The Invisible Political Economy of Algorithms

A Review of Weapons of Math Destruction by Dr. Cathy O'Neill (2017 Broadway Books)

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It's raining. You forgot your umbrella! Do you then, like me, promise yourself to always check the weather forecast before leaving home? If you do change your routine, then you will be updating your personal algorithm, the set of instructions which guide your dressing for the day. . It is a good algorithm because you designed the routine to help attain goals you desire, such as comfort. Also, you can test and adapt it as the circumstances of life alter, as summer turns to fall or as you move from work to social life.

Algorithms are automatic routines, sets of instructions and assessment criteria, which are programmed into computers and which generate invisible decisions that affect our political and economic lives in vital ways such as access to credit, insurance and job interviews. Dr. Cathy O'Neill, author of Weapons of Math Destruction, wants us to understand the difference between good and bad algorithms so that we can gain more control over our lives. The problems presented by these robotic decision makers are not obvious. It took Dr. O'Neill, a child math prodigy and former math professor who helped design algorithms for a hedge fund, quite a while to comprehend that certain types of algorithms are destructive to our personal and social goals and tend to increase inequality. She calls them weapons of math destruction or WMD's.

Be alert! Stay alert! The use of algorithms is spreading fast and worldwide. When you read that 72% of resumes are assessed by algorithms rather than humans, you realize that these are not trivial issues. Dr. O'Neill's goal is to make the problems and possibilities of algorithms visible to us so that we can strive to render algorithms "our tools and not our masters".

THE ELECTRONIC NATURE OF ALGORITHMS AND MODELS

Everything inside a computer, including numbers, words, pictures, colors, and the instructions and rules of algorithms, has been digitized into numeric form in minute detail. Within the computer the digitized information is represented as sets of on and off signals. For instance, a black and white picture subdivided into 1000 pixels would be represented by 1000 sets of on and off signals, each set a measure of the percentage of blackness inside each pixel. Although the resulting number of signals is enormous, computers' vast memories and processing speeds allow us to search this mass of data incredibly rapidly. One doctor cannot memorize the content of medical libraries, but computerized algorithms can search such libraries for needed information in a flash.

The algorithms that coders design for use within computers are based on models. Models simplify, good ones usefully so. Maps do not include buildings, and your dressing routine does not consider the different kinds of wood used in your shelves, but your routine should take the weather into account. To ensure that algorithms' simplifications do not exclude critical information, their models must be both transparent and adjustable.

TRANSPARENCY

Discomfort increases as Dr. O'Neill delves into five reasons that algorithm construction must be transparent. We need to be concerned with suitability, goals, data, criteria and decision rules, and widespread, interactive feedback loops.

Suitability
Algorithm use can be unsuitable for some purposes. . A growing quantification bias in society, the notion that numeric scores are more accurate and fair than human judgement, has led to a growing reliance on algorithms for decision making. However, important activities cannot realistically be quantified. For instance, relying on a rise in students' test grades can result in failing scores for excellent teachers working with advanced students who regularly receive high marks

Goals
The goals of algorithms may aid a few at a significant cost to society. For instance, employers save money by using last minute scheduling algorithms. This pervasive practice prevents part-time workers from holding other part-time jobs or scheduling the rest of their lives, and can limit their ability to care for their children. Growing recognition that this scheduling practice undermines family and community life and imposes costs on society, has led to corrective legislation. One response has been New York City's regulation requiring fast food employers to issue schedules at least a week in advance (NYCHPO 5/30/2017). Another example is found in the insurance industry. While insurance requires assessment of risk for pricing purposes, the use of algorithms to group customers into ever finer risk pools can work against the spread of risk, which serves the social benefit of insurance, which is the bolstering of the strength of society by helping people during periods of difficulty. Government regulation of and provision of subsidies for health insurance for low income people and anti-terrorism insurance for skyscrapers in New York City after 9/11 are two specific examples of a response to this type of problem in the past (Schwabish and Chang 9/2004). The expanding use of algorithms to refine risk pools could make the problem more general.

