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Machina-economicus or homo-complexicus: Artificial intelligence and the future of economics?

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Abstract
Artificial Intelligence has become ubiquitous in all manner of human activity, especially in the era of widespread digitization and enormous data collection and manipulation. It has penetrated many realms of science presenting significant challenges to tried and true methods, especially the primary processes of theory building. One realm where AI's inroads are conspicuously haphazard is economics, much of this stemming from embedded ideological commitments. These predilections make it exceptionally difficult for the mainstream discipline to fully embrace the greater implications of AI found in the study of the economy as a complex adaptive system. This situation further poses a number of additional societal threats as AI ushers in an unprecedented and extremely ill-guided industrial transformation.

The global financial crisis that began in earnest in 2008 (and is yet to be resolved) prompted significant challenges to the theory and methods of mainstream or orthodox (also known as Neoclassical and/or Neoliberal) economics. Even distinguished orthodox economists, Paul Krugman (2009) Joseph Stiglitz (2017), and Paul Romer (2020) have joined with the crescendo of obscure, yet profound, voices, such as: "institutionalist" (e.g. Hodgson, 2004), "heterodox" (e.g. Keen, 2001; and E. Smith, 2010), and "ecological" (e.g. Constanza, et al., 1997; and Fullbrook and Morgan, 2019), as well as Marxist economists.

One especially promising alternative to mainstream economics grew out of work in nonlinear dynamics and systems theory (see, Daneke, 1999), and has been enhanced by huge advances in computational capabilities. This approach, under the catch-all rubric of Complexity Studies, has many variegated and partial offshoots both mathematical and metaphorical. Plus, use of its computational tools is no guarantee of theoretical coherence. Some qualitative applications are especially robust and some quantitative pieces linger too close the event horizons of neoclassical black holes. Nonetheless, at its core, complexity is a completely unique worldview (see, Arthur 2013) with far reaching implications for how economies are studied and policies derived. As one might expect, mainstream economics, has been extremely reluctant to accept these implications and has only tangentially toyed with the isolated elements of the complexity approach. As in the past (e.g. game theory, behavioral economics, etc.), mainstreamers merely graft-on certain tools and concepts without altering their archaic foundations or their ideological commitments. This highly selective retention is made more problematic by recent developments in Artificial Intelligence (AI) and BIG DATA.

AI is primarily about the use of computer algorithms to augment and/or replace human judgements. AI applications have expanded of late given the massive explosions of data collection and manipulation by the mammoth internet monopolies (e.g. Google, Facebook,

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Amazon, Baidu, WeChat, etc.) and government agencies. This Big Data era poses a number of its own threats in an economy already riddled with dysfunctions, and has compounded fears about AI. Some apprehensions are overblown and some remain under appreciated. AI is unlikely to bring the science fiction terror, in which killer robots become sentient and end humanity, but it does harbor the potential for dramatic immiseration. One of the vastly underestimated by-products of AI expansion is that it will further retard the development of economic theory and practice, and indirectly exacerbate social upheaval.

A very brief history of AI

While artificial intelligence has yet to come to full fruition, it has been in the works for eons. Historical foundations would have to include: Gottfried Leibniz' tome *On the Combinatorial Arts* in 1666, the posthumous publishing of Thomas Bayes' paper on statistical inference in 1763 and George Boolean's work in the algebra of difference equations in 1854. There is also McCulloch and Pitts simplified logic of neurons (which would become "neural networks") in 1943, among many others. My list of personal heroes includes the preternatural polymaths: John von Neumann (1903-57) for game theory and cellular automata, Claude Shannon (1916-2001) for communications theory, the Shannon Cipher, and an early chess computer, and John Henry Holland (1929-2015) for nerve-net testing, genetic algorithms, evolutionary adaptation, and emergent processes and properties. However, modern historical views generally focus as much, if not more, upon computation devices rather than upon the big epistemological picture. Its iconic figures usually include: Charles Babbage, Konrad Zuse, Howard Aiken, Alan Turing, Stuart Russell, and Marvin Minsky as well as John McCarthy. Obviously, the art and science of computation actually goes back much further. The ancient Babylonians used an elaborate abacus like device and Muslim scientists built a functioning astrological clock in the early 13th century. Yet, Babbage's steam powered "difference engine" (built in the early 1800s) is probably the first thing we would recognize as a computer. Perhaps one of the best-known founders of AI, is the ill-fated British genius, Alan Turing (1919-54). He and his colleagues at Bletchley Park built a computer for quickly deciphering the German Enigma code, and probably turned the course of the war. Turing went on to spearhead modern algorithmic studies (see, Turing 1950). His career was cut short by his conviction for homosexuality and suicide. He lives on via his theories of AI (e.g. the "Turing Test" for successful machine imitation), a popular theatrical bio pic (*The Imitation Game*), and his visage recently placed on the fifty-pound note. It might have been more appropriate to put his face on a global crypto-currency.

In the popular imagination, as well as that of some current AI practitioners, a more abbreviated historical analysis is given priority. Moreover, as the pace of development quickens, certain threshold events rather than personalities color the timeline, much like "killer apps" which characterize recent technological innovation generally. Hence, winning at Grand National level chess, Jeopardy, or Go, often overshadows much of the science. Monumental advances in language and image acquisition seem mundane in comparison. Moreover, success of certain realms has led to a narrowing of emphasis.

Much of what we view as AI is merely Machine Learning and mostly in the form of "Deep Learning" (or DL, note, LeCun, et al., 2015). DL is an enhancement of basic ML representing a return of "neural networks", the re-development of "back propagation" from control theory, and the introduction "generative adversarial networks" or GANs (note, Goodfellow, et al., 2014). The deep part merely refers to layers of neural nets, and not necessarily profundity.

Furthermore, the neural notion is merely a crude caricature, and does not presume much in the way detailed knowledge of how human neurons actually work. Certain aspects of DL remain hotly contested; for example, many a hard-core statistician question the routine trick of “data splitting” which essentially allows the same data to be utilized for hypothesis generation and verification (not to mention the causality conundrum). With all the convoluted connections of DL, prediction often completely outstrips explanation. Real decisions normally demand detailed back mapping and logical demonstrations. More critically, DL tends to harbor deeply embedded societal biases.

Machine (especially Deep) learning has obviously made great strides, yet at present it a very myopic view of AI. In fact, in some circles, the term AI is reserved for all those things they have yet to accomplish. Despite its limitations, ML is the now the tail that wags the AI dog. Obviously, commercial and/or militaristic pressures push the bulk of AI research into the most lucrative arenas. The Machine Learning focus traces its origins to a two-month workshop held at Dartmouth in the summer of 1956. It was organized by the now legendary AI pioneer, John McCarthy and included a who’s-who of seminal researchers, including: Holland, Minsky, and Shannon, as well as other diverse luminaries such as Ross Ashby, Herbert Simon, John Nash, Nat Rochester, and Oliver Selfridge.

A different McCarthyism

In 1959 McCarthy published his *Programs for Common Sense* which set forth the agenda for much of what we now understand to be AI. In one stroke he not only signaled the ascension of formal algorithmic over biological approaches to intelligence generally, but by defining it as “common sense” he sets the stage for research to proceed without necessarily worrying about how humans are actually thought. Apparently common sense need not be that common. It is noteworthy that AI originally had deep roots in psychology and biology (via the neuro and cognitive sciences), but these efforts are now dwarfed by the computer sciences. McCarthy’s machine manifesto set out the parameters of what he felt would be more meaningful research for years to come. Essentially it argues for objective reality, natural language, non-monotonic logic (abductive vs. deductive reasoning), as well as machine discovery as a valid science (see, McCarthy 1990). In 1964, Daniel Bobrow’s MIT Ph.D. Dissertation, *A Natural Language Input for Computer Problem Solving*, reconfirmed this primary path to progress.

By the mid-1960s computer scientists came to dominate the enterprise. In 1965, Joseph Weinzenbaum developed ELIZA (natural language processor), while Edward Feigenbaum and his Stanford colleagues were developing the first Expert Systems (distilling the knowledge of numerous highly experienced individual in a particular field). In 1966, other Stanford AI Center scholars introduced Shakey, the first general propose robot for DARPA (Defense Advanced Research Projects Administration) with state-of-the-art natural language and computer vision. It was also capable of analyzing and sub-dividing commands. In 1968, Stanford’s, Terry Winograd created a natural language, SHRDLU, in route toward computers having their own semantic memory. In 1969, Harvard’s Arthur Bryson and Yu-Chi Ho further refined the methods of back-propagation via “multi-stage dynamic optimization”. Backprop in neural networks, now aided by forwardprop, forms the basis of deeper learning. The algorithmic avalanche would await, however, the arrival of substantially larger supplies of data still a decade or more away.

