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ARTICLE

Item-level learning analytics: Ensuring quality in an online French course

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Abstract

Learning analytics (LA) offer benefits and challenges for online learning, but prior to collecting data on high-stakes summative assessments as proof of student learning, LA researchers should engage instructors as partners to ensure the quality of course materials through the formative evaluation of individual items (Bienkowski et al., 2012; Dyckhoff et al., 2013; Mantra, 2019; van Leeuwen, 2015). This exploratory study describes a visualization tool that provides actionable data for early intervention with students, and actionable data highlighting odd patterns in student responses (Chatti et al., 2012; Gibson & de Freitas, 2016; Morgenthaler, 2009; Pei et al., 2017), thus allowing instructors to make full use of their teaching skillset in the online environment as they would in a traditional classroom (Davis & Varma, 2008; Dunbar, et al., 2014; Grossman & Thompson, 2008; Lockyer et al., 2013). To answer research questions related to the value of learning analytics and their use in making informed decisions about student learning, a visualization tool was developed for and piloted in an online French course. The findings suggest that using this tool can lead not only to intervention with low- achieving students but can also determine if students struggle due to poor course materials.

Keywords: *Online, Learning, Analytics, Exploratory*

Language(s) Learned in This Study: *French*

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Introduction

Recent definitions of learning analytics (LA) refer to the collection, analysis, and reporting of student data that can then be used to take action to improve online teaching and learning (Bienkowski et al., 2012; Clow, 2012; Gašević et al., 2017; Pei et al., 2017; Sergis & Sampson, 2017; van Leeuwen, 2015). Once the analyses are complete, LA can provide actionable information in real-time to learners as stakeholders, to instructors as stakeholders, and in the form of a feedback loop for instructors and course authors that can positively affect learners (Bienkowski et al., 2012; Chatti et al., 2012; Clow, 2012; Dunbar et al., 2014; Gašević et al., 2017; Lockyer, et al., 2013; Mor et al., 2015). These actionable data, however, are not easily accessed by all stakeholders in order to improve online teaching and learning, especially instructors who do not specialize in statistics or data visualizations (Chatti et al., 2014; Wilson et al., 2017). Solutions for including instructors in the LA process have been suggested, for example, Vatrapu et al. (2012) propose a triadic model of teaching analytics connecting a teacher, a visual analytics expert, and a design-based research expert. Mor et al. (2015), among others, present a model in which teachers are empowered as designers and researchers of learning, because unlike outside researchers, teachers know and understand the curriculum, the course materials, and the students best (Clow, 2012; Kali et al., 2015; Matuk, et al., 2015; Mor et al., 2015). The feedback loop must include instructors as researchers who ask bottom-up, as opposed to top-down, research questions. LA should first support quality control at the item-level because assumptions about student learning outcomes based only on students' summative assessment data, perhaps derived from faulty course items, cannot properly describe the learning process (Tarone, 1994). Only after confirming the quality of course items can LA fully describe student progress toward learning outcomes.

The first step of applying actionable data to online courses, however, should be for the formative evaluation of course materials. Item-level analyses will uncover any anomalies, for example, odd trends and patterns in student responses to course items that might not be attributable to a lack of preparation on the students' part (Gibson & de Freitas, 2016; Manfra, 2019; Mor et al., 2015). Profiting from data based on online instructors' questions and then compiled for instructor use, a cyclical approach to LA will reinforce the importance of applied learning analytics, as seen in the fields of applied linguistics and applied second language acquisition. This exploratory study explores how instructors can use LA to assure the quality of course materials.

Learning Analytics

The description from the 1st International Conference on Learning Analytics and Knowledge (2011) is often used to define LA: "Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs." In 2012, Chatti et al. enhanced the LAK definition, referring to LA as "a generic all-encompassing term to describe a TEL [Technology-Enhanced Learning] research area that focuses on the development of methods for analyzing and detecting patterns within data collected from educational settings, and leverages those methods to support the learning experience" (p. 5). The valuable addition from Chatti et al. (2012) is the specific reference to the patterns in the data that reflect the student experience, and then using those data to improve learning.

Unfortunately, as early as 2011, Long and Siemens drew attention to the problem of term sprawl when referring to LA due to the various approaches to and uses of LA data in different research agendas. The ubiquitous use of the phrase *learning analytics* makes studying LA difficult for education researchers wanting to confine the description of LA to the interactions between and among learners, instructors, and course materials, and not as a general term for institutional or academic analyses (Wilson et al., 2017). Moreover, as LA research becomes more abundant, term sprawl could inhibit progress in education research, as there is some disagreement with regard to the discourse related to LA. Wilson et al. (2017) speak directly to terminology confusion, explaining that the relationship between business intelligence and learning analytics begs the question of what is being analyzed and what link it has to learning.

Aside from defining LA, an example of inconsistent LA terminology is phrases used to describe the granularity of LA research. In an article on using LA data to inform decision-making, Pei et al. (2017) describe three levels of possible analyses: "The nano-level indicates activities in a course; the micro-level points [to] an entire course in an education programme; the meso-level includes many courses in a specific academic year; and the macro-level concerns study programmes in an educational institution" (p. 101). Van Leeuwen (2015) uses the terms *macro* to talk about data related to the course level and *micro* to talk about real, in-time decision making. Yet another study by Gibson and de Freitas (2016) explains levels of granularity with respect to LA, describing units of analysis that are dependent on the context for the interpretation of student data.

Reimann (2016) raises a third problem for LA and regrets the "relative absence of pedagogy, theory, learning or teaching in the LA field" (p. 131), and how the field currently describes what affects learning over time, arguing that LA has not been able to show "how learning is constituted at each moment in time" nor how a "learning event" occurs (p. 134). Other challenges have surfaced over the past ten years with regard to LA and have been reported widely in the literature, for example, data privacy, ethics of data use, and overuse or no use of learning theories when analyzing data (Chatti et al., 2012; 2014; Clow, 2012; 2013; El Alfy et al., 2019; Ferguson, 2012; Gašević et al., 2017; Wilson et al., 2017).

Teachers: Stakeholders and Researchers in Learning Analytics

Teachers are skilled at evaluating and re-evaluating classroom activities, assessment, and interactions to improve the learning environment (Davis & Varma, 2008; Dunbar et al., 2014; Grossman & Thompson, 2008; Lockyer et al., 2013). Pei et al. (2017) argue: “Teachers, usually based on their experience, use their own gut feeling to translate student behavior and suspect if a student might drop out of a course or even abandon [their] studies…But there is [a] low level of certainty in decisions that are based only on experience. Learning analytics has the capacity to add confidence to the decisions” (p. 102). For Greller and Drachsler (2012), the “main opportunities for LA as a domain are to unveil and contextualise so far hidden information out of the educational data and prepare it for the different stakeholders” (p. 47). At this point, then, two obstacles to using LA to improve online learning environments are that first, instructors accustomed to making decisions based on their experience in traditional classrooms do not have access to LA data to make similar decisions in the online environment, and second, data are not normally provided in a form easily understood by individuals who are not data analysts because data need to be prepared (Chatti et al., 2014; Greller & Drachsler, 2012; Wilson et al., 2017). A third obstacle is that often the research questions are designed for large-scale studies created for multiple instructional contexts, and not bottom-up for in-the-moment instructor-led improvements for their course and their students (Dyckhoff et al., 2013; Manfra, 2019). The three commonalities in these problems are that instructors are excluded from making choices about data related to their online teaching.

