Data Use by Middle and Secondary Students in the Digital Age: A Status Report and Future Prospects

Commissioned Paper for the National Academy of Sciences Engineering, and Medicine, Board on Science Education, Committee on Science Investigations and Engineering Design for Grades 6-12

Victor R. Lee, Utah State University
Michelle H. Wilkerson, University of California, Berkeley

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What it means to work with data has changed significantly since the preparation and publication of *America's Lab Report* (Singer, Hilton, & Schweingruber, 2006) in ways that are impacting students, educators, and the very practice of science. This change is expressing itself most obviously in the abundance of data that can be collected and accessed by students and teachers. There are also notable changes in the types of data (e.g., GPS data, network data, qualitative/verbal data) that are now readily available, and the purposes for which data are collected and analyzed. These shifts have both generated enthusiasm and raised a number of questions for K-12 science educators as new science standards are being adopted across the United States.

The questions driving this paper are: In this age of data abundance, what is the state of research on data use to support middle and secondary students' learning? And, how might science and engineering education and educational research for those grade levels adapt to the changes in data availability and use observed in the past 10 years?

We approached this review by conducting a systematic database search with the aid of an academic librarian, complemented by our own reviews of major journals. We also drew upon our own knowledge of the field, informed by a 2016 symposium we co-organized on youth learning around data science sponsored by the National Science Foundation (IIS-1541676; Wilkerson, Lee, Parikh, & Polman, 2015), and our broader involvement in the Cyberlearning (Roschelle, Martin, Ahn, & Schank, 2017), learning sciences, and science education research communities. This report emphasizes work conducted since the mid 2000's, when *America's Lab Report* was prepared and published, specifically examining data use in school science contexts at the 6th grade level and above. As noted in *America's Lab Report*, some age groups, especially at the secondary level, were poorly represented in the literature. While more research has been conducted since then, there is still a lack of research in some areas for the targeted age groups. In these cases, we discuss research with nearby age groups (e.g., late elementary or early college students). When appropriate, we also cite research from out-of-school settings that represent promising models, though they have not yet been adapted for formal school contexts.

We begin with a review of important cross-cutting themes related to students' reasoning about quantitative data use as explored in the science education, statistics education and developmental and cognitive psychology literatures. Following that section, we turn our attention to new and emerging forms of data that are of particular relevance to science education, but have been discussed less in the current research literature. We focus on four such forms of data: 1. Data Collected through Automated Means, 2. Algorithmically-Generated Data, 3. Non-Quantitative Data, and 4. Curated and Publicly-Available Data. For each emerging form of data, we discuss the implications of each for science classroom practice, teacher preparation, and educational research.

1 Student Reasoning About Data

Research continues to show that students benefit from working with data when such work is connected to meaningful inquiry, and when students have opportunities to participate in the construction, representation, analysis, and use of data as evidence in a coherent manner, rather than as separated experiences. Key findings are summarized in the subsections below.

1.1 Understanding the Nature and Purpose of Data

Over the past several decades, considerable research has explored learners' general understandings about the nature and purpose of quantitative data. Recent compendia and reviews (Garfield & Ben-Zvi, 2007; Shah & Lovett, 2007) emphasize that reasoning about data involves understanding several related features of data, as well as how those features connect to the contexts from which those data were collected. For example, students should understand how data are constructed through *measurement and sampling*—what is being measured; how those measurements reflect the system under study; and how much, how often, and where measurements are collected. They should make sense of a dataset's *characteristics* such as measures of center, distribution, and patterns or trends exhibited therein; and *variability* within the data and its sources—for example, this would involve reasoning about whether variation and covariation in data reflect natural variability, errors and biases in measurement, causal relationships, between- and within-group differences, and so on. All of this information about the nature and features of data should inform the *inferences* students make from available data about a population or phenomenon.

1.1.1 Measurement and Sampling

Although measurement is fundamental to science laboratory experiences, it is most frequently taught as a topic in mathematics. It has not been well-connected to measurement activities in science classrooms and has only a limited presence in the literature related to middle and secondary science. Middle school students in the United States have historically performed worse on NAEP assessment items on the topic of measurement than other mathematical topics (e.g, algebra & functions, geometry & spatial sense; Preston & Thompson, 2004), and research in mathematics education has documented the difficulties that students may have with seemingly simple measurement instruments, such as rulers (Clements, 1999).

Perhaps as a result of this lack of focus on measurement as an object of study, students can perceive measurement as yielding exact and 'true' results, rather than as a method for obtaining approximate measures that by their nature include uncertainty (Buffler, Lubben, & Ibrahim, 2009). There are many opportunities, however, for students to learn about the nature of scientific measurement. Obtaining measurements (e.g., how to consider meniscus in a fluid measurement, how to operate a triple beam balance, how to read multimeters, etc.) will continue to be important for completion of many laboratory activities. These are contexts around which some reflection about the nature of measurement would be appropriate. Prior research suggests that actively involving students in deriving and socially negotiating methods for taking measurements is one way to helping students to recognize measurement as a source of error that can produce variability (Lehrer, Kim, & Schauble, 2007). Scale—including the very large or small scales that are often a focus in —also presents challenges for students' reasoning about measurements. A simple empirically tested intervention to improve estimates of linear scale is to ground measurements with familiar entities such as body parts, that can serve as "body rulers" (Jones, Taylor, & Broadwell, 2009).

Understanding uncertainty and precision in measurement, in turn, motivates a need for repeated measures and appropriate sampling. Even prior to instruction, middle school students hold productive though incomplete intuitions about samples from a population. They may consider samples as "part of a larger whole," and many students can recognize possibilities for bias in a sampling strategy given adequate contextual knowledge (Jacobs, 1999). Still, middle school students are known to exhibit inappropriate judgments on sampling such as privileging "fair" treatment in sampling over truly random sampling methods.

A more productive target for student is for students to understand samples as "quasi-proportional, small-scale versions of the population" from which the sample has been obtained (Saldanha & Thompson, 2002). In science contexts, this often extends beyond only proportional considerations to include spatial, phenomenal and temporal ones as complex phenomena unfold across space and time (Bowen & Roth, 2007). Students should be encouraged to build on intuitions that the larger the sample they obtain and the more samples they obtain, the more likely they are to get a better reflection of the larger population (Wagner, 2006). While formal computations of sample size may be unnecessary for middle and secondary school investigations, students as early as sixth-grade can still develop and reflect upon intuitions about sample-to-sample variability, and thus appreciate the need for both larger samples and repeated sampling in the process of scientific investigation (Lehrer & Schauble, 2017).

1.1.2 Measures of Center, Distribution, and Variability

Across the statistics education, cognitive science, and science education literatures, understanding data as an object in itself, and assessing the characteristics of the dataset-as-object, is noted as a hallmark of reasoning about data. Students appear to be initially drawn to examining and focusing on individual data points, or as collections of points (Cobb, 1999) whereas many inquiry activities (and statistical tools) are designed to support examination of aggregate trends and propensities within data. This has been called movement between *local* and *global* views of data (Ben-Zvi & Arcavi, 2001), reasoning about *case* and *aggregate* (Konold, Higgins, Russell, & Khalil, 2015); or leveraging *point* and *set* views of data (Buffler, Allie, & Lubben, 2001). While reasoning about data points is an important first step toward making meaning of datasets, students should be encouraged to consider aggregate features of datasets, for example by comparing two datasets and developing ways to express similarities and differences between them (Ben-Zvi & Aridor-Berger, 2015). Developing aggregate views of data are necessary in order to motivate the need to describe the center, distribution, or shape of data; ideas that are still not well understood by students as they progress through school and into adulthood (Watson & Moritz, 2000).

There is some evidence that understanding features of aggregate data can co-develop with, and be supported by, students' engagement in scientific modeling (Aridor & Ben-Zvi, 2017). This may be because part of the challenge in having students adopt aggregate views of data involves setting expectations for variability in data. Such variability can occur naturally (e.g., plants of the same type grown in the same conditions will still vary in their height and foliage because of natural variation) or because of measurement (e.g., the act of measurement can produce different readings due to the precision and accuracy of an instrument and how it is used; Lehrer & Schauble, 2012). It can occur between samples, within samples, etc. One pedagogical suggestion among statistics educators is to prioritize variability and distribution when students are to work with data (Lehrer & Schauble, 2004). The metaphor that has been encouraged for inspecting data as seen in distributions that contain natural variability is to consider that inspection as a search for a "signal" within "noisy processes" (Konold & Pollatsek, 2002).

Most research on student reasoning with data has focused on features of univariate data such as measures of center, distribution, and variability. There is also an emerging body of research exploring how students reason about bivariate relationships in data, typically through exploration of covariation in data and the use of data representations such as scatterplots (we review this in further detail below). However, working with complex and multivariate data is an important and still understudied aspect of reasoning with data (Kuhn, 2007), with implications for reasoning about complex systems, causality, and advanced statistical concepts (Gil & Gibbs, 2017; Lesh, Middleton, Caylor, & Gupta, 2008). Kuhn (2016), for instance, identified fundamental features of variables including that a variable may play no role, a partial and simultaneous role, or a probabilistic role in affecting an outcome; Goldstone & Wilensky (2008) noted a need to recognize patterns at multiple levels of analysis, feedback loops, and nonlinear and probabilistic elements in data. There is emerging evidence that students can indeed reason about more complex patterns in multivariate data, but more research is needed in this area.

1.1.3 Data Representation

Early work in mathematics and science education has documented common difficulties students have with reading canonical representations that often show data (Leinhardt, Zaslavsky, & Stein, 1990). A well-known example is that Cartesian graphs of velocity of an object are often interpreted by students as indicating the trajectory of the object (Clement, 1989). Similarly, students may expect histograms with flatter distributions to indicate there is less variability in data, or that the x-axis of histograms are meant to indicate time (Kaplan, Gabrosek, Curtiss, & Malone, 2014). They may also treat displays of data as simple illustrations, rather than as tools for reasoning about and describing data (Wild & Pfannkuch, 1999). This extends to non-graphical data representations, such as map-based data visualizations, which middle and secondary students may interpret as being an iconic picture rather than a product and source of data (Swenson & Kastens, 2011).

