THE DATA SCIENCE EDUCATION DILEMMA

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The need for people fluent in working with data is growing rapidly and enormously, but U.S. K–12 education does not provide meaningful learning experiences designed to develop understanding of data science concepts or a fluency with data science skills. Data science is inherently inter-disciplinary, so it makes sense to integrate it with existing content areas, but difficulties abound. Consideration of the work involved in doing data science and the habits of mind that lie behind it leads to a way of thinking about integrating data science with mathematics and science. Examples drawn from current activity development in the Data Games project shed some light on what technology-based, data-driven might be like. The project's ongoing research on learners' conceptions of organizing data and the relevance to data science education is explained.

THE PROBLEM

The ongoing exponential growth (see Figure 1) of our society's storage of and reliance on data is astonishing. The growing gap between the need for a data savvy citizenry and the data science education of students is equally astonishing, greatly troubling, and extremely perplexing. From the author's experience with K–12 education in the U.S., meaningful student encounters with data analysis are rare, teachers' data skills and comfort using data-driven lessons are nearly non-existent, curriculum developers' motivation to weave use of data into classroom materials is extremely low, researchers' efforts to build a knowledge base of how students learn about data are limited, and policy makers' attempts to strengthen data science education in the schools are ill-informed.

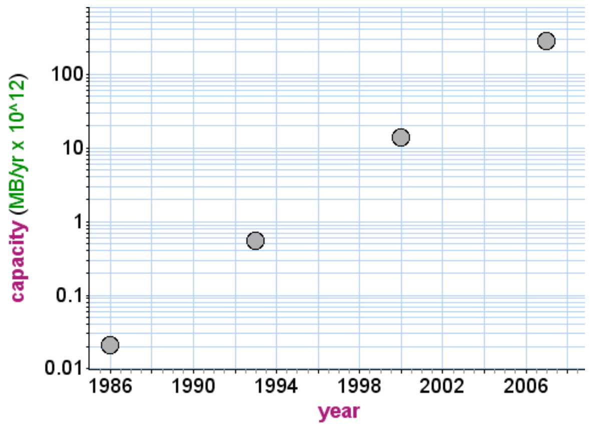


Figure 1. World's technological installed capacity to store digital information, in optimally compressed Megabytes (MB) per year (Hilbert, 2011).

In the fractured landscape of school subject-matter disciplines, data science has no natural home. Mathematics, already uncomfortable housing statistics, resists the incursion of rich contexts that mess with students' ability to focus on abstraction. The physical and biological sciences, steeped in experimental data as they are, are so overwhelmed with teaching concepts that data get relegated to the role of illustration. The social sciences, though increasingly data-oriented in practice, have hardly begun to transfer to educators the quantitative perspective necessary to bring meaningful use of data to K–12 social science classrooms.

The challenge then is to figure out how to change educational systems so that students emerge from their schooling with data science skills and conceptual understanding needed to participate fully in society as citizens and workers.

CONSIDERATION OF EXPONENTIAL GROWTH OF COMPUTATIONAL RESOURCES

	1982	Factor	2012
CPU Speed	1 MHz	3,000	3 GHz
Hard Disk Capacity	1 MB	1,000,000	1 TB
Transmission Rate	30 B/sec	30,000	1 MB/sec

Table 1. The author's personal computing resources in 2012 compared with those 30 years prior.

Table 1 describes the last 30 years of change in terms of the author's computers then and now. Three questions that help bring this change home are: What would it be like if you could get from one place to another

3,000 times as fast? What if you were 1,000,000 times as tall? What if the earth's population were 30,000 times what it is now? The difficulty in imagining such changes points to the difficulty we have in understanding the implications of the state change in civilization caused by the many orders of magnitude increase in computational resources. The change affects all components of society, not least education.

Not long ago data was expensive. There wasn't much of it. Data was the bottleneck for much of human endeavor. Not today. We are no longer data-limited but insight-limited (Abbott, 2009). A huge reservoir of data is backing up, with untapped discoveries within. The people who know how to work with data are in short supply. These people are data scientists. Future data scientists are in elementary school today, but unless the K–12 school curriculum changes so that data science education is a significant part of a young person's learning experience, many fewer data scientists than we need will emerge in the next decades.

WHAT IS DATA SCIENCE?

An early use of the term data science appears in "Data Science: An Action Plan for Expanding the Technical Areas of the Field of Statistics" in which Cleveland (2001) describes data science by laying out a university training programming. His description is notable for including both a *computing with data* strand as well as a *pedagogy* strand.

