Analysis of Consistency in Large Multi-Section Courses Using Exploration of Linked Visual Data Summaries

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ABSTRACT

Higher education courses with large student enrollments are commonly offered in multiple sections by multiple instructors. Monitoring consistency of teaching activities across sections is crucial in achieving equity for all students, and in developing strategies in response to emerging patterns and outliers. To address this need, we present an approach to analyze the multivariate data of sections, assignments and student submissions collected by a learning management system (LMS) using a new data exploration framework that we call linked data summaries. Data summaries are a unit of exploration with uncluttered, analytical, comprehensible visualizations of aggregations of data records attributes. Data browsers link multiple summaries and record lists, and enable flexible and rapid data analysis through tightly coupled interaction. Our analysis approach, developed in collaboration between analytics researchers and university instructors, reveals patterns across many aspects, including assignment and section structures, submission grading and timeliness. We present findings from an analysis of three semesters of an introductory oral communication course with over 1,750 students and 90 sections per semester.

Keywords: Learning analytics, Learning management systems, Information visualization, Student monitoring, Instructor support, Faceted browsing

INTRODUCTION

In higher education, many large courses required by shared curriculums are offered in numerous sections by multiple instructors. While curriculum, major assignments and exams are likely to be coordinated, instructors have some autonomy to better apply their personal expertise to deliver the course. However, to achieve equity between students across sections and instructors, consistency in course delivery is important. Instructor meetings and designing and maintaining course standards are among the necessary, yet time-demanding, efforts to improve their consistency. For universities that offer some courses to hundreds (or thousands) of students in many sections (such as general education courses), maintaining this consistency becomes a serious challenge. Efficient and data-driven ways of measuring and improving consistency are needed.

Data analytics offers opportunities to combat some challenges in learning and teaching (Romero and Ventura (2010); Siemens and Baker (2012)). As the role of learning management systems (LMSs) increases, the LMS data captures richer multi-dimensional views of teaching and learning activities. LMSs commonly offer data analytics within course sections, and can generate reports on student success and online behavior. However, to the best of our knowledge, they are missing tools to measure and generate insights about course delivery consistency for multi-section courses. For example, course coordinators cannot efficiently analyze how instructors modify assessments, how much variation there is in grading speed across sections, if an instructor's rank affects the course structure or grading outcomes, or how course metrics change between semesters.

In this paper, we present an exploratory visual analytics approach to make sense of the rich LMS data using a new framework called *linked data summaries* with the goal of understanding a wide range of patterns in course consistency given multiple coordinated sections of a course. The consistency is analyzed using data common to many courses and LMS systems: course sections, instructors, assignments, student submissions, grading and online discussions. Therefore, our approach can be applied to many multi-section course settings. Our contribution is the description of three data browsers focused on three main record types, and the data dimensions within each browser, built using a new visual data exploration framework, linked data summaries. In this study, this framework is used and described as a seperately developed state-of-the-art data exploration approach that effectively enables the proposed multi-dimensional analysis of rich LMS data.

In our linked data summaries framework, summaries are defined by extracting an existing or calculated attribute of interest per data record. Exploratory data browsers merge multiple summaries (units) and a record list, similar to faceted browsing paradigm. The data browsers in this study include categorical and numeric data summaries. Data comprehension is improved through a minimalist design with effective perceptual encodings of aggregation characteristics, prioritizing length and position. The analytical expressiveness of this minimalist design is extended to support multiple selection modalities for filtering, previewing and comparison. Filtering and interaction within multi-summary browsers are linked (tightly coupled) across summaries and records. Mouse-over interaction for animated result previews enables observing relations across aggregations rapidly. By building upon familiar design patterns, course coordinators, who are likely not experts in data analysis, can use our solution to analyze the complex characteristics of the data directly and intuitively. They are able to see an overview of all sections, filter across multiple dimensions of their data, detect trends and outliers, and analyze, validate and improve course standards.

We present a case study of our approach using data from three semesters of an introductory oral communication course which is required for all freshman at the University of Maryland. This courses provides foundational theory and skills development in public speaking and interpersonal contexts. Exemplifying the common challenges of volume and variety, this course was delivered by 40 instructors across 95 sections to over 1,750 students who made 44,000 submissions to 1,600 distinct assignments in the most recent semester. The previous consistency efforts of course coordinators included using a "master" course on the LMS from which all sections were duplicated (and then modified by the instructors with some autonomy), and setting up learning communities to provide instructors with the opportunity to review assignments and discuss emerging issues. With our new analytics approach, the coordinators, who also are three of the authors of this paper, were able to identify significant trends and relations, leading to the identification of areas that require further analysis using statistical techniques, investigations of course details, and discussions among course instructors. The included screenshots of our design solution, such as Figure 1, present aggregated data from this course.

RELATED WORK

Periodic national surveys have found that oral communication courses have evolved, “perhaps in response to globalization, diversity, and emerging communication technology developments" which have impacted the way people communicate (Morreale et al. (2010)). To respond to changes in communication, departments of communication have increasingly turned to assessment measures to determine what curricular, instructional, and technological approaches will best meet students’ present and future oral communication needs (Allen (2002); Avanzino (2010)). Within this context, Morreale et al. (2009) conclude that “administrators and professors in higher education do face challenges to the consistent delivery of high quality communication instruction... across multiple sections of the basic course at any given academic institution...” (p. 98). This work becomes increasingly essential as the efforts to equip our students with the necessary communication competencies as both speakers and listeners in the information-overloaded 21st century are extended (Wolvin (2012)).

Various case studies from different institutions present strategies to improve consistency, including increased dialogue among instructors (Dunbar et al. (2006)); engaging core constituencies in course design (Valenzano (2013)); blended learning (Perrin et al. (2009)); utilizing a common spreadsheet-based grading tool (Mountain and Pleck (2000)); and assessment (Preston and Holloway (2006)). Boyd et al. (2014) observe that assessment is increasingly important for the purposes of demonstrating student learning outcomes to influence course design, increasing instructional resources, and extending the impact of

