Part 1

Condensation

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1

The Cloud Chambers
Condensed Data and Correlative Reason

What I wouldn't give now for a map of the ever constant ineffable?
To possess, as it were, an atlas of clouds.
—David Mitchell, *Cloud Atlas*

A Beautiful Sight

In physicist Charles Thomson Rees Wilson's Nobel lecture of 1927, he described the cloud chamber experiments he had conducted since the late nineteenth century, and how they had transformed the capacities of modern physics into the twentieth century. From the observatory at the summit of Ben Nevis, Wilson had witnessed what he depicted as "the wonderful optical phenomena" of the formation of clouds.[1] Inspired by what he had observed, Wilson spoke of cloud formations that "greatly excited" his interest so that he "wished to imitate them in the laboratory."[2] For Wilson, the capacity to reproduce in science the formation of clouds in nature became the means to advance understanding of the condensation physics of meteorology, and with it the taxonomy and classification of cloud forms. In Wilson's laboratory, the scientific practice of knowing clouds followed a path from observation to mimetic representation to classification.

When Wilson began to experiment with the formation of clouds in his cloud chamber apparatus, however, what he discovered was an unanticipated potential to see something not otherwise perceptible; phenomena that exceed the paradigms of observation and classification. In contrast to the telescopes of the observatory, where the optic instruments had brought objects into a line of human sight, Wilson's cloud chamber became a different kind of apparatus, one that brought something into perceptibility that could not otherwise be seen. Though ionizing particles, such as alpha, beta, and gamma radiation, could not be observed directly, the condensation trail in Wilson's cloud chamber showed the particle's trajectory of movement. Recalling his experiments with supersaturation levels, temperature, and the expansion of gas in his chambers, Wilson reflects in his lecture, "I came across something which promised to be of more interest than the optical phenomena which I had intended to study." His cloud chamber experiments afforded him a "means of making visible and counting certain individual molecules or atoms which were in some exceptional condition." Though Wilson had set out to reproduce mimetically the formation of clouds in nature, in fact his experiments generated traces of the electrically charged atoms and ions previously unavailable to the sciences.[3]

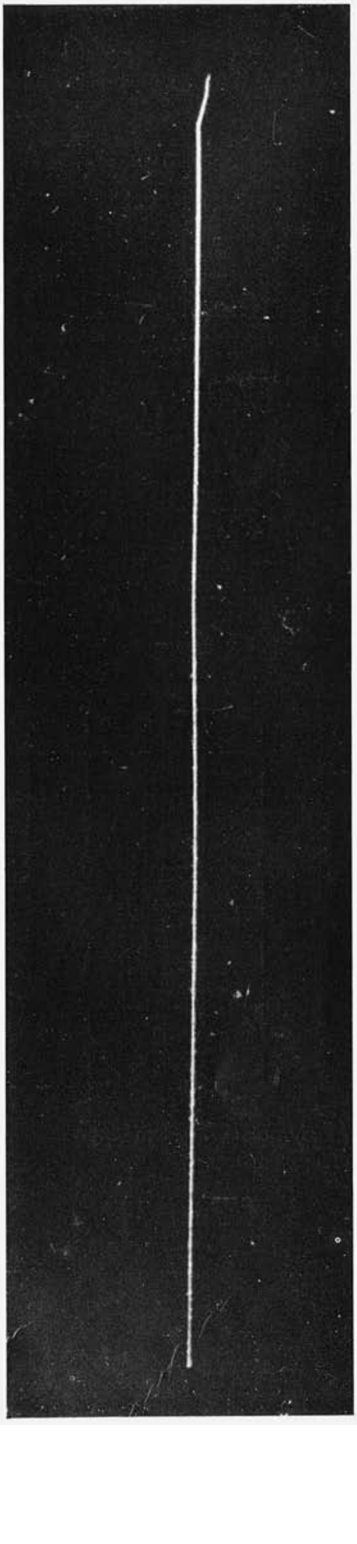
What Wilson's cloud chamber ultimately made possible for the twentieth century's study of particle physics was the ability to photograph and to perceive the movement of particles in an exceptional state (figures 1.1 and 1.2). As historian of science Peter Galison writes in his account of Wilson's work, "After the cloud chamber the subatomic world was suddenly rendered visualizable."[4] Charged or ionized particles could not be observed directly with optic devices, as with the instruments of microscopy or telescopy, but their traces and trajectories of motion appeared indirectly via the cloud tracks condensing on the nuclei. As Wilson reflects on his 1911 experiments, "I was delighted to see the cloud chamber filled with little wisps and threads of clouds" so that "the very beautiful sight of the clouds condensed along the tracks of the alpha particles was seen for the first time."[5] The cloud chamber apparatus, conceived for the human *observation* of processes of formation in nature, had become a technique for rendering *perceptible* the movement of objects beyond the thresholds of human observation.

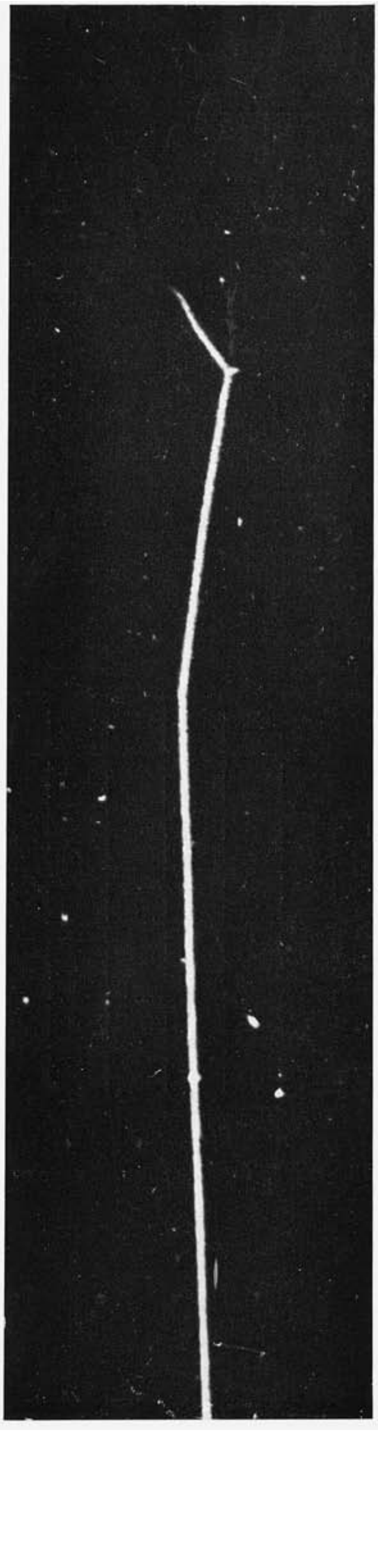
Almost exactly one century on from the publication of Wilson's first cloud chamber images, the idea of *the cloud* is once more describing the advent of processes at scales that appear to transcend the observational paradigm and exceed our human capacities to see, to know, and to understand. Indeed, the *cloud* in cloud computing is widely held to derive from the mapping of infrastructures of computer networks, where the visualization of a figurative cloud stands in for the vast complexity of the internet.[6] In the twenty-first century, cloud computing promises to have effects on the very episteme of our world, analogous to the effects of the cloud chamber on what could be rendered knowable in twentieth-century physics.

More precisely, the advent of cloud computing opens space for a renewed

Figure 1.1
Charles Thomson Rees Wilson's cloud chamber expansion apparatus (1912–13). Science Museum Group Collection, Board of Trustees of the Science Museum, London.

twinning of science and technologies of perception with forms of political sovereignty. Such renewal signals an extension of historical technologies of imaging, mapping, and intelligence data collection into new algorithmic modes of analysis and data correlation. In February 2015, for example, seventeen US intelligence agencies—including the Department of Homeland Security (DHS), National Security Agency (NSA), Central Intelligence Agency (CIA), Department of the Navy, Department of the Army, National Geospatial Intelligence Agency, Defense Intelligence Agency, Office of the Director of National Intelligence (ODNI), Department of the Air Force, Federal Bureau of Investigation (FBI), State Department, and Drug Enforcement Agency (DEA)—launched the ICITE program for the cloud-based storage, sharing, and analysis of intelligence data. Here, once more, one can find the promise of a "beautiful sight" celebrated by Wilson, the making of pictures otherwise unavailable to the senses. ICITE (pronounced "eyesight") is the Intelligence Community Information Technology Enterprise (figure 1.3), a $600 million cloud-computing





contract with Amazon Web Services (AWS) and Cloudera, providing a new intelligence and security data infrastructure. ICITE, it is promised, will "allow agencies to share data much more easily and avoid the kind of intelligence gaps that preceded the September 11, 2001, terrorist attacks."[7] In this specific sense, the data geographies of the cloud can be read as a response to the 9/11 Commission findings of a failure to analyze across data *silos* held by different agencies.[8] As the former US director of national intelligence James Clapper explained at the launch of the ICITE program, cloud computing allows government authorities to "discover, analyze and share critical information in an era of seemingly infinite data."[9] The CIA's chief intelligence officer, Douglas Wolfe, similarly expressed his hopes that the government security agencies would get "speed and scale out of the cloud, so that we can maximize automated security."[10] Let us reflect on the terms once more: *discover, analyze, infinite data, speed and scale out of the cloud, maximize automated security*. The cloud promises to transform not only what kinds of data can be stored, where, and by whom, but most significantly, what can be generated and analyzed in the world. In short, the cloud form of computation is not merely supplying the spatial accommodation of large volumes of data in server farms, but offers the means to map and to make perceptible the geography of our world in particular ways.

The architecture of the cloud is defined spatially by the relations between algorithms and data. As the cloud becomes ever more closely intertwined with geopolitical decisions—from sharing and acting on intelligence data, to border controls, urban policing, immigration decisions, and drone strikes—then what is the precise nature of these algorithmic practices of data gathering, analyzing, and knowing? In this chapter I address the political character of cloud computing across two distinct paradigms. The first, which I term Cloud I, or *cloud forms*, is concerned with the spatiality of data stored in data centers and analyzed in cloud architectures. This Cloud I paradigm sustains an ontology of observation, representation, and classification, and it encloses ethicopolitics within this logic. In the second mode, Cloud II, or a *cloud analytic*, I propose that the computational regimes of the cloud transform what or who can be rendered perceptible and calculable. In contrast with Cloud I's linear logics of observation, representation, and classification, the generative logics of Cloud II are engaged in perception, recognition, and attribution. As the scientific his-

Figure 1.2 Cloud chamber tracks of the alpha rays of radium, among the earliest of C. T. R. Wilson's cloud chamber images. Proceedings of the Royal Society, London.

Figure 1.3 US Intelligence Community Information Technology Enterprise (ICITE) architecture and its imagination of a "world of possibilities." Screenshot archived in 2014, when the Amazon Web Services contract to build ICITE was first announced.

tory of the cloud chamber is concerned with "the character of an instrument and the effects produced with it," as Svetlana Alpers has put it, I am interested here in understanding the character of the instruments of cloud computing and their generative effects.[11]

Cloud I: "Geography Matters in the Cloud"

Cloud I is concerned with the identification and spatial location of the data centers where the cloud is thought to materialize. Indeed, as computer science began to document the emergence of cloud computing, the idea of geography came to have a specific meaning defined by where data and programs are spatially located. In a 2008 Association of Computing Machines (ACM) forum devoted to the advent of cloud computing, a transformation is described "in the geography of computation," with "data and programs" being "liberated" as they are "swept up from desktop PCs and corporate servers and installed in the compute cloud."[12] Such accounts of the cloud appeal to a geography of "scalable" computation, which is thought to change radically with the rise of big data and the concomitant need for flexible storage and computational power.[13] There is need for some caution, however, in understanding the geography of the cloud primarily in relation to the rise of twenty-first-century volumes of digital data. Indeed, the emergence of cloud computing has important origins in grid computing, distributed scientific data, and, perhaps most significantly, the notion of computing as a public utility. "Computing may someday be organized as a public utility," speculated computer scientist John McCarthy in his MIT lecture of 1961, so that "the computer utility could become a new and important industry."[14]

In the second half of the twentieth century, the imagination of computing as a scalable public utility emerged. By 2006, when AWS launched its Elastic Compute Cloud (EC2), the architecture of cloud computing had begun to develop the three components now most widely recognizable as the cloud: *Infrastructure as a service*, in which hardware, servers, storage, cooling, and energy are supplied; *platform as a service*, in which the software stack is accessed via the cloud; and the *applications layer*, in which data analytics capacity—or the deployment of algorithms—is supplied via the cloud. Across the components of cloud architectures, the emphasis is on scalable computing, where the client pays for what they have used, combined with distributed computing, where multiple concurrent users can share and combine their data, their algorithms, and their analyses.

