Network Science, A Decade Later

The Internet and Classroom Learning

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5 Bringing Students to the Data

Imagine this: Students in Riverside, California, are analyzing data they downloaded—data that include measurements of air quality collected locally by classrooms all over the world. Looking at a scatterplot of . . . they notice. . . . Wondering whether. . . , they generate a time-series plot that shows. . . . Excited by their discovery, they e-mail a draft of their findings to collaborating students in Hobart, Australia, They, in turn. . . .

Imagine you must. Although we have read others' accounts of such happenings, in our visits to numerous network science classrooms and our searches through logs of Internet communications, we have found little that captures this level of student engagement and learning with shared data.

One of the reasons students of network science seldom analyze data is that they do not quite know where to start; they have had little experience analyzing data. This is true of their teachers as well (Russell, 1990). Eighty-four percent of the teachers surveyed by Goodman Research Group (1998) said they needed more help with teaching data analysis, and they were quick to point out their own limitations: "Interpreting data is a problem area for me" (p. 31).

Unfortunately, it will take more to solve this problem than short graphing tutorials for students and 1-week data analysis workshops for their teachers. Data analysis involves considerably more than knowing how to make and read a few graphs. There is a large body of research literature showing how difficult it is even

for college students to reason statistically (see Shaughnessy, 1992, for a review). Recent research in classrooms indicates that students have trouble with fairly rudimentary ideas. Younger students do not regard data as a valid basis for beliefs (Hancock, Kaput, & Goldsmith, 1992), nor do they think of data as something they can probe for answers as they can people (Lehrer & Romberg, 1996). Mokros and Russell (1995) described conceptual difficulties that middle school students face in using means and medians to summarize data. More recent studies (e.g., Bright & Friel, 1998; Gal, Rothschild, & Wagner, 1989; Roth & Bowen, 1994; Watson & Moritz, 1998) have found that most students will not freely use means or medians to compare two groups. This is true even for high schoolers who have completed a yearlong course in probability and statistics (Konold, Pollatsek, Well, & Gagnon, 1997).

However, we are optimistic that the situation is improving—that in 10 years, students and teachers will be considerably more facile with data than they are now. One reason is that nearly every K to 12 mathematics curricula now devotes prime space to probability and statistics. This achievement can be credited in large part to the effect of NCTM's (1989) *Standards*, which granted probability and statistics a status equal to that of geometry and algebra. As a result, the mathematics education community is beefing up its efforts to improve instruction in data analysis, designing better tools, materials, and staff development. The previously mentioned problems identified in earlier research should not be taken as evidence of immutable cognitive limitations. Rather, they indicate in what ways students have difficulty given the little instruction they typically have received. An increasing number of researchers are documenting what students at various ages are able to learn with appropriate instruction. Lajoie (1998) provided an overview of how these research and development efforts are proceeding and informing one another.

Of course, network science cannot put student data analysis on hold, waiting for the situation in mathematics education to improve. First, the teaching of data analysis is not the sole domain of mathematics education. Not only is data analysis a fundamental tool of science, but the underlying processes are in many respects similar to what is characterized as the *scientific method*. Another reason to press on is that we can make some progress based on what we already know. By attending to a few simple

principles in designing curriculum and selecting appropriate data and tools, we can improve students' involvement with data.

This chapter begins with an examination of the role that questions play in initiating and then guiding data analysis. As part of this discussion, we present two case studies: one of an expert analyst and the other of fourth-grade students being assisted by their teacher. We use these case studies to illustrate recommendations about how to improve the design of network science curricula. These recommendations focus on the importance of helping students frame empirical questions they care about, locate data relevant to those questions, and explore the data without losing sight of their questions.

AN APPETITE FOR DATA

In the fall of 1997, we hiked with a class of 10th graders out to the fringe of an estuary in South Boston, Massachusetts. This was their teacher's first year using a network science curriculum. She was thrilled with the idea of students collecting real data and sharing these data with distant classrooms. The students were equipped with light meter, jerry-rigged sextant, thermometer, and blank data forms—items they needed to collect information they would send to participating classrooms. In the days prior to this, teams of three or four students had practiced using a particular apparatus, learning the protocol that would result in good measurements. Arriving on the site, the teacher gathered her students around a ledge to remind them of the obligations inherent in being part of a global, network science community.

> These measurements are going into the project data bank. Do you understand the importance of this? Students all over the world are doing the same thing as you are today. They will get different measurements than you, but the process will be the same. It's critical that you do it correctly.

However, this class, like most that uploaded their data that day, would never log back into the data bank to download. Why is this? Consider this analogous situation.

> It's potluck, and all the guests have come. It was "Hi" at the front door and "Where do you want me to put this?" as they moved through the

> kitchen out the back to the pool and volleyball. Now it's time for lunch, but there's no line forming at the plate pile. You go to the back door and discover the problem: It's locked. You easily solve that problem, then announce loudly that lunch is served. After 20 minutes you're still alone in the kitchen. What's the problem now? No need to conduct a survey to figure this one out. Your guests aren't hungry enough yet.

A few years ago, we assumed that classrooms seldom downloaded data because most teachers did not have the means or know-how to access the data electronically, and we attributed the situation to the "locked door." The access problem has been largely solved. All 58 of the teachers surveyed as part of the evaluation by Goodman Research Group (1998) had access to computers—over half of them both at school and home. Seventy percent of them had access in their classroom, and the majority of these described their access as reliable. Over 80% reported using e-mail and the Web to correspond with other teachers and project staff. Most of them are a button click away from retrieving data. Again, why aren't they clicking that button?

Teachers we have asked have reported (after apologizing) that they are short on time and are not sure what to do with the data. As one of the teachers quoted in Goodman Research Group (1998) expressed it:

> I find it difficult to keep up with all of the data coming in. Time is difficult to find to properly analyze it. (p. 31)

Lack of time and skills are certainly understandable reasons for not downloading and analyzing data. We see these explanations, however, as indicators of an even deeper problem—lack of appetite. Teachers and their students have no compelling reason to look at the data.

For most people, collecting data, culling through them, and producing statistical summaries are not rewarding activities. Motivated to do so in a required course, college students often refer to their course in *Sadistics*. Listen to the explanations for their involvement in network science given by two teachers in the report by Goodman Research Group (1998):

> To have our students do exactly what real life scientists do: observe, distribute data and data analysis. (p. 25)

> To teach students how to research accurately and to relay information in a scientific manner. (p. 25)

No turning up of noses at data here, but neither is there a register of excitement or a hint that data analysis is more than an operational appendage of science. What would compel one to analyze data? A person is driven to data when he or she has a problem to solve or a question that begs to be answered. Absent such motivation, analyzing data is simply a chore.

