

# PERILOUS EQUATIONS



E D I S O N M I Y A W A K I

What is the mightiest of the sciences? If judged by the power of its weaponry, math vies for preeminence. Enter Cathy O’Neil, who is a Ph.D. mathematician, once a Barnard academic with a concentration in number theory (the “queen of mathematics,” as the field has been called); then she turned “quant” for a company nicknamed the Harvard of hedge funds; then she left all that in 2009. She has a website called mathbabe.org, where, somewhat at random, I found this rant from 2013: “It seems pretty clear we can chuck trigonometry out the window, and focus on getting the average high school student up to the point of scientific literacy that she can read a paper in a medical journal and understand what the experiment was and what the results mean. Or at the very least be able to read media reports of the studies and have some sense of statistical significance. That’d be a pretty cool goal, to get people to be able to read the newspaper.” Skipping over her employment at start-up internet companies before she returned to

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**Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy**, by Cathy O’Neil (Crown, 259 pp., \$26)

New York's Morningside Heights and Columbia University, we arrive at the present: her new book, *Weapons of Math Destruction*, has no equations in it, yet her subject is scientific. To paraphrase from 2013, she teaches us that we can't yet read the newspaper in our lives – and, be forewarned and forearmed, there's danger in the news.

O'Neil doesn't think that math itself is a device of some horrific sort – and for the record, she has nothing against trigonometry in particular, although she's angry when it's taught poorly in high school. Math isn't the problem, but O'Neil sees in the news and in light of her private-sector experience that math can be coopted and abused – therein lies one nontrivial danger. But there's a far bigger threat. A non-quant (meaning: most of us) hears that a quant (also known as a “data scientist,” as O'Neil calls herself these days) has determined that something is true, proven, or compelling. We agree with the scientist, but in the assent we metaphorically explode ourselves to smithereens. Reviews of O'Neil's crisply written book have not articulated a surprise in it, so let me try. She discusses math as an analytical weapon, but who would anticipate that we turn it upon ourselves? Is it false comfort to argue, as O'Neil does, that there are outside enemies when, in fact, the danger is our own proclivity to analyze? She alleges that “big-data” widens the gap between haves and have-nots and even threatens democracy. Big-data is an Orwellian personification, a controlling, nefarious force perhaps. But data – big, small, or indifferent – are just data; a datum is a datum, nothing more or less. The moment we *use* data, however, there are consequences of the analysis – sometimes good, very often bad. Maybe we'd prefer to ignore data altogether, but it's fascinating to consider that we can't help ourselves. We steal any peek at analysis in the same way that we can't avoid looking at ourselves in a mirror.

In one of her more wilting critiques, a chapter called “Arms Race: Going to College,” O'Neil examines *U.S. News and World Report's* ranking of eighteen hundred American colleges and universities – all the nonprofit four-year institutions in the nation. “The story starts in 1983,” she narrates; that year, the magazine faced lackluster readership vis-à-vis *Time* and *Newsweek*. “A college-ranking issue, editors hoped, might turn into a newsstand sensation. . . . In

the beginning, the staff at *U.S. News* based its scores entirely on the results of opinion surveys it sent to university presidents.” But that ranking, which crowned Stanford as the finest university and Amherst as best liberal arts college, inspired the disappointed wrath of many who believed that they deserved a higher rank. Because surveys and their subjectivism were dubious, so the arguments ran, the magazine should have examined *data*. In fact, looking at the data is where the story gets interesting.

*U.S. News* created new methodology to address criticism it received, and a less subjective ranking appeared in 1988. The magazine “picked proxies that seemed to correlate with success. They looked at SAT scores, student-teacher ratios, and acceptance rates. They analyzed the percentage of incoming freshmen who made it to sophomore year and the percentage of those who graduated. They calculated the percentage of living alumni who contributed money to their alma mater, surmising that if they gave a college money there was a good chance they appreciated the education there. Three-quarters of the ranking would be produced by an algorithm – an opinion formalized in code – that included these proxies. In the other quarter, they would factor in the subjective views of college officials throughout the country.” The surmise was that proxies had something to do with what one really sought to measure. *U.S. News* wanted to judge the excellence of any given institution and the education it provided, but “had no direct way to quantify how a four-year process affected one single student, much less tens of millions of them.” Were the “correlations to success” dubious? A *New York Times* satirist reported in 2016 that Stanford had just achieved an insuperable acme of proxy: a zero acceptance rate to the incoming freshman class. Given that datum alone, Stanford becomes the academic Mecca to which no student could travel, and Stanford irrevocably remains the nation’s finest university.

