statements and operations.

The various subject positions that might speak of, observe, question or decide about machine learning are neither unified ~~or~~ fixed. As the models grow, for instance, they test the capacity of human machine learners to understand how models transform data. Perhaps more profoundly, the growth of neural nets exhibits the deeply competitive imperative that imbues much machine learning practice, and in many way machine learning practice. This competition is not always explicit or overt, but it almost transpires in the form of a test or examination.

Neural nets re-iteratively draw human-machine learning differences. Their own ups and downs, the merging and blending of statistics, computer science and cognitive science they afford, and their potential to drive down error or learn features from data given enough data derives less from some exotic mathematical abstraction or encompassing algorithm, and more from competitively accumulated layers and connections between units of modelling. The oscillating movement of the central algorithm feed-forward and back-propagation is instructive. Because it propagates errors to all elements of the network, and every element in the network adjusts its weights in trying to minimise error, layers can multiply on many scales. The predictive power of the model derives from the networked collective of elementary machine learners driven to optimise their error rates. So too, the competitive examinations that today generalize machine learning as a data practice predicate the ongoing potential of hidden layers machine learners to collectively learn from their rankings in tests of error.

As it disperses subject positions, the back-propagation of errors or optimisation also animates optimism about machine learning.[15]

15. The cultural theorist Lauren Berlant describes optimism as an 'operation':

> The surrender to the return to the scene where the object hovers in its potentialities is the operation of optimism as an affective form (Berlant 2007, 20)

Machine learning hovers in potentiality because neural nets and their kin assimilate and adjust their weights in response to changes in infrastructures and in the generalization of operations to newly adjacent domains. Machine learners generate optimism through and about optimisation, an optimisation that is predictive, prospective and anticipatory. But this adjusting of weights carried out through the propagation of errors is also inherently a ranking or examination.

Human and machine learner differences can be re-drawn in two different directions. In one direction, machine learning operations assign a subject position focused on error rates. Vlad in his corner observing the neural nets occupied such a position. In the other direction, the subjects who operate the neural net ~~in order~~ to fit a model find themselves deeply caught up in a network of machine learners connected into parallel and layered architectures and operations. This feeding-forward, however, is regularized or narrowed down through examination and error, through back-propagation on various scales that ranks and filters machine learners according to their error rates. In this direction, the practice of training and testing generalization error that has long guided the supervision of machine learners becomes a mechanisms for adjusting subject positions of human machine learners. Some will be wonderful people, some will remain remote like Vlad, and some will optimistically re-learn ~~in order~~ to change their ranking.

9

Conclusion: Out of the Data

`These diagrams of the diagrammatic domains, they kernel together in localization.`

`In this contrusion of major forms of invention in natures in machine learning techniques, inter-places, leveraged in and distributed.`

The two sentences above are the products of a generative model trained on the raw text of this book. Without any model of syntax, any dictionary of words or terms, relying purely on character sequences as probability distributions, the neural network that sampled these sentences out of its own unsupervised model of the book vectorised as data was primed with starting text of ‘`If`’ ‘Diagrams of the diagrammatic domains,’ kernelling together in localization, a ‘contrusion’ of major forms of invention in natures, in machine learning techniques, leveraged in and distributed in inter-places: all of that has been put quite well by the generative model, a two-layer ‘long short term memory’ recurrent neural net (Karpathy 2016).

I began with a relatively limited question: if machine learning ~~is transforming~~ the production of knowledge, might the practice of critical thought itself change, whether in its empirical or theoretical orientations? Could the ‘experimentation of concepts’ (Stengers 2000, 153) work with machine learning? My answer is provisionally affirmative. ~~If a book could be a generative model, then I hope this auto-archaeology might generate or multiply the capacity to problematize the present. For such a machine learner, a model that~~ would learn machine learning ~~in order~~ to diagram a diagrammatic domain~~;~~ predictions would figure less as statements that rank, order and classify~~,~~ than as a technology of critical experimentation, a means of effecting a certain number of transformative operations on one’s own conduct, thinking and ways of being amid~~st~~ the determinations of contemporary reality. It would function as a mode of experimentation on statements.

250,000 machine learners

For at least ~~230,800~~ human machine learners— the number of unique authors listed in the corpus of machine learning research literature I have been drawing on—, a new kind of operational formation jells in machine learning. People and things, knowledge and power, combine in novel forms to generate statements. Understanding the distribution and production of elements that make up this emerging common space of decision, classification, prediction and anticipation matters contemporary critical thought in its engagement with power, production, conduct, communication, ways of being and thinking, materiality and experience.

Let us take 146,000 scientific articles, publications and books as statements concerning operations occurring in a variety of sites, modes, and settings connected in the operational formation we are discussing.~~.~~ As in Foucault’s discursive formations, statements in operational formations function by reference to the position of a subject (the expert, the engineer, the doctor, the patient, the judge, the teacher, the student)~~,~~ amid~~st~~ an organised or grouped accumulation of devices, settings and fields (positivity), and with greater or lesser reference to the practices of human-machine interaction~~. For~~ instance, writing the code that allows the recurrent neural net to build a generative model of this text.

Although subjects for Foucault do not author statements, the assignment of subject positions always passes through a human subject. In operational formations, subject positions are less distinct, yet highly populated (as the 230,000 authors of these paper suggest). The machine-human mixing in operational formations is highly variable, dynamic and mutable, sometimes planing through code, sometimes diagrammed in visible forms such as graphs and tables, and often ramifying through infrastructures.

Affective elements have a long-standing connection with computation. Elizabeth Wilson's study, *Affect and Artificial Intelligence* (Wilson 2010), draws on a combination of psychoanalytic, psychological and archival materials discussing the work of key figures in the early history of artificial intelligence such as Alan Turing on intelligent machinery, Warren McCulloch and Walter Pitts on neural nets, and recent examples of affective computing and robots such as the MIT robot Kismet. Her framing of the psychic nexus with machines such as the perceptron is provocative:

> Sometimes machines are the very means by which we can stay alive psychically, and they can just as readily be a means for affective expansion and amplification as for affective attenuation. This is especially the case of computational machines (30).

Under what conditions do machines and for present purposes, computational machines~~,~~ become 'the very means we can stay alive psychically'? Wilson addresses this question by positing 'some kind of intrinsic affinity, some kind of intuitive alliance between the machinic and the affective, between calculation and feeling' (31)~~,~~ and suggesting that the 'one of the most important challenges will be to operationalize affectivity in ways that facilitate pathways of introjection between humans and machines' (31). Introjection, the process of bringing the world within self is, according to psychoanalytic accounts of subjectivity, crucial to the formation of 'a stable subject position' (25). Wilson envisages introjection of machine processes as a good, not as a failure or attenuation of relation to the world.

~~While~~ I ~~tend to go in the same direction as Wilson in relation to~~ 'affective expansion', I don't see that expansion as unfolding from introjection~~,~~ but rather from an intensification of diagrammatic processes, the act of creating a 'concrete being, an intersecting of references' or abstraction (Stengers 2000, 85) diagram~~!affect of~~

A summary of the argument

I have been experimenting with abstraction in midst of ~~data practices of~~ machine learning. Let me resume the argument of the book, an archaeological argument that excavates seven major facets or intersecting planes that belong to the machine learning as an operational formation. Chapter 2 addressed the problem of where amid~~st~~ the mire of data, mathematics, code, infrastructures, scientific and other knowledge fields, a critical engagement with machine learning might situate itself. I suggested that we should consider the formal, mathematical abstraction and certain transformations in the production of software associated with machine learning as diagrammatic processes that organise and assemble human-machine relations. Amid~~st~~ a great accumulation of statements, figures, techniques, constructs, datasets and code implementations derived from many settings, the task is to map the intersecting references, the diagonal connections, and the ~~transformatinos~~ and substitutions that weave through machine learning. The positivity of machine learning, its specific forms of accumulation, regularity and rarety do not attest to the power of algorithms but rather lend liveliness to the field by concentrating expressions from many regions.

Chapter 3 examined the practices of vectorising data, situating machine learners ~~themselves~~ in an organised, dimensioned space accommodating an increasing repertoire of transformations operating on vectors. Viewed as another mutation of the tabular grid, vector space invites transformations of data. Machine learning is a practice of working with data to accommodate all differences within an expanding dimensional space, a space in which data ~~is~~ under the strain of smooth surfaces, straight lines, regular curves and hyper-planes. ~~Both in terms of~~ infrastructure and epistemic cultures, the vector space abstracts and concretises spaces inside data.

What is learning in machine learning? If information and computation can be understood as responding to a crisis in control, what do machine learners do? Chapter 4 examined how learning institutes experimental relays between operation and observation in optimising functions that predict and classify. The proliferation of methods and devices in machine learning and the attempts to unify them as 'learners' was understood as a result of this entwining of operations and observations. The interplay between operational transformations and observational functions in optimisation accounts for much of the 'learning' effect in machine learning.

An important and wide-reaching critical strand of work in humanities and social sciences over the last few decades has focused on knowledge in its entanglements with apparatuses of governmentalised power. Populations and other large aggregates have been central objects of concern. They remain so in contemporary operational formations, although under somewhat altered conditions. Having all the data, chapter 5 suggested, is not the principal stake in contemporary data cultures. Instead, the probabilisation of both data and machine learners as populations, as distributed probabilities, indicates a different axis along which power-knowledge develops in machine learning.

What happens to differences amid~~st~~ vectorisation, learning as optimisation, probabilisation and the generalized diagrammatic abstraction of machine learning? ~~.~~ Are all differences reduced to quantitative comparisons? Treated as pattern, chapter 6 explored different treatments of difference in machine learning. Differences bifurcate between infinitesimal graduation and rigid decision boundaries, sometimes blurring or overlapping, and sometimes distributed into inaccessibly high-dimensional inner data spaces. The archaeological task amid~~st~~ the dispersed patterns is to locate differences in kind.

