FRANCIS LEE

Reassembling Agency

Epistemic Practices in the Age of Artificial Intelligence

Abstract
This article reflects on how sociology can analyse the role of artificial intelligence (AI) in scientific practice without buying into the current AI hype. Drawing on sensibilities developed in actor-network theory (ANT) it introduces the concept of *agencing* (agency as a verb) which refers to how scientists debate and configure the human and machine agency. It suggests that we can come to a more nuanced understanding of the effects of AI in science by attending to actors' *agencing* practices. By discussing three ideal types of agencing, the article argues that AI should not be regarded as a rupture in the tooling and practices of science, but rather as a continuation of long-standing patterns of practice. That is, agency, and the space for action and judgement, is organised differently in the AI-driven laboratory; however, this is not a new configuration of epistemic agency. Rather we might understand these changes as building on statistical epistemic configurations going back to the birth of statistics in sociology in the 1700s and 1800s.

Keywords: agencing, machine agency, practice, epistemic configurations

TODAY, SCIENCE IS producing ever larger amounts of data. New digital tools, methods and infrastructures create a growing flood of 'big data' that science wants to benefit from and analyse. In order to analyse this immense amount of data, many researchers in the sciences are turning to computational methods based on algorithmic processing and machine learning – what is often referred to as artificial intelligence (AI).[1] This flood of data and the use of AI seems to promise a whole new way of producing knowledge about the world. But what are the consequences of introducing data-driven and AI-analyses for knowledge production? What happens to science when human judgement and the traditional scientific method are supplemented with, and sometimes replaced by, AI and the analysis of large amounts of data?

This article explores these questions from the point of view of agency and human judgement, and asks: What happens to human agency and judgement in scientific experiments with the introduction of AI? By drawing on recent theoretical developments in actor-network theory (ANT) and valuation studies, the article discusses (1) how we can analyse and understand actors' different styles of configuring agency in practice, what I here call *styles of agencing*, and (2) how we can analyse and understand how

1 Although this term in fairness is way too unspecific. See for instance (Suchman 2023).

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actors in the sciences value these different configurations of judgement and agency in practice (cf. Lee & Helgesson 2020).[2] This approach allows discussion of the configuration of agency as an empirical phenomenon, and to understand how actors in the sciences struggle with configuring agency in practice. The larger purpose is to nuance how we can understand the role and consequences of AI in scientific practices – by focusing on actors' work to configure and value agency in the laboratory.

In asking these questions, the article aims to create an analytical distance from the hype around data-driven and AI techniques and situate them in relation to other ways of organising and valuing agency in scientific practice (cf. Ziewitz 2016). One of the key take-aways is that we cannot understand the ongoing data and AI revolution as a clean break from previous practices, but rather, we must attend to how agency and judgement are reconfigured in many different ways in the scientific laboratory – some that have very long histories.

Empirically, the article builds on previous and ongoing fieldwork on the algorithmic practices of the biosciences – broadly construed to include both laboratory work and epidemiology – that has been ongoing for more than a decade (Lee 2015, 2016, 2021, 2023; Lee & Helgesson 2020; Lee, Boman & Ostrowska 2021). This polymorphous engagement with the algorithms, data, and the biosciences has entailed laboratory observations, interviews, and document analysis (cf. Marcus 1998). Drawing on this long-term engagement with the practices of knowledge production in the biosciences, this article identifies and discusses three ideal types of configuring and valuing agency that are used in the biosciences: "concentrated assemblages", "panoramic assemblages", and "emergent assemblages." Each ideal type foregrounds certain epistemic virtues and vices – and backgrounds others (cf. Daston 1995; Lee & Helgesson 2020). This empirical entanglement with the biosciences serves as a foil through which I think about different agential configurations – and how scientific actors relate to them.

The biosciences are a nebulous area of research which can include a diversity of research directions ranging from small scale biological experiments, via analyses of genetics and proteomics, to medicine, epidemiology, or even ecological systems. The label bioscience is difficult to define but is used both to direct scientific policy and funding and defines an area of research centred on life and the living. Wikipedia for example lists 46 different basic research areas in the biosciences, ranging from biology to zoology. In this article I use my fieldwork in various parts of the biosciences as an empirical foil for discussing agency in scientific knowledge production. More on this below.