Particularly nefarious are "drilling for pain" algorithms, which seek people's vulnerabilities for the purpose of financial exploitation. Private for profit colleges use such algorithms to locate poorly informed, low income people with eligibility for federal loans. The colleges then recruit them and arrange the loans to pay college fees. Too often, due to low quality degrees, the students cannot pay back the loans with consequent costs to themselves, taxpayers, and society at large. Similar algorithms contributed to the 2008 financial crisis, which caused enormous costs around the world.

Micro-targeting algorithms, which use finely tuned information to subdivide people for purposes of messaging or responding to inquiries, can undermine other social benefits. Sellers can use available data to estimate a customer's ability to pay and charge accordingly. Price discrimination reduces the benefits to those customers who would have benefitted from lower prices. Price discrimination also reduces the incentive that stems from the pressure of lower prices for firms to improve efficiency. Micro-targeted political messaging can undermine political discourse and debate, and also lead to a focus on relatively few "swing" voters, contributing to apathy among other voters.

Data

Data can be incorrect or inappropriate. Such data can block access to credit, insurance, jobs, promotions, parole and more. Data problems include mistakes, old data, and proxies. Just one source of mistakes is coding error, which can occur when the algorithm models' logic statements or flow charts are incorrectly coded into computer programs. Old data can render algorithm outcomes irrelevant. Proxies are approximations about you rather than specific personal information relevant to the decision being made. Zip code income averages can serve as a proxy for your income or your ability to repay a loan. Credit scores, which are not measures of your ability to do a job, are used to screen potential employees, and at least 11 states have made the practice illegal. Proxies can even affect a person's freedom. Algorithms used to determine release from prison can include as a criteria the proxy of having known criminals, which is unavoidable for people from poor crime ridden neighborhoods.

Rules and Criteria

Algorithmic rules and criteria are making invisible political and economic decisions. For instance, when applications such as those for credit, job interviews or parole are processed by algorithms, some score will automatically serve as a criteria for acceptance or rejection. This system does not avoid human biases. Those designing or coding the algorithms can, even unconsciously, incorporate their own biases or assumptions that disadvantage certain groups of the population. They can also incorporate biases resulting from past social, political and economic forces and project them into our futures. For instance, because zip code characteristics reflect the history of social stratification by income and race, algorithms using proxies based on zip code data rather than personal information contribute to the perpetuation of those patterns.

We need sufficient transparency to discover biased criteria that coders have inserted into algorithmic programs. Importantly, transparency also allows us to ascertain whether criteria are based on a proven cause and effect relationship or simply reflect correlations, which do not prove causation and can be simply coincidental.

Special alert here! The artificial intelligence (AI) used in decision rules merits special attention. (*We shall sidestep the controversy over the term's use and use the term AI to refer to neural or learning networks or mathematical models used to query massive data bases*). Criteria selected by AI routines are based on correlations, not cause and effect, and they are not practically discoverable!

A doctors' decision criteria using information gathered through a computer search would be based on cause and effect. However, AI criteria are always based on correlations found as a result of algorithms' comparisons of sets of digitized data. One problem is insufficient diversity in the sets of data used to train algorithms. For instance, there has been overrepresentation of men in training data sets for vocal interactions and of white people in training sets used for recognizing people (Nicodemo 12/4.2017). Also, although humans write the code to train the algorithms asking for the comparisons, we cannot be certain what similarities will be found by the algorithm, and it is possible that, just as we cannot smell everything that a dog can, we might not be able to perceive the patterns or correlations detected by artificial intelligence. While backtracking through the history of the codes' operation on the data in order to discover those patterns and correlations might be theoretically possible, so vast is the data that the computer will have processed that such a search might be impractical, requiring perhaps years of human time.

