Youth Reasoning With Interactive Data Visualizations: A Preliminary Study

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IDC '17, June 27-30, 2017, Stanford, CA, USA ©2017 Copyright is held by the owner/author(s). ACM ISBN 978-1-4503-4921-5/17/06.
http://dx.doi.org/10.1145/3078072.3084302

Abstract
Youth interact with data constantly through visualizations on social feeds and news sites. Unlike traditional graphs that are the focus of school instruction, visualizations use context rich and interactive methods to create narratives and allow users to explore data for themselves. We ask: How do youth make sense of interactive data visualizations? Nine participants ages 12-13 completed semi-structured, think-aloud clinical interviews as they worked with data visualizations about socio-scientific issues. Findings suggest learners used a variety of resources, but often did not coordinate those resources. When they did, they built deeper understandings of the visualizations and their content.

Author Keywords
data visualization; middle school; data literacy; science education; statistical literacy

ACM Classification Keywords
K.3.2 [Computer and Information Science Education]: Literacy

Introduction
Data-intensive artifacts such as interactive visualizations are a growing part of news reporting [10], scientific and professional practice, self-study and civic advocacy [13, 6]. They are also becoming pervasive in youth's media land-

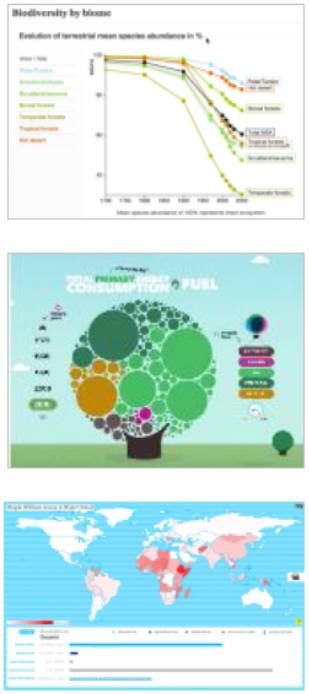

Figure 1: Three visualizations used in interviews: Ecosystems Dynamics (top), Human Impact (middle), Human Impact (bottom).

scapes. There are books of science information graphics for young children [12], and websites tout data visualizations and data analysis tools as useful learning resources [1].

Even as these data artifacts permeate learners' lives, there are still not many opportunities to work with them in the formal K-12 school curriculum. Mathematics curricula emphasize conventional, static data displays such as line graphs, bar charts, tables, or scatter plots, usually to illustrate simple patterns in small data sets. This does not prepare learners for the highly contextual, interactive, and story driven types of representations seen online, at work, or in print [5, 8]. School curricula rarely integrate data visualizations; when they do, they often do not provide support to help learners interpret these artifacts in meaningful ways.

This presents a need and opportunity. Learners may lack prior knowledge to understand what a visualization represents, and struggle to process the complex information they include [17]. Some visualizations are outright deceptive [11]. However, data visualizations also take advantage of new modes of interaction, non-traditional data sources (citizen science projects, online participation data), and storytelling conventions that youth regularly encounter out of school. And in many cases, working with visualizations can be aligned with standards-based content and practices [16].

This is especially true in science, where complex, socio-scientific systems are often presented in data visualizations. Since scientific visualizations combine math and science content with narrative and aethetic features [7, 14], we draw from research that explores math and statistics learning, science education, and how learners construct explanations [15]. For example, youth usually think of statistical data as a collection of individual values rather than an aggregate [2]. Ben-Zvi and Arcavi [3] call these local and global understandings, and showed that local understanding can hinder or support students' global understanding. Attending to the origin and context of data allows learners to develop more sophisticated inferences [4]. Learners should explicitly coordinate patterns in data with relationships that describe systems under study [18]. Personal experiences also inform how connections between data and systems are made [9].

Here we report emerging results from a semi-structured think-aloud interview study with nine middle school youth as they explored data visualizations about socio-scientific topics. Specifically, we explore: *How do middle school youth leverage and coordinate diverse knowledge resources to make sense of data visualizations?*

Methods

We interviewed 9 middle-school students using a semi-structured protocol as they worked with data visualizations.

Participants. Youth were recruited in collaboration with two partners: a 7th grade mathematics teacher who taught at a public school, and an after-school engineering program. 4 identified as girls and 5 as boys; 6 were from the school and 3 from the program. Participants were interviewed after class or program activities ended for the day, and received a US$10 gift card for their participation.

Interview Protocol. Interviews lasted 30-40 minutes. Participants worked with a set of three visualizations focused on either ecosystem dynamics or human impact on Earth (both themes emphasized in middle school science; Figure 1). For each, we presented each visualization and asked participants to interact with it until they were ready to answer questions. Then, we asked a series of eight questions about their initial impressions, the quantitative relationships featured in the visualization, and events or relationships that might explain patterns exhibited in the visualizations. We also asked participants to critique the visualization, and to

Codes Used in Analysis

Hypothesized Relationships. Knowledge of the system and of likely or hypothesized causal relationships.

Mathematical Ideas. Ideas such trend, distribution, quantitative difference, mean, or fit functions.

