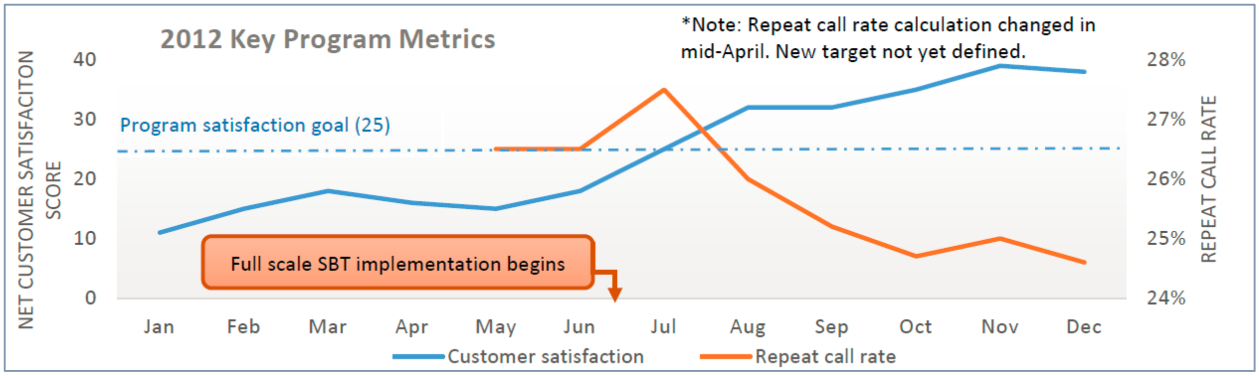

Figure 8: 2012 Key program metrics

By January 2013, six months after the full scale implementation of SBT, over 60 % over key account metrics were being met, up from 25 % in January 2012. By 2015, the client had developed and rolled out training based on these principles to all vendors and they saw strong results and continue to use the approach today.

Internally, these results caught the attention of several members of the senior leadership. Within the next two years, all four of our top clients had agreed to proceed with the development of SBT new hire curricula. Since then data-supported, scenario-based approaches have become an integral part of the learning & development strategy.

Beyond large scale curriculum redesign projects, the tools and approaches developed were also rapidly adopted by individual instructional designers, trainers and operations managers when addressing smaller scale learning, training and performance issues. Ultimately, this points to a cultural shift in the way learning, training and performance improvement were addressed company wide and beyond.

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Identifying Non-Regulators: Designing and Deploying Tools that Detect Self-Regulation Behaviors

Mary E. Pilgrim
Colorado State University
mpilgrim@rams.colostate.edu

James E. Folkestad
Center for the Analytics of Learning and Teaching
Colorado State University

Ben Sencindiver
Colorado State University

ABSTRACT: Calculus I is a gateway course, which commonly contributes to the loss of students in the STEM pipeline. The persistence of this problem is partially supported by the inability to identify those students who will struggle, so that appropriate intervention can occur early in the semester. We hypothesize that self-regulated learning (SRL) behaviors play a key role in identifying students who will be at risk. In this paper we describe the implementation of digital objects that were designed to collect evidence of SRL. We discuss our decision to utilize existing development tools, challenges of such an approach, and initial outcomes.

Keywords: self-regulated learning, evidence centered design, mathematics education, design, behaviors, video, digital objects

1 INTRODUCTION

Mathematics is foundational in Science, Technology, and Engineering, and an in-depth understanding and high level of proficiency in mathematics is needed in order to be successful in such disciplines. Calculus I has been and continues to be a key gateway course for Science, Technology, Engineering, and Mathematics (STEM) programs. However, poor experiences in and ill-preparedness for Calculus I often contribute to a significant loss in STEM majors (Bressoud & Rasmussen, 2015; Seymour & Hewitt, 1997; Sonnert & Sadler, 2014).

2 DESIGNS AND DEPLOYMENT OF DIGITAL LEARNING OBJECTS TO DETECT SELF-REGULATED LEARNING

Weaknesses in Precalculus frequently create challenges for Calculus I students – preventing them from being successful in the course (Agustin & Agustin, 2009). Algebra, trigonometry, and other precalculus topics are heavily used in Calculus I, and understanding this content is necessary for success in Calculus I.

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Further, students are arriving at postsecondary institutions with mathematical deficiencies in Calculus I prerequisite knowledge, even when there is evidence that they have previously taken Precalculus or Calculus I (Sonnert & Sadler, 2014). This is consistent with what we are seeing at our institution – students who enter Calculus I with less than a B in Precalculus have about a 30% chance of passing with a C or better.

To address this problem, we have designed digital objects that encompass Calculus I prerequisite content which can help us detect self-regulated learning (SRL) behaviors. Data from these digital objects are collected and analyzed to better understand student behavior. Ultimately, the purpose is to identify at-risk students early in a semester so that an actionable response can be provided. Such responses could be a recommendation for a change in enrollment to a stretched Calculus I course or attendance to a study skills workshop.

Early identification has been challenging. Predictive models based on historical student data (e.g., high school GPA, entrance exam scores) misclassify many students. We hypothesize that student behaviors, particularly those related to their self-regulation with prerequisite knowledge, may help improve our models. In this pilot project we deployed digital objects designed to capture SRL behaviors. To check the validity of the detected behaviors, we report the relationship to students' self-reports on study habits and related SRL competencies.

3 THEORETICAL FRAMEWORK AND DESIGN

Calculus I students often cannot identify mistakes in their work, why the mistakes exist, nor how to correct them. Additionally, they typically do not know how to change their approaches to learning to address these problems (Zimmerman, Moylan, Hudesman, White, & Flugman, 2011). SRL is a cyclical process through which students develop an understanding of their learning processes so that they can modify their learning behaviors to improve deep learning and transform that learning into academic performance (Zimmerman, 2000; Zimmerman, 2002). Evidence supports the notion that students who self-regulate their learning behaviors perform better in courses (Caprara et al., 2008; Zimmerman, Moylan, Hudesman, White, & Flugman, 2011; Zimmerman, 2008).

For design of digital objects, we drew upon Zimmerman's (2000) SRL process model, which consists of three phases: forethought, performance, and self-reflection. Figure 1 provides an illustration of digital objects and how they fit within these phases. For forethought, we designed a self-assessment implemented through the Learning Management System (LMS) in which we asked students rate their confidence in ability to answer specific precalculus items. For performance, we designed a precalculus content quiz asking them to answer precalculus questions. Following the content quiz, we gave students a planning tool asking them to detail their plan for addressing any identified prerequisite gaps or weaknesses from the content quiz. We collected responses and evidence of usage from each of these tools on individual students in an effort to identify SRL behaviors. Additionally, we developed videos as a resource for improving their precalculus knowledge and skills. Figure 2 provides a screen shot of a prerequisite video implemented through the LMS.

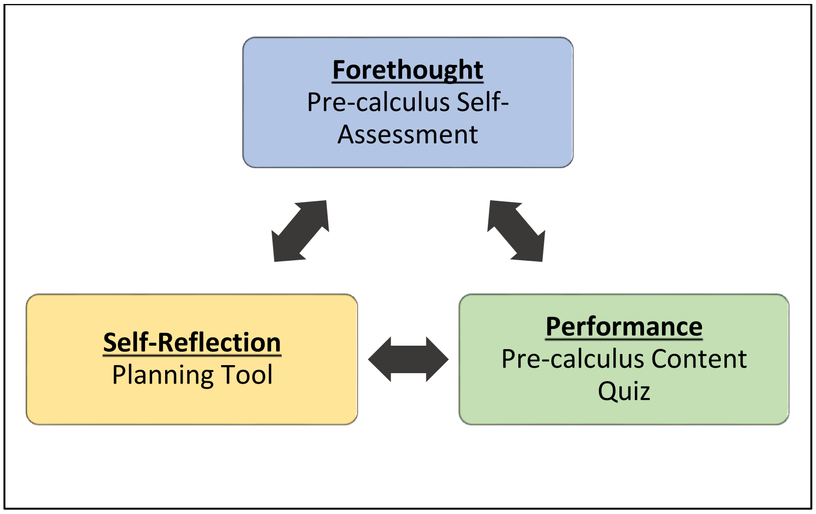

Figure 6: Data tools supporting the self-regulated learning process

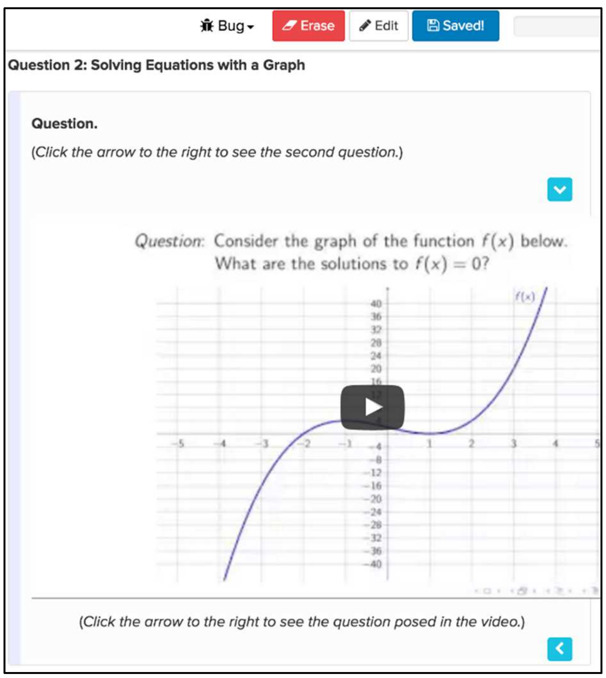

Figure 7: Precalculus video embedded in online homework through the LMS

4 ADAPTATION OF TOOLS: FACTORS OF SUCCESS

Our intention was to adapt existing tools, over which we had control and for which usage data was available. Therefore, we designed the precalculus self-assessment (SA), precalculus content quiz (CQ), and the planning tool (PT) using the our LMS quizzing tool. In addition, we created precalculus instructional videos and organized in-person help sessions. Our designed digital objects were deployed during the first two weeks of the course. Student responses and engagement with resources were categorized for each digital object in the following ways:

SA: High confidence, low confidence, or did not use

CQ: High performance, low performance, or did not use

PT: Used or did not use

Precalculus study materials or help session: Used/attended or did not use/attend

An SRL score (between 0 – 100) was then generated for each student based on their behavioral engagement with the SRL tools and study materials. Students were placed into the High SRL group (SRL score 50 or higher) or Low SRL group (SRL score below 50). For example, poor-performing students who did not seek help received a lower SRL score than poor-performing students who did seek help.

5 OUTCOMES: COMPARING BEHAVIORS TO MSLQ SELF-REPORTS

In an effort to determine if our digital objects were detecting SRL behaviors, we administered specific subscales of the Motivated Strategies for Learning Questionnaire (MSLQ), a self-report instrument designed to measure students' motivation and SRL (Pintrich, Smith, García, & McKeachie, 1991). We selected the following subscales of the MSLQ which quantifies how students:

1. Master tasks (self-efficacy)
2. Apply previous knowledge to new situations (critical thinking)
3. Plan, monitor, and regulate awareness, knowledge, and cognition (metacognitive self-regulation)
4. Control effort and attention in the face of distraction (effort regulation)
5. Manage and regulate study environment (time and study environment).

In the first two weeks of Calculus I, 343 of the 401 consenting students took the MSLQ. Of the 343 students who took the MSLQ, 279 were identified as having a high SRL and 64 were identified as having a low SRL. Independent-sample *t*-tests were conducted to compare High and Low SRL groups and MSLQ self-assessment scores. There was a significant difference between groups on all subscales, which can be seen in Table 1.

Table 1: Independent *t*-tests for students with high and low SRL scores on MSLQ items.

MSLQ Subscales	High SRL Group N=279	Low SRL Group N=64	Statistics
Self-Efficacy	M=5.298	M=4.931	$t(341)=2.644^{**}$ Small-Medium effect size (d=0.37)
Critical Thinking	M=4.215	M=3.737	$t(341)=3.081^{**}$ Small-Medium effect size (d=0.43)
Metacognition Self-Regulation	M=4.728	M=4.315	$t(341)=3.883^{***}$ Medium effect size (d=0.54)
Effort Regulation	M=5.643	M=5.285	$t(341)=2.885^{**}$ Small-Medium effect size (d=0.40)
Time and Study Environment	M=5.376	M=4.988	t(341)=3.376** Medium effect size (d=0.47)

Notes: $^{**}p<0.01$, $^{***}p<0.001$

Expanding our data analysis further, we found a correlation (Pearson's correlation coefficient) between SRL score and Exam 1 in Calculus I ($r(396)=0.108$, $p=0.032$). Although the effect was small we are encouraged that we are seeing positive SRL behavior related to class performance.

6 IMPLEMENTATION AND CHALLENGES

Adapting existing tools to collect evidence of SRL behavior was challenging. Using our LMS's quiz tool we were able to collect evidence of students' SRL engagement. This method allowed us to obtain evidence of use but did not allow for more nuanced evidence of behavior over time. We are currently working to extract and analyze timestamp data, which will allow us to understand when students used each tool.

In addition, we ran into obstacles with the video technology to which we had access. We had used Zaption to build interactive precalculus study content, which was integrated into our LMS. Unfortunately weeks before the semester began, Zaption was no longer available to us. We have since moved to open source platforms over which we have more control and access to data.

7 DISCUSSION: SOLVING A PERSISTENT PROBLEM

High failure rates in Calculus I have been a persistent problem due, in part, to the inability to identify at-risk students early in the semester. We believe that early identification will be possible if we think critically about the design of digital objects. Despite challenges, we are encouraged by the results that show a significant relationship between student behaviors and validated SRL self-report measurements.

We will continue to work with open-source platforms, which provide us with control to develop, design, and implement digital objects for which we control the data. We plan to improve upon design and deployment, data collection processes, and analysis methods. Connections between responses and timestamp data will allow for richer understanding of learning events. We can determine whether students are addressing specific deficiencies and exactly how they are doing so, which will improve our SRL behavioral metric. This fine-grained detail will allow for improvements upon existing digital objects and development of new digital objects.

As we advance our understanding, we believe that we can intervene with instruction to improve SRL behaviours and, subsequently, performance. We theorize that these behaviors will improve performance for at-risk students in Calculus I, and potentially transfer to other disciplines.

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Relationships Between Digital Measures of Student Engagement and Exam Scores: Is the LMS Enough?

Perry J. Samson
Department of Climate and Space Sciences and Engineering
University of Michigan
samson@umich.edu

Alex Czarnik
School of Information, University of Michigan

Melissa Gross
School of Kinesiology, University of Michigan

ABSTRACT: What aspects of a student's digital participation in a course best predict academic success in that course? Participation data was obtained from LMS clickstreams, an in-class student response and note-taking system and the university's student information system for multiple courses at the University of Michigan. Statistical analyses show that several measures of participation including in-class activity participation and number of slides viewed were significantly related to exam scores. Moreover, these relationships remained consistent between courses. A student success model developed to predict who would score less than 70% on exam scores in each course demonstrated an accuracy of 77%.

Keywords: student behavior, student exam grade, student information system, student engagement, incoming GPA, exam grade, student success, digital measurements

1 WHAT'S IN YOUR CLASSROOM?

Large survey courses, often vilified as the anathema of educational environments, nonetheless continue to be commonplace. Their persistence in education is driven more by institutional economics than pedagogical design and, for that reason, are likely to remain a staple of college education for some time to come. Moreover, the trend towards use of massively on-line courses represents an expansion of the challenges already suffered in large face-to-face courses. As class sizes increase, instructors are now being asked to attend to the needs of a much broader spectrum of ability, learning and study skills, prior learning and educational goals.

Several Early Warning Systems (EWSs) have been developed that harness the predictive power of Learning Management System (LMS) and Student Information System (SIS) data to identify at-risk students and allow for more timely pedagogical interventions (Aguilar et al., 2014; Beck & Davidson, 2001; Fritz, 2011; Krumm et al., 2014; Macfadyen & Dawson, 2010). Wang & colleagues (Wang & Newlin, 2000, 2002) proposed that data on student online activity in a web-based LMS may provide an early indicator of student academic performance. Campbell and others (Campbell & Oblinger, 2007; Goldstein & Katz, 2005) found a strong relationship between LMS usage patterns and student exam scores. Many of these systems rely on models developed from the analyses of a combination of SIS, LMS usage data and LMS reported grades.

Recently it has been argued (Waddington et al., 2016) that EWSs would benefit from the incorporation of relevant data about student behaviors into the algorithms underlying EWSs to improve predictors of students' success or failure. They found that students who used exam preparation resources to a greater degree than their peers were more likely to receive a final grade of B or higher. In contrast, they showed that students who used less than their peers were less likely to receive a final grade of B or higher.

This paper identifies to what degree it is possible to predict student success based either solely on student behaviors or a combination of student behavior and student background, including past academic success. As it is unclear whether early warning systems that use exam and quiz results provide feedback early enough for effective interventions we hope to quantify to what degree in-class student behavior data can be used to decrease the time to identify students at risk of failure.

1.1 Environment

This research is based on data from five instances of two survey courses over three semesters at the University of Michigan (Table 1). The two courses studied were CLIMATE 102 and MOVESCI 230, the former taught by three different instructors, the latter by one instructor both semesters. These courses used both the LMS and the Echo360 system.

Table 1: Number of students in courses used in this study (W=Winter, F=Fall).

	SEMESTER		
COURSE	**W15**	**F15**	**W!6**
CLIMATE 102	188	238	198
MOVESCI 230	-	85	98

CLIMATE 102: Extreme Weather

CLIMATE 102: Extreme Weather is a survey course for non-majors that meets "science distribution" requirements at the University of Michigan. The course introduces the physics of extreme weather events with emphasis on how extreme events may be affected by a changing climate. The course is taught in a hybrid manner offering both face-to-face and remote synchronous participation. There are three hourly exams over the semester, each covering one-third of the content.

MOVESCI 230: Human Musculoskeletal Anatomy

MOVESCI 230: Human Musculoskeletal Anatomy focuses on functional anatomy of the human musculoskeletal system. Students learn the names and major landmarks of the major bones, the structure and kinematic characteristics of the major joints, as well as the names and functions of all the major muscles in the human body. The course is taught in a hybrid manner offering both face-to-face and remote synchronous participation. There are four hourly exams over the semester, each covering one-fourth of the content.

1.2 Data Collection

Over the last five years, the University of Michigan has made strategic investments in a series of digital engagement tools. One of the tools, LectureTools, was developed with a suite of in-class functions including a web-based student response system, on-line note taking, and tools for students to pose and answer questions and indicate confusion. LectureTools was commercialized and integrated into Echo360's Active Learning Platform[14]. The Active Learning Platform records data on student engagement before, during and after class that is differentiated from data recorded by the LMS in that it identifies how students interact on a class-by-class basis and includes a broad set of measures including participation in

Table 2: Data from student information system (SIS), learning management system (LMS) and Echo360 student engagement system used in this study.