To tackle the first obstacle described in this section, instructors applying data effectively, LA could serve instructors as a general tool to facilitate their decision-making with respect to the learning process (Clow, 2013). Instructors need “evidence-based recommendations to translate analyses to specific reflective insights” (Sergis & Sampson, 2017, p. 44), a line of argument supported by Bienkowski et al. (2012) because instructors need “near-real-time access and easy-to-understand visual representations of student learning data at a level of detail that can inform their instructional decisions” (p. 46). In this way, instructors receive “context-sensitive feedback on how well the learning design is meeting its intended educational outcomes” (Lockyer et al., 2013).

The second obstacle for instructors is what type of data is valuable and who can understand and apply them. Even though instructors can access some data, “there is no flexibility for instructors to query a specific pattern” (Dringus, 2012, p. 91), therefore “the potentially harmful aspect of LA in evaluating progress in online learning is that poor decisions will derive from what data are visible and extractable in the LMS [learning management system] and from ill-defined indicators of progress” (p. 95) especially because “the stability of online learning depends on sustaining a quality experience” (p. 94). “To judge a learner’s performance merely on, e.g., LMS quantitative data is like looking at a single puzzle piece…because superficial digestion of data presentations can lead to wrong conclusions” (Greller & Drachsler, 2012, p. 52).

With respect to the third obstacle, even though instructors do not usually lead or even partner in research projects, van Leeuwen (2015) seeks to include teachers in research because LA can deliver actionable information. Some articles report on LA tools, but few report on empirical studies indicating whether and how LA can support teachers (van Leeuwen, 2015). Greller and Drachsler (2012) call for the use of LA for teachers because data can improve “curriculum design and on-the-fly adaptations” (p. 47). To improve the learning environment, Reimann (2016) highlights the role of design-based research and that LA need to be connected to learning research. As LA and design-based research have the same objective, “to improve upon learning in specific contexts” (p. 138), using LA beyond a specific course with X number of learners taught by teacher Y leads to overgeneralizations and inaccurate applications of the data. A positive development for LA would be for it to include teachers as an essential and positive part of curriculum development and re-design because “pedagogical and technical interventions… [are] preferable to the use of advanced analytical methods for reinforcing current practices, amongst them, practices that might be considered pedagogically dubious” (p. 139). Persico and Pozzi (2015) call for data to inform the design phase of online courses, combining LA and learning design, in addition to calling for teachers’ involvement in the “scientific enquiry [of LA], because their reflective practice needs to be based on innovative experience, not only their own [experience], and to be informed by data” (p. 232).

Research Questions

The foci of this exploratory study concern the first obstacle described in the previous section, how can LA data extracted from the French online course be applied to item-level analyses, thus allowing instructors to act based on data, in addition to the second obstacle, what type of data is valuable and who can understand and apply them. LA can provide important and valuable information to online teaching and learning if the data are actionable. One way to decide which information to gather is to ask instructors, as stakeholders of the teaching and learning process, what questions they need to have answered in order to improve the student experience (Chatti et al., 2012; Dyckhoff et al., 2013), leading perhaps to a resolution of the third obstacle. But "learning analytics are only likely to effectively and reliably enhance learning outcomes if they are designed to measure and track signals that are genuine indicators of or proxies for learning" (Wilson et al., 2017, p. 12).

The quality of course materials is a key factor in student success, and in traditional classrooms, instructors adapt and alter course materials as needed.[1] Online course material failure can be attributed to human coding or input errors, or to a question or series of questions written poorly and not tested with actual students before being coded into the course; once deployed, instructors and students assume course perfection. From the students' perspective, they do not ask about one incorrect response when they thought they knew the answer; online courses can contain hundreds of items for one lesson or chapter (e.g. Lesson 1 of the course described here contains 214 low-stakes items), and asking questions of every item answered incorrectly would take an enormous amount of time. By the same token, the instructor does not use the course as the student does and would not know if an item had failed. Imperatively, "the opportunity afforded by learning analytics is for educators to refuse to be overawed by the process, to understand the tools and techniques, their strengths and limitations, and to use that understanding to improve teaching and learning" (Clow, 2012, p. 19). Teachers want to evaluate instructional design and online courses (Dyckhoff et al., 2012).

Greller and Drachsler (2012) propose two questions for designing a purposeful LA process:

> "(1) Interpretation: Do the data clients have the necessary competences to interpret and act upon the results? Do they understand the visualisation or presentation of the information? (2) Critical thinking: Do they understand which data is represented and which data is absent? How will they use this information? Will the students still be able to benefit from the analytics outcome, i.e. is the analysis post-hoc or just-in-time?" (p. 45).

Building on these questions and attending to the difficulties noted above, LA data should be configured to afford instructors the opportunity to evaluate their online course materials in a timely manner and prior to relying on summative assessment of students as evidence of learning (Pei et al., 2017). Moreover, exploratory methods must involve the stakeholders, in this case the instructor, in data acquisition, preparation, discovery, and analysis (Gibson & de Freitas, 2016).

With the goal of improving teaching and learning in the online environment, this study asks:

1. How can instructors receive in-time data to analyze students' online work on low-stake items?
2. How can online course instructors use learning analytics for formative evaluation of item-level course data?

Methodology

Exploratory Research

Reimann (2016) calls for LA to become more experimental and more interventionist in order to improve upon teaching and to innovate. This study follows the guidelines of exploratory research based on the methodology described by multiple researchers (Gibson & de Freitas, 2016; Morgenthaler, 2009; Reiter, 2013; Stebbins, 2001). Exploratory research studies in the applied literature cover a wide variety of topics: eye-tracking (Fernández et al., 2014), grammar (Frear, 2019), intercultural awareness (Henao et al., 2019), MOOCs (Goggins et al., 2016), pronunciation (Munro & Derwing, 2006), reading for first and second language students (Kang, 2014), students' views of first language use (Rolin-Ianziti & Varshney, 2008), and teacher education (Downing & Dyment, 2013). Linked to exploratory practice, exploratory research allows instructors to ask new questions based on data, working toward an inductive research approach rather than the traditional deductive approach (Chatti et al., 2012; Reiter, 2013). For Gibson and de Freitas (2016), exploratory data analysis does not start with a hypothesis, but "searches initially for patterns in the data in order to discover broad sets of questions and potential hypotheses that require further study" (p. 14). Reiter (2013) argues further that by posing new questions and looking for new explanations in multiple ways, researchers can see plausible connections not previously explored or understood, because the "outcome of a successful exploratory research project is to propose a new, insightful, fruitful, and plausible way to think about and explain reality" (p. 15). Exploratory research for the purposes of education research, therefore, can aid in the development of LA data focused on instructors and their challenges in online teaching and learning.

