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Making Meaning of Data: Exploring Representations of Classroom Activities from a First Year Engineering Course

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Abstract

Real-time, pedagogical feedback can be useful for instructors and graduate teaching assistants in assessing the effectiveness of their instructional activities. This is especially useful in first-year engineering classes, where laboratory and team activities may be more common. The G-RATE, Global Real-Time Assessment Tool for Teaching Enhancement, is a tool to provide research- based feedback for instructors about their classroom interactions across four areas based on the "How People Learn" framework[1]: knowledge-centeredness, community centeredness, learner-centeredness, and assessment-centeredness. The G-RATE provides a teaching profile across these categories, as well as a chronological profile of teaching interactions.

Given the huge amounts of classroom data captured over large spans of time, the process of effectively representing the depth and breadth of classroom activities becomes messy. How can data be represented in a detailed, meaningful manner that can inform educators' teaching practices? Using data collected among 7 instructors in a first-year engineering course at a large Midwestern university, the authors present an overview of data collection techniques used to inform faculty about their pedagogical instruction. Implications for translating this data into feedback are presented along with sample profiles of faculty instruction using the G-RATE.

Introduction and G-RATE Background

Pedagogical feedback can be used to help instructors and graduate TAs assess the effectiveness of their teaching methods. In response to the lack of such research-based assessment tools, the G-RATE (Global Real-time Assessment Tool for Teaching Enhancement) was developed in 2010 from the VaNTH Observation System, a classroom observation tool used to assess instruction in bioengineering classrooms at Vanderbilt, Northwestern, Texas, and Harvard/MI[2]. The G-RATE provides multidimensional pedagogical feedback to instructors about their classroom interactions based on the "How People Learn" (HPL) framework[1], and can be used to assess instruction in a variety of contexts. HPL considers the extent to which classroom interactions represent four categories: knowledge-centeredness (e.g. how well students learn concepts to support understanding and the development of expertise in a domain), learner-centeredness (e.g. attentiveness to the previous knowledge and beliefs learners have), assessment-centeredness (e.g. providing opportunities for learner feedback), and community-centeredness (e.g. supporting learner abilities to collaborate and learn from each other).

Users of G-RATE can use one of five roles for specific functions during the collection and analysis of classroom interactions. The *administrator* function allows users to modify observation parameters prior to the start of a class or lab. The *observer* function records real-time instructional data as code strings during a class or lab. The *student* function assesses students via Likert scale survey items for formative or summative use for the class or lab. The *instructor* function allows instructors to explore their pedagogy after a class or lab via reflective items. Last, the *researcher* function compiles the data collected by the other G-RATE functions.

Previous papers have traced the evolution of the G-RATE through its development and initial pilot test[3,4]. Representing large quantities of the captured rich classroom data in ways meaningful to instructors and researchers has been an issue of note. In the following sections, we discuss issues in visualizing big data and in representing classroom data using the G-RATE.

Literature Review

A shift to focusing on analyzing large quantities of data has helped provide deep insights across a variety of fields, from medicine to transportation[5]. The term "big data" is used to describe "things one can do at a large scale that cannot be done at a smaller one, to extract new insights or create new forms of value, in ways that change markets, organizations, the relationship between citizens and governments, and more (p. 6)."[6] In the context of education, the terms "learning analytics" and "academic analytics" are often used to describe learners and instructors in their contexts for optimizing learning and analytics to produce action at institutional, regional, and national/international levels[5]. These statistical analytics have often been accompanied by the use of visual thinking to illustrate data patterns and insights[7], and these visualizations come with their own set of unique challenges based on the type of data visualized and the technique used.

Keim[8] described six categories of data that can be visualized: (1) one-dimensional data, (2) two-dimensional data, (3) multi-dimensional data, (4) text and hypertext, (5) hierarchies and graphs, and (6) algorithms and software. Displaying large quantities of these data types can be complex due to technical challenges in data storage and processing and because of challenges in displaying the rich amounts of information in ways that are meaningful without being misleading or overwhelming[9]. Bresciani and Eppler[9] classified these types of visualization disadvantages in Table 1. Visualizations may contain: (1) cognitive disadvantages that impede accurate interpretation of the data, (2) emotional disadvantages where the visualization may not attract the viewer, and (3) social disadvantages that may affect who views the visualization and how. These disadvantages may be designer-induced or user-induced. Designer-induced disadvantages relate to the creation and implementation of visualizations, while user-induced disadvantages relate issues with viewing and interpreting the visualizations. These disadvantages should be considered in the design and presentation of visual data in order to present the most effect display to an audience.