While some incorrect data interpretations are to be expected, these is growing consensus that these misinterpretations be viewed as non-normative products of still useful reasoning processes (Elby, 2000; V. R. Lee & Sherin, 2006). For example, many errors documented in students' understandings of representations are misapplications of otherwise useful conventions that can be remedied through reflection and comparison of the data to the context about which investigation is being conducted; or, they may arise from a case versus aggregate treatment of data (DelMas, Garfield, & Ooms, 2005). With time and support, however, students may notice and begin to make mappings between important features within a representation and the situation being modeled; even treating the representation as a source of data that can be further manipulated in order to answer new questions (Laina & Wilkerson, 2016). However, the precise mappings students are making may not be the correct ones, or the mappings may be only to familiar phenomena (e.g., mapping landforms to continents without recognizing additional details of interest to expert science practitioners; Kastens & Observatory, 2016) and could be adjusted if their attention is redirected to more appropriate features of the graph, map, or display. Another new approach is to encourage students to invent and critique their own representations of data as a way to develop richer understandings of what is being shown and what is properly inferred (diSessa, 2004). We describe more aspects of working with unconventional data visualizations, such as GIS displays, interactive and idiosyncratic visualizations, and more in a later section in this report.

Data representations that are carefully selected and introduced can help scaffold students' understandings of conventional representations, as well as of key features of data—including developing aggregate conceptions of datasets, and attending to measures of center, spread, and distribution, and making inferences from the data (Konold, 2012). Dot and scatter plots that clearly indicate each observation in a dataset relative to others, for example, have been found to be more accessible to students who are still developing graphical competencies, allowing users to visualize how data are concentrated in "modal clumps" (Konold et al., 2002) and build on intuitive ways of "seeing" data. Similarly, Kuhn and colleagues (2015) found that although even adults exhibit difficulty engaging in multivariate reasoning, brief interventions in which middle school students collected, aggregated, and visualized data about topics that have complex causal factors (e.g., Life Expectancy, Body Mass Index) using dot plots yielded promising findings.

1.1.4 Making Inferences from Data

Prior research has established that humans exhibit various biases in their data-based reasoning. For example, information assumed to be more representative of a population or more accessible is favored (Tversky & Kahneman, 1974), and learners are more likely to attend to (Nickerson, 1998) and interpret (Chinn & Malhotra, 2002; Kuhn, 1989) data in ways that support claims or personal 'theories' they have already established. However *Taking Science to School* (2007) has clarified that appropriately supportive instruction and classroom experiences that help orient students toward scientifically accepted explanations or expectations of variability in data can help students demonstrate greater sophistication with use of evidence in specific contexts.

Informal inference typically involves making a determination about populations from which samples were obtained. Unlike statistical inferential testing that would rely upon determining probabilities of a null hypothesis being true, informal inference relies on examining distributions of data, often through exploratory data analysis (e.g., using visual plots), in order to make a claim that is supported by features of the data as represented. Makar & Rubin (2014) further characterized informal statistical inference as involving generalizing beyond data; using data as evidence; and offering probabilistic or uncertain expressions of data. For example, students may use data to investigate plant growth in different conditions. If they observe that the average height of plants in each condition after a set period of time are visibly different, but that the distributions have roughly the same spread, the student may infer that the conditions likely differentially affected the plants' growth. Informal inference appears to be well supported when there is a tight coupling between statistical and contextual knowledge (Makar, Bakker, & Ben-Zvi, 2011). Visualization tools (described above), and situating data work in the context of argumentation (Ben-zvi, 2006) also appear to support students' inferential reasoning.

1.2 Data Analysis as an Epistemic Practice in the Science Classroom

At a national level, school science instruction is re-orienting toward engaging students with science as epistemic practice. One consequence of this shift is that students are expected to construct understandings of content through engaging in constellations of scientific practices including not only data analysis but also scientific modeling, question posing, carrying out investigations, constructing explanations, and arguing from evidence. It is fortunate that these practices are well-aligned with what we know from the literature reviewed above to be ways in which students' reasoning with data can be further developed—collecting data in service of understanding real-world phenomena, using data as evidence, engaging in argument from data, and communicating about and negotiating the meaning of data as it relates to context. In this section, we review a few of the most clear connections between what we know about students' development of sophisticated reasoning about data and the science practices emphasized in the National Research Council's (2011) *A Framework for K-12 Science Education* report.

One of the most obvious ways in which students can work with data in sophisticated and meaningful ways to advance their own scientific inquiries is through measurement and modeling. Lehrer & Romberg (1996) have promoted "data modeling" in which the emphasized practices involve iterative cycles of posing questions, generating and selecting attributes that can be measured, constructing measures, structuring and representing data, and making inferences from data. One of the most prominent features of data modeling compared to other models of inquiry processes is its emphasis on selecting features to measure and deciding how to structure and measure data in service of modeling (Lehrer & Schauble, 2004). This approach has been implemented most frequently in elementary classrooms, but seems appropriate to extend further in middle and secondary school. It also provides students with considerable opportunity to engage in data construction and representations themselves, which can help them recognize uncertainty in data, treat datasets as an aggregate, and to make appropriate inferences from their data (Wu & Krajcik, 2006).

Another clear connection between working with data and other scientific practices is through explanation and argumentation. Science educators have long sought to better support students in using data as scientific evidence. Epistemic scaffolds that explicitly privilege the use of evidence in explanation have proved useful in this regard (McNeil & Kraijcik, 2011; Sandoval & Reiser, 2004). Students may give quantitative data higher epistemic status than other forms of evidence (Sandoval & Çam, 2011); however, as described above, they may also treat data as an objective report rather than an uncertain construction whose validity can be assessed and challenged. The ways in which students make use of data for explanation and argument may also vary depending on the nature of data. Students are more likely, for instance, to pose questions and engage in exploratory analysis using second-hand data (Hug & McNeill, 2008), and the increase of complexity and noise that can be introduced by external data sources may expand students' argumentative discourse (Kerlin, McDonald, & Kelly, 2010).

1.2.1 Data Analysis Across the Curriculum

It is important to note that working with data is a topic that extends across different courses and curricula, and instruction in this area could benefit from better coordination among teachers and communities. Groth (2015) points out a number of inconsistencies in how issues related to data are treated by the somewhat distinct statistics education and mathematics education research communities. For example, whereas the statistics education research community and related policy documents emphasize the importance of negotiating measures in the early elementary years (GAISE 2007), the Common Core State Standards in Mathematics do not include such critical consideration of measurement until high school (2012). Similar issues exist with relation to treatments of variability (GAISE recommends engaging young learners with multiple types of variability early; CCSSM does not mention types of variability until the middle years of instruction), and context (mathematics uses context as a "launching pad" for understanding; statistics uses context as a goal of inquiry).

Such inconsistencies also appear between the Next Generation Science Standards and the Common Core State Standards in Mathematics, notably regarding when students are expected to notice and make sense of bivariate relationships in data (Grade 8 in the CCSSM; Grades 6-8 in the NGSS); using measures of center and variability to summarize and interpret data (High School in the CCSSM; Grades 6-8 in the NGSS); and mapping model fits to data including slope and intercept of linear fits to scientific context (Grade 8 in the CCSSM; Grades 9-12 in the NGSS).

1.3 Supporting Teachers in Working with Data

The work we reviewed above, when taken as a whole, suggests a number of curricular approaches that are especially well-suited to support reasoning about data in the science classroom. These include:

1. **Data should be leveraged in the context of meaningful scientific pursuits.** Data competences examined outside of authentic contexts appear different from those that are situated in familiar and meaningful contexts. In the latter, students have more opportunities to demonstrate and develop sophistication; and, to construct, use, and communicate data in ways that are meaningfully connected to other scientific practices.
2. **Students should be encouraged to consider datasets as aggregates rather than only collections of data points and use related statistical notions.** Students are better equipped to interpret and communicate about data when they have developed ideas of distribution and variability, and when they richly understand how to use measures of center as one of many ways to describe a data set.
3. **Representations are an important part of interpreting and communicating about data.** Data representations can be frequently misunderstood, but those misunderstandings can be refined through reflection on how a given data representation works and corresponds to the situation being modeled. Interpretive work with data representations should emphasize distributions and variability in the data set, and students may benefit from constructing and using data representations as a part of engaging in scientific explanation or argument.
4. **Data engagements in science should be more frequent, with better connections to how topics of data and statistics are encountered in mathematics instruction**. Some specific connections may be made by encouraging students to compare multiple datasets and use data representations when making and justifying claims (thus leveraging notions of center, spread, and representation from mathematics instruction as part of making inferences from data).
5. **More research and instruction should focus on complex, multivariate relationships as they manifest in data**. Most engagements with data in the science classroom focus on univariate or bivariate data, and both students and adults exhibit difficulty reasoning about multivariate phenomena. However, this can be addressed

through instruction that highlights how some outcomes might be influenced by multiple additive, probabilistic, and nonlinear factors.

2 Emerging technologies for data use in science investigations

The underlying assumption in *America's Lab Report* has treated data as equivalent to numerical values obtained about some system of interest. However, conceptions of what constitute "data" today are underspecified (McNeill & Berland, 2017), in ways that have serious implications for education. Furthermore, despite the broad competencies we described above, the specific ways in which particular kinds of data are collected or made available to students can introduce special opportunities and challenges and those should be considered as we look forward. For instance, student-collected "first hand" and educator or curriculum provided "second hand" data each carry different affordances for classroom practice (Hug & McNeill, 2008), with second hand data requiring additional context creation work in the classroom for the data to be made sensible.

As we describe below, there are also important distinctions that educators must consider now between data collected through familiar modes of measurement (e.g., using common instruments in classroom laboratories, such as rulers and scales), and data collected by automated sensors, generated by simulations or other computational means, or publicly-available scientific data re-used by educators (Cassel & Topi, 2015; Wallis, Milojevic, & Borgman, 2006). Furthermore, many examinations of students' data use focus on one specific context, topic, and grade range.

In the remainder of this paper, we work to synthesize and better specify the current literature on student data use, especially as it relates to new and emerging forms of data. We identify four new classes of data of particular interest to the science education community: Data Collected through Automated Means, Algorithmically-Generated Data, Non-Quantitative Data, and Curated and Publicly-Available Data. We review each of these classes of data in turn, with special attention to (1) what are these types of data, and the opportunities and challenges presented by each; (2) what are implications for classroom instruction and practice; and (3) what are implications of each for teaching and teacher practice?

