Computer Supported Collaborative Rocketry: Teaching students to distinguish good and bad data like expert physicists

Matthew d'Alessio and Loraine Lundquist

Citation: Phys. Teach. **51**, 424 (2013); doi: 10.1119/1.4820858
View online: http://dx.doi.org/10.1119/1.4820858
View Table of Contents: http://tpt.aapt.org/resource/1/PHTEAH/v51/i7
Published by the American Association of Physics Teachers

Computer Supported Collaborative Rocketry: Teaching students to distinguish good and bad data like expert physicists

Matthew d'Alessio and Loraine Lundquist, California State University, Northridge, Northridge, CA

Each year our physical science class for pre-service elementary teachers launches water-powered rockets based on the activity from NASA.[1] We analyze the rocket flight using data from frame-by-frame video analysis of the launches. Before developing the methods presented in this paper, we noticed our students were mired in calculation details while losing sight of physical concepts. Sloppy measurements and calculations (even when using spreadsheets with formulas provided) sometimes led to such poor results that physical concepts could not be reliably taught from the data, but students were unmotivated to either notice or correct their errors. We adopted a collaborative, computer supported approach using simple and easily available functions in Google Spreadsheets to pool observations, provide instant feedback, and publicly display results from all teams side-by-side in real time. These instant comparisons promote student accountability and engagement, inspiring them to think more carefully about why answers may be different and notice sloppy data or unlikely outcomes—in short, to facilitate and motivate expert thinking about data.

Theoretical basis for Computer Supported Collaborative Science

Bonham[2] introduced the use of Google Docs to pool data in laboratory activities, which is an example of what we call Computer Supported Collaborative Science (CSCS[3]). Here, we document why CSCS is so effective at improving student understanding of data analysis and interpretation. Research about the differences between novices and experts in a given field indicates that experts constantly monitor and evaluate their progress.[4] In physics, this often means looking at a graph and asking, "Is this reasonable?" However, many novice students have no experience at distinguishing high-quality, precise data from garbage. Colleagues in geoscience education have shown that training novices to recognize complex patterns in visual data works best when students are simultaneously shown an example of the pattern and a related counterexample that does not match the pattern.[5] The comparison calibrates the novice into all the nuances of the pattern. CSCS accomplishes this goal by showing students their own data in the context of everybody else's in the class. Outliers with errors in data or calculation are much easier to spot when seen in comparison with high-quality data.

To test this theoretical basis, we assessed students' ability to recognize "bad data" in graphs by asking them to explain the shape of a height-versus-time curve of a model rocket collected during a class experiment (Fig. 1). Would seeing it next to a peer's graph stimulate reflection on the quality of the measurements and/or calculations? The graph shows a rocket that drops down and rises up unrealistically—it was taken from actual results in one of our courses before the students identified and corrected errors in their calculations. Half the survey respondents saw the error-filled graph by itself ("bad alone"), and the other half saw it plotted beside another team's smooth curve with no major errors ("bad beside good").

Respondents came from two different science courses for future elementary teachers at California State University, Northridge, a regionally focused public university. These students typically have limited backgrounds in science and substantial fear of math.[6] Students in Physical Science 170 ("CSCS class") used CSCS techniques throughout the semester while students in Geology 406 ("Non-CSCS class") all completed Physical Science 170 in prior semesters before the implementation of the rocket project and CSCS (and therefore serve as a control group).[7]

After reading an introduction to the graph and answering a few preliminary questions that primed them to think about possible errors in the data, students were asked to do the following: "Briefly describe a few possible explanations for the shape of the blue curve on the height-versus-time graph. Which explanation do you think is most likely? Why?" Experts responding to this prompt mention that the overall upward trend reflects the rocket's initial acceleration, but the oscillations in height are not easily explained by any physical mechanism except a bizarre wind pattern and likely indicate errors during data collection or processing. Answers by novice science students, however, fell into five main categories (with those closest to the expert response listed first):[8]

1) Mentions data collection/processing errors as a possible explanation of height oscillations, similar to the expert response. May also mention other possible explanations.
2) Explains height oscillations using only physical mechanisms (such as air resistance, an unstable rocket, changes in momentum, loss of fuel, etc.).
3) Mentions height oscillations but does not cite any possible cause.
4) Describes rocket's flight path upward without any mention of height oscillations.
5) Unscorable. Reveals fundamental misunderstanding of the question, an inability to correctly read the graph, or is otherwise uncategorizable.