Rather than any new materiality, I have pointed to transformations in referentiality associated with machine learning. From the standpoint of operational archaeology, the materiality of machine learning refers to the practices of re~~-~~use that stabilise references. Science, by virtue of its experimental inventiveness and truth-authority, cross-validates the referentiality of machine learning. The topic of chapter 7 was a particularly data-intensive contemporary scientific hyperobject, the genome. As a data form, genomic sequence data provokes re~~-~~use, transcription and transmission of classifications and predictions. This incites both infrastructural transformations but also new concretisations of the hyperobject (as for instance in genome wide association studies).

Finally, chapter ~~??~~ explored the subject position of machine learners. Within operational formations, subject positions arise in gaps between operations and statements concerning operations. The argument here concerned human-machine differences and the dispersion of subject positions through operations that alter those differences. Even among~~st~~ machine learners ~~themselves~~, subject positions are not fixed or unified. The deep neural networks that beat Go champions in 2015 and 2016 (Silver et al. 2016) or developed hitherto unseen tactics in playing Atari computer games (Mnih et al. 2015) evidence the deeply competitive or test-based administration of this gap.

In-situ hybridization

~~Beyond these facets of~~ the argument concerning abstraction, inclusion, control, multiplicity, differences, materiality and subject positions, another argument shaped discussion in the preceding chapters, one that affectively underpins of the writing. A central problem for critical thought today (and by critical thought I mean post-Foucaultean engagements with the events that constitute us subjects of what we say, do and think~~-~~) concerns how to engage with operational formations. To an even greater extant than the discursive formations that Foucault and many subsequent scholars have analy~~s~~ed, operational formations in production, communication, and the regulation of conduct become the field in which the work of ethics and politics takes place.

The problem of engagement with operational formations is not so much how to gain control~~,~~ or challenge the asymmetries of access and control that loom so large in them (Facebook can machine learn exponentially more patterns than I can), but to begin to grasp the forms of change that are possible and desirable. Mark Hansen has, for instance, posed the challenge of engaging with data-intensive prediction directly in terms of experience. He writes:

> this imperative enjoins us to use the technologies of data capture, analysis and prediction to create a feed-forward structure capable of marshaling the full productive potentiality of data—its commonality, accessibility, and openness—in order to improve, indeed to improve by *intensifying*, our experience (Hansen 2015, 77).

Treating prediction as more than means of disciplinary control, and instead as a resource for individuals and collective to modulate experience, Hansen's project draws on an extensive engagement with phenomenology and Whitehead's philosophy. The crucial task in his view is creative or inventive: the 'feed-forward structure' must marshal 'the productive potentiality of data.'

One way to do this is broadly aligned with Foucault's emphasis in his later work on care of the self. Technologies of the self 'permit individuals to effect a certain number of operations of their bodies and social, thoughts, conduct and ways of being, so as to transform themselves in order to attain a certain state of happiness, purity, wisdom, perfection or even immortality' (Foucault 1997, 225). Could Hansen's feed-forward structure—the term itself referring to the first phase of ~~neural net's learning~~—operate as a technology of the self, not so much focused on improvement or perfection of experience but ~~in name of~~ the potential to invent new tests of and new relations to pressing realities? For scholars producing critical knowledge in humanities and social science through a variety of textual, empirical, theoretical and increasingly implicitly or explicitly computational practices, technologies of self offer a concrete path wending a way into domains of production, communication and governance. Rather than immortality or purity, operations effected on ways of thinking, living and being might transform oneself in the interests of a limited experience of freedom.

Under what conditions could something like care of the self and technologies of the self have any purchase, relevance or even toehold in the operational formation of machine learning? Five elements, it seems to me, need to be assembled ~~in order~~ to think through that conjunction. The recognition of ourselves as subjects of machine learning is ~~an elementary~~ archaeological task. Whether in relation to knowledge, communication (in the broadest sense), conduct or ways of living, this recognition relies on a description of practices associated with differences, multiplicities, materialities, knowledges and control. Second, as I have endeavoured to emphasise in describing machine learning as an operational formation, the liveliness of ~~machine learning~~ should be understood as a localisation of power-knowledge relations, or a primary field of expressions issuing from many parts (to paraphrase Whitehead). 'They kernel together in localization' as my recurrent neural network puts it. Third, while the accumulating plethora of techniques, applications and sites is ~~neither~~ unified by a master algorithm ~~or by a~~ latent, underlying meaning, it does demonstrate regularities and point of indetermination or slippage. Fourth, understood as a field of the expression of many parts, an operational formation can also be site of collective individuation. Participating in a collective, individual subjects, far from losing whatever defines their unique or essential identity, gain the chance to individuate, at least in part, the share of pre-individual reality that marks the collective within them. Fifth, by participating in a collective, even an operational formation, individuals may transform themselves (~~in order~~ to attain certain states or experiences)~~,~~ but also affect the collective itself.

~~Whether~~ this might affect the internet filter bubble (Pariser 2011), the ‘stack to come’ (Bratton 2016), digital citizenship (Isin and Ruppert 2015), the character of work (Brynjolfsson and Mcafee 2014), the fabric of experience (Hansen 2015), or what counts as knowledge (Bowker 2014) is hard to say. As an operational formation, machine learning does not determine anything in its operations, even if it connects directly to strategies of power. Foucault writes that ‘archaeology describes the different spaces of dissension’ (Foucault 1972, 152). These spaces of dissension, it seems to me, form a field in which initiatives, individuations, and technologies of the self might articulate a certain number of transformative operations.

Critical operational practice?

Under what conditions would that experimental practice and operation on ways of thinking and saying be divergent rather than convergent? Writing this book, and learning to machine learn in order to write about machine learning, involves participation in a collective, the collective of at least 230,000 scientist-machine learners~~,~~ and the tends of thousands of programmers developing machine learners evident on Github.com. By participating in the collective operational formation, running the risk of being mobilized by existing interests, we might also individuate differently a share of the pre-individual reality included within us (Virno 2004, 79). Like Anne-Marie Mol's ‘praxiography,’ which seeks to maintain reality multiples in describing practice (Mol 2003, 6), the description of machine learning as data practice intends to sustain the multiple of reality by identifying the practices that make it multiple.

The path I've taken here combines writing (a discursive practice) and coding (an operational practice). Writing about machine learning is a practice of diagrammatically mapping the re~~-~~iterative drawing of human-machine relations in code, and in particular~~,~~ in coding that learns from data. Datasets, scientific and engineering publications, textbooks such as *Elements of Statistical Learning*, software libraries and packages, spectacular demonstrations comprise a whole series of criss-crossings. ~~While~~ not the path that everyone would or should want to take, for me moving into the data like or as a machine learner perhaps allows writing to become more diagrammatic. 'Between the figure and the text we must admit a whole series of criss-crossings' wrote Foucault (Foucault 1972, 66), in defining archaeology as a mode of exploration of knowledges, politics and ways of being.

Very mundanely, I've read articles and books, downloaded data and software libraries, watched Youtube lectures and presentations, configured and written bits of code and text, made plots and diagrams, and done much configuration work across various platforms (Github.com, linux, Google Compute, `R`, `python` and `ipython`). Amid~~st~~ all of this data practice (and much practising), there is no reason to assume that learning machine learning is solely the performance of a conscious subject. When we look at an equation repeatedly, when we comply with the machine learning injunction to 'find a useful approximation $\hat{(f)}(x)$ to the function $f(x)$ that underlies the predictive relationship between input and output' (Hastie, Tibshirani, and Friedman 2009, 28) by writing code to cross-validate a model, we surrender to 'learn-~~ing' that,~~ however fascinating or surprising, is not that of a conscious human subject but also of human-machine assemblage. To the extent that it is archaeological, operational, diagrammatic writing vibrates around the axis of knowledge/practice, not knowledge/consciousness.

Obstacles to the work of freeing machine learning

As I have emphasi~~s~~ed on several occasions, machine learning is an uneasy mixture of massively repeated and familiar forms~~,~~ and something that is not easily understood. On the one hand, the level of imitation, duplications, copying and reproduction associated with the techniques suggests that a process of remaking the world according to particular forms is in process (~~for instance~~, in chapter 5 we saw how Naive Bayes classifiers are almost demonstrated on spam classification problems~~.)~~ The scientific and engineering literature, with its really frequent variations on similar themes, suggests that imitation and copying are very much at the heart of the movements I have been describing. This is nothing new. It would be strange ~~of~~ these techniques were not subject to imitation and emulation. That imitation is predictable. We expect it and can account for it sociologically.[1] Some symptoms of these imitative fluxes can be found in the scientific and engineering literature. As we have seen, work on image and video classification, ~~on~~ text and speech, ~~on~~ gene interaction prediction or above all, ~~on~~ predictions of relations or associations between people and things (usually commodities, but not always) is striking in its persevering homogeneity. Moreover, the powerful aspirations evident among~~st~~ large media platforms such as Baidu, Google and Facebook to ~~re-ground machine learning in the project~~ of artificial intelligence amid~~st~~ social media or web page-related data in many ways continues business as usual for computer scientists (Gulcehre 2014).

1. Accounts that might do this can be found in science and technology studies, particularly in actor-network theory versions, as well as in recent social and cultural theory that, for instance, draws on the work of the ~~19th century,~~ French sociologist, Gabriele Tarde (Tarde 1902; Borch 2005).

How would we get any sense of what is not so easily digested and laid out in social practice? Archaeologies of operational formations aim to present some of the necessary elements for that purpose. In the closing pages of *The Archaeology of Knowledge*, Foucault writes:

> the positivities that I have tried to establish must not be understood as a set of determinations imposed from the outside on the thought of individuals, or inhabiting it from the inside, in advance as it were; they constitute rather the set of conditions in accordance with which a practice is exercised, in accordance with which that practices gives rise to partially or totally new statements, and in accordance with which it can be modified. These positivities are no so much limitations imposed on the initiative of subjects as the field in which that initiative is articulated (Foucault 1972, 208-209).