The support for methodological diversity in education research, which is to say not only applying the traditional deductive approach, stems from "multiple examples within specific programs of research for how one study or set of studies informed the *development* of the next study" (Moss & Haertel, 2016, pp. 229-230). As a feedback loop, Ferguson (2012) describes how LA can form the basis for good learning design and effective pedagogy, and like Reiter (2013), believes that LA research needs to move away from a pure focus on "summative assessment [of student work] that looks back at what learners have achieved, [but] towards formative assessment that helps them to develop" (p. 313). The evidence of summative assessments as proof of learning is a faulty assumption, describing a false causal relationship, and a research framework should expand to consider other links, that in fact "LA intends to link 'learning' with outcomes, which bypasses multiple steps: knowledge of the learning mechanism and a priori, knowledge of the effectiveness of course materials at their most basic level" (Reiter, 2013, p. 7). Dringus (2012) encourages the use of data to detect "extensive patterns of usage and activity" (p. 91) because "responsible assessment and effective use of the data trail are essential to the advancement of understanding how learning transforms in an online course…[and] must inform process and practice (pp. 95, 98).

As an inductive, bottom-up method, exploratory research can therefore begin with a question generated by any stakeholder in the online learning process, including the instructor. Vatrapu et al. (2011), in their call for a triadic model of LA research and development, rely on the collaboration of teachers in the development of visual analytic tools to describe course data, allowing that this process "shares the goal for sustained innovation in leveraging the design of [the] affordances of [the] visual analytic tools to support teachers' dynamic diagnostic pedagogical decision making" (p. 96). Promoting the agenda of exploratory research, Hanks (2015) calls for "working towards understanding(s), rather than the more common approach of problem-solving" in order to benefit research and pedagogy, which in the end will lead to improved practice for all stakeholders ("Working for understanding(s)" section, para. 1). Dringus (2012) calls for an "awareness-building of learning analytics [that] starts with good questions to drive out good data, leading to responsible assessment and effective use of the data trail in learning analytics … leading to effective [instructional] practice" (p. 98). According to Dyckhoff et al. (2012), asking questions independently of available data will improve the design of learning materials, and moreover, LA "tools should allow for interactive configuration in such a way that its users could easily analyze and interpret available data based on individual [instructors'] interests (p. 60). Using LA actionable data, instructors can detect student outliers, oddities in student behavior patterns, and response patterns (Bienkowski et al., 2012; Chatti et al., 2012; Gibson & de Freitas, 2016; Morgenthaler, 2009; Pei et al., 2017).

Research Context and Participants

In spring and fall 2016, a total of 33 undergraduate students, aged 18-21, enrolled in an online Elementary French 1 course at Carnegie Mellon University.[2] The course was offered in hybrid mode at the pace of one lesson per week during the semester. For this course, hybrid mode meant that the students used the online course materials at home yet met weekly as a class for 80-minutes and individually with a speaking assistant or the instructor for 20 minutes. All students' identities remain anonymous.

This semester-long course is divided into 14 lessons. Each lesson contains seven sections: *Communication 1* (material introduction using videos), *Mots et Expressions* (vocabulary practice using the same videos and offering subtitles), *Structures* (grammar instruction and practice), *Sons* (practice of sounds, pronunciation, listening discrimination), *Communication 2* (further exploitation of the course materials using video and audio), *Culture* (cultural images, texts), and *Activités de synthèse* (production activities involving, for example, synchronous chat prompts, instructions on weekly speaking practice meetings, writing prompts, Internet research). Each section provides students with low-stakes assessment items.

The low-stakes assessment items are located in all sections of the lesson. They are in the form of jumbles, dragging words to make a sentence, or dragging sentences to order them according to audio or written prompts, multiple-choice questions based on visual or audio prompts, matching pictures with words or words with pictures, dictations, fill-in-the-blank based on visual or audio prompts, and multiple-choice questions for reading comprehension with written or audio prompts. Each lesson is followed by a high-stakes test.

Research Question 1, the Data Visualization Tool

How can instructors receive in-time data to analyze students' online work on low-stakes items?

These data are from two iterations of the course, spring 2016 and fall 2016. Logged online course data are normally exported and read as Excel files and routinely contain hundreds of thousands of data points, depending on the class size. Figure 1 shows an Excel file with 33 rows of student data times 214 columns of item data and Figure 2 shows a file of 25 out of 214 rows of low-stakes item names. Not only would it be very difficult for a non-specialist to retrieve this information because most likely the request would have to go to technologists who would send the data to the instructor, but it would be tedious to make any sense of the data as they related to student behavior in the course or any judgment on the quality of course items, and impossible to do in a timely manner.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1		F1L1_2Comn	F1L1_2Comn	F1L1_2Comn	F1L1_2Comn	F1L1_2Comn	F1L1_2Comn	F1L1_2Comn	F1L1_2Comn	F1L1_2Comn	F1L1_2Comn	F1L1_2Comn	F1L1_2Comn
2	Student01	1	1	1	1	0	1	1	1	1	1	1	1
3	Student02	1	NA	1	1	1	1	1	0	1	1	1	NA
4	Student03	0	NA	1	1	1	1	1	1	1	1	1	NA
5	Student04	1	1	1	0	0	1	1	1	1	1	1	1
6	Student05	0	NA	1	0	1	1	1	1	1	1	1	NA
7	Student06	1	1	1	0	1	1	0	1	1	1	1	1
8	Student07	1	NA	1	1	1	1	1	1	1	1	1	NA
9	Student08	1	NA	1	1	1	1	1	1	1	1	0	NA
10	Student09	1	NA	1	1	1	1	1	1	1	1	1	NA
11	Student10	1	1	1	1	1	1	1	1	1	1	1	1
12	Student11	1	1	1	1	1	1	1	1	1	1	1	1
13	Student12	1	1	1	1	1	1	1	1	1	1	1	1
14	Student13	1	NA	1	1	1	1	1	1	1	1	1	NA
15	Student14	1	1	1	1	1	1	1	1	1	1	1	1
16	Student15	1	NA	1	1	1	1	1	1	1	1	1	NA
17	Student16	1	NA	1	1	1	1	1	1	1	NA	NA	NA
18	Student17	1	1	1	1	0	1	1	1	1	1	1	NA
19	Student18	1	1	1	1	0	1	1	1	1	1	1	1
20	Student19	1	1	1	1	1	1	1	1	1	1	1	1
21	Student20	1	NA	1	0	1	1	1	1	0	1	1	NA
22	Student21	1	1	1	1	1	1	1	1	1	1	1	1
23	Student22	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
24	Student23	1	1	1	1	1	1	1	1	1	1	1	1
25	Student24	0	1	1	0	1	1	1	1	1	1	NA	NA
26	Student25	1	1	1	1	NA	NA	NA	NA	NA	1	0	NA
27	Student26	1	NA	1	1	1	1	1	1	0	1	1	NA
28	Student27	1	NA	1	1	1	1	1	1	1	1	1	NA
29	Student28	1	1	1	1	1	1	1	1	1	1	1	1
30	Student29	0	1	1	1	1	1	1	1	1	NA	NA	NA
31	Student30	1	NA	1	1	1	1	1	1	1	1	1	NA
32	Student31	1	NA	1	1	1	1	1	1	1	1	1	NA
33	Student32	1	1	1	1	0	1	0	1	0	1	1	NA
34	Student33	1	1	1	1	1	1	1	1	0	1	1	1

