8. Optimising machine learners to learn on their own

to do

- the programming of ml as the backpropagation and feed forward of machine learning as function finding into finding a function for machine learning
- hinton – backpropagation of error – the 1986 nature paper uses examples of people
- 'generalization error is what we care about' (*Lecture 9 | Machine Learning (Stanford)* 2008)
- deep neural nets (Hassabis et al. 2013) should appear here
- the Higgs Boson challenge
- MF in d&p writes about how the individual internalises the disciplinary mechanism – we are all machine learners now?
- the masculinity of machine learning – how to deal with that? some prominent women, but massively masculinist – takes me back to 1996 publication - also use SI of angelaki on geophilosophy of masculinity. See zotero masculinity folder
- the people change alongside the data; their sense of the power of data has a cost for them too
- put in Perlich stuff about data leakage – really important to focus on competition as a way of showing how people do things
- we finally reach people – why so late? And so what?
- use Lazzarato here – semiotics, etc
- MF from archaeology of knowledge on the subject in the discursive formation

key points for framing

- error is the cross-over
- examination is what allows both parallel architectures and competitions to come together
- examination makes each individual a case – not just the data, but the machine learners are examined
- my own sense of uncertainty about this stuff, and mixtures of optimism and sense of having to keep moving forward, of needing to re-calibrate, to go in parallel, to avoid overfitting myself, but at the same complexifying what I'm doing.

Introduction

> If a proposition, a sentence, a group of signs can be called 'statement' , it is not therefore because, one day, someone happened to speak them or put them into some concrete form of writing; it is because the position of the subject can be assigned (Foucault 1972, 95)

> 'generalization error is what we care about' (*Lecture 9 | Machine Learning (Stanford)* 2008)

Here are the words of Hilary Mason, Chief Scientist at bitly.com (a service that shortens URLs), at a London conference in 2012 called 'Bacon: Things Developers Love':

> You have all of these things that are different – engineering, infrastructure, mathematics and computer science, curiosity and an understanding of human behaviour – that is something that usually falls under the social sciences. At the intersection of all these things are wonderful people. But we're starting to develop something new, and that is - not that all of these things have not been done for a very long time - but we are only just now building systems where people, individual people, have all of these tools in one package, in one mind. And there are lots of reasons this is happening now. But its a pretty exciting time to be in any of these things. (Hilary Mason, Chief Scientist, bitly.com) (Bacon 2012)

These propositions, if they amount to a *statement* in Michel Foucault's archaeological sense of that term, assign subject positions . In what ways? In front of an audience of several hundred software developers, Mason describes shifts in the work of programming associated with the growth of large amounts of data associated with 'human behaviour.' At the centre of this shift stand 'wonderful people' who combine practices and knowledges of communication infrastructure, technology, statistics, and 'human behaviour' through curiosity and technical skills. Mason was, in effect, telling her audience of software developers who they should become and at the same time pointing to the some of the expansive changes occurring around them. The title of her talk was 'machine learning for hackers', and her audience were those hackers or programmers. A change in programming practice and a shift towards machine learning was, she implied, the key to programmers becoming the wonderful people, agents of their own time, capable of doing what is only now just possible because it is all together in 'one package, one mind.' Here, I would tentatively suggest, Mason adumbrates the outline of an agent of anticipation, someone at the intersection of network infrastructure, mathematics and human behaviour.[1] Mason, one of *Fortune*

[1] In earlier work on machine learning (Mackenzie 2013), I presented programmers as agents

magazines 'Top 40 under 40' business leaders to watch (CNN 2011) and also featured in *Glamour*, a teenage fashion magazine (Mason 2012), personifies such a wonderful person. She is not a lone example.[2]

'It is the privileged machine in this context that creates its marginalized human others' writes Lucy Suchman in her account of the encounters that 'effect "persons" and "machines" as distinct entities (Suchman 2006, 269) . Suchman recommends 'recognition of the particularities of bodies and artifacts, of the cultural-historical practices through which human-machine differences are (re-)iteratively drawn, and of the possibilities for and politics of redistribution across the human machine boundary' (285). Could the 'wonderful people' that Mason describes also be marginalized human others? Does the re-distribution of engineering, mathematics, curiosity, infrastructure, or 'something that usually falls under the social sciences' (but perhaps no longer does so) both energise subjects ('its a pretty exciting time to be in any of these things') and assigns them a marginal albeit still pivotal position? This mixture of wonder, curiosity and something much more driven to harden distinctions and reduce the politics and potentials of re-distribution to much more heavily normalised form is the topic of this chapter. The key machine-diagram I draw on here are neural networks, or neural nets, in their various forms ranging from the perceptron, through the multilayer perceptron (MLP), the convolutional neural nets (CNN), recurrent neural nets (RNN) and deep belief networks or deep neural networks of many recent deep learning projects (particularly in machine learning competitions, as discussed below (Dahl 2013)).

