Exploring Teacher Learning through STEM Teachers' Exploration of Data Using a Domain Specific Coding Language

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Abstract: In the following paper we outline a method that endeavors to understand how teachers can systematically utilize data in classroom teaching. Informed by Cultural Historical Activity Theory and teacher education, we interview teachers about how they think about data and use it in their everyday workflow. From these interviews we develop semantic models of actions that teachers take in the classroom to learn about their students. We then convert those semantic models into computer code that can be utilized to both aid teachers' exploration of data and study the teachers' usage patterns.

Background

When teachers engage meaningfully with the data produced by multiple sources (test scores, online programming, classroom observations) they can better respond to the educational needs of students and advocate for them within educational systems. However, these efforts have been met with a mixed response from teachers themselves. This challenge is a matter of balancing both (1) the capacity of teachers to process and utilize growing amounts of data in a meaningful way for instructional purposes and (2) the capacity of software developers and researchers to design teacher-centered, usable, and useful analytic tools. However, while teachers are increasingly collecting data from a variety of assessments and being asked to use this data to inform their instructional decisions, they have very little input about the type of data they collect nor the frequency in which data is collected. This issue is compounded by the tremendous growth in the amount and variety of data collected about students through the advent of online and mobile computing and use of technology in the classroom (Mandinach & Gummer, 2013). We are at the very early stages of utilizing these new forms of data for educational purposes (Ferguson, 2012) and are faced with the daunting task of both determining the utility of new data sources, disseminating that information throughout education systems and ensuring that teachers have the skills to interpret and use it to meaningfully impact instruction.

As the sociotechnical landscape continues to evolve, opportunities for developing innovative STEM curricula that denote multiple data collection points, informed by the needs of classroom teachers could create space for evidence-based decision making that better supports daily instruction. To begin this process, classroom teachers need a systematic and intuitive way to collect, analyze, and disaggregate assessment data to inform real-time decision-making as they teach. This requires not only new skills, but flexible systems in which teachers can creatively incorporate data into their practice. This is particularly true within STEM education that is proved to be the vanguard of these technological changes. STEM is inundated by new technology-based pedagogical aides such as online tutoring platforms for math and science (Kulik & Fletcher, 2016), blended learning applications (Tempelaar, Rienties, & Giesbers, 2015), Virtual Reality for whole body experiences (Potkonjak et al., 2016), and Augmented Reality laboratories (Chang, Chung, & Huang, 2016).

Evidence based improvement cycles have been encouraged as part of teacher training programs for over a decade (Lewis, 2015). Despite this large scale implementation results have been mixed (Mor, Ferguson, & Wasson, 2015). Similarly, teacher utilization of the data dashboards that accompany technology products is highly variable (Molenaar & Campen, 2017). In a substantial review of the utilization of data in education Marsh (Marsh, 2012) outlines four sequential components of the practices adopted by teachers: data, information, knowledge, and action. Marsh is critical of the focus on the professional development of teacher data skills absent focus on the translation of knowledge into action. However Mandinach and Gumner are wary of data dashboards that automate actions without teachers having gained the understanding or skills required to make effective use of what is being presented to them. On the one hand, inquiry cycle-style strategies for incorporating data into teachers' practice are too focused on skills and not on action, on the other hand dashboards seem to be too focused on action absent skills. There is no in-between space in which actions and skills can be suitably matched.

Theoretical approach

For this study, we draw upon Cultural Historical Activity Theory (CHAT) (Engeström, 2001; Vygotsky & Cole, 1978) as a heuristic for analyzing how STEM teachers learn to develop data skills. CHAT scholars posit that learning must be viewed within sociocultural, historical and institutional contexts (Wertsch & Rupert, 1993).

Importantly for this work are three aspects of the framework, 1.) that humans learn through actions, 2.) that they communicate those actions via tools and that community is essential to the act of learning. For the purpose of this study, those contexts converge in a school-based activity system in which classroom teachers draw upon a myriad of tools, rules, and community interactions to facilitate their learning about data literacy and data tool development. This theoretical stance attends both the conceptual and practical tools teachers bring to their teaching, as well as the ideas, theories, and frameworks about teaching and learning.

Computer science, and in particular the domain of computer language construction, has been engaged in the problem of communicating technical information about data with non-technical users for the last 50 years (Najd, Lindley, Svenningsson, & Wadler, 2016). In part, data-driven instruction is the most recent wave of a conversation about how technologies, designed and built by experts in those technologies, can communicate with non-expert users to aid productive use. One particular area, that of domain specific languages, has developed similar more general models to that of Marsh that look to solve similar issues, broadly, to balance user needs with technical constraints (Evans & Szpoton, 2015).

These models are language based, Fowler (2010) introduces a framework for thinking about the relationship between code, user actions and computer actions made up of three components:

- **Target code** - the computer program that executes actions
- **Semantic model** - the model that conveys meaning
- **Script** - the user input

In this model, what Marsh describes as the conversion of information into knowledge is represented as the “semantic model” or sometimes the “domain model”. In a programming language, the semantic model is a representation of the constructs that computer code populates. It is an abstraction or framework that links the real world with the virtual world through code.