Later in the chapter, we offer several suggestions about how to draw students into data analysis and keep them engaged. First, however, we describe the nature of data analysis and examine how questions not only motivate our search of data but also direct us where and how to look.

The Iterative Nature of Data Analysis

Statistical practice has recently undergone some dramatic changes. Twenty years ago, it was standard to design a study with a specific hypothesis in mind, collect the data, run statistical tests hoping to find results significant at the $p < .05$ level, publish the results, and never look any closer than that at the data. In fact, statisticians discourage *snooping* in the data for other than predicted results—although such fishing expeditions turn up interesting findings, many of them are only due to chance variation.

Beginning in the late 1960s, the statistician John Tukey was among those who began arguing that it was silly to use data only to test theories. Why not also use data to help generate new ideas, to search for the unexpected? Certainly scientists could be trusted to remember that findings culled from these explorations require further questioning and testing. To assist in this process, Tukey articulated principles for flexibly exploring data and developed plotting techniques for visually detecting patterns and trends in raw data. However, plotting large amounts of data by hand in the ways he recommended was so time-consuming that few followed his admonitions. Computers have changed that. We now have the means not only to access volumes of data but also to analyze them visually and flexibly in truly exploratory ways.

Tukey's (1977) view of Exploratory Data Analysis contrasts with an often propagated and misleading idealization of science: generate a research hypothesis, collect some data, analyze the

data to either confirm or disconfirm the hypothesis, and form appropriate conclusions. This idealization reinforces various misconceptions about science, among them that all hypotheses are well formed before scientists collect data and that they do not explore data after the fact by searching for unexpected results. The misleading idealization also encourages the view of data analysis as a recipe that experts use to extract *right* answers from a set of data.

As Tukey's work has made clear, data analysis (and the scientific process more generally) is in reality a complex collection of judgments, perceptions, abstractions, hypothetical reasoning, and critical thinking. Experts draw on their vast experience, knowledge, and honed skills to guide their initial choice of questions and, once analysis has begun, to change course when needed. On the one hand, their initial questions, including which data to collect and how to code them, are shaped partly by their knowledge of their statistical tool kit. On the other hand, they know that much research is exploratory and that vague hypotheses become clarified only in the course of examining the data. Investigators' initial hypotheses guide the early stages of the investigation. However, as soon as they begin looking at data, they often modify these questions or abandon them for better ones.

Thus, neither scientific investigation nor data analysis is a linear process where the investigator fixes on a question and then searches for its answer. Rather, they are iterative processes—back and forth dialogues between hunches and what the data reveal. Current hunches (guesses, ideas, hypotheses) guide the exploration of the data—what data values investigators inspect, how they display those values, and what they look for in those displays. What they find in the data, in turn, often prompts them to revise their thinking and ask different questions. With these new hunches, they return to look at the same data in new ways or perhaps search for additional, more relevant data.

Case Study: Analysis of Atmospheric CO_2

To show how questions guide the exploration of data and how, in turn, they are modified as a result of those explorations, we examine an account we recently received from a colleague, Bill Finzer (1997). Finzer was working with a partner analyzing data as part

of an activity that a curriculum designer had developed and was now piloting for classroom use. They were using the analysis tool *Fathom*.

Finzer is an experienced data analyst.[18] Thus, in many ways, this episode is uncharacteristic of what we would expect of students in the classroom. Our purposes for the moment, however, are to exemplify the iterative nature of data analysis and to show how guided explorations can turn into more open-ended ones. This example is revealing because in it Finzer describes not only what he and his partner found while analyzing data on CO_2 emissions, but also thoughts and questions that arose during analysis.

> The topic for the evening was CO_2 emissions and exploring time series data. In the first part of the meeting, we looked at CO_2 in the atmosphere as measured at the Mauna Keo volcano in Hawaii. We could see the CO_2 really [was] increasing. And, even scarier, increasing at an increasing rate!
>
> We began by trying to describe the data and then to estimate rate of increase. The questions we were asked [in the pilot curriculum unit] were open-ended enough that we found ourselves asking lots of our own questions and coming up with our own methods. Time flew by! ... The data show[ed] a strong seasonal variation on top of a general increase.
>
> We wanted to see just the seasonal variation, which we did by plotting CO_2 versus month, and then just the general increase, which we did by plotting CO_2 versus year and filtering out all but January.
>
> Once we got an estimate of rate of increase, we tried to use it to interpolate and then extrapolate. It really hit home that extrapolation [was] dangerous! It assume[d] the inevitable, but we knew that the folks at the Kyoto conference had just come up with an agreement for reducing greenhouse gas emissions.
>
> At the end of the session, we had 5 or 10 minutes to look at another collection—carbon production by region and year. We plotted total carbon versus year [Fig. 5.1].[19]
>
> This was really amazing. Because data for 10 regions are there for each year, the plot separated itself into one line of points for each region. ... Expected, but still striking was seeing our [North America]

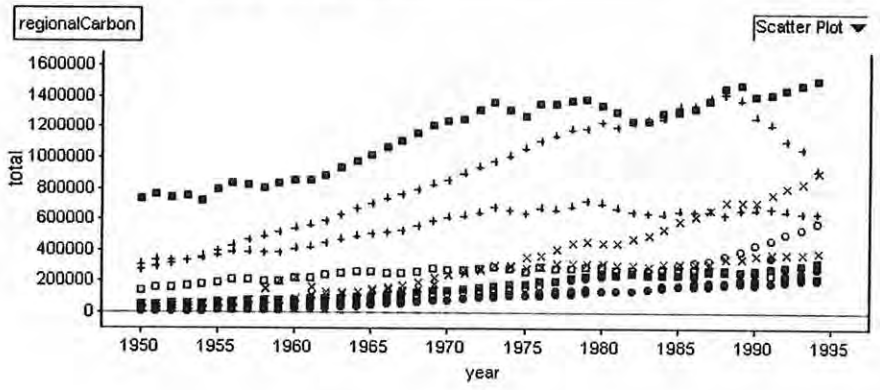

FIG. 5.1. Annual carbon emissions (in metric tons) by region.

carbon production way at the top. But then there was this line of dots coming up to and reaching ours in the mid-1980s, and then falling way off starting in 1989. What could this be? Centrally planned Europe! The dissolution of the Soviet Union and subsequent economic collapse led to a huge falloff in carbon production!

