Machine Learning, Mental Health and Eugenics.

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Abstract

Machine learning is set to become deeply embroiled in mental health diagnosis. The so-called digital phenotype is dizzyingly broad, so that changes in our smartphone usage, data from fitness trackers and the tone of words we use on Twitter will become factors in predictive diagnosis. But this is a collision between computational exactness and the inconsistencies concealed by psychiatric labeling. While the idea of 'precision psychiatry' promises to detect early onset of psychosis before services or the individual themselves are able to, user movements argue that a lot of what is being medicalized is the expression of trauma or distress. The volumes of data needed for AI will require a pervasive surveillance that will amplify the anxiety already instilled by a distrustful and punitive benefits system. AI is not a neutral actor but will weigh in heavily on the side of biological reductionism, reinforcing the understanding of mental health problems as disorders of circuits in the brain rather than accounting for adverse life events. This parallels the emerging field of sociogenomics and the use of Genome Wide Association Studies (GWAS) to correlate social status with distributed genetic factors, re-opening eugenicist narratives that had been thought of as buried in history. Both precision psychiatry and GWAS class mental health problems as innate tendencies and act as smoke-screens to obscure social and political conditions. To overcome the onlooker consciousness of AI, we need critical technical practices that can unlink vectorial distances from social differences. This can come through a feminist AI that draws on standpoint theory and feminist approaches to science, combined

with collective structures of research that include those who are most affected in the process of inquiry. We need an alternative psychopolitics of machine learning.

Digital Phenotype

The generation of data by our many devices and the analysis of that data by machine learning is set to become so deeply embroiled in the diagnosis of disease, that it will blur the boundaries between the digital and the biological and change what is considered knowable about our bodies and brains.

One key idea in these developments is known as digital phenotyping (Jain et al. 2015). Phenotyping describes our observable traits, such as physical appearance, biochemistry and behavior. In contrast to our genotype, the sets of genes which are seen as encoding characteristics, the phenotype is a product of both gene expression and environmental factors. We know eye color is genetically determined and childhood nutrition will effect adult stature. But it is now proposed that keyboard reactions times, screen attention and the digitally captured characteristics of our voices constitute our digital phenotypes (Insel 2017). In other words, these are sufficiently robust corollaries to traditional observations of disease expression that they can be both diagnostic and prognostic, identifying symptoms before they would otherwise be observable and providing potential pathways for early intervention.

The scope of the digital phenotype is dizzyingly broad, and in some cases rather superficial. Smartphone activity during the night is seen as a tracker for insomnia (McIver et al. 2015), and data from fitness monitors is used to characterize cardiometabolic diseases (Kirk et al. 2018). But digital phenotyping has deeper implications both medically and politically. These are becoming visible in its proposed application to mental health, where it will deliver "passive, objective, continuous and ubiquitous longitudinal assessment of mood and cognition" and "signatures for prediction and preemption" (Dagum 2017). Digital phenotyping is proposed as mode of direct access to mental health symptoms; bipolar behaviors captured by social media, sensor signals of entropy correlated to mood ratings, and depression and psychosis spotted by semantic incoherence in speech samples.

It's not only a matter of a frictionless substitution, with digital monitoring as an easy proxy for well established symptoms, but the potential for the digital phenotype to reveal new signals that are clinically relevant, and to alter the notion of how an illness manifests. The pitch is that the predictive power of data plus machine learning will achieve the grail of preventative medicine, as well as becoming a direct channel for behavior change, bypassing the Sisyphean toil of public health education. The term biomarker used to refer to the results of a biopsy or blood test, but now, according to the principle investigator for a national study of trauma in the USA, "the biomarker is some combination of GPS and, from the watch, seeing your heart rate spike", and the director of a university's Center for Digital Mental Health can say, when referring to sensor data from smartphones such as accelerometer and microphone, "this is going to be our MRI scan in behavior" (Biegler 2017).