SIS	LMS	Echo360
Gender	# Uses of Announcements Tool	# Activities Correct
Incoming GPA	# Uses of Assignments Tool	# Activities Points Possible
SAT Math Score	# Uses of Courses Tool	# Activities Participated
SAT Total Score	# Uses of External Tools	# Participation Points Possible
ACT Score	# Uses of Files Tool	Student Attendance
Student Year	# Uses of Gradebooks Tool	# Notes Taken
Section Instructor	# Total Uses of Tools	# Uses of Echo Notes Tool # Uses of QnA Tool # Questions Asked or Questions Answered # Slide Deck Viewed # Slide Deck Views # Uses of Slide Note Tool # Uses of Slide Question Tool # Slides Viewed # Uses of Video Confused Tool # Uses of Video Note Tool # Uses of Video Question Tool # Videos Viewed # Video Views Percentage of Activities Correct / Activity Points Possible Percentage of Activities Participated / Participation Points Possible

[14] The Echo360 *Active Learning Platform* (http://www.echo360.org) used in this study includes technology and the pedagogical underpinnings of LectureTools for which the P.I. was a co-creator.

class discussions, participation and correctness in student response opportunities, number of words of notes typed and how often and for what duration lecture captures are viewed (Table 2).

For this investigation data was collected from three sources:

- Instructure Canvas LMS,
- Echo360 Active Learning Platform, and
- University of Michigan Student Information System

and processed in two stages:

- First, we developed a digital portrait of participating students drawing on all digitally mediated interactions. This portrait required combining data about background from student record systems with information about in-class behavior, performance, and affect from the Instructure *Canvas* LMS and the Echo360 *Active Learning Platform* into a common database with student identity removed.

- Second, we put that portrait to use by creating models that predicted students' exam grades. The modeling was performed weekly, starting before the semester began when all that was available was student background and past success data. As the semester progressed data on their behaviors in class were added to see how these data affected our ability to predict exam scores. Based on other work at the University of Michigan (Huberth et al., 2015) we expected that some skill in forecasting student grades exists based solely on a student's past level of success and that the skill in forecasting will be improved by monitoring students' behaviors in specific courses.

2 DATA PREPARATION

Clickstream data for the LMS were obtained through the university's liaison with Instructure. The clickstream data were quantified per student per action (e.g. how many times a student visited the gradebook over a semester). Data from Echo360 was downloaded directly from the Echo360 dashboard. Data from the University of Michigan Student Information System contains a broad suite of parameters associated with students' background and records at the University of Michigan[15]. Data for the courses studied in this paper were obtained from (**LARC**), which provides an aggregated, extensible portrait of student activities, and goes substantially beyond those available through the LMS (LARC, 2016).

[15] http://bit.ly/UM_LARC

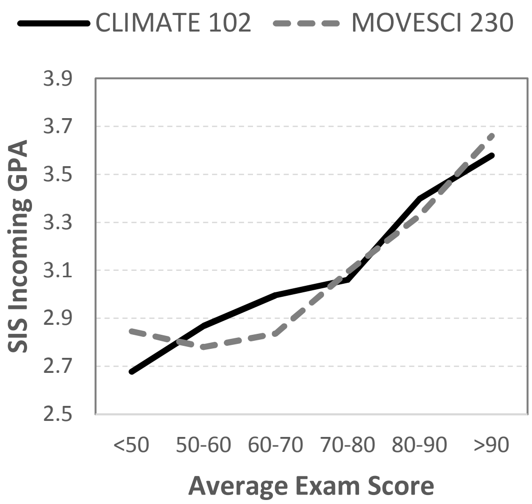


Figure 1a: Average incoming Grape Point Average versus average exam score

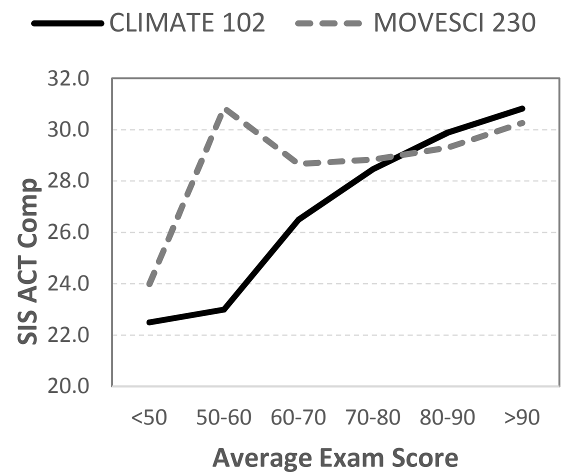


Figure 1b: Average ACT score versus average exam score

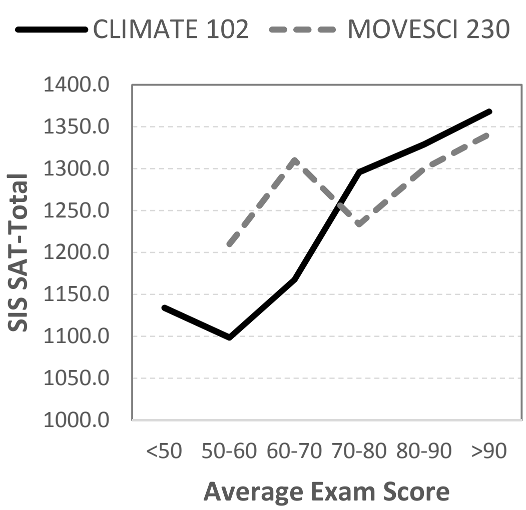


Figure 1c: Average SAT-Total score versus average exam score

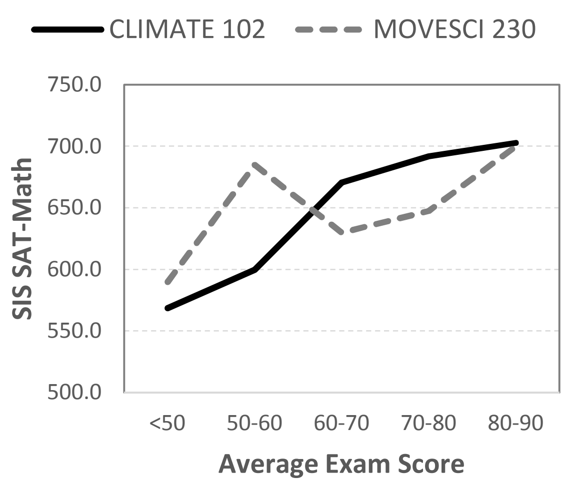


Figure 1d: Average SAT-Math score versus average exam score

Scripts were written to combine background and behavioral data based on students' email addresses. Once combined the emails were replaced with a key to minimize the potential for student identity to be exposed in the data. Keys and email combinations were stored separately, unavailable to data analysts.

3 RESULTS

3.1 Student History and Grades

Several authors have identified the relationship between past and future academic success. In the two courses studied here this relationship was quite clear. Figure 1a-d respectively shows the positive relationship between incoming GPA, ACT, SAT-Comp and SAT-Math scores and average exam grades for CLIMATE 102 and MOVESCI 230. These measures of past academic success were not available for all students (e.g. 1st semester students in CLIMATE 102 would not have had an incoming GPA, and not all students have SAT or ACT scores). Nonetheless, for those who did have records of prior measures of academic success a general positive trend existed regardless of measure.

Such results are not necessarily surprising but they are disheartening in that it illustrates that students with poorer records of past success have been less likely to succeed in (at least) these subsequent courses. The results in Figure 1 beg the questions:

A. To what degree do student behaviors relate to grades?

B. If they do, to what degree do students with poorer histories of performance behave differently than the rest of the students?

3.2 Student Behaviors and Grades

Students' relationships between digital behaviors and exam scores were explored individually for the two courses after combining all data over multiple semesters. For each section of each course an average exam score was calculated after normalizing exam scores to 100-point scale.

A few parameters were found to be consistently related to exam grades. This included the percent correct of formative assessment questions posed during class. Figure 2 shows that while this relationship varies between the two courses studied a positive relationship exists regardless of class (and, not shown, class instance). This is not surprising as students who do well on in-class assessments are likely to do well on summative assessments. Nonetheless, when building a model for forecasting student success on exams measures of correctness on formative questions appears to be a strong predictor.

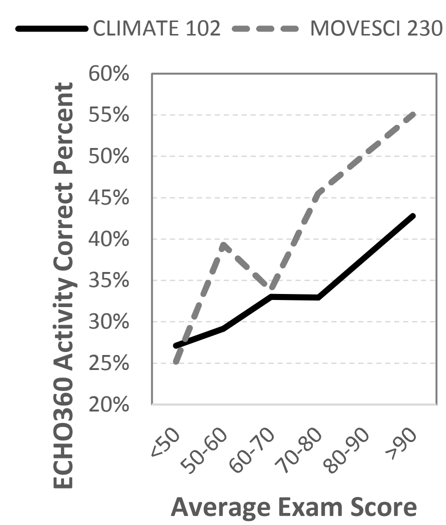


Figure 2: Average percent of in-class questions answered correctly as a function of average exam scores

Another parameter that was related to exam grades was "Slide Views." Slide views counted the number of times a student viewed a slide in Echo360 during or after class (a measure of attentiveness as the student needed to manually switch to navigate through slides during or after class). Figure 3 shows that slide views were positively related to exam grades. The difference in the two courses is because the MOVESCI 230 course offered about twice as many slides over the semester as CLIMATE 102.

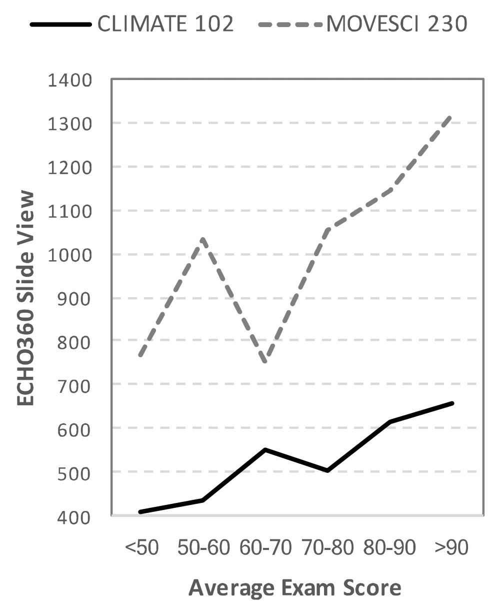


Figure 3: Average number of slide views as a function of average exam scores

Another consistent pattern was found for participation. Participation in these two courses was measured as having logged-into the Echo360 system during class and performing at least a couple of tasks (answering questions, note-taking, asking questions). Hence "attendance" includes those student participating remotely in a synchronous manner. Given this definition no relationship was found for either course as shown in Figure 4. The numbers for CLIMATE 102 are higher as that course meets three times a week for 50-minutes each while MOVESCI 230 meets only twice a week for 80-minutes each.

Student behaviors in the LMS (Table 2) were also included in the analysis but these showed little relation to exam grades as shown in Figure 6

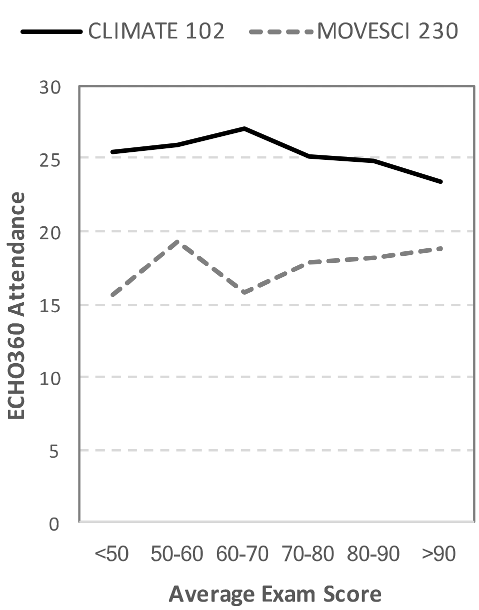


Figure 4: Average attendance as a function of average exam scores

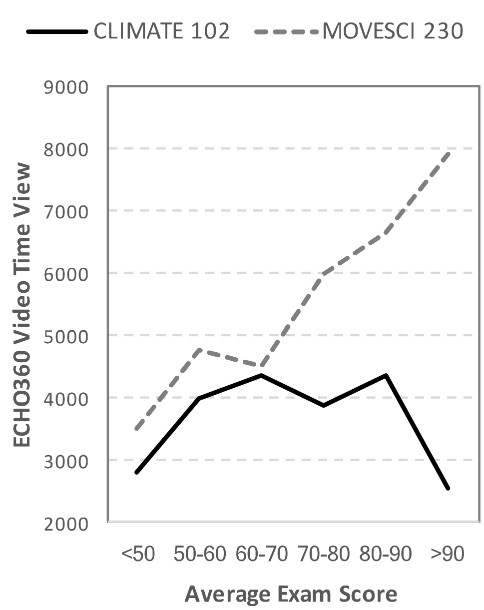
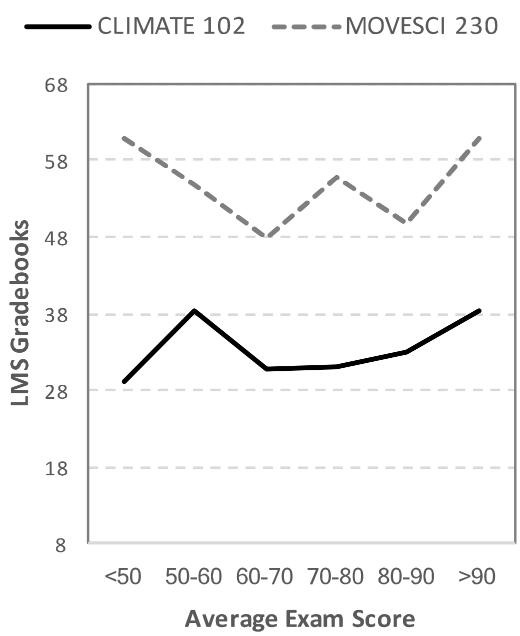


Figure 5: Average lecture capture video time viewed as a function of average exam scores



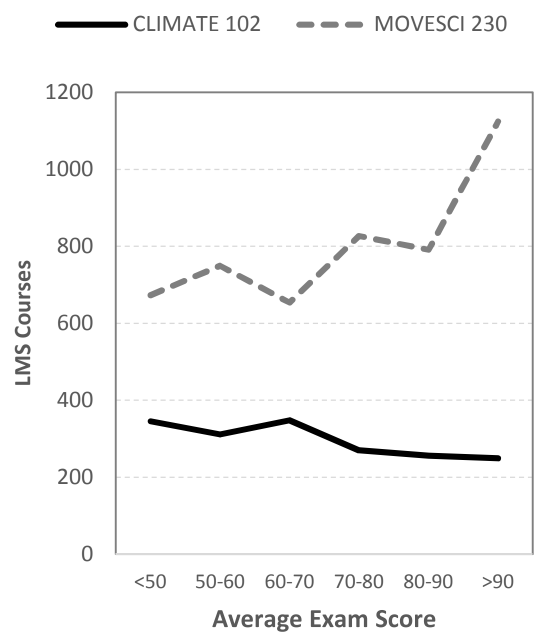


Figure 6a: Average clicks on "gradebook" links in the LMS as a function of average exam scores.

Figure 6b: Average clicks on "course" links in the LMS as a function of average exam scores

On the other hand, other parameters were not consistent between these two courses. The "Video Time Viewed" available from Echo360 measures the time spent viewing lecture captures. Figure 5 illustrates that MOVESCI 230 exhibited a positive relationship between viewing video and grades, CLIMATE 102 did not. It is hypothesized that, as a survey course open to a wide range of students, CLIMATE 102 material did not require the level of review for many of its students that a course focused on those entering a related major might require.

3.3 Modeling Student Success

The results illustrated in Section 3.2 identified relationships between student behaviors and exam grades. A random forest model was created using 65% of the available data from the five courses to relate exam grades with data in Table 2. The increase in mean square error attributable to each term, shown in Figure 7, illustrates the gain in Mean Square Error (MSE) if the data were unrelated to exam grades. In Figure 7, for example, this means that if the "ActivitiesCorrectPercent" were truly random this would increase MSE by about 17%. Consequently, the greater the increase in MSE the greater the importance of the behavior.

The relationship between "Activities Correct Percent" and grades is not surprising as one would assume that if a student knew the answers during class they would likely know the answers on the exam. "Slide Deck View Count" is a measure of reflection as it measures how many times the presentation has been viewed by a user. "Slide View" is a measure of how many slides the student viewed (students must

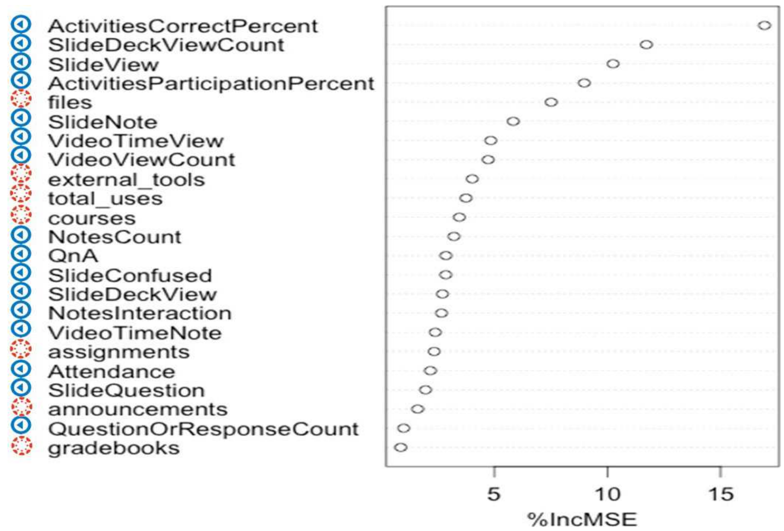


Figure 7: **The percent increase in mean square error attributable to terms from Table 3 where terms from the LMS are noted with and terms from the in-class tool noted by . The term with greatest influence was the percent of activities a student answered correctly in class.**

manually advance slides during class) and is hence a measure of attentiveness. "Activity Participation Percent" measures participation as the percentage of activities answered by a student in class.

OK, so this analysis is based on building a random forest model and the higher the value, higher the variable importance? And thre random forest is computed through permutations of a decision tree that tries to find the best fit to available data?

To find the best fit, the variables listed in Table 2 were used in two different classification techniques, Linear Discriminate Analysis and Classification Tree Analysis. To test the accuracy of these models, the data was split into two subsets, train and test data sets. The training data set was composed of 65% of the original data set, while the testing data was composed of the remaining 35%. Each methodology used the training set to teach the model, which was then leveraged to predict the testing data exam grades. Once the data sets were ready, a classification qualifier was created to distinguish whether a student would pass or fail the class. This qualifier assumed that a student required a C- (70%) or better to pass the course. The results showed that we could accurately forecast student success or failure with about 77% accuracy before the first exam based on the inclusion of in-class student behavior data.