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2 These sensibilities, rooted in actor-network theory (ANT), draw on assemblage-based theories such as Deleuze & Guattarí's (1987) notion of the rhizome (cf. also Latour 1999). However, my introduction of the concept of *agencing* differs from the concept of *agencement*, which denotes the rhizome or assemblage. With the concept of *agencing* – agency as a verb – I aim to emphasise actors' work in negotiating and creating spaces for agency within these assemblages of humans and more-than-human entities.

Analysing Agency in a Technologically Mediated World

> Could non-humans ever be agents? [...] Sometimes it seems that there are all sorts of non-human entities, such as cyborgs, intelligent machines. genes, and demons loose in the world. Along with ozone holes, market forces, discourses, the subconscious, and the unnameable Other. And, or so many claim, such non-human actors seem to be multiplying. For if angels and demons are on the decline in the relatively secularized West, then perhaps robocops and hidden psychological agendas-not to mention unnameable Others-are on the increase. (Callon & Law 1995:481)

One consequence of the use of technologies in science – and more specifically in the biosciences – is that the space for agency and choice is moved around (cf. Mol 1999). By importing an algorithm, a dataset, or a pretrained AI model from another lab or company, you also import choices made elsewhere to your laboratory (cf. Lee 2021); sometimes in a different part of the same laboratory, sometimes in a different laboratory, sometimes outside of the laboratory altogether – in a hospital wing or in a technology development firm. Choices that are made in other times and places shape the choices that can be made in the here and now. Technology reconfigures agency in the laboratory.

How can we then understand and analyse agency in scientific practice in an increasingly technologically mediated world, where the number of machines and technologies seem to be steadily increasing?

This question is one of the key topics in actor-network theory (ANT): [3] A key argument in ANT is that scientific practice can be understood by analysing the relations between humans and machines in practice, through attending to what ANT calls assemblages or networks of human and non-human actors (Callon 1984; Latour & Woolgar 1986; Latour 1987; Callon & Law 1995). As a result of this relational and practice oriented analytical stance, ANT conceptualises agency as an emergent effect that results from the interaction between both human and non-human actors (Callon 1984; Callon & Law 1995; Latour 2005). This conceptualisation of agency in ANT means that agency becomes available for empirical study in scientific practice. It becomes possible to observe and map how facts, ideas, technologies stabilise locally in practice, sometimes in multiple ways (Latour & Woolgar 1986; Latour 1987; Law 2002a; Mol 2002). It also means that it becomes possible to empirically analyse how agency is distributed between humans, machines, and scientific instruments in practice.

3 ANT, like for instance Karl Marx's (1992) sociological analysis takes an interest in how machinery and technological innovations affect how humans organise society. While Marx's main interest was labour, workers, and capital, ANT was first developed out of an interest in scientific knowledge production but has subsequently been applied to a multitude of fields. ANT is sometimes described as eschewing purely social explanations (Callon and Latour 1992), but just like Marx's analysis of machinery and capital it is interested in the organization of society (Strum and Latour 1987).

However, this does not mean that ANT makes no distinctions between different types of actors in empirical work: research building on ANT often makes descriptions of how different types of actors – be they human or non-human – shape the direction of the collective (cf. Callon 1984; Lee 2021; Mol 2002). The point is not that every actor is the same, but rather that the analyst must not pre-establish which types of actors shape the collective. That is, the analyst must remain empirically open as to which actors – human or non-human – are influencing its direction. Agency thus becomes formulated as an empirical question, not a matter of theory or first principles – the overarching goal of the analysis being to understand how the direction of the collective is shaped: be it by human, machine, animal, nature, or culture (Law 2002b; Mol 2002; Latour 2005).

Later theoretical developments in what is referred to as post-ANT (cf. Law & Hassard 1999) have focused on how the configuration of the network shapes the spaces for agency, choice, and action for different actors in different locations – attempting to nuance early ANT studies' focus on strong actors (cf. Star 1990; Mol 1999, 2002; Callon & Muniesa 2005; Cochoy 2008; Lee 2021). For instance, Cochoy (2008) has analysed how the space for calculative agency is shaped by the physical attributes of a grocery store. The architecture of the store and the pricing technologies place the consumer at a considerably calculative disadvantage. Thus, by analysing the configurations of agency in practice, a sociologist can create an understanding of where there is large room for choice in practice, and which actors have the biggest degrees of freedom. We can analyse where choices are made – and where they are possible to make – in practice (cf. Mol 1999).

