Designing Interdisciplinary Arrangements and Infrastructures

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Abstract: Interdisciplinarity in the professional practice of making inferences with data is motivated by the challenge of generating claims in the midst of variability. However, in schools interdisciplinarity it often undermined by structures that separate ideas and practices into rigid, and often separate, spaces. How, then, can we support students to develop ideas and practices related to the interdisciplinary act of making inferences with data? In this paper we share a design framework to guide interdisciplinary learning environments that support the co-development of inferential practice with disciplinary ideas.

Introduction

Competency in constructing and critiquing inferences with variable data is increasingly critical for participation in STEM disciplines and active engagement in the civic responsibilities of a democratic society. Because of this, it is a key developmental goal for diverse stakeholders in STEM education (AAAS, 2011; Franklin et al., 2007; National Governors Association Center for Best Practice & Council of Chief State School Officers, 2010; NRC, 2012). In this conceptual paper we explore the nature of interdisciplinarity in model based statistical inference in both professional practice and designed learning environments, and describe a design framework to inform supporting interdisciplinary learning goals related to making inferences with data models.

Interdisciplinarity in practice for model based statistical inference

Data models of variability inform inferences and knowledge claims within particular disciplinary communities (Cobb & Moore, 1997; Wild, Utts, & Horton, 2018). Yet, the practices that support inferences and the disciplinary knowledge these practices are used to generate do not develop in isolation of each other, but co-develop as practitioners work to make progress in local problems related to their inquiry (e.g. Hall, Wright, & Weikert, 2007). For example, Sir Ronald Fischer developed the F-test in an effort to understand the relationship between different fertilizer treatments and variation in crop yields, but statistical advances generated new knowledge about crops that created new questions requiring further statistical development (Rodgers, 2010; Wild, Utts, & Horton, 2018). As practices and ideas develop, though, they are never static. They are constantly in flux, emerging and being maintained through collective activity of practitioners, as the worth of a measure or model must be continually reconstituted with each new question or problem. Yet, the practices and ideas are stabilized by a "coherence of reasoning and activities that make sense in light of each other and in light of the practice's aim" (Ford, 2015, p.1045). This coherence requires significant, *interdisciplinary* knowledge of the phenomenon under investigation, the data model, and the relationship between them that justifies the inferences. The relations among interdisciplinary components of the models are how scientists specify the "conditions of seeing" for others critiquing what they have claimed to find (Lehrer & Schauble, 2010). Interdisciplinarity, then, is not designed into the professional work of making inferences with data models, but emerges from the necessary connections that provide stable and coherent sets of ideas and practices to guide inference. Of course, designed infrastructures support interdisciplinary work (e.g. Galison, 1997), but the nature of the interdisciplinary arrangement is motivated by epistemic problems being pursued by the practitioners.

Interdisciplinarity by design for model based statistical inference

Standards for both K-12 and undergraduate students include data analysis and modeling as central practices for development. This is not simply a call for students to superficially engage with disciplinary conventions around data models, though. Science educators aim for students to develop a "grasp of practice" for making statistical model-based inferences with data so that they participate in ways that are epistemically congruent with STEM professionals (Ford, 2015; Forman & Ford, 2014). Synergistically, mathematics and statistics educators desire for students to come to see ubiquitous variability as the challenge at the root of statistical practice (Moore & Cobb, 1997; Franklin et al., 2007). Under this vision, students learn about data visualization and statistics as measures of distribution in order to visualize and quantify signal and noise in data (Konold & Pollatsek, 2002). Mathematics educators, then, aim for students to learn to quantify uncertainty using the mathematics of probability, and to build, compare, revise, critique, and use probability models and statistics to make statistical model-based inferences with variable data about chance events (Lehrer & English, 2018).

In schools, though, ideas and practices often develop (or don't) among institutional and disciplinary boundaries that thwart interdisciplinarity. Mathematics and science exist in separate realms, and students regularly struggle to see how one is related to the other. This means that although different disciplines within the STEM umbrella have increased the focus on supporting students to make inferences with data, the ideas and practices often lack coherence due to the lack of connections that stabilize professional inferential practice. This is problematic, because "In data analysis, context provides meaning" (Cobb & Moore, 1997, p. 801). Where the context and the statistical ideas co-develop in practice, they often live in isolation from each other in schools. Without careful design for interdisciplinarity, students are likely to only superficially engage with the context of an inquiry in a math class, and to only superficially engage with data in a science class.

However, very little is known about how to productively integrate concepts and practices across diverse STEM disciplines (Honey, Pearson, & Schweingruber, 2014). Conceptualizations of integrated STEM vary widely, and are often poorly defined (Martin-Paez, Aguilera, Perales-Palacios, Vilchez-Gonzalez, 2019). Integration alone does not necessarily create better learning opportunities, and can at times impede learning because of the complexity of a given set of concepts or practices. Designing for interdisciplinarity in schools must carefully develop both the **arrangement of interdisciplinarity** and the **infrastructure to support it**.