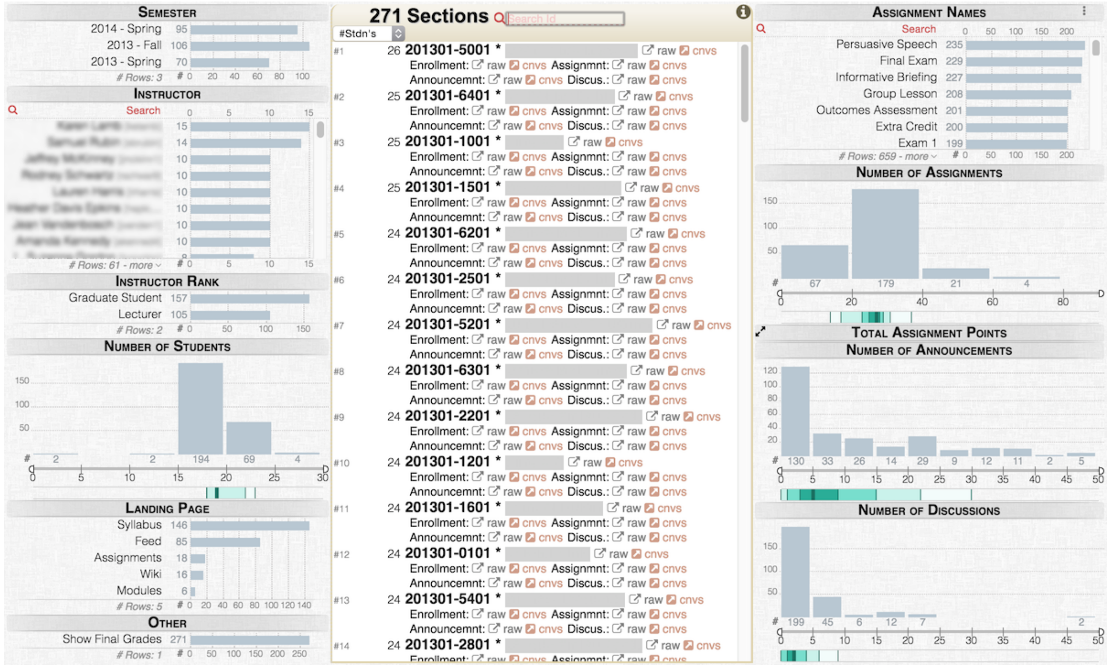


Figure 1. The Section Browser lists sections of the analyzed course, potentially covering multiple semesters. The histograms represent the distributions of the number of sections for each summary aggregate. The left column includes the semesters, anonymized instructors, instructor ranks, the number of students, and other LMS-specific settings per section. The right column includes the assignment overview (the assignment names, the number of assignments, the total assignment points), as well as forum activities (the number of announcements and discussions) per section.

the course. Valenzano et al. (2014) encourage Communication faculty to "pay attention to the basic communication course in terms of content, delivery, assessment, and research opportunities" (p. 363). Dyckhoff et al. (2013) stress that learning analytics can be a valuable resource for such measurement, and categorize many learning analytics indicators by different perspectives (student, teacher, course, content), and different data sources.

Experimental studies have also shown that the instructional method affects student learning and engagement. Deslauriers et al. (2011) studied a large physics course (with over 500 students), and compared two groups which either were taught by traditional lectures with experienced lecturers, or by trained but inexperienced instructors using instruction based on research in cognitive psychology and physics education. Their findings show improved learning for the later group. In our case study to validate our approach, variations across the sections and semesters were not controlled to conduct an experimental study. We instead looked at retrospective data from a single course with multiple sections over multiple semesters.

Analysis of LMS data can reveal unexpected patterns, and derive more detailed questions (Muñoz-Merino et al. (2013)). Efforts to understand how students and instructors use LMSs demonstrate the utility of such platforms to support learning analytics as an increasingly sophisticated approach to measuring curricular, instructional, and assessment consistency (Duval (2011); Merceron (2012)). For example, with an analysis of multiple courses over a semester, Merceron (2012) observed a decreasing trend in the use of specific resources (self-tests) during the semester. To uncover the underlying student behavior, they proceeded to study whether the students are gradually giving up (i.e. stopping resource use at a certain point in course), or if the resource use is more irregular/random in nature. Our approach follows a similar structure in that our tool enables observation of patterns, which can then be studied in further depth to understand why. Another approach to improve academic support is to offer students new means to compare their learning activity data to their peers Fritz (2011).

Information visualization techniques and dashboards are an integral part of LMSs, offering a range of features for students and teachers. CourseVis (Mazza and Dimitrova (2007)) presents several graphical representations of LMS data for instructor use, while also discussing the challenges in distance learning. Among various student progress monitoring tools, proposed designs include faceted browsing (Ballard (2011); García-Solórzano et al. (2012)), the former tool proposing color mappings to show student data metrics as data portraits. To enable exploration of student grades by the instructor and to provide fairer assessment, Friedler et al. (2008) presents a dashboard composed of multiple views, each with a histogram with customizable axes and filtering options, along with the ability to assign final grade thresholds using a slider. Dyckhoff et al. (2013) presents an exploratory Learning Analytics Toolkit (eLAT), a dashboard interface which includes overview monitoring and analysis views. They discuss their design and findings from of a small set of indicators, including activity behavior, accessing students, activity area, top resources and adoption rate. Yet, none of the earlier work is designed to support multiple sections within a course. Our approach is also unique with its use of multiple tightly coupled views represented by multiple histograms that are designed to support rapid exploration, filtering and comparison.

APPROACH

Our analysis approach has been developed in collaboration between educators and computer science researchers, blending pragmatic and theoretical orientations as applied in many educational research experiments (Cobb et al. (2003)). Based on several formative discussions about course consistency goals using LMS data, we developed our solution to be composed of three data browsers using our linked data summaries framework: section browser, assignment browser, and student browser. Each browser summarizes the relevant record type (section, assignment, student) using multiple data attribute summaries (units of exploration). The attributes have been carefully chosen to support analysis of consistency based on common LMS data types and their properties, and we specify the potential uses of these summaries and relations between them to meet our goals. While our design reflects the course we studied [1] and the LMS we use[2], most of the properties we selected are available in different courses and LMSs. In case other data dimensions need to be summarized, as richer LMS data is available or a question focused on some other available dimension arises, the browsers can be extended with new data dimensions in our visual exploration framework. Our analysis approach specifically emphasizes the descriptive statistics on aggregated data summaries and the relations between measured dimensions.

Our analyses covers the following record types: sections, students, assignments, student submissions, submission grading, discussions/announcements, and instructor rank (lecturer vs graduate student). Demographics of students and student LMS use (e.g. time spent on pages) are not included in our analysis. Assignment record types are arguably the richest and most complex, with their shared use in assessing presentations, exams, homeworks, quizzes, group studies or attendance. They can be submitted online (or performed offline, in or out of class), graded with or without rubrics, and weighted differently. Assignments can be grouped in the LMS for organizational purposes (e.g. exams, quizzes, projects, etc). Some assignments are graded out of zero points and are commonly used to record extra credit or to remind students when assigned readings are due. Assignments can be modified, created or deleted per section by instructors, deviating from suggested standards. This freedom makes identifying common patterns across sections challenging. Thus, we found it necessary to analyze assignment records per-section separately. To detect common assignments, our approach uses aggregation on assignment names.

The LMS data of a multi-section course with large enrollment is likely to include many tens of thousands of records with multivariate properties. This non-trivial volume of data must be available at the time of analysis. For our case study, we retrieved the course data once using the Application Programming Interface (API) of the LMS [3], and stored the response data (JSON) locally, on secured computers of the researchers and course coordinators. Then, we loaded the cached, retrospective data in our visual analysis and exploration, with the process approved by IRB (project #648752-1). While it is conceptually possible to load the live, most recent data source directly, it was practically limited by the volume of data and the rate of data queries that the LMS vendor supports. With appropriate infrastructure that can provide large volumes of live course data, analysis of real-time information would be possible. The implementation of our analysis approach uses the implementation of linked data summaries framework (http://www.keshif.me), which is based web standards (HTML5, JavaScript, and CSS3) and runs on modern ubiquitous web browsers without any plugins.

