tiny [table]font=tiny

archaeologyname=archaeology, description=Michel Foucault defines archaeology as a description that questions the already-said at the level of its existence. Alternately, archaeology describes discourses as practices specified in the element of the archive **Foucault_1972**; **131**

Machine Learning: Archaeology of a Data Practice

Adrian Mackenzie

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Mitchell, Tom

machine learner!computer program as

Breiman, Leo

learning!from experience

Chapter 1

Introduction: Into the Data

> *Definition*: A computer program is said to **learn** from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, improves with experience E (Mitchell 1997, 2).

> In the past fifteen years, the growth in algorithmic modeling applications and methodology has been rapid. It has occurred largely outside statistics in a new community—often called machine learning—that is mostly young computer scientists. The advances, particularly over the last five years, have been startling (Breiman 2001, 200)

> The key question isn't 'How much will be automated?' It's how we'll conceive of whatever *can't* be automated at a given time. (Lanier 2013, 77)

A relatively new field of scientific-engineering devices said to 'learn from experience' has become operational in the last three decades. Known by various names – machine learning, pattern recognition, knowledge discovery, code!machine learning as

machine learner!Skynet

machine learner!logistic regression

data science!relation to machine learning

Google Search

Apple Siri

Google!TensorFlow

Facebook!news feed

data mining – the field and its devices, which all take shape as computer programs or code, seem to have quickly spread across scientific disciplines, business and commercial settings, industry, engineering, media, entertainment and government. Heavily dependent on computation, they are found in breast cancer research, in autonomous vehicles, in insurance risk modelling, in credit transaction processing, in computer gaming, in face and handwriting recognition systems, in astronomy, advanced prosthetics, ornithology, finance, surveillance (see the U.S. Government's `SkyNet` for one example of a machine learning surveillance system (Agency 2012)) or robots(see a Google robotic arm farm learning to sort drawers of office equipment such as staplers, pens, erasers and paperclips (Levine et al. 2016). Sometimes machine learning devices are understood as *scientific models*, and sometimes they are understood as *operational algorithms*. In very many scientific fields, publications mention or describe these techniques as part of their analysis of some experimental or observational data (as in the logistic regression classification models found in a huge number of biomedical papers). They anchor the field of 'data science' (Schutt and O'Neil 2013), as institutionalised in several hundred data science institutes scattered worldwide. Not so recently, they also became mundane mechanisms deeply embedded in other systems or gadgets (as in the decision tree models used in some computer game consoles to recognise gestures, the neural networks used to recognise voice commands by search engine services such as `Google Search` and `Apple Siri` (McMillan 2013) or Google's `TensorFlow` software packages that puts deep convolutional neural nets on Android devices (Google 2015)). In platform settings, they operate behind the scenes as part of the everyday functioning of services ranging from player ranking in online games to border control face recognition, from credit scores to news feeds on Facebook . In all of these settings, applications and fields, machine learning is said to transform the nature of knowledge. Might it transform the practice of critical thought!practice of