The model used to calculate Table 3 included three terms: "Activities Correct Percent", "Slide Views" and Incoming Grade Point Average (GPA). In the simulation shown in Table 3 the model produced about an 84%

Table 3: Skill at forecasting which students would receive a grade higher or lower than 70% on the first hourly exam based on measures of digital behaviors prior to the first exam.

		Actual	
		Fail	**Pass**
Predicted	**Fail**	17	3
	Pass	14	71

accuracy. Next we removed incoming GPA from the regression and found that when we used just "Activities Correct Percent" and "Slide Views" without incoming GPA we could still forecast student success and failure (above or below 70% on the first exam) but our skill dropped from 84% to about 70% correct.

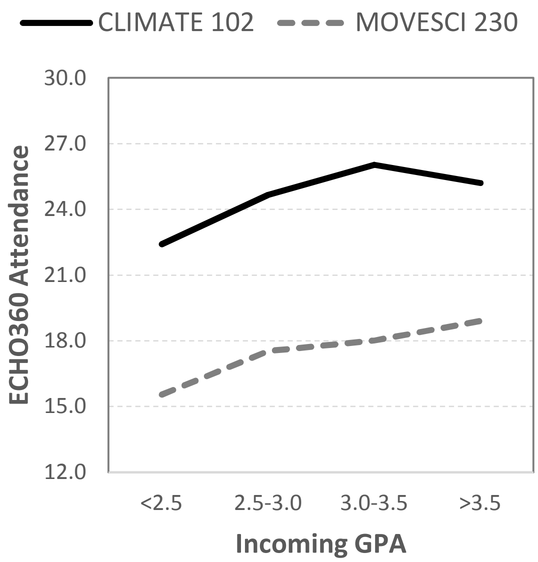


Figure 8a: Class attendance as a function of incoming GPA

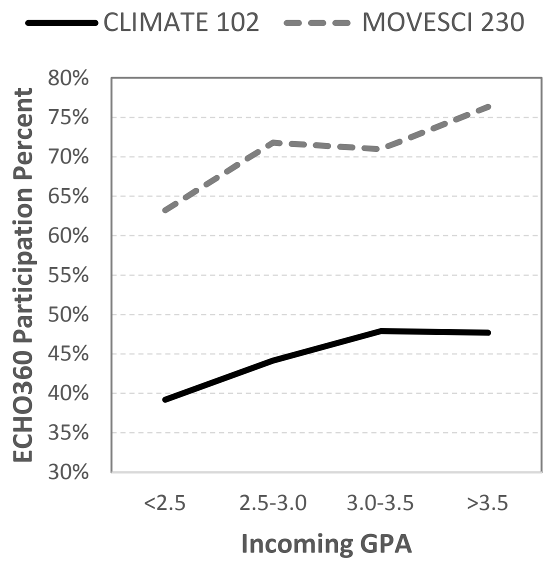


Figure 8b: In-class participation in formative assessment as a function of incoming GPA

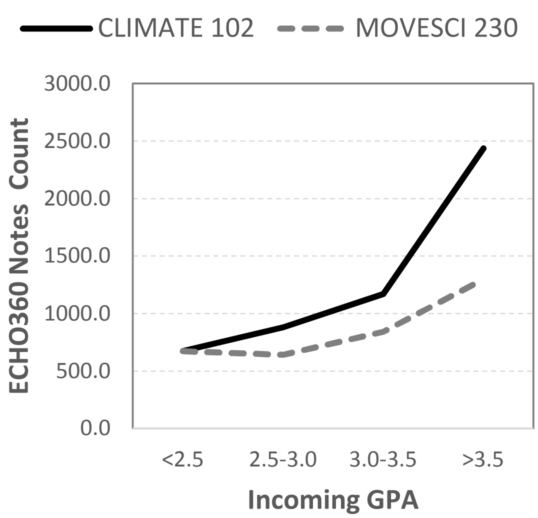


Figure 8c: Number of words typed in notes as a function of incoming GPA

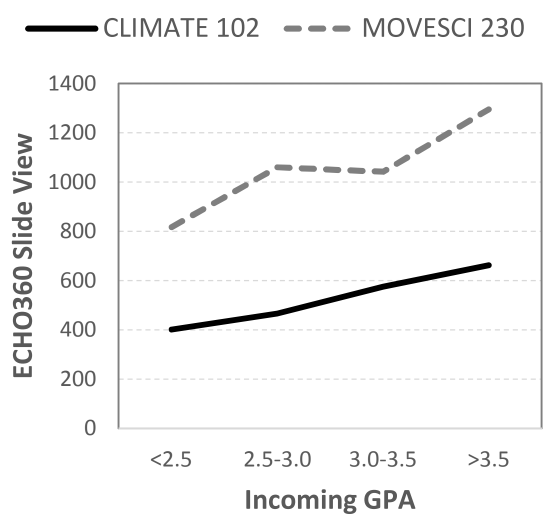


Figure 8d: Number of slides viewed as a function of incoming GPA

This latter point is important. Other analyses we performed showed that student behaviors in class were strongly related to students' incoming GPA. That is, students with lower incoming GPA's tended to participate at a far lower value than students with a higher incoming GPA. Figure 8, for example, illustrates that the number of attendance, participation in questions, notes taken and slides viewed were all higher for students with higher incoming GPAs. That is, there appears to be a reason for the poor performance on the students with lower incoming GPA in the past and it is related to their level of participation and that behavior continues into subsequent semesters.

Using this preliminary model an attempt was made to predict student's average exam score using 1) just student behavior data and 2) a combination of student behavior data and student incoming GPA. Predictions were made starting at the beginning of the semester and after each week thereafter using only data collected up to that week.

Figure 9 shows the accuracy of forecasting whether a student would earn higher than 70% on course exams based on a combination of incoming GPA and in-class student behaviors. This shows that the ability to forecast grade varies early from one course to another and one semester to another. Nonetheless our ability to forecast success is general between 70-80%

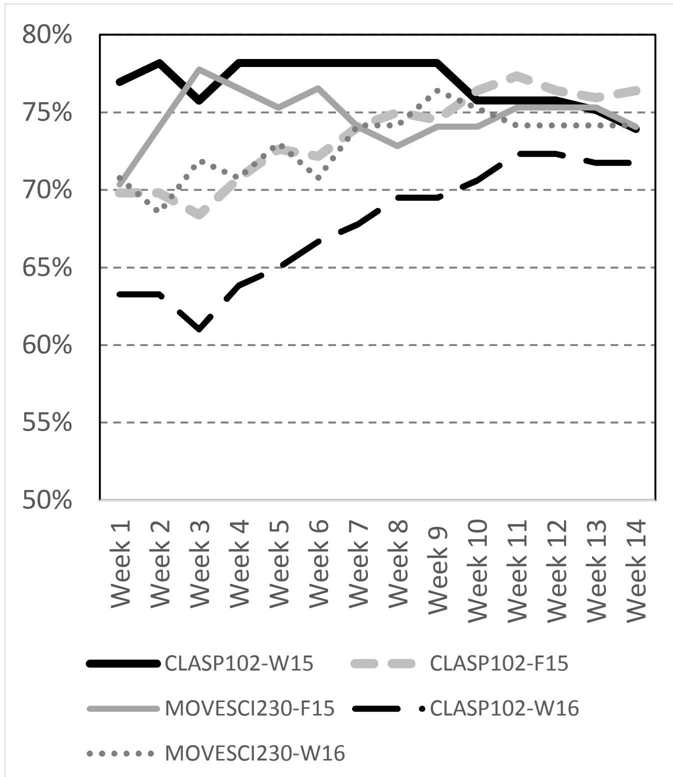


Figure 9: Accuracy in forecasting students' probability of getting less than a 70% on course exams

4 CONCLUSION

Early warning systems may benefit by expanding the data that quantifies student behavior to include behaviors during class time. Being able to measure student behaviors in class offers a higher granularity about student participation that both improves forecasts and provides evidence that may help motivate a student to change their behaviors.

The next step in this research will be to couple the forecast ability presented here with interventions that can inform the students of their forecasted grades along with specific suggestions for changing behaviors based on evidence.

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Competency Map

Jeff Grann
Capella University
jgrann@capella.edu

ABSTRACT: Visualizing learning goals for adult students can promote self-monitoring and is associated with higher persistence rates. Despite these positive outcomes, few academic programs currently deploy such student dashboards on scale. This technology showcase features Capella University's competency map, a dashboard deployed across the university since Oct 2013 and used by over 30,000 students. Several key features are highlighted, including integration with faculty's assessment practices, reporting for faculty and academic advisers, and social media share features. Institutional challenges related to sustaining and scaling this learning analytics product are mentioned along with potential solutions, such as competency interoperability specifications and extended transcripts.

Keywords: visualization, competency-based education, interoperability, extended transcript

1 SUMMARY OF DEPLOYMENT WITH END USERS

Capella University's competency map launched across all academic program in October 2013 and has now become a mature educational technology product. To date, more than 30,000 students in over 1,000 different courses have utilized the competency map. The competency map was redesigned multiple times based on user experience feedback from students and faculty. Multiple enhancements have been made, including integration with a faculty dashboard, social media share (Linkedin, Facebook, & Twitter) and enhanced print functions.

2 FULL DESCRIPTION

This technology showcase is unique in highlighting a mature learning analytics student dashboard and some of the challenges associated with bringing a learning analytics product to scale. My intention is to walk through the faculty, academic adviser, and student experience using the competency map via the following use cases.

1. Faculty assess a student's competency demonstration (see Figure 1)

2. Student reviews faculty feedback

3. Student reviews competency map (see Figure 2)

4. Student reviews assessments and criteria aligned to a specific competency (see Figure 3)

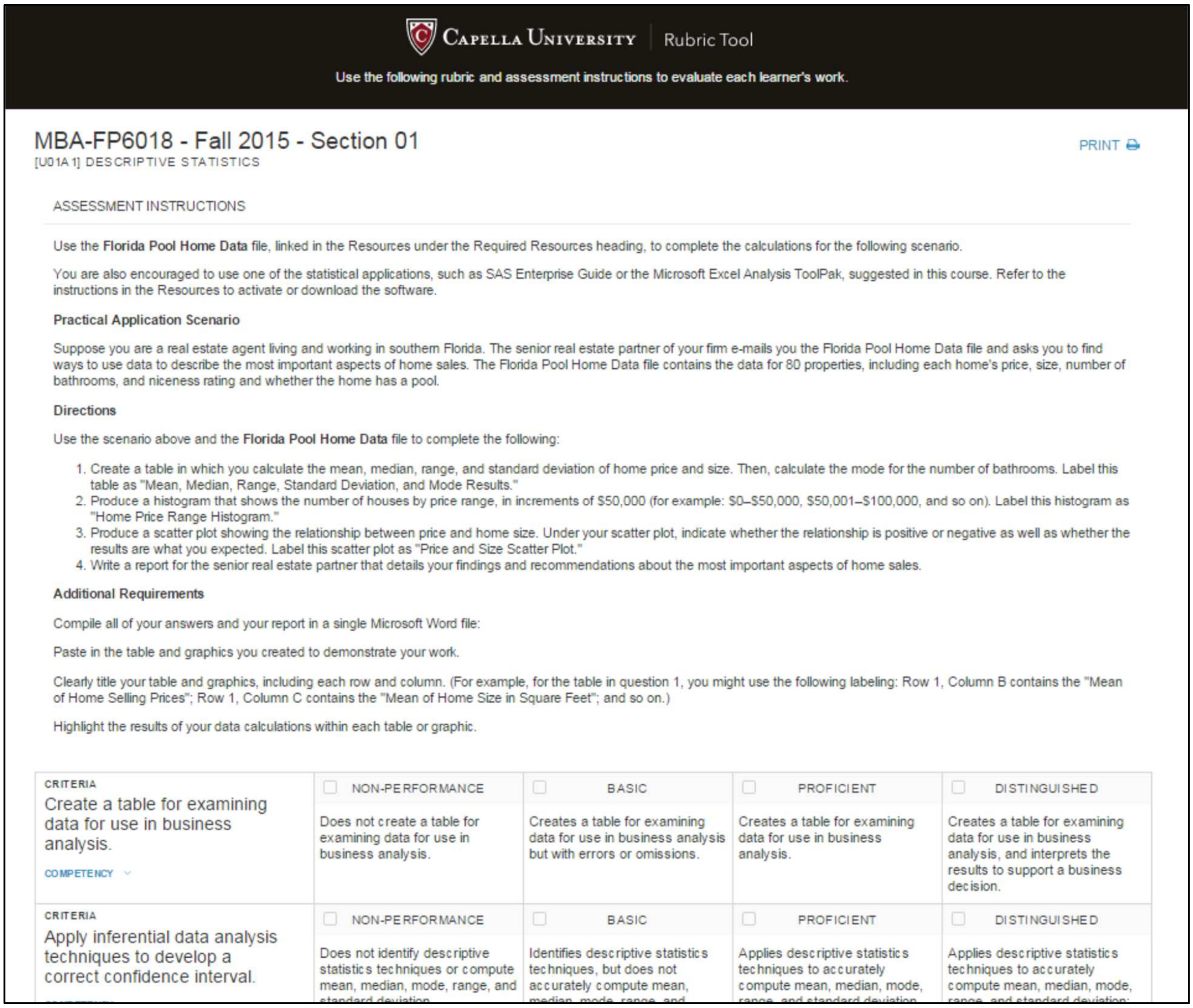
5. Faculty reviews a student's competency map

6. Adviser reviews a student's competency maps

7. Student shares competency map via social media (see Figure 4)

8. Student prints competency map

This showcase will permit attendees to engage with a successful large-scale implementation of a learning analytics solution and to ask questions that may help advance their institutional efforts. Multiple technical integrations are required to sustain the competency map and these challenges will be highlighted during the use case presentations. Specifically, the scoring guide tool used by faculty in use case #1 generates assessment data for display on the competency map. This integration is a custom solution and illustrates a common need to send competency assessment results between two tools. Discussion will highlight the potential for defining a standard CBE technical specification for transmitting such results between educational technology tools. My hope is that by building a critical mass of large scale learning analytic solutions, educational technology companies will invest in supporting open standards for interoperability.



Capella University | Rubric Tool

Use the following rubric and assessment instructions to evaluate each learner's work.

MBA-FP6018 - Fall 2015 - Section 01

[U01A1] DESCRIPTIVE STATISTICS

PRINT

ASSESSMENT INSTRUCTIONS

Use the **Florida Pool Home Data** file, linked in the Resources under the Required Resources heading, to complete the calculations for the following scenario.

You are also encouraged to use one of the statistical applications, such as SAS Enterprise Guide or the Microsoft Excel Analysis ToolPak, suggested in this course. Refer to the instructions in the Resources to activate or download the software.

Practical Application Scenario

Suppose you are a real estate agent living and working in southern Florida. The senior real estate partner of your firm e-mails you the Florida Pool Home Data file and asks you to find ways to use data to describe the most important aspects of home sales. The Florida Pool Home Data file contains the data for 80 properties, including each home's price, size, number of bathrooms, and niceness rating and whether the home has a pool.

Directions

Use the scenario above and the **Florida Pool Home Data** file to complete the following:

1. Create a table in which you calculate the mean, median, range, and standard deviation of home price and size. Then, calculate the mode for the number of bathrooms. Label this table as "Mean, Median, Range, Standard Deviation, and Mode Results."
2. Produce a histogram that shows the number of houses by price range, in increments of $50,000 (for example: $0–$50,000, $50,001–$100,000, and so on). Label this histogram as "Home Price Range Histogram."
3. Produce a scatter plot showing the relationship between price and home size. Under your scatter plot, indicate whether the relationship is positive or negative as well as whether the results are what you expected. Label this scatter plot as "Price and Size Scatter Plot."
4. Write a report for the senior real estate partner that details your findings and recommendations about the most important aspects of home sales.

Additional Requirements

Compile all of your answers and your report in a single Microsoft Word file:

Paste in the table and graphics you created to demonstrate your work.

Clearly title your table and graphics, including each row and column. (For example, for the table in question 1, you might use the following labeling: Row 1, Column B contains the "Mean of Home Selling Prices"; Row 1, Column C contains the "Mean of Home Size in Square Feet"; and so on.)

Highlight the results of your data calculations within each table or graphic.

