May the source be with you: fumbling towards artificial academies

Chris Bigum

November 2014 version

On-Line Paper & Copyright

This draft paper may be cited or quoted in line with the usual academic conventions. You may also download it for your own personal use. The paper may not be published anywhere without the authors’ permission.

You should be aware that this version of the paper was the version that was submitted for publication or the version given at a conference. The final, published version may differ considerably.

If you copy this paper you must:
• include this copyright note
• not use the paper for commercial purposes or gain in any way
May the source be with you¹: fumbling towards artificial academies

In the beginning
Between 1969 and 1971 I undertook research at ANU for a PhD in physical organic chemistry. The year before in my honours year I had my first encounter with a machine, a generic term I will use through this paper to describe various digital bibs and bobs including algorithms, apps, software and its crystalline form aka hardware. The program I used generated nuclear magnetic resonance spectral data from measurements manually taken from an experimentally obtained spectrum. My task was to use the software to get the best possible match between what the spectrometer produced when it scanned a sample and the computed version. A good match allowed you to report the spectral properties of particular organic compounds. I used the software in 1968 in much the same way people use machines today. You put data in and it produced outputs. It was a blackbox. In 1969, my supervisor took a firm view on my use of that code and had me unpack every line of the program. The work led to my first publication (Batterham & Bigum, 1972). Some years later, the manual analysis I had conducted with the aid of a machine had been almost completely delegated to a machine.

We tend to think of automation as a one-way process, i.e. a machine will now do this work. But in any delegation of work to a machine, the distribution of competences between human and machine (Latour, 1992) goes both ways. A delegation of work to a machine results in a prescription (Akrich, 1992) of behaviours back to the human from the machine. If the human does not behave as prescribed, the durability of the heterogeneous network of human and machine won’t be stable or simply won’t work. At about the time Latour, Akrich and others in STS were thinking through human–machine arrangements², I was puzzling about the relationship between humans and machines in education settings. Thinking then and to some degree now, was plagued by forms of determinism. Oblivious to the work going on in STS, I developed a principle of complementarity (Bigum & Kenway, 1998) to draw attention to the requirements that delegation of work to a machine puts back to a human user. It was a simple, crude exchange that was missing the dynamic qualities described by STS-informed accounts. For example, a calculator user without approximation skills can make serious errors, or a user of Google maps when viewing sensitive borders between countries should be aware that the borders in Google maps move depending upon the location from where you do your search.

In the academy
The use of machines varies considerably across disciplines but we can be sure that their use will continue to grow, the machines are not going away any time soon. I will argue in this paper that the ways we think about our relationships with machines and the work they do is important. I will make use of the STS-informed notion of distribution of competencies to examine enactments of machines in the academy.

¹ HT @micahflee

² I use a term that is related to but separate from the more popular assemblage, or agencement in French. The word better gestures to ordering, to putting things in place.
The role of machines in the academy has shifted considerably from the days when a colleague once said to me in a conversation about using word processing software that she was being paid to write, not type! Since those days, we have acquired an ongoing and growing dependency on machines for a great deal of the work we do as academics, and as I will argue in this paper, the machines have developed a related dependency upon us.

Before moving to consider human-machine arrangements I want to briefly sketch some of the contemporary controversies that flow from an ongoing re-arranging of the humans who work in universities and their machines.

We work in social organisations built upon the broadcast logic of print and controlled media that struggle to come to terms with a world in which anyone can publish, or as Jay Weston (1997) presciently put it

> It is well understood that all social institutions have their relative certainties made possible by the centralizing power of the technologies of mass communication. The relative certainties that accompany attenuated access to the means of symbolic production are welded into the fabric of all institutional policies and practices. Assuming, then, that access to the means of cultural expression will be increasingly distributed, it follows that all of the institutions of modern society will be threatened or at least inconvenienced by this development (p. 197)

