An important theme in my current work bears on how people make meaning from data visualizations. I focus particularly on data visualizations in which at least one of the spatial dimensions of the paper or screen corresponds to a spatial dimension of the referent system, in other words spatial data visualizations such as maps and cross-sections. I work in the domain of Geosciences, so the referent system I am dealing with is the Earth System or a portion of it.

The process of making meaning from data begins by perceiving and attending to distinctive patterns or regularities in the representation. Then, through some poorly understood process, the interpreter brings together knowledge and understanding of the referent system, metaknowledge of how data representations work (representational strategies), plus the information obtained by examination of the data representation at hand, to assemble an inference about the referent system (Figure 1). Two common forms of data-based inferences are about causality and about implications: why is the referent system the way it is? And given that the referent system is the way it is, what are the implications for humans or other actors in the system? Underlying this step must be a theory- or experience-based set of ideas about what types of patterns or regularities are likely to have significance as far as either causality or implication.

*Figure 1:* Making meaning from the data visualization of seafloor bathy involves going beyond just describing flattish seafloor with bumps on it.

Observation of the visualization combines with knowledge of representational strategies and knowledge of Earth processes to effect a causal inference that the conical bumps are likely to be volcanoes and a linear trend is likely to be a hot-spot trace.

Spatial attributes, including shape, size and azimuth, are necessary but insufficient inputs to this process.

To my mind, the process of becoming skillful at making meaning from data must surely be a long one, extending over many years of education. Figure 2 sketches some key aspects that I think are likely to be part of a learning progression leading to an adult who can use data powerfully in professional or personal life. At first, students work with small data sets that they have collected...
themselves, such as a map that they made of a stream near their school or a time series of lunar phase observations that they collected themselves. Later on, some students work with larger data sets of data that they did not collect, most often data obtained via the Internet. At first, they work on fairly well-defined problems, problems to which their teacher probably knows the answer. And then finally, they learn to work with large data sets around ill-defined problems, the sorts of problems characteristic of adult life.

Figure 2: Conceptual sketch of an educational trajectory that could lead to an adult who is able to make meaning from complex data sets in the context of ill-defined problems.

Figure 2 sketches this trajectory as having times of gradually increasing proficiency (labeled “business as usual,” when the learner is within one of these three domains, interrupted by poorly understood transitions, when the learner must make big steps in learning. Figure 1 is surely a simplification: we could expect that there would be some cyclic motion back and forth between domains and that an individual could simultaneously be in different domains with respect to different data types. But this sketch has helped me identify and articulate where there are likely to be sticking points in learning to make meaning from data, and where research could be most fruitful. How these transitions happen, and what kinds of curricular scaffolding and teacher professional development can help them happen, is a research agenda I would like to pursue.

For Transition I, both the small-to-large and student-to-professionally-collected aspects are of interest. When students collect their own data which they subsequently interpret, they have had the full embodied experience of the environment of which the data are only a sparse, one-dimensional representation—the wind chilling their skin, a view of surrounding terrain, etc. But when they download data from the Internet, knowledge of context comes primarily from the thin description of metadata. Small data sets can be acquired and processed with simple, comprehensible technology (thermometer, paper and pencil, calculator), but larger data sets are typically acquired and processed with more opaque technology (satellite remote sensing devices; data visualization and statistical software). The up-side of Transition I is that it opens up
access to a wealth of additional Earth processes that were too big or too small, too old, too far away, too dangerous, or too expensive to understand through student-collected data. Transition I could happen as early as middle school, but it typically does not. Many students arrive at college having only minimal experiences in making meaning from data.

Transition II involves moving from the well-structured problems that are typical of formal schooling to the ill-structured problems characteristic of adult life. For well-structured problems, the materials and information needed to solve the problem are usually provided to the problem-solver or the paths to find the required materials and information are straight forward. But for ill-structured problems, the solver has to identify and then find the materials and information needed to solve the problem. In some cases, the solver may need data that don’t exist and have to be acquired from scratch. In extreme cases, the instruments to collect the needed data don’t yet exist, and need to be invented. For most problems encountered in formal education, including college, it can be assumed that the solver has or should have the skills required to solve the problem. But for an ill-structured problem, the solver may not have the skills required to solve the problem; the solver may not even know what the skills are that would help to solve the problem. An ill-structured problem might be set by nature or circumstances beyond human control or by complex social systems, and it is not known in advance that a solution necessarily exists. In a well-structured school problem, the problem was posed by a human being, typically by a teacher who underneath has the solver’s best interests at heart, and the solver has reason to think that a solution to the problem does exist. College can provide an opportunity to foster Transition II, but there are still many people graduating from college without completing the trajectory of Fig. 2.

The stakes are high in figuring out how to move as many students as possible along this data-savviness trajectory, as we move into a more data-infused society. For individuals, ability to interpret data is becoming a workplace expectation in jobs ranging from refrigerator repair to teacher to healthcare provider. For society, we can hope for a society that makes better decisions, decisions informed by evidence ground in data (figure 3).

**Figure 3.** The end goal of improving education around making meaning from data is a society in which decisions are more likely to be informed by evidence grounded in empirical data.