# Caring for the Monstrous Algorithm: Attending to Wrinkly Worlds and Relationalities in an Algorithmic Society

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> I knew nothing then of what I am writing now but simply repeated to myself: "Nothing can be reduced to anything else, nothing can be deduced from anything else, everything may be allied to everything else."[1]
>
> (Latour, 1988, p. 163)

## 5.1 An Algorithmic Epidemic

It seems as if the world is becoming more algorithmic, computational, and mathematical every day. The dream of perfect prediction, 360° dashboards, and computational decision-making is becoming legion in healthcare and elsewhere. Nowhere is this more visible in the pandemic

[1] We dedicate this chapter to the memory of Bruno Latour. May his insights, compositions, and intellectual fireworks always be with us.

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F. Miele and P. Giardullo (eds.), *Reframing Algorithms*,
https://doi.org/10.1007/978-3-031-52049-5_5

world of the early 2020s, where epidemic prediction and modelling became a global issue. Epidemiological computer models became the increasing basis of political decision-making on lockdowns, mask-wearing, and pandemic handling. In a sense, during this period it seems that the world became flattened to the mathematical and algorithmic through the reliance on epidemiological computer modelling. In such a world, materialities, cultures, habits, movements, and people became reduced to general computer models detailing infectiousness and reproduction values of a disease. The world seemed to have become a completely flat domain, where nothing but the model and its calculations mattered.

The computer model, the algorithm—the world without wrinkles or materialities—became the language of the pandemic. The model became the normal view of the pandemic. And voices that tried to re-introduce a wrinkly folded material world into the discussion became treated with suspicion. The model became the political reality. The world became a nuisance of complexity. The model became the centre, and the world became the periphery.

The political power of algorithms can hardly be overstated today, as they invade every facet of our lives (Amoore, 2020; Burrell & Fourcade, 2021; Dourish, 2016; Gillespie, 2014; Lee & Björklund Larsen, 2019; Noble, 2018; Seaver, 2017; Ziewitz, 2016). Over the last decades the trust in quantitative information has become ubiquitous in the expectation that data can provide the foundation of every action, from scientific knowledge creation to healthcare provision (cf. Porter, 1995). Data generated by digital algorithmic technologies are gaining priority in the ambition to base political decisions on evidence (Rieder & Simon, 2016). In many cases the outputs of algorithms take the form of projections, or predictions, that are used to guide action. The political force of algorithms to make visible phenomena has the power to "problematize the taken-for-granted order of society", to make visible, questionable, and understandable phenomena (Jasanoff, 2017). But how should we as critical analysts of this sociotechnical reconfiguration deal with this invasion of algorithms in social life?

## 5.2 Theory: Caring for Our Algorithmic Monsters in the World

> From now on, we should stop flagellating ourselves and take up explicitly and seriously what we have been doing all along at an ever-increasing scale, namely, intervening, acting, wanting, caring. (Latour, 2012, p. 24)

In this chapter, we build on Bruno Latour's discussion about the need for caring for the technological monsters we create (Latour, 2012). His use of the notion of "care" references Mary Shelley's tale of Dr Frankenstein's monster, emphasising the fact that it "was not born a monster, but that [it] became a criminal only after being left alone by his horrified creator" (Latour, 2012, p. 19). In other words, the sin of Dr Frankenstein lies not in *creating* the soon-to-be monster, but in *abandoning* it. It is this very abandonment—the lack of care—that turns the creature into a monster. As such, Latour's use of Shelley's story can be read as a demarcation towards essentialist modes of critiquing technology. Further, it resonates with Latour's (1993) depiction of "the moderns" who fail to notice that their attempts to disentangle objects from subjects have in fact generated a phenomenal rise of entanglements. Care, then, implies that moderns stop "fleeing their past in terror", and realise that it is precisely "flight that has created the destruction" (Latour, 2010, p. 486).

In making use of this particular notion of care, we seek to interrogate our technological creations that proliferate in the form of algorithms and attend to the dangers of releasing uncared-for monsters in the world.[2] In our case, this implies the dangers of not caring for the wrinkly worlds and the material-semiotic relationalities of algorithms.