This was fascinating, but the most surprising discovery [my partner] and I made had to do with "flaring." You may ask, "What is flaring?" Well, it's carbon production that occurs when oil wells burn the gases that vent off from the well rather than attempt to store them up. It's a small part of total carbon production. Looking at the Middle East total carbon production, we found this strong blip in 1991 [Fig. 5.2].

"What's going on?" we asked. Wasn't that the year of the Gulf War? If this blip is because of the war, shouldn't we see a lot of flaring from the Middle East in that year? Sure enough, the flaring graph, made by plotting flaring versus year and selecting Middle East in the bar chart, showed the blip even stronger!

We were excited and had to share our discoveries with the rest of the group. The time was up, but we could see that there were many other interesting features to explore in this flaring graph.

Finzer's account illustrates how the data analysis engine is fueled by questions. A back and forth exchange ensued between his hunches and what he learned from the data. At times, hunches led the way, directing him and his partner to look for specific patterns. At other times, surprises in the data led to new

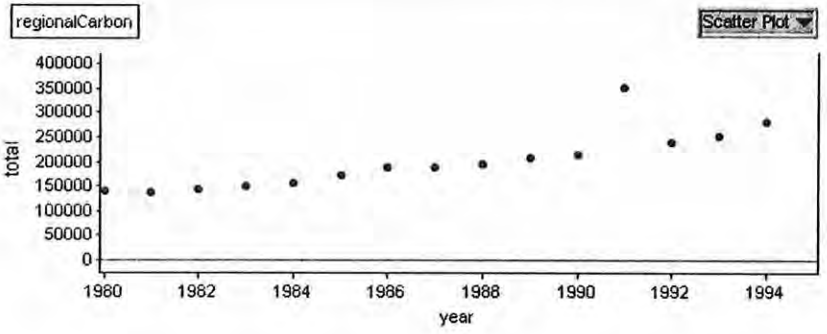

FIG. 5.2. Annual total carbon emissions (metric tons) in the Middle East.

questions and hunches. This interplay is most evident when Finzer surmised that the surprising blip in the 1991 data for the Middle East resulted from the Gulf War, which led them to locate and analyze data on flaring. This is data analysis at its best—a perpetual motion machine driven in turn by hunches and unexpected patterns found in the data.

GETTING DATA ANALYSIS GOING

Without assistance, few high school students working with these data would be able to proceed at Finzer's level of sophistication. Finzer knew the analysis software he was working with and could draw on his knowledge of recent world events to generate plausible explanations for the trends they found. We suggest, however, that given the right data, tools, and teacher support, even young students can reason about data in an iterative style. Before offering several suggestions about how to get students started on data analysis, we look at another case study in which a teacher helped his students formulate suitable questions and analyze relevant data.

Case Study: Tracking Bald Eagles

This account comes from Bob Coulter, who at the time was a fourth-grade teacher in St. Louis, Missouri.[20] Students in his class paired up to conduct a research project in which they selected a

researchable question, analyzed available data, and drew conclusions. Previous to this, they had worked as a whole class tracking the migrations of monarch butterflies via the Journey North web site. The previous year, the same students had also participated in Journey North's study of the blooming of tulips.

This retrospective report gives us some insights into the kind of assistance needed by students new to data analysis. Coulter provided a structure that allowed the students to take on a complex task that was technically beyond their ability. He did this by assisting them where they needed help but otherwise allowing them to do what they were capable of doing. We see Coulter helping his students select and refine appropriate questions, but not giving them the questions; prompting them to generate explanations for what they observe, but not explaining the data for them; and pointing them to other data sources to test their explanations, but letting them analyze those data and draw their own conclusions. From the perspective of Lave and Wenger (1991), Coulter's mentoring allowed these novices to apply and generalize what they knew while learning additional aspects of data analysis as they engaged, with his assistance, in a legitimate scientific investigation.

> The students' first task was to generate a question they could pursue. After exploring a number of possibilities I had listed on the board, Zach and Paul chose to investigate the migration of bald eagles. They had seen other types of eagles locally, as the raptors' Midwest wintering ground was only 20 miles north of St. Louis. The opportunity to track eagles online through Journey North was one of the aspects of this question that attracted them.
>
> In the spring of 1998, Journey North tracked three eastern and four western bald eagles. By accessing weekly updates of their positions online and downloading this information into NGS Works, Zach and Paul were able to study the movement of individual eagles from late March through mid-May as the birds moved north from wintering grounds to their spring nesting sites [www.learner.org/jnorth/spring1998/critters/]. Because of time limitations, I encouraged the student to focus their attention on only two of the eagles. They selected eagle #5 on the West coast and #F42 on the East. With my assistance, they narrowed their question to seeing if there were any differences in the migration behavior of the eastern and western eagles.

> Early in the project, Zach and Paul made weekly maps in NGS Works showing the location of each eagle. These locations shifted a bit from week to week, but basically showed each eagle nesting in one general location. The students noticed a significant difference, however, by visually comparing latitudes on the map they had made—the western eagle seemed to be nesting farther north than the eastern eagle. To see whether this observation held for the other five eagles tracked by Journey North, I suggested they consult the data tables on the Journey North site, which listed the weekly latitude and longitude coordinates of each eagle. By comparing the latitudes, they confirmed that all of the western eagles were wintering farther north than the eastern eagles.
>
> I challenged the students to explain this observation. After some consideration, they mentioned possible differences in habitat and weather. Because information on habitat was not readily available, I encouraged them to explore possible differences in weather between the eastern and western coastlines. They quickly asserted that the west coast was warmer than the east coast. In making this argument they referred to maps from Journey North the past two years, tracking the blooming of red emperor tulip bulbs. Zach and Paul participated in this project last year, and students in other classes were continuing this study by comparing last year's results with this year's data. The maps showed the dates on which tulips bloomed in the spring for 1997 and 1998 for participating classrooms all over the United States. They chose a few sites on each coast and verified that tulips on the west coast tended to bloom earlier than those at the same latitude on the east coast. This was not a new observation for them, as we had had similar discussions the previous year.
>
> I challenged them to go even further. Could they verify that the temperatures differed along the two coasts? To pursue this question, I helped them locate climatological data in almanacs and online (through Accu-Weather). By comparing data for New York City and Seattle, which were the two major cities closest to the eagles' locations, they were able to verify that, at least in this case, the west coast city was warmer during some winter months even though it was at a higher latitude than its east coast counterpart. This was counterintuitive, but a great expansion of the students' thinking about latitude and temperature. The weather data also proved to be quite helpful in supporting Zach and Paul's explanation of the eagle's migration patterns. (see Table 5.1).