To best represent data in ways that minimize these disadvantages, a large number of visualization techniques have been developed. Fields like computer graphics, computer science, industrial engineering, and statistics provide a vast amount of detailed information on the mathematic and algorithmic background of visualization; for the purposes of this paper, an overview of several visualization techniques are presented to introduce the reader to the types of visualizations considered for this study. Four visualization techniques that may be combined to produce specific visualization systems include[8]:

- *Geometrically-transformed displays* – transformations of multidimensional data sets are geometrically displayed through techniques like scatterplot matrices and parallel coordinates.
- *Iconic displays* – attributes of multidimensional data are mapped to features of icons, such as shapes and colors.
- *Dense pixel displays* – each attribute of data is mapped to a colored pixel and group in accordance with similarly colored pixels.
- *Stacked displays* – data is partitioned hierarchically and data dimensions are embedded within each other, such as mapping longitude and latitude along the outer axes of a grid and height and temperature in the inner axes.

Interactivity, the ability to interact with a display and witness its change as a result, may also be implemented in visualizations to help in analyses and provide an additional layer of information about a data set. For example, in visualizations of weather data seen in weather reports on the news, weathermen may display overall weather patterns across a state and zoom into specific cities to reveal those specific temperatures.

	DESIGNER-INDUCED DISADVANTAGES	**USER-INDUCED DISADVANTAGES**
COGNITIVE	Ambiguity Breaking conventions Confusion Cost to make explicit Cryptic encoding De-focused Hiding/obscuring Implicit meaning Inconsistency Low accuracy Not respected gestalt principles Over determinism Over/under–reliability appearance Over-complexity Over-simplification Redundancy Technology/template driven Time consuming to produce Unclear Unevenness	Change blindness Channel thinking Depending on perceptual skills Difficult to High requirement on training and Misuse Wrong salience
EMOTIONAL	Disturbing Boring Ugly Wrong use of color	Visual stress Personal likes and dislikes Prior knowledge and experience
SOCIAL	Affordance conflict Hierarchy, exercise of power Inhibit Rhythm of freezing and unfreezing Turn taking alteration Unequal participation	Altered behavior Cultural and cross-cultural differences Defocused from non-verbal interaction Different Hiding differences of opinion Time consuming to agree

Table 1. Classifications of visualization disadvantages. Adapted from *The risks of visualization* p. 9-10 by Bresciani & Eppler, 2009, *Identität und Vielfalt der Kommunikations-wissenschaft.*

This background information about visualization influenced the researchers' decisions regarding the types of visualizations to implement within the tool, as well the types of visualizations to present to instructors. For example, for the purposes of this study, interactivity was not implemented since paper profiles were presented to instructors. The following sections describe the methodology for the study, as well as the background for how the visuals were created.

Methodology

Sampling. A total of 393 first-year engineering students and 7 instructors from a Midwestern University agreed to participate in the study. The 7 sections were split into three groups and randomly assigned one of three conditions: (1) instructors who were observed twice and received no feedback on their instruction during the semester (Control 1 – (2 sections)), (2) instructors who were observed twice and received e-mail feedback about their instruction mid-semester (Control 2 – (2 sections)), and (3) instructors who were observed twice, received e-mail feedback about their teaching, and engaged in a face-to-face discussion with members of the research team about their instruction (Treatment – (3 sections)).

Observations. Researchers recorded one 2-hour class for each section twice, once at the beginning of the semester and once in the middle of the semester, and used the G-RATE to observe the first 40 minutes of each class. The first 40 minutes were selected to include components of instructors' teaching, as well as student participation in group and class activities. Two researchers coded each instructor and compared results; when differences were encountered, they discussed the difference and agreed on the final code.

Treatment. After the observation, teaching profiles demonstrating the extent of an instructor's HPL activities in the classroom were created. These profiles contained both a visual graphic of the HPL categorical percentages and a table with further details about the particular classroom interactions. Profiles were presented to the Treatment group through one-on-one sessions, and emailed to the Control 2 group. No profiles were presented to the Control 1 group.