The uneven presence of neural nets in machine learning

In almost every machine learning class, neural nets make some appearance. They have an ambivalent status. Neural nets are often described from a deeply split perspective that in some points turns towards human subjects, or at least, the brains of human subjects, and in other ways towards the ongoing expansion of computational platforms. In some ways, they renew long-standing hopes in biology, and particularly, brains and cognition as models of computational power. They stem from a biological inspiration (dating at least back to the work on McCulloch and Pitts in the 1940s [REF TBA]). In other ways, they gain traction as a ways of dealing with changing computational infrastructures,

of anticipation, suggesting that the turn to machine learning amongst programmers could be useful in understanding how predictivity was being done amidst broader shift to the regime of anticipation described by Vincanne Adams, Michelle Murphy and Adele Clarke (Adams, Murphy, and Clarke 2009). Subsequently developments in machine learning, even just in the last three years, confirm that view, but in this chapter and in this book more generally, the focus is less on transformations in programming practice and software development, and more on the asymmetries of different machine learner subjects.

[2]Other figures we might follow include Claudia Perlich, Andrew Ng, Geoffrey Hinton, Corinna Cortez, Daphne Koller, Christopher Bishop, Yann LeCun, or Jeff Hammerbacher. Although some women's names appear here, in any such list, men's names are much more likely to appear. This is no accident.

and the difficulties of capitalising on infrastructure that is powerful yet difficult to manage. On the other hand, they respond to changes in information infrastructures and digital devices. For instance, David Ackley, Geoffrey Hinton (an important figure in the inception of neural nets during the 1980s and in the revival of neural net in the form of deep learning in the last decade), and Terrence Sejnowski wrote in the early 1980s:

> Evidence about the architecture of the brain and the potential of the new VLSI technology have led to a resurgence of interest in "connectionist" sys-terns … that store their long-term knowledge as the strengths of the connections between simple neuron-like processing elements. These networks are clearly suited to tasks like vision that can be performed efficiently in parallel networks which have physical connections in just the places where processes need to communicate. … The more difficult problem is to discover parallel organizations that do not require so much problem-dependent information to be built into the architecture of the network. Ideally, such a system would adapt a given structure of processors and communication paths to whatever problem it was faced with (Ackley, Hinton, and Sejnowski 1985, 147–148).

This convergence between brain and 'new VSLI [Very Large Scale Integrated] technology' – semiconductor chips – sought to implement the plasticity of neuronal networks in the parallel distributed processing enabled by very densely packed semiconductor circuits. The problem here was how to organize these connections without having to hardwire domain specificity into 'the architecture of the network.' How could the architectures adapt to the problem in hand?

We saw in **??** that the psychologist Frank Rosenblatt's perceptron (Rosenblatt 1958) first implemented the cybernetic vision of neurones as models of computation (Edwards 1996) . While the perceptron did not weather the criticism of artificial intelligence experts such as Marvin Minsky (Minsky famously showed that a perceptron cannot learn the logical exclusive OR or `XOR` function; (Minsky and Papert 1969)), cognitive psychologists such as David Rumelhart, Geoffrey Hinton and Ronald Williams returned to work with perceptrons, seeking to generalize their operations. In the mid-1980s, they developed the back-propagation algorithm (Rumelhart, Hinton, and Williams 1985; Hinton 1989), a way of adjusting the connections between nodes (neurones) in the network in response to features in the data (see Figure 1). The back-propagation algorithm did begin to address the problem of discovering parallel network organizations without reliance on problem-specific architectures. Effectively, an architecture of generalization was implemented. While cognition, and the idea that machines would be cognitive (rather than say, mechanical, calculative, or even algorithmic) constantly organised research work in artificial intelligence for several decades, the development of the back-propagation algorithm as a way for a set of connected

