

“Dictates from the Algorithmic Gods”: A Response to “Teaching within Regimes of Computational Truth”¹

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Heather Greenhalgh-Spencer has written a clear, compelling, and well-cited piece that reflects her rare ability to combine philosophical analysis with details from her deep experience of the ways that educational technologies affect the day-to-day work of teachers and students in schools. By looking at some core generalized beliefs about the magic of contemporary educational technologies, along with widespread views about the deficits of teachers, Greenhalgh-Spencer shows us that these beliefs and views (what she calls—after Michel Foucault—“discourses”) combine to form a “regime” of truth that reigns hegemonically, at least in part because these discourses seem unquestionable to many people in, and out, of schools.

I have little to quibble with Greenhalgh-Spencer’s thesis or the details of her argument. The prevailing trend toward “adaptive” learning systems that collect data while also tutoring or assessing students’ understanding has created a huge disconnect between the knowledge and skills necessary to create such learning systems and the knowledge and skills of typical classroom teachers. While Greenhalgh-Spencer follows Cathy O’Neil (and many others throughout educational history) in putting part of the blame upon teachers’ alleged lack of “math” understanding, I would suggest a better “bogeyman” is, more specifically, computational modeling, which uses very different math concepts than those that have been traditionally taught in preK-12 schools (and which continue to be taught to preservice teachers).

Computational modeling applies discrete mathematics to so-called “big data” to generate probabilistic predictions about how well the student is positioned to handle more complicated problems. While such predictions are often taken as “objective” because they supposedly are based on real-world data—and because they look at real data in real time as a student completes various tasks—these predictions are, in fact, like other predictions, steeped in uncertainty, and involve assumptions and algorithms that themselves reflect the biases of the people who create the models. The degree of uncertainty is rarely reflected in reports of the raw or “normalized” scores of students, which are indeed treated in many educational spaces as if they were “dictates from the algorithmic gods.”

Math education has gone through a number of “reforms” in the past 150 years, which reflect: 1) more need for more advanced mathematics as a foundation for science and engineering; 2) greater percentages of young people going to school for much longer periods; 3) the complex nexus among teacher knowledge, parent knowledge, and schools’ primarily conservative role in supporting culture (especially in the United States); and 4) the frustrations of university-level math, science, and computer science educators, who want more of their students to be better prepared for more complex mathematics.² A particular target of reforms was the traditional pedagogical approach that had students memorizing particular problem-solving procedures through repeated practice, without necessarily understanding the numbers and mathematics that made these procedures work. The most famous reform was the “New Math” of the late 1960s and early 1970s, which, among other reforms, introduced *set theory* as a basic conceptual frame of all mathematics. Some of us remember dealing with homework problems that completely befuddled our parents (even if they were “well-educated”). Others might remember skipping the first chapter of math textbooks because a teacher didn’t believe that it was important to what followed. Eventually, many aspects of “New Math”

were set aside by schools due to being “too theoretical” or not sufficiently necessary for more traditional modes of teaching and learning.³

In the 1980s, a new mathematics education reform movement emerged, this one involving math educators from preK-12. This *new* new math was reflected in a set of curriculum standards issued in 1989 by the National Council of Teachers of Mathematics (NCTM) and also in the development of new math learning materials for primary, middle, and secondary grades by the University of Chicago School Mathematics Project (UCSMP).⁴ Central to this reform effort was the collection and use of data (discrete math), a constructivist approach to learning, selected opportunities to use calculators and computers, and more exposures to “ill-defined” problems. These reforms were widely criticized by those who liked and wanted a more traditional approach to learning math procedures (“algorithms”) through directed practice, a critique that became popularized in the so-called “Math Wars.”⁵

It is noteworthy that many of the features of contemporary computational modeling were embedded in these new reforms. Students did get more opportunities to collect and analyze real data, to use math machines (computers) in math class, and, occasionally, to engage in the construction of new algorithms for solving problems. Yet rarely were students expected to grapple with the mathematics of *complex* situations, let alone learn how to program so-called “machine learning” approaches to refining computational algorithms.