Understood as an architecture where data and algorithms meet and entangle, cloud computing's notion of a single computer hosting multiple simulated or virtual machines becomes actualized in space in a particular way.[15] In this respect, the whereabouts of simulated machines is not unknown at all, but rather the cloud is actualized in data centers, located in places within economies of land, tax rates, energy, water for cooling, and proximity to the main trunks of the network. As Benjamin Bratton writes, the "cloud is not virtual; it is physical even if it is not always on the ground, even when it is deep underground."[16] Hence, within the vocabulary of computer scientists at least, "geography" is said to "matter in the cloud."[17] In this limited sense of geographies of the cloud, the architecture of data centers has come to count as a spatial and geographic phenomenon in a way that the spatialities of the algorithm have not. When computer scientists ask "where is the cloud," what they denote as "geographical questions" concern the data centers thought to "underlie the clouds," their "physical location, resources, and jurisdiction."[18] When, for example, Google locates a new data center in the tax-friendly state of Georgia, or the Swedish internet service provider Bahnhof installs a data center in the cool confines of a former nuclear bunker under Stockholm, or Sun Microsystems

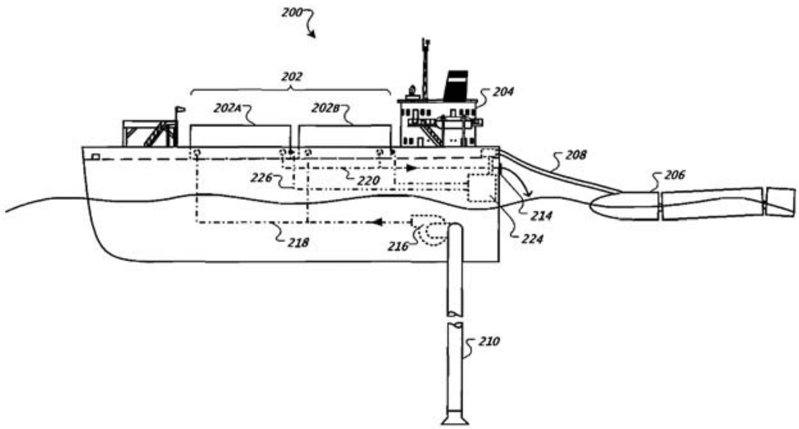


Figure 1.4 The Google-patented "water-based data center," hosting a floating platform of servers, powered and cooled by seawater. US Patent Office US752520782.

designs a portable data center inside a standard shipping container, the matter of geography is thought to reside in the spatial location of data storage.[19] Of course, these materializations of the cloud have ethicopolitical significance, so that when Google patented the floating data center (figure 1.4), the offshore potentials of cloud techniques beyond jurisdiction were actualized in these vast data ships.

Let us capture this geography of the spaces of cloud computing as Cloud I. This imagination of the cloud as a dispersed yet spatially located array of data centers is present in computer science, and that has extended into geographic and even political and geopolitical debate. So, for example, following the Snowden disclosures of the extent of US authorities' access to European citizens' data via US data centers, the EU sought initially to develop a "European cloud," in which they might store safely European data under European jurisdiction.[20] Similarly, following the US subpoena and mining of European financial transactions, the major Society for Worldwide Interbank Financial Telecommunications moved its cloud-computing provision to an underground data center in Switzerland, and the Canadian government has legislated for what it calls "data sovereignty," meaning domestic public data traffic must not leave Canadian territory. Understood as a spatial and territorial question of the jurisdiction of data technologies, then, the political response has been to seek to render the cloud intelligible and governable.

The unintelligibility of the cloud as a form of governing or a locus of geopolitical power has profoundly political implications. Following the exposure of the NSA's PRISM program in 2013, for example, the UK Intelligence and Security Committee (ISC) of Parliament—the sole body responsible for public oversight of security and intelligence powers in the UK—called the then foreign secretary, Philip Hammond, to give evidence before the committee. At the time of his evidence, Hammond was the final signatory on all warrants authorizing the interception and analysis of external communications data, conventionally understood as where one end of the communication is located externally to the UK. In his testimony, this figure of final sovereign authority manifestly failed to understand the complex spatial modalities of data stored, transferred, or analyzed in the cloud:

Q: The distinction between internal and external to the UK is important because there are tighter restrictions on analysing internal data. . . . But if the sender and recipient of an email are both in the UK, will it be treated as internal even if the data is routed overseas on its journey?

A: So, I think . . . er . . . and I invite my colleagues to step in if I get this technically wrong. . . . But I think . . . er . . . it's an internal communication. [At this point, the civil servants flanking the minister lean in to advise.]

Let me finish my train of thought. . . . [M]y understanding is, er, because of the technical nature of the internet . . . it is possible it could be routed to servers outside the UK. . . . Please correct me if I misinterpreted that. . . . I'm sorry, I have misled you in my use of terms. . . . I'm trying to be helpful.

Q: Well[,] you will be relieved to know that was the easy one. Now, the case of social media . . . if all of my restricted group of Facebook friends are in the UK . . . and I post something to Facebook, surely that should be internal?

A: [Following whispers from civil servants] Erm, . . . no[,] actually[,] if you put something on Facebook and the server is outside of the UK it will be treated as an external communication.

Q: What about cloud storage, where no other person is involved at all. It may be my decision to upload photographs to Dropbox. Would these communications be regarded as external because they are on US servers?

A: Aaah . . . er. My colleagues will . . . oh . . . well. . . . Yes[,] I am advised if the server is overseas they will be regarded as external.[21]

The 2014 UK foreign secretary's testimony before the ISC exposes the difficulties and limit points of a territorialized juridical form in the face of cloud computing. In Cloud I, where the geography of cloud forms is everything, the cloud has become centered on *where* data is collected and stored. Indeed, the Anglo-American juridical tradition has founded its privacy protections precisely on the consent required for lawful storage and collection. Hammond's evidence before the committee, however, exemplifies how it may be the very unintelligibility of cloud forms that enables and facilitates contemporary surveillance and intelligence gathering. As Kate Crawford and Jason Schultz argue, the new predictive "approaches to policing and intelligence may be both qualitatively and quantitatively different from surveillance approaches," and thus enable "discriminatory practices that circumvent current regulations."[22] Yet, Crawford and Schultz go on to suggest that an alternative space for democratic oversight might lie in what they call "a right to procedural data due process," where constraints and oversight mechanisms are placed on the algorithmic processes of data analysis.[23] Even as the cloud overflows and exceeds the categories and practices of bureaucracy and law, what has come to be at stake ethicopolitically has become a struggle to wrest the cloud back into a form over which one can have oversight, to expose its "bias" and demand neutrality, to make it comprehensible and accountable in democratic fora, and to render the cloud bureaucratically and juridically intelligible.

Among the critical geographic and artistic accounts of cloud computing, the desire to wrest the cloud into an intelligible form similarly finds expression in methods of visualization. The geographer and artist Trevor Paglen seeks to "make the invisible visible," reflecting that "the cloud is a metaphor that obfuscates and obscures" the material geographies of the "surveillance state."[24] Paglen's work is concerned with bringing the geopolitics of cloud computing back into a human line of sight through visualization. His methods deploy optical devices of many kinds to bring back into human vision that which would otherwise exceed the limits of observation. His ghostly images of the NSA's data centers are photographs taken at night with a long-focus lens from a helicopter (figure 1.5); and his photographs of the secret installations of military and drone bases in the Nevada desert are taken with adapted telescopic instruments of astronomy.[25]

The optical instruments deployed by Paglen belong to a paradigm of observation in which, as Peter Galison describes, one is offered "a direct view" of things otherwise "subvisible."[26] As Paglen accounts for his own work: "My intention is to *expand the visual vocabulary* we use to see the US intelligence community. Although the organizing logic of our nation's surveillance appa-

Figure 1.5 NSA headquarters, Fort Meade, Maryland. Trevor Paglen, 2014.

ratus is invisibility and secrecy, its operations occupy the physical world. Digital surveillance programs require concrete data centers; intelligence agencies are based in real buildings. . . . [I]f we *look in the right places* at the right times, we can begin to glimpse the vast intelligence infrastructure."[27] So, for Paglen the challenge is to "expand the visual vocabulary" to see more clearly the actions of algorithms, and to bring into vision the things that would otherwise be obfuscated by the cloud. Similarly, for the artist James Bridle, "one way of interrogating the cloud is to look where its shadow falls," to "investigate the sites of data centres" and to "see what they tell us about the real disposition of power."[28]

Yet, what are the "right places" and "right times" to look and to observe an apparatus? How does one investigate something describable as the real disposition of power? Indeed, what ways of seeing would be appropriate to what art historian Jonathan Crary calls a "relocation of vision" taking place with computation, or the visual vocabulary appropriate to the digital mediation of cultural objects and urban scenes identified by Gillian Rose and Shannon Mattern?[29] If the cloud is to be observed and revealed in the secret glimmering buildings of the NSA's data centers in Paglen's images, then could his "real buildings" also be located in other places? Could they be observed, for example, in the rented North London offices where a small team of physics graduates write algorithms for risk-based security?[30] Must the material geography of cloud computing be found in the buildings or territories where it is thought to actualize? Could the "right place" to look also be in the spatial arrangements of an experimental clustering algorithm used in anomaly detection, or in the generative logics of emergent machine learning algorithms?[31]

My point is that the desire to "open the black box" of cloud computing and to expand the visual vocabulary of the cloud, to envision the cloud and its properties in geographic space, dwells within and alongside the paradigm of observation. In Stephen Graham's work on cities and warfare, for example, he writes of "systems of technological vision" in which "computer code tracks and identifies."[32] Critical scholarly responses to the cloud—through imaginaries of verticality and the stack—have thus emphasized overwhelmingly spaces of sight and oversight, where observational power is foregrounded. Crucial aspects of these technologies, however, do not operate on the terrain of human vision and, indeed, harness perceptual power on a horizontal threshold of connection and correlation.

And so, Cloud I poses questions within an observational mode: Where is it?; What type is it?; Can we map it?; Can we recognize it? As with the early classification of cloud forms, when Luke Howard first proposed names for cirrus, cumulus, and stratus in 1803, a linear system of genera and species was proposed to "enable people to think coherently about clouds" (figure 1.6).[33] The system of cloud form classification was later described as "quite ridiculous for clouds," because they are not fixed forms but ever in formation, and indeed analog algorithms were devised to diagram the observational pathways of cloud formation. In short, Cloud I sustains the idea that one can have a more beautiful sight, a means of seeing more clearly and rendering something coherent and intelligible. The telescope and camera Paglen brings to the scene of data deployment belongs to a particular history of observation, one that Donna Haraway describes as "visualizing technologies without apparent limit," like "the god trick of seeing everything from nowhere."[34]

What might it mean for us to commit instead *not* to enable coherent thinking about the cloud? If one determines instead to "stay with the trouble," as Haraway has put it, of partial and indeterminate lines of sight, then all apparently coherent technologies of observation become what Haraway calls "active perceptual systems" with "partial ways of organizing worlds."[35] In the second variant I discuss here—Cloud II, drawing on Peter Galison's distinction between mimetic and analytical forms of scientific instruments—cloud computing appears as a *cloud analytic*.[36] Here, the cloud is a bundle of experimental

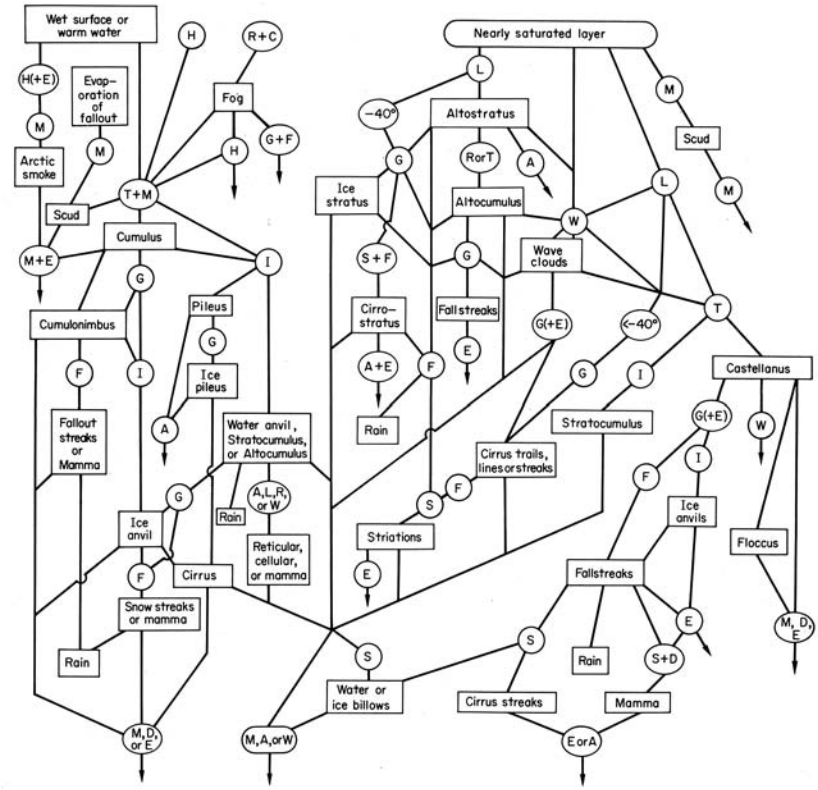


Figure 1.6 Analog algorithm for the classification of cloud mechanisms, 1967. Scorer and Wexler, *Cloud Studies in Colour*.

algorithmic techniques acting in and through data to modify the threshold of perceptibility itself. Put simply, as analytic the cloud resides not within a paradigm of observation, representation, and classification but instead within perception, recognition, and attribution. As Galison reminds us, in the cloud chamber "we do not actually see things," though what we perceive "has a close relation to them," what he calls an "almost seeing" of otherwise subvisible entities.[37] Understood thus, to say the cloud somehow obfuscates a real world of politics is to miss the point somewhat. The cloud is not an obfuscation; far from it.[38] Like the cloud chamber of the twentieth century, contemporary cloud computing is about rendering perceptible and actionable (almost seeing) that which would otherwise be beyond the threshold of human vision. Where some claim the cloud makes the geographies of power in our world unintelligible, I propose that it is becoming an important element of what Karen Barad calls the "condition of intelligibility" of our world.[39]