[1] Oral Communication, COMM107, http://www.comm.umd.edu/undergraduate/oral-communication-program
[2] Canvas by Instructure, http://www.canvaslms.com/
[3] Canvas LMS API, https://canvas.instructure.com/doc/api/index.html

Privacy is another important design factor since the data displayed in the views includes sensitive student information. It is required that only the course coordinators and researchers have access to the raw data for administrative and research purposes. Yet, specific findings that use aggregated data may be captured and shared for purposes of discussion and research dissemination. Our design and implementation supports (optional) anonymization as shown in figures throughout this paper. Our anonymization approach hides student and instructor names, allowing for sharing results from the interface with external audiences in brief forms. Each record also links to its original data sources (LMS pages and raw data) for detailed inspection of individual records.

LINKED DATA SUMMARIES FRAMEWORK

The linked data summaries framework aims to bring a structured approach to exploratory data analysis. This framework decomposes analysis to multiple units of exploration (summaries) and a record list in a linked, synchronized browser. Summaries visualize aggregations of data records attributes in an uncluttered, analytical, comprehensible way. Data browsers enable flexible and rapid data analysis through tightly coupled interaction using multiple selection modalities as described below. This approach shows characteristics of the familiar faceted browsing paradigm (Yee et al. (2003)), as well as effective coordinated multiple views (Roberts (2007)). However, it also introduces effective visualization and interaction design patterns across its components. Through a well-defined design structure, it aims to make exploration more comprehensible and rapid for users, and scalable for data. In this paper, we are not claiming the framework itself as a contribution. The framework is described here to clarify the design and features of the presented data browsers.

Given structured, rich data sources, the analyst first defines units of exploration called data summaries. Each summary represents an existing or calculated attribute of a data record. For example, given a section, an existing attribute may be its instructor, and a calculated attribute may be the average score of the students in the section, or a look-up of the instructor rank through another data source. The summarization of the attribute values follows aggregations using categories and numeric ranges, the data types used in this study. The visualizations are histograms, characterising the number of items within each aggregation. The non-intersecting nature of histograms enables scaling to arbitrary number of summarized data records. The histograms are also familiar chart types, thus there is little to no learning required to read the visualizations. The length-encoding, as used in histogram bars, is known to be the most perceptually effective way to encode and compare numeric values (Mackinlay (1986); Heer and Bostock (2010)). Thus, the basic visual design of data summaries is minimalist and effective.

To enable rich data exploration, such as to observe rich relations across units of exploration and to find items of interest, multiple components need to be merged in a single interface. In this framework, the data browsers link multiple summaries and a record list. While the co-display of multiple summaries increases potential data observations, its real utility arises with interaction. To enable rich interaction, we propose a doubly-connected design: Each aggregate stores the records within, and each record stores the aggregations it appears under. Through this structure, selections and filtering is designed to be fully linked and synchronized. Through selection of an aggregate, the characteristics of the elements within can be easily computed. Likewise, selection of a record can highlight the aggregations it falls under. In this framework, the selection is enabled through three modes: 1) Filter, 2) Preview, and 3) Compare.

Filtering removes elements not matching a query from the view. For categorical data, filtering supports *and-or-not* queries of multiple category selections, as well as text search within the categories. For numeric data, filtering is by a range query. Across summaries, filtering is connected by *and* queries, following the faceted browsing paradigm. Such filtering enables zooming (slicing) into the dataset through multiple summarized dimensions. Yet, it changes the browser configuration substantially, such as removing items from the result list, changing the histogram bar axis scale, and re-sorting categories on the new distributions. It represents commitment to a specific selection that cannot be rapidly reversed and explored, yet can be further explored through other selections of the filtered dataset.

For rapid exploration, the framework offers previews which highlight the characteristics of elements of an aggregation before explicit filtering. The preview is enabled by mouse-over interaction, compared to a mouse-click interaction for filtering. Thus, the interaction is not designed towards a commitment, it is designed towards rapid exploration. It reveals the hidden information of an explicit filtering action before it is executed, since mouse-over is a precursor to mouse-click.

The analytical expressiveness of the framework is further extended by the comparison selection. This model enables one-to-many comparison across aggregate selections, extended on the preview selection model. The *compared* aggregate is selected hovering over the aggregate for 2.5 seconds. Once a compared aggregate is selected, the characteristics of its elements are made visible and allow for comparison to any other aggregate preview selection.

The histogram visualizations are extended to support the different selection modalities as shown in Figures 2,4,6: 1) overview using light colored bars, 2) filtering using a blueish-gray bars, 3) preview using orange bars, and 4) compare using black lines. To further improve the range of analytical questions, this framework extends the histogram visualizations with ratio mode, which presents an alternative view to analysis using absolute numbers. In this mode, previews and comparisons are shown in percentages with respect to the filtered distributions (Figure 2b,6a). With the presented design, a rich set of data patterns in the data can be identified through filtering, previewing, and comparison models with an un-cluttered, intuitive visual design and rapid interaction.

DATA BROWSERS FOR CONSISTENCY ANALYSIS

In this section, we describe the three data browsers with the summaries within, how they support measuring course consistency, and sample results from our case study.

The Section Browser

The section browser (Figure 1) provides an overview of the course sections. We designed it to summarize instructors, assignments, forum use, and section-specific LMS features. Assignment summaries allow checking consistency in the number of assignments with a targeted total point sum, and inclusion of standardized assignments in all sections. The course coordinators can observe how instructors change assignment names and introduce new assignments (Figure 2a, 2c). The forum use summaries enable exploring trends of forum use across semesters and instructors by selection in respective summaries (Figure 2b). Summarizing the number of students per section is useful to depict structural changes in the course throughout the semesters or based on instructor rank. Temporal trends across semesters also can be analyzed in this view. Selecting sections by semester reveals patterns over time, which may be used to discover potential correlations (Figure 2b). The linked summaries allow the coordinators to note and analyze what shifts (if any) occurred in tandem to, or potentially as a result of, course policy changes. The instructor rank summary allows observing potential interactions between instructor rank (e.g., lecturers and graduate students) and use of the LMS (Figure 2d). Rank summaries allow the course coordinators to visualize who is delivering the course and to track if there are any appreciable differences related to an instructor's rank.

Following the focused analysis questions above, we report on the specific case study results below.

- By filtering the assignment summary by "Exam", the coordinators discovered that some instructors split some exams into two parts (Figure 2a). The coordinators used this information to open a discussion with the instructors about whether having two parts can benefit all sections, and whether this separation impacts fairness to students.
- Using the forum and announcement summaries, the coordinators noticed that instructors have been using the discussion features of the LMS less frequently over time, as shown in Figure 2b. An unexpected trend with no apparent cause, the coordinators decided to discuss this in the learning communities to see if it heralds a significant change in how instructors are using the LMS discussion tools or delivering the course.
- The coordinators noticed 25 outlier sections with a higher number of assignments (40 or more), as shown in Figure 1. By filtering to the sections with the high assignment counts (Figure 2c), and previewing those with the highest assignments, they discovered that a single instructor at the lecturer rank was teaching these sections. Upon further inspection, the coordinators found that the instructor duplicated assignments for each group of students in his section, not fully understanding the assignment LMS setup for student sub-groups. To resolve this, the coordinators took note that some instructors need more support for using the LMS.
- In the most recent semester, graduate student instructors delivered two-thirds of the sections (61 out of 95), and represented about three quarters of the instructional staff (29 out of 40). Figure 2d shows that the number of instructors with lecturer rank decreased between the last two semesters of the course, while graduate student instructors have not changed. Although previously known, the visual

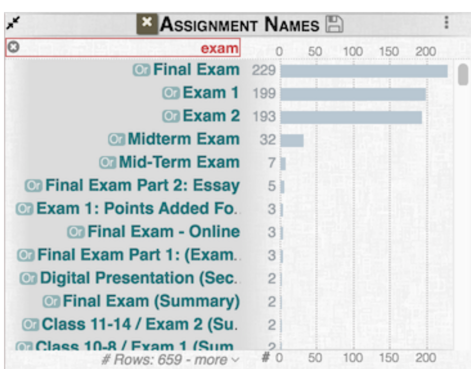
representation of this trend encouraged the coordinators to invest in the graduate instructors with stronger support and professional development opportunities, as they are teaching an increasing ratio of the sections per semester.

