

Teaching within Regimes of Computational Truth

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Around the country (and around the world) teachers are seeing renewed skepticism over their abilities and professional judgement.¹ Teachers and students are being evaluated by algorithms and software packages. Scores generated by machines are taken as more “truthful” than evaluations by humans. Teachers are found lacking; and the machines are taken as infallible in their ability to understand, predict, and promote student learning. There are many discursive forces that shape the current educational landscape: where teachers are suspect and tech is king. EdTech—defined here as a group of software packages, hardware, artificial intelligence, machine learning, and algorithmic models that *compute* what is happening in schools—has reshaped how we understand teacher expertise. This article focuses on three prominent computation-oriented discourses that buttress a regime of truth which devalues teacher knowledge and expertise. 1) EdTech is trustworthy because computers and math are involved. 2) EdTech is complex and requires so much expertise that average citizens and teachers, alike, lack the ability to challenge the judgments and determinations made by EdTech. 3) Teachers are not knowledgeable professionals because teachers are bad at math and technology. These three discourses buttress a regime of truth: that teachers cannot be trusted, and EdTech can be trusted. In order to further analyze these three discourses, I begin with a brief description of terms within the article.

DISCOURSES AND REGIMES OF TRUTH

Foucault deploys the terms “discourse” and “regime of truth” in order to argue that: how we speak, and the messages we hear, create our sense of reality.² And, in turn, that created reality further guides what can be spoken and heard. Discourse is the production of reality through texts; a reality that exists

sometimes in concert with and sometimes in tension with actuality. *Discourse* becomes what we, as individuals and as societies, regard as “truth.” Foucault writes:

Truth isn’t outside power, or lacking in power ... Truth is a thing of this world: it is produced only by virtue of multiple forms of constraint. And it induces regular effects of power. Each society has its régime of truth, its “general politics” of truth: that is, the types of discourses which it accepts and makes function as true; the mechanisms and instances which enable one to distinguish true and false statements, the means by which each is sanctioned; the techniques and procedures accorded value in the acquisition of truth; the status of those who are charged with saying what counts as true.³

Discourse becomes a lens through which we live and understand our existence. In educational contexts, for example, there are many discourses that organize our expectations and assumptions around school. Discourses support the idea that testing is important, that homework is important, that children should be separated by grade levels which roughly correspond to age groups. These are ideas that have been pushed and accepted with such frequency that they have become common sense; a way of knowing and understanding what it means to be in school.

Discourse becomes truth *not* through an appeal to “immanent rationality” but through a web or relationship to other stories, narratives, and discourses at play.⁴ Foucault argues that, while science and statistics are often deployed to cement a discourse into truth, that real effect comes into play when stories and every-day experiences mirror or are seen through the lens of discourse.⁵ Anecdotes are closer to “common sense” truth than statistics, and have more power to enact the discourse *as* truth. Foucault writes that “discoursing subjects”—people who speak stories, and whose stories make sense only through a particular discourse—are part of what makes up “the discursive field.”⁶ Discourse becomes truth only as it is enacted as “subject-positions and subject-functions.”⁷ The narratives people deploy—the words they use—become indicative of regimes of truth. To that end, the examples I provide

of computational discourses will highlight stories—or words and phrases—of these three discourses at play as truth.

I purposefully call these narratives about teaching and EdTech “discourses” in order to draw attention to the ways that these ideas have been pushed and accepted with such frequency that they become ‘truth.’ When these discourses circulate, become institutionalized, and become part of the expected norm of living, they become a regime of truth; truth, connected to other truths, that organize what can be thought, who can make truth claims, and what (and who) can be believed within society.

A “regime of truth” is an organizing, producing, and governmental force that allows some statements to be seen as true, and others to be seen as false or unbelievable. Foucault defines “regimes of truth” as “a synaptic regime of power, a regime of its exercise within the social body, rather than from above it.”⁸ That is to say, these ideas circulate in society, they are not coercive policies from a ruler; they are ideas that get into your head. These ideas become “the truth.” “‘Truth’ is linked in a circular relation with systems of power which produce and sustain it, and to effects of power which it induces and which extend it: A ‘regime’ of truth.”⁹ A “regime of truth” is “the ensemble of rules according to which the true and the false are separated and the specific effects of power attached to the true.”¹⁰ Regimes of truth empower and incite the use of one discourse, rather than another discourse; they pave the way “for people to use these words rather than those, a particular type of discourse rather than some other type, for people to be able to look at things from such and such an angle and not from some other one.”¹¹

My argument is *not* that datamining is bad, or that it is a bad idea to use machines to gather data and then use that data to make predictions about the needs of students and the practices of teachers, or that the use of EdTech is nefarious or de-professionalizing. In fact, data and EdTech can be used to create counter-hegemonic discourses as well as uphold hegemonic, or normative, discourses. Rather, my argument is that there are current discourses around EdTech and the teaching profession that can lead to harm for both teachers and students because they are part of a regime of truth that has come

to organize how we, as a society, understand computers, data, and teaching; and that allows us, as members of a society where this regime of truth circulates, to understand teachers as being less capable than EdTech. I turn, now, to analyzing these three discourses.