Google!Google Trends

artificial intelligence

data mining

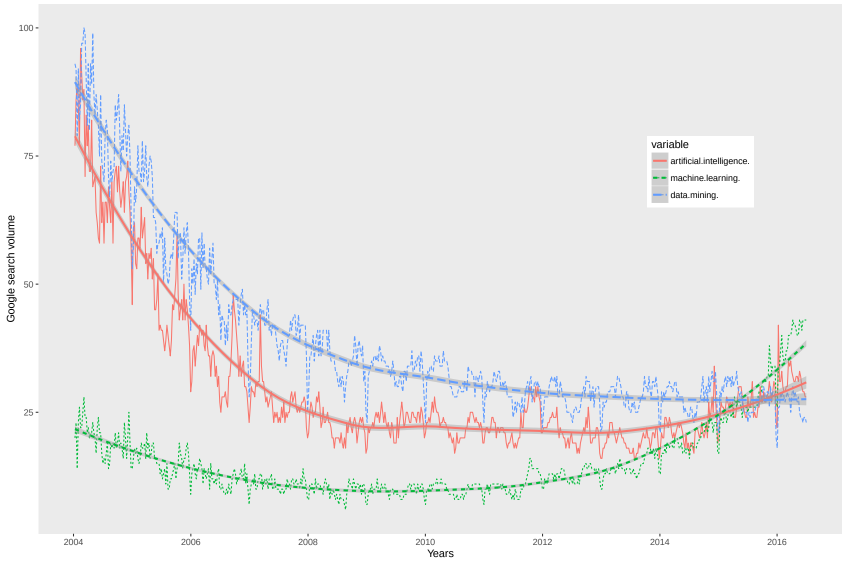

Figure 1.1: Google Trends search volume for ‘machine learning‘ and related query terms in English, globally 2004-2015

critical thought? This book is an experiment in such practice.

Three accumulations: settings, data and devices

Three different accumulations cross-stratify in machine learning: settings, data and devices. The volume and geography of searches on Google Search provides some evidence of the diverse settings or sites doing machine learning. If we search for terms such as `artificial intelligence`, `machine learning` and `data mining` on the Google Trends service , the results for the last decade or so suggest shifting interest in these topics.

In Figure 1.1, two general search terms that had a very high search volume in 2004 – ‘artificial intelligence’ and ‘data mining’ – slowly decline over the years before starting to increase again in the last few years. By contrast, `machine learning` loses volume until around 2008, and then gradually rises again so that by mid-2016 it exceeds the long-standing interests in data-mining and artificial intelligence. Whatever the difficulties in underaccumulation!of settings

Facebook!AI-Flow

machine learner!Skynet

data!plenitude

data!practice

image recognition

kittydar

Arthur, Heather

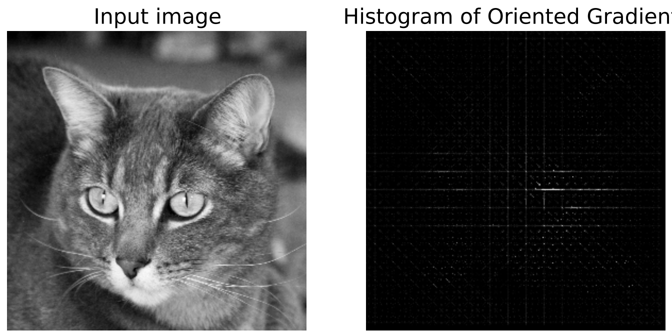

Figure 1.2: Close up of cat. The image on the left is already signal-processed as a JPEG format file. The image on the right is further processed using histogram of oriented gradients (HOG) edge detection. `kittydar` models HOG features. Cat photo courtesy photos-public-domain.com

standing GoogleTrends results, these curves suggest an accumulation of sites and settings turning towards machine learning.[^0.3] What does it mean that machine learning surfaces in so many different places, from fMRIs to Facebook's `AI-Flow` (**Facebook_2016**), , from fisheries management to Al Queda courier network monitoring by `SkyNet`?[^0.0987]

A second accumulation concerns the plenitude of things in the world as data. . If we wanted to describe the general horizon of machine learning as a data practice in its specificity, we might turn to cats. Cat images accumulate on websites and social media platforms as de-centred, highly repetitive data forms. Like the billions of search engine queries, email messages, tweets, or much contemporary scientific data (e.g. the DNA sequence data discussed in chapter **??**), images accumulate in archives of communication. Take the case of `kittydar,` a machine learner in the area of image recognition (see kittydar): 'Kittydar is short for kitty radar. Kittydar takes an image (canvas) and tells you the locations of all the cats in the image' (Arthur 2012) . This playful piece of code demonstrates how machine learning can be amidst mundane accumulation. Heather Arthur, who developed `kittydar` writes:

> Kittydar first chops the image up into many "windows" to test for the presence of a cat head. For each window, kittydar first extracts more tractable data from the image's data. Namely, it computes the Histogram of Orient Gradients descriptor of the image … This data describes the directions of the edges in the image (where the image changes from light to dark and vice versa) and what strength they are. This data is a vector of numbers that is then fed into a neural network … which gives a number from 0 to 1 on how likely the histogram data represents a cat. The neural network … has been pre-trained with thousands of photos of cat heads and their histograms, as well as thousands of non-cats. See the repo for the node training scripts (Arthur 2012). a

data!image as
data!vector
data!vector
machine learner!neural net
code!circulation of
gradient|see gradient descent