CRITERIA	NON-PERFORMANCE	BASIC	PROFICIENT	DISTINGUISHED
Create a table for examining data for use in business analysis. COMPETENCY	Does not create a table for examining data for use in business analysis.	Creates a table for examining data for use in business analysis but with errors or omissions.	Creates a table for examining data for use in business analysis.	Creates a table for examining data for use in business analysis, and interprets the results to support a business decision.
CRITERIA	**NON-PERFORMANCE**	**BASIC**	**PROFICIENT**	**DISTINGUISHED**
Apply inferential data analysis techniques to develop a correct confidence interval.	Does not identify descriptive statistics techniques or compute mean, median, mode, range, and standard deviation	Identifies descriptive statistics techniques, but does not accurately compute mean, median, mode, range, and	Applies descriptive statistics techniques to accurately compute mean, median, mode, range, and standard deviation	Applies descriptive statistics techniques to accurately compute mean, median, mode, range, and standard deviation;

Figure 1: Faculty assess a student's competency demonstration using a rubric

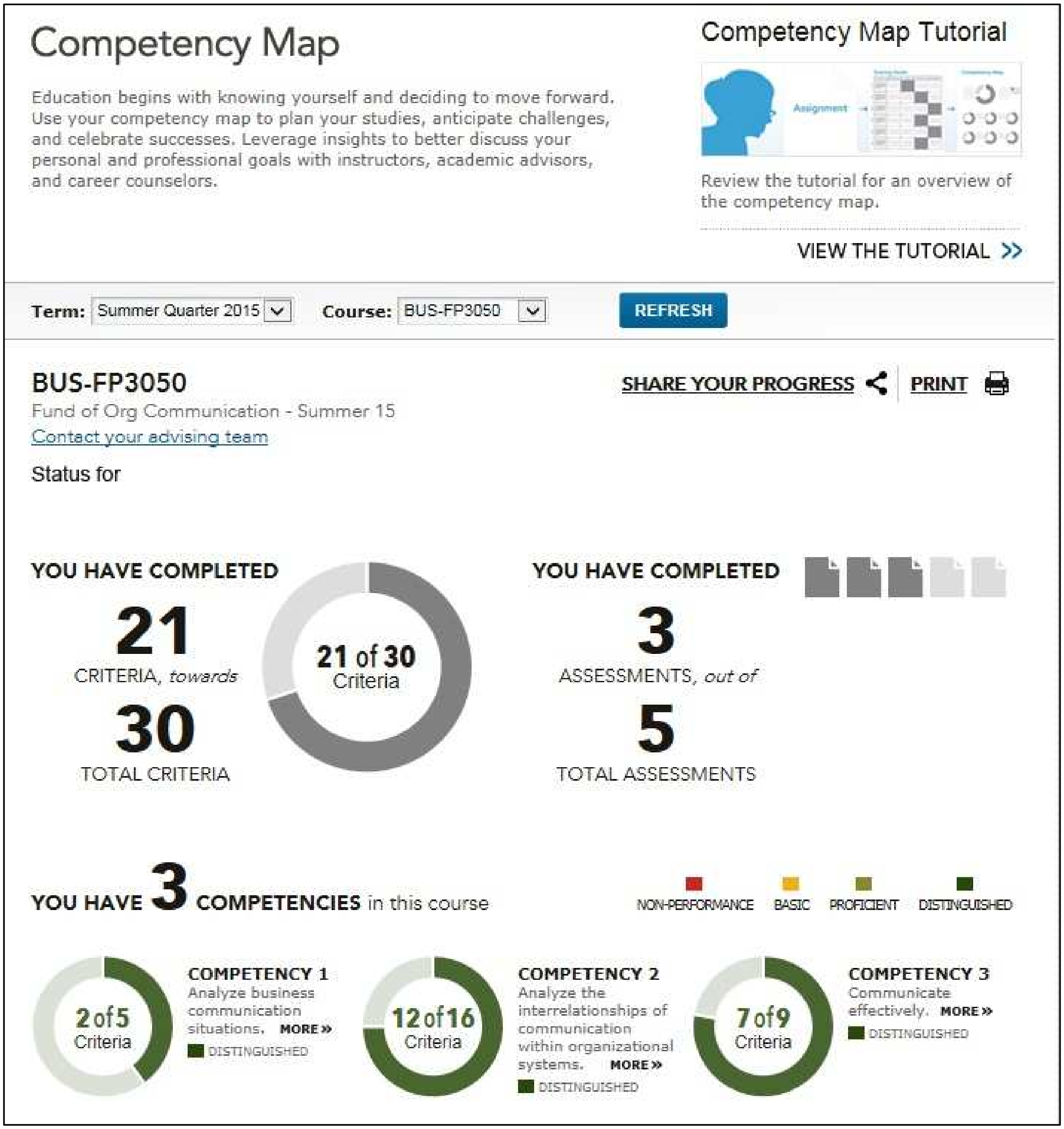


Figure 2: A student's view of their competency map

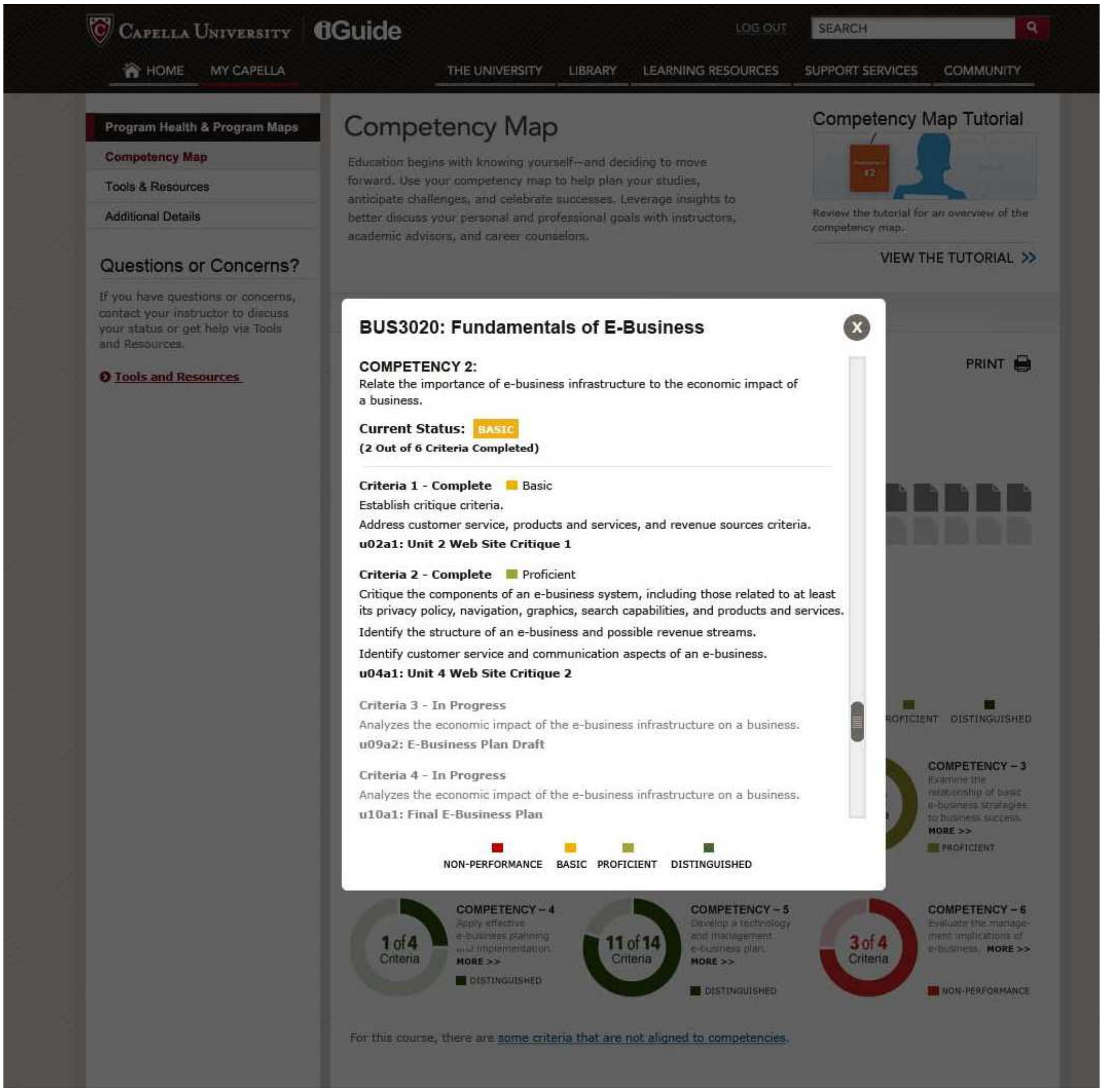


Figure 3: Student reviews assessment and criteria detail for one competency

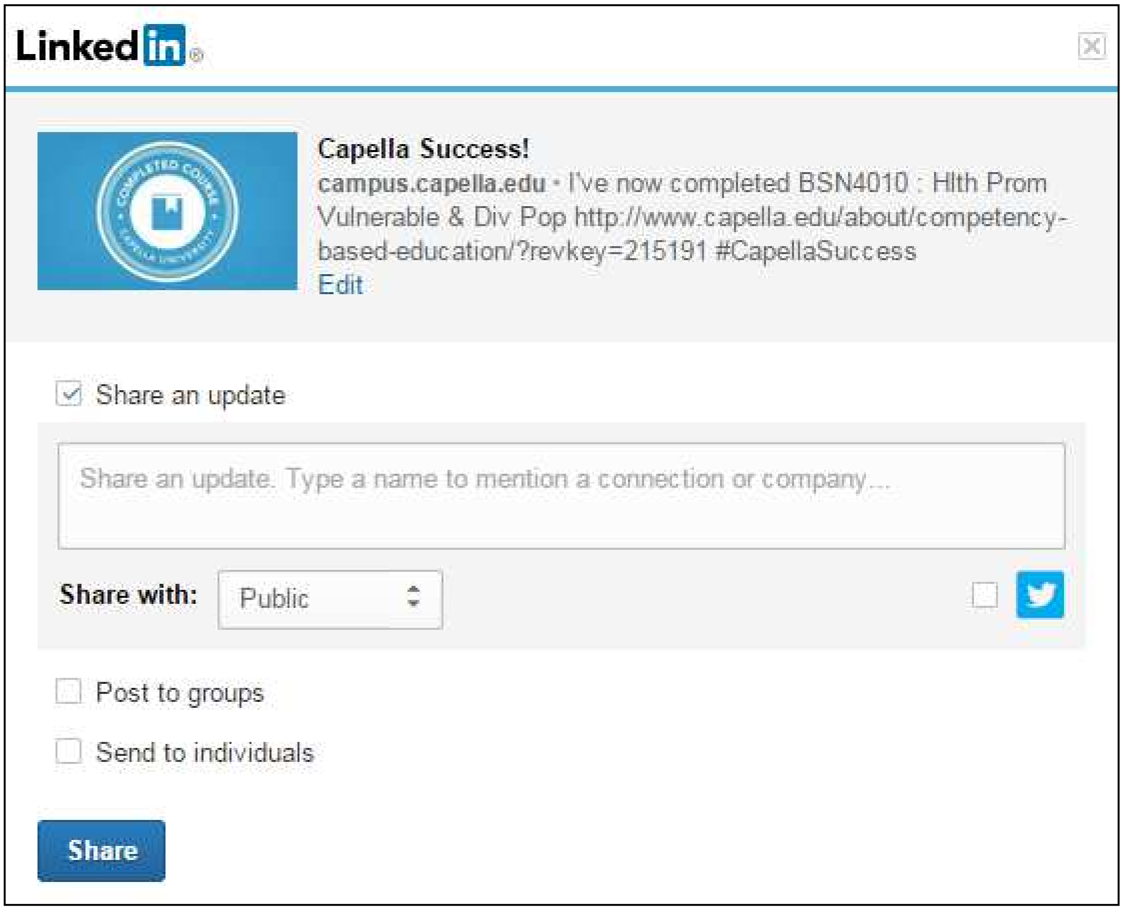


Figure 4: Options to share competency map via social media

Jupyter Notebooks at Scale

Amory Schlender
Coursera, Inc
aschlender@coursera.org

Kara A. Behnke
Coursera, Inc

ABSTRACT: Coursera has deployed a system to host Jupyter notebooks for learners in technology and data science courses. We believe that notebooks can significantly enhance learner and instructor experiences by providing easier setup, interactivity, scaffolding guidance, and standard tooling. In this paper, we describe the architecture for incorporating and hosting Jupyter notebooks into MOOCs. We also describe the preliminary results to a controlled experiment that investigates the learning impact of local and hosted notebook systems on the Coursera platform.

Keywords: MOOCs, Jupyter notebooks, workspace persistence, coding at scale, data visualization, IPython, scaffolding

1 BACKGROUND AND MOTIVATION

1.1 MOOCS and Programming

Over 25 million people from around the world have enrolled in Massive Open Online Courses (MOOCs) offered by Coursera, EdX, and other platforms. Initially heralded as a revolution in higher education access, expectations have been tempered as research revealed that only a small percentage of these millions were completing the courses [Ho 2013]. Nevertheless, research also indicates that learners have a range of motivational reasons for why they engage (or do not engage) with MOOCs [Wang 2015]. For example, learners in developing nations are more likely to participate in MOOCs because of the career and educational benefits [Chen 2015]. And yet, many MOOCs still have high learner attrition rates for varying reasons [Onah 2014]. This high attrition has motivated instructors, researchers, and practitioners to investigate how we can enable learners to complete courses and improve overall engagement with content.

Learning is a high effort activity. One key aspect of building a high-quality learning experience is the removal of unnecessary friction for the learner. When we looked at the completion data for Coursera programming courses and conducted user research, we found a common pattern of learning progress being stalled by problems with computer and development environment setup. Learners taking these courses at an introductory level were especially impacted. With this in mind, we targeted software development environment setup as an area for product improvements, with the hope that reducing or eliminating setup burden would help learners engage more quickly and persist through courses.

Challenging learners is an essential part of a rewarding learning experience, but the level of difficulty should be appropriate for the stage that a learner is in. Introductory computer science education practitioners also argue that cumbersome development environments may negatively impact the learning. Therefore, we hypothesize that by removing the barrier that is the setup of a development environment, learners will be motivated to quickly jump in and make progress with frequent opportunities to practice the skills they are trying to learn. Once such a learner has completed their first programming course, we hope the achievement will give them the motivation and confidence to tackle the challenges of setting up a development environment in future courses.

1.2 Jupyter Notebooks

Notebook environments are interactive documents containing executable code, equations, visualizations and explanatory text. Project Jupyter (née IPython) is an open-source notebook environment with more than 40 available language kernels including Python, R, Ruby and Octave. Jupyter Notebooks run as web applications, and are widely used in the scientific community for ad-hoc analyses, reproducible research, and teaching. There are many public collections of interesting expositions presented as notebooks. You can try running a demo notebook or create your own at https://try.jupyter.org/.

In the last few years, Project Jupyter has become the de-facto standard for notebook environments. Jupyter notebooks support execution using over 40 different language kernels, interactive widgets elements (controls that modify code), and easy publication of results for public consumption (static PDF or HTML, Github Gists etc). Jupyter notebooks are composed using a web application that delegates code execution to a session-scoped software kernel. The kernel evaluates notebook cells on-demand and streams results back to the application for display.

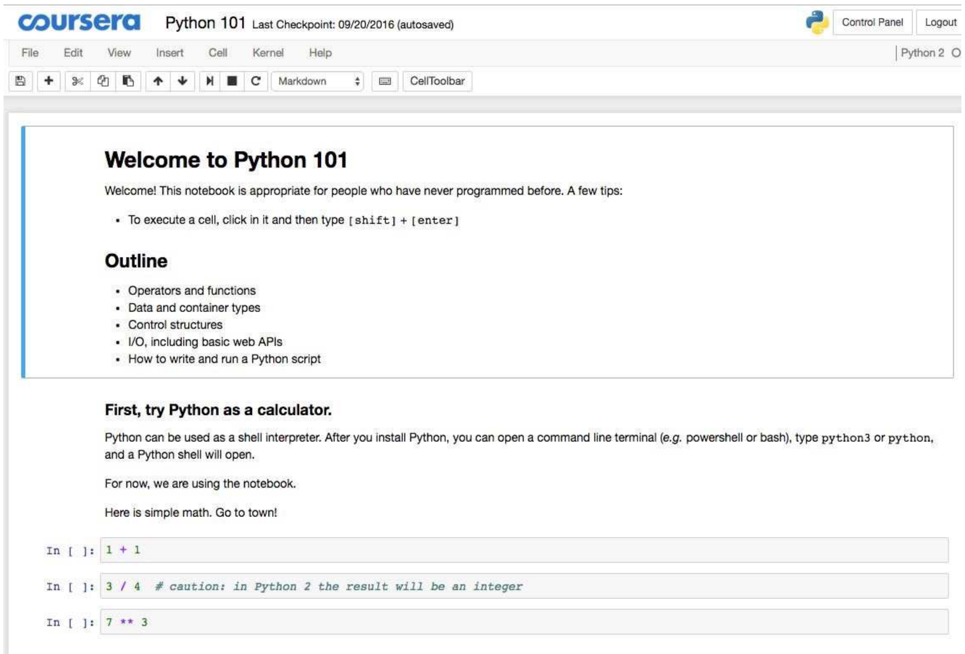


Figure 1: Jupyter notebook on coursera

2 JUPYTER NOTEBOOKS ON COURSERA

We have deployed a hosted Jupyter notebook system that allows instructors to easily compose and deploy notebooks within their MOOCs. We chose notebooks over other technologies because of their versatility and our observation that existing Coursera courses using notebooks received high ratings and consistently positive feedback from learners. Our hope is that by providing a smooth on boarding process for instructors, we can steer toward better pedagogical practices, in particular:

Easier setup: Setting up a development environment is painful. Especially so when it is the first step to learning basic concepts. Eliminating software downloads, installation, and system maintenance will reduce frustration for all learners, and help beginners master concepts without dropping out.

Interactivity: Learner cognition and retention is likely to increase if learners can easily interact with code presented in lessons (videos, readings, narratives, in-video questions) or assessments (quizzes, programming assignments).

Guidance: Because notebooks combine guiding explanations and example code, instructors can craft material that helps learners step through difficult concepts without getting stuck.

Authenticity: Since Jupyter Notebooks are used in the industry, instructors can compose them with standard tools, and learners will gain experience with a career-relevant application.

We encourage course teams to choose hosted notebooks for technology and data science courses that pedagogically pair-well with IPython (or similar Jupyter workspaces). Courses that might otherwise have few active learning experiences can use Jupyter to provide active, guided assignments. From launch in September 2016 to the present date in January 2017, the system has been used as a core component of 4 new MOOCs and over 33,000 learners have launched Notebook workspaces.

2.1 Technical Design

Our system gives each learner a persistent workspace for each course. Workspaces can include custom software, notebook based demonstrations and assignments, and associated data. Instructors are be able to create, edit, and test notebook content hosted by Coursera using standard tools, with minimal Coursera engineering support. We describe our infrastructure for at-scale hosting here.

Our deployed system uses JupyterHub to serve individual user notebooks from a separate coursera-notebooks.org domain. JupyterHub is designed to host monolithic notebook environments for users. These environments include required software packages (language kernels, libraries) and a user-owned file system containing notebook files (*.ipynb) and other resources (scripts, data, images, etc.).

JupyterHub defines two basic components to manage access to notebook Workspaces. When a new notebook session is initiated, an authenticator checks to see which (if any) notebook Workspace the user is allowed to access. This Workspace is identified with a ‘username’, which is passed to a spawner that spins up an appropriately-configured jupyter server to host the Workspace. Authenticators and spawners are easily customizable.

We wrote a simple custom authenticator and spawner that interface with publicly accessible APIs on Coursera.org to manage notebook access and user data persistence. Since we want to organize access at a scale more granular than users, we use the JupyterHub ‘username’ concept as a more generic identifier for a workspace associated with a Coursera user / course pair. While linguistically awkward, this gives us an easy way to provision granular, user-owned, course-level environments.

Figure 2 illustrates the high-level architecture of the system. Individual server instances running JupyterHub communicate with cousera.org to initiate and authenticate user notebook connections. Single-user notebook servers are run as Docker containers, with each Course-level Docker image pulled from a private Docker registry.