Digital phenotyping is not just a matter of having a huge set of data points, but of using software to transform them into something recognizable, which will most often require machine learning because of the volume of points and the complexities of the pattern fitting.

One uncomfortable fact about mental health diagnosis is the inconsistency of diagnosis between individual psychiatrists. Research reveals that inter-rater reliability is statistically poor (Freedman et al. 2013); that is, diagnosis varies so much between psychiatrists that it is empirically unreliable (Carney 2013). Studies also show that the criteria for Major Depressive Disorder are loosely correlated and inconsistent (E. I. Fried 2017), while other researchers question the conceptual basis for a diagnosis of schizophrenia (Owen 2011). The apparently empirical categorizations of psychiatry are mired in various controversies, and are strongly challenged, not least by many users of mental health services. To understand why machine learning takes sides so strongly in this debate, we need to look at the way it learns.

Machine learning learns by iteratively fitting its training data to a set of labeled outcomes, or targets. Its mathematical operations optimize a loss function which sums the mathematical gap between predictions and targets such that the algorithm will be able to classify new incoming data with a minimized error. For mental health, the data are known cases, and the training targets are the diagnoses, defined by the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) (American Psychiatric Association (APA) 2018) or it's World Health Organization equivalent, the International Classification of Diseases version 11 (ICD-11) (World Health Organisation 2018). Some forms of machine learning are conceptually simple, such as K-nearest neighbors, which classifies a point in feature space based on the training points it's closest to. Others, such as the backpropagation used in neural networks, deal with much messier data by using a complex set of parallel calculations (3Blue1Brown 2017). In each case the mathematics of fitting the points to target outcomes is well defined. Yet the consequences of applying machine learning to mental health are seismic, because of the collision between this mathematical precision and the complexities concealed by the diagnostic labels.

Some of these complexities can be seen in the way the upgrade from DSM-4 to DSM-5 was criticized across the mental health professions as medicalizing conditions that were previously understood as natural, such as the depression that may accompany bereavement, temper tantrums in children (Disruptive Mood Dysregulation Disorder) or mild forgetfulness in old age (Minor Neurocognitive Disorder), thereby drawing attention to the behind-the-scenes influence of drug companies (Greenberg 2010) and leading one prominent psychiatrist to warn that a “wholesale imperial medicalization of normality” would be “a bonanza for the pharmaceutical industry” (Frances 2009).

Pointing out that mental health diagnoses may lack firm empirical foundations or be subject to the groupthink of professional committees is not to say that diagnosis is never helpful in guiding treatment or in validating someone's experiences. But the power of psychiatric labeling can radically alter both self-identity and the way a person is treated by services and wider society, while user movements argue that what is being medicalized is often the expression of deep distress or the effects of early trauma such as abuse (Timimi 2012). Under these conditions it is vital to understand the effects of machinic classification; how computational operations that treat diagnoses as givens will not simply automate a process of classification, but constitute a distorting intervention that sets implacable mathematics at loggerheads with the testimony of lived experience and it's irreducible plurality (McQuillan 2018).

For the advocates of predictive analytics, the instability of psychiatric labeling is not a problem but an opportunity. They see the mission of machine learning as delivering precision psychiatry, sweeping away the painful contradictions that cluster around mental distress. Frustrated by the fact that there's no objective laboratory measurement for mental health problems, they search for a combination of biological, behavioral and social factors; a digital phenotype that definitively captures the different kinds of mental malfunction, bringing precision not only in classification but a temporal resolution superior to current clinical practice (Insel 2014), identifying with laser-like accuracy the early onset signs of psychosis or other conditions well before it would be noticed by the individual themselves or picked up by health services.