Agencing: Actors' work to configure and value agency

However, actors in science aren't cultural, or agential, dopes (cf. Garfinkel 1967; Lynch 2012). They live with, and very well understand, the consequences of these hybrid collectives and configurations. In their everyday work, scientists often have lively debates and disagreements about what is the best way to configure agency in their laboratory, the best way to agence – agency as a verb – their laboratory. They debate about particular ways to tool the laboratory, which tools and ways of organising the laboratory constitute good scientific practice, and which is the best road to follow (Lee 2015; cf. also Thevenot 2002; Lee & Helgesson 2020).

Thus, if ANT's sensibilities opened up for tracing and understanding how agency clusters and disperses in practice, I argue that we can also productively observe actors' discussions, debates, and battles over the agencing of scientific work (cf. Lee & Helgesson 2020). My argument is that in attending to actors' debates about agency we can also observe different styles of agencing of the laboratory. This opens up the possibility for study of how scientists configure agency – as well as how they value different configurations of agency. This means that we can study how different scientists organise, value, trust, and prefer certain ways to agence the laboratory, as well as the yardsticks that they use for valuing a particular mode of agencing the world (cf. Dussauge, Helgesson, Lee, *et al.* 2015). An important point is that what a specific tool does in a specific situation is not pre-determined, or what a good tool should do, or how actors should value the tools of the laboratory.

This way of understanding the agency (as noun) and agencing (as verb) in the laboratory opens up for analysing the tooling of the laboratory – algorithms, AI models, and data work – through actors' debates, practices, and valuations. What actors at one juncture might see as the logical and best way to tool the laboratory might at another juncture be seen as completely irrational. At certain points actors might have a goal of efficiency, at other points precision might be the yardstick of excellence (cf. Lee 2015).

A reflection on ideal types, actors, agency, and agencing

Below I discuss and outline three ideal typical styles of agencing the laboratory – of configuring and valuing agency in the biosciences. The first two of these styles of agencing – "concentrated" and "panoramic" – I have identified in empirical work I have published elsewhere (Lee & Helgesson 2020), while the last style – "emergent" – builds on empirical work I am currently undertaking in the project "Big Data and AI in the Biosciences: A Scientific Revolution?" Concretely, identification of these styles of agencing is based on interviews and ethnographic observations of scientists in biomedical laboratories that have been done over several years, starting in 2011 and continuing off and on until today. Thus, this article builds on observations of a bioscientific laboratory working with large-scale datasets – that must remain anonymous – as well as interviews, and document studies of various actors in the life sciences that have been ongoing for more than a decade. As ideal types, these styles highlight certain key features of how actors configure and value agency – how they work to agence the laboratory. These styles are not mutually exclusive in practice, but elements of all three styles are represented in bioscientific laboratories (cf. Lee & Helgesson 2020). The point of this exercise is to identify some of the tendencies and differences that exist between these different styles of agencing in the biosciences. The overarching aim is to discuss "Big Data" and "AI" not as a radical break from other laboratory practices, but as part of a continuum.

Agencing Concentrated Assemblages: Know Your Specimen

> Imagine a group of scientists working with biological experiments on animals. Their goal is to find the mechanisms of limb regeneration. The dream – it seems far off, probably not achievable in their lifetime – is to be able to find a way to regenerate human limbs. Their method is to run experiments with a few animals, and to understand the process of limb generation in excruciating biological detail. Each animal is studied with painstaking attention. Animals are anesthetized and limbs are amputated so that the regeneration process can start. Some of the animals are bathed in a fluorescent solution that makes it possible to study various

> parts of their cells under the microscope. Over several weeks the regeneration process is photographed daily. Computed tomography scans are done to create 3D images of the regeneration process, and 3D models are constructed. Techniques to assess DNA changes and protein activation in the cells are done. Which cells are active? What is happening in the cells? Each animal seems to open up a universe of regeneration in itself. Many hours, and many resources are poured into a few animals to understand – with elaborate precision – how limbs are regenerated.[4]