2.1 Automated Data Collection

The use of automated data collection sensors have become more established in science education since publication of *America's Lab Report*, even as research on the conditions for their effective use is still emerging. In this section, we will review the latest work and emerging trends in these areas. While we refer to these data collection sensors as "automated", we do not mean to imply that they require no oversight from a student or a teacher. Indeed, these tools place new demands on teachers and students that differ from manual data collection activities.

2.1.1 What is automated data collection?

Probeware. One of the most well-known and pervasive examples of automated data collection technology in middle and secondary school science is probeware (Tinker & Krajcik, 2001). Probeware are scientific sensors that can immediately generate data in the form of digital output, designed specifically for school science activities. Common probeware sensors will read temperature, motion, light, sound, and pH, although others exist. These tools are often sold by science education supply companies and as part of existing kits and curriculum packages. Probeware comes with or can be paired with computer-based graphing and data analysis applications, and they may require their own separate mobile device for full functionality.

The historical precursor to probeware came in the form of Microcomputer-based labs (Linn, Layman, & Nachmias, 1987; Mokros & Tinker, 1987) at a time when the designation of "micro" computers was necessary. By the time of *America's Lab Report* in 2006, probeware had become a common, if underutilized, resource in many schools (Trotter, 2008; Zucker, Tinker, Staudt, Mansfield, & Metcalf, 2008) and school spending on probeware for the years of 2006-2011 was projected by school officials in one survey to grow at an almost 20% compound annual rate (The Greaves Group 2006). More recently, the availability of smart phones have made probeware-style activities more accessible to students and teachers without specialized equipment. Tools such as Google's Science Journal application (makingscience.withgoogle.com) offers students access to smartphones' embedded acceleration, light, sound, and other sensors to explore local conditions and to build sensor-activated robotics.

Metcalf & Tinker (2004) have demonstrated that probeware indeed could be used with handheld computers and effectively integrated into middle school science classrooms when coupled with supportive curriculum. In their study, teachers responded positively to the introduction of probeware in their classrooms. Beyond the classroom, field trip and field work experiences, such as water sampling and ecosystem exploration have also served as effective and feasible spaces for probeware use (Kamarainen et al., 2013).

The effectiveness of using probeware up to grade 8 with moderate to large effect sizes in inquiry-oriented science and engineering curricula, across a range of topics, had been documented in Zucker, et al. (2008). Struck & Yerrick (2010) have also documented effectiveness of probeware with high school physics students, which can be augmented even further when those students also participate in digital video analysis. Consistent with prior research on probeware (e.g., Linn et al., 1987), students also improved in their graph comprehension capabilities. Together, these studies affirm that the use of probeware in science and engineering classrooms, when coupled with supportive curriculum and other tools, can be an asset for student learning.

Wearable sensor technologies. As computing has become more ubiquitous, wearables have introduced new possibilities for students to work with data. Like probeware, the effectiveness of wearable technologies (such as step and exercise trackers or fitness apps that make use of sensors embedded in mobile devices to track users' activity levels) for middle and secondary students depends on use of other technologies and carefully planned learning experiences that provide adequate support for students and teachers. This is still an emerging area of work, and thus far has typically involved repurposing of existing commercial technologies to support student learning.

Examples of wearable technologies that have been repurposed for education include the use of fitness trackers to support student reflection of data obtained from their own routine everyday experiences (Figure 1) (Ching, Stewart, Hagood, & Rashedi, 2016; V. R. Lee, Drake, & Williamson, 2015). One challenge that has emerged in the use of commercial wearable technologies lies in the standard forms of data and data visualizations that generated by off-the-shelf products. The measurements and visualizations made available are not always intuitive nor easily comprehended by students (Ching & Schaefer, 2014), largely because they were not initially designed with youth or learner's needs or familiar activities in mind (V. R. Lee, Drake, & Thayne, 2016). However, as the range of possible measurements (e.g., time spent standing, heart rate, electrodermal activity) and the ecosystem of wearable devices expands, these off-the-shelf wearable devices appear to offer familiar options for classrooms that can also produce significant gains in students' ability to reason with data (V. R. Lee et al., 2016; V. R. Lee & DuMont, 2010).

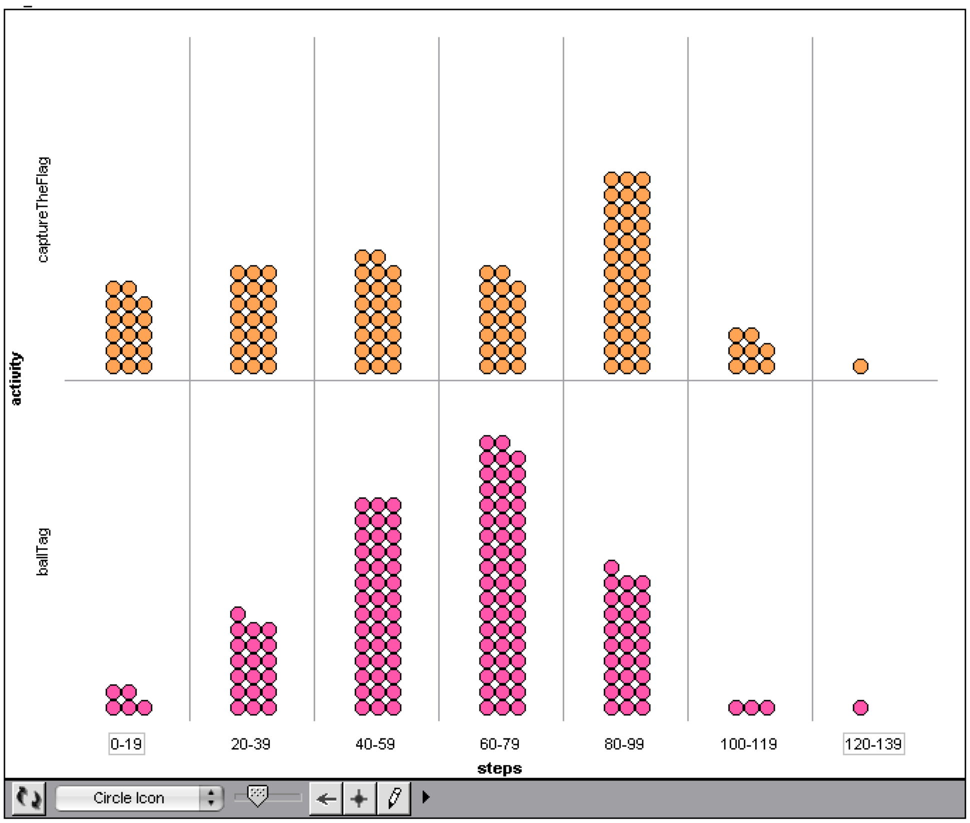

Figure 1. Data obtained from students using wearable activity trackers comparing recorded steps per minute in the game "capture the flag" and "ball tag", visualized in TinkerPlots (Konold, 2012) data visualization software.

While the majority of such work has explored repurposed commercial technologies, tools have also been designed specifically for educational use. In one example, a museum exhibit to teach visitors about variability in climate change and the effects of climate change on living organisms featured gloves with embedded accelerometers. The gloves tracked youths' activity level as they used their hands to paddle polar bears over increasingly large tracts of water, and allowed visitors to compare their own behavior to others to understand that there can be both a clear signal and variability in data (Lyons, 2015). In another, researchers used wearable badges that tracked students' physical proximity to one another to model sociobiological phenomena such as disease spread within a population (Klopfer, Yoon, & Perry, 2005).

We expect wearables to continue to grow in popularity for middle and secondary classrooms some years in the future, both for data collection applications such as those described above, as well as for engineering projects or other computing activity (Buechley, Eisenberg, & Elumeze, 2007). Like probeware, we expect that the increased availability and sophistication of mobile devices (e.g., smartphones) will contribute to this growth. Furthermore, various research projects representing a range of research groups have received funding from organizations, such as the National Science Foundation, to develop and explore learning opportunities involving next-generation wearable sensors. There are ongoing concerns, however, with respect to privacy issues related to using wearable devices in middle and secondary school investigations, and successful use is dependent on a supportive classroom sociotechnical ecosystem (V. R. Lee, 2013).

Log data. "Ambient" or "incidental" computational log data, such as clicks on websites or keystrokes on a personal computer, have become a major concern in popular culture. For commercial purposes, users' incidental data are often examined and manipulated by third parties. For example, a team of engineers working for a large technology company may use machine learning algorithms or pattern detection systems to make predictions about user preferences or purchasing behaviors from large sets of log data. These uses of data present both a need and an opportunity for education—on one hand, many people suggest that an important part of general data literacy is for students to learn about how their data may be used; on the other, there are early and promising findings that engaging students with their own ambient log data can help them develop such literacy as well as to engage more deeply in conventional science content.

A common first step in using log data for pedagogical purposes to computational log data is to return them to the individuals who created the data in the first place, and to encourage learners to engage in self-reflection and reflection upon the broader community using the data. This approach requires not only pedagogical adjustments, but also technological innovations that allow learners to access, analyze, and manipulate their own and others' data in meaningful ways (Rivera-Pelayo, Zacharias, Müller, & Braun, 2012). Some early efforts to support such reflection have included the creation of data blocks in the *Scratch* programming and media creation environment (Dasgupta & Hill, 2017). Those blocks allow youth to query data about the Scratch user community, including information such as how popular a particular user is, or which programming blocks are most frequently used within the community (Figure 2). These experiences have led students to develop a sense of critical data literacy; questioning the fairness of using user-specific information in their code (Hautea, Dasgupta, & Hill, 2017).

Other approaches that have been shown to increase students' engagement in investigations include explicitly situating students relative to one another. Lee and colleagues (2016) have advocated a "quantified selves" approach, rather than a single "quantified self" when analyzing physical activity data. In a quantified selves approach, data across a particular learner population, such as a classroom or a grade level, are pooled together so that patterns and variability are emphasized. Reflecting upon data about self and peers can also shift the social dynamics in a classroom toward more scientifically productive interactions. Yoon (2011) found that making students' own social networks available for reflection, through visualization of social network graphs, encouraged students to shift from nonreflective or social motivations for speaking to peers toward more information-seeking orientations when debating complex socioscientific issues.