We see care as a sensibility that attunes us to the effects and consequences of technology—the political entwinement of technology and society—in this case algorithms and the messy, complex realities—what we call wrinkly worlds. In the words of Bellacasa "This version of caring for technology carries well the double significance of care as an everyday labour of maintenance that is also an ethical obligation: we must take care of things in order to remain responsible for their becomings" (Bellacasa, 2011, p. 90). We want to highlight that caring for algorithms must involve a constant care for the contexts and relationalities that they are

[2] Our analysis does not engage with the affective dimensions of care that Puig de Bellacasa (2011) develops in relation to Latour's notion matters of concern.

part of. Paraphrasing Latour we must care for the monsters we release in the world.

Our argument in this chapter is two-pronged. First, we argue that algorithms without wrinkly worlds are dangerous things. Especially when they travel into arenas of decision-making, such as the politics of pandemic handling. It is far too easy for decision-makers to punctualize agency and accountability to the algorithm. In the famous words of the surly travel agent in the UK TV show Little Britain: “The computer says no”. The accountability becomes delegated to the algorithm. Which ignores the relationalities of the algorithms, models, and computations.

Programmers, modellers, and creators of algorithms are often acutely aware of the limitations of their creations (cf. Mackenzie, 1996). They know the assumptions they have inscribed in their creations, and all the tinkering it takes to build an algorithmic assemblage. They know about the gaps of data, the statistical uncertainties, and the alternative models they have discarded. They have created the algorithms and know the many ways in which their assemblages simplify a very complex world.

But when algorithms travel into other places—for instance to the politics of pandemic handling—this knowledge about the relation between the algorithm and the wrinkles of the world risks slipping away. The algorithm becomes treated as a black box, with the result that agency and accountability are projected onto the algorithm. A rhetorical shift which makes it possible for politicians and other decision-makers to say: “The model has shown”—and base momentous decisions about life and death on a technological apparatus without caring for its wrinkly worlds and material-semiotic relationalities. We need to teach our interlocutors—be they programmers or politicians—to care for the wrinkly worlds that our algorithms exist in.

Second, we argue that critical algorithm studies risks taking over “the powerful algorithm” as both an object of power—and as object of study—thereby risking to repeat our interlocutors’ punctualization of agency and accountability. As Lee (2021) has argued elsewhere, this focus on the power of the algorithm-in-itself makes us focus on the performed object, rather than the algorithmic assemblage. The risk is that by basing our studies of technological creations in the form of algorithms—on the performed object “algorithm” or “model”—we, analysts of algorithms, risk taking onboard punctualized versions of our algorithmic assemblages. These punctualized versions of algorithmic assemblages run the risk of focusing today’s critique of algorithms all-too-much on the transparency and power of our algorithmic and opaque black boxes that need to be made transparent and fair (cf. Burrell, 2016; Diakopoulos, 2020; Larsson & Heintz, 2020; Pasquale, 2016) and audited (Sandvig et al., 2014), so they do not lead to biases (Sandvig et al., 2016) or oppression (Noble, 2018; O'Neil, 2016). Thereby risking to lose the connection to the wrinkly worlds that they inhabit.

This in turn risks turning our much-needed critical accounts of algorithmic power into stories about simplified versions of the objects that we want to care for and critique. We risk oversimplifying the complex relationalities in which algorithms exist to a focus on the "algorithm-in-itself", and thus becoming captives to the banner Fairness, Accountability, and Transparency, with its concomitant focus on the bias, objectivity, and fairness that become inscribed into the algorithmic machineries. This moves risks turning us—analysts of algorithms—into technological determinists. Rather than analysing the complex interplay between actors in particular wrinkly worlds, complex situations, and material-semiotic settings, we risk playing into a technological fix—fixing the algorithm. A dangerous and simplified technological fix, if there ever was one.

In sum, we want to argue that the punctualization of agency to the algorithm is dangerous both in the effects it has in the wrinkly worlds that we study, as well as in our critical analysis of these algorithmic worlds (cf. Callon & Law, 1995; Lee, 2021). By becoming captured by the performance of the object "algorithm" both in the world and in the study of the world we become technological determinists. Therefore, in this chapter, we want to stress the need for attending to—caring for—the infinite relationalities of algorithms—both in the world of decision-making, and in the world of critical analysis. Caring for the algorithm must also include the relations, situations, and actors in order to understand the objects we perform as "algorithms".