In the meantime, Minsky and Papert published their, *Perceptrons*: *An Introduction to Computational Geometry,* in 1969, demonstrating the limits of several elements of machine learning, and nearly single-handedly unleashed a protracted AI Winter. Further cold water was poured on by James Lighthill's report to the British Science Board in 1973. During this initial dark age, medical and military interests kept heat upon the back-burner. Strides continued in robotics and classifier systems, proceeding on a slow, but deliberate pace. In the early 1970s a team at the Stanford Medical School developed MYCIN a nascent backward learning expert system for isolating severe bacterial infections such as meningitis, along with several other diagnostics programs. Solid improvements in object/facial recognition and natural language also gradually emerged and the pace increased. In 1979, The "Stanford Cart", a very early autonomous vehicle, that only took 5 hours to self-navigate a room full of obstacles. By the end of the 1980s probabilistic and uncertainty containments tools grew by leaps and bounds, including IBM's Statistical Approach to Language Translation and Bell Labs hand-written zip code reader.

Following the bang of the 1980s, Academic AI began the 1990s with a whimper. When Melanie Mitchel, a leading figure in complexity theory and methods, was completing her Ph.D. in Computer Science at the University of Michigan under Doug Hofstadter (of *Gödel, Escher, Bach* fame), she was advised not to include AI on her resume. Minsky and Papert (1987) published an extended edition of their perceptron work and re-wet their blanket by contending that too much of the enterprise was bogged down in reinventing others wheels. The return of AI Winter was subdued somewhat, however, by certain high-profile stunts as well as a cavalcade of medical and military applications. Yet significant breakthroughs proceeded in fits and starts. By 1995 Richard Wallace brought forth the chatbot ALICE, which introduced data sampling from the internet. In 1996, German / Swiss researchers, Hochreiter and Schmidhuber, developed "long short-term memory" (LSTM)" a new class of recurrent neural networks that significantly improved hand-writing and speech recognition. This yeoman work was overshadowed by the victory of Deep Blue, IBMs dedicated chess computer, over world champion Garry Kasparov in 1997. Not to mention Furby the robot pet in 1998, as well as Kizmet the human emotion simulator and Honda's ASIMO, the robot waiter, in 2000.

The reign of the big data

A massive watershed moment for machine learning came with the arrival of the BIG DATA era. Plainly, the empire of data storage and manipulation was not built in a day. Large scale data collection dates back to antiquity, and modern data storage and analysis probably began in England in the mid-1600s. John Graunt (1620-1674) founder of demography, collected mortality statistics to track the course of the bubonic plague. Statistical analysis for the sake of business advantage took off following the US Civil War. However, it was the 1890 census, that prompted an enterprising young clerk, Herman Hollerith to develop the key punched card. They were much like those that filled boxes kept in my car while writing my dissertation back in the early 1970s. Hollerith, of course, went on to start a firm which evolved into IBM. In the 1930s IBM would develop an innovative census system for Nazi Germany to catalogue and collect its various "undesirables" and hence promote the Holocaust. Following WWII, business and government intelligence systems burgeoned, and in the 1960s the US built the first huge data center for the storage of nearly 750,000,000 tax returns. In 1970 IBM mathematician, Edgar Codd, introduced the "relational database", which allowed novices to conduct searches.

It was not until the arrival of the personal computer epoch and the "world wide web" (or Internet) in the 1980s, followed by the development of search engines and social networks platforms in the 1990s, that Big Data became its own asset class. By the time, Doug Laney coined his 3Vs (volume, velocity, and variety) approach to info tech investments in 2001, all three aspects of data collection were exploding in all directions. Microsoft CEO, Eric Schmidt, observed that more data was created and stored every two days than in all of human history up to 2003. The National Security Agency's million square foot data farm near Bluffdale, Utah ("the Bumblehive") is on the order of exabytes (some suspect zettabytes), and as Edward Snowden tried to tell us the NAS routinely collects and analyses nearly all our phone calls and emails. Beyond the burgeoning surveillance state, data has taken on a life of its own.

Digitization and agglomeration across multiple domains engendered a powerful new business model from the flotsam and jetsam of the "Dot Com" crash. A small handful of internet platforms were allowed to monopolize new mechanism of data collection, processing, and monetization. Corporations of all shapes and sizes lined up for metaphorical miles for expensive access to segmented consumer profiles and marketing strategies. Data became a vital commodity, nearly on a par with oil. This inherent value brought with it an onslaught of AI activity. Multi-layered neural nets with sensory data training, rather than imposed classifiers, caught on like a house afire. By the end of the first decade of the new millennium, processors were running around everywhere largely "unsupervised" (self-learning). In 2009, Rajat Raina and his colleagues at Stanford published their *Large Scale Deep Unsupervised Learning Using Graphics Processors*, explaining how multicore CPUs would be soon overwhelmed. That same year Google secretly initiated its self-diving car project, later called Waymo. In 2010, an international competition in image recognition was established at Princeton, and new applications expanded for such things as Convolutional Neural Nets (CNNs). Beyond basic problem solving, AI began to take on the mythical mantle of giving meaning, as well as remuneration, to these mountains of undifferentiated data.

More importantly, the Big Data era became the harbinger of a completely new model of science, a MODELESS MODEL, if you will. One might think that science was always about data, but the mining and reprocessing of galactic levels of data with learning tools, may be fundamentally altering scientific theorizing. As Wired Magazine Senior Editor, Chris Anderson (2008) observed "the data deluge makes the scientific method obsolete". He imagines a future where algorithms reveal heretofore unimagined scientific knowledge, with the push of button. Furthermore, he contends that "petabytes allow us say correlation is enough" and thus "we can stop looking for models (p.4)". By contrast, Complexity Scientist, Fulvio Mazzocchi (2015) concludes that "Big Data actually enhances the testing of hypothesis and experimentation, rather than replaces them (p 1)". Be this as it may, AI applied research seems to favor abduction over conventional induction or even deduction. As with the *Pirates of the Caribbean*, AI may soon prove that "the code" of science "is more what you might call guidelines than actual rules". The continued success of AI in many scientific realms appears to be the poof of the pudding. But this short-hand science may yet come back to haunt us.

As impressive as AI progress have been in the Big Data epoch, the promise of complete isomorphism with human intelligence has remained an ever-receding horizon. Several scholars and practitioners forecasted another winter in the second decade of the 2000s. Yet, more PR stunts combined with new military and marketing applications as well as geopolitical tensions to more or less sustain the enterprise at a fevered pitch. In 2011, IBM's Watson, a natural language search engine, defeated the all-time Jeopardy (general knowledge TV game show) champion. In 2012 Google researchers applied a neural net to 10 million unlabeled YouTube videos, and among other things found we have strong attraction to cats. In 2014 Google acquired the British firm DeepMind, and in 2016 its reinforced learning program, AlphaGo, defeated a global champion at Go (the Chinese abstract strategy board game). For the Chinese government this was their “sputnik movement”, accelerating the AI investment race. For the US, the Chinese AI project was a further threat to their dwindling imperial hegemony. For my money, nevertheless, the more impressive victory was the Carnegie Mellon team that combined learning algorithms with game theoretic randomization strategies to detect bluffing in “heads up” (two player) no-limit Texas Hold’em poker. These clever exhibitions as well as other more significant contributions, however, often obscure looming AI/big data dilemmas.