Figure 2. The set of data blocks that enable data queries from Scratch users (above) and a resulting Scratch data visualization showing total distribution of different block-type usage by the Scratch community, provided by Sayamindu Dasgupta.

Remote and Embedded Networked Sensing. The "Internet of Things" (IoT) promotes, among other interactions, the ability to examine data obtained automatically and remotely from a stationary device. While the Internet of Things is still being explored for educational settings, some promising initial efforts are underway. One early effort, the *iSense* project, seeks to enable remote sensing and analysis of relevant proximal and local data using a network of sensors placed around a classroom or within a neighborhood (Martin et al., 2010). Students could log on to an online data repository that included analysis and visualization tools to monitor the data generated by sensors. Similarly, the *InSPECT* project led by the Concord Consortium involves using Internet of Things technologies and student-programmed automated data collection technologies to support high school biology lab activities (Hsi, Hardy, & Farmer, 2017). These are coupled with data visualization tools, such as *CODAP* (*Common Data Analysis Platform*, http://codap.concord.org) to support data analysis activities. Another project using IoT at University of Colorado, Boulder and Utah State University is exploring the use of SparkFun's Smart School IoT platform that will obtain remote sensor data – such as temperature and air quality - for student inquiry activities (NSF Grant No. DRL-1742053).

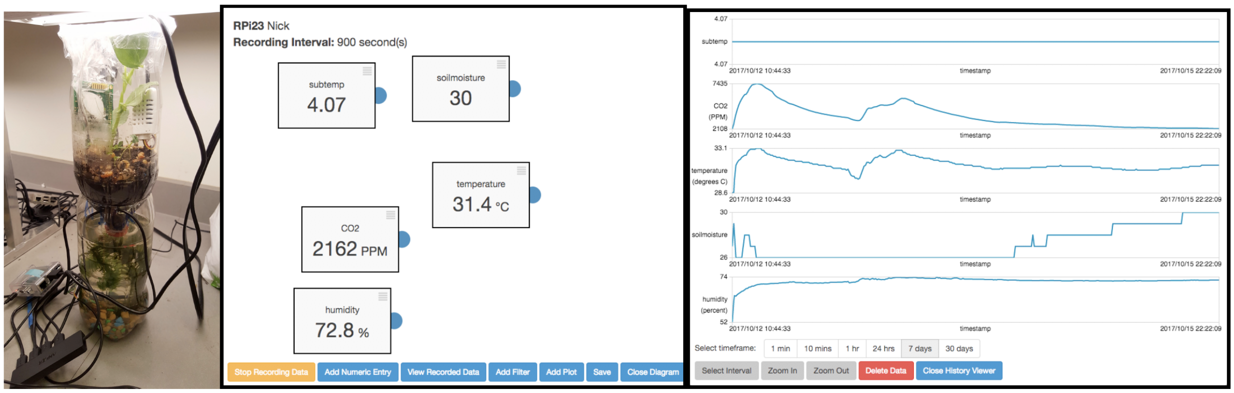

Figure 3. A student data-collection setup using networked sensors and the *Dataflow* tool developed by Concord Consortium (image courtesy of Sherry Hsi)

As it stands, optimism about remote and networked sensors in middle and secondary science and engineering education has been tempered by the reality that further infrastructure work is still needed for these tools to be effectively used in educational settings. The aforementioned projects demonstrate feasibility using a range of paradigms, whether they involve students engineering their own sensor networks (Hsi et al., 2017; Martin et al., 2010) or obtaining and examining data from more public remote sensors. However, the abundance of data that can be collected from such projects yields both technological and pedagogical questions. These include how to effectively store and archive data for subsequent access and examination by classrooms (Wallis et al., 2006; we describe these issues in more detail in Section 2.4); and, how to best support students in designing and navigating complex collections of data sources for which relationships are likely to be especially noisy, multivariate, and caused by unknown or unexpected factors.

Remote laboratories. Remote laboratories allow learners to access and run actual laboratory experiments at remote locations by digitally accessing and controlling real equipment and specimens, typically via the web. Individual and pooled data from the experiments can then be examined to support learning. The appeal of remote laboratories is that they provide learners access to professional grade equipment housed elsewhere, and allow for design of experiments and generation of actual data. Some (e.g., Ma & Nickerson, 2006) suggest that the experiences of using a remote laboratory system can be comparable to hands-on classroom laboratory activities. Hossain, et al. (2016) have shown that middle school students can run experiments and obtain and interpret logged data on the Euglena microorganism's response to light when working in both live (real-time) and batch (pre-programmed experiment instruction) modes. This approach to remote laboratories has thus far been demonstrated as feasible for both face-to-face and online science instruction.

Another study of remote laboratories, although done at the undergraduate level, has suggested that students perceive greater realism in use of remote laboratories when there are more highly realistic images and videos depicting what is happening at the remote laboratory site (Sauter, Uttal, Rapp, Downing, & Jona, 2013). In considering the importance of data contexts noted in the statistics education literature and in the work done with first hand and second hand data (Hug & McNeill, 2008), this finding seems consistent and potentially relevant to optimize the use of remote laboratories in middle and secondary science and engineering classroom investigations.

Over the past decades, several technical and infrastructural questions about how to develop and manage remote laboratories have been examined (e.g., Zimmerli, Steinemann, & Braun, 2003). Though there is still not much awareness about remote laboratories in the science education community, data from remote laboratories appear to have potential for use in real investigations. Important considerations include helping students understand *how* the data are being collected at their remote sites, and how to design appropriate experiments given the tools available. While this is can be implemented in school settings, it also shows promise for distance and online students.

2.1.2 Implications for Classroom Instruction and Practice

Probeware has a strong record thus far as being an effective tool for use in middle and secondary school classrooms, and their continued use in the context of supportive curriculum and complementary technologies (e.g., visualization tools) is encouraged. It is still important that educators acknowledge that probes represent a measurement technique and thus can still produce variability, as do all measurement techniques. Some classroom discussion of how probes work seems appropriate as well. A major strength of probeware use is that it seems to support students in learning to work with and interpret data graphs. It will continue to be important, however, to situate the use of probes as measurement devices and data graphs that result from their use within larger practices of investigation and to the disciplinary knowledge that is to be covered.

With wearable devices and student log data, classrooms have a unique opportunity to both 'personalize' science and engineering activities, and to leverage popular existing commercial technology infrastructures. More work remains to be done in this area, but thus far the questions that students raise when given the opportunity to work with such data are substantive and invite opportunities for investigation about experiences with which they are already knowledgeable (Drake, Cain, & Lee, 2017). An overarching concern with respect to these data relates to student privacy. These can be effectively managed, but norms should be established and steps should be taken within the classroom to address potential concerns about what is disclosed, made identifiable, and made public.

Networked sensors offer opportunities to extend the scope of what can be investigated with data beyond a single sensor, student, or classroom. Infrastructures for networked sensing are still under development, and we expect to see more research and design recommendations related to their potential in middle and secondary classrooms in the coming years. Thus far, it appears that using such sensors can provide students with access to sophisticated environmental investigations, with sufficient support. This support, however, includes not only understanding and making sense of potentially noisy and complex datasets, but also managing the collection and storage of those large datasets. Classrooms should be prepared to support computational thinking activities, including working with various data analysis platforms (e.g. spreadsheet software, visualization tools, and statistical computing languages), to fully leverage networked sensors. As with wearable sensors and log data, there are also potential concerns related to privacy that teachers and students should consider.

Remote laboratories appear promising, especially for students who do not have ready access to scientific experimental and measurement apparatuses. An important consideration for learning with remote labs is how to contextualize the data that are being collected and help students to feel connected to the data collection site, whether it be through vivid depictions of what is being done to generate data or through discussion of the context of the research.

Across all of the types of data discussed in this section, it is important to note that there are a number of new issues to consider about the origin, representativeness, and nature of data collected through automated means. With many of the methods described above, the amount of data being collected can be much larger than has been typical for traditional middle and secondary school investigations. In some cases, these datasets are “complete”, in that they represent an entire specific population (Ainley, Gould, & Pratt, 2015). For instance, one might work from an entire corpus of computational log data obtained from a web service or obtain all data from the 7th graders at their school. This means that questions about the representativeness of the sample and the degree to which one can make inferences about a population are no longer necessary; but, new questions about methods of measurement and ethics abound.

2.1.3 Implications for Teachers and Teaching Practice

Probeware is one of the more established sources of digital data in science education, and consequently also has the longest history of research and practice related to teacher professional learning, and teacher use of probeware as part of their pre-service and in-service development appears favorable (Ensign, Rye, & Luna, 2017; Metcalf & Tinker, 2004). The recommendation is that teacher preparation programs and professional development experiences heavily involve teachers in using probeware through full cycles of inquiry rather than as brief, single-visit in-service demonstrations.

When teachers are working with data about and from students, they may find that they are in a position of restricted expertise. For instance, when students compare activity levels of groups of students during their lunch breaks, the students often have far more to say about what activities transpired at typical lunch times than the teachers do. This represents an important opportunity for teachers to let students lead and to ask questions of the students for greater precision about their claims and how their recollections of experience and numerical data align with one another. The same holds for students' own log data. Teacher education activities with respect to these kinds of personal data have yet to be studied extensively, but one potential model is to have pre-service teachers undergo their own inquiries with their own personal data collected through automated means and reflect upon what inferences and arguments they are inclined to make (Schneiter, Christensen, & Lee, 2018).

With networked sensing and potentially large data corpora, teachers likely will need to develop more familiarity with computational techniques for manipulating data. They also should be aware and help set expectations with students that much of the work with large data corpora includes "data cleaning" (i.e., practices that involve making sure data are structured appropriately and that some algorithmic errors are appropriately addressed).

2.2 Algorithmically Generated Data from Simulations

Simulations were not considered to be lab experiences in *America's Lab Report*. However, though they may not involve direct records from the natural world, these digital artifacts do produce forms of 'simulation data', with the expectation that students will treat data generated as evidence for inquiry and claims. Simulations are also increasingly used to generate data and advance knowledge production in professional practice in areas as diverse as theory development, modeling in complex domains such as in climate studies and epidemiology, and calculating nonparametric statistics (Chandrasekharan & Nersessian, 2015; Gravel & Wilkerson, 2017). Thus, we assert that algorithmically generated simulation data are important to consider and treat seriously in educational contexts.