Figure 1. Excel data file showing 33 rows of student replies and 10 of 214 columns of item data

Due to the difficulty of obtaining actionable course data for instructors, a visualization tool was built using R with the extracted and cleaned course data. Developed and piloted for a Ph.D. project, the author, at times also an instructor of this online French course, brainstormed with colleagues to determine the types of analytics that could improve teaching and learning based on data from the low-stakes items, which are not collected in the course in any assessment format. The desirable actionable analytics for the tool to extract were: Which students completed which items; which items students skipped or answered incorrectly on the first attempt; which lesson items or sections students skipped completely; which students required intervention early in the course; and, which data could the instructor use to identify poor quality course materials, for example, by highlighting outliers, troubling patterns, and odd trends in student responses. To help answer these questions, the tool output allows for the regular exportation and visualization of logged course data for formative and summative evaluations of student work.

	A
1	L1
2	1: Comm1 F1L1_2Comm1.1_p01_ST q_F1L1_2Comm1.1_p01_ST_10_i1 UpdateRadioButton
3	2: Comm1 F1L1_2Comm1.1_p01_ST q_F1L1_2Comm1.1_p01_ST_2_i1 UpdateRadioButton
4	3: Comm1 F1L1_2Comm1.1_p01_ST q_F1L1_2Comm1.1_p01_ST_3_i1 UpdateRadioButton
5	4: Comm1 F1L1_2Comm1.1_p01_ST q_F1L1_2Comm1.1_p01_ST_4_i1 UpdateRadioButton
6	5: Comm1 F1L1_2Comm1.1_p01_ST q_F1L1_2Comm1.1_p01_ST_5_i1 UpdateRadioButton
7	6: Comm1 F1L1_2Comm1.1_p01_ST q_F1L1_2Comm1.1_p01_ST_6_i1 UpdateRadioButton
8	7: Comm1 F1L1_2Comm1.1_p01_ST q_F1L1_2Comm1.1_p01_ST_7_i1 UpdateRadioButton
9	8: Comm1 F1L1_2Comm1.1_p01_ST q_F1L1_2Comm1.1_p01_ST_8_i1 UpdateRadioButton
10	9: Comm1 F1L1_2Comm1.1_p01_ST q_F1L1_2Comm1.1_p01_ST_9_i1 UpdateRadioButton
11	10: Comm1 F1L1_2Comm1.1_p02_t7 F1L1_2Comm1.1_p02_t7a_conversation UpdateOrdering
12	11: Comm1 F1L1_2Comm1.1_p02_t7 F1L1_2Comm1.1_p03_t7_conversation UpdateOrdering
13	12: Comm1 F1L1_2Comm1.2_p01_ST q_F1L1_2Comm1.2_p01_ST_11_i1 UpdateRadioButton
14	13: Comm1 F1L1_2Comm1.2_p01_ST q_F1L1_2Comm1.2_p01_ST_12_i1 UpdateRadioButton
15	14: Comm1 F1L1_2Comm1.2_p01_ST q_F1L1_2Comm1.2_p01_ST_13_i1 UpdateRadioButton
16	15: Comm1 F1L1_2Comm1.2_p01_ST q_F1L1_2Comm1.2_p01_ST_14_i1 UpdateRadioButton
17	16: Comm1 F1L1_2Comm1.2_p01_ST q_F1L1_2Comm1.2_p01_ST_15_i1 UpdateRadioButton
18	17: Comm1 F1L1_2Comm1.2_p01_ST q_F1L1_2Comm1.2_p01_ST_16_i1 UpdateRadioButton
19	18: Comm1 F1L1_2Comm1.2_p01_ST q_F1L1_2Comm1.2_p01_ST_17_i1 UpdateRadioButton
20	19: Comm1 F1L1_2Comm1.2_p01_ST q_F1L1_2Comm1.2_p01_ST_18_i1 UpdateRadioButton
21	20: Comm1 F1L1_2Comm1.2_p02_t7 F1L1_2Comm1.2_p02_t7a_conversation UpdateOrdering
22	21: Comm1 F1L1_2Comm1.2_p02_t7 F1L1_2Comm1.2_p02_t7b_conversation UpdateOrdering
23	22: Comm1 F1L1_2Comm1.3_p01_ST q_F1L1_2Comm1.3_p01_ST_19_i1 UpdateRadioButton
24	23: Comm1 F1L1_2Comm1.3_p01_ST q_F1L1_2Comm1.3_p01_ST_20_i1 UpdateRadioButton
25	24: Comm1 F1L1_2Comm1.3_p01_ST q_F1L1_2Comm1.3_p01_ST_21_i1 UpdateRadioButton
26	25: Comm1 F1L1_2Comm1.3_p01_ST q_F1L1_2Comm1.3_p01_ST_22_i1 UpdateRadioButton

Figure 2. Excel data file showing 25 of 214 rows of item names and types of replies

Statistics per lesson and student, as well as plots, are the first type of actionable LA. Statistical data available in the tool (e.g. mean, median, completion rates) allow the instructor to trace one student's work in the course, sorting by student and by lesson. For example, Figure 3 shows that Student 2's performance was consistent until Lesson 6 when their performance started to decline. The student's pattern of work clearly showed a need for early intervention.

The data in Figure 3 indicate that Student 2 started off strong in the course. Lesson 1 shows that the student attempted 97.7% of the items, answering 81.3% of them correctly (170 items). In Lesson 5, their attempt rate was 90.2% but the correctness percentage for the attempted items was 78.6%. In Lesson 6, the student dropped to a low completion rate of 67.5%, then 32.7% in Lesson 7, and 27.6% in Lesson 8. The pattern shows that the number of items attempted continues to drop, with a spike in Lesson 12, falling again in Lessons 13 and 14. Although the percentages correct seem high except for Lesson 7, when considering the decrease in the number of items attempted, the data describe a struggling student.

