

How Social Science Research Can Improve Teaching*

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Abstract

We marshal discoveries about human behavior and learning from social science research and show how they can be used to improve teaching and learning. The discoveries are easily stated as three social science generalizations: (1) social connections motivate, (2) teaching teaches the teacher, and (3) instant feedback improves learning. We show how to apply these generalizations via innovations in modern information technology inside, outside, and across university classrooms. We also give concrete examples of these ideas from innovations we have experimented with in our own teaching.

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1 Introduction

Humans have theorized how to teach for thousands of years and update the substance of what we teach almost every year. Yet generations have passed without any major improvements in the procedures and style of teaching in our classrooms. If your great-great-grandparents went to college, they probably sat in a classroom with all the other students facing forward, trying to look attentive, while the professor professed. If you're professor at a university today, you probably lecture to the same sea of students, all still trying to look like they're paying attention. To be sure, you may use some newer technology (electricity, radio, TV, whiteboards, powerpoint slides, etc.), you may have added a few group activities, and you perhaps teach a seminar with lots of discussion. But if your ancestors were to walk into a classroom today, they'd know where to sit, what to do, and how to act. Our methods of teaching have changed very little.

We think substantial progress in teaching is now possible. Recent developments in social science research mean we know a great deal more about how human beings think and learn, which, we show, can be marshaled to improve our teaching. In addition, technology has progressed far past that used in most current classrooms. Although no technology used by itself has any necessary effect on learning (and much new teaching technology is merely a distraction), some new technologies make it easier to take advantage of social science insights to improve teaching. Finally, massive societal forces outside the university — including for-profit universities, massive on line courses, commercial and not-for-profit ventures, and the web — are now conspiring to overturn centuries of stable university funding models (King and Sen, 2012). In every other area of society, one either adjusts to forces like these or gets run over. It is time for those inside universities to pay attention and to use their unique advantage — research — to improve teaching.

In this paper, we discuss ways in which social science knowledge and technological innovations can help us teach better. We do this by distilling three principles from social science research: (1) social connections motivate, (2) teaching teaches the teacher, and (3) instant feedback improves learning. We find evidence for these principles in research from social and cognitive psychology, public health, economics, sociology and political

science. To show some ways these principles can be used in teaching, we draw from our own experience developing and using several interrelated technologies in teaching our class, Harvard's Gov2001: Advanced Quantitative Political Methodology (see j.mp/G2001). We illustrate these outside, inside, and across classrooms in Section 3.

We conclude in Section 4 by discussing the growing movement in natural and physical science departments to devote some of their own faculty positions and other resources to education research. That scientists are now participating in what is essentially social science research is gratifying, but social scientists have the same needs, our own teaching issues, and more knowledge of the area we can bring to bear on common problems. It is time we make a contribution in both research, which we take a step toward in this paper, and resources.

2 Social Science Learning Principles

Thanks to advances in methods of causal inference, huge increases in data collection, and improved theoretical understandings, we have a better handle on how and why people learn and behave than ever before. From this massive literature, we extract three principles that can be applied to improve teaching.

Principle 1: Social Connections Motivate. Coaxing individuals to take actions that benefit themselves — such as losing weight, exercising, and not smoking — is often extremely difficult. But getting them to take actions that involve social interaction or which benefit the community — such as recycling or joining the PTA — is often far easier. Social scientists have learned how to use this insight by making individual activities into social activities and thereby increasing the effectiveness of individual-level interventions. For example, the large “get out the vote” literature shows a tiny effect of all types of individual citizen contacts, such as phone calls, in person visits, or mailings. But studies that add a social component — such as explaining to a respondent which of a person's neighbors have already voted — can increase a person's propensity to vote by as much as 8 percentage points (Gerber, Green and Larimer, 2008).

The same insight applies more widely: we tend to lose and gain weight when our friends do (Christakis and Fowler, 2007; VanderWeele, 2011). We drink less, exercise more, and smoke less when our friends and associates do (Rosenquist et al., 2010; Christakis and Fowler, 2008). Social networks influence what we eat (Pachucki, Jacques and Christakis, 2011), how happy we are (Fowler and Christakis, 2008), the probability we end up lonely or depressed (Cacioppo, Fowler and Christakis, 2009), where we live (DiPrete et al., 2011), the kind of health habits we take up (Centola, 2010), and whether our marriages persist or end (McDermott, Fowler and Christakis, 2009). Social connections motivate recycling (Burn, 1991), influence the importance of attending religious services (Lim and Putnam, 2010), and affect many other behaviors and attitudes.

