The Mathematics Enthusiast

Volume 20
Number 1 *Number 1, 2 & 3*

Article 16

4-2023

Putting Math in its Place A Review of Cathy O'Neil's Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy

Nathalie Sinclair

Recommended Citation
Sinclair, Nathalie (2023) "Putting Math in its Place A Review of Cathy O'Neil's Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy," *The Mathematics Enthusiast*: Vol. 20 : No. 1 , Article 16.
DOI: https://doi.org/10.54870/1551-3440.1598
Available at: https://scholarworks.umt.edu/tme/vol20/iss1/16

Putting Math in its Place

A Review of Cathy O'Neil's *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*

Nathalie Sinclair[1]
Simon Fraser University

With its bright yellow cover and its ominous title, this book attracts attention. The subtitle, "How big data increases inequality and threatens democracy" signals very strongly that the "math" in question in the title is primarily that which relates to the statistical and computational means of collecting, analysing and using data. For some readers, the title might be surprising, because it challenges the typical understanding of mathematics as an objective and value-neutral discipline. Worse, it claims that mathematics is significantly involved in creating inequality and compromising democracy. If it is true, then the answer to the perennial student question, "when am I ever going to use this?" has now become, "when will it use you?"

There are plenty of people in the humanities and social sciences who critique the sciences (including mathematics) for their modes of inquiry, which privilege objectivity, precision and abstraction. Some argue that scientific research ignores the historical, social and cultural embeddedness of knowledge and ideas, as well as the consequences of objectively made choices on the health, safety and well-being of humans and the environment. In many instances, these critiques come from people with very little experience actually doing science or mathematics, which means they often criticize the disciplines as a whole. This is not the case with Cathy O'Neil, who has a PhD in mathematics and is very knowledgeable about the use of big data in many different applied contexts, including the financial industry. She's an insider.[2] This is precisely what makes her own critique so powerful: she still loves mathematics *and* she sees the value in some uses of big data. However, she has also seen first-hand the misuse of big data in a variety of contexts, and

[1] nathalie_sinclair@sfu.ca

[2] In the second chapter, which is entitled "My Journey of Disillusionment", O'Neil recounts how she went from an enthusiast to an informed critic. Importantly, her own understanding about the misuse of big data was gained through participation in meetings that included a diverse range of people, which is a stark contrast to the narrow swatch of the population tasked with designing and programming the algorithms making use of big data.

The Mathematics Enthusiast, **ISSN 1551-3440**, vol. 20, nos. 1, 2 & 3, pp. 132-138.

the repercussions of this misuse on the lives of people, many of whom are already disadvantaged because of their socio-economic status, gender, race, disability or sexual orientation. In her book, she shows how the three characteristic features of weapons of math destruction, or WMDs—which are Opacity, Scale and Damage—increase inequality.

The book contains many case studies on the use of big data to make decisions about a range of topics, including college rankings, targeted advertising and credit ratings. While all of these case studies are based in the United States, similar effects have also been documented in Canada (The Montreal Declaration, 2018) and elsewhere in the world (Noble, 2018). There are two particularly interesting case studies for those working in education, one of which involves college rankings and the other, found both in the Introduction and in Chapter 7, which involves evaluating teachers' performance. In the latter, O'Neil describes the use of big data in particular jurisdictions in the USA to evaluate teacher performance (including identifying which teachers to fire). I will describe it in some detail in order to provide a better sense of O'Neil's argument as it relates to the use and abuse of mathematics. To be clear, her point is not that mathematics or algorithms or data are somehow intrinsically bad. She cites many situations in which they can be validly used. What she is interested in is why and when they are poorly used and how that matters to democracy.

In order to use big data to make decisions about things, one needs a model of the phenomenon in question. If we want to decide which teachers are performing well, we need a model of what a good teacher is. One model, which has been used in the past, is that a good teacher is one whose students succeed well on standardised tests. With this model, which might even grade teachers on a curve, it would be possible to look at the average marks of a teacher's students and rank the teachers from worst to best. Because the model does not require the subjective determination of a principal or colleagues or students or parents, who might take into account factors such as the teacher's race and gender, it may strike many people as refreshingly objective—the same way as choosing orchestra players by having them audition behind a curtain. However, the model is deeply flawed: the very same teacher working in very different conditions (with different students, in a different school, with different colleagues) could get wildly different scores.