It’s fair to say that most universities have been at least somewhat inconvenienced by things like MOOCs, open-source data, social media, new measures of academic influence, new forms of credentialing, increasingly sophisticated forms of plagiarism, new forms of peer review, new modes of publishing, disruptive innovation (Christensen, Horn, & Johnson, 2011), the attention economy (Goldhaber, 1998) and the growth of computational approaches to knowledge creation, preservation and dissemination in most disciplines (Constable, 2006). All of these developments are intimately associated with new human-machine arrangements. The pace of these developments, still underpinned by the empirical trend known as Moore’s law, seems to allow little time for thinking about the nature of the new arrangements and particularly the re-distribution of competencies between academics and machines. For example, there is little evidence of what Roger Martin (2007) describes as integrative thinking about the issues that derive from an ongoing deployment of machines through the academy.

**Two levels of effects and the distribution of competencies**

There is a productive tension that is associated with the introduction of machines. It is important here to acknowledge the work of Lee Sproull and Sarah Kiesler (1991) who first identified this pattern. From their research into the introduction of new communication technologies like email into business settings, they made a distinction between what they described as two levels of effect: first-level effects, those claimed about improvements, most often in efficiency, arising from the introduction of the new technology; and second-level effects which derive from the unintended or unanticipated consequences of deploying a new technology.

Second-level effects from communication technologies come about primarily because new communication technology leads people to pay attention to different things, have contact with different people, and depend on one another differently. Change in attention means change in how people spend their time and in what they think is important. (Sproull & Kiesler, 1991, p. 4)

In this framing, machines are improvers of things which when put in place, become things
about which it is difficult or impossible to know if what was begun with has improved, because things have changed. Two logics are at play that don’t fit well.

There is a resemblance here to the observation that Law et al. (2014) make in relation to the syncretism of all practices. In their argument, the coherence and noncoherence of practices has an interdependent, performative, both/and quality. The will to purity, to order and its associated certainty sits uneasily alongside the messy, fuzzy set of practices under the hood, as Law et al. put it. In the instance of practices associated with humans and machines, one might expect similar modes of ordering of syncretism as mapped by Law et al. Rather than re-map Law et al. over human-machine arrangements, I want to examine what flows from the two logics identified by Sproull and Kiesler and consider the distribution of competencies. Edwin Sayes (2014, p. 138) put it well recently,

Nonhumans that enter into the human collective are endowed with a certain set of competencies by the network that they have lined up behind them. At the same time, they demand a certain set of competencies by the actors they line up, in turn. Nonhumans, in this rendition, are both changed by their circulation and change the collective through their circulation.

The bias to messiness is implicit in such an account. It resonates with notions of workaround, bricolage, kludges and tinkering and other improvisational ways of dealing with second level effects. It brings to mind Ursula Franklin’s (2004, p. 106) astute observation that all of this involves often unpaid product development engineering, i.e. finding useful things to do with the new. This contrasts sharply with the will to coherence, purity and predictability that is implicit in the logic of first level effects, of simply improving what is.

Of interest to me are the practices that do or enact various realities of human and machine arrangements in the academy. This performative approach draws upon a range of scholars working in STS and material semiotics that I refer to through this paper. Further, I have clustered the myriad practices of human-machine arrangements based upon similarities in the realities they enact. The clusters are borrowed from a set I made use of in the 90’s (Bigum & Kenway, 1998). They are not much changed. The machines have.

What follows is a brief account of the clusters and their practices: the boosters/pragmatists; the critics/romantics; the doomsters; the digitally homeless and the artificials. The practices associated with each cluster negotiate realities as will be the case for this symposium. Questions like, what is work? what is an academic? what is ‘the digital’? are a but a few of the questions that frame the contested space of humans and their machines in the academy.

**Boosters & pragmatists**
The practices of this cluster thrive on blurring the tension in the things improve/things change binary. There is a tacit recognition of the shift in competencies which typically manifests itself as lists of advice, with a mandatory numeral at the front, concerning how best to make use of a particular machine, i.e. the 9 best ways to make your research visible using Twitter. Unintended outcomes are perfect grist for these practices. Each new machine generates a new set of lists. It is a routine that those who work in the field known as educational technology have been making use of since the 1980’s.