Social connections affect so many aspects of our lives that our argument that they can also be applied to education and learning should be no surprise. It is not only for efficiency that a group of students are all taught together in the same classroom or that elementary schools spend so much time trying to integrate students socially into the class environment. Some research in education provides evidence for this point directly in the context of traditional higher education (Garrison, Anderson and Archer, 1999; Summers and Svinicki, 2007) and online education (Graff, 2003; Rovai, 2003; Shea, 2006; Dawson, 2006; DeSchryver et al., 2009; Barab and Duffy, 2000), where community building has been shown to be of particular importance due to relatively infrequent social interactions.

Of course, social connections can also distract students, detract from a common purpose, and derail lectures, and so finding ways of using this powerful tool in a productive way is of course crucial.

Principle 2: Teaching Teaches the Teacher. Social psychologists have demonstrated that under normal circumstances, we “mind wander” (i.e., think about subjects other than which we are nominally participating in) almost half of all our waking hours (Killingsworth and Gilbert, 2010; Morse, 2012). Although the literature does not include measures of mind wandering while watching university lectures, its hard to believe the rate is any lower. People also tend to be less happy when mind wandering, which can’t possibly help students learn, to say nothing about teaching evaluations.

So how do we get students to pay more attention? One strategy is to use the fact that social interactions eliminate about half of this effect: When engaged in conversation with others, people mind wander only about a quarter of the time (Morse, 2012). If we can turn the students into teachers — arranging for them to explain what they’ve learned to others, having them ask questions, debate, persuade, and otherwise engage the subject matter socially — we can capture a great deal more of their attention than would otherwise be possible.

Almost anyone who has taught understands this fact: Study a subject yourself and you can learn a great deal. But teach that same subject to someone else, and you understand it far better than you ever realized was possible. The person you’re teaching will also learn something, but probably not as much as you learned. That *teaching teaches the teacher* has been demonstrated empirically in many studies (VanLehn et al., 2007; Chi et al., 1994). We believe it is explained by the difficulty of mind wandering while engaged socially, by being forced to organize thoughts in a more productive way, and by active rather than passive engagement.

Principle 3: Instant Feedback Improves Learning. Suppose you are an athlete practicing to make the Olympic diving team and you arrive for practice on a Saturday. How much would you improve if the coach watched you silently all day and then gave you a summary of how you did after practice was over? You would learn some, but you’d learn a lot more if, as is typical, you received detailed feedback immediately after *every* dive.

It’s the same story with university education: economics, psychological, medical, and educational research demonstrates convincingly that immediate and frequent feedback improves learning (Hattie and Timperley, 2007; Dubner and Levitt, 2006; Dihoff, Brosvic and Epstein, 2004, 2003; Hodder et al., 1989). The more chances you have to try and fail, the quicker you’ll master the skill. Implementing this advice involves frequent evaluation: like in science in general, students learn more when they have the chance to be proven wrong. This involves eliminating waiting periods before questions can be answered, understanding the limits of their knowledge, and encouraging students to ask questions as soon as they hit a stumbling block. Requiring them to wait until office hours, section, or

the next class should not be part of the drill.

3 Implementing the Principles

We now give some ways of combining the social science principles outlined in Section 2 with innovations in information technology. We do so outside (Section 3.1), inside (Section 3.2), and across (Section 3.3) classrooms. The technologies we describe are those we have developed or tried ourselves, but they represent only a few of the possible applications of the principles.

3.1 Outside the Classroom

Here we give examples of three innovations, each of which takes advantage of the principles given above. In all cases, we seek to make the class and its social connections continue throughout the week until the next classroom experience.

Making Lectures into Interactive Homework. Putting a university lecture together incurs significant start-up costs for instructors: getting the material together, writing slides, etc. The good news is that once the lecture is written, the marginal costs associated with repeated presentations are low. But the bad news is that minimal yearly improvements result in the same lectures being presented over and over again. This, combined with the fact that lectures today are often videotaped, disincentivizes students to come to class, pay attention, and learn.