Our exercise is meant to destabilise the algorithm as a stable and coherent entity, which is out there ready to receive and handle a reality "out there". Our aim is to force a relational care for the "algorithms"—to highlight the social, political, and institutional relationalities in which algorithms operate. Caring for algorithms is not an easy task. At the same time as they are shaping our lives and futures, they are part of a seductive cultural drama (Ziewitz, 2016), where social, cultural, and political analysts can become captive to the seductiveness of the things that we call algorithms (Muniesa, 2019). We run the risk of importing "algorithm" as a ready-made category, the very things which we want to analyse and criticise (Lee, 2021).

Thus, in this chapter, we argue that we need to care for algorithms by developing a split vision that does not become captured by the algorithmic drama. This means not becoming captured by "the algorithm" as an object of analysis, but also not retreating to a position where algorithms do not matter. It means caring for our algorithmic monsters in the wrinkly relationalities and worlds where they belong.

In attending to the politics of algorithms in the world—in epidemiology, in healthcare, in society at large—we want to urge for a caring and relational analysis that can stay with the algorithmic trouble as it unfolds both *in* the relationalities of our computational tools and in the relationalities *around* them (cf. Haraway, 2010). We need to be aware of the worlding power of algorithms, as well as the worlding power of all of the things that exist outside of the scope of computation. We argue that caring for the algorithm must mean developing a split vision that can attend to all of the complex ontological politics of algorithms (cf. Mol, 1999). Staying with the algorithmic trouble, in our view means caring for our algorithmic monsters in their wrinkly worlds and relationalities.

## 5.3 Two Ways of Caring for Algorithms: The Punctualized and the Relational

We want to think about caring for our monstrous algorithms through an exercise in juxtaposition of the general and the particular—or the generalities of the lone algorithmic monster and the particularities of algorithms in wrinkly worlds and relationalities. We want to think through two models of epidemiology that relate to the general and the particular: "mathematical epidemiology" and "field epidemiology", respectively. The situation in which we ground our ideal types is the juxtaposition of a general flat and empty world of pandemic modelling with the specific wrinkly and messy world of field epidemiology. This means to disassemble the algorithm as a category and to describe how "algorithms" become stabilised technologies. This means staying with the algorithmic trouble to highlight how algorithmic assemblages are put together in particular settings and worlds (cf. Haraway, 2010). As such, our juxtaposition of mathematical epidemiology and field epidemiology is a strategy of de-containment and relationality. It is about showing the politics of the algorithmic drama that unfolded during the COVID-19 pandemic by juxtaposing an epidemiology of the general, and an epidemiology of the particular.

To illustrate our argument, of caring for the relationalities of algorithms and worlds, we attend to two examples drawn from the handling of the COVID-19 pandemic.[3] Here we will attend to the public role of algorithmic assemblages in the form of how COVID-19 models were understood in the public discourse.[4] These examples are chosen as they provide a very public performance of the importance of caring for algorithms and politics. Below we outline two different enactments of algorithmic politics: how algorithms are related to the world in the public spectacle of algorithmic politics.

These two illustrations should not be taken as cases, but rather as examples of how differently algorithms can be understood and handled in the world. The two main protagonists in this account should be read as narrative devices that enable us to highlight the performance of algorithms-as-objects in society. One protagonist—Professor Neil Ferguson, advisor to the UK government—illustrates a stance towards the algorithmic as a universalistic tool that can be used to describe and control anything. The other protagonist—Anders Tegnell, Swedish state epidemiologist—illustrates a stance towards the algorithm as embedded in a complex web of relationality and care. By using these examples, we want to underline the different manners in which we can care for algorithms.

These two examples show what is at stake when algorithms become part of a political game of life and death. In one case, illustrated by the British public algorithmic spectacle in the handling of the COVID-19 pandemic, the algorithms become punctualized black boxes that reconfigure accountability relations. In the other case, illustrated by the Swedish public performance of COVID-19 politics, the algorithm becomes part of a broader professional practice where wrinkly worlds matter. These two approaches to algorithms, in turn, reflect two modes of doing epidemiology: mathematical epidemiology, on the one hand, and field

[3] It is important to note that we do not wish to take sides and adjudicate between these different ways of handling the pandemic.