While it had the advantage of being transparent, in that the students' test scores can be made available to teachers, the mathematicians hired to create the model decided they needed proxy data in order to try to account for the complexity of identifying underperforming teachers.

This gave rise to a new mode, called the value-added model, which was used in New York. This new model tried to be fairer, by not advantaging teachers who worked in prosperous neighbourhoods, for example, or who had very few students with learning disabilities in their classes. Instead of measuring teachers on an absolute scale, the new model tried to adjust for social inequalities. In order to do this, the new model compared students with forecasted models of themselves—how should each student be expected to perform on a test in the future? The students each had a predicted score. If they surpassed the prediction, their teacher received the credit. This constituted a shift from a primary to a secondary model; whereas the former involved direct measurement (of averages on test scores), the latter relied on so-called error terms, which are the gaps between an actual result and an expected one. This secondary model was derived from a bunch of proxy statistics that, argues O'Neil, were based on "guesses on top of guesses". These statistics, which predicted student success, were based on correlations between a person's zip code or their language spoken at home. They were fed into algorithms that weighted a bunch of factors—where positive reviews by an administrator were vastly outweighed by statistics deemed more objective. It can become difficult sometimes to remember that there is a difference between real people and the technical models used to describe them.

A significant problem with this value-added model is that it lacks scalability because it depends on insufficient data, both in relation to the teacher (n = 1) and the student (n = 30, for most classes). Although there were allowances made for SES and disability, it is extremely problematic to make predictions about any individual student, because you cannot run tests on how each child would learn with each different teacher. There are certainly cases in which such data is available: Google can finish your sentence for you because it has millions of datasets that show what is likely to happen next when you write "How are" in a text message. Furthermore, because it receives feedback on what people actually write, it can adjust its algorithm and tailor it to certain demographics, suggesting either ‘How are you?” or “How are things?” Similarly, O’Neil points out how effective baseball statistics can be; they are based on a large number of observations (of where a player hits the ball) that can be used to predict future hits (thus enabling outfields to adjust their positions) and updated in case of changes (the player starts hitting in a different way or in a different direction).

The algorithms used to identify underperforming teachers could not be trained in the same way—there was no feedback into the system. Worse, they lacked transparency. Neither teachers nor district co-ordinators were able to see the algorithm, let alone try to understand it. After all, the models and algorithms are intellectual property produced by the mathematicians working for big data companies. O’Neil argues that self-perpetuating and highly destructive models are very common and that they increase inequality because they often use data from the past to determine or to predict the future, which means that past norms are projected into the future, continuing to disadvantage people who are already disadvantaged. As she writes, “models are opinions embedded in mathematics” (p. 21). For example, when credit rating is used by employees to determine which candidates will be invited in for an interview, those who have had difficulty in the past (for reasons that may have nothing to do with their qualifications or eventual job performance) will be disqualified.

From the above description, it would be easy to conclude that we just need to improve our use of big data, and that we can do so by making sure that models make use of sufficient data and that algorithms are made transparent. Certainly, there are cases in which such improvements would be possible. But in the case of identifying underperforming teachers, it is not really clear it would be possible. O’Neil is arguing that the danger of big data use is not just that it gets used in contexts in which it should not, but, more perniciously perhaps, (1) it gets used because of the assumption that mathematics is somehow objective and value neutral and (2) its use is not questioned because of the widely shared belief that mathematics is something that cannot be understood. And these are the issues that feel to me highly relevant to mathematics education research. If O’Neil is right, the threat to democracy has something very significant to do with our failures in the mathematics classroom.