As an alternative, we assign portions of the lecture videos as homework, using a collaborative video technology that we helped develop.¹ This system has at least three benefits. First, with this collaborative video annotation system, students can hit “rewind” as often as they like. Because social connections motivate, this rarely happens live in a classroom, even when it would be beneficial: Students do not want to be seen by their peers as not paying attention, not understanding the material, or disrespecting the professor or other students, and so they sit quietly, trying to appear attentive. Since so much time is

¹We use a system developed at Harvard University, and which should become available and open source soon. Commercial analogues exist as well.

spent mind wandering, a live lecture can sometimes be described as little more than a sequence of missed opportunities.

Second, if rewind doesn't help, a student can stop the playback and annotate the timeline of the video or one of the associated slides (that turn in sync with the video) with a question or comment (see Section 1). Other students, motivated by their social connections, can then help clarify, as can the teaching staff. A lively, Facebook-style discussion about the material then often develops (often during hours federal regulations require faculty to be asleep). Because, in our experience, students are highly motivated to provide feedback to their peers in near real time, teaching in this way teaches the students who serve as teachers and learning is greatly enhanced.

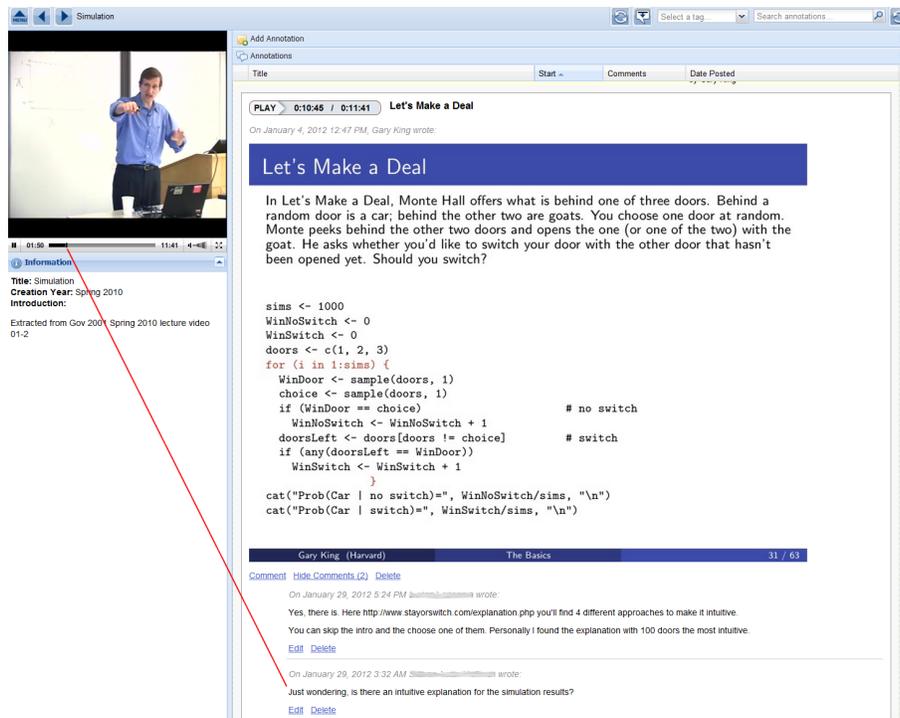


Figure 1: Collaborative Video Annotation. The lecture video on the left, slides on the top right, and discussion forum at the bottom right can all be resized. The red line illustrates the connection between a point on the timeline and the comments.

Finally, collaborative video annotation can improve the classroom experience. For one, it enables the instructor to take and encourage questions even at the cost of not getting through the planned material; collaborative video annotation makes it easy to assign the portions of the lecture for which there was no time during class. For another, students

come to class much more prepared than they otherwise would. We of course also assign written material for students to consume, but social science evidence indicates that seeing the same material via different modalities enhances learning (Mayer, 2003). (Practicing what we teach, we have posted a video explaining many of the points in this paper at j.mp/HUteach.)

Making Reading Interactive. Suppose you're assigned a chapter to read and you can't understand one of the key points on the second page. In the traditional class, you would be expected to meet with a teaching assistant at office hours or in the scheduled section meeting. In either case, that could be days from now; if you wait, you'll lose sight of what you were reading and probably won't have time to complete the assignment. Alternatively, you could skip this key point, pretend you understand it, make some confused assumption about it, and keep reading. Either option violates all three social science teaching principles.