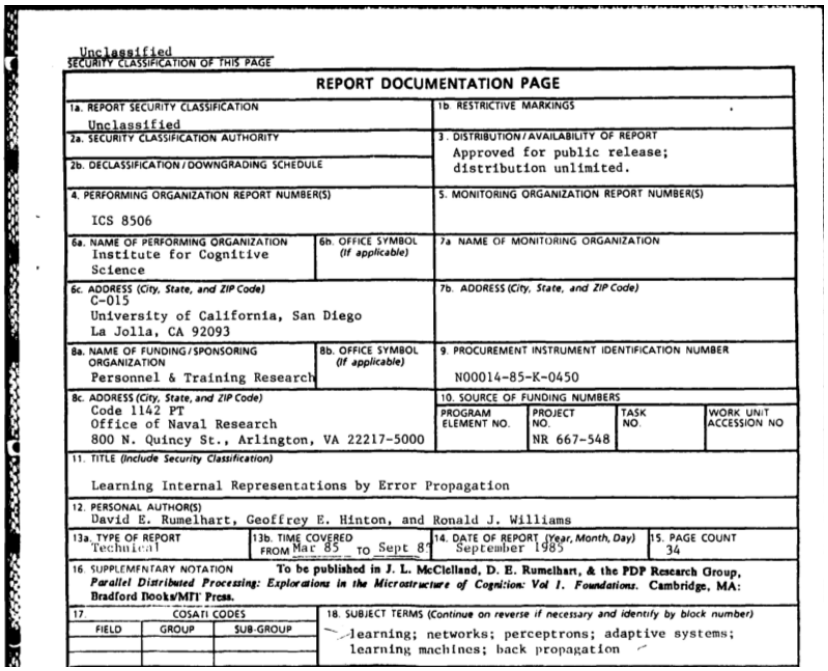

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Figure 1: An early publication of the back-propagation algorithm: Rumelhart, Hinton and William's 1985 paper [@Rumelhart_1985]

computational nodes to learn also had strong infrastructural resonances. These resonances continue to echo today. Like the advent of VSLI in the early 1980s, the vast concentrations of computers in contemporary data centres (hundreds of thousands of cores as we saw in the case of Google Compute in the previous chapter **??**) pose the problem of organizing infrastructure so that processes can communicate with each other.

The back-propagation algorithm will return below, but for the moment, this overlap between cognition and infrastructures, between people and machines, itself suggests another way of thinking about how 'long-term knowledge' takes shape today. At the same time as infrastructural reorganization takes place around learning, and around the production of statements by machine learners, both human and non-human machine learners are assigned new positions. These positions are dispersed, hierarchical and distributed. The subject position in machine learning is a highly relational one, connected to transforms in infrastructure, variations in referentiality (such as we have seen in the construction of the common vector space), and competing forms of authority (as we have seen in the accumulations of different techniques). As Suchman suggests, examining privileged machines is a way to pay attention to variously marginalized human others.

Some machine learners attribute a more privileged and constitutive function to neural nets. Neural nets synchronically spread into many difference disciplines: cognitive science, computer science, linguistics, adaptive control engineering, psychology, finance, operations research, etc, and particularly statistics and computer science during the 1980-1990s. This dendritic growth did not just extend machine learning. It brought engineering and statistics together more strongly. As Ethem Alpaydin writes:

> Perhaps the most important contribution of research on neural networks is this synergy that bridged various disciplines, especially statistics and engineering. It is thanks to this that the field of machine learning is now well established (Alpaydin 2010, 274).

The forms of this field-making bridging are various. We saw some use of neural nets in genomics in the previous chapter (**??**). But the primary space of coexistence of different disciplines around machine learning has perhaps been competitions during the 1990s that pitted neural nets against other machine learners in classifying handwritten numerals such as zipcodes on envelopes. Hastie and co-authors devote a lengthy section to the analysis of these handwritten digit recognition competitions, and like Alpaydin, suggest that they coordinated the development of machine learning in certain ways:

> This problem captured the attention of the machine learning and neural network community for many years, and has remained a benchmark problem in the field (Hastie, Tibshirani, and Friedman 2009, 404).

The handwritten digits used in these competitions, particularly the Neural Information Processing System workshops and KDD (KDD 2013), come from the MNIST dataset (NIST 2012) , and during the 1990s, much effort focused on crafting neural nets to recognise these 60,000 or so handwritten digits. As Hastie and co-authors observe, 'at this point the digit recognition datasets become test beds for every new learning procedure, and researchers worked hard to drive down the error rates' (Hastie, Tibshirani, and Friedman 2009, 408–409).