Visual Features. Conventions such as axes, legends, or use of position, shape, color, or other visual properties.

Text or Other. Supplemental information provided (visualization titles, text descriptions).

Reliability and Origin of Data. Questions, challenges, or inferences about whether data are reliable, sampled appropriately, and/or reflect knowledge or expectations about the system.

Local/Global Tensions. Similarities and differences between single data points or classes of data, and overall trends.

Personal Experience. Learner relates data to personal experiences, behavior, or identity.

propose changes to make it easier to use and understand. Due to time constraints, Mia and William interacted with only 2 of the 3 visualizations.

Data Collection. Interviews were video recorded with cameras positioned to capture participant-interviewer interactions, facial expression and gestures, and on-screen activity. Interviews were transcribed, including descriptions of gesture and other nonverbal cues.

Visualizations Used. We chose visualizations that illustrate a variety representational types, and that had already been recognized as well-designed by popular media or organizations interested in data visualization (see Figures 1 and 2). Some featured conventional representations of data such as linear graphs, others more idiosyncratic ones such as a tree whose leaves were circles colored to correspond to different fuels. Yet others featured a variety of representations, such as a combination of a colored geographic map and bars about the global water usage.

Analysis. We began with an open-ended analysis of transcript data. We annotated transcripts when we found evidence that learners were attending to particular mathematical, representational, or domain-specific resources, but also sought other instances in which learners worked to make sense of the visualizations in other ways. This led us to identify several different categories of, for example, domain-specific resources: some related to learners' own experiences of a particular phenomenon (e.g., their own experiences of local weather when exploring issues of climate, or their own fuel use when exploring issues of natural resource management). Through discussing emergent codes, we identified additional resources, such as text accompanying the visualization. The resulting categories used for subsequent phases of analysis are in the side bar.

Pseudonyn	Interviewer	Topic	Duration
Aminah	Vicky	Eco. Dynamics	35 min
Ryan	Michelle	Human Impact	33 min
Bobby	Vicky	Human Impact	42 min
Meili	Michelle	Human Impact	37 min
Mia	Michelle	Eco. Dynamics	30 min
Jason	Michelle	Eco. Dynamics	35 min
Oliver	Vicky	Human Impact	38 min
William	Vicky	Human Impact	34 min
Lilly	Michelle	Eco. Dynamics	37 min

Table 1: Participant details. Interviewers are authors of this paper.

Applying the Coding Scheme to Transcripts

An iterative, bottom-up analysis procedure yielded seven themes that became the focus of subsequent analysis (Table 2). Once these were identified, we organized transcripts into arguments. Each argument was then coded for evidence of one or more resource codes. An argument is one or more sentences that complete an answer to a question or an assertion. In the following, two arguments were identified:

William: [...] So, I think by the years, gas gets higher, cause gas was 5% and petrol and solid was really, people used it. Then we start to use gas, then we used, still down, then. Now, we're not using solid as much, because gas is like a useful tool, and then, now gas is the most, solid is the least and petroleum is, a little high, it's the second highest. But back then [1970] solid was the biggest, petrol was second and gas was the lowest. I feel like, it's trying to show our usage of these elements from 1970 to 2010, how we're using a lot more gas than we should be.

The first argument is "So, I think by the years, gas gets

An Example of Reporting with Visualization Resources

Meili: So, it's like about [reading text], like how, like the spring snow cover and the carbon dioxide levels and the average temperature, stuff like, change during 1950 and 2015.

I: And, op, yeah?

Meili: So, so like. For the average temperature, so like, you can like easily see like how the temperature is rising [gestures to graph]. So like, in 1952 it was a lot lower.

Meili: So, it's like, in 2014 there was like a lot, there was like a higher average temperature than like 1952. And then like, the carbon dioxide levels, like in October in 1987 it was like, carbon dioxide was a lot less than in, like March 2015. [I: Uhu] And for like the snow cover, it shows that like the snow melts earlier than it did in 1965. So, I think it's probably cause of global warming. In like 2013, it melted a lot earlier.

higher... ...petrol was second and gas was the lowest." and is only part of the first turn of talk. The second is "I feel like, it's trying to show..." More than one code could be applied to each argument. Here, the first argument was coded for evidence of mathematical ideas and hypothesized relationships, the second for personal experiences of data.

Preliminary Results

We expected students who leveraged a wider and balance of (mathematical, representational, domain-specific, and other) resources would exhibit deeper and more accurate interpretations of their content. Instead, our findings suggest a more complicated landscape of sense making. We identified additional categories of resources not well captured as only mathematical, representational, or domain-specific. We also found that students often leveraged resources without integrating them.

Summary of Content Analysis. We identified a diversity of resource type use within participants, and of distributions of use across participants. Table 3 presents results by student and resource. For example, Aminah referred to Hypothesized Relationships (HR) in 57% of her arguments during the interview. She referred to Mathematical Ideas (MI) in only 17% of arguments. Four resource types were identified in all interviews and played a heavy role in most students' reasoning. These were Hypothesized Relationships, Mathematical Ideas, Visual Features, and Text.