Instead, our practice is to follow analogous techniques for reading assignments as we do with videos. To do this, we put all class readings in a collaborative text annotation system.² This system enables students to highlight passages in the text they do not understand and ask questions in a separate text field. Other students, or the professor or teaching assistants, can then see the questions posted and instantly respond — again 24/7. On any given night, even if class isn't scheduled to meet for another week, students are able to receive fast feedback on their questions (in a Facebook-style discussion forum). Since teaching teaches the teacher, considerable pedagogical benefits also go not only to those who get their questions answered but also to those answering questions. And since social connections motivate, students give more time and attention to the readings and the class than they would otherwise.

Email Lists to Create Community. Many university courses today have some sort of “class email list” that instructors use to disseminate logistical information to students. We go further and encourage students to ask questions of the entire list instead of just the

²We use NB; see nb.mit.edu.

22 2 Conceptualizing uncertainty and inference

distinguish between these two cases, I refer to the hypothetical parameter value as $\hat{\theta}$ and the single unobserved true value as θ . In the next chapter, I will introduce $\hat{\theta}$ as a point estimator for θ , based on the maximum of the likelihood with respect to $\hat{\theta}$. **$\hat{\theta}$ is a number** in a single experiment, but a random variable across hypothetical experiments.

The likelihood that a hypothetical model (summarized by the hypothetical parameter value $\hat{\theta}$) produced the data we observe, given \mathcal{M}^* , is denoted $L(\hat{\theta}|y, \mathcal{M}^*)$, where \mathcal{M}^* may again be suppressed since it appears in all subsequent expressions. The likelihood axiom then defines this concept as follows:

$$\begin{aligned} L(\hat{\theta}|y, \mathcal{M}^*) &\equiv L(\hat{\theta}|y) \\ &= k(y)\Pr(y|\hat{\theta}) \\ &\propto \Pr(y|\hat{\theta}). \end{aligned} \tag{2.5}$$

In the second line of this equation, $k(y)$ is an unknown function of the data; since it is not a function of $\hat{\theta}$, it is treated as an unknown positive constant. In the third line, “ \propto ” means “is proportional to.” The third line is only a more convenient way of writing the second without the constant. For a given set of observed data, $k(y)$ remains the same over all possible hypothetical values of $\hat{\theta}$. However, $k(y)$ is a function of y and therefore may change as y changes. The likelihood $L(\hat{\theta}|y)$ is similar to the concept of inverse probability in that it permits one to measure and compare the uncertainty one has about alternative hypothetical values of $\hat{\theta}$. However, the unknown value $k(y)$ ensures that likelihood is a relative rather than an absolute measure of uncertainty. This likelihood axiom is but one way to make the measure explicitly relative. Indeed, one could use any monotonic function of $\Pr(y|\hat{\theta})$.⁵ The choice represented in Equation (2.5) is arbitrary, just as is the choice of making the scale of probability range between 0 and 1. The advantage of likelihood is that it can be calculated from a traditional probability, whereas inverse probability cannot be calculated in any way.

If the data are continuous rather than discrete, the likelihood is calculated in the same way, except that the underlying probability distribution is now a density. Hence, a more general way to write the formula is as follows:

$$L(\hat{\theta}|y, \mathcal{M}^*) \equiv L(\hat{\theta}|y) = k(y)f(y|\hat{\theta}) \tag{2.6}$$