Despite this binding function, neural networks have had a somewhat problematic position in relation to both statistics and other practices of computation. Even in relation to the paradigmatic handwritten digit recognition problem, neural nets struggled to gain purchase. As *Elements of Statistical Learning* puts it, it required 'pioneering efforts to handcraft the neural network to overcome some these deficiencies…, which ultimately led to the state of the art in neural network performance' (Hastie, Tibshirani, and Friedman 2009, 404). It is rare to find the word 'handcraft' in machine learning literature. The operational premise of most machine learners is that machine learning works without handcrafting.

The shifting fortunes of neural nets are frequently discussed in contrasting terms by machine learners themselves, but in recent years they share an awareness of some kind of transformation:

> Neural networks went out of fashion for a while in the 90s - 2005 because they are hard to train and other techniques like SVMs beat them on some problems. Now people have figured out better methods for training deep neural networks, requiring far fewer problem-specific tweaks. You can use the same pretraining whether you want a neural network to identify whose handwriting it is or if you want to decipher the handwriting, and the same pretraining methods work on very different problems. Neural networks are back in fashion and have been outperforming other methods, and not just in contests (Zare 2012).

Neural nets also receive uneven attention in the machine learning literature. In Andrew Ng's Stanford CS229 lectures from 2007, they receive somewhat short shrift: around 30 minutes of discussion in Lecture 6, in between Naive Bayes classifiers and several weeks of lectures on support vector machines (*Lecture 6 | Machine Learning (Stanford)* 2008). As he introduces a video of an autonomous vehicle steered by a neural net after a 20 minute training session with a human driver, Ng comments that 'neural nets were the best for many years.' The lectures quickly moves on to the successor, support vector machines. In *Elements of Statistical Learning*, a whole chapter appears on the topic, but prefaced by a discussion of the antecedent statistical method of 'projection pursuit regression.' The inception of 'projection pursuit' is dated to 1974, and thus precedes the 1980s work on neural nets that was to receive so much attention. In *An Introduction to Statistical Learning with Applications in R*, a book whose authors include Hastie and Tibshirani, neural nets are not discussed and indeed not mentioned (James et al. 2013). Textbooks written by computer scientists such as Ethem Alpaydin's *Introduction to Machine Learning* do usually include at least a chapter on them, sometimes under different titles such as 'multi-layer perceptrons' (Alpaydin 2010). Willi Richert and Luis Pedro Coelho's *Building Machine Learning Systems with Python* likewise does not mention them (Richert and Coelho 2013). Cathy O'Neil and Rachel Schutt's *Doing Data Science* mentions them but does not discuss them (Schutt and O'Neil 2013), whereas both Brett Lantz's *Machine Learning with R* (Lantz 2013) and Matthew Kirk's *Thoughtful Machine Learning* (Kirk 2014) devote chapters to them. In the broader cannon of machine learning texts, the computer scientist Christopher Bishop's heavily cited books on pattern recognition dwell extensively on neural nets (Bishop and others 1995; Bishop and Nasrabadi 2006). Amongst statisticians, Brian Ripley's *Pattern Recognition and Neural Networks* (Ripley 1996), also highly cited, placed a great deal of emphasis on them. But these specific documents against a pointillistic background of hundreds of thousands of scientific publications mentioning or making use of neural nets since the late 1980s in the

usual litany of fields – atmospheric sciences, biosensors, botany, power systems, water resource management, internal medicine, etc. This swollen publication tide attests to some kind of formation or configuration of knowledge invested in these particular techniques, perhaps more so than other I have discussed so far (logistic regression, support vector machine, decision trees, random forests, linear discriminant analysis, etc.).