Unfortunately the clean dream of precision targeting always seems to bring collateral damage in practice, in the same way that smart weapons used in air strikes still result in shocking numbers of civilian casualties. One kind of collateral damage that comes with AI's social application is surveillance, the need for huge amounts of training data in order to obtain any accuracy from the algorithms. In the UK, people with mental health problems already experience a weaponized benefits system which prioritizes a return to productive work over any notion of a social safety net. Under this institutionalized distrust, CCTV footage from Sainsbury's supermarket is combined with gym membership, airport footage and social media posts to suggest that people are lying about their disabilities, in a deliberate policy of surveillance as deterrence intended to instill anxiety and internalize moral suspicion (Big Brother Watch 2018). The irony here, of course, is that the sense of hyper-visibility and being targeted, of being unable to go out for fear of being seen as doing something normal, where the scrounger rhetoric means being seen playing with your kids could be used against you, may bring further disabling levels of fear, anxiety and paranoia on top of any existing mental health issue. And yet talk of targeted treatments delivered on the wings of AI will require even more pervasive monitoring. Huge volumes of data are a must-have for any machine learning, however beneficent its mission, let alone the application of AI-under-austerity, where it is seen as squaring the circle between rising demand and politically diminished resourcing.

AI Reductionism

As well as demanding more and more pervasive surveillance, the application of AI to psychiatric diagnoses will also weigh in heavily in favor of biological reductionism.

In mainstream psychiatry and clinical psychology mental disorders are commonly defined as brain disorders. However complex the phenomena observed and however much they seems to invoke meaningfulness, the feeling is that they can be mapped backwards to dysfunctions of gray matter. However, this belief in mental health issues as brain disorders has not been matched by the ability of neuroscience to pinpoint the problems. Despite decades of effort, there are no definitive biological markers for common psychiatric conditions (E. Fried 2018). Detailed definitions of exactly how mental disorders are brain disorders are hard to come by, and although studies using neuroimaging such as functional MRI are replete with claimed correlations between brain activity and DSM diagnoses, they don't reveal whether they are causes, effects or epiphenomena. At least some of the wonders of making brain functioning visible via MRI are illusory; a meta-analysis in 2017 across hundreds of task-fMRI studies involving thousands of participants showed no consistent brain differences across schizophrenia, bipolar disorder, major depressive disorder, anxiety disorders, and obsessive compulsive disorder. As result it "cautions against attributing undue specificity to brain functional changes when forming explanatory models of psychiatric disorders” (Sprooten et al. 2017). While some of this may stem from diagnostic inconsistencies, fMRI also has its own problems with the reliability of biomarkers at an individual level (Fröhner et al. 2017) and is part of the wider 'reproducibility crisis' in science because of issues p-hacking (where samples are selected to produce apparently significant statistical results) (Pernet and Poline 2015). The counter-narrative suggests that mental health problems don't originate from within the brain but are the mind's response to trauma, abuse or distress (Kinderman 2014). Research shows, for example, that childhood adversities increase the risk of psychosis (Varese et al. 2012). For depression and PTSD, for example, the findings are that adverse life events explain about two orders of magnitude more of the variance than biological factors.

Into this ambiguity of biological and social factors charges precision psychiatry, promoting concepts of mental disorders not as lesions but as disorders of brain circuits which can be identified by a mix of genetics, neuroscience and digital data (Dagum 2017). Smart psychiatry sweeps in everyday digital data that allegedly provides clues to behavior, cognition and mood, whether that is changes in typing speed, physical activity, tone of voice or the form of words we use on Twitter, using the affordances of the smartphone, mediated by the gravitational lens of AI, to reveal the deepest perturbations of our brains.

The capacity of machine learning to work with heterogeneous data, spanning scales from social graphs to tilt sensors, is not used to widen our perspective but to strip social causes from distress and, like a neural GPS, locate the origins back in our cortical structures.

The effect of this digital intervention into the mind-body question is not simply to bolster a reductive epistemology, but to participate in the becoming of the human, the boundaries of which are always co-constructed by the tools of the time. What's a stake is not only the algorithmic colonization of the mind but the way that the epoch of AI draws the borders of the natural.