Cloud II: "Changing the Aperture of Observation"

What I call Cloud II, or the cloud as analytical gathering of algorithms with data, displaces the question, Where is the cloud?, replacing it with, How does the cloud render the world perceptible and analyzable? In this way, Cloud II witnesses the extension of algorithmic modes of reason that surface something for perception and action amid an otherwise profoundly uncertain environment. As historian of science Paul Erickson and his colleagues have traced meticulously in the historical emergence of algorithmic rationality, the profound uncertainties of the Cold War nurtured a desire to extend mathematical logic into the realm of decision. The decision procedures and cybernetic methods of algorithm appeared to extend the faculties of human reason so that they "no longer discriminated among humans, animals, and machines" in the capacity to analyze, to decide, and to act.[40] What we see here is the entwining of human and machine modes of reasoning such that what Henri Bergson calls the "organs of perception" of the world are composite beings formed through the relations among humans, algorithms, data, and other forms of life.[41]

Understood in terms of the intertwined faculties of human and machine, the contemporary spaces of cloud computing exceed the territorial geographies of the location of data centers, becoming instead a novel political space of calculative reasoning. Returning to the site of the ICITE program, what kinds of perceptions and calculations of the world become possible with the algorithmic instruments that gather in cloud space? When the seventeen US intelligence agencies upload or analyze data in ICITE, they access software as a service, so that they are not merely "joining the dots of their data," as the post-9/11 measures claimed, but are in fact combining their modes of analysis. Among the available ICITE platforms is Digital Reasoning software, a set of machine learning algorithms for analyzing and deriving meaning from data across government intelligence databases and open source social media data streams. Describing the Synthesys application available to analysts via ICITE, Digital Reasoning claims that its algorithms are able to "read," "resolve," and "reason" from the correlations in cloud data. The algorithms are said to "extract value from complex and opaque data" and to "determine what's important" among the "people, places, organizations, events and facts being discussed," ultimately "figuring out what the final picture means" by comparing it with "the opportunities and anomalies you are looking for."[42] What this means in terms of the practices of the algorithms is that they identify clusters within the data (to read), derive attributes from those clusters to make them recognizable into the future (to resolve), and compare the output of the algorithms with the target output of the analyst (to reason). This is an iterative and experimental process in which the humans and machines feel their way toward solutions and resolutions to otherwise indelibly political situations and events.

Though Digital Reasoning's machine learning algorithms are now the mainstay of US government defense analysis, they were developed initially for anomaly detection in the wholesale financial industry. The frenzy of the 2008 financial crisis included trading strategies that were in breach of regulations, leading to significant losses for institutions. In the aftermath of the crisis, machine learning algorithms were developed to analyze "terabytes of emails per day to detect hints of insider trading."[43] The cognitive computing software performs the role of what N. Katherine Hayles calls a "cognizer," carrying out the cognitive functions to generate norms and anomalies from the patterns in vast datasets and, as it does so, deciding what or who will come to matter amid the occlusions.[44] At the level of the algorithm, there is profound indifference to the context of whether these norms and anomalies pertain to financial trades or the movement of insurgent forces—what matters is precisely the capacity to generate a final output that can be acted on. By 2015, when Digital Reasoning was pitching to government security and defense officials in Washington, DC, the CEO Tim Estes was offering the machine learning tools to "sift through sensor data, emails and social media chatter," bringing "structure to human language" and "changing the aperture of observation."[45]

What would it mean for algorithms to change the aperture of observation? Let me agree, curiously and peculiarly, with this vendor of cloud-based algorithms to the DHS and the NSA and say, yes, indeed, the aperture of observation is changing, though not in such a way that the promised complete final picture is delivered to the analyst. Indeed, the technology of the aperture is concerned with a specific and discrete opening onto a scene, one in which the notion of a completeness beyond the aperture is occluded and screened out. The aperture, from the Latin *aperire*, to open or to uncover, is not primarily an optic but is rather a means of opening onto or uncovering the world. The point at which a machine learning algorithm condenses the output of multiple layers to a single output is also an aperture in the sense that it is an opening or uncovering of attributes and relations that would not otherwise be perceptible. Put simply, with Cloud II, where we are interested in the analytic, what matters is not so much seeing the "where" of the data as it is the capacity to extract patterns and features from data to open onto targets of opportunity, commercial and governmental.

With the advent of cloud computing, the aperture of observation becomes an aperture of "almost seeing," in Peter Galison's terms, or a means of "correlating and synthesizing large volumes of disparate data" so that action can take place based on what is almost seen of the world.[46] As one analyst puts the problem, "It allows us to say correlation is enough. We can stop looking for models, throw the data at the biggest computing clusters the world has ever seen and let algorithms find the patterns."[47] So, *correlation is enough*. Let us reflect on this claim of an adequacy of correlative associations. In the pages that follow, I propose three characteristics of correlative cloud reason, and I suggest why this form of algorithmic reason has significance for our ethicopolitical present.

Condensing Traces

The algorithmic techniques of Cloud II involve *condensing traces*, practices not primarily concerned with seeing or bringing into vision, but rather focused on engaging a subvisible world by inferring from the traces and trajectories that condense at indeterminate points. Returning to my analogy with the apparatus of the cloud chamber, by the mid-twentieth century, when Charles Wilson's cloud chamber was being used in subatomic physics, the "purpose" of the instrument was described as being "to study the motion of ionizing particles from records of the drops condensed on ions formed along the trajectories followed by these particles."[48] The motion of particles could not be observed directly, but their trajectory could be perceived obliquely, via the visible drops condensed on the ions—the cloud "tracks." Figure 1.7 shows one of the best-known cloud chamber photographs, C. T. R. Wilson's image of alpha-emitting thorium, with the cloud originating from an alpha ray passing through the chamber, its "trajectory disturbed in two places," as recorded in the atlas of cloud chamber images.[49] The newly available images of radioactivity made the object perceptible via the records of condensed drops on the ions, observing the motion of the particles obliquely. In the compelling images from the cloud chamber, one can locate a capacity to perceive the movement of otherwise subvisible entities. The *chamber* of the cloud chamber is akin to an apparatus, in Michel Foucault's terms, in that it "inserts the phenomena in question" within a "series of probable events."[50] In this sense, to condense a trace is not to show or to reveal something existing in the past, but rather to establish a condensed series of possible correlations between entities and events. The cloud chamber apparatus is experimental to the extent that it is concerned with probable tendencies and trajectories, condensing a larger volume down to the probable event.

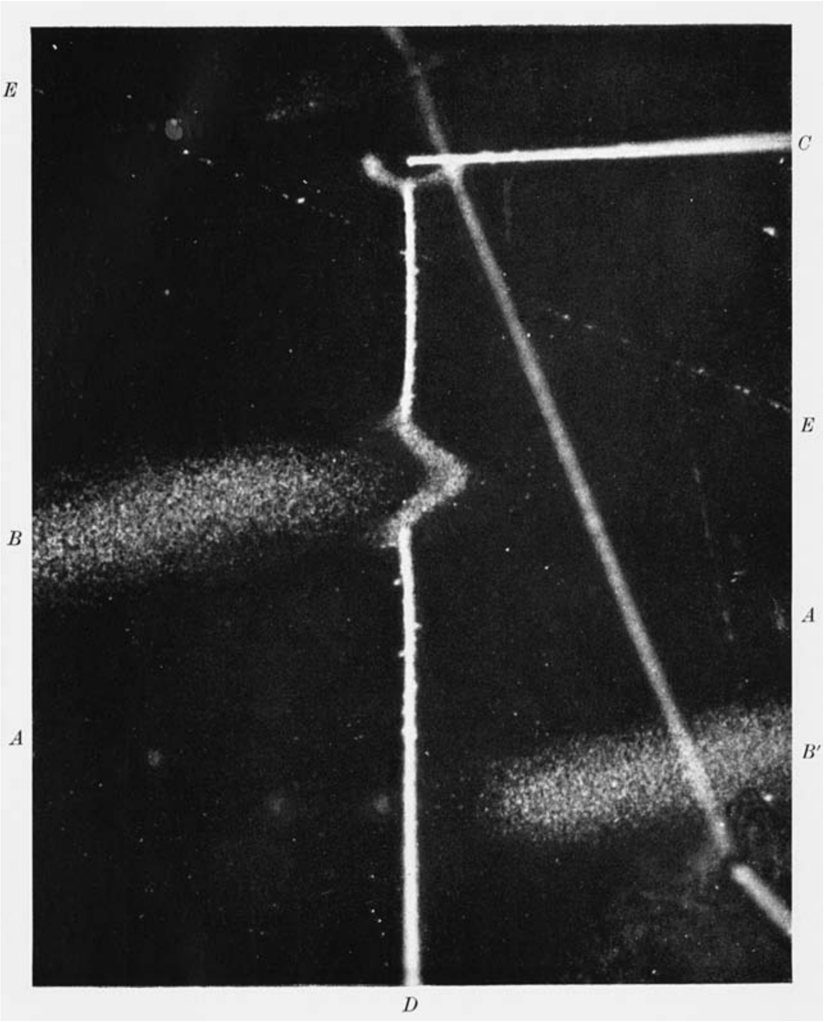


Figure 1.7 Cloud chamber tracks of alpha-emitting thorium. C. T. R. Wilson, c. 1923, *Proceedings of the Cambridge Philosophical Society*.

Like the cloud chamber apparatus of the twentieth century, contemporary cloud computing is a form of experimental chamber or apparatus. It condenses and reduces the volume of data down to that which is probable or possible in the algorithmic model. When Digital Reasoning claims that their algorithms determine what is important in war or in finance, this is because their machine learning apparatus is generating what matters in a series of probable events. As Karen Barad writes on the nature of scientific apparatuses, they are boundary-making practices that decide "what matters and what is excluded from mattering," as they "enact agential cuts that produce determinate boundaries and properties of 'entities' within phenomena."[51] In condensing the probable data traces of what matters in the world, cloud computing enacts the matter of the person of interest at the border, the possible future disruptive protest event in urban space, the acts of fraud or insider trading, or the chains of association of no-fly lists, blacklists, and kill lists—like beaded drops of condensed data making action possible.

Though the movement of an entity cannot be observed directly in the chamber, it is perceived obliquely through tracks and trajectories of mobility. Indeed, Cloud II as a mode of computational power poses significant questions for political and geographic accounts of what it might mean to "secure the volume" or the "volumetric," or to have a "politics of verticality."[52] The analytical techniques available in the cloud do not strictly act on the earth from some novel spatial dimension "above" or "below" the ground, but rather enroll the space of calculation itself. Cloud computing acts on the vast volume of data traces through a series of algorithmic apertures that condense and distill the thing of interest. In contrast with a securing *of* the volume, the pursuit of security *through* the volume precisely reduces and condenses the volume by means of the correlations within the data. The so-called cognitive-computing applications in the ICITE cloud, for example, use pattern recognition and sentiment analysis to identify political protests, civil unrest, and "atypical" gatherings or events. Cognitive computing renders perceptible to the analyst "what matters" in the political scene, using the volume of cloud-based digital data precisely to reduce and flatten the field of vision. The relation between volume and flatness thus becomes one in which the tracks of association and correlation enact the horizon of possibility for the analyst. The volume is radically condensed down to the target data elements, like beaded drops on ionizing particles through which future trajectories of motion can be inferred.

Discovering Patterns

The algorithms gathering in Cloud II involve the *discovery of patterns*, which is a highly specific calculative device deployed in a volume of data. The repository of data in the US intelligence community's cloud, for example, is described as a "data lake" in which the "same raw data" can be analyzed with "statistical functions," such as conventional regression, and with "machine learning algorithms" of "data discovery."[53] Here, the relation of the data lake to cloud computing is metaphorically understood as the formation of clouds from the water vapor rising from lakes into the atmosphere.[54] While the application of statistical analysis to intelligence data involves the analyst beginning with a deductive query, or hypothesis, and building rules to test that hypothesis in the data, the advent of cloud computing presents the analyst with a volume and variety of data too great for conventional human hypothesis or deduction. In the context of a security paradigm that seeks out the uncertain possible future threat, the volume of data in the lake—much of it transactions and social media data—is analyzed with machine learning techniques that promise to yield previously unseen patterns via processes of "knowledge discovery."

In contrast to a deductive form of reasoning by hypothesis testing, machine leaning algorithms deploy abductive reasoning, so that what one will ask of the data is a product of the patterns and clusters derived from that data. As Luciana Parisi writes on the algorithmic logic of abduction, "algorithms do not simply govern the procedural logics of computers" but take "generative forms driven by open-ended rules" or "derive rules from contingencies."[55] Understood in these terms, the machine learning algorithms deployed in the contemporary intelligence cloud are generative and experimental; they work to identify possible links, associations, and inferences. Such abductive forms deploy a distinct kind of causal reasoning, different from deductive reasoning, in which "deductions support their conclusions in such a way that the conclusions must be true, given the premises," and closer to "fallible inferences," in which "the possibility of error remains."[56] Put simply, in the cloud analytic of Cloud II, the algorithms modified through the patterns in data decide, at least in part, which fallible inferences to surface on the screen of intelligence analyst, drone pilot, or border guard.