This toy device finds cat heads in digital photographs, but also exemplifies many key traits of machine learning. Large accumulations of things become in a dataset. A dataset is used to train a typical machine learning device, a neural net, and the neural net *classifies* subsequent images probabilistically. The code for all this is 'in the repo.' Based on how it locates cats, we can begin to imagine similar pattern recognition techniques in use in self-driving cars (Thrun et al. 2006), border control facial recognition systems, military robots or wherever something seen implies something to do.

Faced with the immense accumulation of cat images on the internet, `kittydar` can do very little. It only detects the presence of cats that face forward. And it sometimes classifies people as cats. As Arthur's description suggests, the software finds cats by cutting the images into smaller windows. For each window, it measures a set of gradients – a spatial order of great significance in machine learning - running from light and dark, and then compares these measurements to the gradients of known cat images data!training

classification

neural network|see machine learner!neural net

support vector machine|see machine learner!support vector machine

(the so-called 'training data'). The work of classification according to the simple categories of 'cat' or 'not cat' is given either to a neural network (as discussed in chapter **??**, a typical machine learning technique and one that has recently been heavily developed by researchers at Google (Le et al. 2011), themselves working on images of cats among other things taken from Youtube videos (BBC 2012), or to a support vector machine (a technique first developed in the 1990s by researchers working at IBM; see chapter **??**).

linear regression

machine learner!logistic regression

machine learner!neural net

machine learner!linear discriminant analysis

support vector machine

k-means clustering

\

nearest neighbours|see machine learner!_k_ nearest neighbours

principal component analysis

machine learner!Naive Bayes

data!practices

A final accumulation comprises machine learning techniques and devices. Machine learning range from the mundane to the esoteric, from code miniatures such as `kittydar` to the infrastructural sublime of computational clouds and clusters twirling in internet data-streams. Like the images that `kittydar` classifies, the names of machine learning techniques and devices proliferate and accumulate in textbooks, instructional courses, website tutorials, software libraries and code listings: linear regression, logistic regression, neural networks, linear discriminant analysis, support vector machines, k-means clustering, decision treesdecision tree|see {machine learner!decision tree}, *k* nearest neighbours, random forests, principal component analysis, or naive Bayes classifier to name just some of the most commonly used. Sometimes they have proper names: `RF-ACE`, `Le-Net5`, or `C4.5`. These names refer to predictive models and to computational algorithms of various ilk and provenance. Intricate data practices – normalization, regularization, cross-validation, feature engineering, feature selection, optimisation – embroider datasets into shapes they can recognise. The techniques, algorithms and models are not necessarily startling new or novel. They take shape against a background of more than a century of work in mathematics, statistics, computer science as well as disparate scientific fields ranging from anthropology to zoology. Mathematical constructs drawn from linear algebra, differential calculus, numerical optimization and probability theory pervade practice in the field. Machine learning itself is an accumulation rather than a radical transformation.

mathematics

machine learner|textbf

human-machine relations

positivity!of knowledge

positivity!threshold of

\

Who or what is a machine learner?

I am focusing on machine learners – a term that refers to both humans and machines or human-machine relations throughout this book – situated amidst these three accumulations of settings, data and devices. While it is not always possible to disentangle machine learners from the databases, infrastructures, platforms or interfaces they work through, I will argue that data practices associated with machine learning delimit a of knowing. The term 'positivity' comes from Michel Foucault's *The Archaeology of Knowledge* (Foucault 1972), and refers to specific forms of accumulation of grouped in a discursive practice. Foucault attributes a lift-off effect to positivity:

> The moment at which a discursive practice achieves individuality and autonomy, the moment therefore at which a single system for the formation of statements is put into operation, or the moment at which this system is transformed, might be called the threshold of positivity. (Foucault 1972, 186)Foucault, Michel!