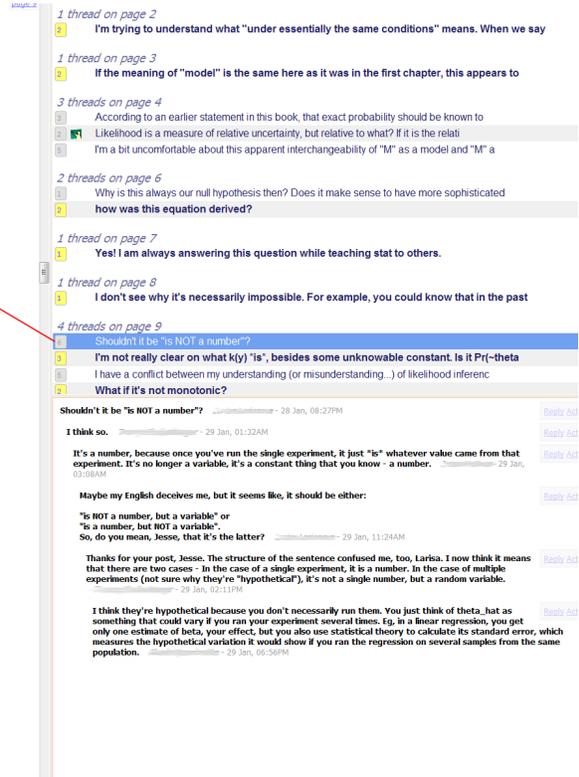


Figure 2: Collaborative Text Annotation, a screen shot of NB software, with a red line added to highlight the connection between the assigned text on the left and discussion forum on the right.

teaching staff, and those who know the answer to make a contribution by responding. This speeds feedback, helps some students get the benefit of being teachers, and motivates them with social connections. And we therefore eliminate any reason to wait until “business hours” to contact, or receive a response from, the teaching staff. To enhance social connections, we allow students to include non-course related information when it can help build camaraderie in the class; this may even include job opportunities, relevant papers, conferences that might be of interest, and class social events.

In addition, we recently discovered that the class’s longstanding email list was available going back for over a decade. So we then turned this information into a searchable knowledge base, as well as a community in its own right. Students now have access to over ten thousand class emails covering many topics and providing instantaneous answers to hundreds of key questions. In addition, we obtained permission from Harvard’s General Counsel to make available not only the questions and answers in the archive, but also

the author of each email. Thus, not only does the archive provide instant feedback, but it allows students a glimpse into a remarkable network of students who have taken this class. A tremendously motivating feature of this innovation is finding a question similar to yours by a student who now happens to be a tenured professor at a major university, partner in a law firm, or leader of a major corporation.

The Gov2001 Archives

You can get [more information about this list](#).

likelihood or log likelihood

About 112 results (0.15 seconds)

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[\[gov2001-l\] poisson log-likelihood](#)
<https://lists.gking.harvard.edu/pipermail/gov2001-l/001928.html>
 [gov2001-l] poisson log-likelihood. Jens Hainmueller /hainmueller. Sun Apr 13 16:42:59 EDT 2008.
 Previous message: [gov2001-l] poisson log-likelihood; Next ...

[\[gov2001-l\] seeing the log-likelihood iterations](#)
<https://lists.gking.harvard.edu/pipermail/gov2001-l/000800.html>
 [gov2001-l] seeing the log-likelihood iterations. Miya Woolfalk woolfalk. Wed Mar 25 18:02:37 EDT 2009.
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<https://lists.gking.harvard.edu/pipermail/gov2001-l/000799.html>
 [gov2001-l] seeing the log-likelihood iterations. Patrick Lam plam. Wed Mar 25 17:49:38 EDT 2009.
 Previous message: [gov2001-l] seeing the log-likelihood ...

[\[gov2001-l\] Assignment 4. Binomial model and log-likelihood](#)
<https://lists.gking.harvard.edu/pipermail/gov2001-l/000659.html>
 Mar 2, 2009 ... Binomial model and log-likelihood Olena, Remember to apply the log function to the entire Likelihood function. Your terms not only reduce from ...

[gov2001-l] likelihood vs loglikelihood

Kosuke Imai [kimai at fas.harvard.edu](mailto:kimai@fas.harvard.edu)
 Wed Mar 5 09:26:56 EST 2003

- Previous message: [\[gov2001-l\] likelihood vs loglikelihood](#)
- Next message: [\[gov2001-l\] likelihood vs loglikelihood](#)
- Messages sorted by: [\[date \]](#) [\[thread \]](#) [\[subject \]](#) [\[author \]](#)

That's right. This is because log is monotone transformation:
 $\log(x) > \log(y)$ if $x > y$.

You should "always" take log. This is a rule whenever you are calculating the density function. The logscale is much more stable numerically. Think about the Gamma function, which is equal to $\Gamma(x+1) = x!$ if x is an integer. You definitely want to take a log if x is large.