Here Foucault refers to the restricted freedom that discursive practices and formations open for us. ~~If it~~ is increasingly difficult for science, media, government and business to think and act outside data. ~~And yet~~ Foucault is quite clear that amid~~st~~ the positivities of knowledge production, knowing the conditions, setting out the rules, and identifying the relations that striate the density and complexity of practice is a pre-condition to any transformations in practice.

As a data practice, however, machine learning is not entirely predictable. Machine learners, as we have seen, vary too much, they are biased, they overfit, they underfit, and they often fail to generalise. Despite this, they have enormous allure. In the history of automata, automation and animation, kinetic lures have long exercised fascination, and this may be part of the effect of machine learning. Animating transformations of data (think of the 366 times the logistic regression traverses the `South African Heart Disease` dataset), and then looking at those optimising animations as 'learning' generates operational power dynamics.

Machine learning more broadly attracts infrastructural, technical, professional, semiotic and financial diagonals—think of the upswing in Google searches for 'machine learning' shown in figure 1.1 in chapter 1 —that render its traits more real, more thickly transformative and more 'performant.' Yet such performant diagrams generate referential effects. Machine learning becomes ontologically potent. As Maurizio Lazzarato writes in *Signs and Machines*, 'ontological mutations are always machinic. They are never the simple result of the actions or choices of the "man" who, leaving the assemblage, removes himself from the non-human, technical, or incorporeal elements that constitute him.' (Lazzarato 2014, 83).

New machine learners arise from diagrammatic superimposition of existing practices or procedures. Neural networks are like a massively proliferating nest of perceptrons. Moreover, machine learning techniques often repeat something familiar by ~~very~~ different means (think of how `kittydar` treats photographs, or how a decision tree is legible but often unfamiliar). The event, then, resides less in either something intrinsic to devices operating as algorithmic models, or in something about the domains and places in which the devices operate (biomedicine, state security and intelligence agencies, finance, business, commerce, science, etc.). Perhaps it is a rather more modest event in which the tending of abstractions through estimation, optimisation, high-dimensional vectorisation, probabilistic mixing of latent and feature variables, and imputation unevenly ~~replace~~ existing ontological and epistemic norms of verification, objectification, and attribution.

I have been less interested in treating these techniques as the predictable re-animation of alienated reason, and more inclined to look for those elements in machine learning that diagrammatically abstract away from structures of representations, subjectification or indeed implementation associated with platforms, services and products ~~(for instance, the interminable implementations of document classifiers, sentiment analyses, or image labelling, or handwritten digit~~

~~recognition, or autonomous navigation, etc.).~~

Glossary

$\hat{\beta}$ is a commonly used symbol for the model parameters, weights or coefficients. Estimating optimum values of β is a preoccupation in machine learning.

$\sum$ is an operator that sums together all the terms to the right of the symbol.

archaeology Michel Foucault defines archaeology as a description that explores the production of statements at the level of knowledge practices (*savoir*). It emphasizes the irregularities and discontinuities in knowledge practices as well as the derivations of operations and functions.

bias of a model refers to its inevitable approximation and misalignment to the actual processes that generated the data.

classifier is a machine learner that assigns instances to classes or categories such as `survive` or `die`, `cat` or `dog`.

cost function is a function that measures the difference between the output of the model (the prediction) and the known values ~~(Whitehead 1960)~~.

cross-validate is an operation that validates a model against a part of the data ~~in order~~ to gauge how well predictions generalize to fresh or hitherto unseen data. Many rounds of cross-validation may be used in training models when data ~~is~~ limited.

data strain borrows from A.N. Whitehead's notion of strain, which refers to implicit forces or tensions in bodies of data that relate to the feeling of geometrically straight or flat loci.

decision boundary is a boundary or surface ~~drawn~~ in vector space by a machine learning classifier to differentiate or separate and hence classify cases.

deep learning a neural network comprising many layers commonly used for image recognition.

diagram is a form of abstraction concerned with functioning and operations. In Gilles Deleuze's reading of Michel Foucault, diagrams display relations of force~~,~~ and construct models of truth (Deleuze 1994).

discourse For Michel Foucault, a discourse groups statements generated by an enunciative function.

enunciative function For Michel Foucault, the mapping of statements to themselves, to subject positions, to correlate domains and their material forms of reuse, replication and transcription together generate statements. ~~In this book, the~~ many predictions, inferences, plots, tabulations, numbers, scores, probabilities, classifications, software libraries and devices comprise the enunciative function of machine learning.

enunciative modality For Michel Foucault, the sites, forms of observing, describing, teaching, perceiving associated with statements.

feature Also known in machine learning as variable, measurement, observation or attribute, a feature occupies one dimension in the vector space inhabited by data.

function Mathematically, a function uniquely maps one set of numbers onto another set of numbers. ~~each other.~~ In machine learning, functions operate diversely, sometimes transforming data to generate feature or vector spaces, sometimes measuring cost or loss for particular models, and sometimes expressing forms such as curves and surfaces that transform data. Across these different usages and domains, the operation of mapping or relation between sets of values such as X and Y can be seen.

generative model uses probability distributions to model the process that generated the data, thus allowing the model to generate or simulate samples from the data.

machine learner refers to humans and machines involved in learning from data together.

operational formation is a variation on Michel Foucault's discursive formation that highlights the collective human-machine regularities of power-knowledge. ~~While~~ operation and operational fields are implicit to discursive practice, they are somewhat overshadowed by the figures of the document, the utterance, and the proposition in Foucault's account.

partial derivative is an operator from differential calculus that expresses the rate of change of one variable with respect to another.

partial observer in Gilles Deleuze and Félix Guattari's concept of what a mathematical function does in science (Deleuze 1994).

perceptron A machine learner developed in the 1950s by Frank Rosenblatt. It is modelled on a neurone that learns to classify the input data or what it 'perceives' by varying parameters or weights on the sum of its inputs to produce values of either ~~'1' or 0'~~.

positivity Michel Foucault's term in *Archaeology of Knowledge* to describe the specific forms of accumulation of a group of statements in a discursive formation.

referential ~~: for~~ Michel Foucault, the referential of a statement is not the referent (the facts, things, realities or beings designated) but the place, condition, field of emergence or principle of differentiation for the entities named, described or designated in the statement. The referentials for machine learning include various hyperobjects such as genomes, social media, epidemics, markets and economies. Such referentials encompass many named entities.

regularization operates on the referentials of machine learning to target subtle, diffuse distributions of difference ~~in order~~ to classify, estimate and rank their ~~effects.~~

statement Michel Foucault's term for the product of an enunciative function that operationally relates a number of elements to a field of objects, establishing subject positions associated with them, and configuring a domain of coordination in which these elements can be invoked, used, and repeated. Statements take many forms including utterances, graphs, equations and numbers (Foucault, 82).

variance of a model refers to its dependence on the particular data it is trained on.

vector Three senses of the term are relevant: 1. ~~A~~ vector as an element of vector space; 2. ~~A~~ data structure in programming languages such as `R` ~~— a one dimensional~~ array of elements; 3. ~~A~~ feeling in the sense used by A.N. Whitehead to describe the transfer from ~~'there' to 'here'.~~

vector space is a hyperspace of indefinite dimensions generated by the projective mapping of data variables or features into distinct coordinate dimensions.

vectorize operations on data that transform vectors of values in aggregate.

Bibliography

Abramowitz, Milton. 1965. *Handbook of Mathematical Functions: With ~~Formulas,graphs,and~~ Mathematical Tables.* In collaboration with Irene A. Stegun and United States. National Bureau of Standards. Dover Books.

Ackley, David H., Geoffrey E. Hinton, and Terrence J. Sejnowski. 1985. "A Learning Algorithm for Boltzmann Machines." *Cognitive science* 9 (1): 147–169.

ACM. 2013. "John M. Chambers Award Winner." Accessed December 12, 2013. http://awards.acm.org/award_winners/chambers_6640862.cfm.

Adams, Vincanne, Michelle Murphy, and Adele E Clarke. 2009. "Anticipation: Technoscience, Life, Affect, Temporality." *Subjectivity* 28 (1): 246–265.

Adler, Joseph, and Jörg Beyer. 2010. *R in a Nutshell.* ~~O'Reilly Germany.~~

Agency, National Security. 2012. "SKYNET: Courier Detection via Machine Learning." Accessed October 29, 2015. https://theintercept.com/document/2015/05/08/skynet-courier/.

Alpaydin, Ethem. 2010. *Introduction to Machine Learning.* Cambridge, ~~Massachusetts~~; London: MIT Press.

Amoore, Louise. 2011. "Data Derivatives ~~O~~n the Emergence of a Security Risk Calculus for Our Times." *Theory, Culture & Society* 28 (6): 24–43.

Anthony, Sebastian. 2012. "Google Compute Engine: For $2 Million/-Day, Your Company Can Run the Third Fastest Supercomputer in the World | ExtremeTech." Accessed October 3, 2012. http://www.extremetech.com/extreme/131962-google-compute-engine-for-2-millionday-your-company-can-run-the-third-fastest-supercomputer-in-the-world.

Arendt, Hannah. 1998. *The Human Condition.* Chicago; London: University of Chicago Press.

Aristotle. 1975. *Aristotle's Categories and de Interpretatione.* Translated by J.L. Ackrill. Oxford University Press.

Arthur, Charles. 2015. "Artificial Intelligence: Don't Fear AI. It's Already on Your Phone—and Useful." June 15. Accessed July 9, 2015. http://www.theguardian.com/technology/2015/jun/15/artificial-intelligence-ai-smartphones-machine-learning.