Feeling content with their justification, Zach and Paul continued tracking their two eagles. As the spring progressed, the western eagle left its wintering grounds earlier and traveled farther north than did the eastern eagle. This time without assistance, the students checked to see if this same pattern was true for the other eagles tracked by Journey North, and in general, it was.

Seeing from their data that these were general behavior trends and not just an aberration, Zach and Paul concluded that western eagles wintered farther north, left their wintering grounds a few weeks earlier than eastern eagles, and headed farther north in the spring. Based on their background reading about eagles, they speculated that this pattern was largely due to differences in weather, which they thought might affect food availability, especially if northern lakes were frozen.

TABLE 5.1
AVERAGE HIGH AND LOW TEMPERATURES FOR SEATTLE AND NEW YORK CITY, JANUARY–APRIL 1998

Month	Seattle Hi/Low	New York City Hi/Low
January	45/36	37/24
February	48/37	38/24
March	52/39	45/30
April	58/43	57/42

In this example, we see again how data analysis was preceded by a question the students cared about and how that question changed as a result of what they observed. New questions prompted them to look at the same data differently and to search for additional data.

In this case, a teacher played a critical role and, in so doing, drew on a rich background of knowledge.[21] Coulter would have had little idea about when and how to assist the students had he no experience with fourth graders or with the use of student projects (see Polman, in press),[22] scant knowledge of data analysis, or a weak understanding of the science content. Specifically, had Coulter not helped focus the students' initial research project into

one that compared eastern and western eagles, the students may never have noticed the difference in latitude of the birds' wintering sites. This simple observation prompted a series of additional questions. We suggest herein a number of principles, several of which are evident in both the Coulter and Finzer case studies, that educators can use to help students begin analyzing data.

Asking Questions That Data Can Answer

Questions that can be answered with data are often referred to as *empirical questions*. This is a novel idea for many students. Ask young students to pose a research question and they will typically generate a question whose answer they could find in a book—What is acid rain? How do volcanoes make lava? Where do monarchs go in the winter? Similarly, if students are asked questions that could be answered by analyzing data—How much rain do we get in Seattle? How acidic is our rain?—they are likely to interpret them as questions that have already been answered. To them, research is locating answers in books or asking experts. Indeed, most of the research even college students are asked to do is typically of this sort. Given this set of expectations, students need guidance in coming to understand that they can answer many questions not by asking experts but by collecting and analyzing relevant data.

Querying Data. In their classroom study of fifth graders, Lehrer and Romberg (1996) worked with students to design a survey of student interests. Among other things, the survey asked students to list their favorite school subject, favorite winter sport, and how many hours they spent watching TV. After they had administered the survey, Lehrer and Romberg asked the students to come up with questions that they could ask about the data. To these fifth graders, this request was ridiculous. Questions, they countered, could be posed to people, but certainly not to data. Lehrer and Romberg prompted the students with various examples, such as, "Which is the least favorite school subject?" The students successfully used these examples to generate a list of similar questions. However, they needed further assistance to see that they could answer some of these by analyzing the data they had just obtained. Their first thought was to conduct another survey using these new questions.

In analyzing data, we organize and summarize data to reveal patterns and trends that otherwise remain invisible. Students need help coming to understand that data are not just a collection of results from which they can directly read off useful information. Rather, they must learn to ask questions of the data.

Narrowing the Inquiry. In the Journey North case study, Coulter helped the students both limit their questions and make them more specific. With his assistance, Paul and Zach modified their original idea of "studying the movement of individual eagles" to asking, "Are there differences in the migration behavior of eastern eagles and western eagles?" and finally, "Do western eagles winter farther north than eastern eagles?" This last question was one that could be directly answered with the data they had.

Curriculum materials often suggest that students generate a list of possible research questions or hypotheses. This is a good technique for getting students to explore alternatives. It is also an opportunity for the teacher to help students formulate empirical questions. However, before students begin analyzing data, they should have in mind only one major question. Generally, the more specific the question, the better.

Basing Questions on Data. For students, coming to view data as a source of belief is a high hurdle. We have observed college students present various graphs and statistics on some issue and then go on to offer as a conclusion their own opinion—an opinion often contradicted by the data they presented. In their classroom studies with fifth to eighth graders, Hancock, Kaput, and Goldsmith (1992) reported that most students did not expect that "collecting and analyzing data might yield knowledge that is more reliable than their own personal judgment" (p. 356). After a year-long teaching experiment, these researchers reported some progress in helping students develop this perspective. Such a perspective could be added to the list of science-specific norms that we offered in Table 4.3. That is, we can view the development of *data as knowledge source* as a cultural practice that is formulated as students participate with the teacher in making empirical claims and supporting those claims not only with logical arguments, demonstrations, and examples but also with observations that have been coded as data—as measurements, counts, or categories.

Predicting What the Data Will Show. Many believe that to remain objective a scientist should not speculate on an issue until after examining the data. In fact, scientists typically have strong expectations even before they collect data. Scientists are objective not because they are free of opinions, but because they hold their opinions subject to empirical refutation. Students as well as scientists are better off if they have specific expectations about what they will observe before looking at data. Here are three reasons why:

First, predictions motivate. Just as most of us are more emotionally engaged watching a sporting event when we care who wins, we are more eager to look at data when we think we know what the data will show. Finzer's excitement came largely from confirming his speculation regarding the cause of the sudden increase in carbon production in the Middle East. As described in chapter 4, before weighing an object in a vacuum, Minstrell asked his students to predict what they would observe. After voicing their predictions, the students were personally invested in the outcome of the experiment especially because they held a variety of conflicting views. When students predict beforehand what they will find, they have a compelling reason to look at data.

Second, predictions direct our attention. An expectation or prediction lets us know what we are looking for; it primes us to detect patterns or differences that might otherwise escape our notice. Finzer's expectation about the flaring data led him to the particular data and informed him precisely what he was looking for—a spike in 1991. At one point in their investigation, Zach and Paul went to the Journey North web site to compare the latitudes of nesting sites of western and eastern eagles. These latitudes were not radically different. Had they not expected to find higher latitudes for the western eagles, they may have never noticed them. When we look at data expecting to see nothing in particular, that is usually what we see. Contrary to what we might assume, having an expectation prepares us not only to uncover supporting patterns, but also to be surprised by findings that run counter to our predictions (Konold, 1995).