Human displacement proceeds apace

Another research “winter” aside, the subliminal blitzkrieg upon our daily lives proceeds at a breakneck pace. The various toy and top-secret applications of the previous decades are now being dwarfed by immense inroads into so many diverse and previously unattainable domains. The contributions AI, even its limited ML/DL form, is completely undeniable. While perhaps more than a bit of hyperbolic, Google CEO’s (Sundar Pichai) claim that AI will be more important “than the discovery of fire or electricity”. The powerful medical diagnostics (especially using radiological and biopsy data) are already well established and new treatments are also emerging on a regular basis. For instance, Jonathan Stokes and his colleagues at MIT and Harvard used a version of DL called “graph net” to discover novel compounds to combat superbugs (antibiotic resistant strains). Other ML devices used to statistically amplify weak signals can be modified to isolate multiple objects and their convoluted trajectories via “numeric integration”. Such programs have exposed a number of additional asteroids and comets converging upon Earth’s orbital keyholes in the next 100 years or so. For example, Spanish engineering student, Gema Parreño. recently applied Google’s TensorFlow tool toward tracking “near earth objects”, in response to a NASA challenge. Her program, Deep Asteroid, can identify changes in shape, color, and the chemical composition, as well as trajectory. ML/DL will undoubtedly produce even more magical extensions of human capabilities in the immediate future.

Nonetheless, we remain, for the foreseeable future, a far cry from the SINGULARITY of Artificial General Intelligence (AGI), or “Strong AI”, as promised by the likes of Ray Kurzweil (2005; also note, Domingos, 2015). Some industry experts (see, Wolski, 2020) already contend that when it comes to AGI, “deep learning is a dead end”. It is worth noting, however, that when we eventually do achieve complete replication, the pace will quicken exponentially. The divergence from the isomorph with human capabilities will be pretty much moot as machine intelligence speeds away. From the very moment of the singularity, machines, by the very nature of their learning mechanisms, will continue to double human intelligence again and again on a daily basis. Along the way, however, practitioners of machine learning might lose track of some of vital the understandings and enhancements that they originally promised. If they have already lost interest in arriving at a full understanding of the human mind and the meaning of consciousness, they might also inadvertently obliterate many ethical and legal considerations in their haste to monetize “superintelligence”.

The Pew Center (Anderson et al., 2018) which describes itself as a “fact tank”, rather than think tank, conducted a survey of nearly a thousand AI pioneers, business leaders, and policy-makers, and almost to a person (particularly positive appraisers) identified a number of negative prospects. In addition to privacy and imbedded algorithmic biases, the destruction of “human agency” was paramount. Given macroeconomic mismanagement and political disintegration, individuals in developed nations have never felt such a sense of loss of control over their lives, and most experts agree that widespread use of AI will make matters much worse. Toxic levels of anomie and alienation could have immense societal consequences. While the experts have diagnosed the loss of norms, personal efficacy, and human capital, treatments are in short supply, and often only placebos. Just as the lack of AGI progress has bred a sort of institutional ignorance as well as arrogance, much hand wringing about social implications have produced a bundle of make-believe solutions. Lack of understanding of the social ecology of AI tends to play down its central, yet subliminal theme. On its current institutional trajectory, AI is not so about enhancing human intelligence as it about insisting that humans become more like machines themselves, and re-order their lives to become more compliant cogs in the bigger machine. Once algorithms know us better than we know ourselves, many an on-going effort to interject legal and ethical concerns might fall by the wayside.

Philosophical imperatives and political mechanism from a bygone era (from basic morality to voting and from legal to regulatory systems) might matter little in the future. Most the university programs and centers to integrate human concerns into the AI enterprise will show themselves as mostly window dressing. Plus, the choice of leading AI scholars to head up these new programs is a bit problematic. For example, the leader of Stanford's efforts is legendary AI researcher, Fei-Fei Lee. She is an earnestly concerned citizen, yet in a recent public discussion at the Humanities Center (Harari & Lee, 2019) she candidly expresses her personal conundrum; that after much of her life spent in developing AI, she finds it hard to believe that it will cause undue societal "upheaval". Professors of moral philosophy might not be much better at imagining the depths of our dystopic future, however. Plus, academics of all stripes (even political scientists) may have little conception of the extent to which our institutional ecology has already been altered to protect the Big Data dynasties (note, Cohen, 2019). In several domains (e.g. oil, finance, pharma, etc.), our current regulatory apparatus is much like the Jim Crow South, when so many local sheriffs were members of the KKK. Moreover, technologies, especially those characterized as vital engines the new economy, have become the pinnacle of sacred cows, even among would-be reformers. All the while, continuing battles with firms like Facebook, over such things as "behavioral distortions" and "algorithmic incitements" tend to confirm that the much-prized neoliberal "self-regulation" has extreme deficiencies.

While new professional standards might provide a useful ancillary approach, the panoply of new institutes and "human centered AI" courses are unlikely to put more than a small dent. We still seem to think that the mere mention of terms like ethics and social responsibility hold some sort of magic. Unfortunately, these normative claims, even when translated into legislation, will make glacial progress, at best, when pitted against institutions so sheltered by law and sanctioned by economic dogma. In a world where humans can be so easily hacked and oligarchy is extolled, those we seek to regulate are more likely to regulate us.

The algorithms themselves might be preprogrammed to search for socially viable solutions, however. For example, they could be simply "supervised" to search for "Rawlsian" (Rawls, 1971; and note, Joseph, et. al. 2016) solutions (i.e. which benefit the least advantaged party first). But I would not hold my breath awaiting widespread implementation of ethics engines in our radically divisive societies. Software engineers have sought for a while now to develop "artificial moral agents" (AMAs) which arrive at ethical directives mostly on their own (note, Anderson & Anderson, 2007). However, a recent appraisal (Cervantes, et. al. 2020) concluded

> "that there is a long way to go, from a technical perspective, before this type of artificial agent can replace human judgement in difficult, surprising, or ambiguous moral situations" (p. 501).

In the meantime, forces will intensify for completely unbridled artificial applications.

The AI arms race and the inordinate power of the Military Security Complex will produce huge pressures to forego basic societal constraints. Moreover, mainstream economists are likely to inject their own ideological biases regarding the limited responsibilities of corporate personhood. They might even be called upon to reinforce AI's embedded behavioral theories, to the effect that humans have no "free will" and hence are not entitled to any of their already diminished dignity. Such a destruction of human agency (for the masses at least) might prevail despite our best efforts at putting humans back into the intelligence equation. In the wake of all the financial mayhem of recent years, AI, both as in industry and in specific applications, might also accelerate the processes of dispossession.

Algorithm and blues

As devastating as declining agency might be, it pales in comparison to more totalitarian undercurrents of AI. Loss of privacy and constant surveillance aside, AI's capacity for customized indoctrination would make any would-be Joseph Goebbels absolutely ecstatic. Having drained us of our basic humanity, they can refill us with hate and fear. We have seen burgeoning black shirts for decades now, but AI gives festering fascism much more powerful tools of societal subjugation. The Cambridge Analytica Case has already illustrated the potential for altering elections with algorithms that segment populations, amplify misinformation, and magnify dread, Meanwhile, we already have social networks that left to their own devices fuel fanaticism while concealing armies troll bots (foreign & domestic). Microsoft researcher and Founding co-director of NYU's AI Now Institute, Kate Crawford (2017), expresses these concerns as follows:

> "Just as we are seeing a step function increase in the spread of AI, something else is happening: the rise of ultra-nationalism, rightwing authoritarianism and fascism. All of these movements have shared characteristics, including the desire to centralize power, track populations, demonize outsiders and claim authority and neutrality without being accountable. Machine intelligence can be a powerful part of the power playbook" (p 2).

Dirk Helbing and an auguste team, including Bruno Frey (Helbing, et. al. 2017) speculated about the fate of democracy in the era of Big Data and AI, in the pages of Scientific American, and were not what one might call optimistic. Plus, Oxford researcher, Vyacheslav Polonsky, told global elites at Davos, "how artificial intelligence silently took over democracy", as if they did not already know.

AI, both for good and evil, is pretty much fully baked into our societies in the near term. While extremely valuable cautionary appraisals abound, the machine learning juggernaut appears invincible. While it moves in fits and starts, its stride is lengthening. One of the best (and most accessible to the lay person) of these flashing construction zone signs is provided by Melanie Mitchell (2019). By way of her profound prudence and prodigious pedagogy, she clearly explains why AI is not quite ready for prime time. Beyond its hyperbole and hackability, having strayed away from the quest for the "core of cognition", it will continue to butt its head against the "barrier of meaning". But these deficiencies may only minutely delay the spread of new applications. One particular set of applications, by the economics profession, remains up for grabs, given the slow pace of progress (or digress). Therefore, it is upon this particular rampart we should make our stand.