Some examples reveal problems of AI correlation based criteria. Experts showed that a slight alteration of a stop sign could lead a driverless car's sensors to read it as a 45 mph sign. (Lu 11/12/2017) An AI routine to schedule lung treatments gave asthmatics a low priority due to their short recovery time. However their faster recovery was due to the already standing practice of giving asthmatics a high priority (Kuang 11/21/2017). With the growing use of facial recognition, we might wonder how AI might categorize us based on similarities in appearance to people around the world, and how those categories might determine our access to the various portals of society. This is speculation about the future, but as Dr. O'Neill warns about the development of this technology, "It is early days yet."

Widespread Interactive Feedback Loops

Decision rules can create negative and interactive feedback loops which increase inequality, especially when the algorithms are used widely. Faultily designed credit reports, based on zip code rather than personal data, can result in the denial of a viable business loan application and lower both a family's and a community's income, which can, in turn, adversely affect health and education opportunities for children. These factors could result in the denial of opportunities by other algorithms. For instance, algorithms can shunt inquiries by lower income customers to more algorithms while directing higher income customers to human customer services. Also, algorithms using area arrest records to assign police can result in increased surveillance in poor and minority communities, which, due to historically greater surveillance, have relatively high past arrest rates. Continuation of more intense observation produces more arrests, perpetuating the cycle. For youth, even minor infractions, such as jumping a subway turnstile, can produce criminal justice system records which can lead to both algorithmic and human decisions that limit their future legal opportunities (Lehrer 3/15/ 2015; Reynolds 10/4/ 2017). The costs to society of these interacting inequalities are staggering. They include unrealized human potential for individuals, families and communities as well as less spending, lower tax revenues, and more crime, with its attendant social and criminal justice system costs.

CHANGE

We need transparency to identify these problems in algorithms, but we must also be able to correct them. However, algorithms can lack updating procedures. Some teacher evaluations have this flaw. Incentives to make corrections can be absent. Regulations require adjustments of mistakes in our FICO credit reports created by the Experian, Equifax and Transunion companies, but not for errors that occur in the varied and unregulated e-scores or electronic profiles that are increasingly used as filters by companies. They are generated by private firms using information from searches of the masses of internet data. (Singer 8/18/2012). The producers of these reports are only interested in further sales, and lack economic incentive for time consuming error correction.

SOLUTIONS

Having alarmed us sufficiently, Dr. O'Neill urges us to realize that protecting ourselves is possible. The challenge is that the savings in time and labor costs encourage algorithms' widespread adoption without incentives to protect the interest of those whose data is being crunched or society at large. Citing people's successes in combatting the harms of the industrial revolution, which also lacked incentives for correction, Dr. O-Neill recommends that in order to safeguard ourselves that we reconfigure the legal and social context of algorithms. Potential tools include professional ethics, public pressure, regulation, and auditing.

Data scientists are realizing their growing algorithmic power and responsibilities to society. Two scientists wrote a "Hippocratic Oath" to promise to "do no harm "and to make their simplifications and assumptions transparent. The Oath is admirable and useful but insufficient. Dr. O'Neill calls for three categories of regulations for algorithms and data collection: measurement, protection and auditing.

We must measure algorithms' hidden costs to society as we do for new federal laws. (This process uses cost-benefit analysis which has its own measurement problems, but the idea of estimating the hidden costs to society, such as those that result from the use of scheduling algorithms, is important). We must also observe model outcomes and seek new data and use this information to update models.

We could better protect ourselves by adopting the European requirement that consumers must opt in to their data being used, and disallowing data transmission to others. We should require both fair and efficient standards and the inclusion of positive feedback loops in which discovered information is used for improvements rather than exclusion. Human decision makers would work with the algorithmic tools. For instance, algorithms were used by one Pennsylvania county agency to identify which troubled families should be prioritized for a visit by a professional to determine the need for assistance. (Hurley 1/7/2018) Also we need to update existing laws that provide relevant protections, such as the Fair Credit Reporting act (FCRA) and the Equal Credit Opportunities Act (ECOA)

We should legally require auditing of algorithms and the elimination of those that are ineffective or harmful. New York City has recently passed a bill establishing a task force to examine its automated decisions systems for any built-in biases and inequities (Roshan 12/19/2017; Powles 12/20/2017). Academics and customers can also contribute to the auditing of algorithms. Some academics already are using bots to search for biases in algorithms. People can use crowdsourcing to share information on how companies are micro targeting them with ads, pricing and access to their products and services. We should require companies like Google and Facebook to provide access to the internal audits of their own algorithms.