Of the remaining resources, seven students explicitly referred to the Origin or Reliability of the Data, four referenced Local and Global Tensions in data, and only three referenced Personal Experience. The distribution of resources leveraged also varied dramatically: William relied heavily on Personal Experience (52% of arguments), versus very low or no reliance from other participants. Four participants

Pseudonyn	HR	MI	VF	Text	OR	LG	PE
Aminah	57%	17%	4%	30%	4%	-	4%
Ryan	42%	48%	14%	10%	-	-	-
Bobby	46%	38%	17%	13%	4%	-	-
Meili	44%	33%	44%	17%	-	-	6%
Mia	31%	15%	31%	31%	15%	8%	-
Jason	26%	26%	16%	21%	16%	5%	-
Oliver	22%	28%	33%	22%	11%	6%	-
William	22%	43%	9%	13%	13%	4%	52%
Lilly	5%	50%	20%	35%	10%	-	-

Table 2: Percent arguments coded for presence of each resource.

frequently cited Hypothesized Relationships (over 40% of arguments); three Mathematical Ideas. Some participants heavily relied on multiple resources in conjunction. For example, Ryan frequently cited both Mathematical Ideas and Hypothesized Relationships to make sense of the visualizations presented, Meili frequently cited Mathematical Ideas and Visual Features.

Sensemaking and Synthesis During content analysis we noticed that resources were often used as justification for an assertion, or they were consulted without synthesis or coordination with other resources. In other words, resources were not always used by learners to build, interrogate, or revise their understandings of the visualization. This happened even in cases where students referenced multiple resources at the same time—something we expected to promote sense making.

For example, in the excerpt featured in the left sidebar, Meili cites several resources when describing the main themes of a visualization, but treats each in isolation. She first consults Text accompanying the visualization as a resource,

An Example of Strong Sensemaking with Visualization Resources

Bobby: Here [indicates spring snow cover] you can see that this is going down [traces blue bars] and this is going up [traces red bars].

I: Which one is going down and which one is going up, sorry?

Bobby: The top, the blue one is going down, and this one is going up, kind of.

I: Uhu, uhu. Why do you think this is so? What's a possible explanation for that pattern?

Bobby: Ah, global warming?

I: Ok

Bobby: Like um, it, if they put heat trapping gases here, and that's important because, like um, we're just trapping the sun's heat cause, the sun's energy [clicks on the graph] is not doing anything that it hasn't been doing.

I: Uhu

Bobby: And... So, it's not whatever is melting all the snow, and glaciers and arctic sea ice, is not the sun's fault.

and reports what this text indicates in her first turn of talk of the excerpt. She then identifies Mathematical Ideas in the form of rising and falling patterns indicated in the graphs ("you can like easily see..."). Finally, she describes a Hypothesized Relationship ("it's probably cause of global warming.") as a source for the patterns identified. However, there is no evidence to suggest that Meili is extending or revising what she already knows—she is reporting what information each resource provides, not how they can be coordinated with one another to tell a story.

To further explore the differences between reporting versus making sense of resources, we isolated arguments where multiple resources were leveraged at once. We then classified each argument as showing evidence of strong, weak, or no sensemaking. Strong sensemaking suggests the student made new inferences about the system, or changed prior inferences based on new information. This analysis is ongoing; here we report our emerging findings.

We were surprised that about 1/3 of arguments we identified as leveraging multiple resources did not represent new knowledge construction, like the example presented with Meili. Another approximately one third included weak evidence for sensemaking, in which *overlaps*—that is, consistencies or disconnects between resources—were noted by the interview participant, but not explored or resolved. Finally, about one third represented strong evidence for sensemaking, whereby students explicitly engaged with overlaps between resources which led them to construct, strengthen, or revise their knowledge. One example of such strong sense making is featured the excerpt to the left.

In this excerpt, Bobby explicitly coordinates the patterns (Mathematical Ideas) exhibited by multiple graphs to highlight that indicators of global warming are affected by a rise in heat-trapping gasses, rather than solar energy (Hypothesized Relationships). While both Meili and Bobby interactied with the same graph, and both noted that the patterns indicated by the graph were likely markers of global warming, the excerpts illustrate very different levels of sensemaking with the visualization. Meili recounted what text and data were presented, while Bobby linked data to domain-specific mechanisms and relationships.

We are careful to note that the examples provided here are to illustrate sensemaking per *argument*, not per student. Of course, sensemaking can be affected by many factors—interviewers' questions, students' framing of the interview task, and the visualization content. Our point here is that sensemaking is characterized by the deliberate coordination rather than merely the presence of diverse resources.

Conclusions

Work is ongoing, and we are currently analyzing episodes of strong versus weak integration of resources to better understand the conditions under which integrative reasoning happens. We are especially interested in probes or cues that interviewers may have used to promote this deeper level of sensemaking. Thus far, our study suggests that supporting learners in coordination of any resources they choose to leverage is more likely helpful than supporting a particular approach or sequence of resource use.

Acknowledgements

This work is funded through Grant IIS-1350282 from the National Science Foundation. We thank Asami Takagi, Elsa Head, Merredith Portsmore, and the Functions group at UC Berkeley for their help and feedback on this work.

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