Representation of Data

The G-RATE captured multidimensional data in the form of HPL activities tracked over 10-second intervals. To best understand the nature of the instructors' interactions, two visualizations were created: (1) a simple categorical visualization of activity percentages used to present to instructors and (2) a stacked-display of classroom activities over time used for analysis by the researchers.

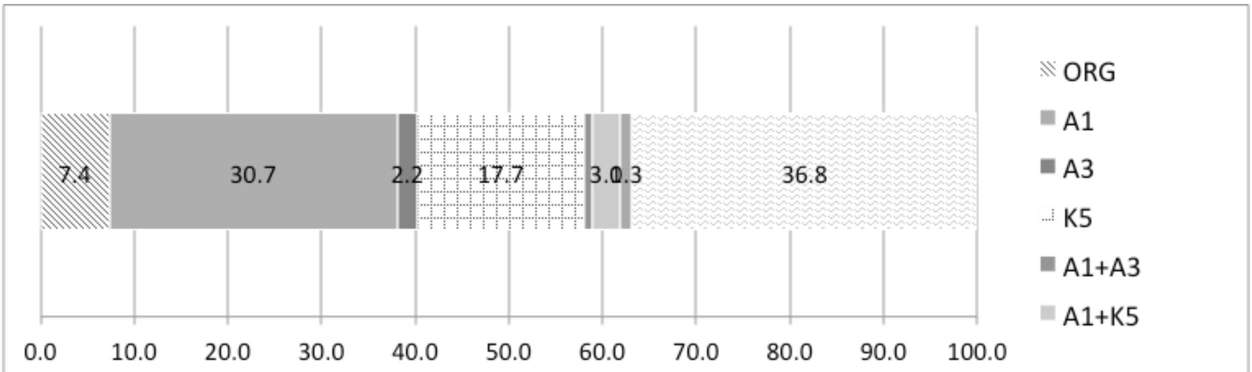
Visualizing Categorical Data

To provide instructors with the simplest visualization of their classroom activities, a two-dimensional pie chart was used. Pie charts are simple enough to easily display relative proportions of categorical data, can be visually checked for accuracy, and are straightforward to understand. For the purposes of this paper, the sample pie chart was converted to a stacked bar chart for its readability in black-and-white. Accompanying the charts are tables further explaining the percentage breakdowns of classroom activities for each round. Table 1 describes all the possible pedagogical codes that can be coded. Figure 1 and Figure 2 display the difference in classroom activities for a Control 2 (emailed feedback) instructor. The "Code" column describes the different combinations of pedagogical activities that occurred in the classroom, with the specific description of the classroom interactions in the column to its right. The

"Overall %" column describes the code combination as a proportion of the total number of pedagogical code combinations recorded. For example, in Figure 1, the instructor was recorded asking students questions (A1) as 30.7% of all the pedagogical classroom interactions. Comparing the two figures, this instructor has spent more time on organizational tasks and having students work on team activities in the second round of observations than in the first round.

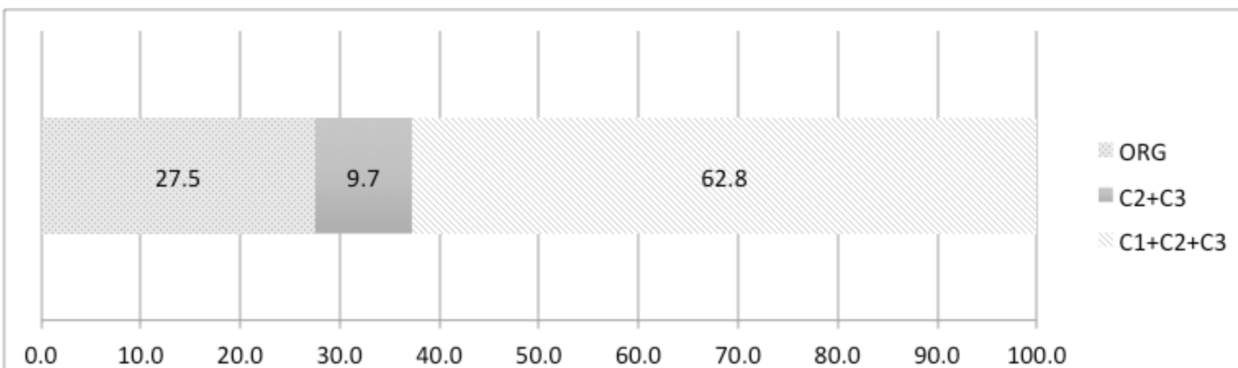
HOW PEOPLE LEARN CATEGORY	CODE	DESCRIPTION
	ORG	Organization of classroom materials and agenda
Community Centered	C1	Engaged students in team activities
	C2	Provided opportunities for students to learn from each other
	C3	Helped teams when they needed assistance
Learner Centered	L1	Acknowledged that learning course concepts can be hard at times
	L2	Acknowledged student's misunderstandings of concepts
	L3	Provided guidance for students during problem-solving activities
Assessment Centered	A1	Asked thought-provoking questions
	A2	Provided verbal or written feedback to students about their progress or performance in class
	A3	Confirmed that the class understood content before moving to a new topic
Knowledge Centered	K1	Shared his/her own practical experiences
	K2	Related course content to everyday situations
	K3	Shared skills students can apply later
	K4	Emphasized learning new skills
	K5	Helped students to understand key concepts