In addition to providing statistics, plots are created by compiling the logged course data, allowing real-time straightforward visualizations intended for use by instructors who are not data analysts. For example, for Lesson 1, the tool can create a plot that shows all students and all items for the lesson, statistics for all students and all items for the lesson, and the statistics of each student's responses to all items across all lessons in a summary format. In Appendix A, a large visualization includes all students across all items in all lessons of the course. Appendix B provides the item data plot of the whole class for all of Lesson 1. The squares indicate items correct on the first attempt (blue), items incorrect on the first attempt (red), and items with no reply (white).

The horizontal axis plots each student as a number for the purposes of the study, and the vertical axis plots the number of items in the lesson. The full plot for Lesson 1 (Appendix B) therefore shows the number of items in the entire lesson (N = 214) and from the plot, the instructor can link directly to the course item. The partial plot in Figure 4 shows the *Communication 1* (indicated as *Comm1*) section of Lesson 1 and instructors can see at a glance that 32/33 students (97%) attempted Item 1. For larger classes where a visual would not be efficient, the tool's *Item stats* tab provides the plot information in a table format showing how many students answered Item 1 correctly on their first attempt among all students (28/33 = 84.8%) and among only the students who attempted Item 1 (28/32 = 87.5%).

Lesson	Mean_Attempted	Mean_Correct
1	97.7	81.3
2	98.8	78.2
3	90	76.7
4	97.3	78.1
5	90.2	78.6
6	67.5	81.6
7	32.7	68.1
8	27.6	83.9
9	38	91.9
10	74.9	83.9
11	51.4	81.1
12	85.2	84.4
13	46.7	83.5
14	53.8	82.4

Figure 3. Student 2's course performance in all lessons

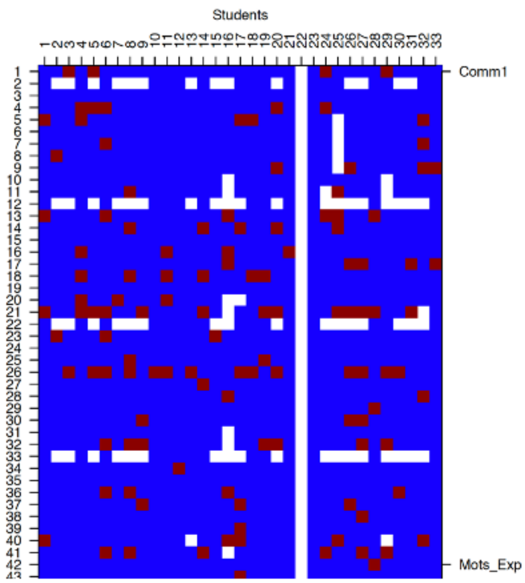

Figure 4. Lesson 1 plot showing all students and the first 43 items of the course, primarily from *Communication 1*

The data visualization tool, designed with instructors in mind, creates plots and compiles basic statistics to gather data, in real-time, on student performance by item and lesson. Even quick glances at statistics and plots provide opportunities for intervention. The tool was developed and tested over a period of months for the purposes of this study. Given such speed and efficacy by a novice programmer, online instructors should always have access to actionable data in order to apply LA to their courses.

Research Question 2, Item-Level Analysis of Course Data

How can online course instructors use learning analytics for formative evaluation of item-level course data?

In traditional classrooms, if all students answer an assessment question incorrectly, the instructor reviews the item to determine if it was faulty. It is possible that every student simply replied incorrectly, but it is just as possible that the item was poorly written, asked for information not learned or mastered, or was too difficult. Additionally, instructors rewrite or eliminate exercises or items from traditional course materials, because in their experience, the items ‘don’t work’ (Kali et al., 2015; Matuk et al., 2015; Mor et al., 2015).

Whereas subsequent textbook editions are published regularly and include corrections noted by instructor-users, this insightful teacher behavior is not currently possible when teaching most online courses. In order for LA to be beneficial, “the data trail from the artifacts of online course production must be measurable, visible and transparent in real time (as it happens)” (Dringus, 2012, p. 98). Most likely the instructor did not write the course materials and is not familiar with each individual item. Even if students do bring confusing items to the instructor’s attention, the instructors cannot access the course’s platform to make corrections. Instructors can of course respond to students’ confusion in real time, but without updating items, the problem persists. Unfortunately, online courses are not updated regularly due to the fact that instructors lack the specialization to understand the technology, technologists are not subject matter experts, it is costly, and faulty items are not readily visible to instructors (Lieberman, 2018).

Nonetheless, the appropriate visualization tool would allow instructors to notify students of course item errors. Although this approach does not update the course, it does update the students and improve their comprehension of materials in which they made errors without knowing why. Prior to high-stakes assessments, students should learn from their unexpected mistakes especially if the errors are related to faulty course items. With data, instructors can also use LA to identify sections of a course that most learners skim or skip without any negative effect, suggesting that these elements are redundant; highlight the sections most students struggle with, which may need to be reworked; and increase efforts to adapt materials to student needs (Feldon, 2007; Mor et al., 2015).

Findings

Following is a series of detailed analyses of outlying patterns and trends in student responses to items as highlighted in the tool’s data visualization plots.

Analysis 1: Item-Level Data: Missed Opportunities for Intervention

In Figure 5, data for Item 2 in Lesson 1 show that 18 out of 33 students attempted the item, or 54.5% of the students. Those 18 students answered correctly on their first attempt, so the correct answer percentage for this item is 100%. This is misleading because only 54.5% of the students replied to the question. The plot data provoke three questions, all concerned with why students answered the items as they did: Why Student 22 did not begin Lesson 1, why Student 25 did not complete Items 5 to 9, and why some students consistently skipped Items 2 and 12. This plot shows that when complemented with instructor vigilance, data visualizations can help instructors distinguish between truth and conjecture about student behaviors, and not lead to faulty assumptions based on incomplete LA data.

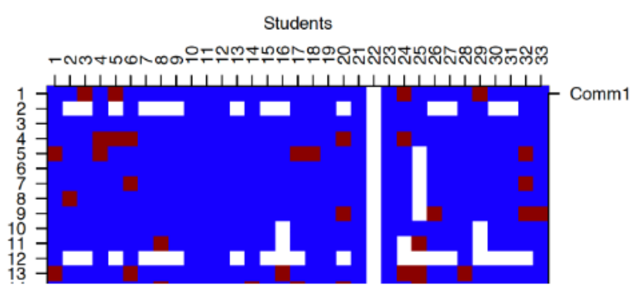

Figure 5. Lesson 1 patterns of the first 13 items in *Communication 1*

Analysis 2: Item-Level Data from Lesson 1, *Sons*: Items 74 To 80

The entire *Sons* section for Lesson 1 is in Appendix C. The following analyses are from the first time that students worked in the *Sons* section of a lesson.