[4] Algorithms are of course a central and major part of models, which are materialised assemblages of algorithmic computation. We here treat algorithms as assemblages. As a composition which shapes a network of agents (Callon, 2007). This type of assemblage analysis has been called: actant-rhizome ontology (Latour, 1999), hybrid collectifs (Callon & Law, 1995), or agencement (Deleuze & Guattari, 1987).

epidemiology, on the other. These examples are not cases where context is central, but should be understood as illustrations of how algorithms are understood and treated in public discourse.

## 5.4 Ferguson's Monster

In June 2020 an economist published a note titled: "The flawed COVID-19 model that locked down Canada" (St Onge & Campan, 2020, p. 1). The author places the blame for the economic slump caused by the lock down of Canadian society in response to the pandemic on the model used by a team of mathematical epidemiologists at Imperial College in the UK led by Professor Neil Ferguson. Around the same time an article in *Nature* reports that this "Influential model [was] judged reproducible—although software engineers called its code 'horrible' and a 'buggy mess'" (Chawla, 2020, p. 323). The model was not only to blame but it was also an ugly and primitive computer code. These statements testify to how the model featured as a monster to blame in the anglophone public discourse on how to manage the pandemic.

Epidemiological modelling played an important role in the development of response measures in the nations affected by the spread of COVID-19 in 2020 and 2021. Across Europe, in the US and Australia, mathematical modellers made projections of how this new virus was likely to spread through populations. Visual presentations of such projections featured prominently in print and visual broadcast media. Politicians in many countries referred to the models when justifying their decisions to lock down much societal activity.

There was also heated debate among scientists with different disciplinary backgrounds about the scientific quality of the epidemiological models. One example reads:

> Epidemic forecasting has a dubious track-record, and its failures became more prominent with COVID-19. Poor data input, wrong modelling assumptions, high sensitivity of estimates, lack of incorporation of epidemiological features, poor past evidence on effects of available interventions, lack of transparency, errors, lack of determinacy, consideration of only one or a few dimensions of the problem at hand, lack of expertise in crucial disciplines, groupthink and bandwagon effects, and selective reporting are some of the causes of these failures. (Ioannidis et al., 2022, p. 423)

Similar criticism had already been voiced in scientific publications as reasons to not interpret modelling projections as reliable forecasts. In scientific publications epidemiological modellers were very cautious, carefully accounting for the weaknesses of their modelling. These caveats, expressing a need to separate scientific modelling from predictions of the future, appear to have been lost in the translation from scientific publications to public discourse. Stripped of contexts, model projections of possible futures were used as justifications for specific actions by politicians and national health authorities and referred to. A summary in *the Lancet* explains that:

> Early projections of the COVID-19 pandemic prompted federal governments to action. One critical report, published on March 16, 2020, received international attention when it predicted 2 200 000 deaths in the USA and 510 000 deaths in the UK without some kind of coordinated pandemic response. This information became foundational in decisions to implement physical distancing and adherence to other public health measures because it established the upper boundary for any worst-case scenarios. (Biggs & Littlejohn, 2021, p. e91)

This quote notes an important thing about the modelling—that it was simulating the unmitigated spread of a contagious disease. This points to an important feature of scientific modelling: it is a way to test theoretical understanding against available data, the questions concern the understanding of causal mechanisms.