The rise of correlative forms of reasoning in machine learning has serious implications for the ethicopolitics of algorithms, not least because error, failure, or fallibility are no longer conceived as problems with a model; rather, they have become essential to the model's capacity to recognize abnormalities and generate norms. Abductive models observe the output signal of the algorithm and adjust the layers of probability weighting to optimize the fit between the input data and the output signal. For this reason, programs such as ICITE claim to be "uncovering answers to questions the analysts don't already know," where the question is not a hypothesis but a speculative experiment.[57] As one of the designers of t-digest pattern-detection algorithms explains, in describing the modification of a model in response to data inputs, "As small fluctuations occur in the event stream, our model can adjust its view of normal accordingly."[58] What this means is that the data inputs and the algorithm mutually modify to optimize the output. The norms and anomalies of the model are thus entirely contingent on a whole series of adjustments, including the adjustment of weights, parameters, and the threshold to tolerate particular error rates. "You can move the slider for a lower false positive rate if that is what you want," I am told by one designer of facial recognition algorithms, "but that will always increase the false negative rate, so you need to decide what your tolerance is."[59] As the politics of our world becomes understood as an "event stream" filtered through infinitely adjustable apertures and thresholds, the apparatus of the cloud deploys algorithms, such as t-digest, to generate its malleable view of what is normal in the world from its exposure to the data stream. To adjust the view of normal, to move a threshold, or to decide a tolerance—these are the ethicopolitical dispositions of algorithms as they act on the world.

Returning to my analogy with the cloud chamber apparatus, the twentieth-century physicists were also engaged in abductive forms of reasoning and pattern detection that exceeded the deductive testing of hypothesis. The cloud chamber made it possible to detect previously unseen and unknown particles via the patterns of unusual or abnormal cloud tracks. "The central problem of the interpretation" of cloud chamber "exploratory photographs," as described in the physicists' guide to cloud chamber technique, was the "recognition of the particles involved in a particular event." To interpret the detected patterns of scattering, cascades, and showers, the physicists inferred from the attributes, or the "characteristic features of particle behaviour."[60] They would not begin with a hypothesis and test it in the chamber, for the uncertainties and contingencies of particle behavior had become the focus of their inquiry. The cloud chamber played a crucial role in the identification of hitherto unknown subatomic particles, rendered detectable through the generation of surprising new cloud tracks and trajectories. In the text accompanying the famous Rochester atlas of cloud images, Nobel physicist Patrick Blackett writes: "The last two decades have seen an increasing use of two experimental methods, the cloud chamber and the photographic emulsion, by which the tracks of sub-atomic particles can be studied. All but one of the now known unstable elementary particles have been discovered by these techniques. . . . This involves the ability to recognise quickly many different sub-atomic events. Only when all known events can be recognised will the hitherto unknown be detected."[61]

The atlases of "typical" cloud chamber images definitively did not offer the scientist a taxonomy or classificatory system for identifying particles, forming the rules of form for unknown future particles. Rather, the images provide a kind of training dataset, allowing the scientists to become sensitive to the patterns and clusters of cloud tracks, so that they could recognize the disturbances and fluctuations of a new event. The discoveries of new particle behaviors—the first glimpse of the muon or the positron in the cloud chamber, for example—were not strictly observations of an unknown object, but more precisely perceptions of something in close relation to it: the patterns involved in an event. As Peter Galison reminds us, the cloud chamber images "traveled" and were "widely exchanged, stored and reanalyzed by groups far distant from the original photographic site."[62] In this sense, *the cloud chamber is the site*, just as *the cloud analytic is the site* in cloud computing, through which the event is recognized via its patterns, and where the algorithm and the analyst are trained in the art of recognition.[63]

Archiving the Future

The recognition of traces in Cloud II involves an archiving of the future, in which particular future connections are condensed from the volume of the data stream and rendered calculable. In a sense, the algorithms of Cloud II are relatively indifferent to the past as a series of data points or significant events. What matters most to Cloud II is the capacity to generate a particular future of dispositions, propensities, and attributes. When AWS supplies cloud computing to corporations and governments, the applications layer is configured as an "app store" so that users can select the analytics tools they want, paying for what they use. As one UK government client of AWS explained to me, "We are cloud first" because "we want platforms; we want to plug in to different suppliers."[64] This flexible deployment of cloud data was an important element of AWS's tender for the ICITE program, with James Clapper, announcing, "We have made great strides, the applications are in the apps mall, and the data is in the cloud."[65] In fact, of course, the significance is that the algorithms and the data dwell together in AWS cloud space, opening the possibility for seemingly infinite calculability, or what Hayles calls "infinitely tractable" data.[66] The aperture opens onto a world of optimized targets, threats, and opportunities so that the analyst experiences a sense of reach into possible futures. The security, policing, or intelligence analyst is thus reimagined by the state to be a desiring and wanting consumer, with the "apps mall and stores available from the desktop," selling to users "thousands of mission applications" and resembling "what Apple provides through iTunes."[67]

Let us reflect for a moment on what the NSA or CIA analyst browsing the ICITE apps mall might find to assist them in their missions. Among the thousands of applications, Recorded Future offers natural language processing and sentiment analysis algorithms to "scrape the web" for signals of possible future threat: "We constantly scan public web sources. From these open sources, we identify text references to entities and events. Then we detect time periods: when the events are predicted to occur. *You can explore the past, present and predicted future of almost anything in a matter of seconds*. Our analysis tools facilitate deep investigation to better understand complex relationships, resulting in actionable insights."[68] Consider the claim: the data stream of social media contains all the attributes of incipient future events, so that one can explore the past, present, and predicted future of almost anything. Recorded Future's applications run their algorithms across the boundary of public and private cloud computing so that the analyst can explore the correlations between, for example, classified structured data in the DHS's files and the language and sentiment analysis of so-called open source Twitter feeds and Facebook posts. In this way, the technology enables action in the present, based on possible correlations between past data archives (such as national security lists) and archives of the predictive future.

With this instrument of Cloud II, the analytic is everything. Archived data in Recorded Future becomes unmoored and derivative of its context, even the so-called dirty, or noisy, data no longer muddying the calculation but rendered useful. As the security analysts draw together social media "junk" data with other labeled entities, tagging metadata and sharing with other agencies, diverse data elements are rendered commensurate and made actionable geopolitically. As Orit Halpern suggests in her account of how algorithmic rationality became a governmental and social virtue, digital computation changes the nature of the archive. The nineteenth-century form of "static" archiving and repository is supplemented in the twentieth century by what Halpern calls "an active site for the execution of operations."[69] Similarly, in the nineteenth-century cloud chamber's attempt to reproduce nature, the cloud tracks had been considered spurious dirt effects, not for scientific archiving. Yet, it was the tracks that became the thing of interest, the atlas of cloud chamber images knowing only the event of the track itself. Contemporary cloud computing is an active site for the execution of operations, as understood by Halpern, in which the archive is generative of particular imagined futures.

The archivization of specific data elements with applications such as Recorded Future, then, produces particular futures; "the archivization produces as much as it records the event," as Jacques Derrida writes.[70] As the photographic recording of the cloud tracks within the cloud chamber archived the possibility of recognizing future subatomic particles, so the digital recording of social media data in cloud computing archives the possibility for future actions at the border or on the city street. Understood in this way, the spatial power of the data center as "archive" could be critically challenged, as we see in Trevor Paglen's images, while leaving entirely intact Halpern's "active site of operations," a site capable of acting indifferent to the "where" and the "what" of data.

And yet, there are creative practices of resistance within Cloud II that offer an alternative sensing of the archive as an active and generative site. In James Bridle's installation *Five Eyes* (figures 1.8 and 1.9)—commissioned by the Victoria and Albert Museum (V&A) for their public archive–focused exhibition *All of This Belongs to You*—the artist invites the viewer to consider anew the relations between the archive and potential futures. Bridle passed the V&A's 1.4 million digital object records through an intelligence analysis system. The algorithms "extract names, things and places, and create searchable connections between seemingly disparate objects," with the resulting connections "difficult to grasp, often inscrutable to the human eye, reflecting the mechanical calculus that was used to generate them."[71] Displayed in a series of five glass cabinets, juxtaposed with the woven artifacts of the V&A's tapestry galleries, the objects surfaced for our attention by the algorithms are placed atop a "stack" of analog museum files. The object displayed is thus generated in and through the archive, through the intimate connections learned by the algorithms. One cannot meaningfully trace how the object displayed has become the thing of interest, or why it is the optimized output from the actions of the algorithms. In Bridle's rendering of the archive, one can sense the "upheaval in archival technology" noted by Jacques Derrida, the infrastructure making a claim on the future, on the infrastructure of the "archivable event."[72]

The Cloud Atlas

When a group of particle physicists showed me their cloud chamber experiments, I had expected the thing of interest around which we would gather would be the cloud tracks—the wispy trajectories of particles that had so captivated Charles Wilson. Instead we gathered around the apparatus, the physicists animated by much discussion on the optimal point of cooling, and whether thorium is a useful radioactive element for the experiment. One of

Figures 1.8 and 1.9 James Bridle's *Five Eyes* installation, displayed in the Victoria and Albert Museum's tapestry galleries. Author photographs.

the group had worked at CERN with the large hadron collider, commenting that "there is no reason why we couldn't have discovered the Higgs Boson using a cloud chamber, but it would take an inordinately long time."[73] So, for the scientists, something exists with potential to be detected—manifest in the alpha tracks and cosmics in the chamber—but this potential entity is rendered perceptible by the specific and contingent arrangement of an experimental apparatus. With the smallest of adjustments to the arrangement of the chamber, the physicists dramatically changed the conditions for what could be traced of the particle's trajectory.

The gathering of scientists and one curious geographer around the experimental apparatus of the cloud chamber resonated with other kinds of gatherings and disputes I have observed around an experimental apparatus. When the designers of algorithms for the detection of credit card fraud gathered around their experimental model, they were concerned to optimize the perceptibility of an anomaly. "The problem with rules," they explain, is that "novel fraud patterns will not be detected."[74] To detect something novel, they suggested, the rules of an algorithm must be generated through the iterations of output signals to input data. Their machine learning algorithms for detecting emergent forms of fraud, then, are not experimental in the sense of not yet validated, but are specifically "experimental" in their capacity to adjust parameters and bring something novel into existence. Isabelle Stengers describes the "paradoxical mode of existence" of subatomic particles in that they are simultaneously "constructed by physics" and yet "exceed the time frame of human knowledge," so "the neutrino exists simultaneously and inseparably 'in itself' and 'for us,' a participant in countless events."[75] In the lines that follow here, I conclude the chapter by commenting on why this matters for our contemporary moment, when the specific apparatus of cloud computing brings something into being, discovering associations and relations otherwise unknowable.

Amid the many contemporary calls to bring algorithms into vision, or to establish human oversight, it is imperative that we formulate accounts of the ethicopolitics of algorithms that do not replay the observational paradigm of Cloud I or the classificatory forms related to that paradigm. In Cloud I, vision is the sovereign sense, afforded both the apparent objectivity of the "most reliable of senses" and the means of securing the state's claim to sovereign violence.[76] And yet, the machine learning algorithms operating in programs such as ICITE work to render perceptible that which could never be observed directly, that which could not be brought into view as with an optical device. The algorithms for identifying insider trading, for credit scoring, or for generating intelligence data from social media bring trajectories and thresholds into being. They are generative and experimental techniques capable of perceiving a thing of interest without seeing it as such. The algorithms available on state analysts' version of iTunes—with their promises of digital reasoning and recorded futures—generate a target of interest through subvisible experimentation. The Cloud II apparatus is not geared to a deductive science of *observation, representation,* and *classification*, but instead signals a paradigm of *perception, recognition*, and *attribution*.

The algorithms identifying the attributes of people and things, then, do not merely observe or record historical data on past behaviors or events. If they did observe and classify behaviors, then perhaps it might be an adequate ethical response to insist on the transparency of the processes. With machine learning programs such as ICITE, a person or entity of interest emerges from the correlations and patterns of condensed data: financial transactions, travel patterns, known associates, social media images, and affects derived from sentiment analysis. The data archive of the neural net algorithms of Cloud II is, as Orit Halpern proposes, "indeterminate in terms of the past," so that it is not possible to identify how the present calculation was arrived at.[77] Little pieces of past patterns enter a training dataset and teach the algorithm new things; the designer of the algorithm experiments with thresholds to optimize the output; new people and things enter a validation dataset to further refine the algorithm; and on and on iteratively, recursively making future worlds. And let us not forget that with this correlative reasoning, sovereign decisions are made: to stop this person at the border, to detain this group as they travel on the subway to a downtown protest, to target this vehicle as it approaches a checkpoint, or to approve or deny this asylum claim.

Isabelle Stengers has written that scientific experiments work through "the power to confer on things the power of conferring on the experimenter the power to speak in their name."[78] Understood in this way, whether an experiment can be said to have worked or to yield proof is of lesser significance than whether it confers the power to speak or to make a claim. In one sense, Wilson's cloud chamber experiments failed in that they did not primarily advance the understanding of the formation and classification of cloud forms. A greater power, though, was afforded to the particle physicists who were able to speak in the name of things that would otherwise exceed their observation. As algorithms written for casino or credit card fraud travel to border control or to security threat analysis, I propose that cloud computing similarly confers on algorithms the power to confer on the analyst the power to speak in their name. What do they say when they speak? What kinds of claims do they make?: here are the people and things with a link to terrorism; here are the possible fraudulent asylum claims; here are the optimal targets for the next drone strike; here are the civil uprisings that will threaten the state next week. The claims that are spoken in cloud computing programs, such as ICITE, confront our fallible, intractable, fraught political world with a curious kind of infallibility. In the cloud, the promise is that everything can be rendered tractable, all political difficulty and uncertainty nonetheless actionable. The ICITE app store marketplace available on the screens of analysts renders the politics of our world infinitely reworkable—the "geopolitical events" in the correlative calculus, a kind of geopolitical cloud chamber. As Timothy Cavendish, a protagonist in David Mitchell's novel *Cloud Atlas*, muses, "What I wouldn't give now for a map of the ever constant ineffable? To possess, as it were, an atlas of clouds."[79] Programs such as ICITE make just such a dangerous promise in the algorithmic governing of society—a kind of atlas of clouds for the ineffable, a condensed trace of the trajectories of our future lives with one another.