The somewhat vacillating presence of neural nets in the machine learning literature itself finds parallels in the fortunes of individual machine learners. Yann LeCun's work on optical character recognition during 1980-1990s is said to have discovered the back-propagation algorithm at the same time as Rumelhart, Hinton and Williams (Rumelhart, Hinton, and Williams 1986). His implementations in `LeNet` led many academic machine learning competitions during the 1990s. In 2007, Andrew Ng could casually observe that neural nets *were* the best, but in 2014, LeCun find himself working on machine learning at Facebook (Gomes 2014). Similarly, the cognitive psychologist Geoffrey Hinton's involvement in the early 1980s work on connectionist learning procedures in neural nets and subsequently on 'deep learning nets' (Hinton and Salakhutdinov 2006) delivers him to Google in 2013. These trajectories between academic research and industry are not unusual. Many of the techniques in machine learning have been incorporated into companies later acquired by other larger companies. Even if there is no spin-off company to be acquired, machine learners themselves have been assigned key positions in many industry settings. Corinna Cortes, co-inventor with Vladimir Vapnik of the support vector machine, heads research at Google New York. Ng himself in 2014 began work as chief scientist for the Chinese search engine, Baidu leading a team of AI researchers specializing in 'deep learning,' the contemporary incarnation of neural nets (Hof 2014). In 2011, Ng led a neural net-based project at Google that had, among other things, detected cats in millions of hours of Youtube videos.[3] In recent years, (2012-2015), work on neural nets has again intensified, most prominently in association with social media platforms, but also in the increasingly common speech and face recognition systems found in everyday services and devices. Many of these neural nets are like `kittydar`, but implemented on a much larger and more distributed scale (for instance, in classifying videos on Youtube).

Finally, neural nets also figure the vicissitudes of human machine learners quite well. They test machine learners for their capacity to understand how models relate to data, and they test them in relation to their knowledge and experience of how of to craft and to regularize the parameters of models in a given situation. Perhaps more profoundly, they figure a much more deeply competitive imperative that frames much of the practice in machine learning, and in many ways constrains thinking around machine learning. This competition is not always explicit or overt but it almost transpires in the form of examination.

[3]Unlike the cats detected by `kittydar`, the software discussed in the introduction to this book, the Google experiment did not use supervised learning. The deep learning approach was unsupervised (Markoff 2012). That is, the neural nets were not given images in which cats were labelled to train on.

For instance, in *Doing Data Science*, Cathy O'Neil and Rachel Schutt offer a pragmatic set of steps for working with machine learners:

> The big picture is that given data, a real-world classification problem, and constraints, you need to determine: >1. Which classifier to use >2. Which optimization method to employ >3. Which loss function to minimize >4. Which features to take from the data >5. Which evaluation metric to use

`[@Schutt_2013, 116]`

Perhaps the order of these steps would be contested by some people, but each of these determinations is definitely a matter of competitive contention. Whether or not this competition deeply structures the field of machine learning is also a matter for further investigation. But in my experience, immersion in the field of machine learning, navigating its social textures, and getting a feeling for how it is to exist in these conditions definitely entails a sense of becoming the subject of examination. This feeling, which is concretised in the numerous machine learning competitions and online instructional materials, is convoluted because it concerns the constitution of machine learners themselves as operations of examination and as a form of documentation or statement of examination, test, and validation focused on errors. As Andrew Ng opines, 'we care about generalization error,' , but error here both refers to something that neither the responsibility simply of the machine or its human others. Rather, responses to and care for this error move forwards and backwards between the human and non-human machine learners.

A privileged machine and its diagrammatic forms

What accounts for the somewhat uneven fortunes of the neural net amongst machine learners? The unevenness of their performance, from limited curiosity in the late 1960s to best performer in the machine learning image classification competitions of the 1990s, from second best competitor in late 1990s to the spectacular promise of deep belief networks in 2012, suggests that some powerful dynamics or becomings are in play around them. These dynamics are not easily understood in terms of celebrity machine learners (human and non-human) suddenly rising to prominent or privileged positions in the research departments of social media platforms.[4] Nor does it make sense to attribute the rising fortunes of the neural net to the algorithms themselves, as if some decisive advance occurred in algorithms. The algorithms used in neural net have not, as we will

[4]In any case, social media and search engines cannot be understood apart from the machine learning techniques that have been thoroughly woven through them since their inception. Hence *Elements of Statistical Learning* devotes several pages Google's famous *PageRank* algorithm, describing it as an unsupervised learner (Hastie, Tibshirani, and Friedman 2009, 576–578).

see, been radically transformed in their core operations since the 1980s, and even then, the algorithms themselves (principally gradient descent) were not new. There have been important changes in scale (similar to those described in the previous chapter in the case of the `RF-ACE` algorithm and Google Compute), but as is often the case in machine learning, their re-invention occurs through proliferation, changes in scale, re-distributions of knowledge and infrastructure and specific optimisations. While machine learners in their machine form can be assigned a privileged position in the transformations of knowledge and action today, human machine learners are not exactly marginalized, at least in high profile cases such as Ng, LeCun, Hinton and others. Rather, the scale of machine learning seems to be changing both for the algorithms and for the human computer scientists, programmers and engineers.