 DOI: 10.1119/1.4820858

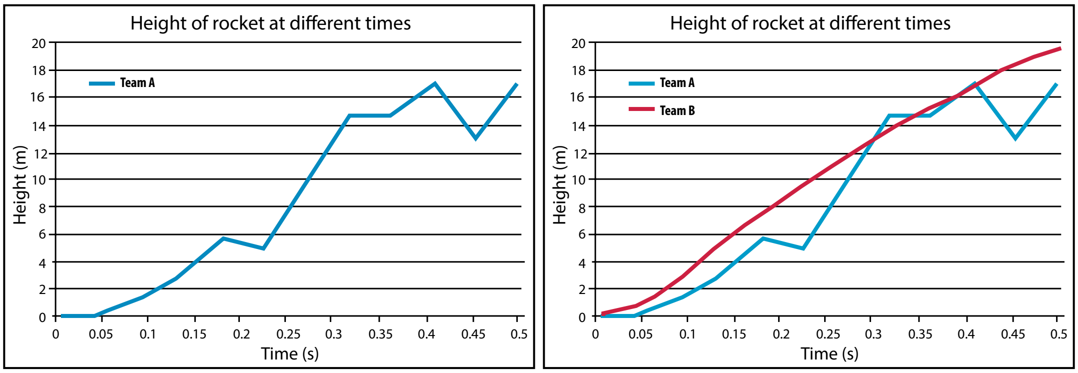

Fig. 1. Students were shown a height-vs-time graph of a model rocket with serious data glitches ("bad alone," left) or beside a smoother curve ("bad beside good," right).

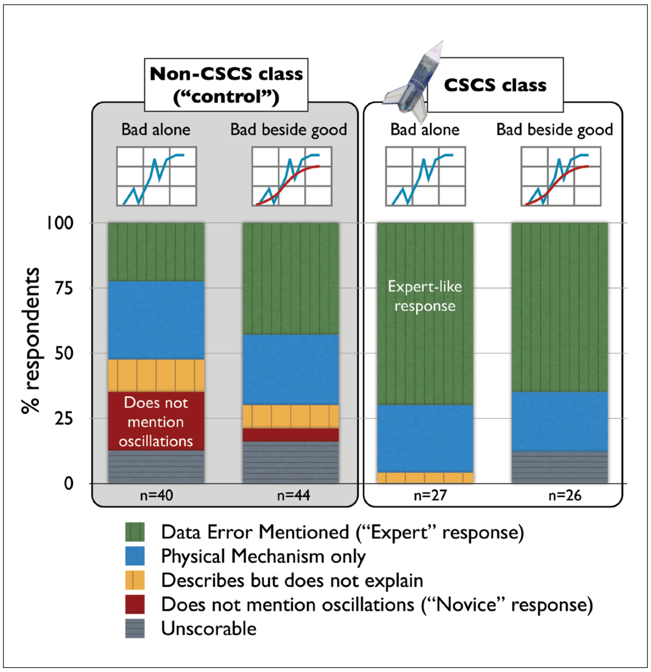

Fig. 2. Different categories of student explanations of the rocket data in Fig. 1.

Within the control class ("Non-CSCS class" from Fig. 2), we find that 23% of those who saw bad data alone made no mention of height oscillations, while only 5% of those shown a comparison failed to notice them—a difference significant at the 99% confidence level.[9] This "bad beside good" group was almost twice as likely to attribute these oscillations to errors (43% versus 23%, significant at 97% confidence). The simple experience of seeing a juxtaposition of good and bad data prompts students to think about why the data sets differ.

CSCS allows students to repeatedly see their own data beside that of their peers. Our claim is that this naturally invites comparison, which stimulates more thought about data than traditional labs. The rest of this paper illustrates this process through a single CSCS activity involving water-powered rockets.

Collecting whole class data

Each team of students builds a rocket from a 2-L bottle, hoping to win our class competition for reaching the highest height. We record launches in video clips using a standard digital camera at 30 frames per second. High-quality measurements can be obtained using video analysis software,[10] but making measurements by hand and calculating distance and velocity helps students practice proportions and rate calculations—mathematical concepts these students will be expected to teach. Students place a clear plastic ruler over the computer screen to measure the height of the rocket above the launch pad in each frame as well as a meterstick "scale bar."

As homework, they enter measurements into a single Google Spreadsheet used by all teams in the class. Each team analyzes its rocket in a separate tabbed worksheet. Each student on the team enters his or her measurements into a separate column on the team worksheet. Because Google Spreadsheets are stored "in the cloud," every student can edit the file from anywhere and multiple students can enter data simultaneously. The spreadsheet has clear labels indicating where to enter measurements, and graphs plot students' data in real time.

Data comparison allows error identification

Throughout the process, students see their team's results in comparison to others. For example, the class calculates the height of each rocket in the last frame before it flies out of view. The camera remains fixed during all team launches, so the height should be roughly identical for all teams. In Fig. 3, Team 2's curve looks reasonable by itself but is well above the others because the students incorrectly measured the height of the scale bar. The team did not notice the error when working in isolation, but quickly corrected the mistake after seeing its data in comparison with the rest of the class.