The wayward rise of machina-economicus

The nexus of mainstream (or neoclassical) economic theory is "homo-economicus" (or economic person). It is a super being who dwells in a fairy tale land with complete information and is obligated to act hedonistically (maximizing their individual utility at the margin). Neoclassic economists merely stamp out this little cookie person, and then chuck out all the inconvenient dough, including: altruism, reciprocation, and "moral sentiments" (as Adam Smith suggested in his virtually unknown first volume), not to mention behavioral proclivities and a modicum of concern for the natural environment. Their poor little cookie person has been bludgeoned to crumbs on empirical as well as philosophical grounds for decades (see, Fleming, 2017), and yet its specter lives on. Many ideas and actions of the mainstream have been widely condemned and disconfirmed, yet they persist, suggesting an inordinate level of scientific lassitude.

Some of the more potentially troubling aspects mainstream economics could receive a renewed lease on life, via selective applications of Artificial Intelligence. This is particularly relevant if it is merely used to shore up faulty theories regarding the dog-eat-dog nature of our society. MACHINA-EONOMICUS could be even more impenetrable and strengthen the illusion that the prevailing ideology is unassailable logic. Just when it began to look like the beleaguered cookie person was finally going to yield to the often befuddled (yet authentic) sense of our common humanity, s/he is being refurbished with even more mechanical workings. As AI further penetrates the *raison d'état* of the clandestine political economy, neoliberalism might be a reinvigorated.

What was to become a patch work of contradictory notions we now call "mainstream" or "orthodox" economics began during the industrial revolution with the highly selective extraction of a few classical ideas (e.g. the "invisible hand", "comparative advantage", "the barter myth", the efficacy of inequality, and the sanctity of accumulation). It did not acquire its mathematical veneer until the Victorian Era (1830s to the early 1900s), via the work of William Stanley Jevons, Leon Walras, and Carl Menger and their Marginal Revolution (e.g. individual utility, diminishing returns, general equilibrium, etc.). What famed American non-orthodox (institutional & evolutionary) economist, Thorstein Veblen, would label "Neoclassical", adopted the Newtonian mechanical worldview. Prominent economic historian, Phillip Mirowski (1989) describes how neoclassical formulas were simply lifted, whole cloth, from outdated physics textbooks, and hence lacked an awareness of thermodynamics (e.g. entropy), or any dynamics for that matter. Their notions of a static equilibrium left them stranded on a cold, dead planet, yet their insistence on perpetual growth and increased consumption, magically endowed it with infinite resources (or technical substitutes). In another prescient book, Mirowski (2002) contends that mainstream economics has also been hell-bent on becoming a "cyborg science" well before the advent of AI. In the process Mirowski chronicles how elements of economics have remained close to the machinations of the Military Industrial Complex (e.g. the Rand Corporation) since the days when operation researchers worked alongside the code breakers and other progenitors of AI, during WWII. As the cold war proceeded, much the prevailing ideology of mainstream economics was also honed, beginning with a small group that met in a Swiss village in 1947.

What is so intriguing about the influence of the Mont Pelerin Society (or Pelerins for short), is that their hidden political pronouncements (now known as neoliberalism) became so easily interwoven with neoclassical methods, which specifically excluded political concerns. Some conflate the radical libertarianism and "market fundamentalism" of neoliberalism with neoclassical theory in economics, but they are not same. The complete capture of economics by a cult of ideologies did not emerge with a vengeance until the 1970s, after a few decades of lavish corporate funding of dedicated think tanks, foundations, and entire university departments, as well as law and business schools. The fake Nobel prizes (actually the Riksbank Prize) that economists award themselves at the same time as the authentic science and peace prizes did not begin until 1969, with a significant number going to Pelerin purists in perpetuity. With the elections of Ronald Reagan in the US and Margaret Thatcher in the UK, neoliberalism arrived at the pinnacles of power, and has maintained its hold, irrespective of political party. The durability of its power is also found in the lifetime appointment of neoliberal judges (Baby Borks), particularly to the US Supreme Court.

Neoliberalism was surreptitiously welded into neoclassicism in order to sustain certain policy prerogatives, and pass them off as scientific truths. Its various ideological contradictions were submerged in a new methodological morass as its global project expanded. Microeconomics tools and concepts became muddled with macroeconomic imperatives (via "efficient markets" "rational expectations", etc.). By early 80s, Milton Friedman (the 2nd Pelerin president) and his colleagues at Chicago with dominated macro options altogether. The only fiscal policies became austerity and tax cutting for the rich, manpower policies focused on rabid union busting, and monetary policy was reduced to constructing a perpetual motion Ponzi scheme force-fed by independent central banks. The financialization ethos displaced all other managerial directives (see, Daneke & Sager, 2015), and clouded risk appraisals. The following frenzy of fraud was rendered unforeseeable and inexplicable by neoclassical / neoliberal models that had made the burgeoning credit economy exogenous. An unaccountable "Shadow" banking industry (hedge. private equity & sovereign wealth funds, and insurance, mortgage, & venture firms) exploded in the void. Speculative excess was backstopped by the printing press (e.g. QE), and deadly derivatives (e.g. credit default swaps) sprang from extremely ill-conceived algorithms (e.g. The Gaussian Copula). Fictitious wealth mushroomed to several times the GDP of the planet. Essentially, the faux entrepreneurial religiosity of neoliberalism when combined with falsely professed neutrality of neoclassicism has made mainstream economics an elaborate smokescreen for kleptocracy.

Just imagine how much better an apologia for the status quo might be presented via the deus-ex-machina of AI. The unearned power of mainstream economics could be made even more potent by a radical new version of scientism. One can only hope that extreme instability which accompanies the rise of the AI Economy (e.g. dramatically accelerating redundancies) will call into question the viability of their parasitic ideologies. We can see, however, why mainstream economics is more likely to embrace the narrow set of AI tools and concepts. The possibilities of methodical refortification for deep seeded ideological biases would just be too enticing. They could merely substitute simple machine models for actual agents and institutions, and create the illusion they have arrived at some sort of preordained nirvana. In the process, they could continue to reject vastly more relevant simulations (e.g. resiliency, emergence, institutional co-evolution, adaption, etc.).

The road not taken, yet

It is essential to point out at this juncture that AI was originally introduced into economics as challenge to myopic neoclassical and neoliberal doctrine (note: Holland & Miller, 1991; Daneke, 1999; Arthur, 2013; Elsner, et al., 2015), and hence the mainstream has been extremely slow to respond. When colleagues and I at the University of Michigan were calling for an "artificial reality check for economists" back in the 1970s, I do not think we were expecting that machina-economicus would be the sole result. Advocates of what is now called COMPLEXITY ECONOMICS or in the less ambitious offshoot Agent-based Economics, obviously had something very different in mind. As one early complex systems economist and UCLA professor, Axel Leijonhufvud (of *Life Among the Econ* fame) once put it, neoclassical theory involves "very smart people in incredibly simple situations", while the real-world entails, "very simple people in incredibly complex situations".

The study of complex systems adaptive has origins in of nonlinear dynamics and statistical mechanics, such as Rene Thom's work in instability and morphogenesis (Catastrophe Theory) and Illya Prigogine's pathbreaking work in "dissipative structures" and "order out of turbulence" (Chaos Theory) among others. It is noteworthy that chaos research was the actually quest for order (or reordering processes), and complexity was search for simple rules (that drive heretofore intractable phenomena). As Niels Bohr once said of the early challenges to the Newtonian mechanical worldview in physics, "we now seek tiny islands of order in a sea of chaos". Harbingers of complex systems insights can be also be found among those in the Systems Theory (General and/or Living systems) movement, heralded by Ludwig Bertalanffy. Nor should we neglect to mention original transdisciplinary field of cybernetics (from the Greek, "the art of the steersman"; see, Wiener, 1961) that also served in the foundations of computer science and AI. Following upon impressive breakthroughs in physics, chemistry, and biology (note, Capra 1997 for an accessible overview), a small handful of social scientists began to contend that the emerging science of complex systems should be amply applied to economics, if it were actually still seeking to be scientific (for an excellent review, see Helbing & Kirman, 2014).