In the ideal type of concentrated agencing the focus of work is often on the individual specimen – a test tube with body fluids, an animal, a cell under a microscope, a plant of corn. The hybrid collective in this ideal type is centred around one specimen, a particular experiment, or a particular scientific apparatus. Imagine a researcher toiling away at their workbench, trying to understand the minutiae of their specimen. Human judgement and assessment are seen as central by the actors. By working closely with individual specimens or data points, researchers describe how they build trust in the data. Observations made on what actors sometimes describe as "raw data" are valued over massive amounts of data (cf. Lee & Helgesson 2020).[5]

An ideal typical example of this type of hybrid collective and this style of agencing the laboratory is described in Evelyn Fox Keller's book *A Feeling for the Organism* where she documents the Nobel Prize winner Barbara McClintock's work in genetics. In her work, Keller documents how McClintock developed intimate knowledge about individual biological specimens – plants of corn. By knowing her corn plants intimately McClintock developed her genetic theories that would eventually earn her the Nobel Prize (Keller 1984).

However, like any mediated human action, this style of agencing the world also draws on hybrid collectives of human technology – collectives of humans and non-humans (Strum & Latour 1987). As the vignette makes clear, in small-scale biology, artefacts and machines abound: Microscopes, sample handling robots, DNA sequencers, test tubes, and so on. In small scale physics, vacuum chambers and particle toolboxes might be in use. In the small-scale psychological laboratory, there might exist behavioural machines to test human or animal behaviour. Even qualitative social research is deeply dependent on technology: papers, pens, computers, printers, databases.

Agency is moved around by all these devices. Choices that were made in the construction of the DNA sequencers, the SPSS software, and vacuum chamber – shape what kinds of analyses can be done. Thus, in any laboratory agency is moved around by hybrid collectives of machines and humans.

However, just like McClintock, in the concentrated ideal type, the actors that I have studied seem to centre the agencing of the laboratory on building hybrid collectives with large possibilities for human assessment and judgement – tied to ideas about knowing the

4 Vignette based on a published paper from an anonymous researcher whom I have interviewed. To preserve anonymity, species and specific techniques are described in a general manner.

5 Although the concept "raw data" is an interesting oxymoron in itself (Gitelman 2013).

specimen and the "raw" data. In these small data settings, the actors' biggest fears seem to centre around not knowing the specimen or data intimately enough. It is a fear about data that has been collected at other times and places (Lee 2016; cf. also Edwards, Mayernik, Batcheller, *et al.* 2011; Amelang & Bauer 2019). It is a fear tied to how algorithms could destroy the data by massaging it too much (Lee & Helgesson 2020).

This style of agencing – this style of configuring and valuing agency in the hybrid collective – is however not constrained to concentrated assemblages alone; the importance of human judgement is often stressed in different situations. In sum, in this ideally typical style of agencing human judgement, assessment and action are highly valued.

Panoramic Agencing: Handling the Multitude

> We are in an anonymous high throughput laboratory somewhere in Europe. I am discussing the use of algorithms for data processing in high throughput bioscience with an informant. He explains that comparing biological samples is not a straightforward thing. That there is just too much data to be able to understand each sample intimately. The details of each sample fade into the fog of quantities and multitudes. But nevertheless, the samples vary in amplitude, and the machines that are used to analyse them can introduce noise. There seems to exist complexity in quantity. My informant explains how they handle these complexities of quantity. He describes how they use algorithms to process the data to remove potential noise introduced by the machinery of the laboratory, and how the dynamic range of each sample is adjusted so they can be compared and analysed for patterns. The questions we are discussing are difficult: What is data and what is noise are not questions that the data scientist can give straightforward answers to – in principle. But the whole laboratory is premised on the possibility of constructing a workable algorithmic solution to the problem. The high throughput nature of the work demands practical solutions – and data processing algorithms provide a workable way out of the data conundrum. Algorithms are imported from other laboratories and adjusted to the local laboratory. But what are sources of noise in the machinery? How can they remove them? How can the samples be made comparable?[6]

What I here refer to as a "panoramic" style of agencing is different from "concentrated" agencing. In this ideally typical style of agencing the virtues of automation and algorithmic action are prized by the actors I have observed and interviewed. In this mode of configuring and valuing agency it is the promise of data-driven inquiry that is valued. The advantages of algorithmic data processing, through automatic cleaning

6 Interview and vignette constructed based on fieldwork in a high throughput laboratory in Europe.

and normalisation, are prized. The epistemic promise of processing massive amounts of data to find patterns and correlations is highly sought after. An ideal type of this style of agencing might be the push towards Data-Driven Life Science that is ongoing (cf. 'Data-Driven Life Science (DDLS)', n. d.), where it is argued that "The concept of data-driven springs from the modern technological advances that continue to bring about mountains of systematic, comprehensive, and deep data" ("DDLS What is data-driven life science?" n. d.).