Another important reason is that the law of large numbers and central limit theorem apply to the loglikelihood function, not to the likelihood function. Do you see how?

Kosuke

On Wed, 5 Mar 2003, Phillip Y. Lipscy wrote:

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> For 2b, if we use the product term of the negative binomial distribution to
> estimate the likelihood rather than the loglikelihood, am I right to assume that
> we should get the same result for the maximum point? i.e. we use loglikelihood
> instead of likelihood to get rid of the product term, but our results should not
> change?
>
> Thanks,
> Phillip.
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Figure 3: Querying the Class Email Archives (Left) and Getting an Answer (Right)

We also encourage the time-spanning nature of the class community by building and regularly posting to a Facebook group exclusive to class alumni. We use this Facebook group to communicate job opportunities, data problems, methodological advice, and other information.

3.2 Inside the Classroom

So if all this (above) is going on outside the classroom, what is the point of the classroom? The innovations in Section 3.1, if used properly and along with other innovations, can improve the classroom experience itself and greatly increase the amount of information learned overall.

Understanding Confusions. With the innovations we introduce outside of class instructors can learn exactly what students have the most trouble with and use that to make the classroom experience far more powerful. Thus, for video and text annotation, and for students querying our email database, we collect data on an ongoing basis about the topics

students discuss, the kinds of questions they ask, and how they answer others' questions. Before each class, we automatically construct and study heat maps of the readings and assigned lecture timelines, colored by the intensity of annotations. By additionally soliciting students' feedback, we can piece together (1) what students *think* or say they are confused about and (2) what students are *actually* confused about, judged by direct evaluations.

But how exactly do we use this knowledge to increase what students learn? We do so in two ways.

Informed Lecturers. The social science learning principles also apply to us as teachers. The instant feedback provided to us on what students are having trouble with, provided by these technological innovations, ought to substantially improve teaching compared to end-of-semester student evaluations or even mid-terms or final exams. We use the information gained to focus more time on material we now know students find confusing or have stumbled over. If they have seen a video presentation from a lecture in a previous year, we develop a new way to approach the material for this year. We also stop and prompt students for questions during parts of the lecture about which we now know they will have difficulty with, or we can ask questions ourselves to generate discussion.

Computer-Assisted Peer Instruction. Second, because students have learned far more outside of class than is typical, and our lectures are more effectively directed to what they do not understand, we spend less time presenting traditional lectures. This can be a substantial benefit because — although lectures may generate a kind of “collective effervescence” that people resonate with, much like they do with concerts, sporting events, or religious rituals (Konvalinka et al., 2011) and that possibly increases cooperation (Wiltermuth and Heath, 2009) and further engagement — lectures also include minimal feedback for the instructor, minimal feedback for the students, minimal social connections among the students, and little opportunity for students to learn by teaching.

We thus spend a portion of the class via a version of “computer-assisted peer instruction” (CAPI). Peer instruction was introduced in Crouch and Mazur (2001); Fagen, Crouch and Mazur (2002) and has seen widespread usage (and is related to another sim-

ilar protocol called “team-based learning”; see [Sweet and Michaelsen 2011](#).) We explain this and CAPI together.

First, we use an automated system we helped develop called “Learning Catalytics” that implements CAPI and that students sign into when they come to class.³ (Instead of prohibiting smart phones in class, we require them or, alternatively, a laptop, tablet, or some other web-enabled device.) We then automatically deliver to their device (and, optionally, a screen in the front of the room) a difficult conceptual question. We then give students a few minutes without discussion to reflect on the question and to indicate their answer on their device. The question can be of many types (multiple choice, a freehand drawing, an algebraic expression, a directional vector, unstructured text, highlighting on a map, drawing, or text, or others). We construct the question out of the most difficult parts of the week’s assignments, so that, ideally, only about 20% of students initially get the answer correct.

Next, our system automatically puts students into groups of 4-5 in preparation for a discussion about the question(s). We use an empirical approach to create the groups so that the conversation will be maximally productive. This is a system that is continually updated, but for predictors we begin with data collected to characterize each student at the start of the semester and add each student’s initial answer to the question just asked, their answers to all previous CAPI questions and answers, their experience in the system, and how productive previous CAPI discussions they participated in were. Finally, data from thousands of other similar students in hundreds of other classrooms taking similar courses can be used as well.