If we overlay Marsh’s data use model with the Fowler’s computer language model (Fig.1) we can produce a useful understanding of how a computer language could be used to organize data use by educators and the division of complexity between the teacher and the engineer. Within this framework, the semantic model is what converts data into information, it is how we organize our understanding of data. The semantic model could be informed by teachers, researchers and software developers. It might be as simple as “failure to do homework = unable to complete in-class activity” but could be hugely complex, incorporating theories of validity, psychological or neuroscientific theories, teacher expertise, school contextual factors or cultural factors. Target code is the machinery that does not need to concern the teacher as long as the script reflects the semantic model accurately and the target code enacts that model with fidelity. In this way Marsh’s knowledge is represented in a script, the way that a teacher instructs a machine to behave in response to data. The script should be an abbreviation of the semantic model, it converts the semantic model into instructions. This could be a menu item or button in a Graphical User Interface (GUI) but could also be a scripting language. The script is the point of communication between the teacher and the engineer. A script that is both interpretable and accurately reflects the semantic model is a very valuable tool.

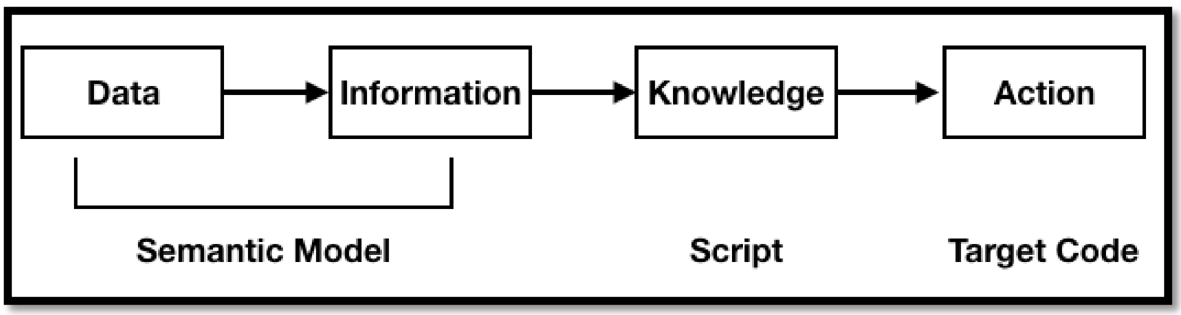

Figure 1. Mapping the Marsh data model onto the Fowler computer language framework.

The value of a script over and above other implementations such as graphical buttons in a dashboard are many fold. Scripts require less effort to generate than graphical elements and are easier to alter or retire if they are not useful or do not reflect the semantic model accurately. Scripts are more extensible, they can be combined to produce new functionality. They provide more autonomy for users to interact in ways that have not been explicitly considered by engineers. Script use can more easily be analyzed as it is already parsed into meaningful chunks, unlike mouse movements on a dashboard. Scripts can also be more intuitive than other forms of graphical interface if they use words that have constrained meanings within a domain such as teaching. But most importantly scripts allow for a common language to exist between technical expert and domain expert so that ideas about functionality can be communicated more effectively (Fowler, 2010).

Methods

In the first phase of the project, we are gaining a deep understanding of the baseline data practices of a cohort of 30 elementary STEM teachers by inductively generating semantic models through an iterative process (Glaser & Strauss, 1967). Teachers are interviewed about what they consider data to be and what they use it for. These interviews work through hypothetical data scenarios to unearth and visualize a.) the data teachers currently engage with, b.) the data teachers want to engage with but do not have access to, and c.) the questions teachers use to interrogate this data and d.) make meaning from it. We then engage in repeated readings of the interviews and focus group transcripts to identity components of semantic models. Next, we will take the semantic models and reduce them to abbreviations. In follow up interviews we then test the interpretability of these scripts with the original teachers and then with a cohort of 100 STEM teachers from different schools. These abbreviations will then form the basis for the domain specific language.

Preliminary results

Currently we have isolated three semantic models and preliminary abbreviations to accompany them. They are visualized in Figure 2 as "`summary.complete[X]`", "`summary.error[X]`" and "`funnel[X]`", "`summary.complete[X]`" queries a database and produces two pieces of information: 1. How many students have completed a task X, 2. The names of students who have not completed the task X. "`summary.error[X]`" queries a database and produces two pieces of information: 1. The percentage correct for the class and the lowest scoring students. "`Funnel[X.Y.Z]`" is a function that clusters students into groups for task Y according to task completion on task X, then again on task Z according to completion on task Y. so as to direct the teachers' attention to clusters of students who need specific help.

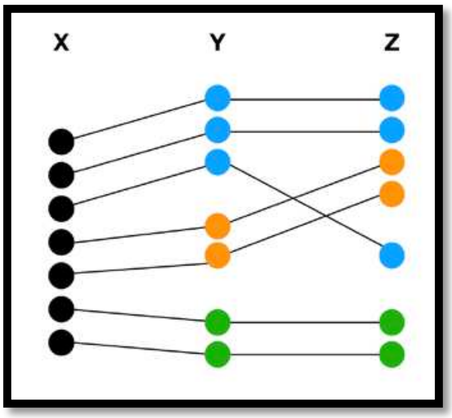

Figure 2. "Funnel" model clustering students based on performance on activity X, Y, Z.

Future work

We hope to have a collection of 100 semantic models such as these by early 2018. Using the initial scripts, we will develop a survey style instrument for a larger distribution to test the scripts on real teachers for difficulty of interpretation and complexity of analysis and provide feedback about their usability. Scripts that cannot be interpreted by teachers in the new sample will be discarded or altered based on feedback. The validated scripts will form the basis of the syntax, grammar and code for the domain specific educational programming language and will be encoded in the Julia language (julialang.org). We will implement through an Interactive Development Environment capable of capturing teacher usage patterns of the language to study aspects of teacher analytic practices.

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