EDTECH IS TRUSTWORTHY BECAUSE COMPUTERS AND MATH ARE INVOLVED

There are multiple discourses that support the idea that EdTech is trustworthy; more trustworthy than teachers. One discourse suggests that EdTech should be trusted because computers and math are involved. There are many examples of this discourse at play. Dreambox, one of the premier content delivery systems for teaching math in schools, advertises their software by deploying the discourse that math (data analytics) and computers can help students succeed. Dreambox announces: “Continuous formative assessment in and between lessons, analyzes over 48,000 data points per student, per hour to provide the right next lesson at the right time.”¹² Khan Academy proclaims that their learning algorithms use “state-of-the-art, adaptive technology that identifies strengths and learning gaps.”¹³ Software, designed to enhance student learning through data analytics, now relies on big data analysis and machine learning techniques. As a recent article on the use of big data in education notes, data mining techniques “find patterns in data and then build predictive models that probabilistically predict an outcome. Applications of these models can then be used in computing analytics over large datasets.”¹⁴ EdTech advertises that it uses the power of computing and math in order to analyze a student’s needs, a student’s learning gaps, and even adapt the delivery of a lesson to the needs of a student. EdTech deploys:

... a suite of computational and psychological methods and research approaches for understanding how students learn. New computer-supported interactive learning methods and tools—intelligent tutoring systems, simulations, games—have opened up opportunities to collect and analyze stu-

dent data, to discover patterns and trends in those data, and to make new discoveries and test hypotheses about how students learn. Data collected from online learning systems can be aggregated over large numbers of students and can contain many variables that data mining algorithms can explore for model building.¹⁵

Advertisements constantly spotlight the use of math, the use of computer algorithms, and the massive amounts of data that are analyzed by the computer; more data than a human teacher could ever analyze. EdTech leverages our societal fascination with math, and belief that “the referential meanings assigned to mathematical constructs ... do not merely inscribe a pre-existing real world situation but constitute it.”¹⁶ Hegemonic and normalizing discourses sustain the idea that math *is* reality.

This discourse—that EdTech is trustworthy because it uses math and computers—is supported by further societal discourses suggesting that computers and math are objective. Eduard Glas argues that, while humans interpret the results of math in various subjective ways, math itself is able to show the world as it is; “conflicting claims about the truth or falsity of particular statements, seem not to exist in mathematics.”¹⁷ Other scholars have pointed out that, in the very act of doing math, we realize that math is objective. “Anything from solving a homework problem to proving a new theorem involves the immediate recognition that this is not an undertaking in which anything goes, in which we may freely follow our personal or collective whims; it is, rather, an objective undertaking par excellence.”¹⁸

Discourses on the objectivity of math support discourses on the objectivity of computer technology. As Cathy O’Neil observes, verdicts that are generated by computers—using math—are taken as absolute truth.¹⁹ You cannot coerce or bribe a computer with a mathematical model. “That’s part of their fearsome power. They do not listen. Nor do they bend. They’re deaf not only to charm, threats, and cajoling but also to logic—even when there is good reason to question the data that feeds their conclusions.”²⁰ Teachers can be charmed and coerced. They can like or dislike a student, and this can shape

how they grade the work of and understand the needs of a student. EdTech is not seen in this same way. EdTech is seen as relying on the objectivity of math and computing, and, therefore, is seen as more trustworthy in its ability to adequately assess and work with students.