Third, predictions highlight theories. By asking students to predict whether an object would weigh more or less in a vacuum than in air, Minstrell elicited his students' theories about weight. It is these theories, and not the predictions themselves, that Minstrell wanted his students to focus on. It was for this same reason that Coulter was not satisfied when Zach and Paul had concluded that western eagles wintered farther north than eastern eagles. He chal-

lenged them to explain why. At this point, the students began exploring factors such as temperature patterns that might account for their observations. Thus, predictions motivate and prime students to detect patterns. In making predictions, students must draw on their theories and beliefs. It is their theories that they ultimately put to the test when they examine data.

Striking While the Iron Is Hot. The best time to analyze data is immediately after students have made predictions and offered reasons for those predictions. In many network science classrooms, a week or more can pass between the time when students collect and submit data and when cross-classroom data are available for analysis. Students may have been excited about the data when they collected them. However, a week later, they may no longer remember the question, and the excitement may have long since fizzled. At that point, a teacher could try to reengage the students in the same discussion, but the issue is likely to seem old hat the second time around. In such cases, it would be better to wait until data are available for analysis to engage students in deep discussions about what they expect to observe.

KEEPING DATA ANALYSIS ON TRACK

We have discussed ways to motivate students to download and begin analyzing data. Obviously, this is only the first step. How can teachers help students sustain these investigations?

In thinking about this question, it is instructive to look back at the two case studies we examined and think about why each worked so well. Neither investigation would have continued for long if those analyzing the data came to believe the numbers had been concocted. We emphasize this point because many early advocates of network science assumed that students would be motivated and engaged once they had real data about serious issues. If we have learned anything from our experience to date in network science, it is that authentic data are not enough. Note that in the two case studies we examined, the data were more than authentic; they were there when the investigators needed them, were comprehensible to the investigators, and contained some interesting trends. Furthermore, the investigators had relevant background knowledge to draw on in explaining the patterns they found. Either analysis would probably have ground to a halt had the investigators needed

data that were hard to get, had they been using unfamiliar statistical plots, or had they not found discernible or explainable patterns.

We do not mean to suggest that data analysis should, or ever does, proceed without hitches. Investigators always encounter difficulties in the course of analyzing data, and their desire to know pushes them on. However, every desire has its limits, and each additional glitch brings them closer to throwing up their hands. In designing curricula for students, educators need to identify possible breakdown points, eliminate those they can, and provide extra support when the going gets tough.

Looking across a range of network science curricula, we see the same problems time and again. Too often students are working with contexts foreign to them, with plots they struggle to interpret, and with data short on interesting trends and so full of errors that even these trends are hopelessly masked.

The remainder of this chapter offers several recommendations about the types of data and statistical displays appropriate for students. To illustrate the types of difficulties students face, we refer to data we analyzed from EnergyNet and Global Lab.[23] EnergyNet data included information from 47 schools in Illinois submitted during the 1996–1997 school year. Students collected these data as part of an energy audit of their school building. Each classroom was asked to collect 50 data values including building occupancy; floor space; R-values of roofs, walls, windows, and doors; and energy expenditures. In the case of Global Lab, we analyzed data students collected in the fall of 1997 as part of the "Snapshot" activity, which we briefly described in chapter 4 (see TERC, 1997). The data included for each of 34 schools—latitude and longitude, air temperature, sun angle, and light intensity—all measured at each site at astronomical noon on the autumnal equinox.

Features of Data Intended for Students

Minimal Errors. Unlike the data that Finzer or the Journey North students analyzed, many network science curricula make use of data collected locally by fellow students. One advantage of using student-collected data is that, as a result of collecting them, the students know quite a bit about the data even before they begin analysis. The major drawback, according to EnergyNet staff, is that such data:

> usually are not accurate enough. And because of the inaccuracies in the data, the role of analyzing data, very unfortunately, has had to be downplayed. (Goodman Research Group, 1998, p. 61)

The current practice in both EnergyNet and Global Lab is to post data they receive from participating classrooms without checking for accuracy. These data tend to be riddled with errors. Some believe that such errors should be left to the students to correct. They argue that the errors are part of what makes the data authentic and that, in any case, students need to learn how to search for and remove errant data. We have seen cases in which teachers were able to take good advantage of the errors in these data. Walters (1996) reported on two EnergyNet teachers whose students developed a sense of pride in their role as sticklers for accuracy.

Unfortunately, the number of errors in student data can be overwhelming. This interrupts the flow of the investigation and requires considerable time and skill to detect. Two trained researchers spent 2 hours grooming data from the Global Lab Equinox unit of fall 1997 before we could begin analyzing them. The 1996–1997 EnergyNet data required 8 hours of checking and editing entries. Some errors were easy to spot—according to one EnergyNet school, the nuclear plant from which they claimed to get power was built in 1910. However, many problems were uncovered through comparing values on different variables to reveal inaccuracies. Dividing floor space by number of students, for example, revealed schools with as many as 400 square feet per student and as few as 10 square feet.

Data submitted by students should be checked for accuracy before they are made available to other classes. Furthermore, we suggest that project staff post archival data sets from previous years from which blatant errors have been purged. Not only can these be used for analyses, but students can compare measurements they have obtained with entries from prior years and in this way check the reasonableness of their data before submitting them.

Salient Trends. Real data analysis is a bit like prospecting for gold—for every nugget found, there is a small mountain of sifted refuse. In introducing students to data analysis, we should not send them off into unknown terrain with the promise of rich returns. Data students analyze should include salient trends and differences. The CO_2 data that Finzer analyzed had been selected

by a curriculum developer in part because these were rich in trends. Had there been little of interest in the data, we would not have gotten an excited report from Finzer. Similarly, Coulter expected different migratory patterns of western and eastern eagles when he encouraged his students to compare the two.

Familiar Contexts. If data analysis is a dialogue between hunches and data, then analyzing data about novel phenomena is like conversing in a foreign language. The more remote those data are from our experience, the slower the conversation. In selecting data for students, we need to take into account how much the students already know about a topic.

Finzer's excitement came from relating what he found in the data to what he already knew. It was this prior knowledge that directed his search for particular variables and set the stage for observing trends in the data. This knowledge included not only rudimentary understanding of the causes and consequences of atmospheric CO_2, but of world geography and recent international events. Lacking this knowledge, Finzer and his partner would likely have not found themselves "asking lots of [their] own questions."

In network science curricula, by contrast, students are too often working with data that are meaningless to them. In the Global Lab Snapshot activity, the primary data are measurements of light intensity. The concept is not unfamiliar. Students know that daylight varies in brightness, and they can name factors that affect how bright the day is. However, in this activity, they measure light intensity with a digital light probe whose units are millivolts. Using a conversion table, they then change millivolts into watts per square meter. These are meaningless units to most of us. What does 925 watts per square meter look like, and is it a believable value given that the reporting school was on the 44th parallel and it was a clear day?