Figure 6 shows isolated patterns of correct and incorrect answers on Items 74 to 80. Although the course provides the correct answer after three failed attempts, a quick email from the instructor could check to see if the students still had questions.

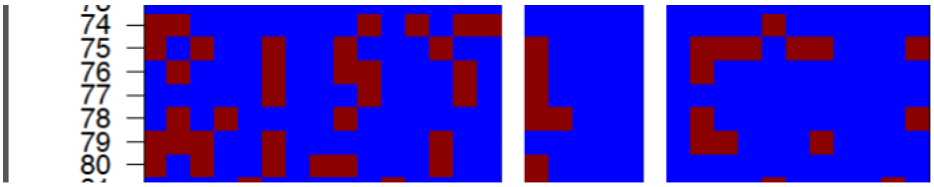

Figure 6. Detail of Items 74 to 80 in Lesson 1, *Sons*

Analysis 3: Item-level Data from Lesson 1, *Sons*: Items 89 to 91

Figure 7 shows a Lesson 1 pattern from Items 89 to 91 on page 57 of the course. These three items comprise a typical course activity that requires ordering aural or written segments of a conversation. This was not the first time that the students saw this content or type of exercise. There are four pages with two questions each in the preceding *Communication 1* section of Lesson 1, ranging from four to seven words to put in order.

In this specific set of questions, the students were provided with an aural model to follow. Item 89 asks students to organize the eight syllables, written phonetically, in the sentence '*Eh, bonjour Monsieur du Corbeau*.' For Item 90, the sentence is '*Que vous êtes joli !*', (five syllables) and for Item 91, the sentence is '*Que vous me semblez beau !*' (six syllables).

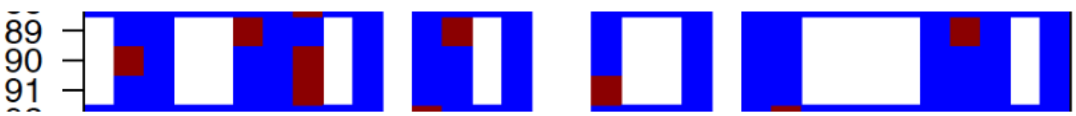

Figure 7. Detail of Items 89-91 in Lesson 1, *Sons*

The white squares in Figure 7 indicate that 12 out of 31 students skipped all three items. Data from *Communication 1* (p. 57) can be easily located in the plot (c.f. Appendix B), thus allowing instructors to reference similar types of activities in previous sections of the lesson. The data do not indicate that students had severe difficulties completing ordering activities (e.g., Items 10 to 11, p. 14; Items 20 to 21, p. 16; Items 31 to 32, p. 18; Items 40 to 41, p. 20). Given their familiarity with the activity type, then, the instructor would need to understand why students did not even attempt Items 89 to 91.

Analysis 4: Item-level Data from Lesson 1, *Sons*: Items 116 to 118

Overall, the students do well until Items 116-118 in Figure 8. This set of questions, on page 2 of the third section of *Sons*, deals with nasal vowels. The first page of this section asks student to distinguish among three primary nasal vowels (i.e. the nasal vowels in the words *bonjour*, *Morin*, and *temps*). In the exercise, students hear one of the nasal vowels pronounced in isolation (i.e., not in a word) and then in five words, on which they can click for pronunciation verification. The students must pick all of the words that contain the nasal vowel in question.

However, even though students would be familiar with this type of activity, Items 116, 117, and 118 required them to choose three correct words, not just one. If students did not read the instructions fully, perhaps they only chose one word and not three, especially for Item 116, the first item in the sequence. An analysis of the responses to the three items shows that of the 31 students who completed Item 116, 3 answered correctly, 9 answered Item 117 correctly, and 14 answered Item 118 correctly. The plot in Figure

8 shows that the students' improved in their recognition of nasal vowels or realized their errors in initially choosing only one word after getting feedback.

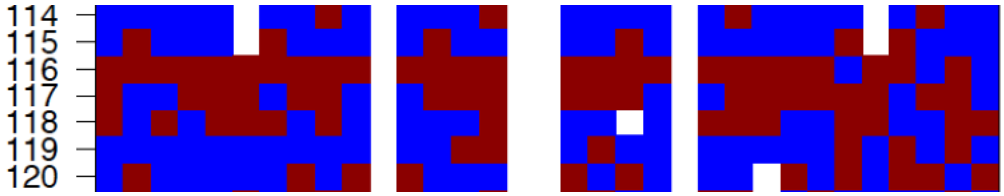

Figure 8. Detail of Items 116 to 118 in Lesson 1, *Sons*

In a class assessment, instructions to students would have been reinforced prior to beginning the exercise. Course designers and authors, however, might not have had a similar intuition, that is, to reinforce on the online course page that students should choose three words for each item. Without knowing the reason for the errors, instructors cannot improve on their teaching.

Discussion

These analyses focused on four sets of data from Lesson 1 of the course. It is vital that instead of assuming ineptitude on the students' part, instructors use data to investigate obvious student outliers (Student 22 in Figure 5), odd response patterns (Figure 6 & Figure 7), and response trends (Figure 8). In a traditional classroom, engaged instructors would ask the students if they had trouble accessing the course (Student 22), or distinguishing sounds and which sounds (Items 116 to 118). Directly addressing any students who skipped multiple items in Lesson 1 could mitigate the number of students dropping the course in frustration due to the new experience of learning a language online, and/or help them develop strategies for dealing more effectively with the course materials. Data anomalies exist, as shown in the four analyses. It is important to determine, however, whether the anomalous patterns exist due to student inattention or can be attributed to poor quality course materials; the learning process cannot be studied if courses are not well-written, vetted, and revised (Tarone, 1994).

Poor LA data lead to poor decisions about the online teaching and learning process (Chatti et al., 2014; Greller & Drachsler, 2012; Pei et al., 2017; Wilson et al., 2017). Fortunately, LA offer many opportunities to learn more about student use of online courses. Unfortunately, the data are not available to instructors, the stakeholders who need them most in order to improve teaching and learning online (Chatti et al., 2014; Wilson et al., 2017). LA provide actionable data that can be used to create a feedback loop of improved course design, data gathering, improved course design, data gathering, until researchers can be certain that the student summative assessment data are actually evidence of learning (Bienkowski et al., 2012; Chatti et al., 2012; Clow, 2012; Dunbar et al., 2014; Gašević et al., 2017; Lockyer et al., 2013; Mor et al., 2015). If teachers are included in the development of research questions, their insight can lead to improved and applied use of LA (Gibson & de Freitas, 2016; Manfra, 2019; Mor et al., 2015).