2

The Learning Machines

Neural Networks and Regimes of Recognition

The peculiarity of men and animals is that they have the power of adjusting themselves to almost all the features [of their environment]. The feature to which adjustment is made on a particular occasion is the one the man is attending to and he attends to what he is interested in. His interests are determined by his appetites, desires, drives, instincts—all the things that together make up his "springs of action." If we want to construct a machine which will vary its attention to things in its environment so that it will sometimes adjust itself to one and sometimes to another, it would seem to be necessary to equip the machine with something corresponding to a set of appetites.

—Richard Braithwaite, "Can Automatic Calculating Machines Be Said to Think?"

Springs of Action

In January 1952 the BBC recorded what was to be the world's first public debate on the mathematics and ethics of machine learning. Participating in the discussion of the question "Can Automatic Calculating Machines Be Said to Think?" were Manchester mathematicians Alan Turing and Max Newman; their neurosurgeon colleague Geoffrey Jefferson; and Cambridge moral philosopher Richard Braithwaite. Turing explains that he has "made some experiments in teaching a machine to do some simple operation," but that "the machine learnt so slowly that it needed a great deal of teaching." Jefferson is skeptical of the use of the verb "to learn" in relation to the machine, and he interjects to ask Turing a question: "But who was learning, you or the machine?"[1]

This distinction, between humans and machines as the locus of learning is of great significance to the neurosurgeon, for whom the electronic circuits of computing machines were not analogous to the "fragments of the nervous system" he encountered in the fleshy materiality of the human brain.[2] Yet, Jefferson's question prompts Turing to reflect on his own embodied experience of experimenting with his machines. In the audio recording of the debate, Turing can be heard to pause for a moment's reflection before responding: "I am inclined to believe that when one has taught it [the machine] to do certain things[,] one will find that some other things one had planned to teach it are happening without any special teaching being required." In response to Jefferson's question of who was learning, the mathematician or the machine, Turing responds, "I suppose *we both* were."[3]

The entangled "we both" of mathematician and machine, learning together, expresses Turing's belief that intuition is a mathematical faculty that "consists of making spontaneous judgements which are not the result of conscious trains of reasoning." For Turing, the intuitive faculty is entangled with what he calls the "ingenuity" of the building of rules as arrangements of propositions.[4] The iterative relationship between intuition and ingenuity in mathematical reasoning necessarily entangles the mathematician's affective and haptic relations to a puzzle with the making of a formal axiom or logic. The human and machinic elements of mathematical learning, then, are not so readily disaggregated for Turing. Though for the philosopher in the discussion, Richard Braithwaite, it is the unique "peculiarity of men and animals" that they are able to learn intuitively by "adjusting themselves to almost all the features of their environment," his notion of a "spring of action" afforded by appetites nonetheless calls to mind today's capacities for machine learning algorithms to learn and to generate things in excess of their taught rules.[5] The 1950s radio discussion of the character of machine learning did, in some respects, envisage a future world in which machines would exceed the rules-based decision procedure and extend to the affective pull of intuitions and appetites for data.

Thus, even in the mid-twentieth century, the mathematics and philosophy of machine learning was centered on the entangled relations of humans and machines. The question, as articulated in the debate on automatic calculating machines, was "Who was learning, you or the machine?," and Turing's reply was "We both were." In this chapter, I focus on the *we* invoked by Turing in this public debate precisely because it runs against the grain of contemporary moral panics amid machine autonomy and algorithmic decisions that appear to be beyond the control of the human. On the contrary, the *we* of machine learning is a composite figure in which humans learn collaboratively with algorithms, and algorithms with other algorithms, so that no meaningful outside to the algorithm, no meaningfully unified locus of control, can be found. In contemporary machine learning, humans are lodged within algorithms, and algorithms within humans, so that the ethicopolitical questions are concerned less with asserting human control over algorithms and more with how features are extracted and recognized from a teeming data environment.[6] In short, the ethicopolitics of machine learning algorithms is located within the figure of the *we*—in the very relations to ourselves and to others implied in the *we* who have a spring of action.

In our contemporary moment, the "we both were" extends the already multiple body via the sinewy and invasive techniques of deep learning and neural network (neural net) algorithms.[7] The extended *we* of the multiplicity of data to which the learning algorithm is exposed heralds an intimate communion of the learning machines with a vast and incalculable *we*: all of us, all our data points, all the patterns and attributes that are not quite possessed by us.

In the pages that follow, I begin by taking up the theme of intuitive learning via the extracted features of a data environment in the context of the twenty-first-century advent of surgical robotics. At the level of this specific type of deep neural network algorithm, there is no technical distinction between learning actions for robot surgery and learning actions for robot weaponry. Across different domains of life, these algorithms are concerned with translating the input data from their environment into a "feature space," mapping the features into clusters of significance, and extracting the object of interest for the action.[8] Thus, algorithms designed to save lives, via robot surgery, or to end lives, via robot warfare, share the same arrangements of propositions. In following the machine learning of surgical robotics, I am concerned to capture the impossibility of establishing definitive boundaries of good and evil in relation to algorithms. The machine learning algorithms deployed in robot surgery do save lives through the lower infection rates of noninvasive methods, but they also endanger life through error and miscalculation. My point is that the ethicopolitics of machine learning algorithms cannot be mapped onto the parameters of good and evil or the securing and imperiling of life. With the extraction of feature spaces, machine learning algorithms are actively generating new forms of life, new forms of boundary making, and novel orientations of self to self, self to other. To begin with robot surgery is to begin in a place where one could never definitively draw a line delineating the algorithmic moral good from some sense of immorality or evil.

Intuitive Surgery: Making the Singular Cut

The intuitive relation to mathematics noted by Turing finds a contemporary form in robotic surgical systems such as Intuitive Surgical's da Vinci robot. The application programming interface (API) and the cloud storage architecture of the da Vinci robot contain the data residue of multiple past human and machine movements. Figure 2.1 displays the "surgical gestures" of the movements of surgeons' hands on the remote console, as mediated through the robotic instruments of the da Vinci.[9] The surgical procedure modeled here is a routine four-stitch surgical suture to close an incision. Though the surgical gestures involved in the cutting and stitching of flesh are a matter of haptic routine for human surgeons, for the designers of the algorithms, the objective is to model the optimal suturing motion so that future human *and* robot surgeons have their intuitive movement shaped by the ingenuity of the model. As the Johns Hopkins computer scientists building the model explain, the process begins with the "automatic recognition of elementary motion" from the extraction of features in the data environment. The model extracts seventy-eight features, or "motion variables," from the vast quantity of video and sensor data archived by the da Vinci robot (figures 2.2 and 2.3)—twenty-five feature vectors from the surgeon's console, and fourteen from the surgical instruments attached to the patient-side robotic arms.[10] In the surgical gesture, the movement of the human hand is thus thoroughly entangled with the remote console and the surgical scalpel held by the robot's hand. The scientists describe the juxtaposed map of surgical gestures: "The left [top] plot is that of an expert surgeon, while the right [bottom] is of a less experienced surgeon."[11] Here, algorithms are enrolled to recognize surgical gestures and to extract the features of movement, to actively distribute cognition across human surgeons and robots, and to optimize the spatial trajectory of the act of suturing flesh. The future surgeon will learn to suture flesh optimally, via the robot's simulation functions, and the robot surgeon will learn to suture autonomously from the data of past gestures of expert human surgeons. Though the computer scientists do envisage autonomous actions by the robot—with "the possibility to automate portions of tasks, to assist the surgeon by reducing the cognitive workload"—this apparent autonomy is entirely contingent on the layered learning from models of past entanglements of human and robot gestures.[12]

The spring to action of surgical machine learning is not an action that can be definitively located in the body of human or machine but is lodged within a more adaptive form of collaborative cognitive learning.[13] Intimately bound together by machine learning algorithms acting on a cloud database of medical

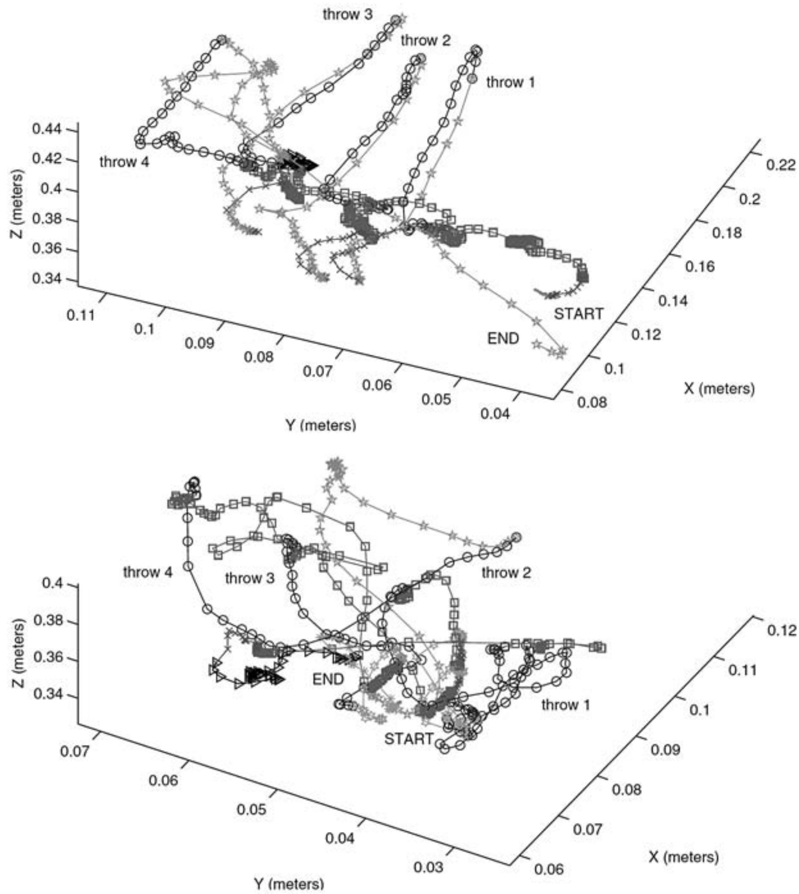
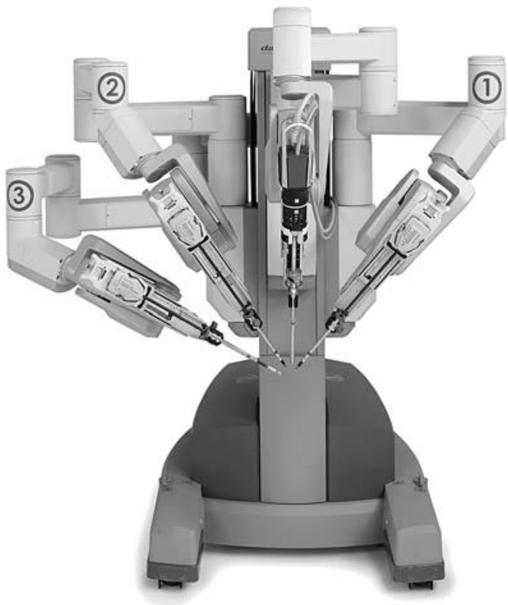


Figure 2.1 A plot of the trajectories of surgical gestures during a four-stitch suturing procedure. The top plot shows the trajectories of an expert surgeon, while the bottom plot shows the trajectories of an inexperienced surgeon, as extracted and analyzed by the surgical robot. Lin et al., "Automatic Detection."

data, the *we* of surgeon and robot restlessly seeks an optimal spring of action—the optimal incision, the optimal target of tumor or diseased organ, the optimal trajectory of movement. Intuitive Surgical's robots hold the promise of the augmented vision and precise trajectories of movement of a composite being of surgeon and machine. As one of the UC Berkeley robotics scientists describes what they term "iterative learning," machine learning allows "robotic surgical assistants to execute trajectories with superhuman performance in terms of speed and smoothness."[14] The drive for superhuman learning iterates back



Figures 2.2 and 2.3
The da Vinci surgical
robot. Intuitive
Surgical, 2018.

and forth across multiple gestures. As the hand and eye movements of a singular surgeon are tracked in the da Vinci's API, they commune with a mathematical model generated from a vast multiplicity of data traces of past surgical gestures. These gestures, in turn, modify the learning model to optimize and augment the future trajectories of future surgeons and robots as yet unknown. As the philosophers and scientists in the 1952 debate anticipated, the machine learning algorithms have something close to appetites, extracting and modeling features from the plenitude of cloud data, rendering springs of action, and acting on future states of being.