Arthur, Heather. 2012. "Harthur/Kittydar." Accessed September 16, 2014. https://github.com/harthur/kittydar.

Bailey, N. T. J. 1965. *Probability Methods of Diagnosis Based on Small Samples.* London: HM Stationery Office, London.

Barber, David. 2011. *Bayesian Reasoning and Machine Learning.* Cambridge; New York: Cambridge University Press.

Barocas, Solon, Sophie Hood, and Malte Ziewitz. 2013. *Governing Algorithms: A Provocation Piece.* SSRN SCHOLARLY PAPER ID 2245322. Rochester, NY: Social Science Research Network.

BBC. 2012. "Google ~~'~~brain' Machine Spots Cats." *BBC News: Technology* (June 26).

Beer, David, and Roger Burrows. 2013. "Popular Culture, Digital Archives and the New Social Life of Data." *Theory, Culture & Society.*

Bellman, Richard. 1961. *Adaptive Control Processes: A Guided Tour.* Vol. 4. Princeton, ~~N.J.:~~ Princeton University Press.

Beniger, James R. 1986. *The Control Revolution: Technological and Economic Origins of the Information Society.* Harvard University Press.

Beniger, James R., and Dorothy L. Robyn. 1978. "Quantitative Graphics in Statistics: A Brief History." *The American Statistician* 32, no. 1 (February 1): 1–11.

Berlant, L. 2007. "Nearly Utopian, Nearly Normal: Post-Fordist Affect in La Promesse and Rosetta." *Public Culture* 19 (2): 273.

Bertin, Jacques. 1983. *Semiology of Graphics: Diagrams, Networks, Maps.* Madison: University of Wisconsin Press.

Bishop, Christopher M., et al. 1995. *Neural Networks for Pattern Recognition.* Cambridge; New York: Cambridge University Press.

Bishop, Christopher M. 2006. *Pattern Recognition and Machine Learning.* Vol. 1. New York: Springer.

Blei, David M., and John D. Lafferty. 2007. “A Correlated Topic Model of Science.” *The Annals of Applied Statistics*, 17–35. JSTOR: 4537420.

Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2003. “Latent Dirichlet Allocation.” *the Journal of machine Learning research* 3:993–1022.

Bollas, Christopher. 2008. *The Evocative Object World.* London ~~&~~ New York: Routledge.

Borch, Christian. 2005. “Urban Imitations: Tarde’s Sociology Revisited.” *Theory Culture Society* 22 (3): 81–100.

Bowker, Geoffrey. 2014. “Emerging Configurations of Knowledge Expression.” In *Media Technologies: Essays on Communication, Materiality, and Society,* edited by Tarleton Gillespie, Pablo Boczkowski, and Kirsten A. Foot, 99–118. Cambridge, MA: MIT Press.

Boyd, Stephen, and Lieven Vandenberghe. 2004. *Convex Optimization.* Cambridge ; New York: Cambridge university press.

Bratton, Benjamin H. 2016. *The Stack: On Software and Sovereignty.* 1 edition. Cambridge, ~~Massachusetts~~: MIT Press~~, January 22~~.

Breiman, Leo. 2001a. “Random Forests.” *Machine learning* 45 (1): 5–32.

———. 2001b. “Statistical Modeling: The Two Cultures (with Comments and a Rejoinder by the Author).” *Statistical Science* 16 (3): 199–231.

Breiman, Leo, Jerome Friedman, Richard Olshen, Charles Stone, D. Steinberg, and P. Colla. 1984. “CART: Classification and Regression Trees.” ~~*Wadsworth: Belmont, CA* 156.~~

Brynjolfsson, Erik, and Andrew Mcafee. 2014. *The Second Machine Age~~–~~ Work, Progress, and Prosperity in a Time of Brilliant Technologies.* New York: W. W. Norton & Company.

Campbell-Kelly, Martin. 2003. *From Airline Reservations to Sonic the Hedgehog: A History of the Software Industry.* Cambridge, MA: MIT Press.

Cassirer, Ernst. 1923. *Substance and Function.* Translated by William Curtis Swabey and Marie Curtis Swabey. Chicago: Open Court Publishing.

Chen, Xi, and Hemant Ishwaran. 2012. “Random Forests for Genomic Data Analysis.” *Genomics* 99, no. 6 (June): 323–329.

Cheney-Lippold, John. 2011. “A New Algorithmic Identity Soft Biopolitics and the Modulation of Control.” *Theory, Culture & Society* 28 (6): 164–181.

Church, Alonzo. 1936. “A Note on the Entscheidungsproblem.” *Journal of Symbolic Logic* 1 (1): 40–41.

———. 1996. *Introduction to Mathematical Logic.* Princeton~~ N.J.,~~ Princeton University Press.

Cleveland, William S., Eric Grosse, and William M. Shyu. 1992. “Local Regression Models.” *Statistical ~~m~~odels in S~~;~~* 309–376.

CNN. 2011. “40 Under 40: Ones to Watch.” Accessed January 22, 2013. http://money.cnn.com/galleries/2011/news/companies/1110/gallery.40_under_40_ones_to_watch.fortune/.

Coleman, Gabriella. 2012. *Coding Freedom: The Ethics and Aesthetics of Hacking.* Princeton ~~N.J.;~~ Princeton University Press.

Collins, Harry M. 1990. *Artificial Experts: Social Knowledge and Intelligent Machines.* Inside technology. Cambridge, MA~~.~~: MIT Press.

Conway, Drew, and John Myles White. 2012. *Machine Learning for Hackers.* Sebastopol, CA: O’Reilly.

Cortes, C., and V. Vapnik. 1995. “Support-Vector Networks.” *Machine Learning* 20, no. 3 (September): 273–297.

Couldry, Nick. 2012. *Media, Society, World: Social Theory and Digital Media Practice.* Cambridge~~.~~; Malden, MA: Polity.

Cover, Thomas, and Peter Hart. 1967. “Nearest Neighbor Pattern Classification.” *Information Theory, IEEE Transactions ~~on~~* 13 (1): 21–27.

Cox, Geoff. 2012. *Speaking Code: Coding as Aesthetic and Political Expression.* MIT Press.

Cramer, J. S. 2004. “The Early Origins of the Logit Model.” *Studies in History and Philosophy of Science Part C: Studies in History and Philosophy of Biological and Biomedical Sciences* 35 (4): 613–626.

CRAN. 2010. “The Comprehensive R Archive Network.” Accessed May 5, 2010. http://www.stats.bris.ac.uk/R/.

Cranor, Lorrie Faith, and Brian A. LaMacchia. 1998. “Spam!” *Communications of the ACM* 41 (8): 74–83.

Dahl, George. 2013. “Deep Learning How I Did It: Merck 1st Place Interview.” Accessed June 17, 2013. http://blog.kaggle.com/2012/11/01/deep-learning-how-i-did-it-merck-1st-place-interview/.

Deleuze, Gilles. 1988a. *Bergsonism.* New York: Zone Books.

———. 1988b. *Foucault.* Translated by Seân Hand. Minneapolis: University of Minnesota Press.

Deleuze, Gilles, and Félix Guattari. 1994. *What Is Philosophy?* Translated by Hugh Tomlinson. European perspectives. New York; Chichester: Columbia University Press.

Dempster, A. P., N. M. Laird, and D. B. Rubin. 1977. “Maximum Likelihood from Incomplete Data via the EM Algorithm.” *Journal of the Royal Statistical Society. Series B (Methodological)* 39, no. 1 (January 1): 1–38. JSTOR: 2984875.

Derrida, Jacques. 1989. *Edmund Husserl’s Origin of Geometry, an Introduction.* Translated by John Leavey. Lincoln: University of Nebraska Press.

Dettmers, Tim. 2015. “Which GPU(s) to Get for Deep Learning: My Experience and Advice for Using GPUs in.” Accessed July 8, 2015. https://timdettmers.wordpress.com/2014/08/14/which-gpu-for-deep-learning/.

Dieleman, Sander. 2015. “Classifying Plankton with Deep Neural Networks.” Accessed July 3, 2015. http://benanne.github.io/2015/03/17/plankton.html.

Domingos, Pedro. 2012. “A Few Useful Things to Know about Machine Learning.” *Communications of the ACM* 55 (10): 78–87.

———. 2015. *The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake Our World.* New York: Basic Civitas Books, September 1.

Doyle, Peter. 1973. “The Use of Automatic Interaction Detector and Similar Search Procedures.” *Operational Research Quarterly*: 465–467. JSTOR: 10.2307/3008131.

Dreyfus, Hubert L. 1972. *What Computers Can’t Do.* New York: Harper & Row.

———. 1992. *What Computers Still Can’t Do: A Critique of Artificial Reason.* Cambridge, MA: MIT Press.

Duda, Richard O., Peter E. Hart, and David G. Stork. 2012. *Pattern Classification.* New York; London: John Wiley & Sons.

Durbin, Richard, Sean R. Eddy, Anders Krogh, and Graeme Mitchison. 1998. *Biological Sequence Analysis: Probabilistic Models of Proteins and Nucleic Acids.* 1 edition. Cambridge; New York: Cambridge University Press, May 13.

Edwards, Paul N. 1996. *The Closed World: Computers and the Politics of Discourse in Cold War.* Inside technology. Cambridge, MA; London: MIT Press.

Efron, B. 1979. “Bootstrap Methods: Another Look at the Jackknife.” *The annals of Statistics* 7 (1): 1–26.

Einhorn, Hillel J. 1972. “Alchemy in the Behavioral Sciences.” *Public Opinion Quarterly* 36, no. 3 (September 21): 367–378.

Ensmenger, Nathan. 2012. "Is Chess the Drosophila of Artificial Intelligence? A Social History of an Algorithm." *Social Studies of Science* 42, no. 1 (February 1): 5–30.