Machine learners today circulate into domains that lie far afield of the eugenic and psychology laboratories, industrial research institutes or specialized engineering settings in which they first took shape (in some cases, such as the linear regression model or principal component analysis, more than a century ago; in others such as support vector machines or random forests, in the last two decades). If they are not exactly new and have diverse genealogies, the question is: what happen as machine learners shift from

generalization
operational formation
statements!forms of
code!writing of
\

localized mathematical or engineering techniques to an everyday device that can be generalized to locate cats in digital images, the Higgs boson in particle physics experiments or fraudulent credit card transactions? Does the somewhat unruly generalization of machine learning across different epistemic, economic, institutional settings – the pronounced uptick shown in Figure 1.1 – attest to a re-definition of knowledge, decision and control, a new operational formation in which 'a system is transformed'?

Algorithmic control to the machine learners?

Written in code, machine learners operate as programs or computational processes to produce statements that may take the form of numbers, graphs, propositions (see for instance the propositions produced by a recurrent neural net on the text of this book in the concluding chapter **??**). Machine learning can also be viewed as a change in how programs or the code that controls computer operations are developed and operate (see chapter **??** for more detailed discussion of this}. The term 'learning' in machine learning points to this change and many machine learners emphasize it. Pedro Domingos, for instance, a computer scientist at the University of Washington, writes:

> Learning algorithms – also known as learners – are algorithms that make other algorithms. With machine learning, computers write their own programs, so we don't have to.(Domingos 2015, 6)Domingos, Pedro|on machine learning]

Viewed from the perspective of control, and how control is practiced, digital computer programs stem from and epitomise the 'control revolution' (Beniger 1986) that arguably has, since the late nineteenth century, programmatically re-configured production, distribution, consumption, and bureaucracy by tabulating, calculating and increasingly communicating events and operations. With the growth of digital communication networks in the form of the internet, the late 20th century entered a new crisis of control, no longer centred on logistic acceleration but on communication and knowledge. . Almost all accounts of the operational power of machine learning emphasise its power to inflect the control of processes of communication – border flows, credit fraud, spam email, financial market prices, cancer diagnosis, targetted online adverts – processes whose unruly or transient multiplicity otherwise evades or overwhelm us – with knowledge (classifications and predictions in particular) derived from algorithms that make other algorithms. On this view, `kittydar` can isolate cats amidst the excessive accumulation of images on the internet because neural net learning algorithms (back-propagation, gradient descent) have written a program – 'a pre-trained' neural net – during its training phase.

control!crisis of
Beniger, James
machine learner!\texttttkittydar
facial recognition
Amoore, Louise

If a newly programmatic field of knowledge-control takes shape around machine learning, how would we distinguish it from computation more generally? Recent critical research on algorithms offers one lead. In a study of border control systems, which often use machine learners to do profiling and facial recognition , Louise Amoore advocates attention to calculation and algorithms:

> Surely this must be a primary task for critical enquiry – to uncover and probe the moments that come together in the making of a calculation that will automate all future decisions. To be clear, I am not proposing some form of humanist project of proper ethical judgement, but rather calling for attention to be paid to the specific temporalities and norms of algorithmic techniques that rule out, render invisible, other potential futures (Amoore 2011).

Munster, Anna

calculation|see mathematics!calculation

decision

machine learning!human-machine difference

machine learning|as automation

infrastructure

calculation!historical specificity of

As Amoore writes, some potential futures are being 'ruled out' as calculations automate decisions. Anna Munster puts the challenge more bluntly: 'prediction takes down potential' (Munster 2013). I find much to agree with here. Machine learning is a convoluted but nevertheless concrete and historically specific form of calculation (as we will see in exploring algebraic operations in chapter **??**, in finding and optimising certain mathematical functions in chapter **??** or in characterising and shaping probability distributions in chapter **??**). It works to mediate future-oriented decisions (although all too often, very near-future decisions such as ad-click prediction).