During the course of following the surgeons and robots of one world-leading oncology department in a UK teaching hospital, I began to note the many occasions when a surgeon used "we" in place of "I" to describe their daily collaborations with surgical robots. This *we* who learns is expansive. It includes the many humans in the research group and the surgical team, but also the many human and technical components of the simulation of a surgery—the multiple layers of medical imaging, video data from past surgeries, and algorithmic models that together composed a kind of virtual presurgery.[15] For example, when the UK surgical team were preparing to conduct a new surgical procedure on a specific type of tumor, they collaborated with other US surgeons who had previous experience of the procedure. This was not merely a dialogue between human experts, however; the research team also imported the data from the US surgeries, inputting them in an algorithmic model and experimenting with the parameters for a new context. As Rachel Prentice documents in her meticulous ethnography of surgical education, "surgical action must be made explicit for computers" so that "bodies and their relations in surgery are reconstructed" in a form that "can be computed."[16] This reciprocal and iterative relationship between human surgeon and computer is what she calls a "mutual articulation" in which "bodies affect and are affected by" one another.[17] When the movement of a surgeon's hands is rendered computable in the robotic model, Prentice suggests that this "instrumentalization" overlooks the "tacit" and "tactile experience" of surgery, such as the "elasticity of a uterus or the delicacy of an ovary."[18]

In Prentice's reading of surgical technologies, the tacit, tactile, and intuitive faculties of surgery define the human as the locus of care and embodied judgment and decision. Yet, in giving their accounts of working with robots, I found that human surgeons testify to their own body's capacities coming into being in new ways. What it means to be intuitive, to touch or to feel an organ, for example, alters with the advent of machine learning modalities of surgery. Seated at their virtual environment console, the surgeons access video feed

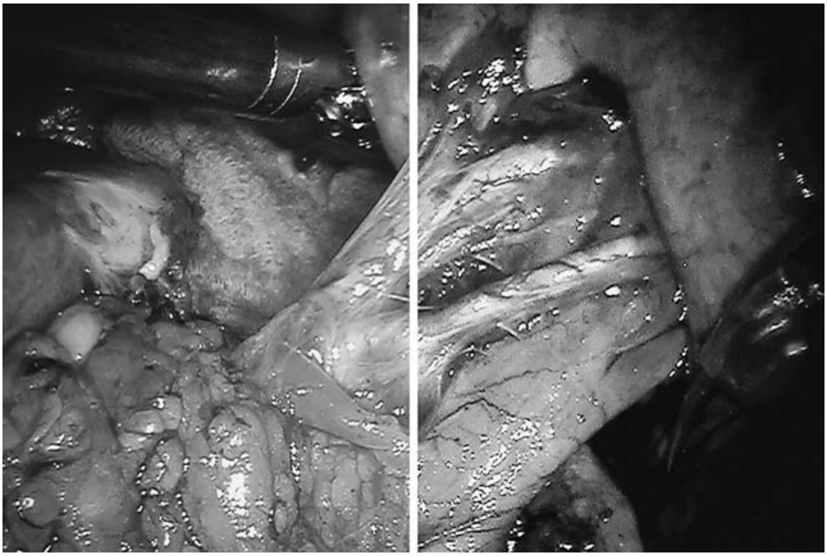


Figure 2.4 Fluorescence imaging of renal parenchyma, as viewed from the surgeon's console. Intuitive Surgical, 2018.

images from the endoscopic arm of the robot (figure 2.4). These images are overlaid with MRI and the fluorescence images of tumors so that, as one of the da Vinci computer scientists explains, "the system provides over a thousand frames per second and filters each image to eliminate background noise."[19] The work of the algorithms here is to extract the features of interest for perception by the surgeon, surfacing the optimal image from a background noise of teeming data.

One surgeon described to me the daily work of obstetric surgery with her da Vinci robot, noting that through the expanded mediated space, she is able to "see the unseeable" and "reach the unreachable" within the patient's body.[20] In contrast to Prentice's sense that human touch—and with it, judgment and decision—is evacuated and instrumentalized by surgical robotics, here the entangled touch of surgeon and robot invokes different relations of judgment and decision. The surgeon's relations to herself and to others—to her patients past and present, her operating theater colleagues, the robots, images, tumors, surgical instruments—are altered in and through the machine learning algorithms. "Touch engages us in a felt sense of causality," writes Karen Barad, so that "touch moves and affects what it effects."[21] Where Prentice foresees a loss of responsibility as the human surgeon's touch is evacuated by the robot, I propose instead an extension of responsibility to that which extends and exceeds human sensibility. The difference is an important one. The terrain of uncertainty regarding whether a specific tumor is operable without major damage to surrounding organs, for example, shifts with the 360-degree mobility of the robot's wrist—what can be precisely touched, sensed, and extracted from the body is altered. Indeed, leading computer scientist and artist Ken Goldberg, alongside his carefully presented accounts of the development of stochastic models and neural networks for the performance of surgical excision by robots, writes essays on the insensible and uncanny worlds that open up with his algorithms. Jochum and Goldberg's account of the "experiential uncanny" describes how robot actions "stretch the boundaries between the animate and inanimate" in new directions, serving to "challenge our beliefs about what, precisely, separates humans from machines."[22] The computer scientist's reflections on the embodied and intuitive capacities of his algorithms—to change the nature of what can be seen, reached, touched, or learned—run against the grain of a surgeon's hands being rendered computable by autonomous machines. Instead, machine learning algorithms work with the incomputable to open up new worlds of intuitive and insensible action.

As machine learning algorithms engage in "stretching the boundaries," the object that is surfaced for perception and action communes intimately with data on the events of past surgeries. This communion on *what is optimal*—the cut, the incision, the surgical strike—belongs properly to a composite being within the cloud analytic I describe in the previous chapter. The da Vinci data are no longer territorially limited to the memory of a specific robot, a server, an individual surgeon, or a group of scientists. Rather, the machine learning algorithms are deployed in a cloud architecture that yields the data residue of many millions of past surgeries. Lodged inside the actions of the singular cut—itself bordered by algorithms optimizing the thresholds of the instrument's trajectory—are the multiple data fragments of other entangled composites of surgeon, software developer, programmer, neural network, patient's body, images, and so on. The singular cut, within which teems a multiplicity, is present also in the autonomous vehicle, the drone, the smart borders system—always also with multiple data fragments lodged within.[23] In every singular action of an apparently autonomous system, then, resides a multiplicity of human and algorithmic judgments, assumptions, thresholds, and probabilities.

The Impossible Figure of the "Human in the Loop"

The neural network's capacity to learn by extracting features from its data environment has made it flourish in the algorithmic architectures of drones, autonomous vehicles, surgical and production robotics, and at the biometric border.[24] This capacity to learn something in excess of taught rules has also characterized the public concern and ethical debates around autonomous systems. Whether in the neural net algorithms animating surgical robots, autonomous weapons systems, predictive policing, or cloud-based intelligence gathering, what is most commonly thought to be at stake politically and ethically is the degree of autonomy afforded to machines versus humans as a locus of decision. I suggest, however, that the principal ethicopolitical problem does not arise from machines breaching the imagined limits of human control but emerges instead from a machine learning that generates new limits and thresholds of what it means to be human. As legal cases proliferate amid the errors, when the spring of action happens at the point of surgical incision, smart border, or drone strike, they consistently seek out an identifiable reasoning human subject to call to account: a particular named surgeon, a specific border guard, an intelligence analyst—the "human in the loop."

In Hayles's field-defining book, *How We Became Posthuman,* she proposes that the "distributed cognition of the posthuman" has the effect of complicating "individual agency."[25] Hayles does not argue that a historically stable category of human has given way, under the forces of technoscience, to an unstable and disembodied posthuman form. On the contrary, the conception of the human and human agency was, and is always, a fragile and contingent thing. As Hayles writes,

> The posthuman does not really mean the end of humanity. It signals instead the end of a certain conception of the human, a conception that may have applied, at best, to that fraction of humanity who have had the wealth, power, and leisure to conceptualize themselves as autonomous beings exercising their will through individual agency and choice. What is lethal is not the posthuman as such but the grafting of the posthuman onto a liberal humanist view of the self.[26]

Hayles's concerns for the grafting of the posthuman onto the figure of an autonomous liberal subject echo across the making of intuitive machine learning worlds. Though technologies such as Intuitive Surgical's robot actively distribute and extend the parameters of sight, touch, and cognition into posthuman composite forms, their ethical orientation is defined solely in relation to the control of an autonomous human subject. While human surgeons speak of an indeterminate *we* who learns, decides, and acts, nonetheless the capacity for judgment retains its Kantian location in the unified thought of a reasoning human subject.[27] Thus, when a violence is perpetuated or a harm is registered—damage, prejudicial judgment, or death—the only ethical recourse is to an imagined unified entity who secures all representations. So, for example, in a series of legal cases against Intuitive Surgical, the reported harms include the rupture of tissue, burns, and other damage to organs, severed blood vessels and nerves, loss of organ function, and fatalities.[28] In these juridical cases, where the robot's machine learning algorithms fail to recognize or to grasp precisely the outline of the target, what is sought is a unified locus of responsibility—a company, a negligent surgeon, or a hospital—an entity imagined juridically to be autonomous and unified, whose choices and agency can be held to account. Similarly, when autonomous weapons systems make errors in their target selection, or cause "collateral damage" amid the so-called precision strike, the ethical appeal is made to an accountable "human in the loop" of the lethality decision.[29] The notion of an ethical decision thus appears in the form of a reasoning human subject or a legal entity with a capacity to be a first person *I* who is responsible.

Yet, where would one locate the account of a first-person subject amid the limitless feedback loops and back propagation of the machine learning algorithms of Intuitive Surgical's robots? When the neural networks animating autonomous weapons systems thrive on the multiplicity of training data from human associations and past human actions, who precisely is the figure of *the* human in the loop? The human with a definite article, *the* human, stands in for a more plural and indefinite life, where humans who are already multiple generate emergent effects in communion with algorithms.[30] Recalling Geoffrey Jefferson's 1952 question, "Who was learning, you or the machine?," and Turing's reply, "We both were," the human in the loop is an impossible subject who cannot come before an indeterminate and multiple *we*.

Perhaps what is necessary is not a relocated human ethics—of feedback loops and kill switch control—for a world of the composite actions of human and algorithm. What is necessary, I propose, is an ethics that does not seek the grounds of a unified *I* but that can dwell uncertainly with the difficulty of a distributed and composite form of being. As machine learning changes the relations we have to ourselves and to others, the persistent problems of a Kantian unity of thought is newly dramatized by algorithmic formulations of learning and acting. To begin to address this different kind of ethicopolitics, one must dwell with the difficulty, as Donna Haraway suggests, making cloudy trouble for ourselves methodologically and philosophically.[31] Such a tracing of algorithmic threads as they meander through unilluminated space involves asking questions of how algorithms iteratively learn and compose with humans, data, and other algorithms. To be in the dark, to dwell there in an undecidable space, is to acknowledge that our contemporary condition is one in which the black box of the algorithm can never be definitively opened or rendered intelligible to reveal its inner workings. To trace the algorithm in the dark is not to halt at the limits of opacity or secrecy, but to make the limit as threshold the subject of study. Such a task begins by asking how machine learning algorithms learn things about the world, how they learn to extract features from their environment to recognize future entities and events, what they discard and retain in memory, what their orientation to the world is, and how they act. If intuition never was an entirely human faculty, and never meaningfully belonged to a unified *I* who thinks, then how does the extended intuition of machine learning feel its way toward solutions and actions? To this task I now turn.

Regimes of Recognition: How a Neural Network Makes the World

Allow me to begin by describing a scene—a laboratory designing machine learning algorithms for border and immigration control systems—where a series of neural networks learn to recognize people and things via the features in their data environments. One of the designers explains that his algorithms are trained on border and immigration data with many hundreds of thousands of parameters. He describes how he "plays with" his developing neural nets—taking the experimental model to the uniformed border operations team in the adjoining building to test it against the specific targets they are seeking in the algorithm's output.[32] This traveling of the model between laboratory and operations center consists of a series of questions about whether the algorithms are useful, or if they are "good enough." This question, Is it good enough?, illuminates some of the politically contested features of the algorithm's emergence. Though for the border operations team, "good enough" may be a measure of the algorithm's capacity to supply a risk-based target for a decision at the border, for the computer scientists, "good enough" means something quite different and specific. In computer science, a "good enough" solution is one that achieves some level of optimization in the relationship between a given target and the actual output of a model.[33] Understood in this way, it is not the accuracy of the algorithm that matters so much as sufficient proximity to a target. Put another way, the algorithm is good enough when it generates an output that makes an optimal decision possible. When the algorithm designers describe tuning or playing with the algorithm, they are experimenting with the proximity between the target value and the actual outputs from their model, adjusting the probability weightings in the algorithm's layers and observing how the actual risk flags generated by their model diverge or converge on the target.

The design of an algorithmic model, then, involves a contingent space of play and experimentation in the proximities and distances between the actual output and a target output. My concept of the space of play designates specifically the distance between a target output and an actual output of the model. This space of play, however, also opens onto an infinite array of combinatorial possibilities in terms of the malleable and adaptable inputs, parameters, and weights of the model. As one designer of machine learning algorithms for anomaly detection frames the question, "What is normal?" and "How far is far, if something is to be considered anomalous?"[34] Precisely this adaptive threshold between norm and anomaly was being negotiated between the laboratory and border operations. A small adjustment in the threshold will generate an entirely different set of outputs and, therefore, a change in the spring of action. I have observed this iterative process of playing with the threshold in multiple situations where algorithms are being trained for deployment, from police forces adjusting the sensitivity of a facial recognition algorithm to casinos moving the threshold for potential fraud:

> You must experiment to determine at what sensitivity you want your model to flag data as anomalous. If it is set too sensitively, random noise will get flagged and it will be essentially impossible to find anything useful beyond all the noise. Even if you've adjusted the sensitivity to a coarser resolution such that your model is automatically flagging actual outliers, you still have a choice to make about *the level of detection that is useful to you*. There are always trade-offs between finding everything that is out of the ordinary and getting alarms at a rate for which you can handle making a response.[35]

What is happening here is that the neural networks are learning to recognize what is normal and anomalous at each parse of the data. But, the shifting of the thresholds for that recognition embodies all the valuations, associations, prejudices, and accommodations involved in determining what is "useful" or "good enough." Sometimes, as with semisupervised machine learning, this regime of recognition emerges iteratively between humans, algorithms, and a labeled training dataset. In other instances, unsupervised machine learning will cluster the data with no preexisting labeled classifications of what is or is not useful or of interest. Even in this apparently unsupervised process, humans recalibrate and adjust the algorithm's performance against the target. In short, in all cases, machine learning algorithms embody a regime of recognition that identifies what or who matters to the event. Machine learning algorithms do not merely recognize people and things in the sense of identifying—faces, threats, vehicles, animals, languages—they actively generate recognizability as such, so that they decide what or who is recognizable as a target of interest in an occluded landscape. To adjust the threshold of what is "good enough" is to decide the register of what kinds of political claims can be made in the world, who or what can appear on the horizon, who or what can count ethicopolitically.