---

3 denial, domestication, separation, care, conflict, and collapse
Such is the proliferation of new machines that often it is difficult to tell just what competencies have been distributed where. The practices of this cluster, with their focus on how humans might best adapt and adjust to each new machine, might be characterised as practices which enact the academic as being or needing to be *machine compatible*. These practices are unevenly distributed across the disciplines.

The recent observation by Michael Lascarides (Madrigal, 2011) that “digital is becoming the horseless of our age” is evident in the way in which different disciplines enact human-machine arrangements. For some, those whose progress has been intimately linked to the ongoing improvement of machines over a long period of time, the machines are part of the disciplinary fabric, commonplace, the norm, barely worthy of mention. For disciplines which have only recently begun to explore the implications of machines for knowledge production, you find the adjective *digital* appended, i.e. digital history, digital anthropology, digital humanities and so on. Then there are fields, like education, which remain stuck in concerns about integration of machines into educational settings.

**Critics & romantics**

There has been a long tradition of practices which enact realities in which the unintended and unanticipated outcomes of deploying machines figure prominently. The *things improve/things change* binary is a means of drawing attention to what is not improved and how things have changed for the worst. There is nostalgia for human competencies distributed to machines that now appear irretrievable or too costly to retrieve. Nicholas Carr (2008, 2011, 2014) and Evgeny Morozov (2013) are two prominent critics in a long line of people whose writing enact realities in which they argue, the distribution of competencies has been made opaque. These are realities in which we use machines about whose workings we know less and less. All we know is that they work. Further, as the machines know more of our habits they *anticipate* what we are about to do and *helpfully* do it for us (Tucker, 2014).

For a time there were enactments in which some human competencies were identified as being unable to be automated, to be distributed almost totally or totally to a machine. Humanist, romantic realities have dwindled rapidly as human practices like music composition, some forms of writing and many instances of significant human decision making are delegated to machines (Steiner, 2012).

Like the realities enacted by boosters and pragmatists, critics too are guaranteed an ongoing supply of grist for their mills. In the main, the realities enacted in this cluster are recyclings of realities enacted when the machines were less powerful and far less ubiquitous. There are notable exceptions and the work of Jaron Lanier (2010a, 2010b, 2011, 2013) is important in this regard.

**Doomsters**

In this cluster of realities, the distribution of competencies is heavily biased in favour of the machine: you get to sit in the back seat of a Google driverless car which *knows* where you are likely to go and suggests to you alternative routes. This has been the stuff of science fiction for a long time, the prospect of little or no work for humans as a consequence of the deployment of machines (Vonnegut, 1966). The work of Martin (Ford), Erik Brynjolfsson and Andrew McAfee (2011, 2014) enact realities in which the economics of human labour and
the relative ease of automation\(^4\) prompt investment. Here, the long and complex chain of human-machine arrangements that underpin any move to delegate work to a machine is black-boxed.

In education, the realities enacted are more or less incremental, crudely automated versions of some of the habits of good teachers. Here too, some disciplines appear to be more amenable to the distribution of human competencies to machines\(^5\), though there is now a significant body of work associated with machine assessment of essays. The university as business is enacted as being as subject to automation as much as any other business (See, for example, Smith, 2014).

**The digitally homeless**
Nicholas Negroponte (1998) coined this term to describe people who new little of machines but held positions of power and influence and took important decisions about the deployment of machines. In Australia, the decision making by universities about human-machine arrangements have been framed by an odd mix of “we-too” and university promotion\(^6\). Like schools, universities seek to enact human-machine arrangements that distinguish them from their competitors. A recent instance of this pattern is “my artificial intelligence is better than your artificial intelligence”\(^7\). These enactments overlap with those of the boosters and pragmatists. The distribution of competencies is glossed by assertions of new forms of literacy required of students. The machines, some of which are well past their use-by date, are fixtures, intimately interwoven into the complex set of practices that enact the modern, corporate university\(^8\).