Turning our attention to the EnergyNet data, we presume that students can draw on their experiences to reason about things such as energy costs and speculate about how such cost might be affected by leaving lights on or doors open. However, few high school students have intuitions about what a reasonable electric bill might be for a home, let alone a school building. Before they could intelligently analyze the data, they would need to develop these sorts of intuitions.

Several elementary school network science curricula have students measure pH levels of local streams. If the idea of acidity was not itself a reach, the logarithmic scale on which it is measured would certainly place it on a high shelf. Yet the curriculum instructs students to calculate arithmetic means of multiple water samples—an activity that takes them into yet a higher realm of abstraction. Data like these can prevent even highly motivated students from engaging in thoughtful analysis.

Data are not just numbers; they are measures or codings of some phenomena. In Moore's (1992) words, they are "numbers with a context" (p. 15). If students are to find and explain trends in the data, they must keep in mind where the numbers come from and what they express. The Journey North fourth graders easily handled the data when these were presented as locations on a map. With the data in this form, they noticed that one eagle was farther north than the other. Had they been looking only at the global coordinates posted on the Journey North web page, this difference would probably have escaped their notice. Thus, even for fairly intuitive notions such as location, brightness, or school size, the process of measuring or classifying can nonetheless make the data remote. Conventions for quantifying or coding values constitute part of the meaning that must be carried with the data. Thus, we need not only involve students in explorations of phenomena with which the students have some familiarity, but also ensure that students understand how to turn observations of events into numbers and codings.

Plots Appropriate for Students

The previous section looked at features of data that can pose difficulties for students once they begin analysis. If data are unfamiliar, full or errors, or lack salient trends, students may quickly abandon their search. This section examines how features of the data displays and summaries that students use can also thwart meaningful analysis.[24] Ironically, the same properties of statistical plots that make them suitable for detecting statistical trends make it difficult for novices to see how the data are encoded in the plots.

Roth and Bowen (1994) adapted the idea of *cascade of inscriptions* to describe how, as we present data via maps, lists, graphs, and finally equations, we move from more concrete to more abstract statistical representations. As we move along this cascade, individual data are progressively aggregated. This aggregation allows the expert to perceive ever more general features of the data at the expense of being able to identify individual data values. It is easy to forget, however, the learning required to interpret the more abstract statistical plots. As a result, we often encourage students to use plots and summaries before they sufficiently understand them and, by doing so, effectively pull the rug from beneath them.

To illustrate this progression of ever more abstract representations, we show several alternative displays of January snowfall accumulations in 20 U.S. cities. These data (Williams, 1995), include 11 cities located near the 39th parallel and 9 cities near the 47th parallel.

Note that the data are fairly concrete. They would be suitable for quite young students, at least with respect to criteria we have specified. Students could easily visualize snow piled 6 inches high. They generally know that it is colder the farther north one goes and could use this intuition to predict differences in snowfall in the two groups. The difference in the data is not subtle: The majority of cities near the 47th parallel had more than 10 inches, whereas none of the cities near the 39th parallel had that much snow.

One way to compare the two groups is to display them as *case-value bar graphs* (see Fig. 5.3). This is perhaps the most common type of graph used by newspapers. Each bar in the graph shows the value of the variable ("inches of snowfall") for a particular case (city). Cities along the 47th parallel are grouped in the upper part of the plot and ordered by amount of snowfall.

Using this plot, we can more easily compare the values of the two groups than if the data were simply listed in a table. If we rotated the plot 90 degrees, we could imagine the bars as columns of snow that fell on each particular city.

Figure 5.4 shows the same data displayed as two *stack plots* (also referred to as *line plots*). Each case is represented in this plot with a small square located on the horizontal axis to show its value. We could make a stack plot by placing a ruler vertically at the end of each bar in the case-value bar graph and marking the length of the bar near the horizontal axis. We could also make a stack plot with sticky notes or build a graph using small blocks.

By stacking cases of the same value, the stack plot gives a slightly different perspective on the data than the case-value bar graph. The stack plot shows how the cases distribute themselves

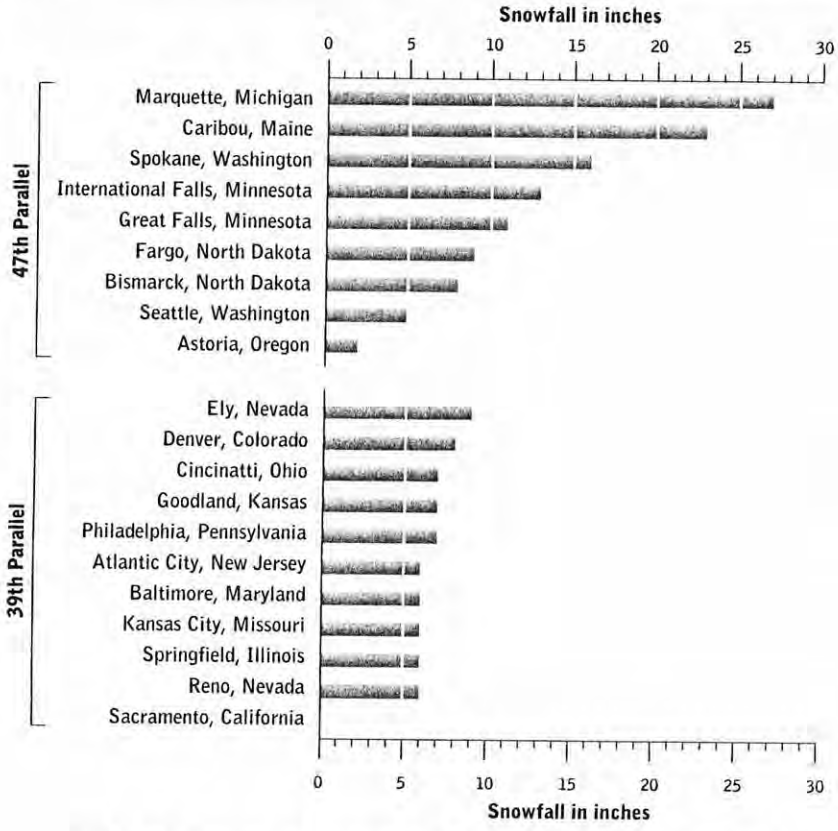

FIG. 5.3. Case-value bar graphs of January snowfall in U.S. cities along the 39th and 47th parallels.

over the range of possible values. We can see that for cities along the 47th parallel the snowfall accumulations are quite variable—the values are spread out fairly evenly over the range. By contrast, there is relatively little variability in accumulations for cities along the 39th parallel. With the exception of Sacramento, which had no snowfall, the values are all clustered between 6 and 9.