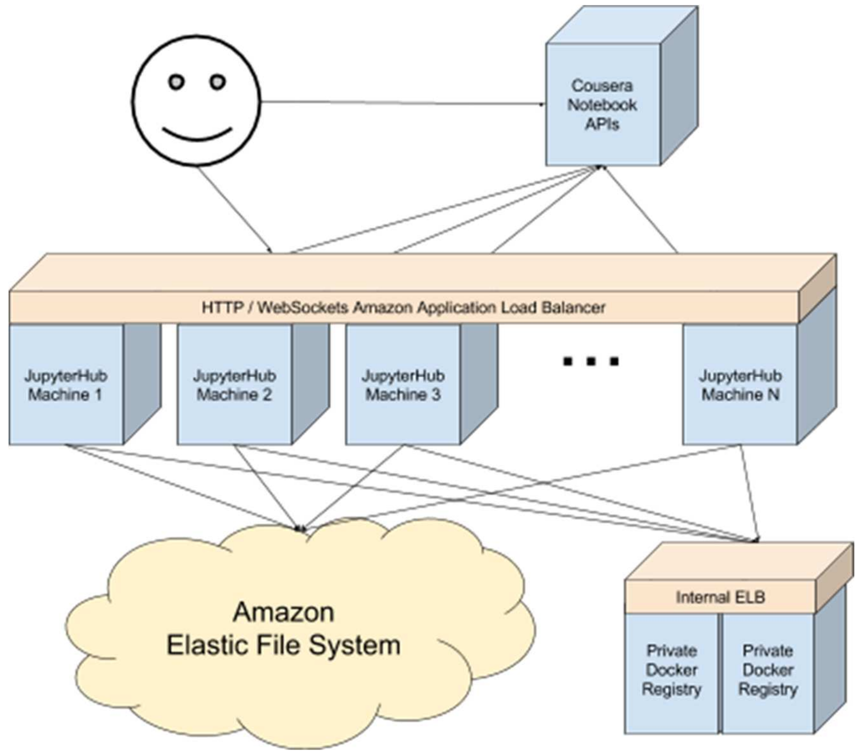


Figure 2: High-Level system for Jupyter notebooks

The architecture is designed to be horizontally scalable in a limited manner. The Coursera notebooks handler system is responsible for assigning notebooks to one of N machines running identical copies of JupyterHub, each with a TCP-based Elastic Load Balancer in front of them.

Every JupyterHub machine has the same Amazon EFS filesystem mounted via NFS. This allows Coursera and instructors to update and make changes to shared data files and user files using one control point. All container images come from a standard docker registry and are mounted in --read-only mode.

As with all Coursera grading environments, security is very important. We use typical docker container methods to contain our notebook environments. In addition, we use iptables to allow a limited form of Docker to communicate with the on-instance HTTP/HTTPS proxy as some of our notebooks require a limited form of Internet connection for communication purposes.

3 LOCAL-TO-HOSTED NOTEBOOK EXPERIMENT RESULTS

Because of our scale Coursera is in a unique position to run pedagogical experiments with large learner populations. Our first experiment with hosted notebook system comes from a pilot project in our *Machine Learning Foundations* MOOC, created by the University of Washington. The course team agreed to let us use their course as a pilot for our hosted notebook system, and we chose to roll out the the hosted notebook experience as an A/B test to measure the impact of hosted notebooks on learner behaviors. The original course version used Jupyter to teach machine learning via case study examples. Our test version adapted the course structure to give learners notebook access through our Coursera hosted notebook system. When the experiment began, enrolling learners were randomly assigned to a control group using the original course material or a treatment version that made notebooks available through the Coursera-hosted notebook system.

Table 1: Course module progression.

Module	Control (local)		Treatment (hosted)	
	Start	Completed	Started	Completed
1	13,566	4,013	13,576	5,868
2	6,065	2,828	6,213	2,886
3	3,696	2,228	3,682	2,233
4	2,760	2,012	2,755	2,052
5	2,257	1,838	2,287	1,838
6	2,199	1,695	2,190	1,691
7	2,149	1,003	2,260	968

Learners in the treatment group were significantly more likely to complete the first week of course material. However, completion of Module 1 did not lead to higher rates of progress on to Module 2, and we observed no significant difference for completion or progression for other modules.

4 NEXT STEPS

The effects observed in our pilot course experiment are clearly underwhelming. More work remains for us to understand why the large completion increases from the first module of the course did not persist through the remainder.

Nevertheless, we remain committed to Jupyter notebooks as an important part of our content ecosystem. Recently launched courses that use the notebook system show high satisfaction ratings and relatively high learner engagement. Further, instructors are currently developing content to conduct experiments on topics such as assignment data localization and learner code parse tree clustering. We believe that by providing an at-scale platform for interactive programming and data activities, we are encouraging better pedagogy and will facilitate unique research by our university partners.

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Lessons Learned from a Faculty-Led Project: Using Learning Analytics for Course Design

Matt Farrell
Fanshawe College
mfarrell@fanshawec.ca

ABSTRACT: This showcase describes a project that used student activity data from the Learning Management System (LMS) to inform course design decisions in a blended learning context. Two blended courses were offered in the General Education curriculum at a community college, with each course employing a different design configuration. Student activity was tracked and compared across both classes to determine whether one design resulted in more engagement with the online course materials. The two courses shared similar subject matter, and were taught by the same instructor. Initial results indicated that student engagement and performance were higher in the *frontloaded* configuration compared to the *bookend* design. Findings were then applied to a course redesign aimed at increasing online student engagement in the underperforming course. The secondary comparison also found higher levels of engagement and performance in the redesigned course. The results offer a potential template for faculty and course designers to make use of data generated by student activity in the online environment.

Keywords: learning analytics, blended learning, course design, evidence-based teaching

1 DEPLOYMENT

In 2015, an Ontario community college introduced a number of elective courses in a blended format. Some courses had been offered previously in a face-to-face (F2F) format, while others were new courses. Many faculty members expressed concern over the new format, feeling that students would simply ignore the online portion of their coursework. Additionally, there was uncertainty over how to best to design courses for the blended context. One faculty member sought to use learning analytics to explore whether some course design configurations proved more effective than others. As learners interact with the Learning Management System (LMS) they leave a trail of data which can provide "actionable intelligence" for guiding pedagogical decisions (Campbell, Peter, & Oblinger, 2007). By using this data, a process which Vivolo (2014) calls "pocket data analytics", courses could be designed to utilize the most effective elements. Moreover, a successful application of learning analytics could provide a template for faculty in future course design initiatives.

2 IMPLEMENTATION

The project began in the fall term of 2015 by comparing two elective blended courses. Each course utilized online learning modules, readings, instructor screencasts, low-stakes online quizzes, and active-learning exercises. Aside from the specific content, the courses were presented in similar format by the same instructor, however, each course was structured with the online and F2F components in a different order. Student activity data and performance data were tracked to determine if the completion of course material differed between courses.

2.1 Course Characteristics

Two different designs were compared. Course A used a *frontloaded* design, whereby students completed the online portion prior to the in-class session. Course B employed a *bookend* structure, in which students completed online elements before and after their in-class meeting. Both courses, shown in Table 1, were General Education elective courses in the same discipline[16].

Table 1: Courses used for initial comparison.

Course	Course Name & Code	Enrolment	Design
A	POLI-1022 – Rights & Freedoms	58	Frontload
B	POLI-1015 – Canadian Politics	44	Bookend

Students in group A were resident in a variety of different vocational programs, while group B students were all from the same program cohort.

2.2 Data Collection

The courses were compared using measures of students' *activity data* and *performance data*. Activity data includes LMS clickstream data which can be used to track page views, assignment submission, and participation in collaborative activities such as discussion forums (Vivolo, 2014). This project examined online page views, instructor screencast views, and completion of weekly content quizzes. While page views in an LMS activity log do not necessarily correspond to task completion, they can be indicators of engagement and comprehension (Little, et al., 2016). The performance data – grades – were included in an attempt to measure comprehension as well as completion.

The *Brightspace* Learning Management System was used to track how many students, as a percentage of the total, had viewed the course material each week. The same metric was used to track completion of weekly content quizzes. *YouTube* analytics were also used to track views of lecture screencasts[17]. Both indicators would reveal if there were differences in the levels of interaction across the two courses. Additionally, student performance was compared using weekly quiz scores and final grades.

[16] College students in Ontario are required to take a minimum of 1 elective course that lies outside of their core subject area. These are known as *General Education* electives.

[17] Screencast videos – approximately 10 minutes long, were hosted on YouTube and embedded in the LMS. This enabled the use of YouTube's viewing analytics.

2.3 Initial Analysis

The frontloaded design used in course A outperformed course B's bookend design across all indicators.

2.3.1 Activity Data

Figures 1, 2, and 3 show the differences in online engagement across the two courses. Students in course A viewed more of the course material than the students in course B, as shown in Figure 1.

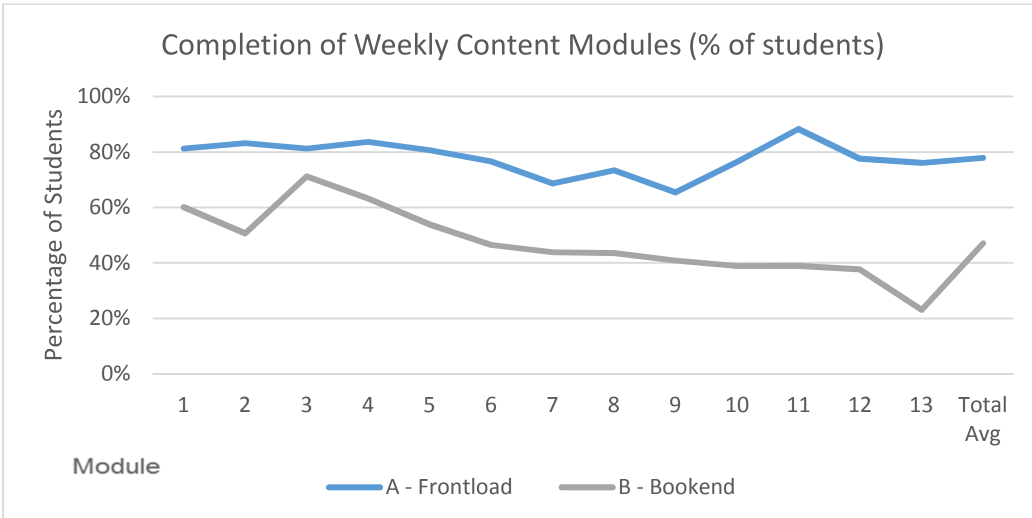

Figure 1: Activity data | Weekly content

On average, 78% of the students in course A viewed the weekly content module, compared to 47% of the students in course B. A similar pattern, shown in Figure 2, was observed when comparing *YouTube* viewing data. The videos in course A were viewed more than once per student each week, whereas the average video in course B was viewed 21 times despite having 44 students.

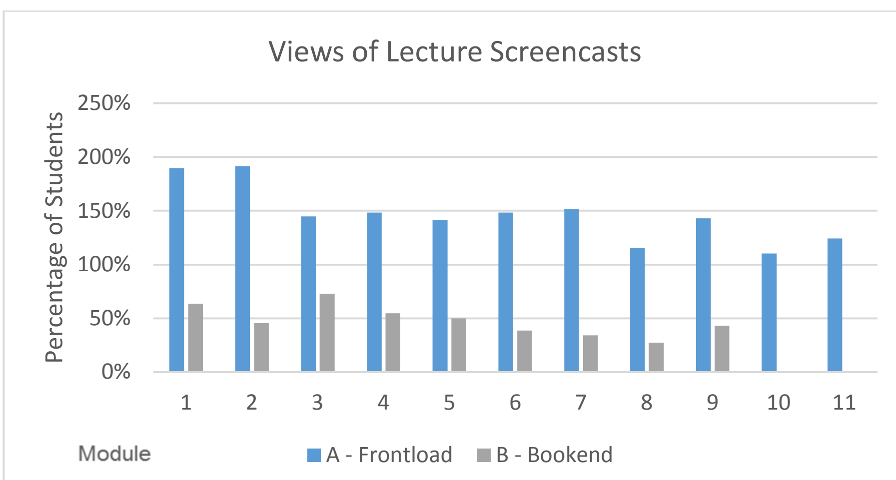

Figure 2: Activity data | Weekly lecture videos

Finally, as shown in Figure 3, students in course A also completed more weekly content quizzes.

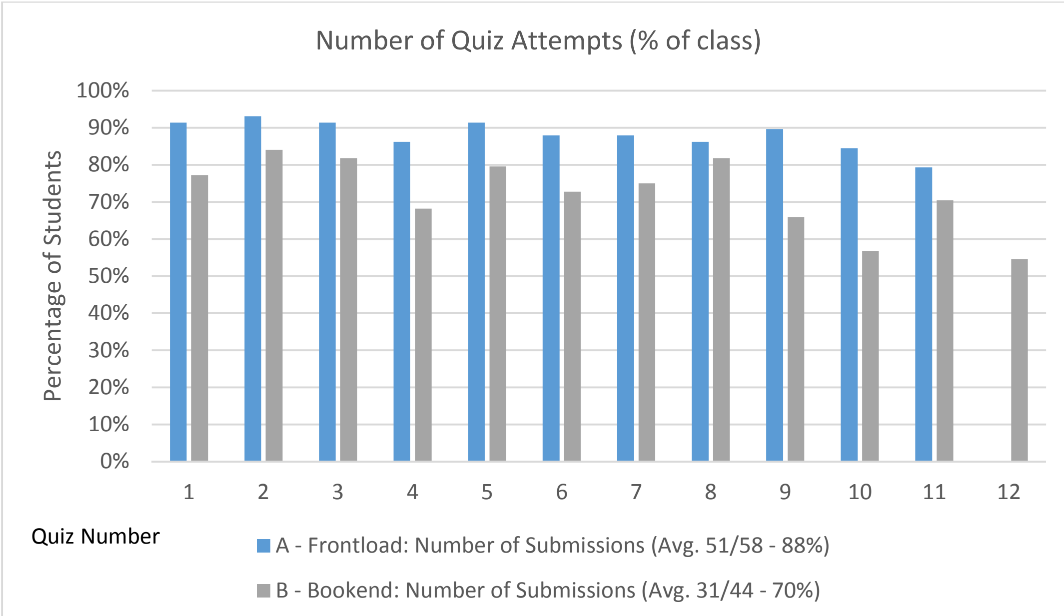

Figure 3: Completion of weekly quizzes

2.3.2 Performance Data

Similar to the activity data, students in course A outperformed their counterparts in course B across both performance indicators. Figure 4 highlights the differences in quiz scores and final grades across the two groups.

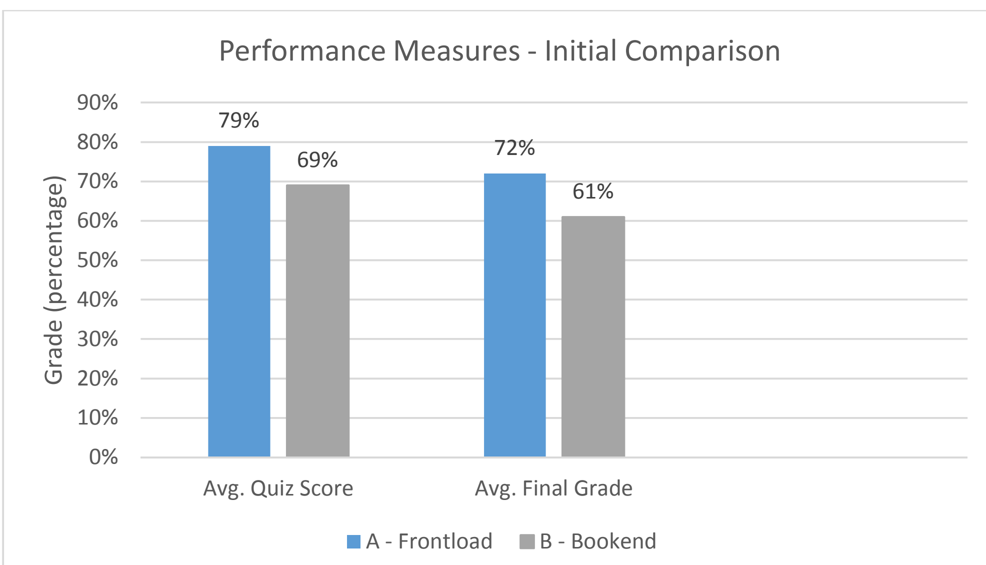

Figure 4: Performance measures

Students in the frontloaded course scored a full letter grade higher on their weekly quiz attempts and on their final grades.

2.4 Observations

The Initial comparison provided actionable data that could be easily accessed by the instructor. The data revealed clear differences in activity and performance, with the frontloaded design outperforming the bookend design. A higher percentage of students in the frontloaded group were participating in the course and they achieved greater mastery of the course content as demonstrated through weekly content quizzes and final grades.

Despite the apparent difference in engagement between the two course design configurations, the project was constrained by one key factor: structural differences in student groups. Given the elective nature of course A, students had actively chosen to enroll in the course. They chose their elective course out of a list of options, while the group B course was a mandatory elective - students were forced to take the course[18]. It is possible that the compulsory nature of the elective, or other inherent difference in student groups, may have contributed to the differing levels of engagement and performance. To more fully understand the effect of course design on student engagement, the project would need to be replicated using similar student groups.

3 REDESIGN

In an attempt to more accurately assess the effect of course design, course B was redesigned to incorporate the frontloaded structure. The subsequent offering of course B – Fall 2016 – was delivered with the new design. The same comparison was then conducted using both versions of course B, which offered two groups that, while still of different composition, would be structurally more alike than the groups used in the initial comparison.

Table 2: Courses used for secondary comparison.

Course	Course Name & Code	Enrolment	Design
B15	POLI-1015 – Canadian Politics (Fall 2015)	44	Bookend
B16	POLI-1015 – Canadian Politics (Fall 2016)	24	Frontload

The two groups were then compared using the same measures of activity and performance.

[18] Despite being a mandatory course, POLI-1015 was classified as an elective. Students could place-out of the course if they had covered the subject matter in a similar course.

3.1 Secondary Analysis

As in the initial comparison, the frontloaded design produced higher levels of engagement across all activity measures: content completion, video views, and quiz completion, and higher performance compared to the bookend format.

3.1.1 Activity Data

As Figure 5 illustrates, the redesigned, frontloaded version of the course produced higher levels of completion for the weekly modules, with one exception in the introductory week of the term.

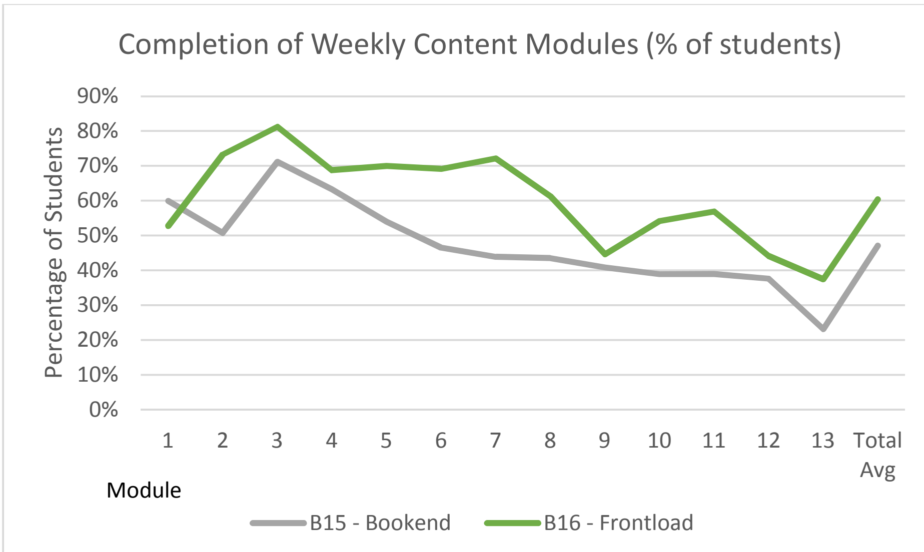

Figure 5: Activity data | Weekly content

On average, there were 13% more students viewing the content modules each week. Similarly, as shown in Figure 6, the updated[19], frontloaded course design elicited more video views from the class with 79% of the students viewing the weekly lecture videos, including two weeks where each lecture video was viewed more than once per student. This level was never reached in the previous offering, with only 48% of students watching videos each week.