We also see practices in which universities or groups of universities align with publishing houses in ever new business models to exploit new human-machine arrangements in the delivery of university courses. These practices tend to favour arrangements in which more and more human competencies are delegated to the machine. There are many collateral realities (Law, 2012) being enacted in these practices that while germane to the focus of this symposium go beyond the scope of this paper.

**Artificials.**
The final set of practices are perhaps the most interesting. The current digital context is one of an almost perfect storm for the field of Artificial Intelligence (AI). We see the coming together of very large data sets and sufficient computing power, courtesy of Moore’s law, to allow AI techniques developed decades earlier to be used. I illustrate this with an example.

In 2009, Michael Schmidt and Hod Lipson (2009) reported the development of software, *Eureqa*, that generated natural laws from data obtained from experiments. As they put it,

\(^4\) Christopher Steiner’s (2012) detailed account of the history of automation of trading on US stock exchanges illustrates this well.

\(^5\) Here Andrew Ng’s course on machine learning exemplifies real-time incremental fine-tuning: https://www.coursera.org/course/ml

\(^6\) The use of machines to promote and distinguish one educational organisation from another has been one of the persistent practices in the history of the use of machines in education.


\(^8\) It might be argued, for instance, that the modern corporate university is the necessary infrastructure for a LMS.
We demonstrated this approach by automatically searching motion-tracking data captured from various physical systems, ranging from simple harmonic oscillators to chaotic double-pendula. Without any prior knowledge about physics, kinematics, or geometry, the algorithm discovered Hamiltonians, Lagrangians, and other laws of geometric and momentum conservation. The discovery rate accelerated as laws found for simpler systems were used to bootstrap explanations for more complex systems, gradually uncovering the “alphabet” used to describe those systems. (p. 81)

This work, a spin off from the development of Lipson’s work with self-aware robotic devices generated a great deal of interest. Lipson, who asserted to Mark Stevenson (2011, p.94) that he wanted “to create something nobody can argue isn’t intelligent. I was thinking, what’s an unequivocal hallmark of intelligence? I think it’s creativity, and particularly curiosity.”

Here, the means a machine uses to produce results which are labeled curious and creative are different from the means a human might deploy. Eureqa begins by building a very large number of random equations. The only restriction is that the equations obey the basic syntax rules of algebra. The software then proceeds to make random variations to build a first generation of equations. It then tests each equation against the data for which it is attempting to build a model. The software eliminates equations based upon how well a particular equation can predict and describe the data. The software generates the next generation of equations by making random changes to successful equations. It then continues eliminating equations that are poorer fits. It’s a brute force, approach made possible today by the continued exponential improvement in the performance of machines.

The lexicon used to describe this approach draws from evolutionary biology. The algorithms are dubbed genetic, i.e. only the fitter equations survive each round. The final, successful equations that the machine ends up producing are easily recognised by humans who are familiar with the commonly known equations of Newtonian mechanics.

So here is a practice, in which models can be generated from experimental data with little human involvement. The machine has been delegated a rather low level set of human competencies, randomly try an equation and test it against the data, but which because of the speed with which it can do this mundane work gives the process an appearance of creativity.

Stevenson recounts an instance in which the model the machine produced was less obvious than Newton’s laws of motion. Eureqa was working on data obtained from observations taken from the soil bacterium Bacillus subtilis by Gürol Süel. The bacterium is of interest because under extreme conditions it can change into a spore and is related to anthrax. His interest was in working out the network of genes that govern this transformation. Süel had been able to produce a model with sixteen variables using standard statistical techniques. When he fed his data to Eureqa the machine produced a model with only seven variables. The software had identified variables Süel had assumed were important but were not. The model was clearly elegant but no one could make sense of it. Lipson, Stevenson (2011, p.100) recounts, wondered if it was like “explaining Shakespeare to a dog.” The quandary eventually led to new insights into the problem (Mullins, 2011).