Epidemiological modelling, originating in the early twentieth century, is conceptually simple, the population is divided into three categories: Susceptible (S), Infected (I) and Recovered (R), sometimes models also include Exposed (E) that may not get infected when exposed. Today there are many different SIR models to choose from to create projections, but one particularly influential model has remained in use since the early days of epidemiological modelling. Named after the inventors Lowell Reed and Wade Hampton Frost the Reed Frost model is believed to have gained a lasting influence through the pedagogical mechanical analogues used to explain it. Engelmann (2021) describes how Frost:

> …used an angled trough and a box with approximately one hundred coloured marbles to demonstrate the essential dynamics of an epidemic. To simulate an outbreak, marbles were poured into the angled trough in

> a single file. The resulting colour pattern determined the ratio of infected, susceptible, and recovered individuals for a given time period. (Engelmann, 2021, p. 105)

This mechanical analogue was mathematically expressed as a deterministic model in which the outcome is fully determined by the parameters and initial conditions, which means that when these are the same the outcome will always be the same. This algorithm was understood to be less useful when considering actual epidemics and Engelmann explains how Reed and Frost created a stochastic model with a different mechanical analogue that:

> …consisted of marbles of four different colours in a trough: susceptible (S) were green, infected cases (C) were red, immune (I) were blue and blocks, or "contact neutralizers" (N), were white. Shaking the container with the marbles randomised the population after which they were poured into the trough in single file. In this row, individuals not separated by neutralizers were considered to have made sufficient contact, and susceptible marbles adjacent to infected marbles were now considered infected. This population of marbles was recorded, and susceptible marbles were replaced by infected marbles, while infected marbles were replaced by immune marbles. (Engelmann, 2021, p. 105)

This analogue explained the complex mathematics of a model with an element of chance included in a way that made it very useful in the scientific community working on communicable diseases at the time. The Reed Frost model became paradigmatic in epidemiological modelling and SIR models remain at the core of the field today, they have been coded in different ways to enable computer simulations to address different questions and drawing on various data sets.

The COVID-19 pandemic offered mathematical epidemiologists opportunities to improve their models in several different ways, ranging from the parsimony of code to the fidelity of simulations to observed data. Vespignani et al. (2020, p. 279) explains that "the challenges faced during infectious disease threats set the questions and problems for the rigorous and foundational research that allows the field to advance after the emergency is gone". COVID-19 data could help mathematical modellers improve the models that expressed their understanding of contagious diseases previously based on limited data of historical pandemics and local outbreaks in modern time. In the midst of this scientific bonanza a model ended up getting the blame for unpopular political decisions.

Without access to the actual discussions leading to decisions to implement select public health measures to mitigate against the COVID-19 pandemic in different countries the public debate shows us that a rather mundane mathematical model, with mechanistic algorithms, used in epidemiology for more than a century, was animated through badly written computer code and then somehow turned into Ferguson's monster and blamed for the havoc caused by locking down whole societies. In our framing this is understood as a lack of care. The care to make the constraints of scientific models clear and interpret them in complex contexts that are emphasised in scientific discourse was lost when this particular way of generating knowledge became the only way.

## 5.5 Caring for the Particular in Field Epidemiology: Tegnell's Relational Perspective

In the case of our native Sweden, mathematical epidemiology featured prominently in the public discourse on how to deal with the pandemic. However, the field epidemiologists tended to control the actual decision-making. State epidemiologist Anders Tegnell raised concerns about relying too much on modelling, and devised a COVID-19 strategy with reference to a more applied, field-inspired approach to dealing with pandemics. Thus, the strategy was concerned with the particularities of people successfully using masks, or the long-term public health concerns of confining children and adults alike to their homes. This approach led the Swedish public expert authorities to a position that was significantly more liberal than the strategies of similar countries. In turn, this caused Tegnell and Sweden to be vilified on the global stage. In the flat world of pandemic modelling, such a relational approach was an outrage. The particularities of situations in different societies, countries, and populations became a threat to an algorithmic, modelled, and flat world. The general algorithmic model of the pandemic seemed to trump the particular experiences of disease control in a messy world.

Almost a year and half into the pandemic, on the 7th of September 2021, the first World Field Epidemiology Day was celebrated among participating organisations across the globe. Set against the everyday circulation of models and projections for a potential fourth wave of the pandemic, the event was organised as a means "to recognize and raise awareness of the vital role of field epidemiologists" (TEPHINET, 2021). In an interview recorded in conjunction with the special occasion, epidemiologist Adam Roth at ECDC (European Centre for Disease Control and Prevention) pointed out that the covid experience had shown that field epidemiology is crucial for countering pandemics. Thus, the medical and policy communities can ill afford to keep neglecting the discipline (Roth, 2021).