2.2.1 How are Simulated Data Used in Classrooms?

Screen-based Computer Simulations and Virtual Labs. Many computer simulations intended for use in school science feature data in the form of graphs, quantitative outputs, or visualizations. However, these are often not designed to store and allow students to analyze these data systematically. Instead, it is often expected that they will demonstrate the general outcomes of different system conditions in a way that is relatively intuitive or obvious. Thus while simulations are generally well established pedagogical tools in science (see for example Clark, Nelson, Sengupta, & D'Angelo, 2007), there also are several reasons that interpreting the data produced by simulations may not be straightforward to students. These data are not classic observational measurements, but are rather generated by algorithms to which students may have limited or no access. Additionally, the data presented by simulations may be encoded in arbitrary units of measurement, or they present idealized results that do not exhibit the variability or noise one would expect from data collected in the real world. At the same time, simulations can offer unique representational and experiential supports for reasoning with data, as we describe below.

Screen-based simulations often depict scientific phenomena through an interface that allows users to modify initial or environmental parameters, and observe the effects of those modifications. The phenomenon of interest, and related simulated data, are often represented in multiple, hyperlinked visual and graphical forms. These connected representations can help students build an understanding of the connections between scientific phenomena and the measurements and patterns commonly used to describe them. Popular, freely-accessible examples of such simulations are available through the *PhET* suite of science simulations (Figure 4) (http://phet.colorado.edu; Perkins et al., 2006; Wieman, Adams, Loeblein, & Perkins, 2010), and the *Molecular Workbench* collection of simulations developed by Concord Consortium (http://mw.concord.org; Xie et al., 2011).

Figure 4. The *PhET* projectile motion simulation environment makes data available for inspection in the form of motion traces and inspector windows.

The above-mentioned simulation environments are at times described as "virtual labs" or "microworlds", in that they allow interactive exploration of a simulated environment with the expectation that users will recognize through interactions, or otherwise infer in the outcomes they observe, some common underlying patterns or mechanisms. However, a different genre of virtual labs provides more specific scaffolding to help students understand and treat simulations as a *source of data*. These include activities such as virtual animal dissection (Hug, 2008), as well as activities that support more systemic observations and measurements of simulated phenomena through the use of virtual instruments, science notebooks, and observation protocols that support students in recording and reflecting upon data. A prominent example of these latter forms of virtual labs comes from the *Web-Based Inquiry Science Environment* (*WISE*) project (Figure 5; Linn et al., 2014). The benefits of such data-retaining virtual labs are that students appear to efficiently gain content knowledge from generating and working with data in these lab environments, and they are much less costly and more easily scaled than physical laboratory experiences (de Jong, Linn, & Zacharia, 2013). They also reposition data as something to be obtained through inquiry with simulations, rather than simply provided (masking the importance of measurement, error, and variability in data acquisition).

Despite this, comprehension of data representations produced by virtual labs is still largely unaddressed in middle school science inquiry research (Lai et al., 2016). Research has identified the need to scaffold students' interpretation and reasoning about data representations in virtual labs. When such scaffolding deliberately orients students toward comprehending data representations, middle school students appear to show greater learning gains than when that scaffolding is missing (Vitale, Madhok, & Linn, 2016).

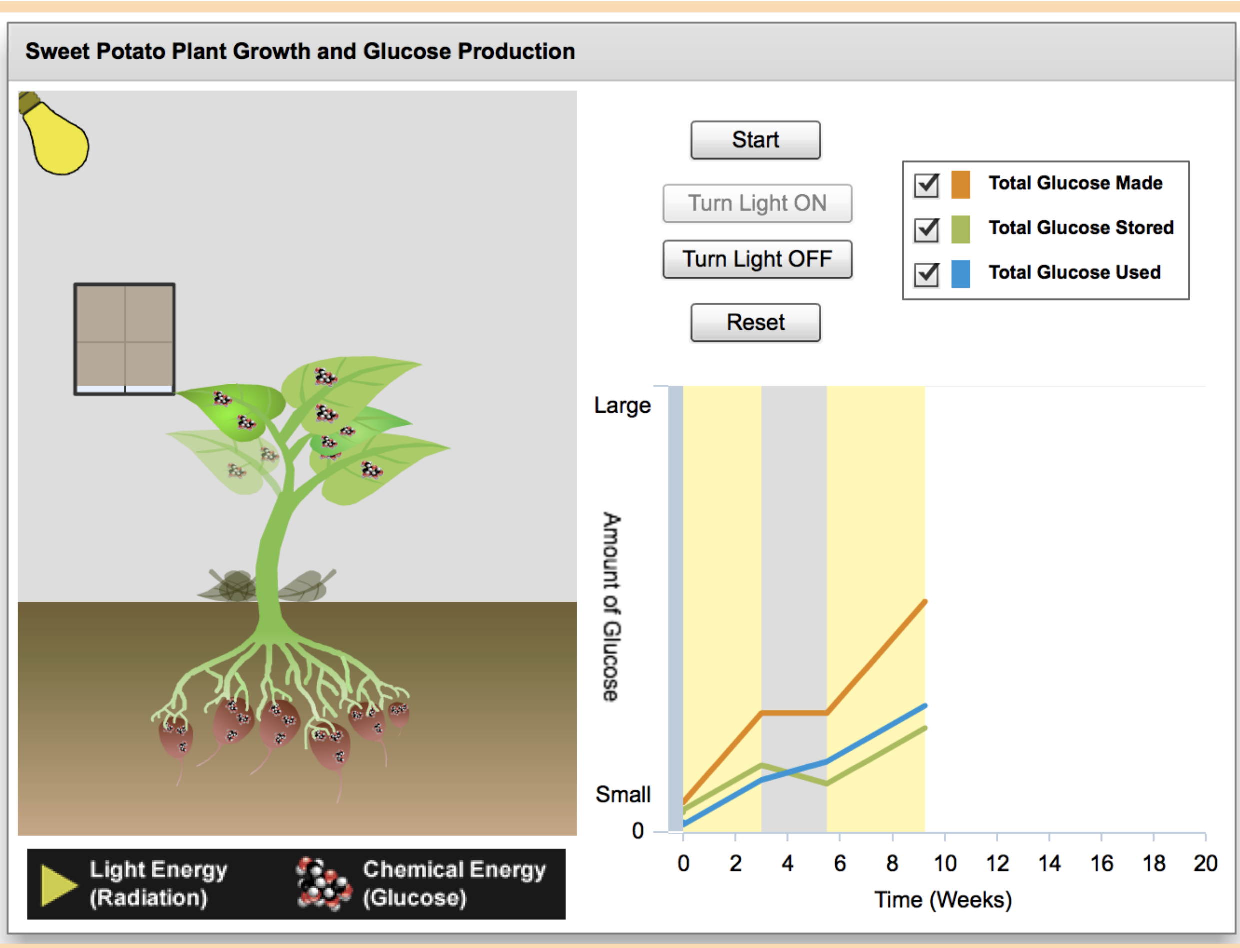

Figure 5. Virtual lab activity embedded in a *WISE* (*Web-based Inquiry Science Environment*, http://wise.berkeley.edu) unit on cellular respiration.

Games and Immersive Simulations. While most simulations offer *representational* support to make meaning of data, there are a growing number of simulations and games that seek to create *experiences* that connect users themselves to the production and interpretation of data. One example are the virtual laboratories described above. Another is to connect students to data generation and interpretation through game-like or immersive experiences. For example, distributed simulations (Moher, 2006) embed data about fictional events such as insect infestations or earthquakes into a physical classroom space. Students use the provided data – such as visualizations of insect populations, or simulated seismographs, to describe and physically "locate" ecosystems or earthquakes that are virtually embedded within the classroom space (See Figure 6 below).

Figure 6. Images of *RoomQuake* immersive simulation in which simulated seismographic data are presented to devices at different locations in a classroom and students work with the data to locate the epicenter.

Other environments use augmented reality or virtual worlds to immerse students within simulations and to generate and/or explore related data. For example, location-based science games use handheld devices such as smartphones to collect virtual and real place-based data (photos, measurements, location history) from physical locations marked by GPS (Klopfer & Squire, 2008; Land & Zimmerman, 2015). Yet, many questions remain with respect to the most effective uses of augmented reality in science education (Wu, Lee, Chang, & Liang, 2013). With few exceptions (such as the *Mad City Mystery*, where users obtained quantitative data by physically visiting sites and using augmented reality technology - see Squire & Jan, 2007), the research emphasis in augmented reality in science education research has not yet been on how data competence is leveraged nor developed through such experiences.

One well known immersive environment that has incorporated both game-like and virtual world-like elements is the *River City*/*EcoMUVE* project (Metcalf, Kamarainen, Tutwiler, Grotzer, & Dede, 2011). These environments embedded students as avatars in three-dimensional, multi user virtual worlds in which a mysterious health or ecological issue had taken place. Students were encouraged to collect data – including through interviews with virtual denizens, scientific sample collection from rivers and lakes, observations, and so on – to solve the scientific mystery. One interesting feature of this approach is that many of the aspects of data construction that are often hidden or missing in simulation data – including methods of measurement, sampling, error and variability – were reintroduced to the simulation context. In one study, students participating in *EcoMUVE* became more self efficiacious with respect to inquiry and developed an orientation toward data and evidence over authority as criteria for scientific validity (Chen, Metcalf, & Tutwiler, 2014).

The *Data Games* and *Data Science Games* projects (St. Clair, 2016) explicitly uses game-like mechanics to encourage students to interpret and manipulate data about science and mathematics concepts. Students are invited to interact with online games or simulations that illustrate core scientific, mathematical, or engineering concepts (such as a Bayesian card game or a predator-prey game that reproduces the mechanisms of natural selection). As they play, both the game and the log data it generates are embedded within the *Common Online Data Analysis*

Platform (*CODAP*), which allows players to build visualizations of, organize, and manipulate their gameplay logs in real time. Though these data are tightly coupled to gameplay, students do not have control over what dimensions of their play are captured, how they are measured, or how they are first organized. Instead, the games are designed to require some degree of transformation before the data are useful for improving gameplay or understanding the game's underlying scientific principles (Finzer, 2014).