Fico. 2015. "FICO®Analytic Modeler Decision Tree Professional | FICO™." Accessed November 1, 2015. http://www.fico.com/en/products/fico-analytic-modeler-decision-tree-professional.

Fisher, R.A. 1938. "The Statistical Utilization of Multiple Measurements." *Annals of Human Genetics* 8 (4): 376–386.

Fisher, Ronald A. 1936. "The Use of Multiple Measurements in Taxonomic Problems." *Annals of eugenics* 7 (2): 179–188.

Fix, Evelyn, and Joseph L. Hodges. 1951. *Discriminatory Analysis-Nonparametric Discrimination: Consistency Properties.* DTIC Document.

Flach, Peter. 2012. *Machine Learning: The Art and Science of Algorithms that Make Sense of Data.* Cambridge University Press.

Foucault, Michel. 1972. *The Archaeology of Knowledge and the Discourse on Language.* Translated by Allan Sheridan-Smith. New York: Pantheon Books.

———. 1977. *Discipline and Punish: The Birth of the Prison.* Translated by Allan Sheridan-Smith. New York: Vintage.

———. 1991. *The History of Sexuality.* Translated by Robert Hurley. London: Penguin : Viking : Pantheon.

———. 1992 [1966]. *The Order of Things: An Archaeology of Human Sciences.* Translated by Allan Sheridan-Smith. London: Routledge.

~~Foucault, Michel~~. 1997. *Ethics: Subjectivity and Truth.* Edited by Paul Rabinow. New York: New Press.

———. 1998. *The Will to Knowledge: The History of Sexuality.* Translated by Robert Hurley. Vol. 1. London: Penguin.

Frey, Carl Benedikt, and Michael Osborne. 2013. *The Future of Employment: How Susceptible Are Jobs to Computerisation?* Oxford: Oxford Martin School, Oxford University.

Friedman, Jerome H. 1997. "On Bias, Variance, 0/1—~~l~~oss, and the Curse-of-Dimensionality." *Data ~~m~~ining and ~~k~~nowledge ~~d~~iscovery* 1 (1): 55–77.

Fuller, Matthew, and Andrew Goffey. 2012. *Evil Media.* Cambridge, ~~Mass~~: MIT Press.

Galloway, Alexander. 2014. "The Cybernetic Hypothesis." *~~d~~ifferences* 25, no. 1 (January 1): 107–131.

Galloway, Alexander R. 2004. *Protocol: How Control Exists ~~a~~fter Decentralization.* Leonardo (Series) (Cambridge, Mass.) Cambridge, ~~Mass.:~~ MIT Press.

Garling, Caleb. 2015. "Andrew Ng: Why ~~'~~Deep Learning' Is a Mandate for Humans, Not Just Machines | WIRED." Accessed July 9, 2015. http://www.wired.com/2015/05/andrew-ng-deep-learning-mandate-humans-not-just-machines/.

Gillespie, Tarleton. 2010. "The Politics ~~Of 'platforms'."~~ *New Media & Society* 12 (3): 347–364.

———. 2014. “The Relevance of Algorithms.” In *Media Technologies: Essays on Communication, Materiality, and Society,* edited by Tarleton Gillespie, Pablo Boczkowski, and Kirsten A. Foot, 167–194. Cambridge, MA: MIT Press.

Gitelman, Lisa, ed. 2013. ~~“~~*Raw Data” ~~is~~ an Oxymoron.* Cambridge, ~~Massachusetts~~; London, England: MIT Press.

Glorot, Xavier, and Yoshua Bengio. 2010. “Understanding the Difficulty of Training Deep Feedforward Neural Networks.” ~~In~~ *International Conference on Artificial Intelligence and Statistics,* 249–256.

Gomes, Lee. 2014. “Machine-Learning Maestro Michael Jordan on the Delusions of Big Data and Other Huge Engineering Efforts ~~-~~IEEE Spectrum.” October 3. Accessed March 5, 2015. http://spectrum.ieee.org/robotics/artificial-intelligence/machinelearning-maestro-michael-jordan-on-the-delusions-of-big-data-and-other-huge-engineering-efforts.

Google. 2015. “TensorFlow~~—~~ an Open Source Software Library for Machine Intelligence.” Accessed June 7, 2016. https://www.tensorflow.org/.

Gruber, John. 2004. “Markdown: Syntax.” Accessed July 1, 2013. http://daringfireball.net/projects/markdown/.

Guattari, Félix. 1984. *Molecular Revolution~~-~~: Psychiatry and Politics.* Harmondsworth, Middlesex, England~~-~~; New York~~, N.Y., U.S.A.;~~ Penguin.

Guattari, Felix, and Gilles Deleuze. 1988. *A Thousand Plateaus: Capitalism and Schizophrenia.* London: Athlone~~, 1988~~.

Gulcehre, Caglar. 2014. "Welcome to Deep Learning." Accessed October 24, 2014. http://deeplearning.net/.

Hacking, Ian. 1975. *The Emergence of Probability.* Cambridge; New York: Cambridge University Press.

———. 1990. *The Taming of Chance.* Cambridge University Press.

Hallinan, Blake, and Ted Striphas. 2014. "Recommended for You: The Netflix Prize and the Production of Algorithmic Culture." *New Media & Society* (June 23): 1–21.

Halpern, Orit. 2015. *Beautiful Data.* Durham, ~~N.C.:~~ Duke University Press.

Hand, D. J., and K. M. Yu. 2001. "Idiot's Bayes~~—~~ Not ~~so~~ Stupid ~~a~~fter All?" *International Statistical Review* 69, no. 3 (December): 385–398.

Hansen, Mark B. N. 2015. *Feed-Forward: On the Future of Twenty-First-Century Media.* University of Chicago Press, January 12.

Haraway, Donna. 1997. *Modest-Witness@Second-Millennium.FemaleMan-Meets-OncoMouse: Feminism and Technoscience.* New York; London: Routledge.

Hastie, Trevor, Robert Tibshirani, and Jerome H. Friedman. 2001. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* 1st edition. New York: Springer.

———. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* 2nd edition. New York: Springer.

Hayles, N. Katherine. 1999. *How We Became Posthuman: Virtual Bodies in Cybernetics, Literature, and.* Chicago~~, Ill.~~; London: University of Chicago Press.

Heis, Jeremy. 2014. "Ernst Cassirer's Substanzbegriff Und Funktionsbegriff." *HOPOS: The Journal of the International Society for the History of Philosophy of Science* 4, no. 2 (September 1): 241–270. JSTOR: 10.1086/676959.

Helmreich, Stefan. 2000. *Silicon Second Nature: Culturing Artificial Life in a Digital World.* Berkeley, ~~Calif.~~; London: University of California Press.

Henson, Joseph, German Tischler, and Zemin Ning. 2012. "Next-Generation Sequencing and Large Genome Assemblies." *Pharmacogenomics* 13, no. 8 (June): 901–915. pmid: 22676195.

Hey, T., S. Tansley, and K. Tolle, eds. 2009. *The Fourth Paradigm: Data-Intensive Scientific Discovery.* Microsoft Research.

Hilary Mason ~~-~~ Machine Learning for Hackers. 2012. June 6.

Hinton, Geoffrey E. 1989. "Connectionist Learning Procedures." *Artificial intelligence* 40 (1): 185–234.

Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. 2006. "A Fast Learning Algorithm for Deep Belief Nets." *Neural Computation* 18, no. 7 (July): 1527–1554.

Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. 2006. "Reducing the Dimensionality of Data with Neural Networks." *Science* 313 (5786): 504–507.

Hof, Robert D. 2014. "Chinese Search Giant Baidu Thinks AI Pioneer Andrew Ng Can Help It Challenge Google and Become a Global Power." August 14. Accessed May 18, 2015. http://www.technologyreview.com/featuredstory/530016/a-chinese-internet-giant-starts-to-dream/.

Hood, Leroy, and Daniel J. Kevles, eds. 1992. "Biology and Medicine in the Twenty-First Century." In *The Code of Code,* 136–63. Cambridge MA: Harvard University Press.

Hothorn, Torsten. 2014. "CRAN Task View: Machine Learning & Statistical Learning" (December 18).

Hothorn, Torsten, Kurt Hornik, and Achim Zeileis. 2006. "Unbiased Recursive Partitioning: A Conditional Inference Framework." *Journal of Computational and Graphical Statistics* 15 (3): 651–674.

IBM. 2014. "IBM's Watson Learns the Language of Science." August 28. Accessed April 16, 2015. https://www-03.ibm.com/press/us/en/pressrelease/44697.wss.

ILSVRC. 2014. "ImageNet Large Scale Visual Recognition Competition 2014 (ILSVRC2014)." Accessed July 6, 2015. http://www.image-net.org/challenges/LSVRC/2014/.

Inc., Google. 2012. "Behind the Compute Engine Demo at Google I/O 2012 Keynote - Google Compute Engine — Google Developers." Accessed August 13, 2012. https://developers.google.com/compute/io.

Isin, Engin, and Evelyn Ruppert. 2015. *Being Digital Citizens.* 1 edition. Rowman & Littlefield International.

Issenberg, Sasha. 2012. “The Definitive Story of How President Obama Mined Voter Data to Win A Second Term | MIT Technology Review.” Accessed January 9, 2013. http://www.technologyreview.com/featuredstory/509026/how-obamas-team-used-big-data-to-rally-voters/.

James, Gareth, Daniela Witten, Trevor Hastie, and Robert Tibshirani. 2013. *An Introduction to Statistical Learning.* Springer.

Jockers, Matthew L. 2013. *Macroanalysis: Digital Methods and Literary History.* Urbana: University of Illinois Press.

Kaggle. 2012. “The Hewlett Foundation: Automated Essay Scoring | Kaggle.” Accessed July 1, 2015. https://www.kaggle.com/c/asap-aes.