The kind of ethicopolitics I am opening up here is somewhat different from the attention that others have given to the inscription of racialized or other prejudicial profiles in the design of the algorithm.[36] Though identifying the human writing of prejudicial algorithms as a site of power is extraordinarily important, the regimes of recognition I have described actively exceed profiles written into the rules by a human. The machine learning algorithms I observed, from borders to surgery, and from facial recognition to fraud detection, are producing modes of recognition, valuation, and probabilistic decision weighting that are profoundly political and yet do not reside wholly in a recognizable human who writes the rules. They are also, of course, calculative spaces where prejudice and racial injustices can lodge and intensify, though not in a form that could be readily resolved with a politics of ethical design or the rewriting of the rules.[37]

The Hitherto Unseen: Detecting Figures, Detecting Objects

If machine learning algorithms are changing how something or someone comes to attention for action, then how does this regime of recognition come into being? Often the most apparently intuitive of human actions—to recognize a face in a crowd, to distinguish the features of a cat from a dog, to know how best to reach out and grasp an object—present some of the most difficult computational problems. When algorithms are understood as a series of programmable steps formulated as "if . . . and . . . then," it is precisely in the writing of the rules for the sequence that one decides the result: who or what will be of interest, or who or what can be recognized.[38] A common exemplar of the problem of recognizing the unseen is the capacity of algorithms to recognize handwritten digits.[39] The variability of the form of a figure—its "profile"—exposes the limit of rules-based algorithms that define the features in advance. How would one formulate rules for recognizing the handwritten number 3? In the traditional decision trees designed by J. R. Quinlan in the 1980s, the "product of learning is a piece of procedural knowledge that can assign a hitherto-unseen object to one of a specified number of classes."[40] To recognize an unseen object, the decision tree algorithm classifies it according to "a collection of attributes" describing its important features.[41] How would one begin to define the attributes of the figure 3 amid the variability of its form? As Quinlan acknowledged, the limits of the procedural knowledge of rules-based classifiers are encountered in unknown features that were absent in the training dataset. "The decision trees may classify an animal as both a monkey and a giraffe," wrote Quinlan, or the algorithm may "fail to classify it as anything."[42] Procedural classifiers such as decision trees, then, learn to recognize hitherto unseen objects according to the presence or absence of a set of properties encountered in the training data. Returning to the example of handwritten digits, would the variability of the form of the figure result in the decision that a 3 is not a 3? Or indeed that a 3 is not classifiable, or has the attributes of a 5? Though the recognition of handwritten figures is a common exemplar, the limit of procedural classifiers also applies to many other recognition problems, from facial recognition technologies to security threats, weather patterns, advertising opportunities, or the likely pattern of votes in an election. Put simply, while a rules-based classifier recognizes according to the profiled properties of an entity, the contemporary neural network algorithm learns to recognize via the infinite variability of features it encounters.

What does it mean to learn about the world in and through the variability of features in the environment? With the growing abundance of digital images and cloud data for training machine learning algorithms, the process of learning shifts from *recognition via classification rules* to *recognition via input data clusters*. Let us explore this further through the example of recognizing numeric figures. Figure 2.5 shows a simplified illustration of the spatial arrangement of a deep (multilayer) neural network—of the type I have sketched on many whiteboards at conferences and workshops. If the target of the algorithm is to optimize the likelihood of correctly identifying a handwritten digit, for example, then the training data will consist of a dataset of handwritten digits, each figure segmented to the level of pixels. What this means is that the algorithm does not learn to recognize the profile of the figure 3 per se, but rather learns to recognize the clustered patterns in the array of pixels in the image.[43] The input data in the neural net—and consider that in other instances, this could be anything: images, video, biometric templates, social media text—is assigned a series of probability weightings for its significance, with the output

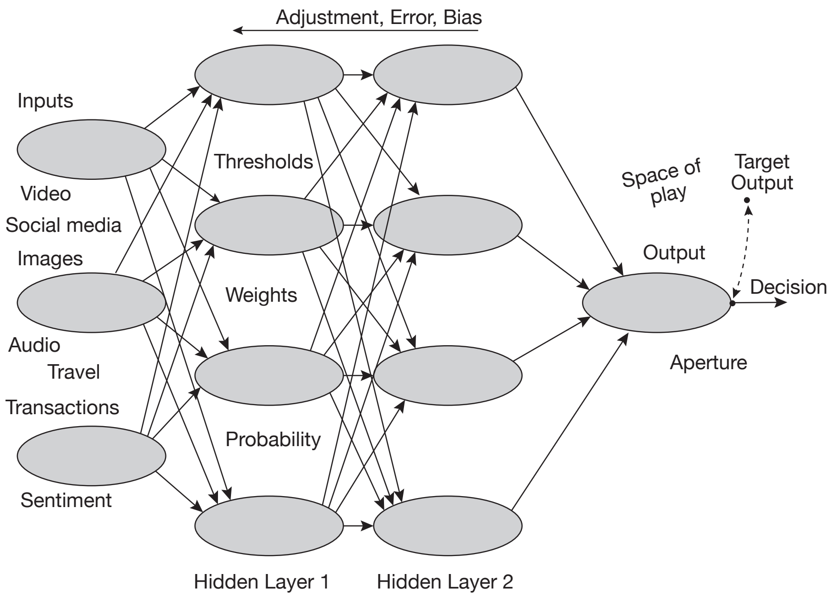


Figure 2.5 A representation of the arrangements of a deep neural network.

of each neuron to the next "hidden layer" dependent on whether the weighted sum of inputs is less than or greater than some threshold value. Each layer of the neural network detects some discrete aspect of the figure. As the computer scientists describe image recognition, "the learned features in the first layer" detect "the presence or absence of edges," with the second layer "spotting particular arrangements of edges," and the subsequent layers "assembling motifs into larger combinations that correspond to parts of familiar objects."[44] The recognition of edges, motifs, and familiar arrangements is not designed into rules by a human engineer but is definitively generated from the exposure to data. To be clear, this spatial arrangement of probabilistic propositions is one of the places where I locate the ethicopolitics that is always already present within the algorithm. The selection of training data; the detection of edges; the decisions on hidden layers; the assigning of probability weightings; and the setting of threshold values: these are the multiple moments when humans and algorithms generate a regime of recognition.

Adjusting the Features: The Variability of What Something Could Be

The computational problem of how to recognize people and things has become of such commercial and political significance that computer scientists enter their experimental algorithms in competitive image recognition contests. One particular algorithm, the AlexNet deep convolutional neural network, won an image recognition contest in 2012 and has become the basis for multiple subsequent commercial and governmental recognition algorithms, with the scientific paper cited more than twenty-four thousand times.[45] The AlexNet gives an account of itself—in the terms of a partial account I am advocating—that manifests just how its output is contingent on its exposure to data features, and the series of weightings, probabilities, and thresholds that make those features perceptible. As I recount something of how the AlexNet algorithm does this, I would like you to consider that if an algorithm is deciding "Is it a leopard?" or "How likely is it that this is a shipping container?" then it is also deployed to decide "Is this a face?" and "Is this face the same face we saw in the street protest last week?"[46] Understood in this way, the regime of recognition is political in terms of both arbitrating recognizability and outputting a desired target that is actionable.

As the computer scientists who designed AlexNet describe the relationship between recognition and cloud data, "objects in realistic settings exhibit considerable variability, so to learn to recognize them it is necessary to use much larger training sets."[47] The AlexNet CNN was trained on 15 million images, each image labeled by a human via Amazon Mechanical Turk's crowdsourcing labor tool.[48] Figure 2.6 shows eight test images for the algorithm, with the five labels considered most probable by the model assigned beneath each image. The algorithm is able to recognize a previously unseen image of a leopard or a motor scooter because the feature vectors of the image have close proximity to the gradients encountered in the training data. The capacity of the algorithm to recognize an incomplete creature at the edge of the frame (the mite) is considered to be a major advance in neural nets for image recognition. Where the algorithm failed to recognize an entity—the grille, the cherry—the scientists refer to the "genuine ambiguity" of which object is the focus of the image, and where the patterns of edges are occluded (e.g., the Dalmatian's spots and the cherries). To be clear, the logic of the AlexNet algorithm is that if one exposes it to sufficient data on the variability of what a leopard could be, then it will learn to anticipate all future instances of leopards. Indeed, deep neural nets are exposed to infinite variabilities—voting behaviors, faces in crowds, credit histories, kidney tumors, social media hashtags—to recognize the feature vec-

Figure 2.6 Test images of the AlexNet image recognition algorithm. Krizhevsky, Sutskever, and Hinton, "ImageNet Classification."

tors of all future instances. Whether someone or something can be recognized depends on what the algorithm has been exposed to in the world. Since the algorithm makes itself—adjusts thresholds and weights, for example—through its exposure to a world in data, it is becoming the contemporary condition of recognizability as such.

Like the cloud chambers of chapter 1, the propositional arrangements of the neural net are instruments of mattering, methods for making some things matter more than others. To seek to open or to make transparent the black box of this arrangement would be neither possible nor desirable, for the arrangement *is* an important site of politics, the spatiality of the calculus being politically significant in and of itself. This is significant for the ethicopolitical interventions one might wish to make because, for example, it could never be sufficient to demand that facial recognition algorithms that fail to recognize black faces be trained on a greater variability of images. For the algorithm also learns how to afford weight or value to one pixelated part of an image over others (the Dalmatian and not the cherry, the edges of this face and not that one). Indeed, as one computer scientist explained to me, a neural net like AlexNet, with six or eight hidden layers, is too complex even for the designer of the algorithm to explain the conditional probabilities that are learned. “I might adjust the weighting in that layer,” he explains, “and I know that this will change the output, but I cannot say exactly how.”[49] As with the design of AlexNet, the computer scientists work with the essentially experimental and unknowable nature of the algorithm. They perceive the fractional changes in the output of the model as they adjust the weightings, working with the emergent and unknowable properties of machine learning.

Bias Can Be a Powerful Ally

When deep neural network algorithms learn, then, they adjust themselves in relation to the features of their environment. To be clear, to learn, they have to weight some data elements of a feature space more than others—they have to have assumptions about how the world is ordered. Notwithstanding the widespread societal calls for algorithms to be rendered free of bias or to have their assumptions extracted, they categorically require bias and assumptions to function in the world. Indeed, even the textbooks used by the next generation of computer scientists address directly that “there can be no inference or prediction without assumptions,” particularly the assumptions of “the probability assigned to the parameters.”[50] Thus, when a team of European computer scientists discuss how they might move the threshold for their neural net algorithm to recognize the likelihood of a person of interest (a future person, yet to arrive) being a “returning foreign fighter” and not a “returning aid worker” from Syria, they mean that they will adjust the sensitivity of the algorithm to particular elements of weighted input data, such as increasing the probability weighting of particular past flight routes.[51] While some of this adjustment of the threshold is done by humans, today much of it is invested in the power of the algorithm to adjust itself in and through the emergent properties of the data, understood as a feature space. The “we both” of Turing’s reflections seems to reassert itself here in the accounts of adjustment given by computer scientists Yann LeCun, Yoshua Bengio, and Geoffrey Hinton of Facebook AI, Google, NYU, and the University of Toronto: “We compute an objective function that measures the error (or distance) between the output scores and the desired pattern of scores. The machine then modifies its internal adjustable parameters to reduce this error. These adjustable parameters, often called weights, are real numbers that modify the input-output function of the machine. In a typical deep-learning system, there may be hundreds of millions of these adjustable weights."[52]

Like the abductive methods of intelligence gathering I discuss in chapter 1, this computational method observes the effect of the calculation—or the output signal—and theorizes back to the adjustment of parameters, like the mechanical knobs on a calculating machine. The distance between an agreed target output, or desired pattern, and the output scores is the *error* or the *bias*. Significantly, for the algorithm, *error is distance*; it is the playful and experimental space where something useful or "good enough" materializes. There is nothing normatively wrong about error in a machine learning algorithm, for it is a reduction of difficulty and difference into a mere matter of distance. Likewise, let me be clear, bias and weighting are not negative things for an algorithm. They are, on the contrary, essential elements of learning, so that, in computer science, "bias can be a powerful ally."[53] My point is that one could never satisfactorily address the ethicopolitics of algorithms by calling for a removal of human or machine bias and a reduction of error because the machine learning algorithm would cease to function at this limit point. Bias and error are intrinsic to the calculative arrangements—and therefore also to the ethicopolitics—of algorithms. At root, the algorithm can never be neutral or without bias or prejudice because it must have assumptions to extract from its environment, to adapt, and to learn. It is, ineradicably and perennially, a political being. To begin from here is to begin from the idea that all machine learning algorithms always already embody assumptions, errors, bias, and weights that are fully ethicopolitical. In the adjustment of parameters one can locate a shifting terrain of the relations of oneself to oneself and to others. The output of the algorithm is but a mere numeric probability, fragile and contingent, so that a tiny adjustment of the weights in the algorithm's layers will radically change the output signal, and with it the basis for decision and action.