The distribution of competencies between machine and human for genetic algorithms, like

---

9 It parallels, but on a larger scale, the practice of Picasso who reportedly painted eight pieces a day.
much of human-machine arrangements has an iterative aspect to it. From a basic set of rules, a model is produced that requires human judgment or meaning making which leads to further modeling and so on. As the machine learns, more decision making is given to it over time. There is a growing efficiency in extracting models from data. The meaning making and the design of algorithms remain delegated to the human, for now.

The lexicon deployed in the discourses which enact this particular arrangement of humans and machines draws on familiar biological and human terms. Machines learn. Algorithms select on the basis of survival of the fittest and so on. It is a practice that has persisted from the early days of AI, one that Drew McDermott (1976) ridiculed comprehensively, to little effect. The fascination for machines that take vast amounts of data and, just as mathematicians turn coffee into theorems, turn data into predictive models has grown rapidly over the past few years. The continuing shift of competencies is argued to be a good or even natural consequence of the arrangement. Tyler Cowen (2013) writes enthusiastically of human-computer teams in which both parties to the arrangement learn from each other.

The argument I have tried to develop, one of multiple realities enacted through different sets of practices (Mol, 2002) is at odds with the ontological assumption of a one-world out there and it is our job is to represent it (Law, 2011). If we resist the downgrading of realities to perspectives on a single reality as Law argues, the various realities of human work and its arrangement with machines can be interrogated. What keeps each reality stable or steady? What are the practices that work to mask the sense that a single one-world is being done in each cluster of practices? What are the gaps, the tensions, the paradoxes between the practices and their realities (Law, 2012, p169)? In this sense, reality need not be destiny. In each cluster of practices, the world of academic work is being enacted differently. The distribution of competencies between human and machine are different. In each set of practices, how are these differences being held together? Are they being kept apart? Does it all hang together or not?

To take up some or any of these questions prompts examination of both sides of the arrangement, peeking under the bonnet of the machine a little more than we do. While we can discern some of the distributions between human and machine, we can only probe so far.

**Digital habits, the programming academic, towards artificial academies**

Nir Eyal (2014) observes that “(t)he convergence of access, data, and speed is making the world a more habit-forming place”. His interest is in habit forming machines. For some time, I have been interested in human habits, specifically, the digital habits of academics. They are part of larger set of practices which Barbara Kamler and Pat Thomson (2002) aptly named secret academic business. How much longer these digital habits remain secret, at least to those interested in building habit forming machines is uncertain. Working with machines as we now have come to understand, leaves digital traces of one kind or other. While these traces can be mined to build machines better suited to academic work, they can also be used to build machines in which few competencies remain with the academic. Importantly, delegation of academic work to a machine does not necessarily rely on digital traces as I discovered in the early 1970’s.

It would seem that developing a sensibility about the distribution of competencies between academics and machines ought to be a key issue in any consideration of academic work in an era of the digital. Is it, as Douglas Rushkoff (2010) argues a matter of program or be
programmed? Is it a matter of heteromation\(^\text{10}\) as Hamid Ekbia and Bonnie Nardi (2014) argue? Or is it, as some of the clusters I have mapped come together that we will begin to see artificial academies? The source will not be with us then. It will be with those who can.

**Acknowledgements**

I acknowledge the help of the following machines: Scrivener, EndNote, Skim, various Google search and mapping utilities, Google Chrome, Notebook, DevonThink, Calibre and Apprentice Alf’s deDRM plugin, Kindle, an iPad, Notability, VLC media player, OSX 10.9.5, and a MacBook Pro.

**References**


\(^{10}\) Crudely, of making sure humans have control at key points in the decision making of any human-machine arrangement, a matter of biasing the distribution of competencies.