———. 2015a. “About | Kaggle.” Accessed June 3, 2015. https://www.kaggle.com/about.

———. 2015b. “Competitions | Kaggle.” Accessed June 3, 2015. https://www.kaggle.com/solutions/competitions.

———. 2015c. “Data Science Jobs Forum | Kaggle.” Accessed July 2, 2015. https://www.kaggle.com/jobs.

———. 2015d. “Description - Facebook Recruiting IV: Human or Robot? | Kaggle.” Accessed July 2, 2015. https://www.kaggle.com/c/facebook-recruiting-iv-human-or-bot.

———. 2015e. “Description - Leaping Leaderboard Leapfrogs | Kaggle.” Accessed June 4, 2015. https://www.kaggle.com/c/leapfrogging-leaderboards.

Karpathy, Andrej. 2016. "Karpathy/Char-Rnn." Accessed June 28, 2016. https://github.com/karpathy/char-rnn.

KDD. 2013. "Call ~~F~~or KDD Cup." Accessed July 23, 2013. http://www.kdd.org/kdd2013/call-for-cup.

Keating, Peter, and Alberto Cambrosio. 2012. "Too Many Numbers: Microarrays in Clinical Cancer Research." *Studies in History and Philosophy of Science Part C: Studies in History and Philosophy of Biological and Biomedical Sciences* 43, no. 1 (March): 37–51.

Khan, Javed, Jun S. Wei, Markus Ringner, Lao H. Saal, Marc Ladanyi, Frank Westermann, Frank Berthold, Manfred Schwab, Cristina R. Antonescu, Carsten Peterson, et al. 2001. "Classification and Diagnostic Prediction of Cancers Using Gene Expression Profiling and Artificial Neural Networks." *Nature ~~m~~edicine* 7 (6): 673–679.

Kirk, Matthew. 2014. *Thoughtful Machine Learning: A Test-Driven Approach.* ~~1~~ edition. Sebastopol, ~~Calif.:~~ O'Reilly Media.

Kitchin, Rob. 2014. "Big Data, New Epistemologies and Paradigm Shifts." *Big Data & Society* 1 (1): 2053951714528481.

Klimt, Bryan, and Yiming Yang. 2004. "The Enron Corpus: A New Dataset for Email Classification Research." In *Machine Learning: ECML 2004,* 217–226. Springer.

Krzywinski, Martin I, Jacqueline E Schein, Inanc Birol, Joseph Connors, Randy Gascoyne, Doug Horsman, Steven J Jones, and Marco A Marra. 2009. "Circos: An Information Aesthetic for Comparative Genomics." *Genome Research*.

Kuhn, Thomas S. 1996. *The Structure of Scientific Revolutions.* Chicago, IL: University of Chicago Press.

Lamport, Leslie, and A. LaTEX. 1986. *Document Preparation System.* Reading, MA: Addison-Wesley.

Lander, Eric S., Lauren M. Linton, Bruce Birren, Chad Nusbaum, Michael C. Zody, Jennifer Baldwin, Keri Devon, et al. 2001. "Initial Sequencing and Analysis of the Human Genome." *Nature* 409, no. 6822 (February 15): 860–921.

Lanier, Jaron. 2013. *Who Owns the Future?* London: Allen Lane.

Lantz, Brett. 2013. *Machine Learning with R.* Birmingham: Packt Publishing.

Larsen, Jeff. 2012. "How ProPublica's Message Machine Reverse Engineers Political Microtargeting." Accessed August 28, 2014. http://www.propublica.org/nerds/item/how-propublicas-message-machine-reverse-engineers-political-microtargeting.

Larson, Roland E. 1996. *Elementary Linear Algebra.* 3rd ed. In collaboration with Bruce H. Edwards. Lexington, ~~Mass~~: DCHeath.

Lash, Scott. 2007. "Power ~~a~~fter Hegemony: Cultural Studies in Mutation?" *Theory, Culture & Society* 24 (3): 55–78.

Latour, Bruno. 1993. *We Have Never Been Modern.* New York; London: Harvester Wheatsheaf.

Lazzarato, Maurizio. 2014. *Signs and Machines: Capitalism and the Production of Subjectivity.* Cambridge, MA: Semiotext(e).

Le, Quoc V., Marc'Aurelio Ranzato, Rajat Monga, Matthieu Devin, Kai Chen, Greg S. Corrado, Jeff Dean, and Andrew Y. Ng. 2011. "Building High-Level Features Using Large Scale Unsupervised Learning" (December 28). arXiv: 1112.6209.

Lecture 1 | Machine Learning (Stanford). 2008.

Lecture 10 | Machine Learning (Stanford). 2008. In collaboration with Andrew Ng. July 23.

Lecture 13 | Machine Learning (Stanford). 2008. In collaboration with Andrew Ng. July 23.

Lecture 2 | Machine Learning (Stanford). 2008. July 23.

Lecture 3 | Machine Learning (Stanford). 2008. July 23.

Lecture 6 | Machine Learning (Stanford). 2008. In collaboration with Andrew Ng. July 23.

Lecture 7 | Machine Learning (Stanford). 2008. In collaboration with Andrew Ng. July 23.

Lecture 9 | Machine Learning (Stanford). 2008. In collaboration with Andrew Ng. July 23.

LeCun, Yann, Bernhard Boser, John S. Denker, Donnie Henderson, Richard E. Howard, Wayne Hubbard, and Lawrence D. Jackel. 1989. "Backpropagation Applied to Handwritten Zip Code Recognition." *Neural computation* 1 (4): 541–551.

LeCun, Yann, and Corinna Cortes. 2012. "MNIST Handwritten Digit Database, Yann LeCun, Corinna Cortes and Chris Burges." Accessed June 24, 2013. http://yann.lecun.com/exdb/mnist/.

Lee, D. D., and H. S. Seung. 1999. “Learning the Parts of Objects by Non-Negative Matrix Factorization.” *Nature* 401, no. 6755 (October 21): 788–791. pmid: 10548103.

Leonelli, ~~S.~~ 2014. “What Difference Does Quantity Make? On the Epistemology of Big Data in Biology.” *Big Data & Society* 1 (1): 1–11.

Levine, Sergey, Peter Pastor, Alex Krizhevsky, and Deirdre Quillen. 2016. “Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection” (March 7). arXiv: 1603.02199 [cs].

Levy, Steven. 2016. “How Google Is Remaking Itself as a “Machine Learning First” Company-—Backchannel.” June 32. Accessed June 27, 2016. https://backchannel.com/how-google-is-remaking-itself-as-a-machine-learning-first-company-ada63defcb70#.fj3u7o3t2.

Lury, Celia, Luciana Parisi, and Tiziana Terranova. 2012. “Introduction: The Becoming Topological of Culture.” *Theory, Culture & Society* 29 (4-5): 3–35.

Lynch, Michael. 1993. *Scientific Practice and Ordinary Action-: Ethnomethodology and Social.* Cambridge: Cambridge University Press.

Mackenzie, Adrian. 1997. “Undecidability: The History and Time of the Universal Turing Machine.” *Configurations* 3:359–379.

———. 2006. *Cutting Code: Software and Sociality.* Digital Formations. New York: Peter Lang.

Mackenzie, Adrian. 2010. “Every Thing Thinks: Sub-Representative Differences in Digital Video Codecs.” In *Deleuze in Science and Technology Studies,* in collaboration with Caspar Bruin Jensen and Kjetle Rodje, 139–154. Oxford: Berghahn Publishers.

———. 2011. “More Parts than Elements: How Databases Multiply.” *Environment and Planning D: Society and Space* 29 (6): 335–350.

———. 2012. “Sets.” In *Devices and the Happening of the Social,* edited by Celia Lury and Nina Wakeford, 219–231. Routledge.

———. 2013a. “From Validating to Verifying: Public Appeals in Synthetic Biology.” *Science as Culture* 22 (4): 476–496.

———. 2013b. ~~“‘Wonderful People’:~~ Programmers in the Regime of Anticipation.” *Subjectivity* 6 (4): 391–405.

———. 2014a. “Multiplying Numbers Differently: An Epidemiology of Contagious Convolution.” *Distinktion: Scandinavian Journal of Social Theory* 15 (2): 189–207.

———. 2014b. “UseR! Aggression, Alterity and Unbound Affects in Statistical Programming.” In *Fun and Software: Exploring Pleasure, Paradox and Pain in Computing,* edited by Olga Goriunova. New York: Bloomsbury Academic.

———. ~~2015.~~ “Distributive Numbers: A Post-Demographic Perspective on Probability.” In *Empirical Baroque,* edited by John Law and Evelyn Ruppert. Mattering Press.

Mackenzie, Adrian, Matthew Fuller, Andrew Goffey, ~~Mills , Richard~~, and Stuart Sharples. 2016. “Code Repositories as Expressions of Urban Life.” In *Code and the City,* edited by Rob Kitchin. London: Routledge.

Mackenzie, Adrian, Richard Mills, Stuart Sharples, Matthew Fuller, and Andrew Goffey. 2015. “Digital Sociology in the Field of Devices.” In *Handbook of Sociology of the Arts and Culture,* edited by Mike Savage and Laurie Hanquinet. London ~~&~~ New York: Routledge.

Mackenzie, Adrian, and Simon Monk. 2004. “From Cards to Code: How Extreme Programming Re-Embodies Programming as a Collective Practice.” *Computer Supported Cooperative Work (CSCW)* 13 (1): 91–117.

Madrigal, Alexis C. 2014. “How Netflix Reverse Engineered Hollywood.” Accessed August 28, 2014. http://www.theatlantic.com/technology/archive/2014/01/how-netflix-reverse-engineered-hollywood/282679/.

Malley, James D., Karen G. Malley, and Sinisa Pajevic. 2011. *Statistical Learning for Biomedical Data.* 1st ed. Cambridge University Press.