- The coordinators analyzed if the course standard regarding grading policy was being followed. They had agreed that 85% of the assignments should follow the standard curriculum with 15% being left to the instructor. In addition, assignments should total 200 points. Using the *Total Assignment Points* summary, the coordinators identified an outlier section that used 1,010 points of assignments, as well as some other sections that used only about 170 points. By looking at the sections with low totals, they identified these sections were offered in the first semester of available data. By filtering out the first semester sections, the coordinators observed the variations have largely diminished in the recent two semesters, to a range between 198 to 223 points. While these results validated their ongoing standardization efforts, the results also led to discussions for further structural improvements.
- The studied course had policy and structural changes between spring and fall semesters of 2013. Specifically, the number of students per section was lowered, and the course coordinators formalized assignment scaffolding, increasing the number of assignments. The implementation of these changes was confirmed by selecting related semesters.

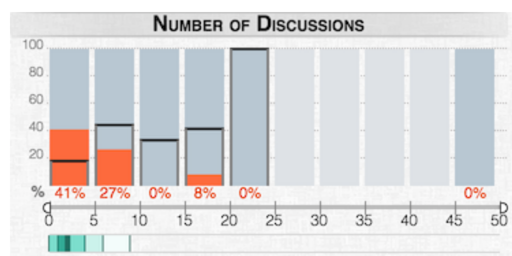
The Assignment Browser

The assignment browser (Figure 3) supports the analysis of assignments across sections with the goal of understanding assignment consistency, i.e. how instructors modify and create assignments. Figure 3 shows the layout and the content of this view. The assignments in different sections are summarized and filtered as distinct records.

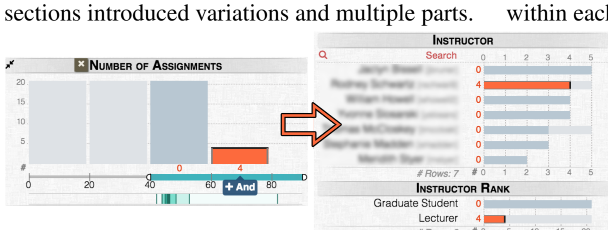
The *Assignment Name* summary merges common assignments. By selecting an assignment name, it is possible to analyze how the structure of a common assignment changes between sections. Section and semester summaries show the number of assignments per aggregate (section or semester), similar



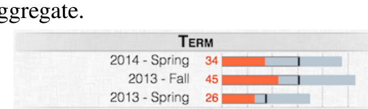
(a) Searching for assignment names that include "exam". 3 main exams are common, yet many sections introduced variations and multiple parts.



(b) The use of discussions forums have decreased from the first semester (black lines) to the third semester (orange bars). The summary chart shows percentages within each aggregate.



(c) Sections are filtered to those with a high number of assignments (40 or more). 7 instructors are teaching these 25 sections. 4 sections with 60 or more assignments are selected in preview. These 4 sections are delivered by one instructor with lecturer rank.



(d) The term summary. The black lines show the number of sections taught by graduate student instructors. The orange bars show those taught by lecturers. In the last semester, graduate students taught the same number of sections as the previous semester while lecturers taught fewer.

Figure 2. Details from the Section Browser.

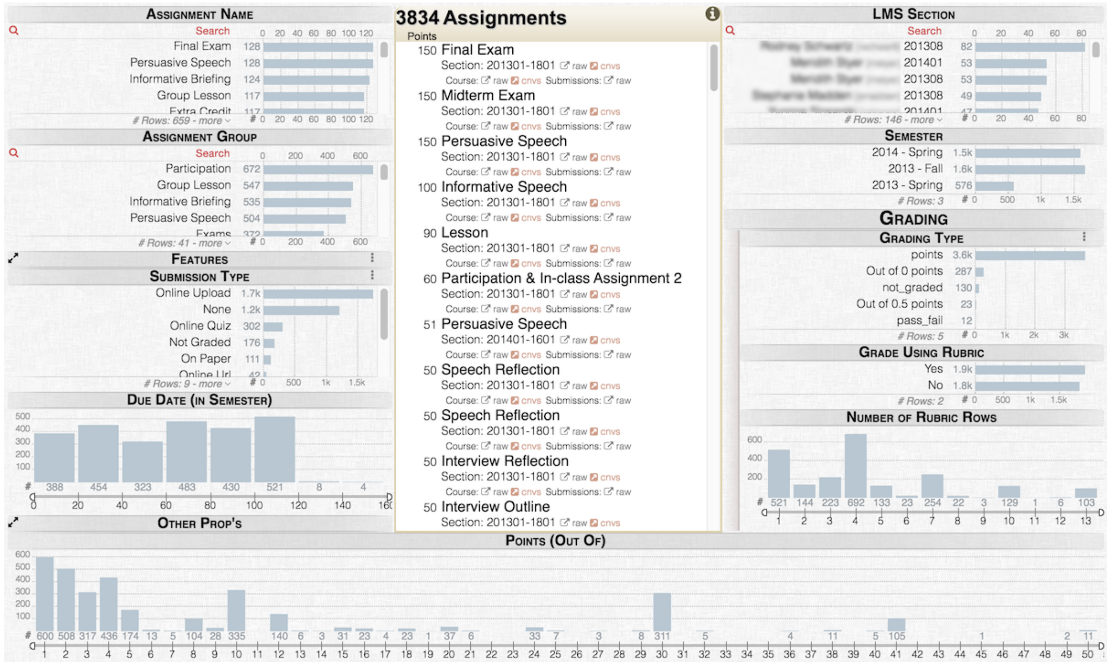


Figure 3. The assignment browser lists assignments in every section of the course as a separate record. When the same assignment name is used in multiple sections (common assignment), it appears multiple times in this view, once per each section. The histograms represent the distribution of the number of assignments for each aggregate in the summaries. The left column includes assignment names (used to merge and filter common assignments), assignment group names, assignment LMS features, submission types and due dates within the semester per assignment. The right column includes course sections, semesters, and grading information (grading point types and rubric use) per assignment. The bottom row includes point (out of) distribution per assignment.

to other summaries in this view. The *Points (Out Of)* summary shows the distribution of points of the assignments. To see the point distribution of assignments specific to a semester, section, assignment name or assignment group, the coordinator can simply select aggregates on the relevant summaries. The *Features* summary is included to analyze the use of LMS-specific assignment features.