The Venn diagram in Figure 2 provides a simple mechanism for thinking about what constitutes data science. First, there is the disciplined, quantitative thinking found in mathematics and statistics. From statistics comes an understanding of variability and experience using statistical tools to work with data. Second, substantive expertise gives a data scientist an understanding of the disciplinary context for a data set without which choosing a valid analysis methodology will be difficult or impossible. Finally, computing and data skills which, combined with creative problem solving abilities, allow one to see inside the machine and to visualize the structure of the data.

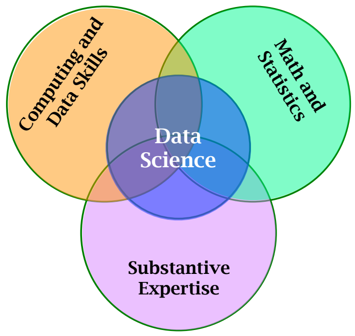


Figure 2. Data Science Venn diagram adapted from Conway (2010).

Task	Primary Expertise
Set up a server as a repository of data streaming in real time from a large array of geographically distributed sensors.	CD
Explain the origin of outliers in a particular data set.	SE
Decide to what extent the conclusions drawn from analysis can be generalized.	MS
Design a data visualization suitable for publication in an article for non-experts.	CD
Decide what data should be gathered.	SE
Decide whether certain disparate data sets can be meaningfully merged.	SE
Automate the merger of multiple data sets.	CD
Detect the signal within the noise.	MS
Reduce the number of variables that need to be considered for a particular analysis.	MS
Set up a version management system for data that will be gathered over a number of years.	CD

Table 2. Representative data science tasks and the portion of the Data Science Venn diagram from which they primarily draw. (CD = Computing and Data Skills, MS = Math and Statistics, SE = Substantive Expertise)

Table 2 lists some tasks that might reasonably be labeled as part of doing data science. It should be clear that someone well-versed in only two of the three areas of expertise will be seriously hampered in any attempt to work with real data. For example someone with no computing skills will have difficulty automating the process of cleaning data and be at a loss for how to transform a very large raw data set into something ready for analysis. In practice data scientists works in teams, and it is the team as a whole that embodies the complete range of required expertise. Even so, data scientists with a complete set of these inter-disciplinary skills, combined with the ability to collaborate productively, will likely contribute more than those who are lacking in one or more areas. For many projects it may be that just as data come to underly every aspect of the work, data scientists frequently provide the glue that holds the work together.

Computer scientists have begun to pay serious attention to the tasks of data science, as detailed in an article on "data wrangling" (Kandel, 2011) that describes the current complexity of transformations a data scientist makes to bring data into a "credible and usable" form.

CONFRONTING THE DILEMMA

The remaining sections of this paper attempt to put forward some ideas, drawn primarily from the author's work in designing educational software, on what needs to be done to bring data science into K–12 education. The gap between the magnitude of the problem and small scale of the ideas is very large, and no attempt is being made here to give a survey of the many outstanding contributions others have made to curricula and technology in this area.

DATA ACROSS THE CURRICULUM

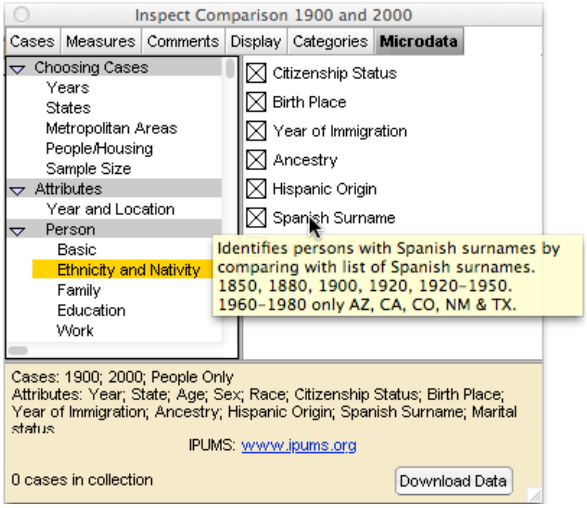
Two observations suggest that data science should not aspire to become a new subject area in the school curriculum: There are more subject areas already than fit comfortably; and learning to work with data makes most sense within a relevant context. Imagine a data science experience, K–12, in which work with data occurs in every subject as appropriate to the current content being studied. In history, migration patterns are studied through analysis of census microdata. Most science labs involve use of data science to reveal not just the textbook "answers" to the investigation, but the interesting deviations from what is expected. In physical education, data gathered from video lead to insight into how to improve athletic performance.