In a panoramic style of agencing, certain types of machines and technologies are central. The statistical massaging of data, databases, algorithms, and computation are essential components of this style of agencing the laboratory. In panoramic science, technology is deeply entrenched in a specific type of scientific practice. By amassing huge amounts of data – ecological, biological or other data – it is hoped that we could unlock secrets to biological, social, and natural facts. Here what is centred is not human action but rather *algorithmic action* on wide arrays of data. In this style of agencing human judgement is not the centre of attention. It is the configuration and assembling of a certain type of machine agency that is at the actors' centre of attention.

In this ideal type the focus of actors seems to be on building hybrid collectives with the right types of machines and machine-like judgement. "Raw data" is not sought after to know intimately but the variability of different data points is seen as a challenge to be computationally solved – so that large-scale algorithmic comparisons can be made. The complexity of quantity is seen as a challenge that only algorithms and computational techniques can solve in practice. The biggest fear isn't being close enough to the data but rather to use computation to clean the data from biases, confounders, and noise.

This style of agencing – this style of valuing different configurations of the hybrid collective – is not constrained to big data settings. The importance of data and the statistical cleaning of data is stressed in many epistemic locations. We can recognise these ways of understanding science from a multitude of locations. Social science, biology, psychology, and sociology are increasingly turning to the panoramic styles of agencing epistemic work.

Emergent Agencing: Find Your Function

> "Approximately 85% of machine learning work is data work. I'm exaggerating a little. But that is the legend in the field." I am having coffee with a computer scientist who has been working with artificial intelligence for 30 years. He has been working with medical and biological data for much of that time. We are discussing the changes brought about by machine learning. He is describing how he can adapt machine learning models to local situations by retraining them on a local dataset, and how different metrics of success can be used to evaluate the model. He is fascinated by the power of the machine learner to find patterns that he has not told it to look for: The image recognition AI – used to detect

> depression in mothers' faces – not only sees different emotional expressions, but also groups the data on actors' faces. It seems magical. But the initial statement highlights that the power of machine learning is premised on making a good data world, selecting and curating the data that the machine learner is both trained and retrained on. It is also premised on finding metrics of success – to evaluate if the machine learner is good at what it does. What is good data for the machine learner, and how can we measure its success?[7]

Our third style of agencing science pertains to work using AI and machine learning. In this ideally typical style machine learners are valued for their "magical" power to find statistical links where humans cannot (Campolo & Crawford 2020). This style of agencing stresses the power of machine learning to find the right function that can generalise from a massively multidimensional dataset (Mackenzie 2015). Thus, the machine learner generalises through function finding, and humans test the performance of models on sets of data – so-called "ground truth" datasets (Jaton 2017). While the panoramic style focuses on pattern finding across large datasets, the emergent style prioritises predictive modelling and function generalisation through machine learning.

In this style of agencing, working with data is not mainly tied to working with specific data points or to a specific specimen like in the concentrated style of agencing. Nor does it seem to be about removing noise or finding confounders like in the panoramic ideal type. Instead, in the emergent style, worries are centred around making the data tractable for the machine learner; to incorporate data into data standards so they can be used to train a machine learning model; and removing outliers that make the machine learner less adept at prediction. The function that describes the dataset's characteristics shouldn't be too close or too loose, or the machine learner loses predictive capacity.

A common practice is to assess a machine learning model based on performance metrics grounded in evaluations against a particular dataset – what is often called a ground truth dataset (a term borrowed from meteorology) (Krig 2014a; Jato 2017, 2021). Ground truth datasets are sometimes described as the true measurements of what you want to predict. Sometimes these ground truth datasets are made publicly available for others to use in other settings (Krig 2014b). Sometimes the dataset is divided so the machine learner is trained on one part of the sample, and assessed on the other part (Lee 2021).