One important area of assignment consistency is grading methods, including the use of rubrics. A grading rubric breaks down the assessment of student work for an assignment into distinct categories (rows) and criteria for success levels (poor to excellent). Thus, a rubric creates a guideline for assessment, potentially improving consistency between instructors, while also helping students prepare their assignments. The student grade can be directly calculated from the rubric, or the rubric can be solely used to give feedback to a student on assessment category. For standard assignments, rubrics are expected to be the same across all sections. In this view, rubric use is summarized by whether a rubric is used to grade the assignment, and the number of rubric rows of the assignment, if it has one. The default view shows the overall pattern for rubric use in all assignments. By selecting assignments graded using a rubric, as in Figure 4a, the grading type and the number of rubric rows can be highlighted. To check consistency of rubric use for a common assignment, the coordinators can select an assignment name and explore variations.

The assignment due dates are also an integral part of the course structure. The course coordinators aim to avoid congestion of due dates, i.e. they aim to distribute the assignments throughout the semester. Further, common assignments across sections should be due at certain periods for fairness to students in different sections. To analyze these consistency questions, this browser includes the *Due Day (In Semester)* summary, where the x-axis shows the due date from the start of the semester, measured in days. By selecting a specific assignment name, assignment group or section, this summary visualizes the characteristics of the underlying assignments, and allows for checking due date consistency (Figures 4b, 4c, 4d).

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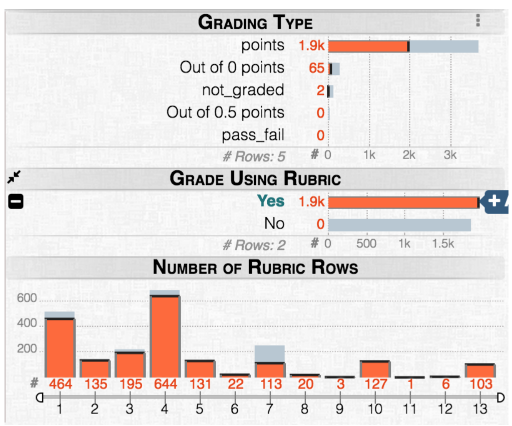
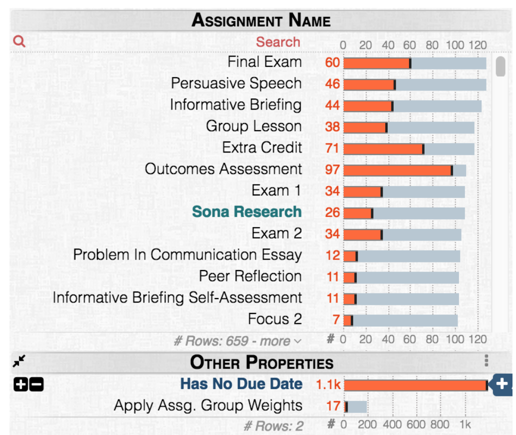
Following the focused analysis questions above, we report on the specific case study results below.

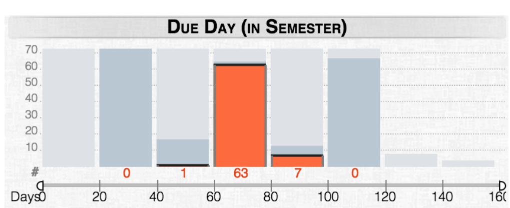
- Variations of assignment names across sections were detected, such as "Exam £10 2," "exam 2," and "Exam 2!," related to the standard "Exam 2", and "Group Lesson Assignment" related to the standard "Group Lesson". These cases were detected by the trends, outliers and text search within assignment names. To improve the analysis, we converted all assignment names to ProperCase and manually edited some assignment names to be consistent with the standards.
- The point summary overview (Figure 3) shows that most of the assignments were at or below 10 points, with further peaks appearing at 30 and 41 points. By filtering common assignments using the *assignment name* summary, the course coordinators identified sections that modified the point scales from suggested standards in the course.
- In assignment due date analysis, the coordinators first identified outliers. They noticed due dates of 20 assignments that were set to be turned in before the semester started, which were instructor mistakes. The coordinators also observed that assignments without due dates (30% of all assignments) were distributed across many assignment names, including common assignments (Figure 4b). This highlighted another source of inconsistency in the use of the LMS for the studied course. Communications following these outliers revealed that some instructors were assigning due dates for non-graded tasks, such as assigning a due date for a non-graded class reading so that it would show up on the calendar view of the LMS. This led to broader discussions among course coordinators about the best practices in LMS use and whether assigning due dates for other purposes are helpful.



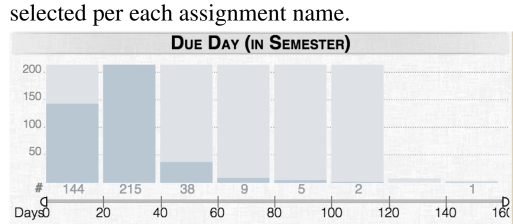
(a) Grading rubric summaries. The assignments that are graded using rubrics are higlighted. This shows that 2 of them are not graded, and 65 of them are graded out of 0 points. Also, for assignments that were not graded using rubrics, some still had rubrics. Only half of the assignments with 7 rubric rows are graded using these rubrics, as the distribution of the selection show.



(b) Assignments without a due date are higlighted in *Other Properties* summary. The distribution within the *Assignment Name* summary shows a high level of inconsistency within common assignments regarding whether assignments had due dates or not. The expectation was that to have all or no assignment selected per each assignment name.



(c) Due dates of assignments within *Exam* group across sections. There are 3 major exams in this course. "Exam 2" is selected, and the due dates of these assignments are highlighted in orange.



(d) Due dates of assignments with the name *Informative Briefing* across sections. Informative briefings were expected to be completed in the first 40 days in semester. This view shows some outlier assignments, which can be selected to find related sections.

Figure 4. Details from the assignment browser.

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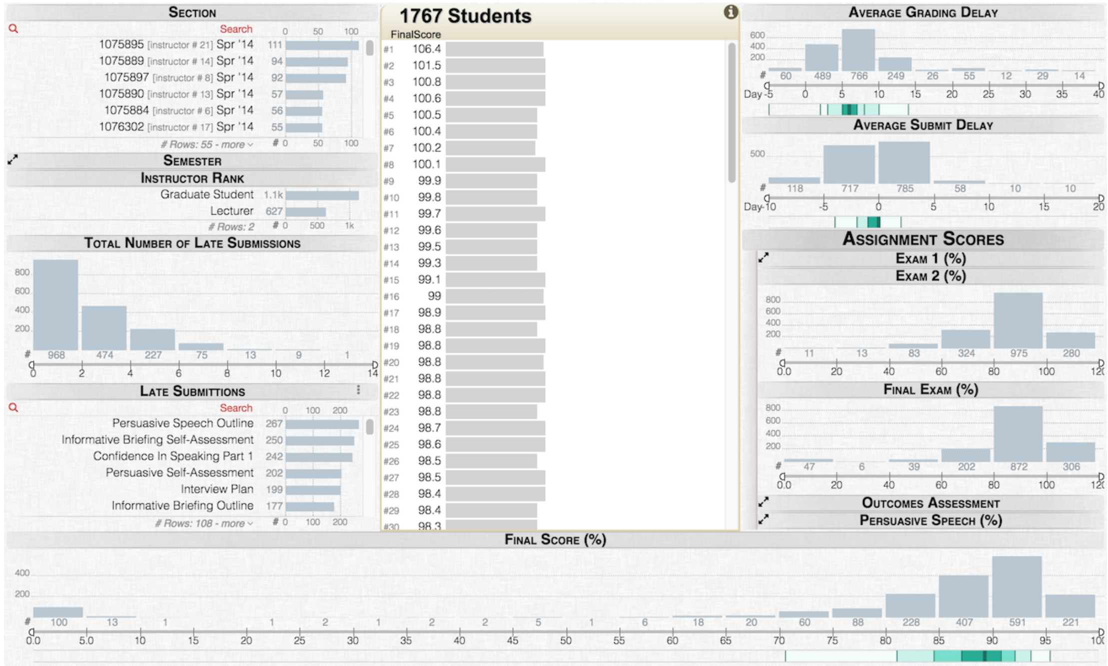