Field epidemiology is sometimes referred to as "applied" or "interventional" epidemiology, and these alternative labels give a sense of how the discipline differs from "general" epidemiology. If the latter is a theoretical affair which trades in numerical models of prediction, the former is more hands-on and action-oriented. It is associated with on-the-ground operations in urgent situations; that is, in the midst of epidemics. As such, it is also policy-oriented, mediating between divergent policy objectives—be they broad public health concerns, socio-economic outcomes, or security-related issues. For those reasons, field epidemiology also tends to lean on supporting competencies, relating to public relations, behavioural science, logistics, and management.[5]

A distinguishing factor of field epidemiology is, as the name suggests, an attentiveness to the field—that is, to the particular characteristics of the cultural and geographical context of contagion. Whereas general, model-based epidemiology presumes that good models are generic—and thus amenable to frictionless travel—field epidemiology presumes that the movement of knowledge requires work and constant experimentation. This concern goes all the way back to the supposed father of epidemiology, the physician John Snow, who famously battled the 1854 London Broad Street Cholera outbreak with the help of local priest Henry Whitehead. Whereas Snow's theoretical intuitions regarding the spread of the disease were correct, it was the local knowledge and legwork of Whitehead that led the pair to find the source of the contagion. The term "shoe-leather epidemiology" points to this legacy, which in turn is claimed by today's field epidemiologists: The choice of the 7th of September as the World Field Epidemiology Day refers back to the date on which Snow presented his findings to the local authorities.

In a rare long-form statement on his work on Swedish public service radio, State Epidemiologist Anders Tegnell also presents himself as a part

[5] Indeed, following Simon's (1996) taxonomy, one may describe mathematical epidemiology as a natural science, and field epidemiology a design science.

of this tradition (Tegnell, 2020). Right off the bat, he advises his listeners to be wary of predictions and projections, and goes on to spell out his biography and professional development, recounting his work as a junior epidemiologist in different sites of contagion, emphasising the need for an attentiveness to the particularities of the site. For instance, the go-to disinfectant in Stockholm may be a potential danger in some sub-Saharan African settings.

What, then, are the broader stakes of what it is to do field epidemiology? Here, we may reconnect with the theme of this chapter: First, notions of the mathematical universal and the wrinkly particular, and secondly, the question of care for our algorithmic monsters.

This tension between mathematical epidemiology and field epidemiology can be understood from the point of view of Andrew Barry's (2013) discussion of oil pipeline politics in Georgia. His rendering of what it means to be an engineer dealing with metals invites a comparison with a field epidemiologist like Tegnell. Both professions deal with complex mixtures that "cannot be understood as combinations of pure substances" (Barry, 2013, p. 138). Thus, the properties of the entities they are dealing with—alloys, epidemics—"cannot simply be deduced from fundamental physical principles". For Barry's metallurgist, "the behaviour of metals in the conditions encountered in power stations or aircraft is quite different from any laboratory setting or simulation". For the field epidemiologist, the behaviour of a virus is a reflection of the social, geographical, and cultural environment.

Indeed, readers of Steven Johnson's (2006) rendering of the John Snow story will recognise this point: if you want to understand the Broad Street Cholera outbreak, you must first understand the London of 1854. In this way, both the field epidemiologist and the metallurgist can be said to follow the proto-sociologist Gabriel Tarde's contention that "there is no discontinuity between the realm of the social and the natural, the human and the non-human, or between the informational and the material, the living and the non-living" (Barry, 2013, p. 142).

More broadly, both field epidemiology and metallurgy must be understood as field sciences—a broader set of knowledges that include "agricultural research, zoology, geology, engineering, anthropology and geography" (Barry, 2013, p. 142).[6] The thing that unites these sciences, Barry

[6] While the metallurgist played a crucial role in the premodern era, the modern field science *par excellence* is agronomy. The formalisation of agricultural extension—not least

suggests, is that they are reliant on field research—an artisanal and itinerant mode of practice—and do not operate through laboratory work or algorithmic simulations or models. For Barry, field sciences are of particular interest to STS scholars, as they are attuned to the specificity of the case; it aspires to be attentive to the general problem of how to address the study of the particular.