Table 1. A description of all the possible pedagogical codes that can be recorded with the G-RATE.



CODE	DESCRIPTION	OVERALL %
C1+C2+C3+L3	The instructor allowed students to work on an in-class activity. Students had the option to ask each other and instructors for assistance, and the instructor provided guidance to individuals and teams as needed.	36.8
A1	The instructor asked the class questions pertaining to concepts they would use in a project.	30.7
K5	The instructor gave a lecture on regression and the two-point method.	17.7

Figure 1: Visual representation of round 1 observations along with top three occurrences.



CODE	DESCRIPTION	OVERALL %
C1+C2+C3	The instructor allowed students to work on an in-class activity	62.8
ORG	The instructor provided a roadmap for classroom activities and discussed the exam	27.5
C2+C3	The instructor monitored students during a quiz	9.7

Figure 2: Visual representation of round 2 **observations along with top three occurrences.**

Visualizing Time-Series Data

Stacked displays were created to help the researchers understand the order classroom activities occurred over time. Time was represented on the x-axis in 10-second intervals, HPL categories on the y-axis. Each bar represents one instructor. Colors were used to represent each category of the instructors (Control 1 – plain colors, Control 2 – polka dotted, Treatment - striped), with different shades of the color used to distinguish individual instructors. Figure 3 represents a small sample of the chart demonstrating differences in how instructors engaged students in team activities (pedagogical code C1) between observation rounds. It can be noted how Control 1 instructors (plain grey shaded bars) and one Treatment instructor (striped bar) included more team activities at the beginning of their classes in the second round of observations than in the first round.