In training machine learners, it seems that actors' focus on creating suitable configurations of agency is shifted even more away from individual samples. In constructing machine learners, actors focus their energies on creating a good hybrid collective for the machine learner. The actors' focus lies on massaging data, transforming the data into vectors (a mathematical representation that is amenable for machine learning), choosing the right clustering algorithms for the particular aims and datasets, and

7 This vignette is a composite of multiple interviews and conversations about how machine learning is used in the practices of the biosciences.

sometimes dividing the data into suitable periods so that the machine learner does not apply an old analysis to a new dataset (cf. Lee 2024).

The challenges that actors bring to the fore in the emergent ideal type seem to focus on the needs of the machine learner to predict, classify, and decide about the world. Here the style of agencing becomes centred around valuation of the predictive power of the machine learner. Human action is taken to order the world for the machine learner to be able to predict. There is a constant oscillation between human tinkering with data and evaluation of the machine learners' predictive outcomes.

In the emergent style of agencing it is not the treatment of individual data points that is central, nor is it tinkering with the parameters of the algorithm that is central, but tinkering with data that is used to train the model, and different ways of evaluating what is the right function that describes high dimensional datasets.

Agential Reconfigurations of the Sciences: Overestimations and Underestimations

How then is agency reconfigured in scientific investigations in a science driven by AI? What is seen as a good way to configure agency and judgement with the introduction of AI in the biosciences? Is there a wholesale change of culture of bioscience with the introduction of AI? These are large and complex questions that do not have a singular answer. It is easy to both overestimate and underestimate the changes brought about with the introduction of AI into the biosciences. There are as many ways of organising laboratories as there are laboratories, and the cultural forms of scientific investigation vary between laboratories, but also in the same laboratories (Knorr Cetina 1999; Lee & Helgesson 2020).

Underestimations: It would be a mistake to treat the ongoing introduction of AI technologies into the biosciences and other scientific fields as more of the same or business as usual. The retooling of scientific laboratories often changes how we can know and what we can know, leading to new scientific discoveries and ways of understanding the world. For instance, new technologies such as X-rays have allowed us to see inside living bodies leading to new understandings of the body and how it works (Jülich 2002). Some biologists lament the ongoing introduction of AI, criticising the AI revolution for giving up on understanding the causes and biological basis of phenomena in favour of statistical correlations (cf. Fujimura & Chou 1994). There is a change going on in the scientific culture and organisation of biosciences.

One such change is that the agencing of laboratories is different in a small-scale wet lab from in a big data oriented bioscientific laboratory using AI technologies. Just as Knorr Cetina (1999) observed the differing epistemic cultures of high energy physics and biology, the content and tooling of work in the bioscientific laboratory is changing the cultures of research. Agency, and the space for action and judgement, is organised differently in a big data- or AI-driven laboratory, from in a traditional biological wet lab. New ways of putting together the hybrid collectives of science emerge. New spaces for agency and choice are created and old ones are destroyed. For example the intimate knowledge of the specimen that is espoused in traditional wet labs is made more difficult in a big data setting – especially when data collection is done by other actors in other settings and locations – perhaps decades and continents away – and thus produce different patterns of calculative agency (cf. Callon & Muniesa 2005; Amelang & Bauer 2019).

Another change in the epistemic culture of the biosciences is that the traditional tinkering with specimens in the wet lab is replaced with tinkering with AI models in certain laboratories, offices, and situations. If concerns associated with traditional wet lab work are related to tinkering with biological samples, the big data laboratory adds fears about the dangers of "raw data", while the AI lab adds concern for the machine learning model and its predictive capacities (Lee & Helgesson 2020). These concerns are additive, not exclusive. But the concerns surface in different locations, situations, and places.

Consequently, we are witnessing a reconfiguration of the hybrid collectives – the agencing – of the life sciences. The division of labour between different actors – seen for example in the advent of the field of bioinformatics and in the birth of professional data stewards – is changing. Spaces for making judgement calls and for making choices are changed when the life sciences start working with data-driven methods and applying machine learning to datasets.

Overestimations: However, AI and big data do not change everything about the biosciences, nor about science more broadly construed. It would be a mistake to treat science as undergoing a wholesale change because of the introduction of new technological tools for investigation. Some scientists still worry about individual samples and data points. There is a lively discussion about applying AI to scientific work and the need for collaborations between AI experts and so-called domain experts (read life-scientists) that can help interpret and understand the data that AI experts, with the help of machine learning technologies set out to analyse (Lee, Boman & Ostrowska 2021). The varied, detailed, and intimate knowledge about the biological world that underlies the interpretations of the data that we feed learning machines seems still to be valued and necessary in the bioscientific laboratory.