Once grouped, the system delivers to each student’s device instructions regarding which other students to talk with and (optionally) where to move their seat to have the discussion. (Most instructors spend time and effort trying to convince students to fill in seats up front; as an alternative, we can let students sit where they like when they walk in, but on the first CAPI question automatically assign each student a seat where we want them to sit. Then we avoid transaction costs for the remaining CAPI questions and choose groups that do not require students to move.)

³See LearningCatalytics.com.

We then instruct the students to try to persuade the other members of their group of the veracity of their answers. Since social connections motivate, we typically get highly animated discussions. (Over the course of the semester, we use different groupings so students get to know more than just the friends they came in with.) We allow the ensuing discussion to continue for approximately 2–7 minutes, permitting the time to vary according to the complexity of the question. During this time, the teaching staff moves among the groups as participants or just listening in and learning about the students' misunderstandings and difficulties. Since teaching teaches the teacher, the students trying to persuade their classmates improves their understanding of the subject matter. This is often true for those who got the answer right the first time.

We then deliver the same question to each student's device again and have them answer it. A minute or two later we project on the screen in front of the classroom a summary of the answers before and after discussion, which gives them immediate feedback. For multiple choice, we use overlapping histograms. For freehand drawings, we superimpose all the drawings on top of one another (using alpha-transparency). For equations, we automatically check for algebraically equivalent versions. For free text, we cluster responses. Etc. When it works well, the proportion of correct student answers increases from 20% to more than 80%. (CAPI can also be used for subjects with no right answer, which encourages students to hone their arguments and debate skills; the only difference is that we don't necessarily expect a particular directional change in the percent giving each answer.)

Figure 4 gives an example of a multiple choice question delivered to a student's phone (at the left) and the instructor's view (left part of bottom right panel). After the first round, a personal message is delivered to each student's phone or other device that tells them who to discuss their question with (see brown note in phone at the left). A seating chart appears at the top right for the instructor, coded with letters for each answer and green for correct; the grouping is also shown. The instructor can also see, and optionally can show to the class, histograms of student answers before and after discussion (right of the bottom panel). Finally, students are given the option of indicating whether they "get it

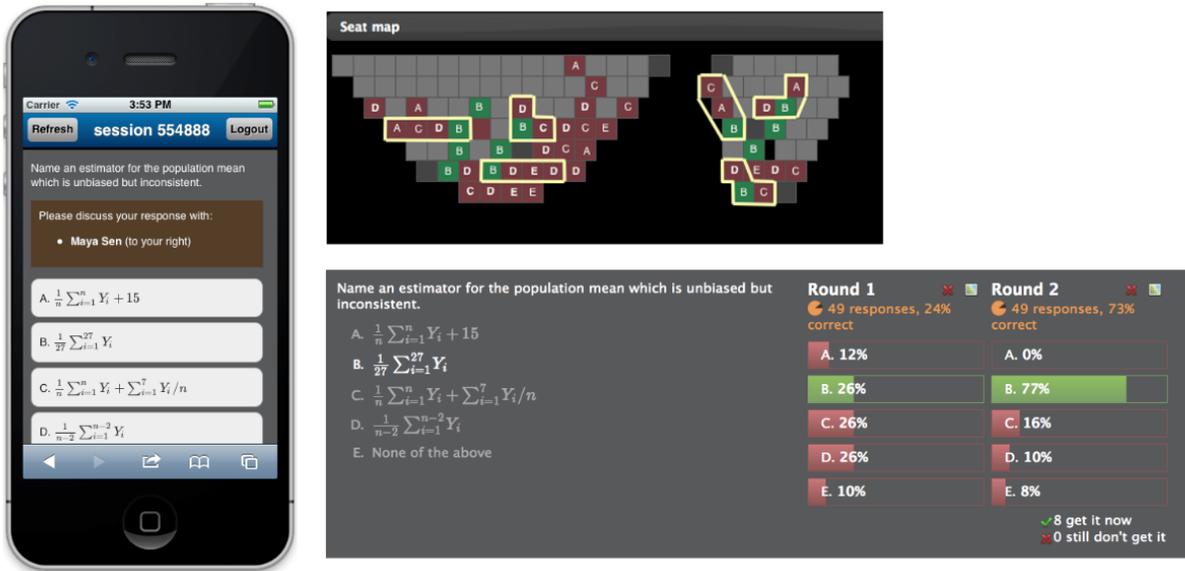


Figure 4: Sample question as seen on student smart phone (left), example class discussion groupings (above right), and histograms for the instructor (and optionally to share with students) showing student responses before and after discussion (below right)

now” or “still don’t get it” (see current tally at bottom right of the bottom right panel) in order to provide instant feedback to the instructor.