The complexity approach pretty much turns neoclassical economics on its head. First of all, it confronts the notion of equilibrium (particularly the General Theory) originally set forth by Walras, as well as certain aspects of John Nash's "strategic equilibrium" via game theory). According to complexity theory, economic systems are essentially in disequilibrium and thus often buffeted by nonlinear dynamics. This stands in stark contrast to linear and static results of neoclassical methods. Even when markets appear to spontaneously "self-organize", it is their systemic and "emergent" processes and properties where one should focus. Moreover, unlike standard economic regression models, chaos/complexity tools (e.g. Lyapunov exponents) can comb through the discarded randomness for the faint signals of divergent trajectories.

From complexity point of view, the economy is much like the Earth with a thin crust of stability, over a turbulent core that often dramatically impacts the surface. Economists would be much better served to understand the unstable ground upon on which they stand, especially in light of recent financial turmoil. Moreover, complexity accepts a good deal of flux in the very institutions that economists take for granted (e.g. fragilities enforced by history, culture, and power differentials). As the one of the fathers of the Santa Fe approach, Brian Arthur (2013) elaborates:

> "Where equilibrium economics emphasizes order, determinacy, deduction, and stasis, complexity economics emphasizes contingency, indeterminacy, sense-making, and openness to change…This view, in other words, gives us a world closer to that of political economy than to neoclassical theory, a world that is organic, evolutionary, and historically-contingent" (pp. 1-2).

On the rare occasion that "exogenous shocks" or any of all the other interesting ingredients excluded from mainstream models are referenced, they merely assumed the system will quickly restabilize in accordance with a Gaussian distribution (like a bell curve). As complexity studies often show, even in absence of strong or systemic perturbations, deviations in time series often present "fat tales" suggesting some sort of "power law" distribution. But one might ask, what if bubbles and crashes are the norm, and stability is the aberration? What if the economy is not a fine turned machine, but a rather a messy and constantly evolving system, often experiencing the rapidly cascading effects of "strange" or chaotic attractors as well as "limits cycles"? British scholars have already begun to raise these issues in anticipation of the next global financial crisis (Haldane & May, 2010).

Evolution and agency revisited

Over 120 years ago, the grandfather of Institutional Economics, Thurston Veblen (1898) asked his colleagues "why economics is not an evolutionary science?" It still remains an open question today. Reasons probably include that for the sake of scientism, economists have come to believe they must remain as constant as the Northern Star. Time itself often stood still for the sake of mathematical representation. Over the years, increasingly bizarre machinations emerged in economics, in name of formal elegance. Consider for example the crazy notion of path independency (which results in dictum that history does not matter). The mainstream so dearly needed for messy matters to converge to a single equilibrium that they merely assumed that most untoward events were transitory and even differing initial conditions were irrelevant. They proceeded to maintain this collective ignorance even the face of obvious network effects. When Brian Arthur first introduced his studies on "increasing returns" to a panel across the bay (Berkeley), he was told "that if they did exist, economists would have to outlaw them."

More important, perhaps, than their lack of evolutionary and institutional awareness, is their stultifying characterizations of human agency. Complex systems seek to encompass a wide spectrum of agents, well beyond those resulting from "information asymmetries", and allows for a smorgasbord of motives including: behavioral biases, altruism, reciprocity, old fashioned morality, etc. Mainstreamers mainly reject this notion believing that these transrational elements, that they label "anomalies", are irrelevant since "other regarding" or merely stupid agents will always be overwhelmed by cold blooded cookie persons. This notion remains despite studies which show how these purely economic (i.e. greedy) agents are themselves often side-lined in the aggregate (see, Frey and Gallus, 2014). Plus, the continuous co-evolution of divergent individuals and their institutions can periodically produce dramatic results that defy rationality completely. The rise and amalgamation of the Pelerins might well be a case in point.

Complexity economics also seeks to model multiple-levels of "interconnectivity" between diverse agents and changing preference maps. In complex systems the unit of analysis shifts ever so slightly toward the interaction between individuals, their institutions, and the evolving economy; A "three-body problem", if you will. This endeavor might be characterized as

HOMO-COMPLEXICUS, for lack of a better term. It has always been curious to me how mainstreamers maintain that the autonomous individual is their unit of analysis, since they care so little about real individuals and their actual psychology, not to mention sociology. Plus, their agents are never really "free to choose" anything that contradicts their super-mechanistic economic models. The mainstream has agents without agency. Real agents participate in a number of wildly interactive or systemic choices. At any given point in time, we might be unaware of many of the institutional forces impinging upon prerogatives, but we are periodically awoken to some. Rather than having us exist in an economically induced coma, complexity studies assume we can reflect upon and occasionally actively explore rule changes that enhance rather than suppress our choice parameters. Moreover, we might even awaken to a larger role in our own evolution with choices that facilitate more resilient and sustainable systems.

An authentically "agent-based" economics does not apply top down principles, deductively derived from dogma. Rather, it grows systems, literally from the ground up. As Brookings Institute Scholars Joshua Epstein and Rob Axtell (1996) explain:

> "[W]e give agents rules of behavior and spin the system forward in time and see what macroscopic social structures emerge…we part company with certain members of the individualist camp insofar as we believe that the collective structure, or institutions that emerge have feedback effects in the agent population, altering the behavior of individuals" (p. 16-17).

At the fundamental level, complexity models reverse, yet revitalize, the idea of agency. In complex systems, agents not only arrive with a bundle of mixed individual motives, but adapt and learn by way of their cooperative (as well as competitive) experiences. If we were only self-interested, short-term, personal utility maximizers, then we would probably have gone extinct long ago. And, if we remain in the grip of our neoclassical/neoliberal delusions we might yet make it.

Unlike our currently anti-social and anti-democratic economics, complex systems thrive on inclusion. Early complexity pioneer, John Casti (1994) observed that many, if not most, orthodox inquiries, with their draconian economic strictures, merely assume "simple systems" where only a small number of firms or very few oligarchs determine the outcomes. He cites "political dictatorships, privately owned corporations and the Catholic Church, with their low interaction between the lines of command and a centralized authority". Complex systems, on the other hand, assume a "diffusion of authority" and hence are ultimately more robust. He points out that,

> "...in actuality the power is spread over a decentralized structure. Actions of a number of units then combine to generate the actual system behavior. Typical examples of these kinds of systems include democratic governments, labor unions and universities. Such systems tend to be somewhat more resilient and stable than centralized structures because they are more forgiving of mistakes by any one decision-maker and are more able to absorb unexpected environmental fluctuations" (p. 272).

Complexity Economics is at its core a science of socio-cultural evolution and "emergence". Interactions generate properties that are "greater than the sum of their parts". My Michigan colleague, John Holland, coined the phrase "perpetual novelty" to explain these processes.

His famed "Holland Schema" allowed "fitness landscapes" to be studied in topological configuration. Brian Arthur (2013) contends these processes of unfolding and "formation" should be of great concern to economists. In his own words, formation involves:

> "…how an economy emerges in the first place, and grows and changes structurally over time. This is represented by ideas about innovation, economic development, structural change, and the role of history, institutions, and governance in the economy" (p.17).

In their classic multi-national study, *Why Nations Fail: The Origins of Power, Prosperity and Poverty*, MIT Institutional Economist, Daron Acemoglu, and Harvard Political Scientist, James A. Robertson point out that historically speaking inclusive systems generate greater prosperity.

New wine in old bottles

Mainstream economists, however, are much more likely to adopt a far narrower take on AI. As they tend to seek some sort of inescapable (even if "bounded") rationality, it seems perfectly reasonable that they embrace machine models. One might also expect they would seek to use them to shore up their teetering ideological base. Apparently, they share a common commitment to a bionic cookie person with certain elements of computer science. This is precisely the point that David Parkes and Michael Wellman (2015) make in the prestigious pages of *Science.* They assert that,

> "The field of artificial intelligence (AI) strives to build rational agents capable of perceiving the world around them and taking actions to advance specified goals. Put another way, AI researchers aim to construct a synthetic homo-economicus, the mythical perfectly rational agent of neoclassical economics" (p. 267).