Identifying calculation errors

Each team calculates the average vertical speed of its rocket between each pair of successive frames in the video and enters its calculations into the team's worksheet. In a separate hidden worksheet, the instructor programmed formulas that auto-

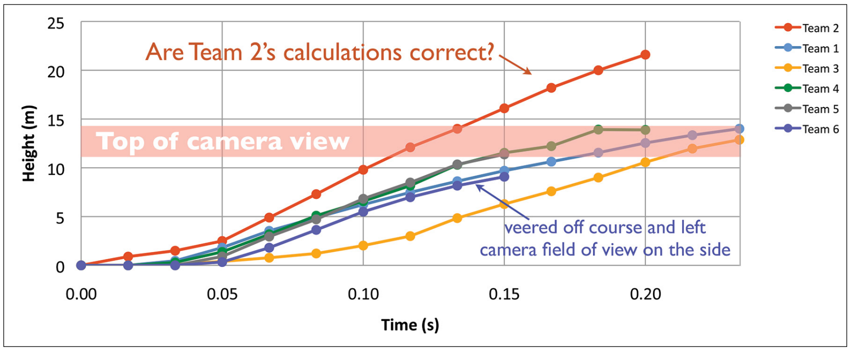

Fig. 3. Rocket height vs time reveals that Team 2 is an outlier.

matically calculate the velocity for each team from their raw data. Using the "Conditional Formatting" option of Google Spreadsheets, each cell turns green when the team's calculation matches the hidden calculations or yellow if the team makes one of a series of common minor mistakes. While students perform their calculations, we display a summary worksheet of all teams' progress on the computer projector. The instructor can glance at the screen to quickly determine which teams need assistance or which teams are finished and can be given more advanced challenges. This instant feedback encourages teams to locate errors themselves, which they often do before the instructor reaches their table.[11]

Creating a forum where mistakes can be identified and corrected

While automated color-coding helps students fix errors, we ideally want students to identify their own mistakes. CSCS enables this process by allowing: 1) comparison between teams, and 2) the ability to see improvement instantly when errors are corrected. Professors can track this kind of self-correction (in addition to inappropriate "correction" such as cheating or unethical changes to data) because Google Spreadsheets record every change by every student in a time-stamped revision history.

In one example, we have a minute-by-minute narrative[12] illustrating how a team thought it completed its calculations but reconsidered its results once other teams' results were posted [Fig. 4(a)]. Since the team's result was created using an average of each teammate's individual measurements [a process also facilitated via CSCS techniques, see Fig. 4(b)], they began examining each individual's work and testing what happened when one individual's "outlying" data were excluded. This prompted the individual to redo his or her measurements and discover the mistake—voluntarily [Figs. 4(c)-(d)].

The clear data ownership and public accountability to peers makes students want to seek out errors and correct them. This is a major improvement over the first time we used the rocket activity with calculations by hand when students simply said, "I guess I did things wrong. It won't hurt my score much, will it?"

Using high-quality data to discover physical processes

Eventually, all teams refine their data and calculations enough to allow meaningful comparisons between teams —and thereby discover interesting physical processes. For example, all the rockets experience roughly the same upward force (since they are pumped to the same pressure at launch using a bicycle pump with a pressure gauge), but they have different masses due to differences in design and initial fuel volume. We plot initial acceleration versus mass to find that lighter rockets accelerate faster—a trend only apparent when multiple teams compare high-quality data. But students also discover a tradeoff with stability—rockets with extra mass in the nose cone typically travel higher. (The stability benefits of moving the rocket's center