Manning, Christopher D., Prabhakar Raghavan, and Hinrich Schütze. 2008. *Introduction to Information Retrieval.* 1st ed. Cambridge University Press, July 7.

Marchese, ~~Dr~~ Francis T. 2013. “Tables and Early Information Visualization.” In *Knowledge Visualization Currents,* edited by Francis T. Marchese and Ebad Banissi, 35–61. ~~Springer London,~~ January 1.

Markoff, John. 2012. “In a Big Network of Computers, Evidence of Machine Learning.” *The New York Times* (June 25).

Maron, M.E. 1961. “Automatic Indexing: An Experimental Inquiry.” *Journal of the Association for Computing Machinery* 8:404–417.

Marx, Karl. 1986. *Capital ~~A~~ Critique of Political Economy. The Process of Production of Capital.* Moscow: Progress.

Massumi, Brian. 2002. *Parables for the Virtual.* Durham, ~~N.C:~~ Duke University Press.

Matloff, Norman S. 2011. *Art of R Programming.* San Francisco: No Starch Press.

Mayer-Schönberger, Viktor, and Kenneth Cukier. 2013. *Big Data: A Revolution ~~that~~ Will Transform How We Live, Work, and Think.* Boston: Eamon Dolan/Houghton Mifflin Harcourt.

McClelland, James L., and David E. Rumelhart. 1986. *Parallel Distributed Processing. Explorations in the Microstructure of Cognition.* Vol. 1. Cambridge~~, MA &~~ London: MIT Press.

McKinney, Wes. 2012. *Python for Data Analysis: Data Wrangling with Pandas, NumPy, and IPython.* Sebastapol, CA: O’Reilly & Associates Inc.

McMillan, Robert. 2013. “How Google Retooled Android With Help From Your Brain.” February 18. Accessed August 4, 2015. http://www.wired.com/2013/02/android-neural-network/.

McNally, Ruth, Adrian Mackenzie, Jennifer Tomomitsu, and Allison Hui. 2012. “Understanding the ‘Intensive’ in ‘Data Intensive Research’: Data Flows in Next Generation Sequencing and Environmental Networked Sensors.” *International Journal of Digital Curation* 7 (1): 81–94.

Meza, Juan C. 2010. “Steepest Descent.” *Wiley Interdisciplinary Reviews: Computational Statistics* 2 (6): 719–722.

Minsky, Marvin, and Seymour Papert. 1969. “Perceptron: An Introduction to Computational Geometry.” ~~*The MIT Press, Cambridge, expanded edition* 19:88.~~

Mitchell, Tom M. 1997. *Machine Learning.* New York~~, NY [u.a.]:~~ McGraw-Hill.

Mnih, Volodymyr, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. 2013. “Playing Atari with Deep Reinforcement Learning” (December 19). arXiv: 1312.5602 [cs].

Mnih, Volodymyr, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves, et al. 2015. “Human-Level Control through Deep Reinforcement Learning.” *Nature* 518, no. 7540 (February 26): 529–533.

Mohamed, Abdel-rahman, Tara N. Sainath, George Dahl, Bhuvana Ramabhadran, Geoffrey E. Hinton, and Michael A. Picheny. 2011. "Deep Belief Networks Using Discriminative Features for Phone Recognition," 5060–5063. IEEE, May.

Mohr, John W., and Petko Bogdanov. 2013. "Introduction—Topic Models: What They Are and Why They Matter." *Poetics* 41, no. 6 (December): 545–569.

Mol, Annemarie. 2003. *The Body Multiple: Ontology in Medical Practice.* Durham, ~~N.C.:~~ Duke University Press.

Montfort, Nick, and Ian Bogost. 2009. *Racing the Beam: The Atari Video Computer System.* MIT Press, January 9.

Moore, David S. 2009. *The Basic Practice of Statistics.* 5th ~~E~~dition. New York; London: W. H. Freeman.

Morgan, James N., and John A. Sonquist. 1963. "Problems in the Analysis of Survey Data, and a Proposal." *Journal of the American Statistical Association* 58 (302): 415–434.

Morton, Timothy. 2013. *Hyperobjects: Philosophy and Ecology After the End of the World.* ~~Univ Of~~ Minnesota Press.

Muenchen, Robert A. 2014. "The Popularity of Data Analysis Software." Accessed September 2, 2015. http://r4stats.com/articles/popularity/.

Munster, Anna. 2013. *An Aesthesia of Networks: Conjunctive Experience in Art and Technology.* MIT Press.

Myers, Eugene W., Granger G. Sutton, Art L. Delcher, Ian M. Dew, Dan P. Fasulo, Michael J. Flanigan, Saul A. Kravitz, Clark M. Mobarry, Knut ~~HJ~~ Reinert, Karin A. Remington, et al. 2000. "A Whole-Genome Assembly of Drosophila." *Science* 287 (5461): 2196–2204.

NCBI. 2016. "Homo Sapiens Chromosome 15, GRCh38.p7 Primary Assembly" (June 6).

Neyland, Daniel. 2015. "On Organizing Algorithms." *Theory, Culture & Society* 32, no. 1 (January 1): 119–132.

NIST. 2012. "Gallery of Distributions." Accessed September 21, 2012. http://www.itl.nist.gov/div898/handbook/eda/section3/eda366.htm.

Olazaran, Mikel. 1996. "A Sociological Study of the Official History of the Perceptrons Controversy." *Social Studies of Science* 26, no. 3 (January 8): 611–659.

Pariser, Eli. 2011. *The Filter Bubble: What the Internet Is Hiding from You.* ~~Penguin UK.~~

Parisi, Luciana. 2013. *Contagious Architecture: Computation, Aesthetics and Space.* Cambridge~~-~~; ~~Malden~~, MA: MIT Press.

Parry, R. M., W. Jones, T. H. Stokes, J. H. Phan, R. A. Moffitt, H. Fang, L. Shi, A. Oberthuer, M. Fischer, W. Tong, et al. 2010. "K-Nearest Neighbor Models for Microarray Gene Expression Analysis and Clinical Outcome Prediction." *The pharmacogenomics journal* 10 (4): 292–309.

Pasquinelli, Matteo. 2014. "Italian Operaismo and the Information Machine." *Theory, Culture & Society* (February 2): 1–20.

———. 2015. "Anomaly Detection: The Mathematization of the Abnormal in the Metadata Society." Berlin.

Pearson, Karl. 1901. "LIII. On Lines and Planes of Closest Fit to Systems of Points in Space." *Philosophical Magazine Series 6* 2, no. 11 (November 1): 559–572.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, et al. 2011. "Scikit-Learn: Machine Learning in Python." *Journal of Machine Learning Research* 12:2825–2830.

Peirce, Charles Sanders. 1992. *The Essential Peirce: 1867-1893 v. 1: Selected Philosophical Writings.* John Wiley & Sons.

———. 1998. *The Essential Peirce – Volume 2: Selected Philosophical Writings: (1893-1913) v. 2.* Indiana University Press.

Perez, Fernando, and Brian E. Granger. 2007. "IPython: A System for Interactive Scientific Computing." *Computing in Science & Engineering* 9 (3): 21–29.

Petrova, Svetlana S., and Alexander D. Solov'ev. 1997. "The Origin of the Method of Steepest Descent." *Historia Mathematica* 24, no. 4 (November): 361–375.

Pevzner, Pavel A., Haixu Tang, and Michael S. Waterman. 2001. "An Eulerian Path Approach to DNA Fragment Assembly." *Proceedings of the National Academy of Sciences* 98, no. 17 (August 14): 9748–9753. pmid: 11504945.

Quinlan, J. Ross. 1986. "Induction of Decision Trees." *Machine learning* 1 (1): 81–106.

Quinlan, John Ross. 1993. *C4. 5: Programs for Machine Learning.* Vol. 1. San Francisco, ~~Calif.;~~ Morgan Kaufmann.

Rabiner, Lawrence. 1989. "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition." *Proceedings of the IEEE* 77 (2): 257–286.

Ramaswamy, Sridhar, Pablo Tamayo, Ryan Rifkin, Sayan Mukherjee, Chen-Hsiang Yeang, Michael Angelo, Christine Ladd, Michael Reich, Eva Latulippe, Jill P. Mesirov, et al. 2001. "Multiclass Cancer Diagnosis Using Tumor Gene Expression Signatures." *Proceedings of the National Academy of Sciences* 98 (26): 15149–15154.

RexerAnalytics. 2015. "Rexer Analytics 7th Annual Data Miner Survey~~—~~ 2015." Accessed May 9, 2011. http://www.rexeranalytics.com/Data-Miner-Survey-2015-Intro.html.

Richert, Willi, and Luis Pedro Coelho. 2013. *Building Machine Learning Systems with Python.* Birmingham: Packt Publishing.

Ripley, Brian. 1996. *Pattern Recognition and Neural Networks. 1996.* Cambridge~~–~~; New York: Cambridge University Press.

———. 2014. *Tree: Classification and Regression Trees.*

Robinson, Derek. 2008. "Function." In *Software Studies: A Lexicon,* edited by M. Fuller, 101–110. The MIT Press.

Rose, N. 2009. "Normality and Pathology in a Biomedical Age." *Sociol. Rev.* 57:66–83.

Rosenblatt, F. 1958. "The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain." *Psychological Review* 65 (6): 386–408.

Rumelhart, David E., Geoffrey E. Hinton, and Ronald J. Williams. 1985. *Learning Internal Representations by Error Propagation.* DTIC Document.

———. 1986. "Learning Representations by back-Propagating Errors." *Nature* 323, no. 6088 (October 9): 533–536.

Russell, Matthew A. 2011. *Mining the Social Web.* Sebastopol, CA: O'Reilly.