Questions about what constitute the human body and mind, their composition and limits, are always attenuated by the technical practices available to us. Genes, as contemporary objects of self-knowledge, depend for their concreteness on the mechanisms of distributed technoscience; sequencers, biobanks, databases, algorithms, institutions and the internet. Similarly, the digital phenotypes of mental distress will come to exist through the vertical stacking of psychiatric diagnosis with smartphones and the algorithms of artificial neural networks, and the substrate of GPU microprocessors able to carry out massively parallel computation in feasible time (Shaikh 2017). Instead of the fantasies of Silicon Valley transhumanists that our minds will be uploaded to the cloud and thus escape fleshy constraints, the circuits of the data analytics are instead becoming fused into our embodied brains.

The computational-psychiatric complex constructs authoritative explanations of our behaviors by chaining reductive assumptions about the mind to the correlations of machine learning. This attempt to construct a computational-psychiatric complex doesn't occur in a vacuum but parallels the emerging field of sociogenomics which, by seeking to save the explanatory power of genetics by wedding it to big data, has resurfaced some supremacist biases in science that had been thought of as safely buried in history.

Despite the promises that accompanied the race to sequence the human genome, the inconvenient fact is that few common diseases can be attributed to single genes. So there are now studies of the whole genomes of large groups of people looking for patterns of variations across as many as a million single-nucleotide polymorphisms, or SNPs, in a process known as genome-wide association studies (GWAS) (Witte 2010). The idea is to find correlations between these patterns and observable phenotypic traits. If a statistical pattern can be found then the genome of any subsequent individual can be compared to it to generate a a polygenic risk score (Dudbridge 2013); the predictive likelihood of that person having or developing the trait. Using data from public repositories and consumer genomics companies like 23andMe, GWAS studies have found patterns of SNPs associated with a dizzying array of traits. The UK Biobank list includes results related to cancer and other diseases, but also genetic correlations to "Job involves shift work", "Time spent driving" and "Frequency of light DIY in last 4 weeks", and of course patterns apparently associated with depression, anxiety and schizophrenia (The Neale Lab 2018).

Like machine learning, sociogenomics is based on correlation rather than causation. While the presence of these correlations suggests these traits may be heritable, sober practitioners point out that even if something is at some level heritable, environmental and cultural differences are frequently the primary drivers of difference (Coop 2018), Even if some portion of phenotypic difference can be attributed to polygenic scores it doesn't mean a trait is immutable or natural, as many phenotypes are modifiable. Most critically, the identified variations are often small, a matter of a few percent, so that environmental and cultural factors overwhelm them in terms of significance. Yet some scientists are keen to cite GWAS as the genetic underpinnings of complex social phenomena, promoting the idea of report cards predicting risks not only of various diseases but also propensities for future behavior such as marital fidelity or financial prudence (Comfort 2018a).

Hardcore advocates like Robert Plomin insist that "Individual differences in income are, like everything else, substantially heritable, about 40 percent. Income correlates with intelligence, and genetics drives this correlation" (Plomin 2018). The justification of entitlement, which is as old as the hills, is transformed by his notion of 'genetic wealth' into a kind of genomic neoliberalism, where SNPs are the elements into a free market mechanism that will necessarily produce the optimum result.

Meanwhile the so-called human biodiversity movement, part of the wider family of the alt-right, seizes on GWAS studies to assert a scientific basis for racial inequalities and uses the notion of 'race realism' to justify racism as reasonable and empirical. Let us remember that such distorted views can become part of the machinery of society. In the early 20th century, eugenic views led to US laws against miscegenation (the mixing of different racial groups through marriage or sexual relations) and were behind the policy of sterilizing the 'unfit'.

Darwin's cousin, Francis Galton, was a heartfelt hereditarian who actually coined the term eugenics, and believed that civilization depended on breeding out the weak. As part of his pursuit of a stable population he developed the concept of mathematical correlation, which became a central pillar of statistics. His equally eugenicist follower Karl Pearson created the concept of the correlation coefficient (Comfort 2018b). Of course, the notion of correlation and the correlation coefficient transcended their origin to become part of general numerical analysis, as likely to be applied in favor of social justice as against it. But in a conjunction of supreme historical irony these statistical methods are at the mathematical core of machine learning, and risk being enrolled in distorted forms of social sorting such that the mathematics that originated alongside eugenics would be reunited with it through AI.