We intersperse CAPI questions at different points in the lecture. To ensure that students are in a participatory mood during lecture, we usually begin class with a CAPI question. We also use others at the most difficult points in the lecture. Indeed, many who use CAPI do not lecture at all, thus completely “flipping the classroom” as the practice is sometimes called. Students are told that answers to these questions do not count to their grade (except for their participation).

3.3 Across Classrooms

Social scientists have been highly successful over the last few decades convincing the world outside of academia about the value of large-scale observational and experimental data collection and analysis. After all, this type of quantitative social science has already remade most Fortune 500 companies; established new industries; led to a huge increase in the expressive capacity of human beings; and had a role in reinventing medicine, friendship networks, political campaigns, public health, legal analysis, policing, economics,

sports, public policy, and program evaluation, among many other areas. In recent years, this has even been popularized through movies and books like *MoneyBall*, *SuperCrunchers*, *The Numerati* and others. There's no reason why those of us in social science departments, responsible for creating, applying, and popularizing the innovations that made these changes possible, shouldn't also turn this productive machinery to improve our own teaching.

Unfortunately, using data collection to improve teaching and learning beyond a single classroom is rare, at least aside from comparing end-of-semester teaching rating. And although we have been able to increase greatly the amount of data collected about the classroom we control, many of us need to work together with university officials to implement big data strategies for education. With appropriate protections for individual student privacy and Federal regulations, we should do what most businesses do now and instrument as many aspects of the university as possible. The results may well be substantial. For example, instead of students getting ad hoc, idiosyncratic advice from a few other students they happen to know regarding what to major in, what classes to take, and what careers to pursue, good data collection and analytics can get all students systematic advice from tens of thousands of previous students they would never have time to know. They can study many more paths through a college education and see which suit them, understand what hurdles stand in their way, what roadblocks they should avoid, and which choices will confront them. We can use the instructional staff more efficiently, and help us learn from each other what works, what doesn't, and what only works well for some instructors. Instead of instructors experimenting by changing what they do in their classroom and never evaluating it because of the absence of a proper control group, they can learn by observational studies — if we make the effort to collect the data and apply the methods we do for research to our teaching as well.

University officials, faculty committees, and staff need to take on board the overwhelming impact social science research has on every area it touches and how it can revolutionize university operations to improve teaching and learning as well.

4 Concluding Remarks

In recent years, rigorous education-related research has taken root within physics (Deslauriers, Schelew and Wieman, 2011; Crouch and Mazur, 2001), chemistry (Golde, McCreary and Koeske, 2006), computer science (Porter et al., 2011), medicine and nursing (Rao and DiCarlo, 2000; Hodder et al., 1989; Ende, 1983), and other areas. In addition, numerous science departments now have dedicated research groups, faculty lines, post-docs, and other staff who specialize in education research adapted to their disciplinary areas — e.g., the physics education groups at Arizona, CU-Boulder, Harvard, Kansas State, Maryland, Ohio State, and others; the chemistry education groups at Iowa State, Purdue, and Cambridge Universities; the computer science education groups at Bowdoin, Duke, and Villanova, and the medical education research and evaluation group at Stanford, among others.

These groups are studying an aspect of human behavior — that is, social science research. It is gratifying to see another area where we have had an influence, but social scientists are, of course, especially well situated to making major contributions to these emerging literatures. We should accept the challenge and encourage our colleagues to join in, systematize social science knowledge, harvest useful social science generalizations for teaching, develop new technologies and innovations that improve our teaching and our students' learning, and contribute our valuable faculty lines. The result will likely be that are classrooms will be filled with better educated and knowledgeable students, albeit trying very hard to look attentive.

Conflict of Interest Declaration

Gary King is co-founder of Learning Catalytics.

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