[19] The actual lecture screencasts were substantively similar. Minor updates were made to some videos to account for a change in government, which produced different names of the office holders being studied.

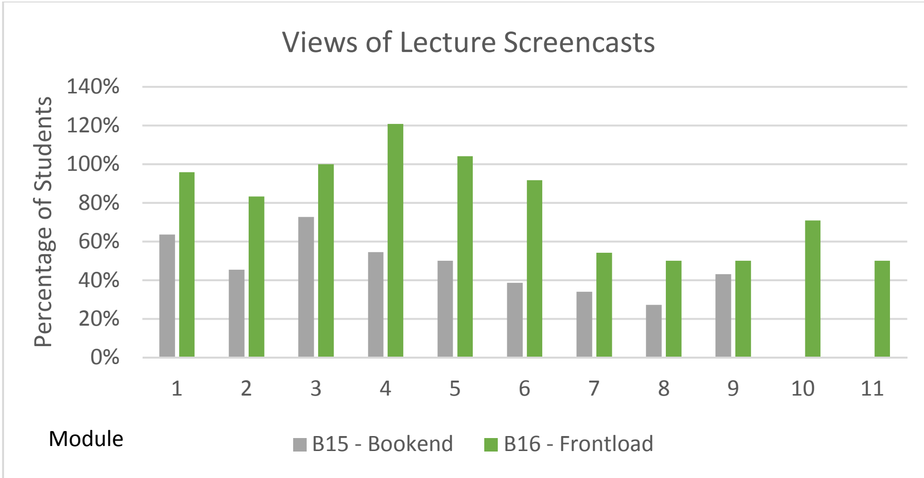

Figure 6: Activity data | Weekly lecture videos

Quiz completion, shown in Figure 7, also increased by 5% over the previous year.

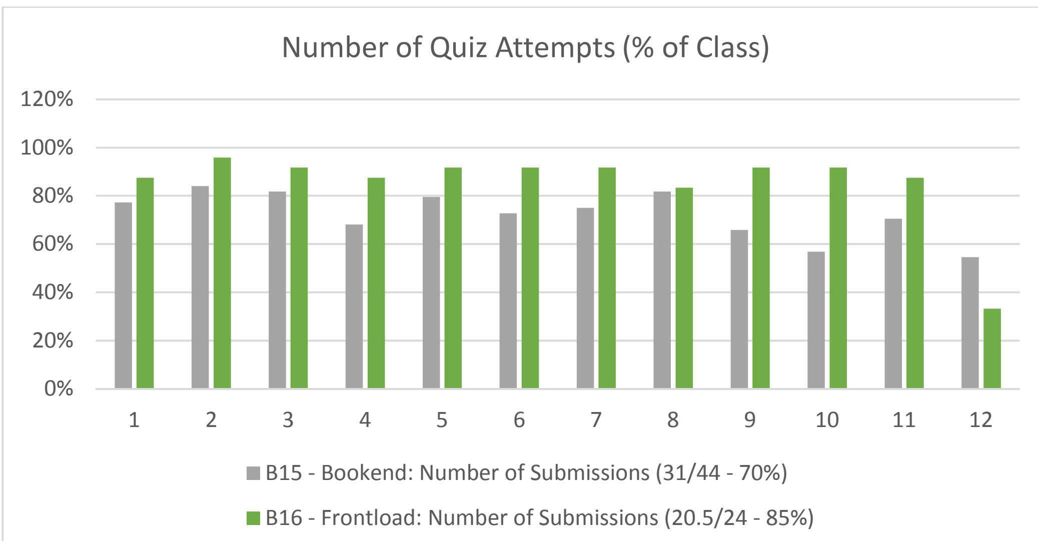

Figure 7: Completion of weekly quizzes

3.1.2 Performance Data

Students performed better in the redesigned, frontloaded offering. Performance on both the weekly content quizzes and final grades had improved compared to 2015, as shown in Figure 8.

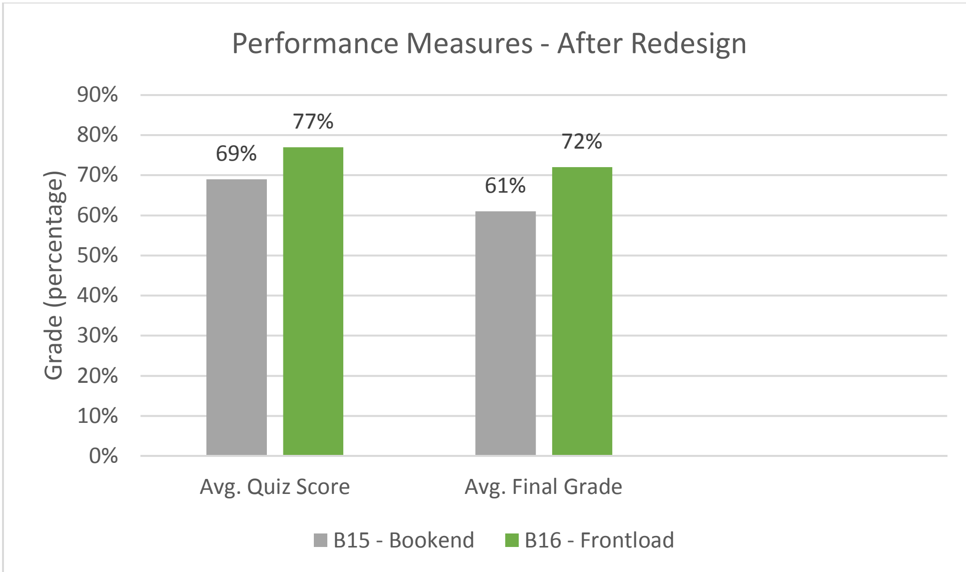

Figure 8: Performance measures

4 LESSONS LEARNED

In this project, student activity and performance data were used to determine that a specific course design configuration produced higher levels of engagement and performance in the online portion of a blended course. Evidence from the initial comparison was then incorporated into a course redesign to determine if there would be a corresponding increase in engagement and performance. The results were positive, as the redesigned course outperformed its prior offering. While it is difficult to draw conclusions as to what specific elements of the frontloaded design were superior (if at all), the more useful observations pertain to the potential for using pocket data analytics at the faculty level to improve course design, and, ideally, outcomes.

The instructor used accessible user data from the LMS, without the use of specialty applications or dashboards, and no data was gathered using administrator access. The Information used was available to all faculty at the institution. There is tremendous potential for using such readily available data in the context of evidence-based education. For instance, faculty and, as appropriate, instructional design staff can use activity and performance data from the LMS to assess the effectiveness of course components in the online environment. Most learning platforms make use of similar tools and features, including checklists, surveys, discussion boards, and quizzes, in addition to a variety of content display options. If a given tool is observed to elicit more student engagement, or greater mastery of content, then courses can be designed – and redesigned – to bolster engagement. Similarly, ineffective tools and techniques can be phased out.

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Measuring Learner Engagement

Amrita Thakur
D2L Corporation
amrita.thakur@d2l.com

Sean Yo
D2L Corporation
sean.yo@d2l.com

ABSTRACT: The amount of data in the edtech ecosystem is growing. While new kinds of data are now available, it is frequently siloed across multiple systems, resulting in delayed access making it less effective. At D2L we focus on in-situ analytics, enabling on-line instructors to gain visibility on the behavioral cues of learner engagement. We are working towards leveraging the strengths of online learning to build better methods of on-line engagement observation so that faculty can intervene earlier. This session will provide an interactive hands-on demonstration of our recently released product, the Class Engagement Dashboard.

Keywords: engagement, data, analytics, learning analytics, predictive analytics, risk prediction, students at risk, edtech, LMS, Brightspace, D2L

1 DEPLOYMENT

The Class Engagement Dashboard has been shipped and is in production. At the time of writing, this feature is being actively used by over 40 institutions with an average of 650 instructors and administrators using this product monthly.

2 CLASS ENGAGEMENT DASHBOARD

As instructors seek to better utilize data-driven decisions in their teaching, the problem of effectively bringing together relevant data, at the right time, in the right context to enable an action, is emerging as a key challenge. One of the strengths of online learning platforms is the opportunity to track and aggregate student activity and performance data. Taking advantage of this strength is the foundation of our work on the Class Engagement Dashboard (CED).

As part of the Brightspace Learning Platform, the Class Engagement Dashboard provides a consolidated view of learner course activity, progress, and achievement. The CED enables instructors to easily identify who is a top performer and who is at risk based on data points that measure their level of engagement in a course. We selected data points such as current grade, last course visit, and discussion participation based on extant publications (Brown, 2012). The dashboard also enables immediate action by intervening with the identified students. This engagement data is optionally combined with our predictive analytics system the "Brightspace Student Success System"[20] that predicts the final grade of each learner. The consolidated view brings together both descriptive and predictive data in a single view, creating a powerful student support and intervention resource for faculty.

2.1 Class Engagement Dashboard Visualization

The top of the Class Engagement Dashboard presents the instructor with interactive data tiles. These tiles serve to provide data to the instructor and act as dynamic filters of the learners enrolled in the course. The roster of learners is underneath these data tiles, in a table. Instructors can navigate this data by selecting elements within the interactive data tiles and through the standard interaction of sorting by column in the table of learners.

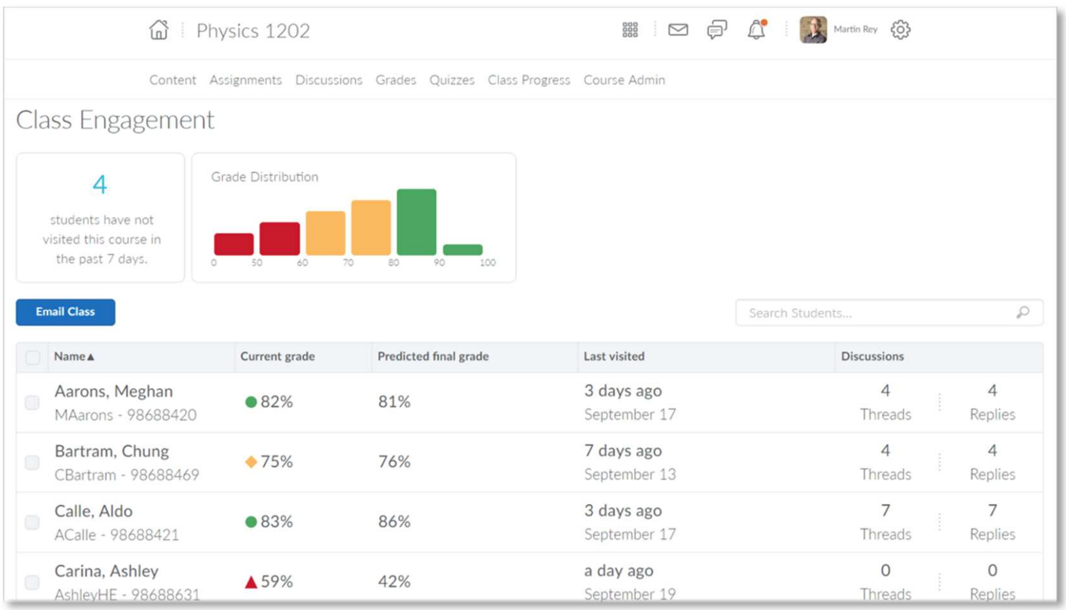

Figure 8: Brightspace Insights | The Class Engagement Dashboard

The first interactive data tile is a single, actionable call-out indicating the number of learners who have not visited the course in the last 7 days (see Figure 2). By selecting this data tile, by clicking or tapping on the tile, instructors can view a filtered list of learners who have not visited the course during this period. This creates an opportunity and a means through which instructors can follow up with potentially at-risk learners through readily-available buttons that allow them to automatically connect via email with the entire class, a group of selected individuals, or an individual learner.

[20] For more information about the Brightspace Student Success System, please see Early Intervention System for Student Success by Shady Shehata. (https://solaresearch.org/wp-content/uploads/2016/04/Final-LAK-16-Practitioner-Proceedings-.pdf)

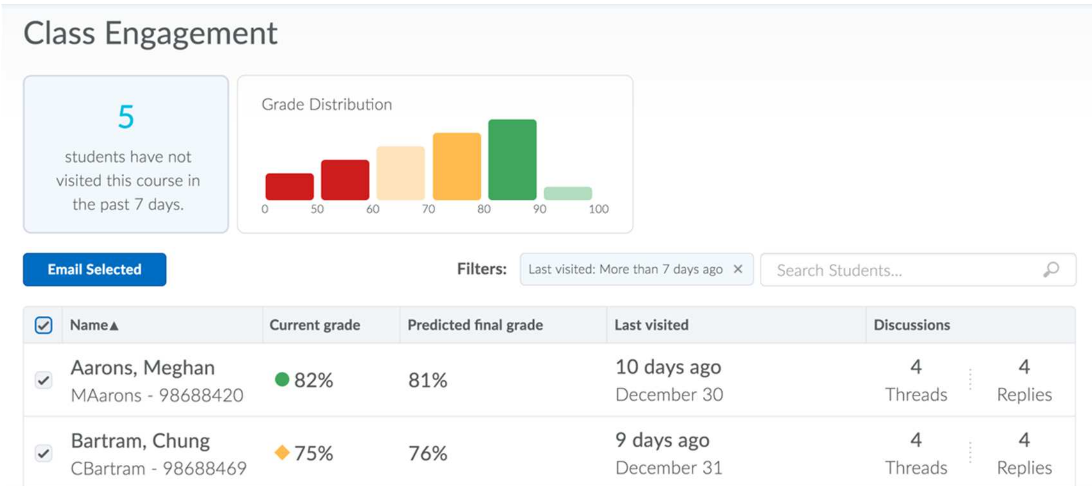

Figure 9: Brightspace Insights | Filtered showing students who have not logged in the last 7 days and are selected to receive an email by the instructor

The second interactive data tile provides a color-coded grade distribution chart representing the number of learners within a certain grade distribution percentile: 0-50%, 50-60%, and so on. By selecting individual bars in this data tile, instructors can dynamically filter their learners by current grade, providing another opportunity for instructors to reach out to at risk students.

2.2 Class Engagement Dashboard Interventions

To describe the intervention workflow, we will provide a short use-case to illustrate how an instructor might use this feature.

Once the instructor has filtered her class list to her satisfaction, she is then able to immediately intervene directly from this workflow. Let us assume she is interested in identifying students who are underachieving by assessment and have disengaged from this online course. The instructor can quickly and interactively filter for this by filtering for all learners who have a grade between 0% and 60%, by selecting both the 0-50% and 50-60% columns on the Grades Distribution tile and selecting all learners who have not logged in the last 7 days by selecting the Course Access tile.

Now that the instructor has this list, she has two key options: individual or group intervention. The Class Engagement Dashboard makes it easy and simple to email the list of all filtered learners or a subset of them, including an individual learner. For the learner, there is no necessary visibility of the intervention being individual or group, as group messages are automatically sent via BCC (Blind Carbon Copy).

The CED leverages the rich messaging platform of Brightspace to intervene and support at risk learners. This means that when the instructor creates this message, there is very broad range of options for content, from quick linking to course content within Brightspace, to simple linking to external videos, such as YouTube, or any external link such as Khan Academy or other resources. In addition, the instructor can record an audio or video message as part of this workflow, a practice which is typically more effective than a written message on its own.

This intervention workflow brings together the enablement of the instructor with the opportunity to easily scale her intervention across many students in timely and efficient manner. The ability of the CED to filter and select a group of students with similar engagement indicators means that intervention messaging can be shared when communicating with the selected group of students, saving time for instructors which is a key goal for this persona.

3 DESIGN CONCEPT

3.1 Increasing Visibility of Online Engagement

Analytics can easily fall into the trap of measuring what's easy to measure rather than what's effective. (Booth, 2012). Therefore, we used a design process which utilized a wide variety of prototype designs for many different possible indicators to better understand what instructors find useful and can effectively interpret the behavior of their learners. This process helped to identify key indicators, supported by other research. This work was very productive both in terms of providing an evidence-based rubric for selecting and refining our designs and in providing a strong foundation for future research.

The key issue that drove our design and our research is enabling on-line instructors to gain visibility on the behavioral cues of learner engagement. In face-to-face teaching and learning, instructors have access to a broad range of physical cues to assess the learner's understanding: who shows up, facial expressions, body language and vocal intonation of learner questions. The majority of these signals are not visible to instructors in the online space.

The Class Engagement Dashboard doesn't eliminate this gap between the behavioral signals available in classroom and online. However, we believe it is an important step in closing the distance between the two. Moreover, we are not seeking to simply replace the signals available to face-to-face instructors. Rather, we are working towards leveraging the strengths of online learning to build on the better-understood methods of in-class engagement observation and complement these with methods of on-line engagement observation.

For example, a key opportunity in designing on-line engagement observation experiences for an LMS is the ability to bring together descriptive analytics and predictive analytics in a single interaction for instructors.

3.2 Increasing Visibility of Online Engagement Enabling Instructors

In any analytics project for education, a key decision is to mobilize data through the practices of Educational Data Mining (EDM) or Learning Analytics and Knowledge (LAK). EDM, characterized by focusing on automated discovery, coming from the traditions of software engineering and student modelling, sets a frame for analytics that is algorithmic and best suited to automated adaptation. LAK, characterized by focusing on enabling human judgement through analytics, coming from the traditions of the semantic web and outcome prediction, sets a frame for analytics that informs and empowers instructors and is best suited to human interventions (Siemens, Baker 2012).

For this work, we chose to utilize LAK practices as we continue to see tremendous value in extending and amplifying the ability and expertise of instructors with digital tools. The alignment of our goal and the instructor viewpoint with regards to our product is evidenced in this response from a participant in our user research:

> *"The kinds of things you are trying to surface here are about academic accomplishments and how can I get everybody to hit their learning goals. That's all great. The most important thing about this is that these are also the kinds of symptoms that student who are in grade distress will show. When your making choices about what goes in the algorithm...these are indications about students who might be in distress…the difference between someone who's been chugging along at 68% and it's always been a 68% and they're always going to be that student, and somebody who is suddenly at a 68% because the bottom fell out of their world – I need that trajectory, because I need to be able to say to that student 'Are you ok.'"*

4 USER RESEARCH AND DESIGN ITERATIONS

From the starting point of our design concept, we anchored our design process in an iterative process of design and user research to guide and refine the design of the Class Engagement Dashboard. We went through several iterations of our designs; each iteration being measured and validated with user research.