I am less certain about treating machine learning as automation. Learning from data, as we will see, does often sidestep and substitute for existing ways of acting, and practices of control, and it thereby re-configures human-machine differences. Yet the notion of automation does not capture well how this comes about. The programs that machine learner 'write' are formulated as probabilistic models, as learned rules or association, and they generate predictive and classificatory statements ('this is a cat'). They render calculable some things which hitherto appeared intractable to calculation (for instance, the argument of a legal case). Such calculation, with all the investment it attracts (in the form of professional lives, in the form of infrastructures , in reorganisation of institutions, corporations and governments, etc.) does rule out some and reinforce other futures. [ˆ0.001] If this transformed calculability is automation, we need to understand the specific contemporary reality of automation as it takes shape in machine learning. We cannot conduct critical enquiry into the calculation that will automate future decisions without opening the very notions of calculation and automation into question.

Does the concept of algorithm help us identify the moments that come together in machine learning without resorting to a-historical concepts of automation or calculation? In various scholarly and political debates around changes business, media, education, health, government or science, quasi-omnipotent agency has been imputed to algorithms (Pasquinelli 2014; Neyland 2015; Totaro and Ninno 2014; Smith 2013; Beer and Burrows 2013; Fuller and Goffey 2012; Wilf 2013; Barocas, Hood, and Ziewitz 2013; Gillespie 2014; Cheney-Lippold 2011; A. R. Galloway 2004) or sometimes just 'the algorithm.' This growing body of work understands the power of algorithms in the social science and humanities literature in different ways, sometimes in terms of rules, sometimes as functions or mathematical abstractions, and increasingly as a located practice. but there is general agreement that algorithms are powerful, or at least, can bear down heavily on people's lives and conduct, re-configuring, for instance, culture as algorithmic (Hallinan and Striphas 2014).

algorithm!primacy
Pasquinelli, Paolo
algorithm!as abstraction

Some of the critical literature on algorithms identifies abstractions as the source of their power. For instance, in his discussion of the 'metadata society,' Paolo Pasquinelli proposes that

> a progressive political agenda for the present is about moving at the same level of abstraction as the algorithm in order to make the patterns of new social compositions and subjectivities emerge. We have to produce new revolutionary institutions out of data and algorithms. If the abnormal returns into politics as a mathematical object, it will have to find its strategy of resistance and organisation, in the upcoming century, in a mathematical way (Pasquinelli 2015).

'Moving at the same level of abstraction as the algorithm' offers some purchase as a formulation for critical practice, and for experiments in such practice. Since in mathematics let alone critical thought, abstraction can be

mathematics!historicity of
abstraction!algorithm as
human-machine relations!practice in
knowledge!power

understood in many different ways, any direct identification of algorithms with abstraction will, however, be difficult to practice. Which algorithm, what kind of abstraction and which 'mathematical way' should we focus on? Like automation and calculation, abstraction and mathematics have mutable historicities. We cannot 'move at the same level' without taking that into account. Furthermore, given the accumulations of settings, data and devices, there might not be any single level of abstraction to move at, only a torque and flux of different moments of abstraction at work in generalizing, classifying, circulating and stratifying in the midst of transient and plural multiplicities.

The archaeology of operations

Given mathematics and algorithms do loom large in machine learning, how do we address their the workings without pre-emptively ascribing potency to mathematics, or to algorithms? In the chapters that follow, I do explore specific learning algorithms (gradient descent in chapter **??** or recursive partitioning **??**) and mathematical techniques (the sigmoid function in chapter **??** or inner products in chapter **??**) in greater empirical and conceptual depth. Following much scholarship in science and technology studies, I maintain that attention to specificity of practices is an elementary prerequisite to understanding human-machine relations, and their transformations. The archaeology of operations that I will develop combines an interest in machine learning as a form of knowledge production and a strategy of power. Like Foucault, I see no exteriority between techniques of knowledge and strategies of power ('between techniques of knowledge and strategies of power, there is no exteriority, even if they have specific roles and are linked together on the basis of their difference' (Foucault 1998, 98)).