When teachers are compared with technology in their ability to know and address the needs of students, it is often the teachers who are found lacking. The U.S. Department of Education released a report noting that data-driven instruction was the trend of the future, and that technology would enable data-informed learning that was beyond the reach of most teachers.²¹ The Institute of Education Sciences released a report arguing that modern education requires data-informed instruction, and that teachers are not yet trained enough to be able to use data and analytics in a meaningful way.²² Technology is seen as the panacea; more than that, teachers are seen as incapable learners who have still not adapted to technology's ability to tell truths about our students. This haling of technology over teachers can be seen in the U.S. Department of Education's release of their National Educational Technology Plan.²³ It calls for the increased usage of technology in: student assessments, teacher evaluations, educational content, and curriculum development. The plan notes that, in order for students to be "future ready," teachers and schools must adapt to the new technology-driven needs of our world. Schools should establish "robust technology infrastructures," in order to guide both teaching and assessment. Teachers and students must adapt; EdTech is king.

EDTECH REQUIRES EXPERTISE, AND CANNOT BE CHALLENGED

Another discourse that supports the dominance of EdTech over human teachers is the discourse that EdTech requires expertise; and that it is so complex that most humans cannot understand it, and therefore, humans should not challenge the way it works or the conclusions it generates. O'Neil gives an example of how this works. She spotlights the IMPACT assessment tool for evaluating teachers. IMPACT was created by Princeton-based Math-

ematica Policy Research. The firm describes the test as one that can measure what teachers are *truly* teaching, and they can measure this as an independent variable from socio-economic status. The test is supposed to measure student learning gains and growth over time, and also be able to reliably describe what portion of that student growth is attributable to teachers. Many school districts use this test, and many teachers have been fired for failing to score above a certain threshold on the test.²⁴ O’Neil describes a number of teachers who went to the districts that fired them and complained about the IMPACT test. These teachers said that they had always received stellar teaching evaluations. They showed the laudatory notes from parents and students. They asked about the assumptions that went into IMPACT. What was it measuring? “It’s an algorithm, they were told. It’s very complex. This discouraged many from pressing forward. Many people, unfortunately, are intimidated by math.”²⁵ These teachers were told that statisticians worked on the algorithm and that all of the scores were computed by a machine. IMPACT was merely letting “the machines do the talking.”²⁶ The teachers could not fight against the verdicts of IMPACT because they did not know the assumptions that undergirded the model on which IMPACT relies. The teachers were told over and over again that the model was simply too complex for them to understand.

O’Neil points out that EdTech often relies on algorithms or mathematical models that are hidden from the public. The public does not see the assumptions that undergird the models. The software generates the ‘answers,’ and then discourses suggest that the ‘answers’ cannot be questioned. As O’Neil contends, the verdicts generated by these algorithms and EdTech firms “land like dictates from algorithmic gods.”²⁷

The model itself is a black box, its contents a fiercely guarded secret. This allows consultants like *Mathematica* to charge more, but it serves another purpose as well: if the people being evaluated are kept in the dark, the thinking goes, they’ll be less likely to game the system. Instead, they’ll simply have to work hard, follow the rules, and pray the model registers and appreciate their efforts. But, if the details

are hidden, it's also harder to question the score or protest against it.²⁸

Discourse suggests that this is how the world is; and how it *should be*: math and computers are objective; math and computers are also really difficult to understand; you do not have the expertise to understand the math that undergirds EdTech, and you do not understand the algorithmic functions that are computing assumptions about teachers and students. Therefore, you cannot challenge the verdicts generated through EdTech.

The discourse that EdTech is objective suggests that we, as humans affected by EdTech, *do not need to* question the assumptions and verdicts generated by EdTech. After all, it's objective. The discourse that EdTech is very complex suggests that we, as humans, *are not capable of* understanding what the algorithm or software package is doing. The first discourse says we *should not* challenge or disagree with EdTech. The second discourse says *we cannot* challenge or disagree with EdTech. These discourses support a 'common sense' notion that we should trust what the machines or numbers say, instead of what the teachers say.

TEACHERS ARE NOT PROFESSIONALS, AND ARE BAD AT MATH AND TECHNOLOGY

A discourse that adds to this "common sense" notion of trusting machines over teachers is the discourse that suggests: teachers are not professionals because they are bad at math and technology. This discourse is powerful and believable because it links into discourses about gender. According to a US Department of Education survey, in 2017, seventy-seven percent of the nation's teachers were women.²⁹ In the US, one of the powerful discourses that shapes how we think of women is the discourse that says: women are bad at math and technology. Many scholars have pointed out that men and women receive social messages suggesting that women are not good at math.³⁰ Schools, parents, and the media often confirm the idea that women and girls are not good at math.³¹ Gerstenberg et al. provide a riveting account of the

ways that girls and women will second guess their abilities, even when they perform well in math courses.³² Furthermore, when women and girls finally do acknowledge that they can do math, they tend to see themselves as the exception to the rule, rather than considering that the “rule” might be wrong.³³