A prerequisite to meaningful implementation of "data across the curriculum" is agreement on a progression of encounters with data science concepts and skills, without which each teacher at each grade level is condemned to work with a lowest common denominator of prior experience because anything more will require an intolerable digression from the subject matter lesson. With a coherent conception of data science education, teachers can build incrementally on skills and knowledge acquired earlier in a student's school experience.

ACCESS TO DATA

It is not possible to have meaningful learning experiences in data science without frequent use of the technologies that have brought about the data revolution. Drawing graphs by hand or sorting piles of surveys do not build understanding of distributions or how to clean data. Online tools for gathering, cleaning, exploring, and visualizing data are beginning to reach a level of accessibility and usability appropriate for school use.

The author is the lead developer of *Fathom® Dynamic Statistics Software* (Finzer, 2006), a desktop application widely used in secondary schools and colleges for introductory statistics, mathematics, and science. Fathom has many features especially helpful in immersing students in data, not least among them multiple ways to access data.



☒ Citizenship Status
☒ Birth Place
☒ Year of Immigration
☒ Ancestry
☒ Hispanic Origin
☒ Spanish Surname

Identifies persons with Spanish surnames by comparing with list of Spanish surnames. 1850, 1880, 1900, 1920, 1920–1950. 1960–1980 only AZ, CA, CO, NM & TX.

Cases: 1900; 2000; People Only
Attributes: Year; State; Age; Sex; Race; Citizenship Status; Birth Place; Year of Immigration; Ancestry; Hispanic Origin; Spanish Surname; Marital status
IPUMS: www.ipums.org
0 cases in collection

Figure 3. Fathom's census microdata import interface makes it easy to sample from historical data.

Listed below are the primary means of getting data into *Fathom*.

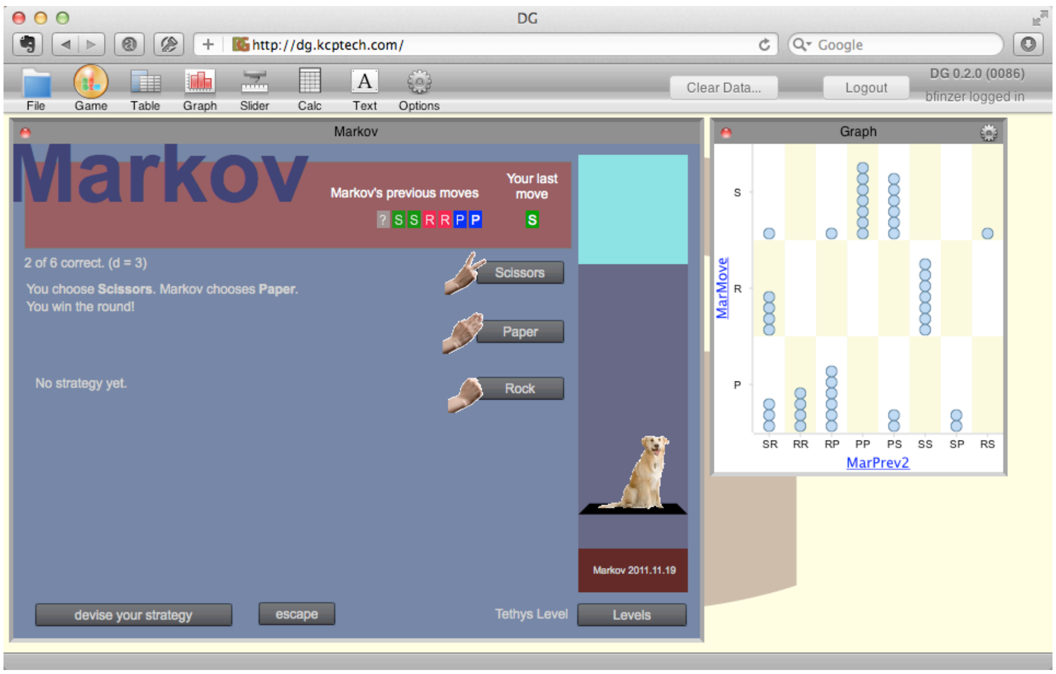
- Type data by hand into a spreadsheet-like table.
- Copy data from a spreadsheet, a web page, or as tab-delimited text and paste into *Fathom*.
- Import from a tab-delimited text file.
- Drag the URL from a web page containing data into a *Fathom* document. *Fathom* parses the HTML from the page and looks for data in a variety of formats.
- As shown in Figure 3, use the U.S. Census microdata interface built into *Fathom* to select a sample of individuals who filled out the long form of the census from 1850 to 2000, choosing from 65 attributes.
- Connect one or more Vernier probes to the computer and configure *Fathom* to accept data from the probes in real time.
- In *Fathom* create a survey that appears on the web. Responses to the survey can be brought into *Fathom* at the push of a button.
- Create a simulation in *Fathom* that generates data.