Agent-based models. Agent-based models and modeling environments are a specific type of simulation that has gained much traction in middle and high school science education research. These simulations are particularly well suited for exploring emergent systems, whereby a system is comprised of many elements (such as atoms, electrons, or organisms – see Figure 7) which, when they interact with one another and their immediate environment, create an often unexpected outcome that is observable at a different level than the elements themselves (liquid diffusion; current; or the SIR pattern of disease spread (for a recent review see Wilensky & Jacobson, 2014; Wilensky & Reisman, 2006).

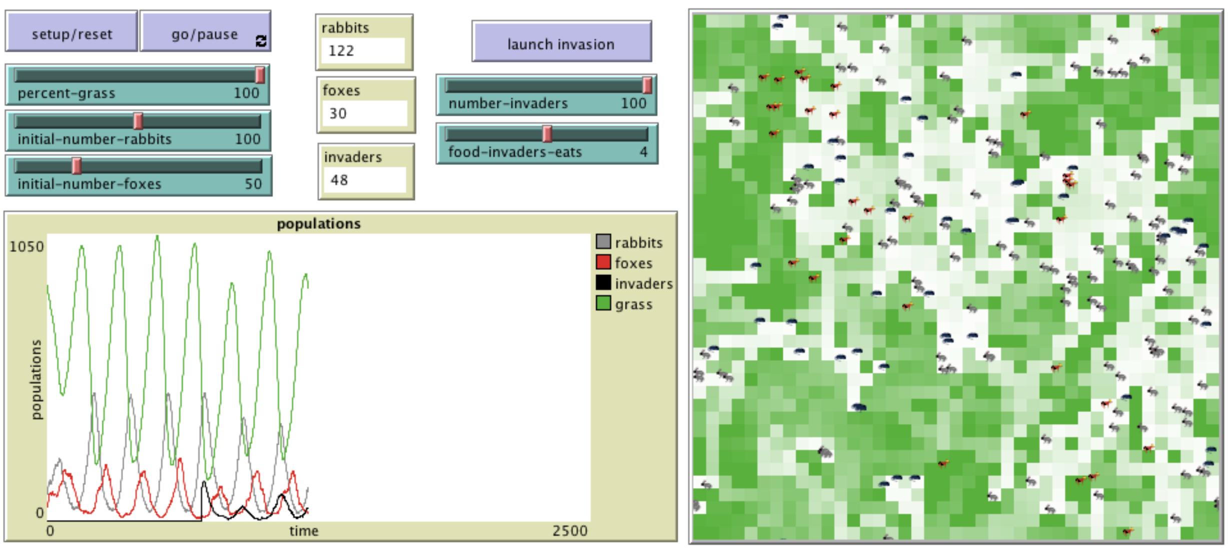

Figure 7. A *NetLogo* model that generated data of an ecosystem consisting of foxes, rabbits, grass, and an invasive species used in the *IQWST* curriculum (Krajcik, Reiser, & Fortus, 2011). Students participate in argumentation activities using the graphs generated from this model as they work on persuading their peers, using the data generated, what role the invader plays in the ecosystem.

Agent-based models appear to support learning of multi-leveled complex systems reasoning, and they have potential for use in argumentation and argument construction activities using simulation data (graphs) as evidence (Berland & Reiser, 2011). However, these researchers found that some middle school students blurred the distinction between inferences and evidence when engaged in scientific argumentation with a simulation of ecosystem dynamics. This is potentially due to the often opaque relationship between algorithm and data in simulations—the students believed that differences in graphs within the simulation reflected fundamentally different *computational* rules rather than randomly-generated variation. Those students who did attend to the distinctions between inference and evidence tended to construct more persuasive arguments for their peers. Similarly, Hmelo-Silver and colleagues (2015) described how two teachers engaged their students differently in agent-based simulation-mediated inquiry. They found that one teacher, Mr. Fine, encouraged students to explicitly treat the simulation as a representation of the real world, and to reason through its mapping to real-world elements. The authors of that study noted that this approach was likely to help students use the technology for reasoning and knowledge construction, rather than only for content acquisition.

While data from agent-based models has been successfully used in service of argument construction and modeling, the multi-level nature of agent-based models and their inclusion of random elements can pose special challenges for students. Connections between simulated behaviors—which occur at the individual or "agent" level within the simulation—and the data those behaviors generate—which are measured or computed at the collective or "aggregate" level—are not always immediately apparent to students (Wilkerson-Jerde & Wilensky, 2015). Support from teachers is necessary, especially as the behaviors are emergent and thus may involve explanations that go beyond simple causal ones. One method that has been found to be effective is asking students to attend to and reason about the source of *noise* (random variation) that appears in many agent-based simulations.

Agent-based models also present challenges and opportunities due to the sheer number of possible outcomes that may emerge in complex systems. The random nature of these simulations, and the phenomena they represent, means that a simulation with the same settings may generate different outcomes at key "tipping points" in the simulation. This departs from many traditional simulations which generate the same results given the same inputs. Recent research has begun to explore how students might conduct large-scale investigations by analyzing patterns in results across many simulation runs, in a project called *InquirySpace* (H.-S. Lee, Pallant, Tinker, & Horwitz, 2014). Early results suggest that students who iterated with *InquirySpace* improved in their parameter space reasoning skills—that is, their ability to look across several data outputs from multiple simulation runs to reason about broader patterns underlying some phenomena under study.

2.2.2 Implications for Classroom Instruction and Practice

Simulations are often commended for making phenomena accessible—visible and interactive. However, improved visualization or access to data alone does not seem to contribute to learning with simulations (Rutten, Van Joolingen, & Van Der Veen, 2012). Instead, simulations must be understood by students as a *source of data* that can be used for reasoning. Studies have demonstrated that with the proper tools and support, students as early as the middle grades can manipulate and structure data in novel ways (Konold, Finzer, & Kreetong, 2017). To better understand when and how students engage in data analysis to answer questions about scientific issues, it is important to understand data activities as nested within a broader, goal-oriented inquiry activity. Moreover, students seem to engage in data manipulation primarily when they identify an explicit need to change the available data (which they did not collect themselves and thus may be in the wrong structure or scope for their particular questions) to be more useful for their inquiry goals. This involves students' explicit consideration of the available data, including questions about its nature and origin, validity, and structure (Wilkerson et al., 2018).

Not all computer-based simulations emphasize data, and thus while simulations are often considered to be a useful way to integrate data analysis into classroom instruction, additional research on students' interpretation and analysis of the data generated by simulations is still needed. One way that has been explored and appears promising is through coupling simulation with argumentation activity. To support students in using data to support arguments or to construct models, additional deliberate scaffolding appears to orient students toward the data that are produced in those simulation environments. Some activities can emphasize scientific practices in conjunction with use of models, such as argumentation activities around the relationships between agents in an agent-based model. However, those activities require that teachers consider appropriate classroom norms and the challenges that students face with respect to constructing explanations around the computer-based simulation environments that are being used.

An important observation with respect to argumentation with data generated within agent-based models in middle school classrooms is that the practice of argumentation will be adapted to each classroom site depending on the role the teacher takes in discourse interactions and who the students consider to be the audience for their constructed arguments. Both sense-making and persuasion must be addressed for students to learn to see data in different ways and in support of stronger claims. One finding in this line of work has also been the need for students to feel that they can 'save face' when their arguments are being challenged or refuted in order to change their own argument, even when there is compelling simulated data immediately present that challenges their initial claims (Berland & V. R. Lee, 2012). Another way to position simulations as fallible sources of evidence that has been discussed less here, but worth mention is to have students construct their own simulations as scientific models that both generate, and can be compared to, data (Sengupta, Dickes, & Farris, 2018; Wilkerson-Jerde, Wagh, & Wilensky, 2015).

2.2.3 Implications for Teachers and Teaching Practice

Teachers should have ample experience working with computer-based simulations and learning about effective design and integration strategies and rationale for incorporating such simulations into larger classroom units (Lin & Fishman, 2004). It is also important for teachers to recognize that simulation environments may be effective for content knowledge learning but still require additional support for students to interpret and critique data that are produced within them. Also, for teachers to support students in constructing new forms of data-supported explanations and arguments from models that involve emergent processes or are highly probabilistic, teachers themselves could benefit from having models of what such explanations and arguments would look like and how they are constructed.

We note that while teacher familiarity with simulations and algorithmically generated data represent important areas for future teacher learning, effective teaching practice with simulation data may involve positioning one's self as a member of the audience and a fellow learner rather than the expert on how a given simulation works (Berland & Reiser, 2011). Indeed, despite their popularity, it is not well understood how simulations are meant to serve as representations even among professionals, and these understandings vary from community to community (Grüne-Yanoff & Weirich, 2010). Scientists and philosophers of science are still debating how simulations represent real-world systems, or to represent theory about those systems and their inner workings (Grimm et al., 2005). Thus, making sense of what simulations can actually tell students about a system is a matter of collaborative meaning making among peers (Chandrasekharan & Nersessian, 2015), and teachers should foreground questions of what role simulations play as tools for experimentation and model-based reasoning alongside argumentation, observation, measurement, and so forth (Greca, Seoane, & Arriassecq, 2014).

2.3 Non-Quantitative Data: Spatial Data, Video, and Images

Often when people discuss data in the context of science investigation, they implicitly refer to numeric measurements. However, there are also emerging types of data that make different visual, spatial or behavioral relationships evident. Tools for capturing and analyzing these data are making them more similar to quantitative data in terms of scope, manipulability, and treatment.