This study presents the lowest-level of granularity of item-level evaluation, the nano-level (Pei et al., 2017). Using nano-level data can ensure the high quality of course materials, a necessary first step so that learning theories can be truly applied to LA, allowing researchers and instructors to have confidence in their data. The hidden information should not remain hidden (Greller & Drachsler, 2012), and the key stakeholders in the improvement of teaching and learning online must be part of the research, in the ways that make the most sense (Bienkowski et al., 2012; Clow, 2013; Sergis & Sampson, 2017; van Leeuwen, 2015) Instructors can ask questions of straightforward visualizations that show what students are actually doing (Dringus, 2012; Reimann, 2016), and these questions will inform course design, involve instructors in the course design process, and move the field forward (Persico & Pozzi, 2015).

Conclusion

Good pedagogy begins with good course materials and an instructor who has a voice in the process (Davis & Varma, 2008; Dunbar et al., 2014; Grossman & Thompson, 2008; Lockyer et al., 2013; Reimann, 2016). LA draws on multiple fields and related areas (Chatti et al., 2012; Ferguson, 2012). This study connects previously disparate ideas: That detailed LA need to be made accessible to teachers in real-time who, aside from learners, are the closest stakeholders to the teaching and learning process; that LA need to provide a variable granularity of detail to instructors in order for them to make supported pedagogical decisions; and that valuable bottom-up pedagogical and methodological questions can be instigated by course instructors as well as researchers outside of a specific teaching and learning environment. And although LA are clearly beneficial, the benefits will remain theoretical unless the potential beneficiaries engage in an active process of inquiry into learning (Mor et al., 2015).

LA provide a picture of the strengths and weaknesses of the learning process in the moment (Persico & Pozzi, 2015). However, LA do not focus on the most basic and vital information that could enable more consistent student learning. For instructors, it is not simply a case of knowing the percentage of answers correct and incorrect, but why were the answers correct or incorrect—due to faulty study habits or due to faulty course items; it is not simply a case of knowing which items were skipped, but why the items were skipped—due to student inattention or disengagement with the course materials, or due to materials that are too hard, too easy, repetitive, or simply boring. Instructors merit the opportunity to find errors in and suggest improvements to online course materials based on their actual experiences.

This study presents a very small portion of the logged course data for this online French course. The analyses presented here are certainly at a basic level. However, many more detailed and comprehensive questions could be asked of the data. Certainly, more questions could be asked at the item-level. Questions could also be asked at the lesson level: Are there considerably more items in this lesson than another, which might lead to student fatigue and less efficient learning? What would an analysis show from a dataset of five thousand students in which all students answered multiple questions correctly?, and at the course level: Are there activity types that students skip routinely? If students skipped the entire grammar section, how is it possible that they passed the lesson test? When the instructions and explanations changed from English to French, was there an effect on their learning? Instructors believe they know the answers to some of these questions, but data would provide proof one way or the other.

In the future, and in order to make full use of LA, a more standardized and rigorous approach to the data would have to be undertaken to determine if students in every offering of the course, and with different populations, make the same errors. The challenges to full-scale implementation of studies of the type discussed here are that instructor-friendly visualization tools need to be developed and applied to every online course, no matter the course content; that instructors in all contexts should have input into course design and revision in order to participate in the feedback loop; and that researchers and instructors must work together to ask and study questions relevant to the feedback loop. Without an iterative cycle, beginning with the quality of course materials, any judgments made about students and whether they meet learning outcomes in online courses are ambiguous at best.

Acknowledgements

This research could not have been imagined without the work of Alan E. Mishler, a Ph.D. student in the Department of Statistics and Data Science at Carnegie Mellon University. Alan developed the tool used in this research and although it may not be 'elegant' by the standards of data scientists, it functions exactly as it needs to for the benefit of online instructors and online students. For his intuition, his dedication, and his unerring patience in dealing with a non-specialist (me), I will be forever grateful. His advisor, Dr. Rebecca Nugent, was also key to Alan's success both with me and the online course data.

Notes

1. c.f. https://www.qualitymatters.org/; https://www.ppic.org/content/pubs/report/R_615HJR.pdf
2. https://oli.cmu.edu/product-category/language/