What accounts for this acceleration and slowing-down, the intensified interactions and abandonments of neural nets over the last three decades? Despite their apparent differences in origin, neural net share much with other machine learners. The language of brain, neurones and cognition associated with neural net covers over their much more familiar vector-space, function-finding and optimisations they draw on in practice. 'The central idea,' write Hastie and co-authors, 'is to extract linear combinations of the inputs as derived features, and then model the target as a nonlinear function of these features. The result is a powerful learning method, with widespread applications in many fields' (Hastie, Tibshirani, and Friedman 2009, 389).

The 'central idea' can be seen in the algebraic expressions that Hastie and co-authors provide for the basic neural net model (see equation 1:

$$\begin{aligned} Z_m &= \sigma(\alpha_0 m + \alpha_m^T X) m = 1, ..., M \\ T_k &= \beta_0 k + \beta_k^T Z, k = 1, ..., K, \\ f_k(X) &= g_k(T), k = 1, ..., K, \end{aligned} \tag{1}$$

> where $Z = (Z_1, Z_2, ..., Z_M)$, and $T = (T_1, T_2, ..., T_K)$. The activation function $\sigma(v)$ is usually chosen to be the sigmoid $\sigma(v) = 1/(1 + ev)$
>
> (Hastie, Tibshirani, and Friedman 2009, 392)

Equation 1 is a diagram with some familiar elements as well as some novelty. Some of the diagrammatic operation of the neural net is already familiar from the linear models. The neural networks traverse data in a vector space denoted by X. That is common to nearly all machine learners. They make use of the non-linear sigmoid function that lies at the heart of one of the main linear classifiers used in machine learning, logistic regression . Their training and learning processes have come to rely on the same kinds of cost, loss or error functions we have seen in other machine learners. Their apparently increasingly

power to learn (to see, to find, to predict) again seems to owe much to reconfiguration, to the diagrammatic movements that recombine operations in new intersections.

There are, however, some differences in this diagram. Equation 1 has three lines rather than one, and this layering and its diagonal patterns of indexical referencing running between subscripts distinguishes neural nets from linear models more generally.

$$\hat{Y} = \hat{\beta}_0 + \sum_{j=1}^{p} X_j \hat{\beta}_j \tag{2}$$

Whereas the standard linear model shown in Equation 2 indexes a single common vector space X_j and approximates a single function $\hat{Y}$ by searching for the values of the parameters β_j that best incline a plane through the given data, it seems that the three lines of the neural net model show in equation 1 are woven through each other much more consecutively than the linear regression and logistic regression models. Much hinges on the unobstrusive sigmoid function operator written as σ: 'a neural network can be thought of as a nonlinear generalization of the linear model, both for regression and classification. By introducing the nonlinear transformation σ, it greatly enlarges the class of linear models' (Hastie, Tibshirani, and Friedman 2009, 394). σ, it seems, allows neural nets to work as generalize beyond the linear model.

The common diagrammatic operations of neural nets and other supervised machine learners immediately appears in almost any actual example of a neural net. In the code vignette shown below, the data is a spreadsheet of information about passengers of the Titanic. The `titanic` dataset, like `iris` or `boston` is often used in contemporary machine learning pedagogy. It is for instance, the main training dataset used by (kaggle.com)[http://kaggle.com], an online machine learning competition site I will discuss below . The first few lines of the `R` code load the dataset and transform it into vector space. For instance, variables such as `sex` that take values such as `male` and `female` become vectors of `1` and `0` in a new variable `sexmale`.

```
{r neural_net1, echo=TRUE, message=FALSE, warning=FALSE,
cache=TRUE, fig.cap=''} library(neuralnet) titanic = read.csv('data/titanic3.csv')
titanic_transformed = as.data.frame(model.matrix(~survived +
age+ pclass + fare+ sibsp + sex + parch + embarked, titanic))
head(titanic_transformed) train_index = sample.int(nrow(titanic)/2)
titanic_train = titanic_transformed[train_index,] titanic_net =
neuralnet(survived ~ age +pclass + fare + sexmale + sibsp +
parch + embarkedC + embarkedQ + embarkedS, data=titanic_train,
err.fct='ce', linear.output=FALSE, hidden=5) titanic_test =
titanic_transformed[-train_index,] test_error = round(sum( 0.5 <
compute(titanic_net, titanic_test[,-c(1,2)])$net.result)/sum(titanic_test$survived),
2)
```