Science alone is not the bulwark we might hope against such developments. As Sandra Harding and others point out, its model of objectivity is effective at cross-checking between experiments but is myopic at identifying culture-wide biases (Harding 1992). Nevertheless, science claims for itself the power to disqualify other modes of explanation and, embedded in institutional asymmetries of power, algorithmic judgments will inherit this authority. Institutional decisions will be based on predictive metrics like those from the Allegheny County child protection system (Eubanks 2018) or the Washington D.C. teacher evaluation rankings (Rinehart 2018). Whether based on sociogenomics or digital phenotypes, predictive analytics will acquire the force of law even when not explicitly mandated by it, especially when part of closed loops like the prediction-intervention-monitoring cycle of precision psychiatry. Assuming people are not blank slates is not the same as asserting a natural ordering, nor is the existence of differences between brains the same as saying these are the most important factor in mental health, but sedimenting these questions beneath algorithmic opacity will lead to their promotion via states of exception (McQuillan 2015). The reductionist assumptions embedded in machine learning systems, which are in turn embedded within the unreflective urgencies of front-line services, will operationalize preemption, exclusion and detention.

Psychopolitics of machine learning

Targeting people through digital biomarkers, backed by biologising assumptions about brain disorders, reinforces a reductionist view that mental health problems are an innate propensity, an individual curse. The so-called smart psychiatry of AI becomes a high-tech smoke screen that obscures social factors, such as emotional and psychological trauma and the devastating effects of precarity, poverty and homelessness. The aftershocks of austerity drive more of the population into desperate circumstances, compounded by a punitive benefits system that also blames the individual, producing debt and despair. The mental health toll of such a system can be seen in the suicides of people who have had their disability benefits denied (Barr et al. 2016),(Pring 2015).

In his report on Britain, the UN's Rapporteur into Extreme Poverty and Human Rights concluded that austerity was not the direct cause of, but the cover story for, a revolutionary reduction in levels of fairness and social justice that amounted to a dismantling of the social contract:

"Compassion for those who are suffering has been replaced by a punitive, mean-spirited, and often callous approach apparently designed to instill discipline where it is least useful, to impose a rigid order on the lives of those least capable of coping with today's world, and elevating the goal of enforcing blind compliance over a genuine concern to improve the well-being of those at the lowest levels of British society" (Alston n.d.).

He identifies automation and AI as core to this intensification of government strategy through fully automated risk analysis and real-time recalculation of benefits and sanctions; an algorithmic mobilization of Margaret Thatcher's mantra that "there's no such thing as society" (Thatcher 1987). Yet we already know that, when it comes to wellbeing, social determinants outweigh biological determinants. Research suggests the biggest impact on mental health outcomes comes from factors external to treatment, such as a person's social circumstances and levels of support. Instead of allowing AI to define individualized targeting and intervention as the only option, we should ask whether we can re-imagine our algorithmic methods so they reduce social risk factors, and create public goods that increase the wellbeing of communities, because prevention rather than preemption implies raising up the whole population.

Technology, like science, is both the product of the social matrix and constitutive of it. It not only acts in the world but reflects a collectively held vision of what is both possible and desirable, which Sheila Jasanoff calls a sociotechnical imaginary (Jasanoff and Kim 2015). A culture's hopes and fears are bound up with its machineries of knowing, a process which is in constant flux, as technologies like genetics and computation inherit a history yet point at different ways to attain promising futures. The sociotechnical imaginary binds together our sense of what is and what ought to be, co-producing meanings about the nature of the world and our place in society which endure because they are collectively performed, but which mutate as new possibilities emerge.