Spatial Data. Location-linked data has been a growing development, enabled with curricular tools such as *MyWorld GIS* (Edelson, 2000), enables high school students to conduct complex spatial data inquiries on maps as long as there is appropriate scaffolding. More recently, overlay tools on Google Maps or with demographic spatial data sets such as *SocialExplorer* (Figure 8) have enabled custom data to be generated by students in the specific neighborhoods and cities where they live (Taylor, Headrick, & Hall, 2013; Van Wart, Tsai, & Parikh, 2010). This demographic and movement-oriented map data system allows for students to tap into their own knowledge of a personally-traversed space. Spatial data allow educators to leverage students' experiences of space and place to inform inquiry and data interpretation. It has opened up a new area for data use in science related to topics that involve larger scales and more complex relationships, such as those between ecological, climatological, and geological systems. At the same time, some of the longstanding questions related to maps as comprehensible data representations continue to persist and require further examination (Swenson & Kastens, 2011). Additionally, early educational design experiments suggest that there is still need to design supports to help students remain aware about inherent limitations in spatial data and how error figures into the inferences that can be made from such data (Radinsky, Hospelhorn, Melendez, Riel, & Washington, 2014). Maps showing demographic data also often reflect histories that include past injustices and reflect on current inequities, thus raising new tensions for teachers to navigate in the classroom (Enyedy & Mukhopadhyay, 2007).

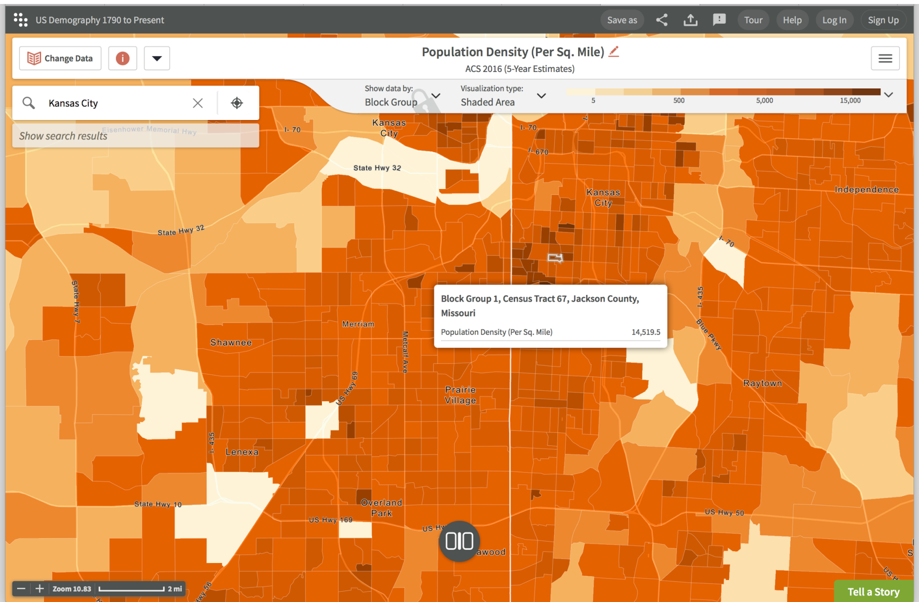

Figure 8. Spatial data visualization from socialexplorer.com

Video and Images. Another form of data that has become more readily accessible are those that are video or image-based. With the increased availability of mobile devices and advances in digital camera technology, it is now possible for many classrooms to obtain their own video or camera footage of various scientific phenomena. Indeed, use of video is common in areas of professional scientific research, such as in biology (Sbalzarini & Koumoutsakos, 2005). To date, the limited literature on the use of video and images in middle and secondary science and engineering classrooms suggest that educators have not yet fully capitalized on the opportunity for middle and secondary students to work with such visual data.

Some exceptions include use of video clips in the *Animal Landlord* environment (Figure 9), a scaffolded tool for high school classrooms in which students examined footage of animal behavior and were tasked with articulating theories of behavioral ecology (Smith & Reiser, 2005). An important finding from that design experiment was the need for effective modeling of how to view and interrogate video as a source of data. Another use of video for science learning includes a biomechanics modeling unit that coupled slow-motion video footage with stop-motion animation (V. R. Lee, 2015). The coupling of video footage with materials to re-present observed phenomena in an animation medium appeared to support student participation in scientific modeling. In high school physics, digital video analysis where students' own motions were recorded and examined was comparably successful to probeware, and in some situations, yielded greater learning gains with respect to graphing knowledge and ability to interpret motions (Struck & Yerrick, 2010).

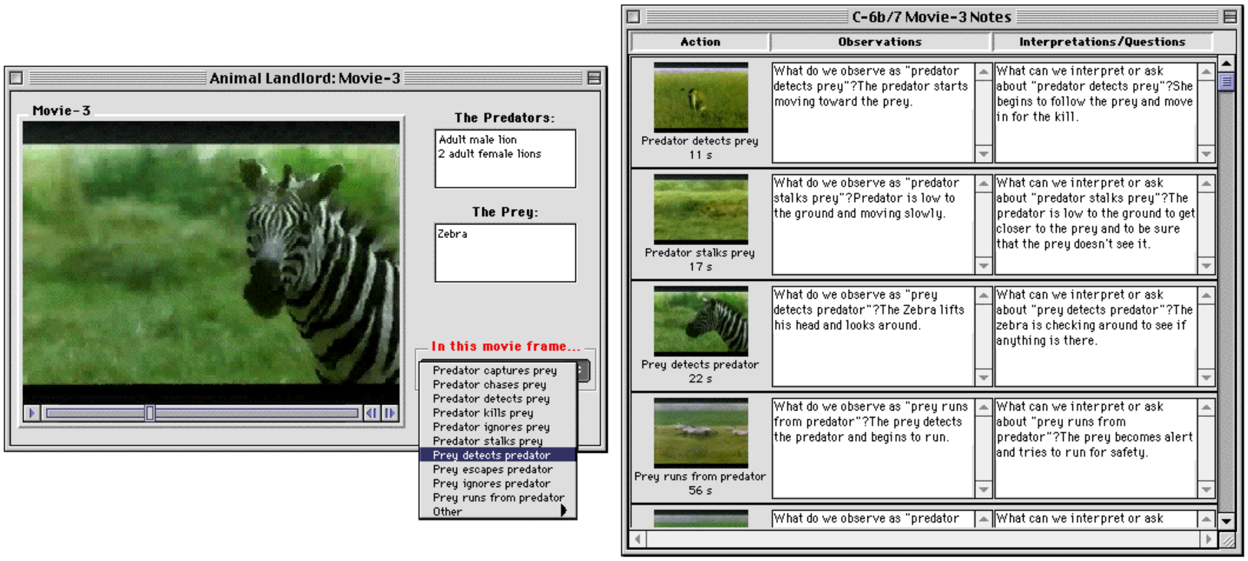

Figure 9. Interface for animal landlord with questions and prompts as scaffolding (from Smith & Reiser, 1997)

The aforementioned studies often used specialized tools and equipment (e.g., high speed cameras). One additional example using more familiar and readily available mobile devices involved middle school students capturing images and video of everyday instantiations of mathematical ideas. While noted as highly engaging and supportive of rich discourse, White & Martin (2014) noted also a tension between the students' familiarity with the everyday domain being documented and the goals of developing and refining disciplinary knowledge through the use of those videos and photographs.

A similar tension between using personally-obtained high-fidelity still images and encouraging participation in disciplinary practices had also been observed by Rivet & Schneider (2004) in their study of how middle school students related to digital photographs they obtained in an ecosystems investigation. Rivet & Schneider noted that while students tended to more richly comment on complex systems relationships within ecosystems when discussing photographs, students could still exhibit a tendency to focus heavily on aesthetics of images and how they were to be presented publicly. Photographs that students captured were rarely used as a source of evidence for claims. Rather, and consistent with other research (e.g., V. R. Lee, 2014), photographs served as an opportunity for students to reflect on science content or previous engagements with the phenomenon. Thus, the use of student-collected photographs in the classroom remains an intriguing opportunity for pedagogical purposes, but best practices to support sustained participation in scientific practice have yet to be identified.

2.3.1 Implications for Classroom Instruction and Practice

While each are different from the other, spatial and visual data offer bring with them the appeal of potential personal relevance to a science or engineering classroom. More tools are becoming readily available, whether they are web services such as *SocialExplorer*, census data sets, the open source *Tracker* video analysis software, and commercial apps allow for the collection and inspection of high fidelity video or images. However, the current documented cases of the use of spatial and visual data suggest that the tension between personal familiarity and disciplinary learning must be thoughtfully managed in the classroom. The high fidelity of images and rich pools of personal knowledge students have about the particular phenomenon being examined can ultimately dominate classroom time. Carefully designed scaffolds that direct attention and pose questions for students to consider coupled with teacher modeling of how to best use such data for creating arguments and building models both appear necessary for these data to be used optimally in the classroom as data.

2.3.2 Implications for Teachers and Teaching Practice

Teachers should be aware of the appeal and high levels of engagement that accompany the use of video, images, and spatial data in middle and secondary school classrooms. This can lead to active participation and enthusiastic participation from students, but that increased participation may not lead to participating in targeted scientific practices. It becomes incumbent on the teacher to model how to examine and inspect such data for students and to utilize scaffolds, whether they are embedded in a tool, curriculum, or in teacher actions, to guide students. Professional development experiences that continually encourage teachers to go beyond noticing student engagement with classroom activities and help to orient teachers toward and notice student thinking as it relates to the content and practices that are targeted, as takes place with video clubs (Sherin & Van Es, 2009), may be promising in helping teachers best support students use of such data in the classroom.

2.4 Curated and Publicly Available Data

We anticipate that publically accessible datasets and data visualizations will dramatically affect the nature and use of data in science classrooms is the coming years. These datasets and visualizations are not necessarily constructed with pedagogical purposes in mind, and students do not have access to or full knowledge of how they were constructed. Using these complex, second-hand data (Duschl, 2008 calls these “databases”) is an increasingly common feature of science communication and practice writ large, and we argue that they should be more explicitly integrated into the middle and high school science curriculum.

Public Datasets. Public have existed for years, but their accessibility and visibility have exploded in the past decade. There are also a growing number of initiatives to make public data available for educational use (see, for example, the U. S. National Oceanic and Atmospheric Administration’s *Data in the Classroom* initiative, dataintheclassroom.noaa.gov; or the North American Space Association’s *MyNASAData* project, mynasadata.larc.nasa.gov). While some of these efforts come with accompanying curriculum and simplified data, early research suggests that students can benefit from interacting with complex, “messy” public data, perhaps even more than from textbook-like second-hand data. For example, Kerlin and colleagues (2010) found that students exploring earthquakes were more likely to engage in a full breadth of discourse related to data—including early theorizing, questioning the data collection process, exploring patterns, and predicting and evaluating—when working with "raw" data from the United States Geological Survey, rather than when working with clean textbook data.