As Parkes and Wellman are engineers, and perhaps unfamiliar the many travails of cookie personage, they might be forgiven for letting the "machina economicus" cat out of the bag, so to speak. It worth reminding you that most of this this discussion revolves around the small subfield in AI known as "machine learning", employing deep (meaning layers of neural nets) techniques, and not necessarily genetic or adaptive algorithms. Parkes and Wellman mention multi-agent systems, yet they seem to believe that ML/DL will provide sufficient training to homogenize rationality as their caricature of economics demand. They clearly believe that neither field needs significant modification. I would suggest that they are definitely a good match, but not necessarily one made in heaven.

Stanford superstar business and computer science professor, and Microsoft advisor, Susan Athey is just as gung-ho as these engineers, but much more meticulous in her efforts to adapt machine learning to the particular needs of econometricians, who are surprisingly rare among the empirically challenged mainstream. Many orthodox economists merely want to use formal proofs and avoid data like the plague. Athey is an especially rare breed. She started at Duke at the age of 16, and matriculated with majors in math and computer science as well as economics. She was the first woman to receive the John Bates Clark Medal (for contributions to econ before 40) in 2007. As their fake Nobel prizes are given as much to co-opt as condone, I'd suspect she will have one of those before much longer. But she might have to share it with an even deeper defender of the faith. Her own faith might be a bit conditional for an otherwise hard-core econometrician and she also has a Big Data burr under her saddle. Thus, she has issued a number of calls (Athey, 2016; 2019; also note: Athey & Imbens, 2017) for economists to embrace machine learning, especially “supervised ML” as well as “generative adversarial networks (GANs)”. In a candid interview at MIT/Sloan (Mason, 2018), she admits to a substantial amount of “push back” from the establishment over the issue of “correlation versus causation” and “prediction versus decision-making”. Ergo, she maintains how the blending of machine learning with estimations drawn from conventional counterfactual policy research is her focus for the time being. Meanwhile, of course, AI researchers will continually enhance the isolation of multi-directional correlation in their predictive algorithms. While the old adage that “correlation is not causation” still pertains, machine scientists generally see it as a bit of red herring.

Bayes-ed and confused

I am still a bit ambivalent on this subject myself, but I suspect that it might be more accurate to suggests that economists concern for sanctity of causality in their relatively sparse empirical inquiries is a bit of a canard. I believe that many mainstreamers are really concerned that Bayesian tests imbedded in most machine learning protocols would expose the fairy tale nature of several of their sacred priors. Some cherished pillars like the “efficient markets hypothesis” would not survive a Bayesian bombardment. When applied to AI, Bayesian inference assumes that all priors are merely probabilities that will be continuously reassessed as the machine discovers new “patterns of association.” This famed theorem was actually afterthought of the Right Reverend, an amateur statistician and an early defender Darwin, which he never sought to publish. Econometricians have played around with Bayes for decades (see, Lancaster 2004) but with far less vigor than current AI researchers. Meanwhile, mainstreamers appear to have decided to let sleeping dogmas lye. Nonetheless, workarounds abound that combine Bayesian like processes with tools such as decision trees and Monte Carlo simulations as well as other emerging DL tricks. Harvard economists (Mullainathan & Spiess, 2017) have even managed to set aside the prediction versus policy problem for certain machine applications. Adding to the confusion, some computer scientists still defend “relative frequencies” and a small number of mainstream economists (e.g. Nobel Laureate, Chris Sims) argue “why econometrics should always and everywhere be Bayesian” (2007, p.1). Besides, he adds that “Bayesian inference is a way of thinking, not a basket of methods.”

My best guess is that more than a measure of legerdemain will be involved in fully substituting the new machine model of science for the antiquated and unrealistic aspirations of mainstream economists. But then they do have most of the brightest kids in the room on their team. From a diabolical perspective, it really serves their ambitions well to hitch their creaky handcart to the AI bandwagon, and various black box applications can hide even more sleight-of-hand. Moreover, I suspect that Athey and others will discover new devices for keeping neoliberal corpses on display. At the very least economists might come to appreciate that meaningful data was once just so damn difficult come by, employing armies of graduate assistants. Hence, as Athey (Mason, 2018) pointed out “they should embrace the benefits of effectively having a robotic research assistant”. The dearth of data, of course, was always far less meddlesome than the issue of the poor approximation of actual human aspirations, and collecting and processing of a great deal more misinformation might make matters immensely worse. Once machina-economicus is fully operationalized, we might open a Pandora’s Box of much thornier problems.

When algorithms rule the world

One of the more obvious dilemmas is that the Big Data decathlon is the combination of information implantation with extraction. Many of the minions of information monopolies want to train people as much as algorithms. When self-driving cars began to run over people, the first suggestion was more training for pedestrians, and the second was banning humans from the main roads that their taxes built and maintain. AI can be an extremely powerful instrument of social control, and we can imagine that many old guard economists are, when push comes to "nudge", perfectly okay with this prospect mass re-education. As Brian Arthur once observed,

> "economists got away from really questioning how the world works, how decisions actually got made. If something doesn't conform to neoclassical models, then people are not somehow behaving themselves properly. It's like seeing real economic behavior as impurities in a physical system or chemical system that are messing things up" (Kurtzman, 1998, p. 2).

Versions of machine economics could be enlisted to aid in processes of purification. They might provide packaging for the essential super-suds used in the humongous mental carwash, and issue rain checks for those who don't come clean (or quietly). While trust in economists should be less than robust after various recent debacles, the public at large are readily taken in. While the US is an inherently an anti-intellectual enterprise, especially of late, mainstream economists can often convince the rubes that they are somehow both more book-smart and yet more streetwise than say the typical environmental scientist or epidemiologist for that matter. While mostly speaking of the past, before political economy was outlawed in the mainstream, Robert Heilbroner referred to them as *The Worldly Philosophers.* Their theory and methods became increasingly unworldly, yet their influence still continues to climb, mostly by pandering to plutocrats. Replenishing their antiquated and ethereal arsenals with aspects of AI might make their snake oil even more delectable.

Just as mainstream economists are refurbishing their Frankenstein cookie monsters, machine learning developers are providing their own retrograde version of human behavior by resurrecting the rogue psychologist, B.F. Skinner, from nearly three quarters of a century ago. His misguided use of manipulation as explanation as well as learning via "operative conditioning" have now been interwoven into the epistemology and ideology of machine learning. One might have thought that Skinner's (1971) obliviation of human "freedom and dignity" was laid waste by its many critics decades ago. Some of the most devastating blows were leveled by famed MIT activist scholar, Noam Chomsky who was a pioneer of cognitive science as well as linguistics. However, as AI settled upon the machine learning path, it strayed a good bit from its cognitive science origins. In her epic, *The Age of Surveillance Capitalism*, Harvard Business Professor, Shoshana Zuboff (2019) chronicles how Skinner has returned as the patron saint among the Big Data daddies. Afterall, they can't be taking away something we never had. Since they became as rich as Croesus by herding humans like cattle (or batteries in *The Matrix*), it should come as no surprise that they seek legitimizing theories, wherever they can find them. Monetizing "behavioral exhaust", by recombing and re-injecting it like a turbocharged engine, is not enough for the new *Madmen*, they want us to cherish our chains. These same devices can be used to further atomize, alienate and undermine communal values. But worse yet, ML/DL can allow individuals to be herded into the lower cubbyholes of a "new caste system", according to Kissinger Associates VP, Joshua Cooper Ramo (2016). Skinner is being resurrected to prepare us for this "brave new world", (or his own utopian novel, *Waldon Two*). He thus joins the Palo Alto pantheon of neofeudal heroes which includes: Nietzsche and Ayn Rand, as well as various “neo-reactionary (NRx)” and “Dark Enlightenment” oracles.

The moguls of Silicon Valley and Seattle have found additional solace in encyclopedic and only mildly dystopia writings of Israeli historian, Yuval Noah Harari (of *Sapiens* fame). In his tome, *Homo Dues: A Brief History of Tomorrow* (2017), he predicts that the AI will join forces with genetic engineering to usher in a totally new and more “god-like” species, CRISPR critters as it were. Yet, even these superior beings may not necessarily have “free will”, which he contends has always been a dysfunctional myth. Of course, techno-godhood will be reserved for the very few, and the vast majority of us mere homo sapiens will be serfs. AI induced serfdom, however, is still a tiny step above, Harari’s “useless class” (i.e. having no meaningful role whatsoever). As AI proceeds pell-mell to displace a huge swath of employment and exacerbate the already grotesque levels of inequality, its own self-congratulatory ideology provides a built-in justification for further dispossession. Much of this intellectual cover may come from the type of economists whom have defended rentiers for decades. Misguided analytics can merely be extended and refocused from the hero worship of Robber Barons to a new techno-idolatry. We already have our ersatz royals with no sense of noblesse oblige, but machina-economicus could give them another layer of insolation. Plus, when machines can code themselves (and us), the paths to nobility (or ignobility) will, as in the past, be very few and far between. Social mobility may mostly be downward.