Furthermore, agencing the AI-driven research laboratory is still dependent on biological samples translated into data points, which are then harnessed to train AI models that are used to predict or classify other data points. However, care for the individual biological sample in the AI style of doing research is often handled in one situation – where data collection happens (sometimes in a completely different part of the world) – while AI analysis of the data happens in another situation – in a computationally driven analysis of the characteristics of the world; the *world-as-specimen* and the *world-as-data*. However, this division between the *world-as-specimen* and the *world-as-data* does not differ much from epidemiology, quantitative sociology, or other quantitatively oriented fields of inquiry. Just as quantitative fields of any kind rely on data collection work done elsewhere, AI analyses of biology depend on data collection work done in other settings.

Thus, the biosciences seem to be going through a technological and cultural change, but it would be a mistake to understand this as a completely new configuration of epistemic agency. We might even understand this configuration of agency in the AI laboratory as building on statistical epistemic configurations going as far back as the birth of statistics in sociology in the 1700s and 1800s (Gigerenzer *et al.* 1989).

Scientists Have always Been Hybrid: Three Styles of Agencing the Laboratory

What happens with human judgement in science, when we retool our epistemic endeavours? In this article I have explored this question from the point of view of the concept hybrid agency which was developed in ANT. I have paid particular attention to different styles of agencing (agency as verb) science and the AI laboratory. I have discussed how agency clusters and disperses depending on different technological configurations of laboratory work, and tentatively sketched three ideal typical styles of agencing laboratories in the life sciences: in concentrated assemblages, in panoramic assemblages, and in emergent assemblages, using machine learning.

Theoretically, the article contributes in two ways: First, by developing a sensibility to the actors' work of agencing (agency as a verb), which suggests that we can analyse different configurations of agency, and how actors value it. This concept builds on ANT's insight that agency can be analysed as an empirical phenomenon but refocuses our analytical attention on how actors construct different configurations of agency in practice. This analytical approach allows us to construct empirically sensitive accounts that allow us to describe how different technologies reshape scientific practices. Second, the article highlights that agency is not only an emergent phenomenon, but is also contested by the actors who actively debate which hybrid collectives should count as good science (Lee 2015, 2016). Actors are not agential dopes, but actively work to shape the hybrid collective (cf. Garfinkel 1967).

This way of approaching agency in knowledge production could also help actors in biomedicine – or in knowledge production more broadly – reflect on how they tool their laboratories. Different ways of agencing the laboratory shape how and what we can know – and today, with rapid technological developments in AI, there is a crucial need for critical reflection on how different ways of configuring agency in the laboratory shape expertise, the space for judgement and choice, and ultimately our possibility to produce knowledge.

Analytically, I have argued that there are both underestimates as well as overestimates of the epistemic changes that AI brings about. On the one hand there are huge changes in how agency, judgement, and the possibility of choice is distributed in an AI laboratory. The traditional focus on specimens in the laboratory is complemented with increasing focus on the predictive capacities of the model. On the other hand, it is easy to overestimate the differences that the sciences are undergoing in the push towards data-driven and AI methods. Extensive expertise is still required in the specific domains where AI is applied, both to train the models effectively and to understand how to manage and interpret the data. And the epistemic culture of data-focused knowledge production is at least as old as the birth of sociological statistics in the 1700s and 1800s.

In sum, the article has argued that AI and big data should not be regarded as a sweeping rupture in the tooling and practices of science – but rather as a continuation of long-standing patterns of practice. By analysing the agencing of the laboratory as part of a historical continuum, rather than buying into an ongoing “AI revolution” as a wholesale package, this article offers a critical and analytical lens that attends to ongoing and historically situated practices of doing science (cf. Ziewitz 2016). In conclusion, the idea that data-driven science and AI are replacing the scientific method seems vastly overstated. Agency, judgement, and choice are crucial for science with AI to work. Agency is reconfigured with technology. But we are not seeing a wholesale reconfiguration of the biosciences yet.

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Author presentation

Francis Lee is associate professor of technology and social change. He works as a lecturer at the Department of Media Technology at Södertörn University, Stockholm and senior researcher at the Department of Science, Technology & Society at Chalmers University of Technology, Gothenburg.
Contact: https://francislee.org.