Point Clouds and the Robot's Grasp

To extract something from the features in a data environment, to anticipate and to act, is a critical computational problem for deep machine learning algorithms in production line robotics, surgical robotics, drones, and IED (improvised explosive device) detection. Across these diverse domains, the capacity to recognize the three-dimensional form of an object and to decide on the optimal action is a challenge that animates computer science. Indeed, the failure to recognize multidimensional and mobile forms—such as those of human organs, vehicles, or facial features—has been a common feature of many highprofile mistakes and accidents by machine learners. In the fatal Tesla autonomous vehicle crash of 2016, for example, one way to articulate the error would be to say that the CNN algorithms failed to recognize the profile of a white van against a pale sky as the vehicle turned across the Tesla's path. The probabilistic answer to the question "Is this a vehicle?" was, fatally, "no." Discussions among computer scientists regarding the causes of such accidents are revealing in terms of a persistent determination to locate the source of the fatal flaw and to annex the algorithm from its milieu. For example, one group of IBM scientists urged caution "not to blame the algorithm for a failure of the sensors, the ambient lighting, or the human operator."[54] My point, though, is that what the sensor can sense, or the operator can decide, is only meaningful in the context of how the neural nets arbitrate what the objection could be, what it could mean. Similarly, in a Volkswagen factory in 2015, a robot failed to recognize the outline of a human coworker on the production line, mistaking him for a car door and crushing him to death. At the level of machine learning algorithms and their regimes of recognition, the da Vinci surgical robots' failures to recognize the boundary delimiting kidney tumor from human organ is not dissimilar to the biometric facial recognition systems that closed automated border controls at an airport when the setting sun changed the ambient lighting conditions. In all these instances, the algorithms have learned from the features of the environment they have been exposed to. Sometimes events and sensors in the environment will present them with a set of input features they have not encountered previously, and their assumptions and weightings may lead to a *spring of action* that misrecognizes the target.[55] Is this an error? Or is error merely a matter of distance?

The contemporary advent of cloud robotics has sought to address this problem of the limit point of exposure to features in a multidimensional environment. Cloud-based robotics, as we saw in the discussion of surgical robots, circulate data and aggregate computational power across a distributed system of machine and human learning. Just as the surgical robots are no longer limited to the data and computation stored within a bounded system, so the cloud-based intelligence system I discuss in chapter 1 recognizes its targets from exposure to data and analytics methods across borders and jurisdictions. Where machine learning intersects with cloud computing, the neural network algorithms are exposed to features from a vast archive of cloud data, including the Point Cloud Library of open source 2D and 3D images.[56] A point cloud is a set of topological data points mapping the 3D space of objects. Computer science research in cloud robotics is addressing the question of whether exposure to a vastly increased volume of point cloud data on objects can optimize the neural network's capacity to learn how to recognize and to act. Consider, for example, the computer science team at UC Berkeley's Automation Sciences Lab, whose research into cloud robotics is funded by the NSF, Google, and the US Department of Defense. Presenting their Dex-Net 1.0, or Dexterity Network algorithm, the Berkeley scientists experiment with CNNs to optimize the capacity of a robot to recognize and grasp a range of objects. The algorithm represents an advance on image recognition technologies such as AlexNet because it recognizes 3D objects from multiple viewpoints, and it outputs an optimal action based on this recognition.[57]

The Dex-Net algorithm is trained on an archive of Google point cloud data on "3D object models typically found in warehouses and homes, such as containers, tools, tableware, and toys."[58] The neural nets are learning to recognize the object's geometry and topology and then to optimize the robot's capacity to reach out and grasp the object. In a sense, the algorithm is asking a two-step question—What is this object? and How can it be most effectively grasped? This shift toward CNNs that can recognize *and* optimize an action is absolutely critical in the advance of robotics in manufacturing, medicine, and the military. The scientific papers on Dex-Net show something of the logics at work in coupling regimes of recognition to what I call a spring of action. When the Dex-Net algorithm is exposed to a training dataset of one thousand 3D point cloud objects (in figure 2.7, a household spray bottle), it is not able to find a "nearest neighbor" object that will allow it to recognize the query object. When the algorithm is exposed to the point cloud features of ten thousand objects drawn from the Point Cloud Library, however, it finds two proximal objects, or nearest neighbors, allowing it to recognize the object and optimize its grasp.

Though at first glance the Dex-Net's machine learning may appear as though the cloud is supplying "big data" volume to the algorithms, in fact the process of reduction and condensation I describe in chapter 1 is also taking place here. As the computer scientists propose, the significance of the "cloud-based network of object models" is actually to "reduce the number of samples required for robust grasps" and to "quickly converge to the optimal grasp."[59] Put simply, the Dex-Net algorithm is better able to condense and filter out the occlusions to recognize the most similar object. Each of the ten thousand cloud-based objects is prelabeled with 250 parallel-jaw robot grasps, each weighted with a probability of a successful grasp. "The goal of cloud robotics," as the computer scientists explain, is to "pre-compute a set of robot grasps for each object" so that "when the object is encountered, at least one grasp is achievable in the presence of clutter and occlusions."[60] Understood in these

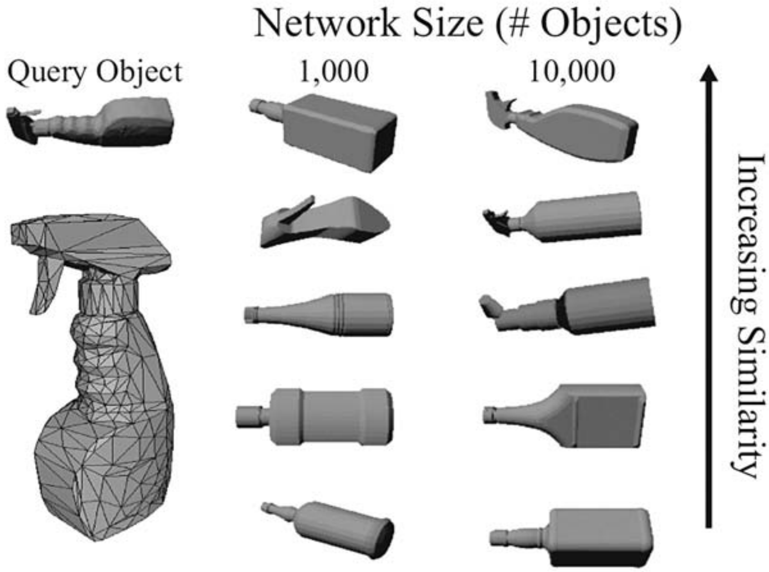


Figure 2.7 Point clouds for object recognition and grasp optimization. Mahler et al., "Dex-Net 1.0."

terms, the weightings and probabilities of the point cloud make it possible to precompute something, so that the encounter with the unknown object can always yield an action that is optimal. With the point cloud, an algorithmic system does not only ask "Is this a face?," "Is this a bottle?," "Is this a military vehicle?," but rather it has already precomputed an optimal action in relation to the topologies it has encountered.

Precomputation: "The Fundamental Thing Is We Know What Good Looks Like"

On the horizon of research in neural net algorithms for robotics, then, one finds this notion of *precomputation* to make an action achievable amidst *clutter* and *occlusions*. Precomputation captures the neural net computational problem that extends from the recognition and grasp of the shape of a human organ amid "noisy" surgical data, to the recognition of a civilian body in the screened occluded data of the drone. One computer scientist, who now designs algorithms for human gait recognition, described to me how he had been "working with surgeons modeling the perfect operation," this human-algorithm collaboration itself deploying point clouds to precompute the trajectory of "a perfect procedure."[61] He has developed his algorithms for multiple applications, with each iteration another step in optimization: "The fundamental thing is we know what good looks like," he explains, "and then if you're doing anomaly spotting, you can see when something's wrong." For example, when the online gambling platform BetFair sought algorithms to recognize and act on patterns of addition, the designer suggests, "that's something we can spot because we know what addicted play looks like." This malleable normative assumption of "what good looks like" or "what addictive play looks like" is generated in and through the algorithm learning in a feature space.[62]

Precomputation implies that some sense of what is a "perfect procedure" or "at least one achievable grasp" action is always already present within the algorithm as such. The ethicopolitics of machine learning algorithms like AlexNet and Dex-Net is in the bias, weights, thresholds, and assumptions that make recognition precomputable. To precompute is to already be able to recognize the attributes of something in advance, to make all actions imaginable in advance, to anticipate every encounter with a new subject or object, a new tumor or terrorist, by virtue of its proximity to or distance from a nearest neighbor. The condition of possibility of the algorithm's action is its exposure to an archive of cloud data, condensed via the infinitely malleable value system of weights, probabilities, thresholds, and bias.

This is a pressing problem of the politics of algorithms in our contemporary moment. All our handwritten digits; all our online data traces; the biometric templates of our facial geometry; the point clouds of household objects and military hardware; all the movements of the hands, eyes, and bodies of surgeons, pilots, soldiers, consumers, production line workers: these are the teeming conditions of possibility of the machine learning algorithm. We are it, and it is us. We could never stand outside it, even if we might wish to. Each of the data fragments that enters the point cloud has a part to play in the learning. Whose is the grasp that caused the injury? Which of the 2.5 million objects in the archive became the nearest neighbor? Which of the possible 250 grasps for each object? Which of the many tens of thousands, or millions, of cloud-derived probabilities was responsible for the grasp that intuitively decided to pull the trigger, so to speak?

The harms inflicted through machine learning are not located primarily in the ceding of human control to machines, as is so often assumed in the ethical and moral debates on algorithmic decisions. Indeed, as we have seen via the surgeon who learns to reach and touch differently with her da Vinci robot, what it means to be human is significantly transformed in and through the machine learning algorithm. To appeal to the human as locus of ethics, then, is to appeal to a being already entangled with new forms of knowing and learning. The principal harm, in contrast, is manifested instead in a specific threat to a future politics. The tyranny of proliferating machine learning algorithms resides not in relinquishing human control but, more specifically, in reducing the multiplicity of potential futures to a single output. The claim to precompute the future, or to know "what good looks like" at the border, in the operating theater, in the economy, forecloses other potential futures. To be clear, the neural net does not reduce multiplicity as such. After all, as I have outlined, the spatial arrangement of the neural net algorithm contains within it multiple probabilities, infinitely adjustable weights whose emergent effects can never be entirely known, even to the designer. The finite elements of each hidden layer of the neural net, one might propose, contain within them infinite possible correlations to other elements. The spatial arrangement of the neural net does not foreclose alternative readings, different arrangements of what or who matters and what or who does not. Crucially, however, at the point of action, this intrinsic multiplicity is reduced to a single output. The insistence on a single output is the algorithm's orientation to action. Though I am reminded by the computer scientists that the output need only be between 0 and 1, and that there are infinite numbers between 0 and 1, there is nonetheless a single numeric output. Let us not forget that the algorithm's output signal lies behind the risk score at the border, the credit decision, the target assessment of the drone, and the decision on sentencing, detention, or the incipient dangers of a gathered protest on a city street. It is as though all the many potentials held in parallel, simultaneously distributed across the layers of the neural net, could never have been. With the output of the machine learning algorithm, one might say, things could never have been otherwise. The output is a probability whose value is transformed by the smallest of adjustments in the parameters of the model. And yet, nonetheless, all political uncertainty is rendered tractable on the horizon of the action triggered by this single output.

At this point, one might reasonably ask how giving such an account of the contingent politics of machine learning algorithms is of any possible critical use. How might a cloud ethics work with the incompleteness, the undecidability, and the contingency of the algorithm's space of play? If one wants to inquire whether a given algorithm is responsible for a flash crash in the financial markets, or if one seeks a human rights law adequate to the task of holding autonomous weapons or autonomous surgery to account, then some ethical grounds might be considered essential—or at least some method for accountability. As Michel Foucault proposes in his discussion of ethics, however, what may be necessary is not to appeal to grounds or to the juridical domain of statutes, but rather to "ask politics a whole set of questions that are not part of its statutory domain."[63] A cloud ethics must be capable of asking questions and making political claims that are not already recognized on the existing terrain of rights to privacy and freedoms of association and assembly. Cloud ethics belong properly not to the individual as bearer of rights, but to the many touch points and data fragments that are aggregated from the relations between subjects and objects. Thus, a cloud ethics must be capable of asking questions such as How did that Dex-Net algorithm weight the probability of that future grasp?; Why did the training data teach the algorithm to recognize this and not that object amid the occlusions?; How was the distance between target and output signal (bias) used as a space of experimentation?; and, In outputting that score, what were the traces of the rejected alternative weights and parameters? Such questions are necessary and urgent, even and perhaps essentially when they are unanswerable. The unanswerable questions reawaken the multiplicity that was, in fact, always present within the machine learning algorithm. All the many contingencies and alternative pathways are reopened, and the single output bears the fully ethicopolitical responsibility for the actions it initiates. The processes and arrangements of weights, values, bias, and thresholds in neural nets are, I think we can safely say, not part of our statutory political domain. And yet, I suggest that they must be presented as questions and political claims in the world.

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Part 2

Attribution