The arrangement of interdisciplinarity defines the ideas, practices, and how they relate to each other. Where this arrangement is motivated by the goals of the community in professional work, designed interdisciplinarity can be motivated by a diverse set of rationale. For example, the logic may be pedagogical (i.e. "this science question will bring this math idea to life"), motivational (i.e. "students are more engaged in interdisciplinary STEM units), or institutional (i.e. "we have a STEM initiative with the local zoo"). However, the motivation for interdisciplinarity in supporting students to make inferences with data is *epistemological* since we aim for students' ideas and practices to correspond with professionals in ways that are epistemically consistent.

The infrastructure, then, should be designed to support the envisioned forms of interdisciplinary arrangements. Competing priorities from different disciplines vie for attention. Interdisciplinarity often introduces a new level of complexity, which can confuse both teachers and students (Honey, Pearson, & Schweingruber, 2014). Because of this, design frameworks are needed to inform interdisciplinary learning environments.

We have developed a design framework to guide our work in designing interdisciplinary arrangements and infrastructures for making inferences with data in undergraduate biology classes, which we refer to as Data MAKER Biology: Data Modeling and Argumentation Knowledge Explorations to Rethink Biology. In the following sections we describe the Data MAKER Biology framework, and illustrate how it has informed our work to engage undergraduate students with measurement, variability, and statistics to make claims about the relationships between sponge form (Phylum: Porifera) and the function of filter feeding in marine ecosystems.

Data MAKER biology design framework

The Data MAKER Biology design framework guides the coordination of the biological and data modeling learning goals by first identifying an appropriate data modeling practice, and then finding biological contexts which make use of data and analyses that are consistent with the target practice. We privilege data modeling goals as a starting point because supporting learning with increasingly sophisticated data modeling practices requires particular forms of data. For example, repeated measures data is a powerful way to make variability and distribution visible to students (Konold & Pollatsek, 2002). Different biological investigations, though, use diverse data forms and techniques which may or may not correspond to the type of data necessary to support students. By identifying an appropriate data modeling learning goal and then carefully selecting a biological phenomenon and context that allows students to grapple with foundational practices and ideas, students can have the opportunity to participate in the generation of new (to them) biological knowledge.

However, such grappling with ideas and generation of biology knowledge claims requires the design of infrastructures to support students' investigations. While disciplinary knowledge and practice often develops over long timescales (years, or even centuries) and takes an uncertain path, students' ideas and practices must develop over much shorter timescales (days, weeks, and years) and need to develop in ways that have a meaningful correspondence to disciplinary ideas and practices. Our framework guides the development of infrastructures that support students to engage with data modeling and inference practices, forms of scientific argumentation to compare the merits of different data modeling approaches and justify knowledge claims with evidence and biological reasoning, and coordinating their work with disciplinary conventions in a way that emphasizes the epistemic aspects of the conventions.

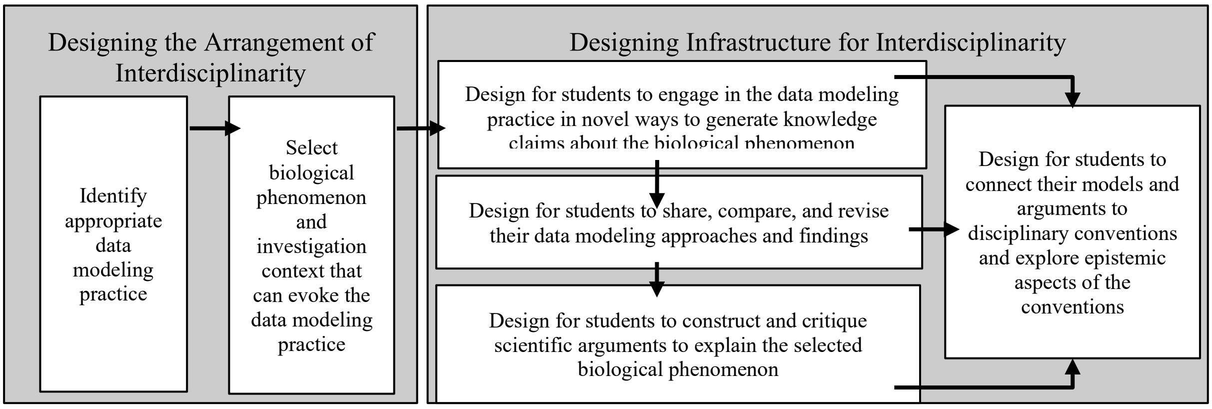

Figure 1. *Data MAKER Biology* design framework.

Making data and claims about sponge (Phylum: Porifera)

Here we illustrate the Data MAKER Biology framework by describing how it informed the development of an investigation in an undergraduate, non-major biology class. Although the illustration includes student quotes from one design study, this is not a research report. Instead, this is meant to illustrate the ways the Data MAKER Biology framework can guide the work of designing for the interdisciplinarity of making inferences with data and generating knowledge about biological phenomena.