Figure 5. The student browser lists student enrollments in the course. The histograms represent the distribution of the number of students for each aggregate in the summaries. The left column presents sections, terms, instructor ranks and late submissions per each student. The right column presents timeliness (for submission and grading, based on assignment due date) and score histograms from selected common assignments. The bottom row presents the final score distribution of students.

- By filtering on the *Exam* assignment group, the coordinators confirmed that the 3 major exams of the course were spread over 3 time ranges (Figure 4c), with some outliers that were separately analyzed. Likewise, by filtering on a specific assignment group, *Informative Briefing*, they confirmed the assignments in this group were mostly due in the first 40 days of the course, as they were required to be completed early in the semester (Figure 4d). Outliers were noted as opportunities for improvement.
- The coordinators observed that an instructor used the "student peer review" LMS feature that was not part of the suggested LMS course structure. By selecting this feature, the coordinators identified that it had been applied for the assignment *Group Lesson*. The standard course structure included manually managed peer reviews for the *Group Lesson* assignment using another assignment, *Peer Reflection*; it was not done through the LMS feature that coordinates online student peer reviews. The assignment browser first confirmed that the assignment point scale of the specific peer-reviewed assignment followed the norm of 30 points. By selecting the section that used the LMS peer review feature, the coordinators noted that the *Peer Reflection* assignment was also included in this section, with its standard scale of 4 points. They suspected that although the LMS online peer review setting was enabled, it was not actively used within the section. The coordinators confirmed this result by checking the grades of this rubric, which were not assigned. They also took note to investigate the online peer review features and if it could improve the course structure.

The Student Browser

The student browser (Figure 5) enables analysis of the student data across multiple sections to understand student success, and submission and grading timeliness. Although student records are individually listed and summarized, the analysis using this browser is not aimed at detecting individual students who need more assistance during the semester, in contrast to other educational analytics approaches such as early warning systems for at-risk students (Macfadyen and Dawson (2010); Krumm et al. (2014)). Nevertheless, since this browser lists individual students, it can also be used to select individual students as well as student groups based on aggregations within units of exploration (summaries).

The influence of instructor rank (graduate student or lecturer) on learning outcomes of students is one of the leading concerns among course coordinators. Lecturers can be assumed to have more teaching experience than graduate students, and therefore may exhibit different grading and LMS use patterns. Selecting an instructor rank identifies all students that are taught by an instructor of the selected rank, and all summary aggregate distributions are updated to show the distributions of these selections, as shown in Figure 6a. In large multi-section courses, the goal is to offer consistent teaching regardless of the instructor rank, so the hope would be to find no significant differences among instructor ranks and demographics.

Timeliness is another fundamental metric for measuring teaching consistency and understanding student success. A late student submission or slow feedback in returning grades can cause cascading problems for subsequent student work and lower student success. One of the course coordination goals is to make sure that the late submission policies are effective, the students are submitting their work on time, and grading is performed on time for student submissions. The coordinators also would like to understand how submission and grading timeliness impacts student success based on retrospective course data. Even though the LMS data enables this form of timeliness analysis, we should note that immediate results may be imperfect because only assignments that have a due date in the LMS can be analyzed, and the due date of assignments on the LMS may not fully reflect the due dates the students experienced, either through input mistake, or lack of effort by the instructor to make adjustments on the LMS.

Student timeliness can be analyzed based on individual late submissions as well as average timeliness of student submissions, in the number of days before/after assignment deadlines. The *Late Submissions* summary lists the assignment names, and the histogram distribution shows the number of students with late submissions per arch assignment. The overview shows which assignments were more commonly submitted late, helping identify potentially problematic assignments or scheduling conflicts. Students with high or low numbers of late submissions can also be filtered using the *Total Number of Late Submissions* summary, which will then transform all other summaries to show the final grades, exam scores, sections, etc. of the selected students (Figure 6b). The *Average Submit Delay* summary extracts, given each student, the average number of days before/after assignment deadlines for all his/her submissions. It is aimed to measure how early or late a student submits assignments with respect to due days, in total over the course of the semester. The expectation is that the students are submitting their assignment earlier than the due dates on average. For the analysis of consistency, the coordinators can identify sections in which late submissions were different than normal, and which assignments these late submissions are for. Course coordinators can then use this information to initiate a deeper inquiry into the best practices for scheduling the assignments appropriately, encouraging students to turn in work on time, improving the existing late policies, and setting assignment due date reminders for selected assignments.

Timeliness of grading feedback is the instructor-focused aspect of timeliness analysis. The *Average Grading Delay* summary can be used to analyze timeliness of grading feedback from the students perspective. It shows the average time (in number of days) between the assignment due date and grading time, integrated over all student assignments with due dates. For example, a student who received grade feedback 3,5,4 and 1 days after assignment due dates will be mapped to the value 3 (=round(13/4)) in this facet. Analysis through this summary can expose trends across instructor ranks (Figure 6c) and sections (Figure 6d) through filtering and selection.

Following the focused analysis questions above, we report on the specific case study results and approaches below.

- Because the course structure changed between semesters, the course coordinators did not find it practical to compare submissions between semesters, and focused on the most recent offering. Also, a single browser can only include a limited number of assignment grade distributions. Thus, the coordinators chose 3 major exams and 2 standard assignments to be included in this browser, with the histograms showing student score distributions, as shown in Figure 5.
- The coordinators identified that the low point outliers (<5%, 100 students) were students of a specific instructor who did not use the LMS to log student grades, thus resulting in low total grades for students in his/her sections. The coordinators thus removed students enrolled in these sections from subsequent analyses, and used this as an opportunity to make sure that all assignment grades will be logged using the LMS in the future.
- The *Persuasive Speech Outline* assignment was observed to be the most common late assignment in the overview (Figure 5). This assignment comes at the end of the semester, so the coordinators