Satire pales to reality. O’Neil describes fallout in the aftermath of avid interest in the *U.S. News* rankings, an interest that exceeded any prognostication of success by the publisher: “Some administrators have gone to desperate lengths to drive up their rank. Baylor University paid the fee for admitted students to *re-take* the SAT, hoping another try would boost their scores – and Baylor’s ranking. Elite small schools, including Bucknell Univer-

sity in Pennsylvania and California's Claremont McKenna, sent false data to *U.S. News*, inflating the SAT scores of their incoming freshmen. And Iona College, in New York, acknowledged in 2011 that its employees had fudged numbers about nearly everything: test scores, acceptance and graduation rates, freshman retention, student-faculty ratio, and alumni giving. The lying paid off. . . . *U.S. News* estimated that the false data had lifted Iona from fiftieth to thirtieth place among regional colleges in the Northeast." Compared to the cheats by Bucknell, Claremont McKenna, Iona, and presumably others, Baylor seems noble: at least it tried to submit honest data, but then again there's the pointlessness of retaking an SAT after acceptance to a university. From a Baylor student's point of view, maybe she or he got compensation exceeding the price of the SAT itself, to make the exercise less pointless for her or him.

O'Neil defines algorithm as an opinion in code. In context, *code* means something like "computer program," but the word connotes secrecy — a dangerous opacity in how analysis proceeds. She also refers to algorithm or code as "a model": "When you create a model from proxies, it is far simpler for people to game it. This is because proxies are easier to manipulate than the complicated reality they represent. . . . In the case of the *U.S. News* ranking, everyone from prospective students to alumni to human resources departments quickly accepted the score as a measurement of educational quality. So the colleges played along. They pushed to improve in each of the areas the ranking measured." "Algorithm," "opinion in code," and "model" all refer to some kind of device by which we see something more clearly, if the instrument is good enough. O'Neil's sees math in all her algorithms, codes, and models, but it might be useful to step back historically to consider a different tool in science.

Rewind to the early eighteenth century: a French scientist named Xavier Bichat voices doubt about a new Dutch device, first built by spectacle makers in the seventeenth century, called the microscope. Bichat thinks that it introduces error to observation by the naked eye. He's not wrong, because a microscope does distort reality under its lens. The Dutch microscope makers were fully aware of the problem, and well into the 1670s they improved their devices to fix lens distortion. Anton van Leeuwenhoek's most

powerful microscope, of the 247 that he constructed in his long lifetime (1632–1723), had a resolution to about one or two one-thousandths of a millimeter. English and German scientists used microscopes throughout the late seventeenth century, but important publications based on microscopy date only to the early nineteenth century, as in Thomas Hodgkin’s “On Some Morbid Appearances of the Absorbent Glands and Spleen” (he described the disease that would be named after him). Why did Bichat-like bias against the microscope persist for roughly a century? Answer in three parts: Bichat wasn’t wrong in the first place; the microscope improved as a device from the seventeenth through the nineteenth century; and, as all orthodoxies are inclined to do, scientific orthodoxy resisted change.

Fast forward to the sad gaming of algorithms in American education: O’Neil distrusts the *U.S. News* ranking as “squishy” even at its most algorithmic. She thinks that too many models are accepted *prima facie* – long before they, as tools, have improved enough to be used meaningfully; and, worst of all, since numbers have orthodox credibility in the twenty-first century, we accept quant-conclusions, only to retake entrance exams after admission or lie outright to outrank peers. As in the history of the microscope and its reception over time, perhaps all we really need is a device with finer resolution or a contemporary Leeuwenhoek to build us one. Also, it wouldn’t be bad to dump preexisting bias from time to time – which is the point of a critical look at anything.

Maybe the shibboleth “best institution” is absurd. Universities themselves, we recall, chided *U.S. News* for its lack of data in 1983. They unwittingly asked: *Seriously*, isn’t there a best of the best; can’t we find some facts to back an opinion? The line of questioning persists today, even if all good sense explodes in the process. To make a reasonable counterstatement, such as “The best university is the best one . . . for you” sounds tepid by comparison, with a hint of acrid defeat: did the best ones snub you or your daughter or son? O’Neil says early in her book, as a mantra applicable to rankings, “The math could multiply the horseshit, but it could not decipher it.”

How rampant is her multiplication problem? Algorithm is a contagion with epidemic reach, O’Neil thinks. Math-based codes

“leap from one field to the next, and they often do.” As an example, she describes one tried-and-true method called a Monte Carlo simulation, a type of statistical sampling. She asks us to think about a croupier spinning a roulette wheel ten thousand times; each outcome is a datum. Let’s just consider the numbers assigned to slots where the roulette ball lands. In European Roulette, there are 37 possibilities for any one spin – slots numbered 0 to 36. After ten thousand spins, what distribution of numbers might one expect? If you answer a random distribution, then you’re only partly correct. A Monte Carlo simulation pushes us to ask what kind of randomness we observe after thousands of spins – or after any number of spins. Would the distribution of numbers 0–36 materially differ after a million spins? If we had a different croupier? In a simulation, you could introduce any variable you like. Applications of Monte Carlo are legion, because *any* random series of events – *apparently* random, one should say – could be studied in simulation.