If we understand machine learning as a data practice that re-configures local centres of power-knowledge through a re-drawing of human-machine relations, then the specific roles and differences associated with machine learners in the production of knowledge should be a focus of attention. Differences are a key concern here since many machine learners classify things. They are often simply called '.' Some of the practice of difference works in terms of categories. `Kittydar` classifies images as `cat` with some probability, but categorisation and classification in machine learning occurs much more widely.[^0.007] We might understood the importance of categories sociologically. For instance, in his account of media power, Nick Couldry highlights the importance of categories and categorisation:

classifier
Couldry, Nick
categories|seealso differences|categories
power

> *Category* is a key mechanism whereby certain types of ordered (often 'ritualized') practice produce power by enacting and embodying categories that serve to mark and divide up the world in certain ways. Without *some* ordering feature of practice, such as 'categories', it is difficult to connect the multiplicity of practice to the workings of power, whether in the media or in any other sphere. By understanding the work of categories, we get a crucial insight into why the social world, in spite of its massive complexity still appears to us as a *common* world (Couldry 2012, 62) ,

The orderings of categorical differences undergo a great deal of intensification via machine learning. Categories are often simply an existing set of classifications derived from institutionalised or accepted knowledges (for instance, the categories of customers according to gender or age). Machine learners also generate new categorical workings or mechanisms of differentiation. As we will see (for instance in chapter **??** in relation to scientific data from genomes), machine learners invent or find new sets of

machine learning!regularization
differences!orderings of

categories for a particular purpose (such as cancer diagnosis or prognosis). These differentiations may or may not bring social good. The person who finds themselves paying a higher price for an air ticket by virtue of some unknown combination of factors including age, credit score, home address, previous travel, or educational qualifications experiences something of the classificatory power.

Both the intensification of ordering categories and the invention of new classifications feed directly into the regulation of conduct, communication, and ways of living, as will be familiar to readers of Foucault (Foucault 1977). the mathematical abstractions, whether they come from calculus, linear algebra, statistics, or topology, maximise regularities. The power of machine learning to find patterns, to classify or predict regularizes and normalizes differences, although perhaps via some novel ordering practice.

Asymmetries in a common world

What can critical thought, the kind of enquiry that seeks to identify the conditions that concretely constitute what anyone can say or think or do, learn from machine learning? If we see a massive regularization of order occurring in machine learning, what is at stake in trying to think through those practices? They display moments of formalisation (especially mathematical and statistical), circulation (pedagogically and operationally), generalization (propagating and proliferating in many domains and settings) and stratification (the socially, epistemically, economically and sometimes politically or ontologically loaded re-iterative enactment of categories). I am not sure that understanding how a support vector machine or a random forest orders differences would change how would we relate to what we see, feel, sense, hear or think in the face of a contemporary webpage such as

Amazon's that uses Association Rule Mining , an app, a passport control system that matches faces of arriving passengers with images in a database, a computer game, or a genetic test (all settings in which machine learning is likely to be operating).

Amazon!recommendations

Association Rule Mining|seemachine learner!\textitapriori algorithm

Hammerbacher, Jeff

advertising, online

digital humanities!use of machine learning

Jockers, Matthew

Machine learners themselves sometimes complain of the monolithic and homogeneous success of machine learning. Some expert practitioners complain of a uniformity in its applications. Jeff Hammerbacher , previously chief research scientist at Facebook, co-founder of a successful data analytics company called Cloudera, and currently working also on cancer research at Mount Sinai hospital, complained about the spread of machine learning in 2011: 'the best of my generation are thinking about how to make people click ads' (Vance 2011) . Leaving aside debates about the ranking of 'best minds' (a highly competitive and exhaustively tested set of subject positions; see chapter **??**), Hammerbacher was lamenting the flourishing use of predictive analytics techniques in online platforms such as Twitter, Google and Facebook, and on websites more generally, whether they be websites that sell things or advertising space. The mathematical skills of many PhDs from MIT, Stanford or Cambridge were wrangling data in the interests of micro-targeted advertising. As Hammerbacher observers, they were 'thinking about how to make people click ads,' and this 'thinking' mainly took and does take the form of building predictive models that tailored the ads shown on websites to clusters of individual preferences and desires.