While this neofeudal dystopia seems remote, we have already witnessed the new emperors of information beginning to dabble in the darker arts of AI. The negative influence upon the electoral process in dwindling democracies is now well documented. More importantly, the specious corralling of cohorts is becoming well developed, and we already have a number of black box algorithms determining our diminishing opportunities. Who gets into which college or gets what loan (at which interest rate), or who goes to jail and for how long is pretty much predetermined by proprietary applications (with code, data, and correlations as trade secrets). Harvard Ph.D. in mathematics and former Wall Street trader, Cathy O’Neil (the famed “math babe”) really says it all in the title of her New York Times Best Seller (and National Book Award winner in 2016), *Weapons of Math Destruction: How Big Data Increase Inequality and Threatens Democracy*. In essence, many of us are having our lives completely red-lined before we even get the chance to live them. While perhaps not as blatantly oppressive as the Chinese “social credit” (or increment of association score) system, existing data manipulations, when combined with facial recognition and other algorithmically enhanced surveillance, is a fairly Orwellian possibility. If you have nothing to hide, they can create something for you.

The policy use of partial and problematic predictive algorithms is burgeoning, even in the light of persistent challenges. Researchers at Dartmouth (Dressel and Farid, 2018) demonstrated that complete novices could out predict the infamous COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) algorithm that is deployed by several states in projecting recidivism and making sentencing and parole decisions. Another prodigious study headed up by Princeton sociologists and public affairs scholars, Sara McLanahan, Ian Lundberg, and Matthew Salganick involved a literal army of social and information scientists (PNAS, 2020) over 15 years, with 4,000 families and nearly 13,000 data points, under the title, *Fragile Families and Childhood Wellbeing*. It concluded, in the words of MIT senior AI writer, Karen Hoa (2020), “AI can’t predict how a child’s life will turn out even with a ton of data”. Perhaps AI will prove better at persecution than prediction. Beyond illustrating the amplification of racial, gender, and class biases, Virginia Eubanks (2017), SUNY Albany Political Scientist, documents how algorithms are being used to further torment the down-trodden via what she calls the "digital poorhouse". Plus, she details that most of these applications are far more expensive than simple programs aimed at enhancing opportunities.

We experienced how mathematicians and physicists employed by Wall Street ("quants"), aided and abetted monumental financial shenanigans and nearly brought down the entire global banking system (and it has yet to really recover). Yet, new algorithmic devices for skirting regulatory measures as well as building increasing exotic in-securities are still proceeding as if the melt down never occurred. The mere presence of our malfunctioning financialized economy adds pressure to further ignore the numerous flies in the ointment of our info-tech salvation. Machine processes, with their labyrinth of inexplicably connections, are difficult to unwind, let alone comprehend, once hastily implemented. AI practitioners, involved in pecuniary projects, have little time or access to opacity problems when black boxes proliferate themselves.

Concluding observations

One can still hope that our continuing financial lunacy and AI associated economic dislocations will finally unleash a Kuhnian "scientific revolution" within mainstream economics. Yet, when it comes to the level of "normal science" to be overcome, we could debate how much there is still there. Unacknowledged ideological elements may have made the mainstream more cult than science, per se. The engrained model eating aspects ML/Big Data, however, might be like the bomb within that sets off the nuclear device, a revolution within a revolution, as it were. My own best guess is we are not quite there yet, we still have a few more shifty paradigms to dislodge before a true paradigm shift is probable. I could be wrong, and hope I am. Some of colleagues in complexity economics try to convince me that we've already won, but then I ask them in which journals they are publishing and how many card-carrying economists they have on their transdisciplinary teams? Conversely, how many non-economists (aside from quants) participate in AI econ projects?

Thus far, as mainstream economists go forth to master and manipulate the artificial, they continue to neglect much real social science. It has long been suggested, as far back as Veblen, that economics should more fully integrate with the other social sciences (history, anthropology, political science and psychology as well as others humanities). Some among the complexity camp contend that this marriage of the minds is near at hand. I once thought so myself, but obviously, I am no longer sure. Mutual respect is seriously lacking, and some of my hardcore colleagues contend that economics is not a social science at all. Back in the 1970s when the National Sciences Foundation was initiating its interdisciplinary research agenda, an inquiry of inquiries gleaned that economists were the least likely to play well with others. And, they have become the increasingly recalcitrant over the years. The mainstream has extended their isolation, along with their ideological adherence, self-appointed supremacy, and growing political and commercial power. Moreover, mainstream economists have managed to make transdisciplinarity a one-way street. Beyond completely overrunning business, law, and public service schools, they have spread their "freakonomics" far and wide (from child rearing to love and marriage, etc., etc., etc.). Veblen would certainly be disturbed to see his *Journal of Political Economy* merely applying economic models to the behavior of politicians (rather than the reverse). This insularity amid intellectual imperialism, suggests that those wishing to use AI to push economics in the direction of inherently transdisciplinary adaptive systems research have their work cut out for them.

At the ground level, we can fully expect a new phalanx of mainstream shock troops. The on-going cross breeding of economists and computer scientists could produce super-true believers, and they might even end up further darkening long standing scientific and ideological blind spots. The theory bomb of AI could fizzle-out in their incurious hands. In Washington in 1970s, it was relatively easy to spot the overzealous ideologues of the newly initiated joint law and economics programs, and at Stanford in the 1980s, the engineering and economics hybrids, especially those already running stochastic programs for shadow bankers on Sand Hill Road, stood out for their myopia turned glaucomic by inordinate hubris. This more intensely pretentious priesthood is quickly becoming the norm. The new generation of economists is already much heavier on coding and computational tools and much lighter on understanding of their own discipline. It has often been asserted that even the large glob of economics in the typical MBA program functions as “a little bit of knowledge being a dangerous thing”. With more AI courses encroaching upon the already limited mainstream curriculum, we will soon have vast armies of newly minted economists who are little more than mindless quants and extremely dangerous.

Rather than giving their blessings to these mangled marriages, engineers should rekindle their own traditions in “sociotechnical systems” (STS). They became somewhat sidetracked early on via the Travistock Institute and “organizational development”, workplace design, “industrial democracy” elements (e.g. Emery & Trist, 1965). As vital as these tangents might be, it was by way of more broad-based technology assessments and “social factors” research where STS came into its own (see, Baxter & Summerville, 2010). In particularly, it has generated valuable insights into the barriers and bridges associated the transition to a post carbon economy (e.g. Cherp, et al., 2018; and Büscher, et al., 2018) and sustainability studies generally. STS was instrumental in the early development of AI, and could be called upon again.

Unfortunately, Veblen’s contention that engineers (as opposed to business and banking saboteurs), aided by diverse social scholars, form the basis for a well-run economy never came to pass. Plus, top engineering schools are now being overtaken by their programs in “financial engineering”, as well as computer science. Hence, we are stuck trying to reform a deeply entrenched and soon to be rejuvenated adversary, pretty much on our own. Homo-complexicus (or complexica if you prefer) might at least serve as a new rallying point. I hope we are up to the task.

References

Anderson, C. (2008) “The End of theory: The Data deluge makes the scientific method obsolete.” *Wired Magazine*, (June).

Anderson, J., L. Rainie and A. Luchsinger (2018) *Artificial Intelligence and the Future of Humans*. Philadelphia: Pew Research Center. December.

Anderson, M. and Anderson, S.L. (2007) “Machine ethics: Creating an ethical intelligent agent.” *AI Magazine,* 28 (4): 15-26.

Arthur, B. (2013) “Complexity economics: A Different framework for economic thought.” SFI Working Paper 2013-04-012. Santa Fe: Institute for the Study of Complexity.

Athey, S. (2016). *Susan Athey on how economists can use machine learning to improve policy.* News, Stanford Institute for Economic Policy Research (March). https://siepr.stanford.edu/news.