Similar messages exist about women and computers or other forms of digital technology. Multiple scholars have highlighted the ways that social messaging works to convince the public that girls and women are bad at technology.³⁴ The Annenberg Center and FEM inc. put together a report on prevalent media messages about women and girls in technology fields.³⁵ In their report, they detail the many ways that the media reinforce the idea that women and girls are not interested in technology, and lack the abilities to do well in technology-driven fields like computer science and software/hardware development. If women are bad at math and technology, and most teachers are women, then it seems obvious that teachers are bad at math and technology. These discourses about gender, math, and technology reinforce the devaluing of teacher expertise, especially if teacher expertise is pitted against a computer algorithm.

Teacher expertise is already suspect because of circulating discourses that reinforce the idea that teaching is the job of unskilled labor: it is babysitting. Nelson et al. contend that teachers often have to defend their dignity and their abilities, because so many parents, as well as the public, see them as “babysitters.”³⁶ Evidence for this discourse is everywhere. One Reddit thread targets elementary school teachers by claiming: “It’s not a real job; you have to make sure the kids don’t stab each other with scissors or eat crayons and glue. A couple 15yo kids could do it, so stop complaining that you’re not paid enough.”³⁷ Penelope Trunk, a prominent blogger in the home school sphere, writes: “Public school is a huge infrastructure set up as a social service program. It is terrible at teaching kids how to be successful adults, but it’s great at providing a safe way to care for kids, no matter what their income level.”³⁸ Normative discourses suggest that teachers are unskilled and do not deserve to be paid much more than minimum wage. When this discourse is added to other discourses about women, technology and math, it is particularly difficult

for teachers to be taken seriously when they challenge the edicts of computer algorithms.

REGIME OF TRUTH: IMPLICATIONS FOR TEACHERS, SCHOOLS, AND STUDENTS

Foucault argues that hegemonic discourses—discourses that are accepted as truth or “normal common sense”—bind together to create a regime of truth; a structuring of reality. A regime of truth “incites, it induces, it seduces, it makes easier or more difficult; in the extreme it constrains or forbids absolutely ... It is a matter of guiding, leading the conduct of others; it is a question of ‘government’; to exercise power in the sense of ‘government’ is ‘to structure the possible field of action of others.’”³⁹ There is a regime of truth that structures the ways that information developed through algorithms is treated as sacrosanct, and “teacher knowledge” is treated as suspicious. This regime is buttressed by multiple societal discourses; I have focused on three of them. This regime of truth supports a reality whereby teacher expertise is devalued and students (and student learning) is made synonymous with whatever the computational models can measure. Increasingly, EdTech, and the computational models undergirding EdTech, are producers of reality; at the expense of student, parent, and teacher experience. This is not the *fault*—so to speak—of EdTech, but rather, it is evidence of discursive effects. EdTech is not the danger so much as the discourses that buttress the “truth” that EdTech is objective and accurate. This is dangerous, because the computational models embedded in EdTech are neither objective nor completely accurate.⁴⁰ I end this article with an “on-the-ground” experience of interacting with teachers, students, and algorithms.

VIGNETTE

Observation:

Student #1 is taking a math quiz using a computer program

that not only measures how many answers she gets correct, but also measures “grit.” For this computer program, “grit” is measured by whether or not a student continues to work on a math problem even if it is difficult for her. “Difficulty” on the math problem is measured by how much time the student spends on answering each question. Student #1 completes the math quiz; she gets all of the answers correct; and she spends fifteen minutes on the quiz. The computer program congratulates her at the end of the quiz because she got all of the answers correct; and she spent fifteen minutes rather than the “normal” ten minutes that she ordinarily spends on similar tests. The computer program assumes the student has shown evidence of “grit” because the student spent more than the “normal” amount of time on the quiz.

Student #2 is sitting next to student #1. She is taking a math quiz using a computer program that not only measures how many answers she gets correct, but also measures “mastery.” For this computer program “mastery” is measured by how much time it takes a student to choose the correct answer compared with an established norm of how much time it *should* take. Student #2 completes the math quiz; she gets all of the answers correct; and she spends fifteen minutes on the quiz. The computer program tells her that she must repeat the quiz because she has not yet achieved mastery. “Mastery” would have required getting all of the answers correct in eight minutes.

Teacher says:

Neither computer program is correct! The computer models are wrong. The students each took fifteen minutes be-

cause they talked to each other rather than focusing on the quizzes.

I ask:

Will you believe the teacher?

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