Invoking the term care is another way of speaking of this attentiveness to the particularities and wrinkly worlds of our algorithms. To care for the algorithm is to accept that if one wants to move it from one context to another, a certain amount of legwork and experimentation is required. To care for the algorithm is to put it in its proper place, alongside other modes of knowing and doing. Again, we are not arguing that the Swedish modes of handling the crisis were more successful from those employed in the UK. However, the field epidemiological approach suggests that there are alternative ways in which to work with algorithms, and ultimately to care for them.

## 5.6 Concluding Discussion: Epidemiologies Across Rationalism and Empiricism

One difference between mathematical and field epidemiology is epistemological. They pivot on different views on how knowledge is best produced. Both approaches have historical roots in seventeenth-century philosophy. The trust in mathematics was foundational in modern science and philosophers like Descartes and Leibnitz developed entire systems based on the power of mathematical reasoning to produce knowledge that was not only true about the world as experienced but true for all possible worlds at all possible times i.e. laws of nature. In similarity to laws of nature the algorithmic assemblages constructed by mathematical epidemiologists are not about the reality of disease but about how contagion would play out given that all other things are equal, i.e. with a *ceteris paribus* condition. These models travel well because they are mathematically universal. The computational tools available today make it possible

associated with the so-called Green Revolution—represented a concerted effort to institutionalise the geographical extension of the modernisation front. (Lindberg & Palmås, 2013) Traces of this approach may be detected in contemporary field epidemiology: Curiously, Tegnell was born into artisanal and itinerant field science, having grown up with a father who worked in agricultural extension.

to refine and validate the mathematical representations in unprecedented ways.

In contrast, field epidemiology inherits the thinking of Bacon and Hume, insisting that observation is the basis of all true knowledge. The empiricist philosophers of science insisted that true knowledge could only be achieved through systematic observation of the world. This places the emphasis of the scientific pursuit on the collection of data and today we can collect and analyse enormous amounts of data with digital algorithmic technologies. However, field research echoes not only a focus on data originating in the scientific revolution but also of the inductive reasoning that attends to local variations in context. While the digital tools available to present-day scientists enable the collation and comparison of very large numbers of observations, field observation of the particularity of every outbreak of a disease provides an important key to understanding the impacts of disease.

In decision-making today we often see a preference for knowledge claims based on mathematical reasoning due to the illusion of certainty that numbers and quantitative knowledge provide (Porter, 1995). This was also the case in the public health strategies developed in response to the COVID-19 pandemic in countries for instance such as Germany, the UK, Canada, and the US. In these countries the strategies were directly linked to analyses of the expected spread of infection in the population presented by epidemiological modellers. The most effective option in light of this type of knowledge was total lock down.

In contrast, the Swedish COVID-19 strategy emphasised social distancing, socialising outdoors, working from home, and staying at home when feeling ill. Epidemiological modelling was an important element in the Swedish strategy too, but it was not the only type of knowledge taken into consideration. Indeed, in the radio address of the Swedish state epidemiologist, the knowledge provided by models gets short shrift in relation to the wisdom that he has acquired in the field.

Along with the epistemological stakes of these two modes of doing epidemiology, there are also ontological ones. To be clear, both camps were equally concerned with limiting the human suffering associated with the pandemic, but their respective understandings of the nature of reality seemed to diverge significantly. The contrasting ontologies of the two parties caused the phenomenon of the COVID-19 outbreak to be interpreted in two divergent manners. For the mathematically oriented model epidemiologist, the numbers on the ground could be understood as a somewhat distorted representation of a deeper logic of general epidemiology. Indeed, these skewed and twisted sets of data could—after a bit of cleaning—be used to hone the mathematical models, and perhaps unravel further secrets of the underlying patterns of pandemics. This, in turn, would help epidemiology produce better predictions. This ontological position was based on understanding the world as structures of numbers and mathematical patterns.