Excellent counter-examples to this can be found and described. The Center for Learning Technologies for Urban Schools (LeTUS) at Northwestern University created a number of computer-based learning applications that involved complex situations in science and mathematics.⁶ The Jasper Project involved video-based scenarios with complex, ill-defined problems.⁷ And, there is a deep literature on using computers

as cognitive tools, rather than simply as replacements for more traditional communication technologies.⁸ Yet, while the use of computational modeling advances rapidly in the educational technology arena, most students are never given the opportunity to understand—let alone embrace—complexity and its accompanying mathematics. Rather, in the contemporary environment, the educational technologies *themselves* are built with such understandings, but these are almost always hidden from the teacher or student.

So, the discourses and regimes of truth identified by Greenhalgh-Spencer remain, despite ongoing efforts. In some ways, this is a “bootstrap” problem: how do we increase the understanding of computational modeling in (a) the teacher population and (b) the public at large? To attack the problem somewhat indirectly (but perhaps more effectively in the long term), how do we create compelling *counter*-discourses which do not lead to teacher deskilling or curricular dumbing down, but which reflect reality as we come to know it?⁹

The problem may be inherently unsolvable, or “wicked” as we might call it. Can general knowledge about major new technological developments actually keep up with the pace of technological change? Or, as seems possible, are most citizens happy to use an inscrutable technology if it “works” for them, and teachers should “get with the program”?

1 As cited by Greenhalgh-Spencer, Cathy O’Neil, *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy* (Location: Broadway Books, 2016), 8.

2 David Lindsay Roberts, *American Mathematicians as Educators, 1893-1923: Historical Roots of the “Math Wars”* (Boston, MA: Docent Press, 2012).

3 Marti L. Abbott, Duane Baker, et al., *Winning the Math Wars: No Teacher Left Behind* (Seattle: University of Washington Press, 2015).

4 National Council of Teachers of Mathematics (1989); Professional Standards for Teaching Mathematics, Reston, VA: NCTM; see, for example, Zalman P. Usiskin & University of Chicago School Mathematics Project (UCSMP) (1992); Douglas Smith,

Maurice Eggen, and Richard St Andre, *Transition Mathematics* (Chicago, IL: Scott, Foresman and Company, 2014); Max Bell and University of Chicago School Mathematics Project, *Everyday Mathematics: Fifth Grade* (Chicago, IL: Everyday Learning Corp., 1995). Many of UC SMP's materials were first published by the University of Chicago, or by its spin-off, Everyday Learning Corporation, and then later purchased and published by various commercial publishers.

5 I was personally involved in the Everyday Mathematics development project when I was a graduate student at the University of Chicago. It is interesting to note that as the "reform" curriculum was adopted and adapted for the commercial textbook market, it began taking on more features of more traditional curricula.

6 See, for example, B.A. Top of Form

Crawford and M.J. Cullin, "Supporting Prospective Teachers' Conceptions of Modelling in Science," *International Journal of Science Education* 26, no. 11 (2004): 1379-1401; Bottom of Form

Planetary Forecaster (2002) The Center for Learning Technologies for Urban Schools; Barry Fishman, Steven Best, Jacob Foster, and Ron Marx, *Fostering Teacher Learning in Systemic Reform: A Design Proposal for Developing Professional Development*, paper presented at the Annual Meeting of the National Association for Research in Science Teaching, New Orleans, Louisiana (ERIC Clearinghouse, 2000); What Works Clearinghouse, ed., *The Center for Learning Technologies in Urban Schools (Letus) Program[R]. What Works Clearinghouse Intervention Report* (ERIC, May 2012).

7 Cognition and Technology Group at Vanderbilt, *The Jasper Project: Lessons in Curriculum, Instruction, Assessment and Professional Development* (Mahwah, NJ: Lawrence Erlbaum Associates, 1997). For a typology and examples from the early 2000s, see Terri L. Kurz, James Middleton, and H. Bahadir Yanik, "A Taxonomy of Software for Mathematics Instruction," *Contemporary Issues in Technology and Teacher Education* [online serial] 5, no. 2 (2005), <https://www.citejournal.org/volume-5/issue-2-05/mathematice/a-taxonomy-of-software-for-mathematics-instruction>.

8 David H. Jonassen, Jane Howland, Joi Moore, and Rose M. Marra, *Learning to Solve Problems with Technology: A Constructivist Perspective* (Columbus, OH: Merrill Prentice Hall, 1998).

9 A minor, but important discomfort I have with Greenhalgh-Spencer's article is her final example. The teacher who suggests an alternative explanation for the students' performance on a computerized assessment does not reveal any complex knowledge of computational models or even of pedagogical efficacy. Even a relatively untrained computer lab aide could have made this observation.