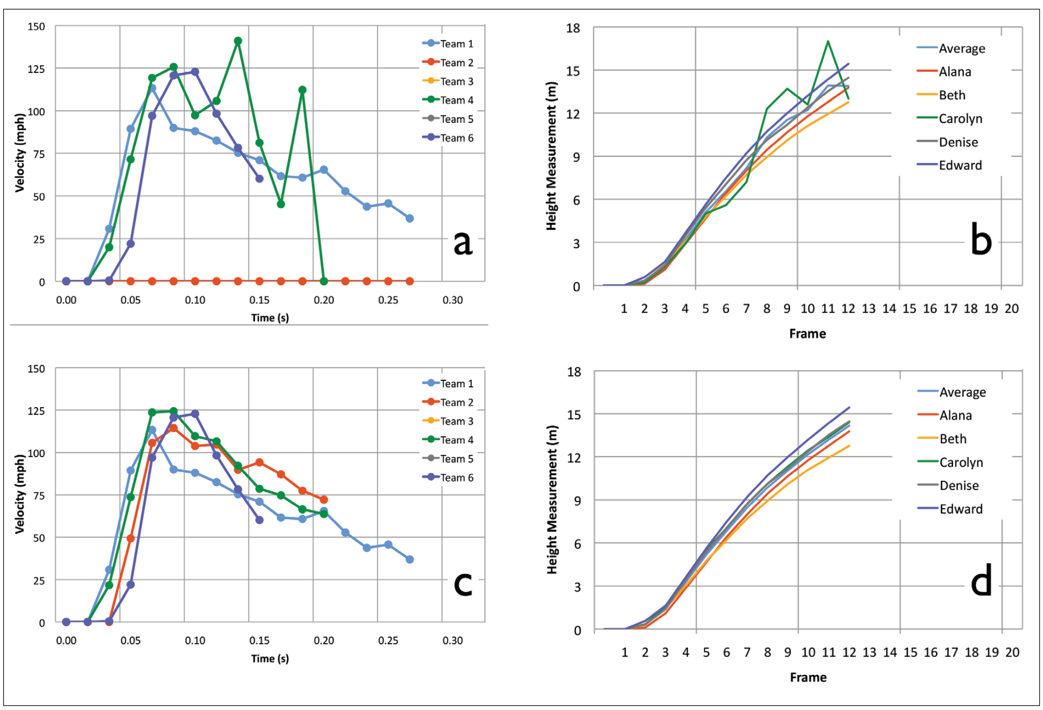

Fig. 4. (a) Speed-vs-time graph for all six teams that inspired Team 4 to look at their raw data in (b); (c) Revised speed-vs-time graph reflecting the corrected input data in (d).

of mass in front of its center of pressure are emphasized in the design phase, using language appropriate for the students' backgrounds, but are not fully appreciated until this analysis.) This engineering-style optimization helps support new Next Generation Science Standards, which embed engineering practices within the science curriculum.

Conclusion

To assess the data interpretation skills of students that completed the CSCS rocket project, we presented them with the graphs in Fig. 1 and coded student descriptions of the data as we did for the non-CSCS class (Fig. 2). CSCS-class students provided expert-like responses two-thirds of the time, nearly twice as often as the control non-CSCS case. Unlike the control case, the "bad alone" and "bad beside good" groups in the CSCS class performed about the same (70% versus 65%, difference not statistically significant), implying that these students no longer needed the comparison because they had developed an internal sense of what good and bad rocket data can look like, much like an expert in this domain might have. In future studies, we will investigate how well students are able to transfer this skill to assessing data in new domains. After completing a semester of instruction using frequent CSCS activities, even students with limited science backgrounds can begin to see data like experts see it—subject to error. The rocket project we describe here is just one example of how cloud computing tools can transform hands-on activities into authentic, collaborative science experiences.

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6. In a typical introductory physics class in the nation, 85% of the students have taken some form of high school physics (P. M. Sadler and R. H. Tai, "Success in introductory college physics: The role of high school preparation," *J. Res. Sci. Teach*. **42**, 111–136). In PHSC 170, only 35% have, and most of those took a physical science course targeted towards non-science students. In terms of math, 20% report that math "terrifies" them.
7. For further information on the experimental design, see Appendix A at *TPT Online* at http://dx.doi.org/10.1119/1.4820858.
8. See Appendix A for details about inter-rater reliability.
9. See Appendix A for technique to calculate statistical significance.
10. Douglas Brown and Anne Cox, "Innovative uses of video analysis," *Phys. Teach*. **47**, 145–150 (March 2009).
10. See Appendix B at *TPT Online* at http://dx.doi.org/10.1119/1.4820858 for further discussion of the appropriate use of conditional formatting.
11. See Appendix C at *TPT Online* at http://dx.doi.org/10.1119/1.4820858.

Matthew d'Alessio is an assistant professor at California State University, Northridge (CSUN), where he teaches science content courses to future teachers. He is a former high school teacher and Google Faculty Fellow.
Loraine Lundquist is an adjunct professor and education researcher at CSUN.
California State University, Northridge, 18111 Nordhoff St., Northridge, CA 91343-8266; matthew.dalessio@csun.edu

Little Green Man Physics

J. Higbie, jackhigbie1@gmail.com

Here's an interesting thought for you. Suppose you were in a lab with a large copper sphere that you charged up to 10,000 volts so that it had lots of static charge. And suppose also, for simplicity's sake, that your lab was located on the equator. When you measure the electric field, you see that it radiates outward uniformly, and when you measure its magnetic field, you see that it doesn't have any. No surprises here.

However, there is a little green man hovering out there in space, and he sees this charged body spinning around the Earth at 1000 miles per hour generating a magnetic field!

So, who's right, you or the little green man?

Editor's Note: What do you think? Go to our Facebook page (https://www.facebook.com/AAPTHQ?ref=ts) to read what other physics teachers are saying about this question.

DOI: 10.1119/1.4820859