A famously bizarre instance involves dropping any number of matchsticks, toothpicks, or pins onto a surface marked with parallel lines. You’re curious to know how many toothpicks of a specific length cross any of the parallel lines (the distance between lines is specified as well). You conduct multiple trials; you vary the number of toothpicks dropped, vary the distance between the parallel lines. The exercise seems random, until you discover that toothpick length, number of toothpicks dropped, distance between lines, and number of crossings all relate to each other unexpectedly. A ratio of length and number divided by distance and crossings gets closer and closer to 3.14159 . . . (the number pi), which is the ratio of any circle’s circumference divided by its diameter. Okay, who cares? Is it all a multiplication of horseshit?

Phrased more delicately, does math based on thousands of past trials predict unknowns in the future? Monte Carlo is simulation, or is it prediction? As we turn to O’Neil’s retelling of an American economic tragedy called “mortgage-backed securities,” we might recall a warning, mandated by the U.S. Securities and Exchange Commission in any solicitation for investment, that “past performance does not necessarily predict future returns.” Mortgage-backed securities were widespread until a collapse of both the mortgage and the stock market in 2008. To define it simply, the

security in question was a financial instrument: a dividend-paying IOU backed by a pool of debt backed by collateral. The “pool” – a vast mortgage debt paid by heartbreakingly large numbers of the poor – had reached about \$3 trillion by 2007. Money to pay mortgages as well as the IOU dividends flowed long enough for mortgage-backed securities to become a hot item to buy, sell, and trade, but the risk model used to study those securities relied on errant algorithms. What if the value of the original collateral decreased or debt payments stopped; what if there were defaults? Past experience suggested that defaults were random and unrelated to each other. If defaults were sporadic, then debt payments and IOU dividends still could be paid in general, even if occasional failure was inevitable. Models suggested tolerable risk. But, as O’Neil chimes in, the risk models assumed that the future would be no different from the past. The upshot was disaster in the second half of 2008: “That’s when everyone finally saw the people on the other side of the algorithms. They were desperate home owners losing their homes and millions of Americans losing their jobs. The human suffering, which had been hidden from view behind numbers, spreadsheets, and risk scores, became palpable.” Millions of Americans took a beating, both rich and poor, the latter more deeply and viscerally than the former.

Here’s a personal question (mind you, there are algorithms for all these events in daily life): the next time you invest, make an online purchase based on marketing that targets you individually, seek your credit score, answer a questionnaire in search of employment, communicate with “friends” on Facebook, or perform any activity that generates privileged data for others to see do you lapse into irrevocable paranoia and fear of interaction with others? O’Neil suggests distrust isn’t enough – and, frankly, it’s defeatist. She wants scientific literacy for the sake of all, so that we can dismantle the weapons used against us. She’s strident on the subject; she thinks the future of liberal democracy hangs in the balance.

That tone starts to grate after a while in *Weapons*, but eventually her rhetoric subsides to a tamer whisper. Then she asks the best question in her book: “How do we start to regulate the mathematical models that run more and more of our lives?” Following the

2008 crash, quants drafted a document to advance the ethical use of algorithm. O’Neil likes the idea of an oath such as students take at the end of medical school – oaths, Hippocratic and otherwise, are about standards of conduct. I’ll quote only one line from “The Financial Modeler’s Manifesto” of 2009:

*I will remember that I didn’t make the world, and it doesn’t satisfy my equations.*

The meaning, of course, is that the world doesn’t *necessarily* satisfy one’s equations, even if there’s an ongoing effort to craft models to predict all our futures reliably: it’s the work that science does, as do Google, Amazon, Facebook, enforcers of civil and criminal law, your financial and educational institutions, your government. But note the specific words of the manifesto’s promise. Do the modelers actually need “to remind” themselves that they didn’t make the world? At what point did they slip into the blind delusion that they did make it? One needs to be very careful about what is taken to be analysis these days, and ever since medical school and my own oath, I’ve found an allegory helpful as a reminder to self-correct my science often and repeatedly.

Two doctors stand under a streetlight in the jet-black night. The light is the only illumination as far as the eye can see. One doctor throws a set of keys into the darkness, then begins to search everywhere in the area illuminated by the streetlight. The other doctor asks, “What are you doing?” The doctor answers, “I’m looking for my keys.” The other doctor is mystified. “But didn’t you just throw your keys into the darkness?” “Yes,” the doctor responds, “but I’m looking where the light is.”

Which doctor are you? Speaking for myself, I’m often the one who throws keys into the night, in search of my keys where the light is. Searching depends on tools, and you use the tools you’ve got: you don’t have a choice. Then again, sometimes I’m the other doctor in a state of utter mystification, because I know the keys are in the darkness. Both doctors are scientists, by the way. Both are ardent in what they do, pursuing their work “purely and devoutly,” as Hippocrates insists that they do. A person could say the doctor in search of keys is an idiot, but that doctor could be the one using the available tools of the mightiest science.