By contesting the psychiatric vision of mental health, the user and survivor movement has already shown the possibility of a bottom-up articulation of knowing and a different vision of what is desirable, mobilizing around the poles of trauma, abuse and distress rather than illness and disease, and developing self-help strategies such as 'harm minimization' and 'coping with voices' (Cresswell and Spandler 2009). The need for an alternative psychopolitics of mental health is intensified by the new forms of machinic knowing and the nascent becoming of a computational-psychiatric complex. There is a social and political need for alternative, value-led practices, drawing on the principles of solidarity and mutual aid, pushing a counterculture of AI through all its strata of infrastructure, data, algorithms and statistics.

This is not only an urgent issue for mental health, as the pattern of AI-backed reductionism will be repeated across healthcare, social care and the justice system. The real bias in machine learning is the way it will distort the sociotechnical imaginary through GPU-enabled onlooker consciousness. Rather than relying on the representation of incommensurable experiences by computational vectors, we need new algorithmic practices that question the resonances generated between vectorial distances and social differences, and unlink the optimization of the neural network from the neoliberal optimization of markets. These critical technical practices can only by carried out with the inclusion of those directly affected.

Re-imagining the psychopolitics of machine learning means working with programming and politics at the same time, solving technical problems while sustaining a focus on social impacts, a process which is neither engineering nor social policy. It requires both precision at a mathematical level and and openness towards the different possible realities that might be articulated.

One approach is offered by the model of feminist science articulated by Roy, Spanier and Harding (Roy 2004), who expand the scientific methodology as a mode of inquiry to include (1) locating the origins of problematics, (2) uncovering the purposes of inquiry, and (3) establishing a relationship between the inquirer and their subject of inquiry. Those of us wishing to develop non-oppressive machine learning should not accept a problem as given, but should start by locating its origins; in other words, become cognizant of the structural forces which have prioritized it and what its formulation reveals about the social algebra of power. Uncovering the purposes of machine learning means going beyond accurately predicting the validation data by optimizing hyperparameters. It means considering this narrow technical purpose as part of a broader set of impacts, asking who's ends it will serve, who it might exclude, and how it would effect the wider wellbeing of society. Perhaps most radically for machine learning, this feminist methodology establishes a relationship between the inquirer and their subject of inquiry, requiring us to purposefully put aside the onlooker consciousness that fuels AI's hubris. The most direct way to put this feminist method into practice with machine learning is through collective structures of research that include the 'target group' in the process of inquiry. The new machine learning must combine critical pedagogy with critical technical practices [^fn40].

Conclusions

The questions raised by AI-under-austerity are not made up of abstract philosophizing about how to live with thinking machines, but center on the ways concrete operations will be enrolled by punitive politics and the need to imagine alternatives that resonate with liberation. The computational-psychiatric complex will be one of many that conceal repressed accommodations at every level, from social categories to data analytics to signal processing, folding dimensions of the political out of view.

We already know that the dualistic modernism of our sociotechnical imaginary has a dark heart; that certain iterations of its technical-social unfolding support wrongdoing at scale, whether through the craniometry of colonialism or the Hollerith machines of National Socialism (Black 2012). It is particularly dangerous to biologise distress during a time of a rising far right politics, a politics that expresses what Roger Griffin calls palingenetic ultranationalism; seeking to end the degeneration of the nation and bring about its imminent rebirth from decadence through rationalized xenophobia and biologically determinist ethnocentrism (Griffin 2003).

But even when we have refused the revaluation of eugenics and slayed fascism again, we will need to continue to contest the boundaries of the political and the natural. As Donna Haraway reminded us, 'the point is to learn to remember that we might have been otherwise and might yet be, as a matter of embodied fact' (Haraway 1997). Calculative forms of life-capture, like AI and sociogenomics, are sedimenting into our societies; given that machine learning channels these changes, we urgently require a structural renewal of machine learning itself through a collective agency of empathy and solidarity, the application of feminist methods, and a commitment to anti-fascist mutual aid.

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