Hammerbacher's unhappiness with ad-click prediction resonates with critical responses to the use of machine learning in the digital humanities. Some versions of the digital humanities make extensive use of machine learning. To cite one example, in *Macroanalysis: Digital Methods and Literary History*, Matthew Jockers describes how he relates to one currently popular machine topic model

Mohr, John

Jockers, Matthew!on topic models

data!latent variables in

Galloway, Alex|on knowledge production

learning or statistical modelling technique, the topic model (itself the topic of discussion in Chapter **??**; see also (Mohr and Bogdanov 2013)):

> If the statistics are rather too complex to summarize here, I think it is fair to skip the mathematics and focus on the end results. We needn't know how long and hard Joyce sweated over *Ulysses* to appreciate his genius, and a clear understanding of the LDA machine is not required in order to see the beauty of the result. (Jockers 2013, 124)

The widely used Latent Dirichlet Allocation or models provide a litmus test of how relations to machine learning is taking shape in the digital humanities. On the one hand, these models promise to make sense of large accumulations of documents (scientific publications, news, literature, online communications, etc.) in terms of underlying themes or latent 'topics.' As we will, large document collections have long attracted the interest of machine learners (see chapter **??**). On the other hand, Jockers signals the practical difficulties of relating to machine learning when he suggests that 'it is fair to skip the mathematics' for the sake of 'the beauty of the result'. While some parts of the humanities and critical social research exhorts closer attention to algorithms and mathematical abstractions, other parts elides its complexity in the name of 'the beauty of the results.'

Critical thought has not always endorsed the use of machine learning in digital humanities. Alex Galloway makes two observations about the circulation of these methods in humanities scholarship. The first points to its marginal status in increasingly machine-learned media cultures:

> When using quantitative methodologies in the academy (spidering, sampling, surveying, parsing, and processing), one must

> compete broadly with the sorts of media enterprises at work in the contemporary technology sector. A cultural worker who deploys such methods is little more than a lesser Amazon or a lesser Equifax.110 (A. Galloway 2014, 110)

decision tree

credit scoring|FICO and Equifax

Galloway highlights the asymmetry between humanities scholars and media enterprises or credit score agencies (Equifax). The 'quantitative methodologies' that he refers to as spidering, sampling, processing and so forth are more or less all epitomised in machine learning techniques (for instance, the Association Rule Mining techniques used by Amazon to recommend purchases, or perhaps the decision tree techniques used by the credit-rating systems at Equifax and FICO (Fico 2015)). Galloway's argument is that the infrastructural scale of these enterprises along with the sometime very large technical workforces they employ to continually develop new predictive techniques dwarfs any gain in efficacy that might accrue to humanities research in its recourse to such methods.

Galloway also observes that even if 'cultural workers' do manage to learn to machine learn, and become adept at re-purposing the techniques in the interests of analyzing culture rather than selling things or generating credit scores,they might actually reinforce power asymmetries and exacerbate the ethical and political challenges posed by machine learning:

> Is it appropriate to deploy positivistic techniques against those self-same positivistic techniques? In a former time, such criticism would not have been valid or even necessary. Marx was writing against a system that laid no specific claims to the apparatus of knowledge production itself—even if it was fueled by a persistent and pernicious form of ideological misrecognition. Yet, today the state of affairs is entirely reversed. The new spirit of capitalism

Galloway, Alex!on capitalist work

capitalism!intellectual work in

machine learning!production of knowledge in

knowledge!positivism of

> is found in brainwork, self-measurement and self-fashioning, perpetual critique and innovation, data creation and extraction. In short, doing capitalist work and doing intellectual work—of any variety, bourgeois or progressive—are more aligned today than they have ever been (A. Galloway 2014, 110).

This perhaps is a more serious charge concerning the nature of any knowledge produced by machine learning. The 'techniques' of machine learning may or may not be positivist, and indeed, given the claims that machine learning transforms the production of knowledge, positivism may not be any more stable than other conceptual abstractions. Hence, it might not be so strongly at odds with critical thought, even if remains complicit – 'aligned' – with capitalist work. Intellectual work of the kind associated with machine learning is definitely at the centre of many governmental, media, business and scientific fields of operation and increasingly they anchor the operations of these fields. Yet neither observation – asymmetries in scale, alignment with a 'positivist' capitalist knowledge economy – exhaust the potentials of machine learning, particularly if, as many people claim, it transforms the nature of knowledge production and hence 'brainwork.'

What cannot be automated?