Figure 5.5 shows the same data displayed as two *histograms*. The histogram groups cases together into equal-sized intervals. In this histogram, the intervals are five units (inches) in width, but they can be any width we choose. As we change interval width, however, the appearance of the histogram also changes.

The height of the each bar in the histogram shows the number (frequency) of cases in that interval. Thus, histograms, like stack

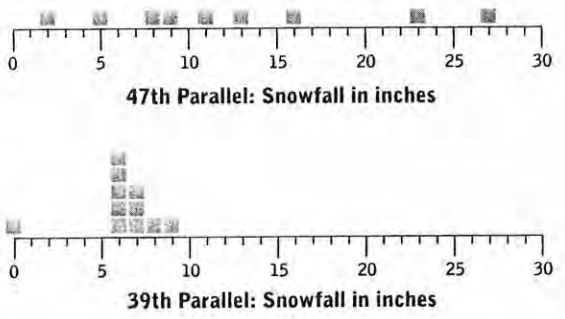

FIG. 5.4. Stack plots of January snowfall in U.S. cities along the 39th and 47th parallels.

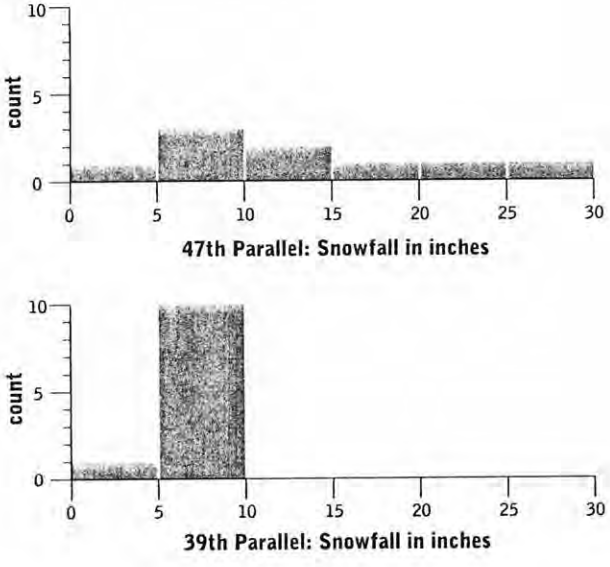

FIG. 5.5. Histogram of January snowfall in U.S. cities along the 39th and 47th parallels.

plots, are frequency graphs. Analogous to stepping back from a painting where we were looking at the brush stokes to now take in the whole scene, the histogram can in some instances provide a better sense than the stack plot of the overall shape of the distribution of values. This perspective is especially useful when the number of cases we are considering become numerous.

Finally, the data are displayed in Fig. 5.6 as two *box plots*.[25] This display provides summary information that is not directly available in the previous plots. The length of the rectangular box, also called the *interquartile range*, is often used to summarize the spread of the data. Its length in the upper box plot dwarfs by comparison that of the lower plot, making the differences in the variability of the two groups even more pronounced. The vertical lines within the boxes (at the left edge of the box in the lower plot) show the location of the median of each group—a measure of center not represented in any of the previous plots. For those who understand what medians and *interquartile ranges* are, and how they effectively summarize a group of values, this representation provides a quick way to compare the two sets of data.

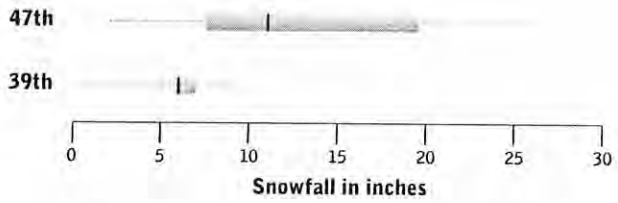

FIG. 5.6. Box plots of January snowfall in U.S. cities along the 39th and 47th parallels.

As we have pointed out, these various plots reveal different qualities of the data. As we move from the case-value bar graph to the stack plot and finally to the histogram and box plot, we actually lose information about individual cases. In the case-value bar graph, we see the snowfall values for each individual city. Displayed in this way, students could use their visual abilities to establish, for example, that Spokane had about twice the snowfall as Fargo. Thus, for most students, the case-value plot is an easy data representation to work with—perhaps even better than a table listing the values and cities.

In the stack plot, we still see individual cases, but we no longer know to which city they belong. Furthermore, we have to keep in mind that each plot symbol is a measurement and that its value is determined by sighting down to the scale on the x axis. For these reasons, the stack plot tends to be a little harder than the case-value graph for young students to interpret.

In the histogram and box plot, we no longer can identify individual values. Someone looking at the histogram for the cities along the 47th parallel would know that three of them had snowfalls between 5 and 9 inches. However, they would not know whether they were all 5 inches or whether the cases were distributed evenly in the interval. That information is sacrificed for a more global view of the shape of the data. In return for losing this information about individual cases, we get a better sense of group characteristics—how the data cluster and spread out. Although this is helpful information to the experienced eye, students can become disoriented as the plots they are using begin including less and less information about individual cases. This is one reason that histograms, box plots, and means are not ordinarily used in the early grades. Younger students need considerable experience before they can use such representations meaningfully (Bright & Friel, 1998; Mokros & Russell, 1995).

A Framework for Task Selection

This section provides a framework that integrates issues discussed earlier regarding choice of data and representational tools. We hope this framework is useful to teachers and curriculum designers in choosing and creating tasks and environments for students at various levels of statistical sophistication.

Figure 5.7 lists along the horizontal axis various statistical plots, including those discussed previously. These plots are ordered from left to right according to how easy it is for students to read and identify individual case values.

Although certainly other features of plots affect their interpretability, the ease with which cases can be identified is, by itself, a powerful predictor of the abstractness of a representation. The order of plots along the horizontal axis of Figure 5.7 predicts fairly well the first appearance of these plots in the mathematics curriculum. The order also concurs with results from research by

Bright and Friel (1998), who have studied students' abilities to interpret various types of plots. The major educational implication is straightforward. Although there is power to be gained by using representations listed toward the right-hand side of Fig. 5.7, using them puts students at risk of losing their grounding. Thus, most of our introductions, even with students in the upper grades, should begin with representations on the left-hand side.