The first issue raised by O'Neil's book is one that has been addressed extensively in the research literature, particularly by scholars working by focusing on social justice issues (see, for example, Gutstein and Peterson, 2013). However, despite the growing size of such research, it is still dwarfed by studies that fall in the *Predict* and *Understand* paradigms identified by Stinson and Walshaw (2017), rather than in the *Emancipate* and *Deconstruct* ones, which tend to investigate how mathematical meanings and values are legitimised, as well as how certain forms of knowledge are privileged or marginalised. So, it could be argued that more such research needs to be done. This might lead to more opportunities for teachers and students to learn about the various ways in which mathematics can be used to oppress and to silence, as well as to celebrate and to recompense.

In many ways, the book should have been titled 'Weapons of statistics destruction'. O'Neil provides examples of statistical errors that have occurred in the past, sometimes with terrible consequences. From this point of view, it may be that statistical literacy is what is needed, something which some Canadian provinces (such as Ontario) recognised early on, while others (e.g. British Columbia) still have not. The more recent push for computational literacy, which has come in the form of provisions for more coding experiences in K–12 schooling, seems to have eclipsed statistics literacy, and may even go on to overtake mathematics as the gatekeeping discipline. However, none of the existing K–12 curricula in Canada seem to have an ethical or social responsibility component to their coding courses, which means we will most likely replicate the current situation. That said, there is little leadership from university computer science departments on this issue.

O'Neil's second point is just as troubling, as it depends on the fact that too many people do not feel that they can question mathematical formulas or models. This may be about insufficient knowledge, but it is likely also to be much more dependent on mathematical anxiety: when people see numbers, they look the other way. *We are not producing mathematically literate citizens who see it as their right to understand the mathematics* that is determining more and more aspects of their lives. Can we really afford to wait for a whole new generation of students? Similarly, can we really afford to continue to allow financial and technology industries to gobble up all of the extremely mathematically literate students graduating from universities? What courses could they be taking that would entice them to use their mathematical talent towards enhancing a more just society?

Indeed, for Stengers (2018), the fact that there are weapons of math destruction is a consequence of the long-standing mistrust and lack of communication between the (hard) sciences—which are the “thinking, rational brain of humanity”—and the (soft) humanities. Even though many universities now require science students (although not mathematicians, nor computer scientists) to learn something about the epistemology and history of science, what they learn is often forgotten. Stengers believes this is, in part, because, “they have learned that the sciences allow problems to be ‘well-posed’ and therefore amenable to being given the ‘right solution’” (p. 11). Brown (1993) offered a very similar critique of mathematics education and its false ‘aesthetic unity’ that refuses to acknowledge the complex, value-laden and changing nature of problems in the real world. Stengers argues that scientists need more intentionality to refuse to have their expertise used against the concerns of the public and must avoid spreading the belief that scientific progress will resolve all of society’s problems. In the context of WMDs, Stengers would urge mathematicians to engage more openly and with the public in making clear what kind of knowledge it is capable of producing.

References

Brown, S. (1993). Towards a pedagogy of confusion. In A. White (Ed.), *Essays in Humanistic Mathematics* (pp. 107–121). Washington, DC: The Mathematical Association of America.

Gutstein, E., & Peterson, B. (Eds.) (2013). *Rethinking mathematics: Teaching social justice by the numbers* (2nd edn). Milwaukee, WI: Rethinking Schools.

Noble, S. (2018). *Algorithms of oppression: How search engines reinforce racism*. New York, NY: New York University Press.

O’Neil, C. (2016). *Weapons of Math Destruction*. New York, NY: Crown.

Stengers, I. (2018). *Another science is possible: A manifesto for slow science (S. Muecke, trans.)*. Cambridge, UK: Polity Press.

Stinson, D. & Walshow, M. (2017). Exploring different theoretical frontiers for different (and uncertain) possibilities in mathematics education research. In J. Cai (Ed.), *Compendium for research in mathematics education* (pp. 128–155). Reston, VA: National Council of Teachers of Mathematics.

Université de Montréal / Research. Montreal Declaration for a Responsible Development of Artificial Intelligence - La recherche - Université de Montréal. (2018). Retrieved from https://recherche.umontreal.ca/english/strategic-initiatives/montreal-declaration-for-a-responsible-ai/