One particular challenge in using publically available datasets in education concerns the many multivariate relationships that may be present. Students can become overwhelmed searching for meaningful relationships, or they can lose sight of the goals of inquiry as different patterns are revealed. Another challenge lies in manipulating these datasets so that they are appropriate for student-driven goals—which are likely to be quite different from the original motivations for assembling a given public dataset. However, early studies suggest that even young students are capable of some aspects of data wrangling – for example, merging datasets that may each address the same investigation, identifying subsets or specific parameters within a given dataset that are relevant for inquiry, or recalculating or recoding values so that they better align with a student or classroom's path of inquiry (Chick, Pfannkuch, & Watson, 2005; Wilkerson et al., 2018; Wilkerson & Laina, n.d.).

Data visualization. Data visualization is another important area of recent growth in science education. Here, we refer specifically to visualizations that utilize visual organization strategies that go beyond canonical data representation forms of line, bar, scatter, and pie graphs, or blend these with idiosyncratic and interactive elements, as may happen with "infographics". Research suggests that even students and members of the public with high interest in science thus far have little exposure to such visualizations (Börner, Maltese, Balliet, & Heimlich, 2016). Though generally considered engaging and aesthetically pleasing, data visualizations and infographics are far from transparent and unbiased representations of knowledge. They employ complex mathematical and computational conventions to promote both *explanation* and *exploration* of important socio-scientific and patterns using narrative methods that may be illuminating, but may also be unfamiliar or even deceptive (Pandey, Rall, Satterthwaite, Nov, & Bertini, 2015; Segel & Heer, 2010). And, they often consolidate multiple dimensions of data (for example, conflating distribution versus absolute value, or emphasizing relative change over time by displaying differences rather than measurements) in ways that can encourage students to focus on some patterns at the expense of others (Laina & Wilkerson, 2016).

In many cases, these mathematical, computational, and socioscientific aspects of data artifacts are well-aligned with disciplinary and technical practices that school is expected to support. At the same time, they take advantage of novel modes of interaction, non-traditional data sources (e.g., citizen science projects, mobile phones, online participation data), and storytelling conventions that youth interact with regularly outside of school. It is no surprise, then, that research in both education and the professional literature on data visualization suggest that multiple dimensions - scientific narratives, rhetorical conventions, mathematics and statistics, visual and interactive techniques - are all needed for productive engagement with data visualizations. This presents an opportunity for students, who are thus able to bring heterogeneous resources to bear when making sense of visualizations and the data they describe (Buck Bracey, 2017; Wilkerson & Laina, 2017).

One strategy that is especially promising for helping learners make sense of a variety of forms of data visualization seems to be through interactive prediction, whereby students are encouraged to draw what they expect data to look like within a given representational framework before they see it (Kim, Reinecke, & Hullman, 2017). Some projects are also beginning to explore developing students' data visualization literacy through not only the interpretation, but also the construction of visualizations and infographics. Thus far, the most noteworthy example of recent educational projects within the target grade bands deals with infographics (Gebre & Polman, 2016). Research has also begun to explore the strategies that students use to analyze data presented in the form of computational data visualizations, and to construct their own using simple mapping algorithms (Laina & Wilkerson, 2016). While these projects are not yet mature enough to yield solid conclusions, they do suggest visualization construction can be a promising approach to engaging students with scientific data.

2.4.1 Implications for Classroom Instruction and Practice

While there are growing efforts to make data accessible and integrate it into science instruction, students do not have control over how these publically-available data are collected or organized. In fact, most publically-accessible datasets have not been collected for educational purposes at all. Therefore they may use unfamiliar or unknown measurements and methods, include parameters that are not of central concern to students, or include information that is only partially or tangentially relevant for a given science investigation. Similarly, data visualizations may emphasize particular stories or paths through data that do not align with students' or curricular goals.

We do not necessarily see these as obstacles, but rather as opportunities for students to develop literacy with these public artifacts. Classroom educators and curriculum developers will necessarily need to consider "data wrangling"—the process of making data useful—and critical visualization literacy an important part of this work (Kandel et al., 2011). Data wrangling and making sense of idiosyncratic or complex visualizations should not be considered only as an aspect of curricular preparation, but also a pedagogical goal.

There is still a need to better facilitate the use of publically-available data by educators, in particular to improve the ways in which educators may search for, access, and import data into educationally-oriented software platforms for analysis. Standards for metadata and data structuring need to be established and followed, but are still emerging. This remains a promising area for future research and education with data, but much still remains to be done to understand how curricular units can be developed and both teachers and students adequately supported given the abundance of data that can be obtained. One possible model that could provide some inspiration includes citizen-science data collection projects, which confront similar challenges but have some established norms to make distributed data gathering and investigation more fruitful (Kermish-Allen, 2016).

2.4.2 Implications for Teachers and Teaching Practice

As with other emerging forms of data, we expect that one critical component of teacher learning as relates to public datasets and data visualizations lies in developing teachers' experience and comfort with these artifacts. In some of our own preliminary work with teachers, we have found that providing case-study examples (through video or transcript) of students reasoning through complex datasets and visualizations can be inspiring and motivating for teachers. Drawing from known findings in more established areas such as probeware and simulations, we expect that providing teachers with opportunities to engage with data and visualizations as a part of their own inquiry, as well as helping them to "step back" and understand these resources as sources of information, rather than communications of objective truth, can also be effective. Given the novelty of complex data and visualizations in the classroom, and their primarily *supportive* role as resources embedded within larger, goal-oriented inquiry or modeling activity, this is also an area that may benefit from educative curriculum materials (Davis, Palincsar, & Arias, 2014) that support teacher learning at the same time as they support instruction. This could take the form, for instance, of specialized annotations and images of classroom interactions around visualizations embedded in curriculum materials. Certainly, however, more research is needed in this area.

3. Looking Forward: Data Science Education on the Horizon

In Section 1 of this paper, we reviewed a number of dimensions known to be important for data use in middle and high school science – including understanding measurement and sampling as it relates to data construction; understanding measures of center, distribution, and variability; developing familiarity with conventional data representational forms; and developing inferences from data. However, a number of the emerging paradigms we discussed in Section 2 challenge these basic dimensions. Students may not have a sense of how measurements are taken or what they mean when using automated data collection tools, simulations, or publically-available datasets. Many simulations omit variability in algorithmic output, and many contemporary narrative data visualizations and non-quantitative data may not emphasize or provide simple ways to consider variability. Log data that capture entire corpora of data wholesale (such as measurements taken from a whole population) may negate the need for sampling considerations or careful inference. And, a new class of data visualizations eschew conventional representational forms in favor of colorful, interactive, and often idiosyncratic visual markers.

We see this tension between a "cradle-to-grave" understanding of data production on one hand, and the fragmentary and obscure nature of these new forms of data on the other, as an especially ripe area for further work. We also see important commonalities between traditional treatments of data in science education and these emerging types of data. For example, students' possibly more distant or fragmentary understanding of the nature of data generated using probeware, simulations, tracking devices, or derived from others' research only strengthens the need for data to be positioned as a fallible, constructed source of evidence, and placed in relation to other practices including engineering, modeling, and theorizing.

Related to this, we foresee the emergent field of Data Science Education, blossoming at the undergraduate level (De Veaux et al., 2017; Hardin et al., 2015; Nolan & Lang, 2015), moving into the secondary space and affecting science education. While there are strong overlaps with statistics, and data science may ultimately just be a new name for statistics, our view is that Data Science Education (1) will emphasize the use of computation to manage and manipulate large quantities of data for analysis, visualization, and modeling, and (2) place new emphasis on the recycling of data, and the necessary considerations that go into such data reuse. Data Science has been identified as a core area of computational thinking as it relates to science education (Weintrop, et al., 2016). Several fledgling projects are exploring the use of tools such as *R*, *CODAP*, and *Tableau* in middle and high school spaces (Deitrick, Wilkerson, & Simoneau, 2017; Gould, Machado, Ong, Johnson, & Molyneux, 2016; Srikant, 2017), though these projects are not yet mature enough to produce robust findings. And, an emerging literature related to the ways in which data intersects with race, class, power, and ethics suggests educators should attend to these dimensions across the curriculum (Philip, Olivares-Pasillas, & Rocha, 2016).

If current practices associated with data science are an indication, then we would expect Data Science Education to help establish the foundations for students to address these new challenges with emerging data forms through some of the following:

- Manipulating moderately large sets of data (hundreds to thousands of data points), using algorithmic processes and instructions implemented through digital tools. This may include practices such as "data wrangling" in which data are restructured in order to be useful for new questions and goals.
- Clustering and classification within moderately large data sets through the use of computational algorithms. This would involve recognizing how groups of data could be detected and characterized by proximity to a central case. These groups may exhibit enough regularities such that noteworthy correlations may be observed and given a categorical designation.
- Understanding and describing the basic underlying logic of machine learning, whether it involves processes of regression or other supervised or unsupervised learning techniques. While it remains to be determined, we anticipate students will benefit from becoming familiar with the importance of training data sets and foundational ideas such as decision trees and Bayesian inference as they progress in their understanding of how large sets of data can lead to prediction.
- Implementing, inventing, and critiquing visualization techniques involving large amounts of data. These visualization techniques can include canonical forms of graphs and charts and include novel spatial arrangements and relationships that help to make features or patterns more apparent to the human perceptual system.
- Recognizing limitations of data science including false correlation, computational modeling without adequate considerations of model fit, and the nature of individual variability despite aggregate commonalities. Furthermore, students should appreciate that

data science represents one of multiple productive epistemologies for developing and advancing knowledge.

- Reasoning through the ethics associated with data collection and inference, including issues of disclosure and the consequences of decisions that are made on analyzed data corpora. Furthermore, there should be a recognition that data science algorithms can embody particular biases that require critical reflection and consideration.

As education research continues to develop in this area and intersections between science education and data science are more clearly established, we still maintain that many of the recommendations and findings articulated above related to how data are used and understood in educational practice will continue to be foundational. While we expect there to be new developments with respect to what can be done and discovered through data, we feel that improving educational practice through further developing models and strategies for how educators can best use data in middle and secondary school science investigations given the existing research base should be our near term goal.

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