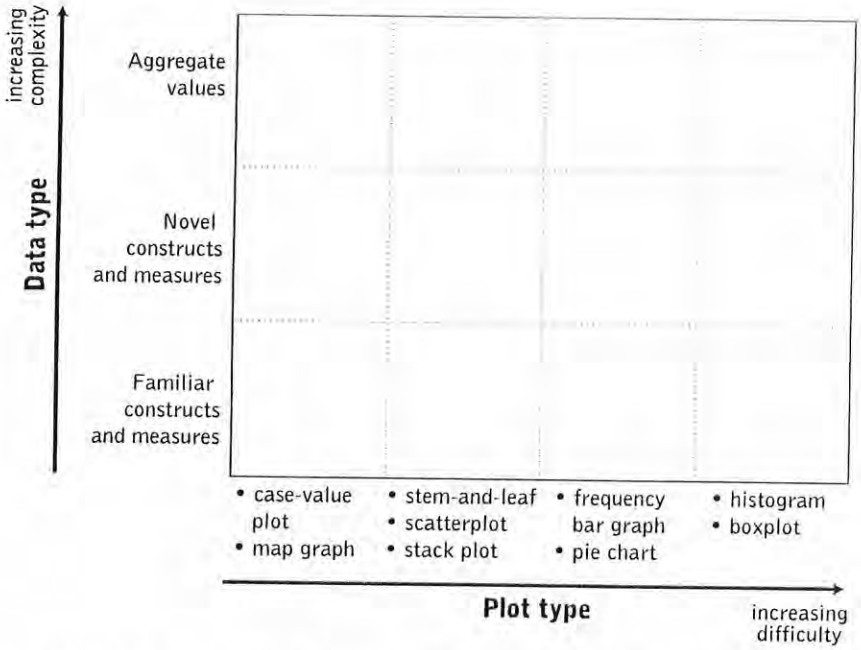

FIG. 5.7. Two dimensions of difficulty: Data and their representations.

We emphasize that this recommendation concerns where instruction should begin—not where it should end. Students have a tendency when analyzing data to attend to values of individual cases rather than to group characteristics (Hancock, Kaput, & Goldsmith, 1992; Konold et al., 1997). Students often ignore differences between group medians and instead base decisions about whether two groups differ on the location of extreme values. It could be argued that representations that highlight individual cases at the expense of group features, such as shape and dispersion, do little to develop statistical thinking. However, having students trying to reason from displays such as histograms often does little more than confuse them. We should not encourage students to use such representations until we have established the need to base decisions on group trends.

How difficult it is to reason about data represented in a statistical plot depends not only on the nature of the plot but also on the data being portrayed. Increasing levels of data complexity are depicted on the vertical axis in Fig. 5.7. Inches of snowfall is an example of a construct and measurement that would be fairly accessible to most students. Data become more difficult for students to reason about when the data involve measurements of unfamiliar constructs (e.g., insulation R value as used in EnergyNet), novel measurement units and/or scales (e.g., pH), or aggregate values (e.g., yearly electric use per student).[26]

In general, we should design introductory activities that fall in the lower left of the matrix in Fig. 5.7. This is true even for high school students with little formal exposure to statistics. Furthermore, when the science content is particularly difficult, beginning with simple statistical displays and constructs is even more important. Imagine, for example, the added difficulty Minstrell's students (see chap. 4) would have faced had he pursued the question about the effect of air pressure on weight by having students make multiple observations and average them. This would have required them to reason simultaneously about two difficult constructs—the meaning of an average and the nature of a vacuum. Similarly, when introducing students to new statistical displays and ideas, the introductory activities should involve science content and data that are relatively well understood.

Journey North is one of the more successful projects at involving students in data analysis. Note that most of the activities they support fall in the lower left of the matrix in Fig. 5.7. As with the eagle data we referred to earlier, most of the investigations they sponsor involve data that can be represented as locations on a map of North America. Given the concrete nature of the data and students' familiarity with the map of North America, students can draw on what they already know to predict or explain what might cause a bird to change direction during a migratory flight, for example. Furthermore, students are not suddenly overwhelmed with a mass of data. Each week, a few new values are added to the data set. This gives students the chance to build gradually on their understandings and interpretations. To help students raise

questions, Journey North also poses questions to students on its web site and later posts a sample of student answers. Thus, not all of the responsibility of raising or answering questions is left to students or their teacher, and a model is provided for the kinds of questions that can engage students' reasoning.

Roth and Bowen's (1994) idea of *cascade of inscriptions* points to how successive representations become more complex but also suggests how we might introduce students to a new plot by helping them see how they could create it from a plot they already understand. This technique was used earlier in the chapter when we suggested that a stack plot could be made by projecting the ends of the bars of a case-magnitude plot down onto the x axis. Cobb (1998) reported recent success in teaching data analysis to middle school students: Students, supported by data analysis software, were asked to spend time using case-value plots to explore data that are naturally displayed as the length of bars (length of lizards, braking distance, hours of service from a battery). After a couple of weeks working only with this plot, students were introduced to the stack plot by first relating it to the case-magnitude plot. During 8 weeks of instruction, these were the only representations that students used.[27] Because they were not spending considerable time learning newer and more abstract representations and could keep in mind the meaning of the data, the students could focus their class discussions on more substantive issues.

SUMMARY

The fundamental premise of network science is that students can undertake science-like investigations by sharing locally collected data with student collaborators at different geographical locations. Data collected at any site may be of limited value, but by pooling observations collected over a wide variety of sites, students can work with data that are not only real but also potentially relevant to an important question. Those of us who believed that task authenticity and student ownership of data would motivate students to analyze data they collected were quickly disabused of these notions. Helping students and teachers analyze data is now widely viewed as one of the difficult issues with which network science must struggle.

The difficulties—lack of classroom time, lack of access to appropriate tools, error-full data, complexity of data analysis, lack of support in the curriculum, and teachers with little prior data analysis experience—can seem overwhelming. All of these problems can be better understood and systematically approached by envisioning data analysis as a process that is guided at every turn by a real-world question and that requires that we remain grounded in our understanding of the data.

The primary reason network science classrooms do not download data is that students do not have relevant questions they want answered. Thus, helping students raise such questions should be our first priority. However, students will not persist if they have difficulty locating appropriate data, if the data they do locate is meaningless to them, if they do not understand the plots and statistics they use in analysis, or if they can find little of interest in the data. Nearly every problem associated with getting students to download data and keeping them engaged in analysis ultimately stems from students not making or losing the connection between the data they have and a real-world question. This being the case, the solution to most of the problems can be found in focusing on how to make and maintain these connections.

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