Savage, M. 2009. "Contemporary Sociology and the Challenge of Descriptive Assemblage." *European Journal of Social Theory* 12 (1): 155.

Schutt, Rachel, and Cathy O'Neil. 2013. *Doing Data Science.* Sebastopol, ~~Calif.:~~ O'Reilly & Associates Inc.

Segaran, Toby. 2007. *Programming Collective Intelligence: Building Smart Web 2.0 Applications.* Sebastapol CA-: O'Reilly.

Silver, David, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. 2016. "Mastering the Game of Go with Deep Neural Networks and Tree Search." *Nature* 529 (7587): 484–489.

Slikker, W, Jr. 2010. "Of Genomics and Bioinformatics." *The pharmacogenomics journal* 10, no. 4 (August): 245–246. pmid: 20676063.

Smith, Marquard. 2013. "Theses on the Philosophy of History: The Work of Research in the Age of Digital Searchability and Distributability." *Journal of Visual Culture* 12, no. 3 (December 1): 375–403.

Stamey, Thomas A., Mitchell Caldwell, ~~JOHN McNEAL,~~ Rosalie Nolley, Marci Hemenez, and Joshua Downs. 2004. "The Prostate Specific Antigen Era in the United States Is ~~over~~ for Prostate Cancer: What Happened in the Last 20 Years?" *The Journal of ~~u~~rology* 172 (4): 1297–1301.

Stamey, Thomas A., John N. Kabalin, John E. McNeal, Iain M. Johnstone, F. Freiha, Elise A. Redwine, and Norman Yang. 1989. "Prostate Specific Antigen in the Diagnosis and Treatment of Adenocarcinoma of the Prostate. II. Radical Prostatectomy Treated Patients." *The Journal of ~~u~~rology* 141 (5): 1076–1083.

Steinberg, Dan, and Phillip Colla. 2009. "CART: Classification and Regression Trees." *The Top Ten Algorithms in Data Mining~~:~~* 179–201.

Stengers, Isabelle. 2000. *The Invention of Modern Science.* Theory ~~o~~ut of ~~b~~ounds~~ ; v.19.~~ Minneapolis ; London: University of Minnesota Press.

———. 2005. "Deleuze and Guattari's Last Enigmatic Message." *Angelaki* 10 (1): 151–167.

———. 2008. "Experimenting ~~w~~ith Refrains: Subjectivity and the Challenge of Escaping Modern Dualism." *Subjectivity* 22, no. 1 (May): 38–59.

Stengers, Isabelle. 2011. *Cosmopolitics II.* Translated by Robert Bononno. University of Minnesota Press, September 26.

Stevens, Hallam. 2011. "Coding Sequences: A History of Sequence Comparison Algorithms as a Scientific Instrument." *Perspectives on Science* 19 (3): 263–299.

———. 2013. *Life out of Sequence: A Data-Driven History of Bioinformatics.* Chicago~~;~~ London: University ~~Of~~ Chicago Press.

Stigler, Stephen M. 1986. *The History of Statistics: The Measurement of Uncertainty before 1900.* Cambridge, ~~Mass.;~~ Harvard University Press.

———. 2002. *Statistics on the Table: The History of Statistical Concepts and Methods.* Harvard University Press.

Stone, Mervyn. 1974. "Cross-Validatory Choice and Assessment of Statistical Predictions." *Journal of the Royal Statistical Society. Series B (Methodological):* 111–147. JSTOR: 2984809.

Suchman, Lucy. 2006. *Human and Machine Reconfigurations: Plans and Situated Actions.* 2nd ed. Cambridge University Press, December 4.

Suchman, Lucy A. 1987. *Plans and Situated Actions : The Problem of Human-Machine Communication.* Cambridge: Cambridge University Press.

Suchman, Lucy A, and Randall H Trigg. 1992. "Artificial Intelligence as Craftwork." In *Understanding Practice: Perspectives on Activity and Context,* edited by Seth Chaiklin and Jean Lave, 144–178. Cambridge ; New York: Cambridge University Press.

Sunder Rajan, Kaushik. 2006. *Biocapital: The Constitution of Postgenomic Life.* Durham: Duke University Press.

Tarde, Gabriel de. 1902. *Psychologie Économique.* Paris: F. Alcan.

Teetor, Paul. 2011. *R Cookbook.* O'Reilly Media, Incorporated.

Thacker, Eugene. 2005. *The Global Genome: Biotechnology, Politics, and Culture.* Cambridge, ~~Mass.,~~ MIT Press.

Therneau, Terry, Beth Atkinson, and Brian Ripley. 2015. *Rpart: Recursive Partitioning and Regression Trees.*

Thrun, Sebastian, Mike Montemerlo, Hendrik Dahlkamp, David Stavens, Andrei Aron, James Diebel, Philip Fong, John Gale, Morgan Halpenny, and Gabriel Hoffmann. 2006. "Stanley: The Robot that Won the DARPA Grand Challenge." *Journal of ~~field~~ Robotics* 23 (9): 661–692.

Tibshirani, Robert. 1996. "Regression Shrinkage and Selection via the Lasso." *Journal of the Royal Statistical Society. Series B (Methodological):* 267–288. JSTOR: 2346178.

Totaro, Paolo, and Domenico Ninno. 2014. "The Concept of Algorithm as an Interpretative Key of Modern Rationality." *Theory, Culture & Society:* 29–49.

Tuv, E., A. Borisov, G. Runger, and K. Torkkola. 2009. "Feature Selection with Ensembles, Artificial Variables, and Redundancy Elimination." *The Journal of Machine Learning Research* 10:1341–1366.

Valiant, Leslie G. 1984. "A Theory of the Learnable." *Communications of the ACM* 27 (11): 1134–1142.

Van Dijck, José. 2012. "Facebook and the Engineering of Connectivity: A Multi-Layered Approach to Social Media Platforms." *Convergence: The International Journal of Research into New Media Technologies*~~;~~ 1354856512457548.

Vance, Ashlee. 2011. "This Tech Bubble Is Different." *BusinessWeek: ~~m~~agazine* (April 14).

Vapnik, Vladimir. 1999. *The Nature of Statistical Learning Theory.* 2nd ed. ~~2000,~~ Springer, December 1.

Vapnik, Vladimir N., and A. Ya Chervonenkis. 1971. "On the Uniform Convergence of Relative Frequencies of Events to ~~t~~heir Probabilities." *Theory of Probability & Its Applications* 16 (2): 264–280.

Venables, William N., and Brian D. Ripley. 2002. *Modern Applied Statistics with S.* Springer.

Venter, J. Craig, Mark D. Adams, Eugene W. Myers, Peter W. Li, Richard J. Mural, Granger G. Sutton, Hamilton O. Smith, et al. 2001. "The Sequence of the Human Genome." *Science* 291, no. 5507 (February 16): 1304–1351. pmid: 11181995.

Virno, Paolo. 2004. *A Grammar of the Multitude: For an Analysis of Contemporary Forms of Life.* Semiotext(e) foreign agents series. Los Angeles: Semiotext(e).

Warner, Homer R., Alan F. Toronto, L. George Veasey, and Robert Stephenson. 1961. "A Mathematical Approach to Medical Diagnosis: Application to Congenital Heart Disease." *Jama* 177 (3): 177–183.

Warner, Homer R., Alan F. Toronto, and L. George Veasy. 1964. “Experience with Baye’s Theorem for Computer Diagnosis of Congenital Heart Disease*.” *Annals of the New York Academy of Sciences* 115, no. 2 (July 1): 558–567.

Wasserman, Larry. 2003. *All of Statistics: A Concise Course in Statistical Inference.* New York: Springer.

What We’re Learning from Online Education | Video on TED.com. 2012. In collaboration with Daphne Koller. August.

Whitehead, Alfred North. 1956. *Modes of Thought; Six Lectures Delivered in Wellesley College, Massachusetts, and Two Lectures in the University of Chicago.* New York: Cambridge University Press.

———. 1960. *Process and Reality, an Essay in Cosmology.* New York: Macmillan.

Wiener, Norbert. 1961. *Cybernetics, Or, Control and Communication in the Animal and the Machine.* 2nd ed. Cambridge, MA: MIT Press.

Wikibooks. 2013. “R Programming – Wikibooks, Open Books for an Open World.” Accessed June 27, 2013. http://en.wikibooks.org/wiki/R_Programming.

~~*Perceptron.* 2013. In *Wikipedia, the Free Encyclopedia,* by Wikipedia.~~

Wilf, Eitan. 2013. “Toward an Anthropology of Computer-Mediated, Algorithmic Forms of Sociality.” *Current Anthropology* 54, no. 6 (December 1): 716–739. JSTOR: 10.1086/673321.

Wilson, Elizabeth A. 2010. *Affect and Artificial Intelligence.* University of Washington Press.

Witten, Ian H., and Eibe Frank. 2005. *Data Mining: Practical Machine Learning Tools and Techniques.* Morgan Kaufmann.

Wu, X., V. Kumar, J. Ross Quinlan, J. Ghosh, Q. Yang, H. Motoda, G. J McLachlan, A. Ng, B. Liu, P. S Yu, et al. 2008. "Top 10 Algorithms in Data Mining." *Knowledge and Information Systems* 14 (1): 1–37.

Xie, Yihui. 2013. "Knitr: A General-Purpose Package for Dynamic Report Generation in R." *R package version* 1.

Xie, Yihui, and J. J. Allaire. 2012. "New Tools for Reproducible Research with R." Warwick, UK.

Zare, Douglas. 2012. "Difference between Logistic Regression and Neural Networks - Cross Validated." December 7. Accessed May 26, 2015. http://stats.stackexchange.com/questions/43538/difference-between-logistic-regression-and-neural-networks.

Zerbino, D. R., B. Paten, and D. Haussler. 2012. "Integrating Genomes." *Science* 336, no. 6078 (April 13): 179–182.

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