4.1 Research Methodology

We set our initial direction by conducting a design studio, a collaborative session meant to foster a wide variety of directions from stakeholders. The session was informed by previously conducted surveys and semi-structured interviews targeting the information needs of instructors teaching online and blended courses. For the first round of testing, stakeholders chose the two most promising prototypes to start testing.

An evolving set of prototypes were tested weekly in 1–3 sessions (more than 50 sessions taking place overall). Recruited participants fit the target of a higher-ed instructor actively teaching online or blended classes as a part of their normal teaching assignment. In these sessions, a UX researcher, UX designer, and a product manager gathered contextual information from participants via a semi-structured interview followed by a participant led walkthrough of the current prototype. This method allowed stakeholders to gauge the applicability of the design and understand what resonated with our target persona.

After completing a session, we coded data to record positively received features, negatively received features, and existing gaps that would be promising to pursue in future sessions. The prototypes would be altered based on our cache of ideas and feedback we had amassed in previous sessions. Though the prototype was constantly evolving, informally we targeted at least 3 participants exposed to a feature before significant alteration.

4.2 Participant Responses[21]

Overall, we have very positive feedback on the concept and the framework of the Class Engagement Dashboard. For example, one participant shared: "I'm concerned when I'm monitoring…that someone will fall through the cracks and I won't catch it until it's too late. This [the Class Engagement Dashboard] would take some of that anxiety away; that risk of human error." In response to a bar chart of course access, which is used elsewhere in Brightspace, "Everything I can learn about how my students learn will make me a better instructor."

In an early prototype of the CED design, we heavily employed scatterplots as a visualization modality. This was a polarizing design, correlating to the participants' familiarity with scatterplots. This led to responses as varied as:

"I'm very bad at reading graphs"

"That's a confusing chart", later followed by "Oh, I guess that makes sense"

"[I] Love it actually, it's Ideal", in response to viewing hours spent versus current grade (a data point which is not in the final version of the CED)

Early designs were more colourful and busier than the final designs. Our hypothesis was to heighten the visual appeal for a better user experience. This hypothesis was not confirmed, as seen in the following responses:

"[It's] a little overwhelming; colors and shapes are a little too extreme. My eyes just don't know where to go. However, the information here, once you're able to get past the bright colours, is useful."

"I feel like I'm looking at abstract art"

Once we adapted our designs to these responses, we provided a simpler set of visualization which directly led to the final designs, we received this response: "there's less information for my eyes to take in all at once and it helps me identify those students I need to intervene with."

[21] All respondents are anonymous and are not identified.

5 CONCLUSION

Enabling and amplifying instructor capabilities to measure online learning engagement and intervene within a single workflow is the key goal of the Brightspace Class Engagement Dashboard. By using a user-research centric design method, we validated and refined our design to provide effective data points to close the gap between the behavioral observations of engagement made through in-class instruction and on-line instruction.

The Class Engagement Dashboard brings together effective engagement metrics with interactive data tiles enabling instructors to quickly select and identify groups of learners and take an immediate action to intervene. This work is intended to bring together the strengths of online learning and established practices of in-class engagement observations in way that enables pedagogical interventions which are personalized and scalable.

This work has strong success indicators as in-market product and sets the foundation for future work and research on learner engagement metrics, progress tracking and predictive analytics.

6 ACKNOWLEDGEMENTS

The authors of this paper would like to recognize the contributions of their colleagues in this work. Many thanks to Tony Bergstrom, Mary Riesland, Shady Shehata and Marilyn Powers. All errors remain our own.

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OUAnalyse: Two Dimensions of Scaling Learning Analytics at the Open University

Martin Hlosta
Knowledge Media institute
The Open University, Milton Keynes
martin.hlosta@open.ac.uk

Zdenek Zdrahal
Knowledge Media institute
The Open University, Milton Keynes
zdenek.zdrahal@open.ac.uk

Jakub Kuzilek
Knowledge Media institute
The Open University, Milton Keynes
jakub.kuzilek@open.ac.uk

Michal Huptych
Knowledge Media institute
The Open University, Milton Keynes
michal.huptych@open.ac.uk

Michal Bohuslavek
Knowledge Media institute
The Open University, Milton Keynes

ABSTRACT: The OU Analyse is the project at The Open University providing early prediction of at-risk students based on their demographic data and interactions with VLE. From two pilot courses in 2014 with only module chair as users, the project has scaled within two years to the current 26 courses with about 1000 users - mostly tutors. The presentation will explain the concept of scaling in these two dimensions, lessons learned; the features of the system and also it will include a demonstration of the OU Analyse system.

Keywords: learning analytics, predictive modelling, learning dashboard, scaling learning analytics, scaling up, scaling out

1 INTRODUCTION

The Open University (OU) is the largest British university offering distance education for more than 170,000 students. In each module, students are divided into groups of about 20 students and assigned a tutor who supports each group. OUAnalyse is a system that provides additional support for tutors. Using student data, the system predicts students who are at risk, as early as possible in the course so that the tutor can intervene appropriately. Module assessment typically consists of 4-6 formative Tutor Marked Assessments (TMA) and a final exam. OUAnalyse predicts whether a student will submit the next TMA and their expected score. In 2014, the system was piloted with two modules. From 2014 until February 2016, the system was used by 40 modules with more than 70,300 students. Since October 2016, 26 additional modules have been included. VLE data is collected daily and predictions are calculated weekly. The tutors can access predictions via the OUAnalyse dashboard (http://analyse.kmi.open.ac.uk).

2 BEYOND THE PILOT: MOTIVATION

The feedback from module chairs in the early pilot and the initial deployment confirmed the importance of the predictions and the dashboard. This provided us with the motivation to scale the project yet also introduced the following challenges:

- Infrastructure: Access for a large number of tutors which has to be simple, user-friendly and at the same time guarantees the safety of students' personal data.
- Modelling: Building predictive models by machine learning for a large number of modules, particularly if data from previous presentations are not available.
- User acceptance: Enabling large numbers of tutors from different disciplines and backgrounds to use and benefit from the predictions.
- Closing up the loop: Encouraging tutors to provide feedback on the system and influence its future development.
- Ethical: Taking into consideration the ethical use of students' personal data.

We see the scaling in two dimensions, (1) by increasing the number of modules with more students under analysis (scaling-out) and (2) by extending the number of users in each module using the system (scaling-up), see Fig.1.

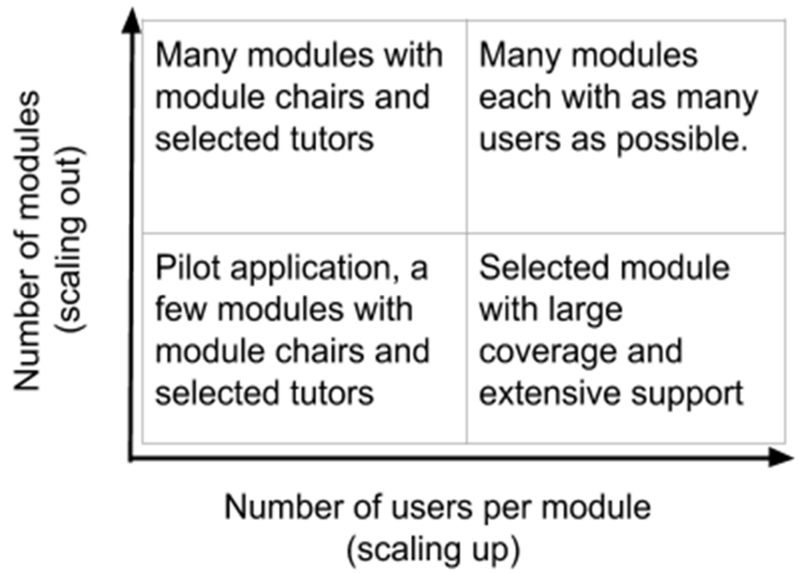

Figure 1: Two dimensions of scaling

3 SCALING-OUT

Adding more modules enables the university to support more students under analysis and covers the Infrastructure and Modelling challenges.

The current research shows that creating hand-tailored prediction models increases the accuracy of the predictions. While for two pilots this might be manageable, for a large number modules it is necessary to have an automated or semi-automated approach. We addressed this scalability challenge by implementing the 'Maximum Relevance Minimum Redundancy' procedure, which selects the most informative features with the minimum mutual information in the set.

This approach works well for the modules with previous history, but for new modules, we had to propose different solutions. The first was to find a course with a similar structure and use the data generated by that course for the initial model construction. Identifying such a "surrogate course" and mapping it onto the predicted one, can be be time-consuming and sometimes requires significant effort. For this reason, we have developed a novel algorithm that constructs the model for the running module presentation by exploiting data about the students that have already submitted their assessment. The benefit of his approach is the full automation of the process, but the price to pay is the lower prediction accuracy and the cold start problem. The available dataset is inherently unbalanced, in the extreme case, it is impossible to predict when there aren't any prior submissions.

Though attention is usually focused on level one courses, which have the highest number of students and the highest drop-out, the interest in predictions also comes from the more advanced courses. Our primary interest is not in improving retention, which is usually already satisfactory, but rather on increasing the performance of the students and motivating them towards better results. For those modules, we created the enhanced predictive models that are able not only to identify at-risk students but also to estimate the grade of each student in their next assessment.

4 SCALING-UP

Another dimension comes into play when including more people engaged in the design and the presentation of courses. The OU has a vast network of tutors supporting groups of around 20 students in each module. So, for one module with 1,000 students in addition to 2 module chairs, there are 50 tutors to support as new users.

The goal is to provide access and cover the needs of various user roles, while keeping the design simple and easy to use. Many of the tutors at the OU cannot access the internal network where the system was originally running, so it needed to be moved onto the Internet and secured accordingly. This was a time-consuming process, and therefore, while it was being moved, we provided a weekly email notification system sending an excel spreadsheet with the key information presented in the dashboard.

The users' responses to this feature incentivized us to keep the email notifications even though the offline spreadsheets are no longer the means of informing the users. The assumption was that email notifications without the spreadsheets, might attract more user engagement with the tool, and the tutors will therefore be better informed about the students. The initial analysis supported this claim, showing that the highest number of visits occur on the day after the notifications are sent. We wanted to extend this analysis by being able to confirm this on the larger number of tutors with A/B testing, i.e. assigning the users to receiving/not receiving group randomly. However, the feedback from the users showed that these notifications should remain voluntary.

The Fig 2. shows the module overview of OUAnalyse with all the registered students and their prediction that is generated every week.

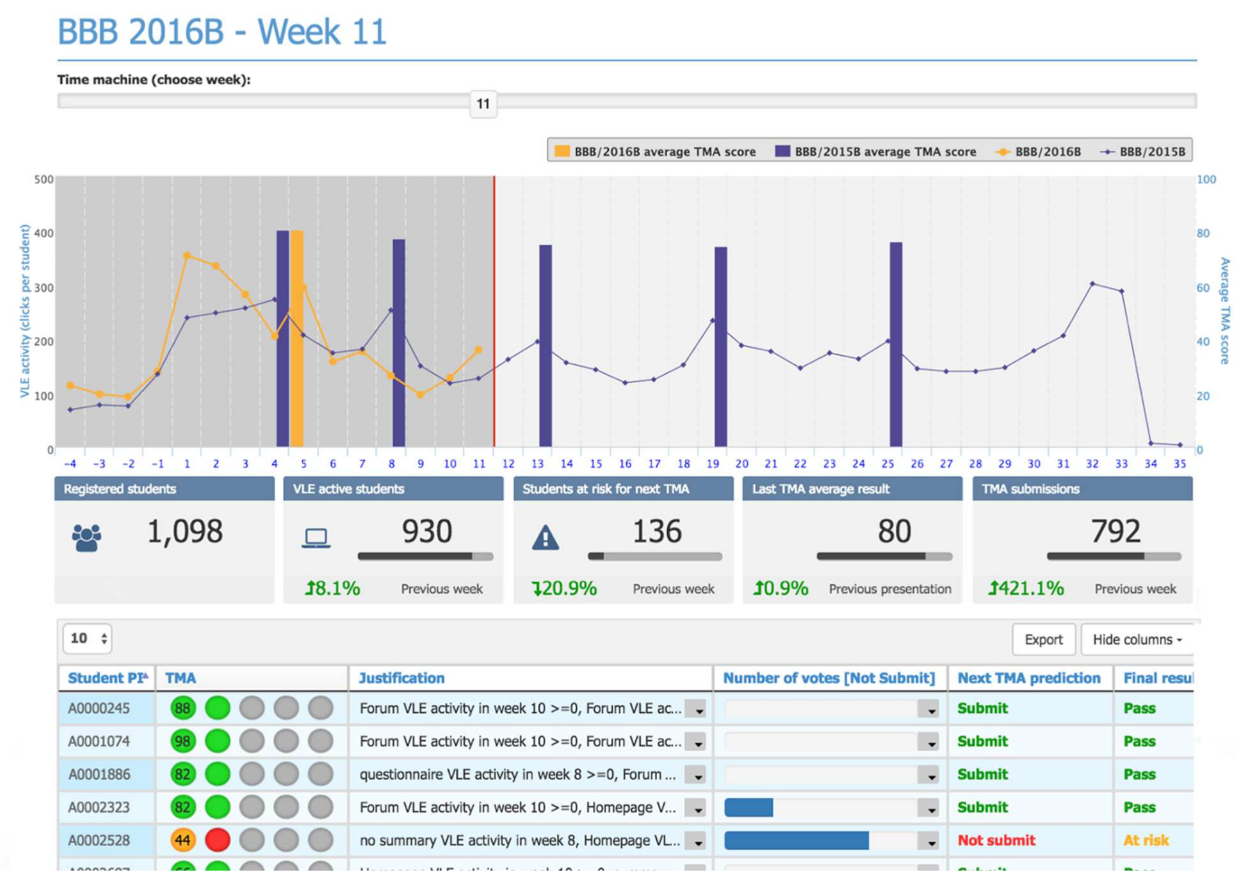

Figure 2: Module overview of OUAnalyse Dashboard

To ensure data privacy for students, we created a new view with the current functionality but showing only the tutors' assigned students. Moreover, tutors are the first and probably most important contact for students, and therefore, we wanted them to be able to note any experience with the predictions and information, in case they initiated any conversation with the student. We created a simple form, see Fig. 3, and left the usage entirely voluntary. 82% of the feedback comments confirms that the tutors find the predictions useful.

Having a large number of users presents the challenge of how to introduce them to the system, and provide them with adequate support. One of the concepts is to utilize the feedback from early adopters of the system, *super-tutors*, and to use their expertise to introduce the system to the new users. Further, we divide the workload of support to two layers. The first one is trying to answer the questions and resolve the issues directly and passing it to the second, i.e. technical/development team, in case of a more advanced problem. Although this model worked for us perfectly so far, we are planning to include even more users in the future, and we are investigating new options.

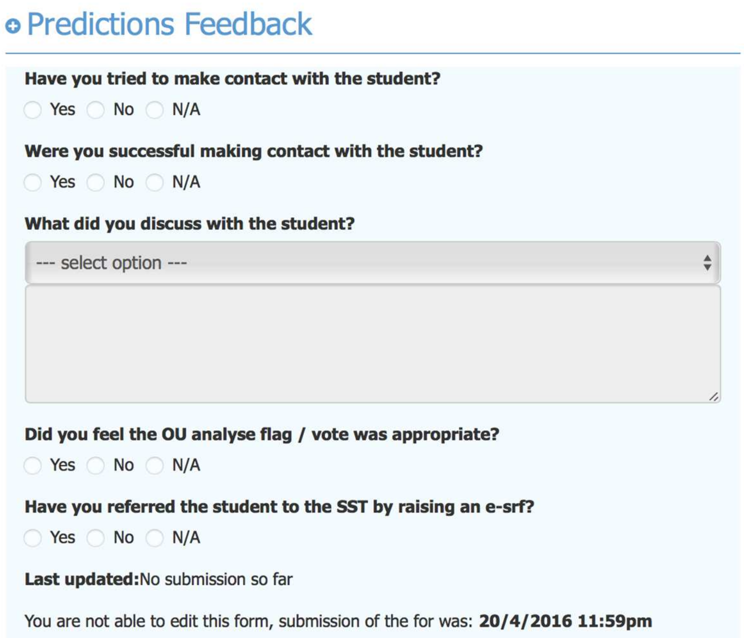

Figure 3: Tutor feedback form

5 RESULTS, SUMMARY AND LESSON LEARNED

Different challenges need to be taken into account when scaling up or out. When deploying technology that is novel for many users, feedback from final users and methods of participatory design, may significantly improve technology adoption. This applies to the acceptance of the technology and methodology. The usefulness of this approach has emerged in the first pilot applications in 2014, but turns out to be essential in the mass deployment. The "super-tutors" proved to be helpful mediators.

Initial analysis shows that email notifications are an excellent tool to increase user engagement with the dashboard system.

6 CURRENT FOCUS AND FUTURE DIRECTIONS

Because of the success of the scaling-up, the current goal is to extend the reach to all the modules at the OU, which should be around 300 per academic year. This will bring a new challenge of how to provide users with the sufficient support while keeping the team as small as possible. Also, we will test the time and resources needed to support this number of modules in the next year.

The identification of at-risk students isn't the final step the system should be able to provide. We are working on a personalized recommender that will provide tutors with advice of what should be the student's' next action to improve their learning. We believe that the next step to explore should be delivering the learning analytics directly to the learners. This is not expected to be easy, because of the technical and ethical challenges that need to be addressed, however, it is certainly worth exploring.

7 SUMMARY OF DEPLOYMENT WITH END USERS

OUAnalyse was piloted in spring 2014 by two courses, with two users each. Currently, 26 modules are using the system with 1,000 users in total (involved a range of roles). The history and the current state of scaling is summarized in Fig. 4. The primary focus is to help tutors that have direct contact with students by identifying the students' potential problems and understand their learning pathways. There are challenges with scaling-out to other courses and scaling-up to more users, finding the balance between automating the process and addressing specific needs. The plan is to further scale the system to support most of the OU courses (i.e. around 300 courses per year).