For the field-oriented epidemiologist, on the other hand, the outbreak made another reality come into being. As hinted in the previous section, field epidemiology is somewhat agnostic regarding the deep patterns of pandemics. Its interests lie instead in the supposed existence of another strange and veiled character: The composite of cultural habits, technological arrangements, geographical circumstances, economic incentives, public sector organisation, and bonds of civic trust that come together to form an unpredictable life of its own during the crisis. Indeed, much like the Gaia of Bruno Latour's later work, this environment is not a static backdrop to the pandemic play—it is the "thing" that intrudes on the dealings of the "regular" protagonists of the story. Crucially, this story plays out differently, in each particular site. Therefore, any differences between different stories—different outbreaks in different sites—are not distorted representations of something more general. On the contrary, those differences in the plot *are* the story. This ontological position also resonates with Gabriel Tarde's proposition "to exist is to differ" (Tarde, 2012, p. 40)—one that Latour reiterated in different contexts (Latour, 2002, 2005, 2011; Latour & Lépinay, 2009).

These epistemological and ontological stakes may be transposed onto the question of how to care for algorithms. The different commitments of the two branches of epidemiology suggest that such care may imply divergent interests—either in ever-more sophisticated problem-independent metaheuristics, or in devising modes of coping with unpredictable environments. Caring for algorithms in STS, in epidemiology, and in the social sciences, must include this split vision for algorithms. Algorithms as mathematical and computational objects with deep-seated roots in seventeenth-century philosophical thinking, but also as parts of vast and specific relational rhizomes that must include the messy part of epidemics, taking into account the myriad differences of the world as difference.

## 5.7 Conclusion

In this chapter, we have argued for attending to—caring for—the relationalities of algorithmic assemblages. To not get trapped by simplistic conceptualizations of "algorithm" but to care for the many relationalities that they are part of. To care for algorithms, we need to keep aware of the reductionism inherent in focusing on the algorithm as our analytical focus. The drive towards analysing algorithms as FAccT—Fair, Accountable, Transparent—risks taking over the computational delineations, boundaries, and ontologies of Descartes and Leibniz, reducing the job of the critical analyst to an auditor of algorithmic fairness (cf. Lee, 2021). This perspective risks making us captives to a mathematical world, where the Tardean world as assemblage and difference fades away in a haze of mathematics.

On the other hand, if we neglect the power of algorithms in the making of differences, we risk becoming blind to the power of mathematics and numbers in society (cf. Porter, 1995). Calculative agencies are powerful accumulators of power in society, and seem to be gaining agency as a basis for political decision-making in a society transfixed by algorithmic tools for prediction, modelling, and decision-making. If we reduce the job of the critical analyst by neglecting the construction and effects of algorithms, we risk treating the algorithmic world of computation as a *Deus ex machina*—impinging, unexplained, on society.

Above, we have used two examples to illustrate our argument that we need to care for the algorithm: mathematical epidemiology and field epidemiology. Our goal has been to illustrate the importance of attending to the relationalities of algorithms and models. We showed how two different manners of enacting the COVID-19 pandemic—one heavily based on epidemic modelling and one based in a more relational version of the world—drew on two different sets of epistemologies and ontologies and thus enacted different versions of the COVID-19 pandemic. We argue, that rather than accepting a reduction of the pandemic—and of the world—to an algorithmic model, we, analysts of algorithms, need to push back against a reduction of the critique of algorithms to studying "the algorithm". We believe we need to keep the relationalities of algorithms alive.

By keeping the relationalities of the objects that our informants call "algorithms" in focus rather than accepting their predefined objects, we can get a clearer grip on two problems in studying algorithms. First, the technological determinism that is inherent in focusing on "the algorithm" as a clearly delineated object that can be made fair, accountable, and transparent, rather than the multitude of relationalities that give algorithms their power. Second, by resisting the object "algorithm" and caring for the relationalities of an algorithmic situation we can also be critical of the accountability relations that are produced in the algorithmic drama of our times. Rather than allowing the computer to say no, we can untangle the many accountability relations that are produced around them.

We want to urge our fellow analysts of algorithms to care for the relationalities of algorithms, rather than the simplified notion of the fairness of the algorithm. How can good and productive relationalities be produced with and around algorithms? How can we create situations and rooms where there is room for tinkering with good relationalities? *Keeping this split vision alive—letting Descartes and Leibniz meet Bacon and Hume—must be the point of departure of caring for our algorithmic monsters.*

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