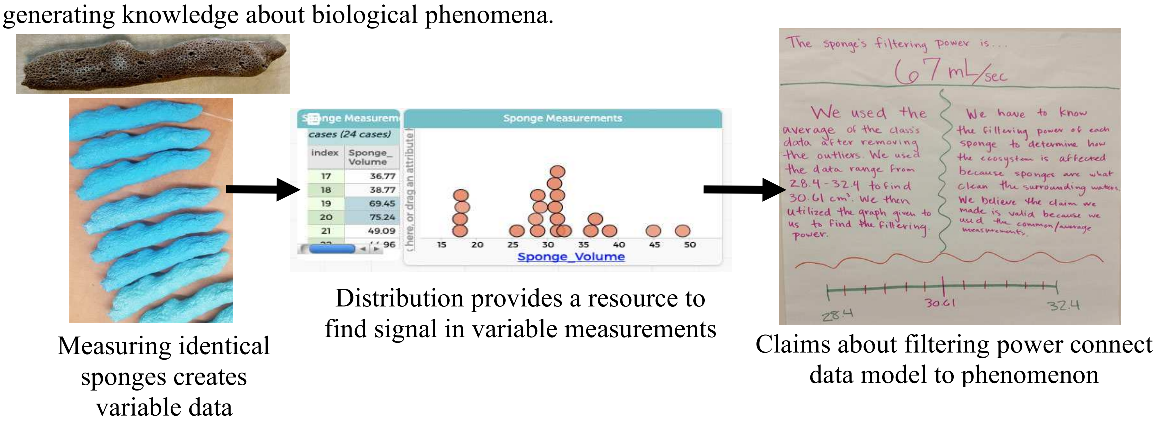

Figure 2. Designed infrastructure to support students to grapple with making claims with variable data.

This investigation focused on the data modeling practices of measurement, reading distribution, and creating statistics in the context of studying structure function relationships in sponges. We chose the sponge filter-feeding context to provoke a need for distribution and statistics in order to make claims in the midst of measurement variability due to irregular shaped organisms. Students engaged in this investigation to address the driving question: **How quickly can this sponge filter water on a coral reef?** Students began by examining sponge specimens (top left of Figure 2) and creating sketches to discuss the ways the physical attributes of the sponge supports filter-feeding. We then leveraged this discussion to motivate a need to quantify the qualitative descriptions of the sponges to inform filtration rate. Student groups invented and negotiated measurement methods, and then used their group's methods to independently measure the volume of identical 3-D printed sponge fragments (bottom left of Figure 2). The identical printed sponge fragments proved to be an important piece of infrastructure for students to consider repeated measures of an object within the context of a large class. Although students measured identical sponges, these measures were highly variable due to the irregular shape of the sponge and variation in measurement methods. This variability, though, provided a ripe context for students to grapple with the practice of measurement, and the role of variability in quantifying biological qualities of an organism. For example, many students anticipated that everyone should measure the "exact same value," and were troubled by the variable measurements. The class next constructed a data distribution (Center, Figure 2), leading some students to claim that the variability in measures made the sponge volume unknowable because "the data is way too widespread to make a conclusion that that's the true size." However, during the class discussion of the data other students quickly noticed that some measurements were similar or identical. As previous research has shown, this gives the center and spread of the distribution an epistemic role by informing the students' claims about “true” size (Lehrer & Schauble, 2007). We then asked students to make a claim about the filtration rate of the sponge model they measured and to justify how the data (e.g. statistics describing characteristics of the class data distribution) and biological concepts (e.g. the relationship between sponge structure and function) supported their claim. Students collaboratively constructed one argument per group (Right, Figure 2), and negotiated what claim to make and how to support it. After each group constructed their argument on chart paper, they critiqued arguments constructed by students in another class.

In pilot work we have identified tentative evidence about how students conceived of measurement practice in biology based on the comments they made during class discussions. Many students initially treated measurement as the search for exact values, stating that “we all gotta have the same numbers.” Others, though, expected that the measurements would not be identical, but “should be around the same area.” Many of the students that once thought of measurement as the search for exact values came to use distributional characteristics, such as center, for making claims about sponge volume. By the end of the investigation, we saw some students beginning to account for variability in their claims about filtering rate.

Discussion

Designing to support students to make inferences with data that meaningfully correspond to disciplinary practice is challenging work. The Data MAKER Biology design framework informs both the design of the arrangement of interdisciplinarity in classrooms, and the infrastructure to support student learning. We believe this work is closely related to the conference theme and the design strand by providing a theoretical description of design that considers fundamental differences in the nature of interdisciplinarity in practice and designed learning environments. We believe this has the potential to contribute to a theoretically grounded conception of interdisciplinarity in STEM learning environments that engage students with making inferences with data about disciplinary specific phenomena.

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