The importance of this list is that it illustrates that data come in a wide variety of forms that is increasing with time. Any barrier between the learner and the data to be analyzed can be a serious problem.

CURRENT WORK—DATA GAMES

A number of sets of mathematics curriculum materials have been developed over the years to integrate use of data with the study of mathematics, among them the *Data-Driven Mathematics Series* (1998) and *Discovering Algebra* (Murdock, 2007). These materials, while they have demonstrated the efficacy of a data-driven approach, have barely begun to integrate use of technology with the mathematics and data science.

With support from the National Science Foundation[1] for the Data Games project at KCP Technologies and UMass Amherst, the author and his colleague Cliff Konold are exploring a promising, technology-based vehicle for integrating data science into the teaching of mathematics using games.



2 of 6 correct. (d = 3)

You choose **Scissors**. Markov chooses **Paper**.
You win the round!

No strategy yet.

Figure 4. Data Games runs entirely in a browser and consists of a set of games, each of which streams data into a surrounding data analysis environment during game play.

The idea of a Data Games activity is that students play a simple game that streams data to a surrounding data analysis environment, so that the data is available for exploration. An example is shown in Figure 4 in which the player attempts to save the dog Madeleine from the Dr. Markov by playing the game of rock, paper, scissors. Unfortunately for Madeleine, the game is rigged so that the evil doctor wins all ties. The player's only hope is to make good use of the graph that shows the conditional probabilities associated with Markov's strategy.

Students are expected to analyze the data to create a model of what is happening in the game with which they can improve their strategy. By design, the models that underlie the games are based on mathematical concepts that are a normal part of the school curriculum; e.g. linear relationships, quadratic equations, statistical measures, and probability. Erickson (2012) describes the challenges faced in designing and teaching with these games.

DATA HABITS OF MIND

A "habit of mind" is a way of thinking, questioning, and problem-solving. A "data habit of mind" is a habit of mind that grows out of working with data. An important objective of any attempt to integrate data science into the curriculum should be to inculcate learners with data habits of mind. Consider two seemingly straightforward data habits of mind relevant to the Data Games project.

Look for the Data

One such habit of mind is to *look for data* that might be helpful in solving the current problem. A data game generates data. The data are easily examined and highly relevant to improving one's game playing strategy. But students do not necessarily come equipped with a built-in look-for-the-data habit of mind. Rather, it develops with repeated experiences in which they are given the opportunity to look for the data and the discover that these data are quite useful.

A typical progression for a high school student is: (1) Practice playing the game with minimal use of quantitative thinking. (With a well-designed data game, the students won't improve their scores much this way.) (2) Begin using the information displayed by the game in a systematic way. (3) Express a desire for a record of prior moves. "This must be keeping track of what I'm doing. (4) Make systematic use of tabular or graphical representations of prior moves and games to devise an improved strategy that results in higher scores.

In pilot classes with students who have repeated encounters with data games, students show that they have adopted this habit of mind by creating a table and/or graph even before they being playing the game as a way of saying, "I know I'm going to need to work with the data." While there are certainly students who follow this kind of progression unaided, observations in field test classrooms suggest that the teacher and the learning environment play a critical role in developing data habits of mind.

Graph the Data

Consider the habit of mind *graph the data*. A graph may make evident a potentially useful pattern in the data, a pattern that is difficult to discern by staring at a table of numbers. In Data Games, creating a graph requires no more than a button press, and, by default, it shows the most useful configuration of attributes. Yet, unless instructed to, very few students in the Data Games field test make graphs in their first encounters with a data game. They are more likely to make a table. Some conjectures about why are: Graphs are unfamiliar and will require more effort than tables to use; tables appear to give more exact information than graphs; graphs are pigeon-holed as function plotting tools rather than tools for data exploration.

Most students in the field test did not initially have the habit of mind of graphing data. By the end of the 2012 school year, we should be able to determine whether they acquire it after repeated exposures so that, at least in the context of a data game, they voluntarily make graphs and use them to figure out a strategy.

Other Data Habits of Mind

Among the many other data habits of mind that eventually will become part of a data science curriculum, some are beginning to show themselves as important in the Data Games work: Become immersed in the data, use (and invent) measures, and look for and tell the story behind the data.

LEARNERS' CONCEPTIONS OF DATA

Most education research that has to do with data falls within the traditional boundaries of statistics education. It is research about students' understanding of the center and spread of distributions, of informal inference, of sampling distributions, and of some standard plots. But new research frontiers are opening up. What are learners' conceptions of data, and how do these change with increasing experience working with data? What do learners think is going on when they transform data to clean it, parse it, change its scale, merge it, or do any the many other things that are routine for a data analyst?