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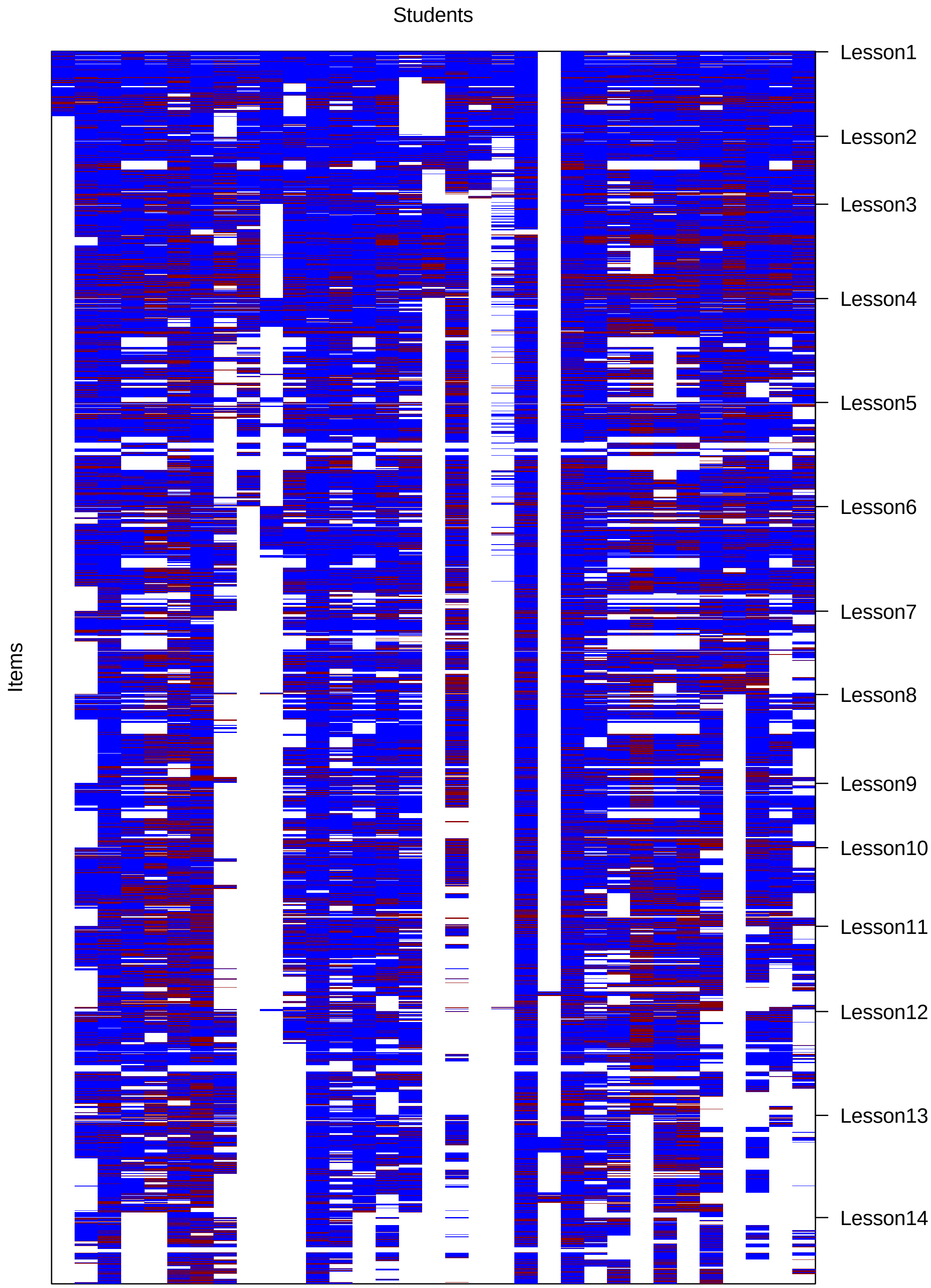
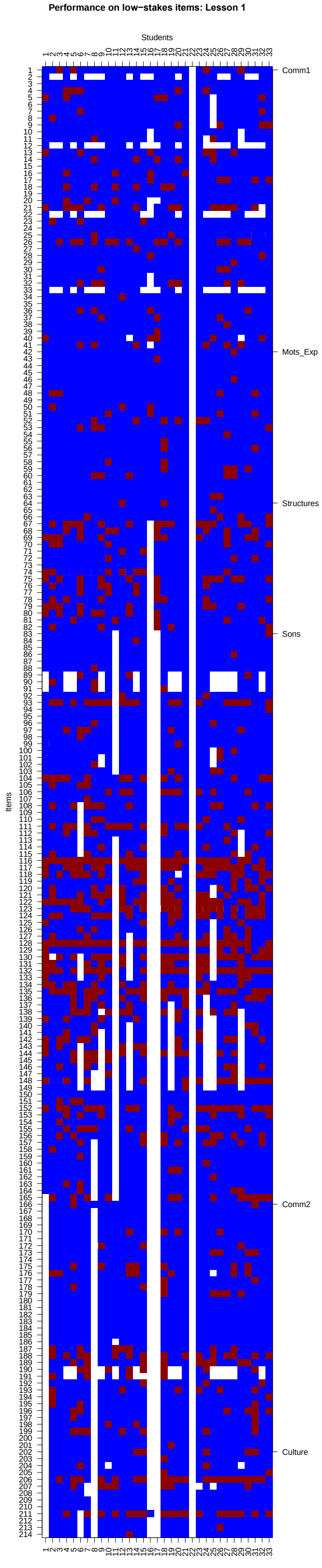
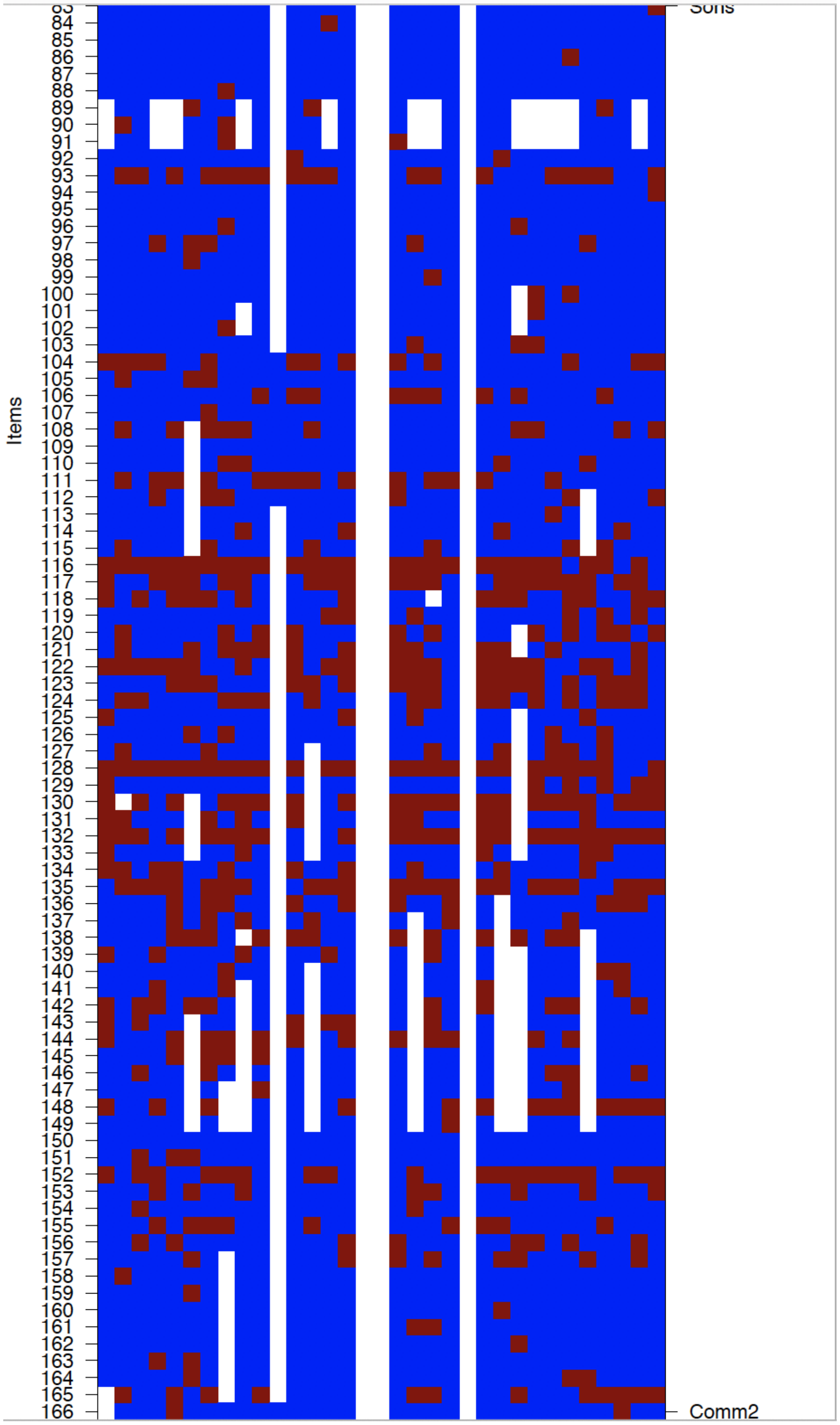
Appendix A. All course data for all students by lesson and item



Appendix B. Lesson 1 data for all students and all items



Appendix C. Lesson 1, *Sons*, all students



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