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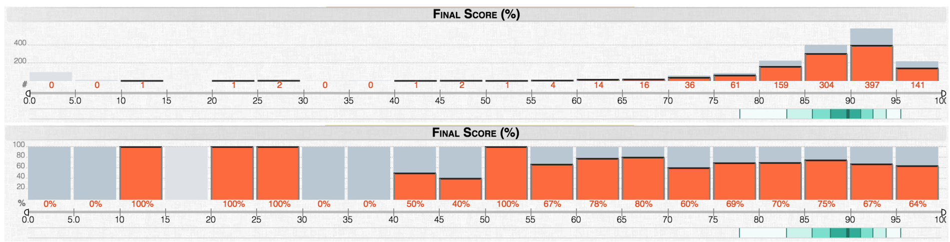
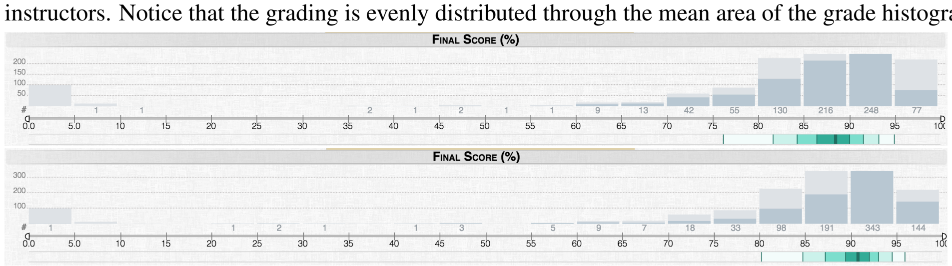
are expecting that students are frequently managing a number of the end of the semester tasks. The course coordinators noted that they need to communicate to instructors that they should make sure to post the assignment as early as possible and to remind students that it is coming and also to consider the timing of its due date.

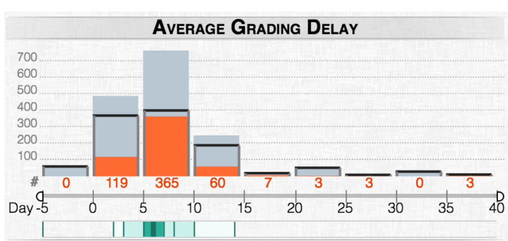
- The coordinators observed no significant difference between the students taught by instructors with different ranks (Figure 6a). To confirm their visual analysis, an independent samples t-test was conducted. The results showed no significant difference between the two groups, indicating that students received similar grades regardless of the instructor status. The coordinators observed no significant difference between the average final grade of students taught by instructors at the graduate assistant rank (M = 84.72, SD = 13.66) and those taught by instructors at the rank of lecturer (M = 84.20, SD = 13.74), $t(1616) = 0.702$, $p = 0.482$. The coordinators extended their analysis to the selected exams and assignments and found that the average score on the three most important assignments were comparable between the two instructor groups.
- To understand if late submissions correlated with final student score, the coordinators filtered to students with two or more late submissions. As shown in Figure 6b, the grade distribution of the students with two or more late submissions is lower than those with at most one late submission.



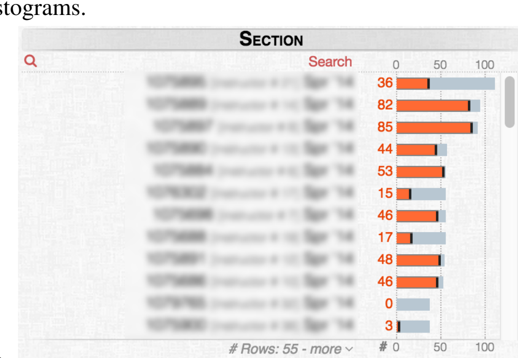
(a) Final student score distribution. Orange bars highlight the students taught by instructors with graduate student ranking. The chart above shows the absolute number of students within each grade range aggregation. The chart below shows the ratio of students within bins that are taught by graduate student instructors. Notice that the grading is evenly distributed through the mean area of the grade histogram.



(b) Two grade distribution histograms. Above, the grades are for students who submitted two or more late assignments. Below is the rest of the students, which has a higher distribution in average, as also shown by the percentile chart in green color below the histograms.



(c) The average grading delay summary, comparing students taught by instructors (black lines) vs graduate students (orange bars). Notice that students in both negative (<0) and high (>400) ends of this metric are mostly taught by graduate students.



(d) Upon selecting a high average grading delay (5-10 days), the differing characteristics of different sections/instructors are revealed.

Figure 6. Details from the student browser.

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The course coordinators followed with statistical analysis to study the trends between the number of late submissions and student scores. They found that the number of late submissions was slightly negatively correlated with final grades ($r = -.083$, $N = 1618$, $p < 0.001$, two-tailed), as would be expected since the course policy dictates that late submissions incur grade penalties.

- Visual analysis of the facets did not reveal a strong correlation between total grading time and final grade. Statistical analysis showed that the average grading delay was slightly negatively correlated with the final grade ($r = -0.120$, $N = 1618$, $p < 0.001$, two-tailed) such that students who were given feedback more slowly received slightly lower grades This result emphasizes the importance of early grading feedback. Statistical analysis also revealed that there was a significant difference between the average grading delay (in days) of graduate assistants and the average grading delay of lecturers, as our visual analysis suggested. Graduate student instructors took a longer time on average (M = 7.78 days, SD = 7.44) to grade student submissions than lecturers (M = 6.92 days, SD = 3.021); $t(1614) = 3.330$, $p < 0.01$, Cohen's $d = 0.151$.
- By looking at student groups by instructor rank and observing the *Summed Grading Delay* summary, the coordinators noted that both negative sums (earlier grading than due-date) and high sums (above 300, high delays in grading) were for the students instructed by graduate students, as shown in Figure 6c. Their analysis then focused on the very late grading outliers. By looking at the selection of the assignments of sample students in the high tail, the coordinators observed that late-graded assignments generally were low-weight and due early in the semester, yet graded near the semester end. The coordinators concluded that the instructors probably adjusted their grading schedule with other teaching/learning activities of their own, and put the low-stake assignments on hold until the end of the semester.
- By analyzing the distribution of the *submit time delay* histogram (Figure 5), the coordinators observed that more than 25% of students submitted assignments later than due dates on average over the semester. Through filtering, they found that the submit time delay is highly correlated with the number of late submissions (as expected). Likewise, they observed that some sections were more likely to have late-submitting students (Figure 6d). This led to an understanding that the relevant sections must be analyzed manually (perhaps by talking with the instructors) to understand if there is a common property of these sections, or if other sections apply methods (such as forum announcements) to prevent late student submissions.

CONCLUSIONS

Siemens and Long (2011) observe that big data and learning analytics are dramatically reshaping higher education, stressing that analytics in education "must be transformative, altering existing teaching, learning, and assessment processes, academic work, and administration" (p. 5). Our analysis approach and the presented case study supports the point that analytics can establish a baseline for understanding how that transformation should be shaped. In this study, we designed visual data exploration interfaces using a new framework called linked data summaries to analyze the rich LMS course data. This framework enabled us to scale to data covering many sections and over a thousand students while maintaining a minimal and visually comprehensible design. We demonstrated its use in a very large-scale course that included 40 instructors, 95 sections, and over 1,750 students in its most recent semester. The analysis in the case study revealed areas for future improvements in consistency efforts, as well as confirming implemented improvements through analysis of multiple semesters.