Research undertaken during the last two years in the Data Games project may serve as an example of the kind of work that can be done to provide the foundation of knowledge on which tools and learning environments can be built. A situation involving traffic was used both in an interview protocol with individual students and a group protocol for whole class administration. Figure 5 shows one of two road segment snapshots presented to students. They were asked to create an organized record (not a drawing) of all the data values that appear on the snapshots.

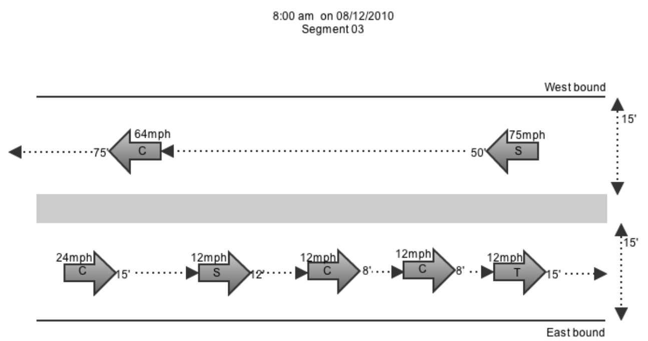


Figure 5. One of the segments of road for which subjects are asked to devise a scheme for recording data.

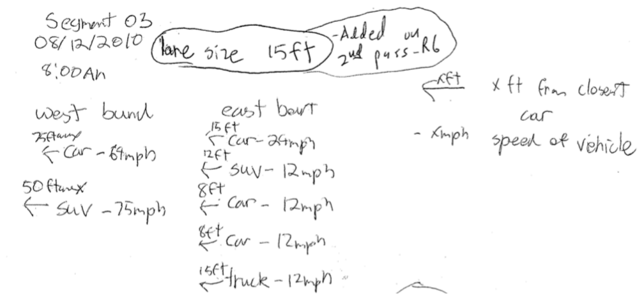

Segment 03
08/12/2010
8:00Am
lane size 15ft
-Added on 2nd pass-R6
west bund
75ft away
← Car - 64mph
50 ft away
← SUV - 75mph
east bourt
15 ft
← Car - 24mph
12ft
← SUV - 12mph
8ft
← Car - 12mph
8ft
← Car - 12mph
15ft
← truck - 12mph
← x ft
x ft from closest car
- xmph
speed of vehicle

Figure 6. A portion of one student's work from an individual interview. Note the similarities with the original schematic.

Students from grades 7–14 have been interviewed or have been part of a group administration, and the responses are being analyzed. One rough categorization groups responses into narratives, attempts to summarize as opposed to record, unstructured listings of values that lose most of the case structure, hierarchical (nested) structures of two or three levels, and fully flat row-by-column tables with each row representing a vehicle. Figure 6 shows a hierarchical representation with levels for road segment, lane direction, and vehicle. Its incomplete naming of the direction, vehicle type, and distance attributes suggests another categorization of responses according to use of labels as evidence for understanding of cases, attributes, and values.

A conjecture going into the study was that it would be easier to for subjects to use flat tables than hierarchical structures. (Probably this supposition arose from familiarity with flat tables on the part of the researchers!) But, in fact, hierarchical representations were common among less sophisticated respondents while flat tables were only used by those who evidenced greater understanding of how to work with data. In retrospect this makes sense because the schematic subjects worked with had a naturally nested appearance, and because assigning values representing road width to rows in a table that represent vehicles may seem unnatural. A paper dealing with this work is in progress.

THE ROLE OF STATISTICS EDUCATION

Statistics itself is rapidly changing under the influence of the data revolution (Friedman, 2001). Inevitably, statistics education lags behind in accepting that

Statistics educators, more than educators of any other discipline, are in a position to advocate for the changes required to increase the flow of the data scientist pipeline. They understand data and make use of data habits of mind. Many have sophisticated computing and data skills and have acquired substantive expertise. Some have begun to make important changes in the undergraduate statistics curriculum and advocate for a new approach to statistics (Nolan, 2003). But the advocacy role will require statistics educators to step outside their comfortable disciplinary silo and reach out to other STEM educators and come to understand how data science can be integrated into their curricula.

The challenge is big. The pressure on educational establishments to make changes will grow inexorably as the need for more data science in industry and science becomes ever more apparent. In the U.S. the federal government can help by forming a National Center for Data Science Education as a place to bring together people from science, industry, and education to establish paths of communication, to initiate research, to incubate new teaching methodologies, and to recommend education policy changes.

NOTES

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