Athey, S. (2019) "The Impact of machine learning on economics." In: A. Agrawal, J. Gans, and A. Goldfarb (Eds). *The Economics of Artificial Intelligence*. Chicago: University of Chicago Press. pp. 507-547.

Athey, S. and G. Imbens *(*2017) "The State of applied econometrics: Causality and policy evaluation." *Journal of Economic Perspectives,* 31 (2): 3-32.

Baxter, G., and Sommerville, I. (2010) "Socio-technical systems: From design methods to systems engineering." *Interacting with Computers,* 23 (1): 4-17.

Büscher, J., P. Schippl, and P. Sumpf (Eds) (2018) *Energy as a Sociotechnical Problem: An Interdisciplinary Perspective on Control, Change, and Action in Energy Transitions*. London: Routledge.

Capra, F. (1997) *The Web of Life: A New Scientific Understanding of Living Systems.* New York: Anchor Books.

Cervantes, J.A., L. Lopez, L.P. Rodriguez, S. Cervantes, F. Cervantes, and F. Ramos (2020) "Artificial moral agents: A Survey of the current status." *Science and Engineering Ethics*, 26, 501-532.

Cherpa, A., V. Vinichenkoa, J. Jewell, E. Brutschind, and B. Sovacool (2018) "Integrating techno-economic, socio-technical and political perspectives on national energy transitions: A meta-theoretical framework." *Energy Research & Social Science,* 37, (March): 175-190.

Cohen, J. (2019) *Between Truth and Power: The Legal Constructions of Informational Capitalism.* New York: Oxford University Press.

Constanza, R., J. Cumberland, H. Daly, R. Goodland, R. B. Norgaard (1997) *An Introduction to Ecological Economics.* Baca Raton: CRC Press.

Crawford, K. (2017) *Dark days: AI and the rise of fascism.* Austin: Session at the South by Southwest Conference.

Daneke, G.A. (1999) *Systemic Choices: Nonlinear Dynamics and Practical Management.* Ann Arbor: The University of Michigan Press.

Daneke, G. and A. Sager (2015) "Ghoshal's ghost: Financialization and the end of management theory." *Philosophy of Management,* 14 (1): 29-45.

Domingos, P. (2015) *The Master Algorithm: How the Quest for the Ultimate Leaning Machine Will Remake Our World*. New York: Basic Books.

Elsner, W., T. Heinrich, and H. Schwardt (2015) *The Microeconomics of Complex Economies.* New York: Elsevier.

Emery, F. & Trist, E. (1965) "The causal texture of organizational environments." *Human Relations*, 18, 21–32.

Eubanks, V. (2018) *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor.* New York: St Martin's Press.

Fleming, P. (2017) *The Death of Homo-economicus: Work, Debt, and the Myth of Endless Accumulation*. London: Pluto Press.

Frey, B. and J. Gallus (2014) "Aggregate effects of behavioral anomalies: A New research area. Economics: The Open-Access." *Open-Assessment Journal*, 8: htttp://dx.doi.org/10.5018/economics-ejournal.ja 2014-18.

Fullbrook, E. and J. Morgan (Eds) (2019) *Economics and the Ecosystem*. Bristol: World Economics Association Books.

Goodfellow, I., J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. (2014) *Generative adversarial nets*. Montreal: Proceedings of the International Conference on Neural Information Processing Systems. 2672–2680.

Haldane A. and R. May (2010) "Systemic risk in the banking ecosystem." *Nature*, 469 (Jan.): 351-355.

Harari, Y. N. (2017) *Homo Dues: A Brief History of Tomorrow.* New York: Penguin.

Harari, Y. N. and F.F. Lee (2019) *The Coming upheaval, Marta Sutton Weeks Discussion.* Palo Alto: Humanities Center, Stanford University.

Helbing, D. and, A. Kirman (2013) "Rethinking economics using complexity theory." *Real-world Economics Review*, 64: 23-52.

Helbing, D., B. Frey, G. Geiringer, E. Hafen, M. Hager, Y. Hofstetter, J. van den Hoven, R. Zicari, A. Zwitter (2017) "Will democracy survive big data and artificial intelligence?" *Scientific American*, Feb. 25.

Hoa, K. (2020) "AI can't predict how a child's life will turn out even with a ton of data." MIT Technology Review, https://www.technologyreview.com/s/615434/ai-machine-learning-social-outcome-prediction-study/

Hodgson, G. (2004) *The Evolution of Institutional Economics*. London: Routledge.

Holland, J. H. and J. H. Miller (1991) "Artificial adaptive agents in economic theory." *American Economics Review*, 81 (2): 365-371.

Joseph, M., M. Kearns, J. Morgenstern, S. Neel, and A. Roth (2016) "Rawlsian fairness and machine learning." Working Paper, Simons Foundation, Cornel University.

Keen, S. (2001) *Debunking Economics: The Naked Emperor of the Social Sciences.* London: Zed Books.

Krugman, P. (2009) "How did economists get it so wrong?" *New York Times Magazine,* (June).

Kurtzman, J. (1998) "An Interview with W. Brian Arthur." *Business + Strategy* Issue 11 (April).

Kurzweil, R. (2005) *The Singularity is Near: When Humans Transend Biology.* New York: Viking.

Lancaster, T. (2004) *An Introduction to Bayesian Econometrics.* Malden, MA: Blackwell Publishing.

LeCun, Y., Y. Bengio, and G. Hinton (2001) "Deep learning." *Nature*, (521): 436-444.

Mason, E. (2018) "Why leading economist is embracing machine learning." MIT/Sloan of Management/ *Ideas that Matter*. (Oct., 29).

Mazzocchi, F. (2015) "Could big data be an end of theory in science: A few remarks on the epistemology of data driven science." *EMBO reports*, 16 (10): 1250-1255.

McCarthy, J. (1990) *Artificial intelligence, logic and formalizing common sense.* Palo Alto: Position Paper, Computer Science Department, Stanford University.

Minsky, M. and S. Papert (1987) *Perceptrons Expanded Edition: An Introduction to Computational Geometry.* Cambridge: MIT Press.

Mirowski, P. (1989) *More Heat than Light: Economics as Social Physics, Physics as Nature's Economics.* New York: Cambridge University Press.

Mirowski, P. (2002) *Machine Dreams: Economics Becomes a Cyborg Science.* New York: Cambridge University Press.

Mitchell, M. (2019) *Artificial Intelligence: A Guide for Thinking Humans*. New York: Farrar, Straus & Giroux.

Mullainathan, S. and J. Spiess (2017) "Machine learning: An Applied econometric approach." Journal of Economic Perspectives*,* 31 (2): 87-106.

PNAS (2020) "Measuring the predictability of life outcomes with a scientific mass collaboration." Proceedings of the National Academy of Sciences, https://www.pnas.org/content/early/2020/03/24/1915006117.

Rawls, J. (1971) *A Theory of Justice.* Cambridge: Harvard University Press.

Romer, P. (2020). "The dismal kingdom." *Foreign Affairs* (February). https://www.foreignaffairs.com/reviews/review-essay/2020-02-11/dismal.html.

Ramo, J. C. (2016) *The Seventh Sense: Power, Fortune and Survival in the Age of Networks*. New York, Little Brown.

Sims, C. (2007) "Bayesian methods in econometrics, or, why econometrics should always and everywhere be Bayesian." Princeton, Working Paper, Economics Department (August 6).

Skinner, B. F. (1971) *Beyond Freedom and Dignity*. New York: Peregrine Books.

Smith, E. (2010) *Econned: How Unenlightened Self Interest Undermined Democracy and Corrupted Capitalism*. New York: St. Martin's Press.

Stiglitz, J. (2017) "Where modern economics went wrong." National Bureau of Economic Research, Online Working Papers. https://www.nber.org/papers/w23795

Turing, A. (1950) "Computer machinery and intelligence." *Mind* (49): 433-460.

Veblen, T. (1898) "Why economics is not an evolutionary science." *Quarterly Journal of Economics*. 12(4): 373-397.

Wiener, N. (1961) *Cybernetics: Or Control and Communication in the Animal and the Machine*, Revised Edition. Cambridge: MIT Press.

Wolski, M. (2020) "Why is current deep learning technology a dead end for Artificial General Intelligence?" *Start-Up*, https://medium.com/swlh/56f781c36d82.

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