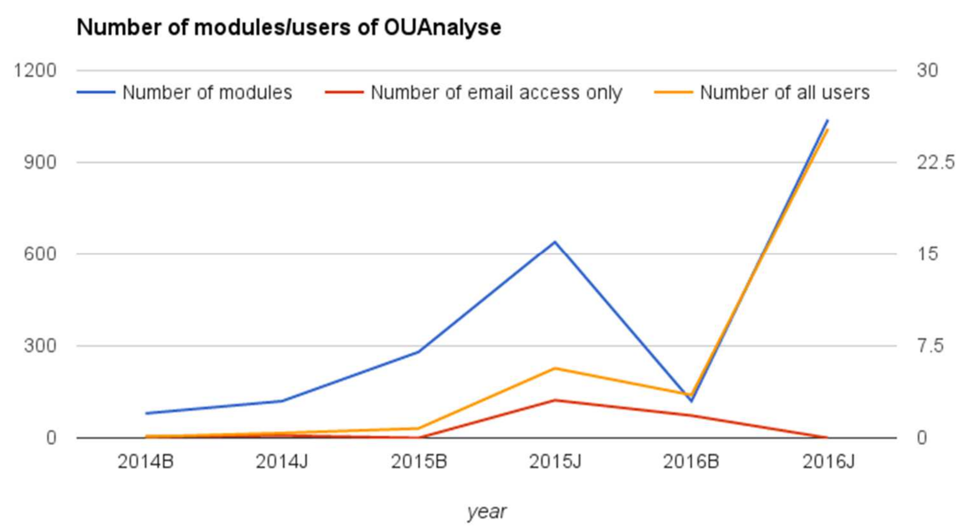

Figure 4: Number of modules/users of OUAnalyse from 2014B presentations to 2016J presentations, (B denotes Spring presentations, J autumn presentations)

M2B System: A Digital Learning Platform for Traditional Classrooms in University

Hiroaki Ogata
Learning Analytics Center
Faculty of Arts and Science
Kyushu University, Japan
hiroaki.ogata@gmail.com

Yuta Taniguchi
Learning Analytics Center
Kyushu University, Japan
yuta.taniguchi.y.t@gmail.com

Daiki Suehiro
Learning Analytics Center
Kyushu University, Japan

Atsushi Shimada
Learning Analytics Center
Kyushu University, Japan

Misato Oi
Learning Analytics Center
Kyushu University, Japan

Fumiya Okubo
Learning Analytics Center
Kyushu University, Japan

Masanori Yamada
Learning Analytics Center
Kyushu University, Japan

Kentaro Kojima
Learning Analytics Center
Kyushu University, Japan

ABSTRACT: We present M2B system, the digital platform of learning in Kyushu University, Japan. Combined with our "Bring Your Own PC" program, currently the M2B system is used by about 19,000 students and 10,000 faculty staffs, and more than 700 courses have been registered in the system since September 2014. What makes M2B system unique is that it is designed to be integrated into traditional classrooms. The system consists of three subsystems Moodle, Mahara, and e-book system, and it provides functionalities needed by classes such as managing assignments, delivering textbooks as e-books, and storing journal writings. This results in availability of learning logs from traditional classrooms and outside classes, and we can perform learning analytics on them. We have developed learning analytics methods, and they are provided as tools on M2B system for supporting teaching and learning in classes on site. As of October 2016, totally 28 millions of learning logs are collected from our system and have been used in our learning analytics. In this paper, we describe our system and learning analytics tools that we have developed. In technology showcase event, we demonstrate how our tools work and how we are using them in our classes.

Keywords: traditional classroom, learning logs, learning analysis, real-time processing, e-book, Moodle, Mahara

1 INTRODUCTION

Recently, researchers have examined Open Educational Resources (OERs), such as Open Course Ware (OCW) and Massive Open Online Courses (MOOCs) (Eisenberg & Fischer, 2014; Siemens & Dillenbourg, 2013). Compared with OERs, traditional educational resources, such as books, textbooks, or their learning contents, cannot be easily accessed online, and data on students' learning activities are unavailable. Therefore, verifying the educational effectiveness of traditional educational resources remains challenging. Despite the variety in types of traditional learning resources, research on the measurement of their educational effects is limited.

In Kyushu University, we have developed a digital learning platform, named M2B system, and it has been used in more than 700 courses over few years. M2B system is designed to be used in traditional classrooms, and we have been collecting students' activity data (learning logs) from face-to-face classes, which now forms an educational big data. We have been doing the Educational Big Data Learning Analytics Project on it, which has been supported by Commissioned Research of National Institute of Information and Communications Technology, Japan (No. 178A03, 80,000,000 JPY, 2014—2017).

In this paper, we describe the architecture of M2B system and learning logs collected from the system. We also provide introductions to tools available on the current system, which has been developed by us to support teachers and students based on the outcomes of learning analytics.

2 THE STRUCTURE OF M2B SYSTEM

M2B system and the learning analytics environment is built on on-premise servers in Kyushu University. We have combined three subsystems into M2B system: Moodle, Mahara, and e-book system; and we have built an environment for learning analysis and developed tools on top of it. In the rest of this section, the components are described individually.

2.1 BYOPC

Kyushu University implemented the “Bring Your Own PC” (BYOPC) program in 2013, and therefore all students have their own computers into the traditional classroom. Although this is not a system component actually, this program plays a fundamental role in introducing a digital learning platform into face-to-face classes.

2.2 Moodle

Moodle is an open source learning management system. Both instructors, including teachers and teaching assistants (TAs), and students use our Moodle system. Students can use this system to take tests and submit reports, whereas instructors can use it to take attendance, distribute questionnaires, carry out tests, manage students’ achievements, and carry out questionnaire surveys.

2.3 Mahara

Mahara is an e-portfolio system, and it is also open source. We currently use a Mahara system to store students' journals. In some classes, teachers encourage students to write journals for reflection, and also teachers and TAs sometimes write journals themselves. Those journals written by students are automatically shared to the instructors so that instructors can make use of them for improvement of classes. We create Mahara’s blogs for each course and student in advance and have students write a blog entry for each week.

2.4 E-book System

We store lecture materials, such as slides or notes, into the e-book system, and users can access them through a dedicated reader application. With the application, students can read learning contents used in classrooms not only in classes but also at home. All user actions performed on the application, such as turning pages and opening a material, are recorded as learning logs and automatically sent to our database when a network connection is available. Table 1 shows an example of learning logs. The reader application provides additional functions bookmarking, highlighting, noting, and searching; and related data like the input text of a note taking are also included in a log.

Table 1: Example learning logs from our e-book system.

User ID	*Action name*	*Document ID*	*Page Number*	*Action time*
Student1	Next Page	00000000NBU4	16	2014/10/22 8:40:55
Student1	Previous Page	00000000NBU4	15	2014/10/22 8:42:15
Student2	Add Highlight	00000000NBU4	15	2014/10/22 8:42:16
Student3	Add Note	00000000NBU4	15	2014/10/22 8:42:18

2.5 Integration

We integrated the above three systems so that they cooperate and users can use them seamlessly. For example, M2B system provides single sign-on authentication, which means that one can use any of the subsystems without authentication as long as one of the subsystem is logged in. This also makes it possible to connect user activities on different subsystems and to analyze students' learning logs in an integrated manner.

2.6 Learning Analytics and Tools

We perform learning analytics and provides development of teaching and learning support tools are based on the above system stack. Learning logs from the three subsystems are stored in the common database of M2B system. In most cases, we develop plug-ins for Moodle or Mahara systems, and these plug-ins can access every log in the database.

The integration of subsystems enables us to observe students' learning activities from multiple viewpoints to improve traditional classrooms. For example, we can combine logs of reviews of e-books and scores of weekly mini-exams to analyze the underlying relationships among these activities and learning outcomes. Furthermore, teachers can make some actions for students in classes and/or on M2B system based on the analysis.

3 LEARNING AND TEACHING SUPPORT TOOLS

We have developed many tools for teachers and students to analyze their classes and see the relative status of students themselves in M2B system. Most of the tools are provided as plugins, and thus they could be used in other systems using Moodle or Mahara. The following list shows the summary of our tools.

3.1 Active Learner Tools

As Kyushu University encourages active learners, we developed a measure to quantify how active a student is, the score of which is called active learner point. The active learner point is calculated from many students' activities from the three subsystems. Table 2 shows the activities used for the calculation. We provide three tools to visualize students' active learner points from different perspectives.

3.1.1. *Active Learner Process*

This shows temporal sequences of active learner points differently for teachers and students. On one hand, it shows the average points of students and scores of selected activities for teachers to see how the entire activeness of their classes changes week by week (left hand side in Figure 1). On the other hand, for students, it shows temporal sequence of his or her active learner points as well as the average ones of a class. This enables students to relatively position his activeness in the class.

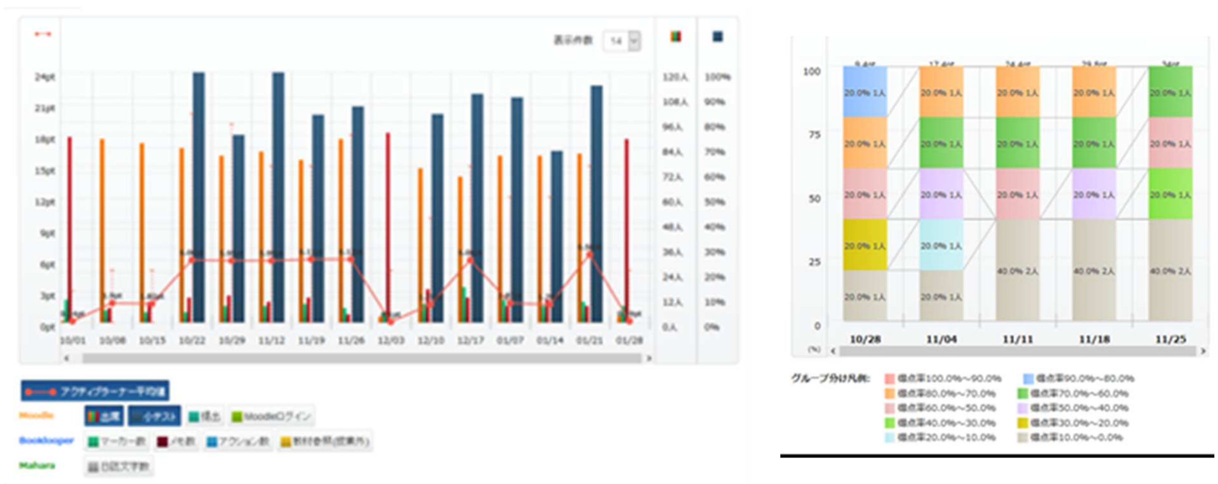

Figure 1: Active learner process (left hand side) and active learner distribution (right hand side)

Table 2: Activities considered in computation of acitive learner points and evaluation methods.

Subsystem	*Activity*	*Evaluation Method*
Moodle	Attendance	Attend: **5**, late: **3**, absent: **0**
	Quiz	**5** if score >=80%, **4** if score >=60%, **3** if score >=40%, **2** if score >=20, **1** if score >=10%, **0** otherwise
	Assignment	**5** if submitted, **3** if late submitted, **0** if no submission
	Viewing Course	Relative percentile scores from **0** to **5**
E-Book	Reading Time	Relative percentile scores from **0** to **5**
	Number of Highlights	Relative percentile scores from **0** to **5**
	Number of Notes	Relative percentile scores from **0** to **5**
	Number of Actions	Relative percentile scores from **0** to **5**
Mahara	Number of Characters	Relative percentile scores from **0** to **5**

3.1.2. *Active Learner Distribution*

This tool shows the distribution of students categorizing them into a specified numbers of levels by their scores for each week (right hand side in Figure 1). Compared to the previous tool, this can be used to know the overall activeness of a class.

3.1.3. *Active Learner Ranking*

This shows the ranking of students according to the active learner points that they acquired. We can know who are the most active students from the ranking table.

3.2 Real-time Analysis Tools

We have developed tools that analyze the states of students in classes to help teaching on site. Currently there are two tools of this kind: response button and e-book heatmap. The former is a simple tool that provides two buttons "Got it" and "Don't get it" on Moodle's course page, and students can tell their understanding by clicking either button. The tool aggregates the responses and shows the time sequence of the responses as a bar plot like one shown in Fig. 2.

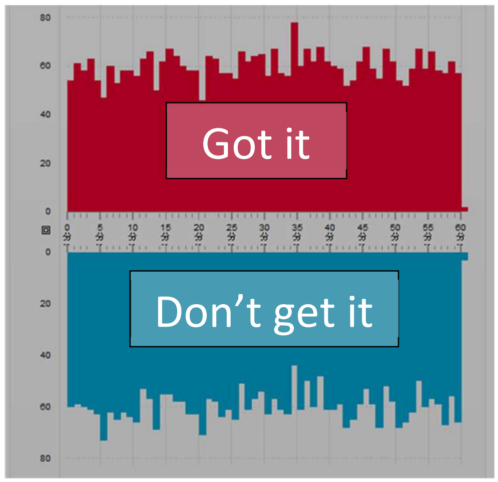

Figure 2: An example of bar plot of response buttons tool

The latter tool presents the reading status of students. Every minute, it computes the distribution of users over the pages of the e-book used in a class, and show the distribution as a heatmap on the system. Figure 3 shows an example of a heatmap, and horizontal axis corresponds to time and the vertical axis represents pages of a material. Every cell is colored according to the number of students who are reading the corresponding page at the corresponding time. From the figure, we can see whether students are being able to follow a teacher or not.

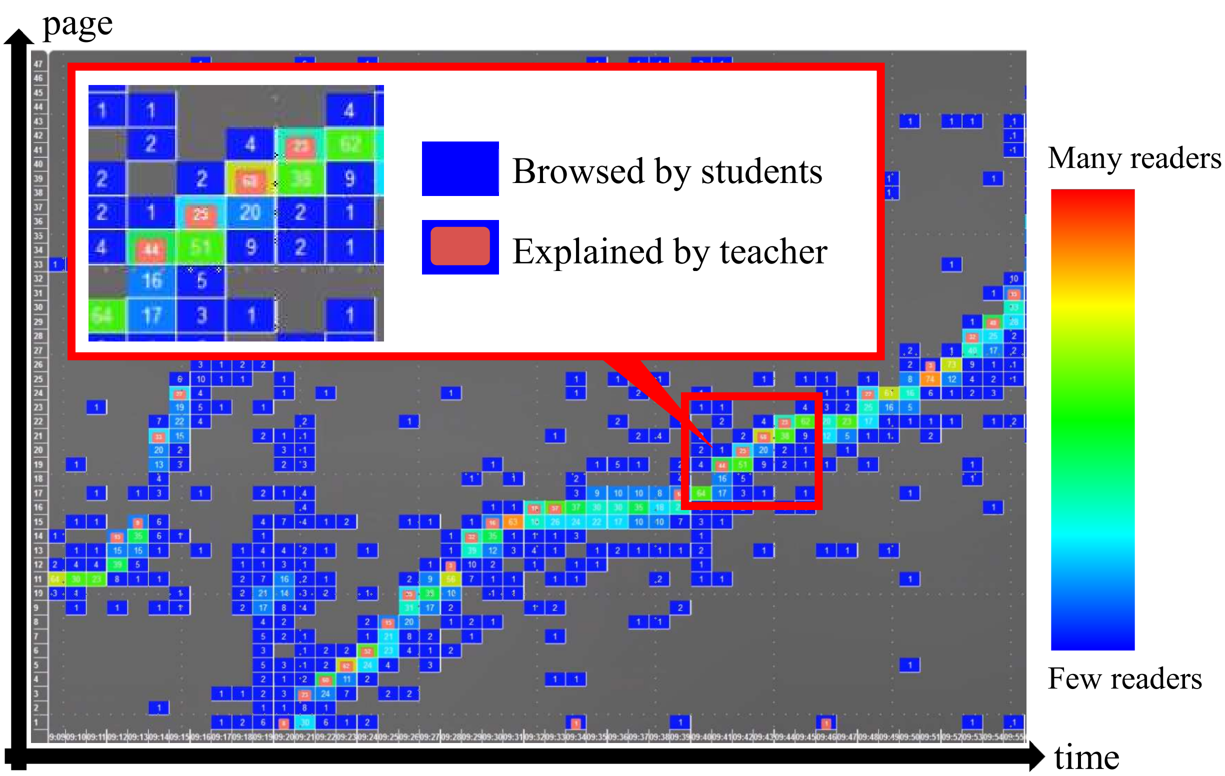

Figure 3: Real-time e-book heatmap

3.3 E-Book Analysis Tools

We provide three simple tools for analyzing the usage of e-books based on our work (Ogata et al., 2015).

3.3.1. *Learning Activities*

In this category, we provide four indicators for teachers to know students' learning activities that uses e-books. The *overall achievement indicator* shows the histogram of percentages of previewed pages for a week, and the *individual achievement rate* shows the same for each student. The *marker indicator* presents the distribution of markers made on an e-book. The *view time indicator* shows the average view time for each page.

3.3.2. *Page Ranking*

This show a ranking of pages which are most viewed by students.

3.3.3. *Word Cloud*

As e-books provide search functionality, we can obtain the history of the queries. This tool shows an image of so-called word cloud (tag cloud) for an e-book.

3.4 Journal analysis tool

This makes a summary report for a lecture from students' journals. For teachers, students' journals are full of resources to improve teaching and makes it possible that teachers assess the learning outcomes of students from a different view point than exam scores. Nevertheless, it is difficult for teachers to read all the journals since a class can have more than a hundred of students and they usually teach several courses.

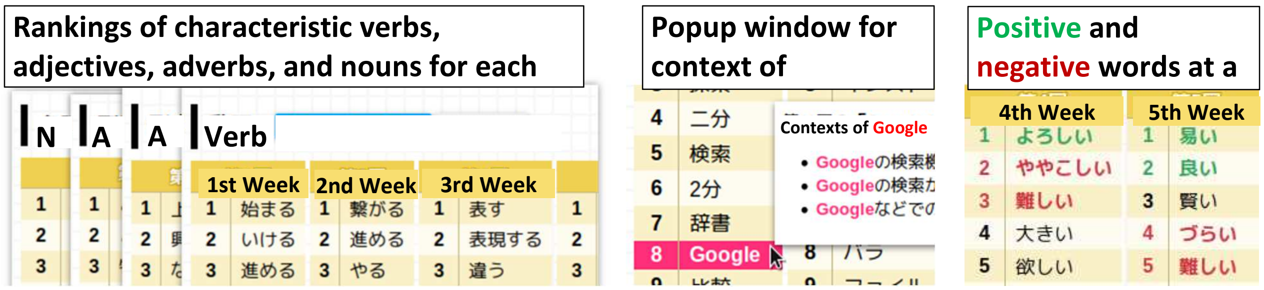

Figure 4: An example of a summary report generated by the journal analysis tool

This tool addresses the problem by enabling teachers to pick up only important sentences from the journals. Figure 4 shows a summary report, which this tool generates. The report shows rankings of week-specific nouns, adjectives, verbs, and adverbs for each week. From the rankings, teachers can briefly see what are mentioned by students and how they felt in the class. It is also possible to read the actual sentences where a word is used to understand it precisely if one needs.

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