Dr. O'Neill argues that algorithms, used appropriately, can benefit us individually and as a society, if they are well built, adjustable, and have positive feedback loops. But we must learn to see their potential flaws and pass laws to make them accountable to us and not the other way around. Start by reading her book. You will be glad you did.

References and Sources Used

References

Abraham, Roshan. 12/19/ 2017. New York City Passes Bill to Study Biases in Algorithms Used by the City https://motherboard.vice.com/en_us/article/xw4xdw/new-york-city-algorithmic-bias-bill-law

Hurley Dan. 1/7/2018. Predicting the Worst: One Pennsylvania county has embarked on a radical experiment: using an algorithm to forecast which kids are most at risk. New York: New York Times.

Kuang Cliff.11/21/2017 Can A.I. be taught to explain itself? https://www.nytimes.com/2017/11/21/magazine/can-ai-be-taught-to-explain-itself.html

Lehrer, Brian. “Caught:” Podcast on the Brian Lehrer show. March 15, 2015 https://www.wnyc.org/story/the-brian-lehrer-show-2018-03-15

Lu, Yuren. 11/12/2017.Hackers’ Delight. The NYT magazine. p.38 New York: The New York times

(NYCHPO) New York City Hall Press Office. May 30, 2017. Mayor de Blasio, Speaker Mark-Viverito Announce That New York City Is The Largest City To End Abusive Scheduling Practices In The Fast Food And Retail Industries http://www1.nyc.gov/office-of-the-mayor/news/372-17/mayor-de-blasio-speaker-mark-viverito-that-new-york-city-the-largest-city-end#/0

Nicodemo, Allie. 12/3/2017. How to Create unbiased Algorithms in a Biased Society https://news.northeastern.edu/2017/12/04/how-to-create-unbiased-algorithms-in-a-biased-society/

Powles, Julia. December 20, 2017. New York City’s Bold, Flawed Attempt to Make Algorithms Accountable. New York: New Yorker https://www.newyorker.com/tech/elements/new-york-citys-bold-flawed-attempt-to-make-algorithms-accountable

Reynolds, Matt. 10/4/ 2017. Biased Policing Is Made Worse By Errors In Pre-Crime Algorithms News And Technology. https://www.newscientist.com/article/mg23631464-300-biased-policing-is-made-worse-by-errors-in-precrime-algorithms/

Schwabish, Jonathan A. and Chang, Joshua. September 2004. New York City and Terrorism Insurance in a Post-9/11 World Partnership for New York City http://www.pSeptembfnyc.org/reports/2004_09_terrorism_insurance.pdf

Singer, Natasha Aug. 18, 2012. Secret E-Scores Chart Consumers’ Buying Power. http://www.nytimes.com/2012/08/19/business/electronic-scores-rank-consumers-by-potential-value.html

Sources: The information in this review comes largely from Dr. O’Neill’s book. Some examples from external sources have been cited. Additionally I benefitted from consulting with two people who had more understanding of how the innards of computers worked than I did. Elizabeth Albin, a software engineer, helped me understand how images are stored and learned. Fred Ford, who worked for over 40 years with computers and electronics for Burroughs/Unisys and Cadence Design Systems, checked and deepened my understanding of artificial intelligence, algorithm modeling and helped me identify points to be made more explicit

Acknowledgement: Editorial comments by Anthony Anderson, Carol Kahn, Nancy Butler Ross, and Roger Szajngarten re gratefully acknowledged.