Jaron Lanier's question – how will we conceive at a given time what cannot be automated? – suggests an alternative angle of approach. Like Galloway, I'm wary of certain deployments of machine learning, particularly the platform-based media empires and their efforts to capture sociality (Gillespie 2010; Van Dijck 2012). Machine learners do seem to be 'laying claim to the apparatus of knowledge production.' Yet even amidst the trashy ephemerality of targeted online advertising or the more elevated analytics of literary history, the transformations in knowledge and knowing do not simply simply appropriate intellectual work to capitalist production. Empirical work to describe differences, negotiations, modifications and contestation of knowledge would be needed to show the unevenness and variability of that appropriation. As I have already suggested, machine learning practice is not simply automating existing economic relations or even data practices. While Hammerbacher and Galloway are understandably pessimistic about the existential gratifications and critical efficacy of building targeted advertising systems or document classifiers, the 'deployment' of machine learning is not a finished process, but very much in train, constantly subject to revision, re-configuration and alteration.

machine learning!coincidence with critical thought

machine learner!as human-machine relation

experiment!in critical thought

Importantly, the familiar concerns of critical social thought to analyse differences, power, materiality, subject positions, agency, etc. somewhat overlap with the claims that machine learning produces knowledge of differences, of nature, cultural processes, communication and conduct. Unlike other objects of critical thought, machine learners (understood always as human-machine relations) are themselves closely interested in producing knowledge, albeit scientific, governmental or operational. This coincidence of knowledge projects suggests the possibility of some different articulation, of modification of the practice of critical thought in its empirical and theoretical registers. The altered human-machine relations we see as machine learners might shift and be re-drawn through experiments in empiricism and theory.

Where in the algorithms, calculations, abstractions and regularizing practices of machine learning would differences be re-drawn? Machine learning in journalism, in specific scientific fields, in the humanities, in social sciences, in art, media, government or civil society sometimes overflows the platform-based deployments and their trenchantly positivist usages. A fairly

ProPublica

machine learner!Message Machine

natural language processing

Bogost, Ian

Netflix

explicit awareness of the operation of machine learning-driven processes is taking shape in some quarters. And this awareness supports a situationally aware calculative knowledge-practice.

For instance, the campaign to re-elect Barack Obama as U.S. President in 2011-12 relied heavily on micro-targetting of voters in the leadup to the election polls (Issenberg 2012; Mackenzie et al. 2016). In response to the data analytics-driven election campaign run by the US Democrats, data journalists at the non-profit news organisation *ProPublica* reverse engineered the machine learning models that the Obama re-election team used to target individual votes with campaign messages (Larsen 2012). They built their own machine learning model - the ‘Message Machine’ - using emails sent in by voters to explore the workings of the Obama campaign team’s micro-targetting models. While the algorithmic complexity and data infrastructures used in the Message Machine hardly match those at the disposal of the Obama team, it combines natural language processing (NLP) techniques such as measures of document similarity and machine learning models such as decision trees to disaggregate and map the micro-targetting processes .

This reverse engineering work focused on the constitution of subject positions (the position of the ‘voter’) can be found in other quarters. In response to the personalised recommendations generated by streaming media service Netflix, journalists at *The Atlantic* working with Ian Bogost, a media theorist and programmer, reverse engineered the algorithmic production of around 80,000 micro-genres of cinema used by Netflix.(Madrigal 2014) While Netflix’s system to categorise films relies on much manual classification and tagging with meta-data, the inordinate number of categories they use is typical of the classificatory regimes that are developing in machine learning-based settings.

Both cases explore the constitutive contemporary conditions of doing, saying, and thinking of subjects, not only to recognise how subject positions are assigned or made, but to grasp the possibility of change. While these cases may be exceptional achievements, and indeed highlight the dead weight of ad-tech application of machine learning, knowledge production more generally is not easily reducible to contemporary forms of capitalism labour.

Glossary

classifier A machine learner that assigns instances to classes or categories.. 6

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 intrinsic to Foucault's account of discursive practice, they are somewhat overshadowed by the figures of the document, the utterance, and the proposition.. 8

vectorised Operations on data that transform vectors of values.. *see also* vector

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