We believe our approach is an initial step to support emerging needs for data-driven analysis of large multi-section courses, and future improvements will follow. We expect that content-based classification of student submissions, instructor feedback, and forum use will provide important metrics to observe trends through not only metadata, but richer, loosely structured content within LMSs. Our report on qualitative analysis of instructor feedback (Anderson et al. (2015)) using a version of the data browsers presented in this paper, demonstrates how content analysis can be transformed into developing teaching strategies. The analyzed data can be expanded to extend other sources, such as demographics of students and instructors, as well as non-conventional sources such as course evaluations by students. Our case study present results from a single course and demonstrates how our approach can lead to informed steps. The data analysis can be extended to multiple courses within an institution to observe which trends and results would carry under different course settings.

REFERENCES

Allen, T. (2002). Charting a communication pathway: Using assessment to guide curriculum development in a re-vitalized general education plan. *Communication Education*, 51(1):26–39.

Anderson, L. B., Gardner, E., Kirby-Straker, R. R. J. L., Wolvin, A. D., and Bederson, B. B. (2015). Utilizing learning analytics to improve the basic course: A qualitative analysis of the instructor feedback captured in revealer. In *The annual meeting of the Eastern Communication Association*, Philadelphia, PA, USA.

Avanzino, S. (2010). Starting from scratch and getting somewhere: Assessment of oral communication proficiency in general education across lower and upper division courses. *Communication Teacher*, 24(2):91–110.

Ballard, C. (2011). Analysing education data with Silverlight 5 PivotViewer.

Boyd, J., Morgan, M., Ortiz, A. V., and Anderson, L. B. (2014). Taking initiative in the age of assessment. *Communication Teacher*, 28(2):117–129.

Cobb, P., Confrey, J., diSessa, A., Lehrer, R., and Schauble, L. (2003). Design experiments in educational research. *Educational Researcher*, 32(1):9–13.

Deslauriers, L., Schelew, E., and Wieman, C. (2011). Improved learning in a large-enrollment physics class. *Science*, 332(6031):862–864.

Dunbar, N. E., Brooks, C. F., and Kubicka-Miller, T. (2006). Oral communication skills in higher education: Using a performance-based evaluation rubric to assess communication skills. *Innovative Higher Education*, 31(2):115–128.

Duval, E. (2011). Attention please!: Learning analytics for visualization and recommendation. In *Proceedings of the 1st International Conference on Learning Analytics and Knowledge*, LAK '11, pages 9–17, New York, NY, USA. ACM.

Dyckhoff, A. L., Lukarov, V., Muslim, A., Chatti, M. A., and Schroeder, U. (2013). Supporting action research with learning analytics. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge*, LAK '13, pages 220–229, New York, NY, USA. ACM.

Friedler, S. A., Tan, Y. L., Peer, N. J., and Shneiderman, B. (2008). Enabling teachers to explore grade patterns to identify individual needs and promote fairer student assessment. *Computers & Education*, 51(4):1467 – 1485.

Fritz, J. (2011). Classroom walls that talk: Using online course activity data of successful students to raise self-awareness of underperforming peers. *The Internet and Higher Education*, 14(2):89 – 97. Web mining and higher education: Introduction to the special issue.

García-Solórzano, D., Cobo, G., Santamaría, E., Morán, J. A., Monzo, C., and Melenchón, J. (2012). Educational monitoring tool based on faceted browsing and data portraits. In *Proceedings of the 2Nd International Conference on Learning Analytics and Knowledge*, LAK '12, pages 170–178, New York, NY, USA. ACM.

Heer, J. and Bostock, M. (2010). Crowdsourcing graphical perception: using mechanical turk to assess visualization design. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 203–212. ACM.

Krumm, A. E., Waddington, R. J., Teasley, S. D., and Lonn, S. (2014). A learning management system-based early warning system for academic advising in undergraduate engineering. In *Learning Analytics*, pages 103–119. Springer.

Macfadyen, L. P. and Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & Education*, 54(2):588–599.

Mackinlay, J. (1986). Automating the design of graphical presentations of relational information. *Acm Transactions On Graphics (Tog)*, 5(2):110–141.

Mazza, R. and Dimitrova, V. (2007). CourseVis: A graphical student monitoring tool for supporting instructors in web-based distance courses. *International Journal of Human-Computer Studies*, 65(2):125 – 139.

Merceron, A. (2012). Investigating the core group effect in usage of resources with analytics. In *Proceedings of the 2Nd International Conference on Learning Analytics and Knowledge*, LAK '12, pages 230–233, New York, NY, USA. ACM.

Morreale, S. P., Worley, D. W., and Hugenberg, B. (2010). The basic communication course at two- and four-year u.s. colleges and universities: Study VIII—the 40th anniversary. *Communication Education*, 59(4):405–430.

Morreale, S. P., Worley, D. W., and Hugenberg, L. (2009). Follow-up to the NCA basic communication course survey VII: Using learning objectives in the course. In *Basic Communication Course Annual*, volume 21 of *BCCA*, pages 99–133.

Mountain, J. and Pleck, M. (2000). Multi-section course management using 3d spreadsheet tools. In *Frontiers in Education Conference, 2000. FIE 2000. 30th Annual*, volume 2, pages F4F/9–F4F13 vol.2.

Muñoz-Merino, P. J., Valiente, J. A. R., and Kloos, C. D. (2013). Inferring higher level learning information from low level data for the khan academy platform. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge*, LAK '13, pages 112–116, New York, NY, USA. ACM.

Perrin, K., Rusnak, L., Zha, S., Lewis, D., and Srinivasan, S. (2009). Using blended learning to ensure consistency and quality in multiple course sections. *Journal of the Research Center for Educational Technology*, 5(1):42–48.

Preston, L. M. and Holloway, R. (2006). Case study of a basic course: Using assessment to legitimize innovation. In *Basic Communication Course Annual*, volume 18 of *BCCA*, pages 283–302.

Roberts, J. C. (2007). State of the art: Coordinated & multiple views in exploratory visualization. In *Coordinated and Multiple Views in Exploratory Visualization, 2007. CMV'07. Fifth International Conference on*, pages 61–71. IEEE.

Romero, C. and Ventura, S. (2010). Educational data mining: A review of the state of the art. *Trans. Sys. Man Cyber Part C*, 40(6):601–618.

Siemens, G. and Baker, R. S. J. d. (2012). Learning analytics and educational data mining: Towards communication and collaboration. In *Proceedings of the 2Nd International Conference on Learning Analytics and Knowledge*, LAK '12, pages 252–254, New York, NY, USA. ACM.

Siemens, G. and Long, P. (2011). Penetrating the fog: Analytics in learning and education. *Educause Review*, 46(5):30–32.

Valenzano, J. M. (2013). Directing the winds of change: The basic course and general education. In *Basic Communication Course Annual*, volume 25 of *BCCA*, pages 1–37.

Valenzano, J. M., Wallace, S. P., and Morreale, S. P. (2014). Consistency and change: The (r)evolution of the basic communication course. *Communication Education*, 63(4):355–365.

Wolvin, A. D. (2012). Listening in the general education curriculum. *International Journal of Listening*, 26(2):122–128.

Yee, K.-P., Swearingen, K., Li, K., and Hearst, M. (2003). Faceted metadata for image search and browsing. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 401–408. ACM.

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