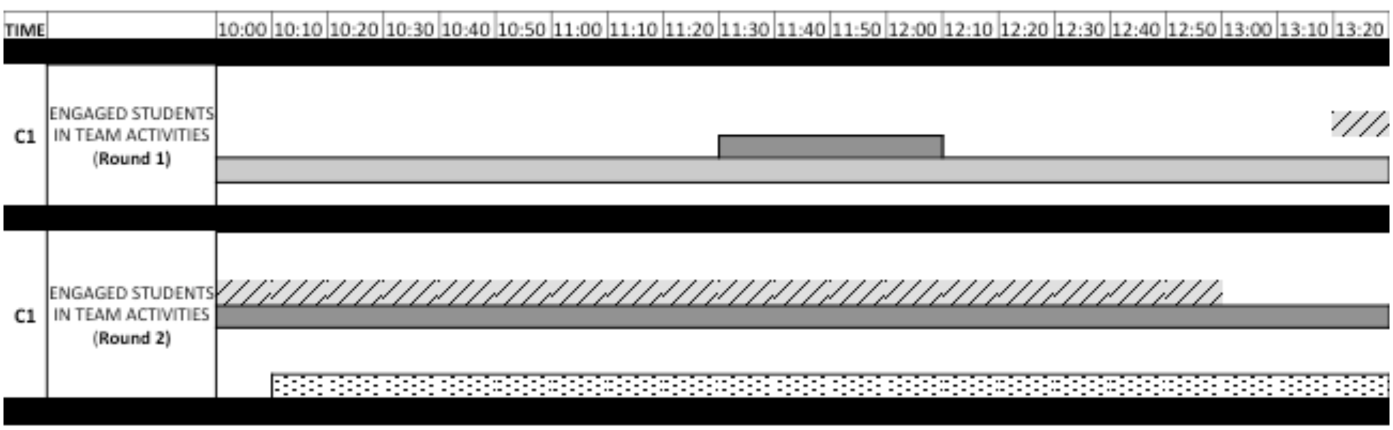


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Figure 3. Stacked display representing the difference in how instructors engaged students in team activities (pedogagocial code C1) in the first and second rounds. Times of the observation are recorded at the top of the chart; the C1 label represents a 'community centered' HPL element observed in the class.

Discussion

Data shown in the results section have been chosen to represent very small pieces of a very large data set. Looking at large quantities of this data, especially in the stacked display format, often become very messy and overwhelming, especially in black-and-white figures. In color, it is easier to identify patterns, but involves a myriad of color representations (e.g., differences across control and treatment groups, different rounds of data collections). This is an issue that the G-RATE project is continuing to overcome moving forward with publications of the project's large data sets.

Instructors were provided data during the G-RATE project as a way to guide their thinking about their teaching activities, habits, and practices. Data for instructors were primarily shown through an individual pie chart without comparing an instructor's habits to those of any other instructor. In general, instructors found this familiar form of representation easy to use and easy to digest, whereas presenting them with unfamiliar forms may have been potentially more stressful for them and may have been perceived to be more punitive than constructive.

In this way, as with all forms of communication, choosing the best kind of representation to suit not only your data but the needs of your audience is paramount to conveying information effectively. For example, in our G-RATE data, the stacked time-series data is impressive and interesting to researchers who are interested in comparing data and activity break-downs for different groups of professors in control and treatment groups. However, the data and figures that we show to professors is not given in its entirety—that would be overwhelming and simply not useful for the instructor, who is interested in mapping her or his classroom activity to teaching performance. Students will be interested in different aspects of data, as will instructors, as will researchers, so selecting the representational form that meets the needs of each stakeholder audience is crucial. This also applies to researchers when they are selecting data to show to other stakeholders (especially to non-researchers in administration interested in performance indicators) or are noting correlations across data representations and student outcomes.

In the same way, the way data are represented is as important as the results themselves. Although large data sets can be displayed impressively, the graphs mean very little without well-situated contexts regarding the educational environment surrounding the data. Selecting the correct data and the correct form of representation is the start to telling a compelling story with the data, but the accompanying text or spoken communication must reinforce the value of the visual aids. This is the other side of thinking about figures as ways to enhance or better understand text: Both should mutually enhance each other. Selecting the wrong data to represent, even in an aesthetically-pleasing way, may present an unimportant or inaccurate story rather than an important, accurate story. For example, in our data, there are some classrooms observed that took place by happenstance on a day where the class was mainly teacher-led and focused on the preparation of students for material on an exam. This led to very little interesting activity, but if we would have portrayed this data in our results section, the consensus regarding the usefulness of our tool would have been very different. We selected data from a different day to best show different representation forms. However, if our focus would have been overall usage, the data shown would be different and potentially in a much different format. As researchers, we have the ability to subjectively tell different stories with the data, so it is important to tell an interesting and accurate story.

Conclusion

The construction of appropriate data displays impacts the research story told to the stakeholder. Instructors interested in changing his or her teaching activities based on previous observations have more interest in basic descriptive statistics. In this case, providing percentages of codes in the context of the class content is appropriate. Allowing instructors to view stacked displays comparing teaching activities over time may be interesting for those instructors curious to see how their teaching compares to their colleagues; however, providing this data and drawing appropriate comparisons is difficult since the graph of classroom activities varies depending on the class content for the day. While instructors reacted positively to feedback, details regarding the specific reactions instructors had, as well as the effect of presenting feedback on instructors' future teaching interactions, will be addressed in future work.

For future studies, G-RATE data will be analyzed for investigating overall patterns of classroom activity percentages (together with standard error and standard deviation) over time, and correlations amongst the codes. Regression can also be conducted to investigate deeply each code's impact on dependent variables (i.e., student grades). As the dataset begins to grow through repetition of the study, considerations will need to be given to sample sizes and the types of inferences that can be applied to an overall instructor population.

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