The line of the code that constructs a neural net using the `neuralnet` library (Fritsch and Guenther 2012), and the description of the classifier here is a familiar one. Despite its biological inspiration, the `R` formula for the neural net looks very similar to other machine learners. It models whether someone `survived` the wreck of the Titanic in terms of their age, class of fare (`pclass`), sex, number of siblings/spouse (`sibsp`), number of parents/children (`parch`) and port of departure:

```
survived ~ age +pclass + fare + sexmale + sibsp + parch + embarkedC
+ embarkedQ + embarkedS
```

As is normally the case in `R` model formula, the response or target variable `survived` is expressed as a combination of other variables. In this case, the plus sign `+` indicates that the combination is linear or additive. As Hastie puts, 'the central idea is to extract linear combinations of the inputs' or predictor variables. If this model formula looks so similar to other machine learning techniques we have been discussing, what do neural networks add? Why did and do so many people turn to them?

In the code vignette above, the expression `hidden = 5` points to the distinctive architecture of these models, an architecture that does not appear in the model formula but does figure in the lines of Equation 1. The hidden units are indexed in the first line of the model in the variables Z_m. These 'hidden units' are key to neural net since they construct the 'derived features' that the model learns from the input data X. As Rumelhart, Winton and Williams announce the algorithm in a letter to *Nature* in 1986 entitled 'Learning representations by back-propagating errors' :

> We describe a new learning procedure, back-propagation, for networks of neurone-like units. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal 'hidden' units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure (Rumelhart, Hinton, and Williams 1986, 533).

Again, despite the common reference to biology, the description of the 'new learning procedure' starts to sound more like machine learning. There is talk of minimizing a measure of difference between actual and desire output vectors, as well as mention of 'features' and 'weights' (usually a synonym for model parameters: 'the neural network model has unknown parameters, often called weights, and we seek values for them that make the model fit the training data well' (Hastie, Tibshirani, and Friedman 2009, 395)). The novelty consists in the

'hidden' units whose interactions 'represent important features.' In other words, the flat additive combination of features expressed in the `R` model formula above does not convey the interactions of these units. Yet these units can only viably interact in the neural nets because the back-propagation algorithm offers a way to create 'useful, new features' from the data. As Hastie and co-authors put it, 'the units in the middle of the network, computing the derived features Z_m, are called hidden units because the values Z_m are not directly observed' (Hastie, Tibshirani, and Friedman 2009, 393).

The final major form in which neural net appear is the network diagram. Network graphs already appeared in Rosenblatt's perceptron work (Rosenblatt 1958), but they ramify tremendously in the aftermath of back-propagation. Almost every book and article relating to neural net presents some version of the diagram shown in Figure 2.

```
{r plot_neural_net, echo=FALSE, cache=TRUE, fig.cap=''} source('plot_nn.r')
pdf(file = 'figure/titanic_net.pdf') print(plot.nn(titanic_net,
fontsize=8, show.weights=FALSE)) dev.off()
```

The network topology of the model appears in countless more complicated forms, and it practically seems to do several things in neural net literature. First, it presents a layer – the input layer – that indexes something in the world. The input layer, shown as X in the algebraic diagram, becomes like an organ, an eye or perhaps a camera. Early neural net papers on the handwritten digital recognition problem sometimes describe camera's mounted above tables (LeCun et al. 1989). Importantly, it presents an output layer that can contain single or multiple notes. In the `titanic` examples, a single target node (figures as T in the equations 1). In the `MNIST` handwritten digit recognition models, there are usually ten output nodes, one for each of the digits 0 … 9. Second, the network diagram presents some order forms of hierarchical movement. Data and calculation can from bottom to top or vice-versa. (Sometimes the networks are rotated, and the flow is horizontal, but still bi-directional). Bi-directional hierarchical movement is key to the back-propagation algorithm in feed-forward neural nets. Third, it renders visible in principle the vital hidden nodes. Without the hidden nodes, neural nets revert to linear models. With the hidden nodes, the Z_m of the equations 1, neural nets, like some other machine learners we have discussed such as support vector machines, effectively expand the common vector space by constructing new dimensions in it. The derived features or 'learned representations' (to use the language of (Rumelhart, Hinton, and Williams 1986)) can expand indefinitely, according to different network topologies. Hidden nodes and hidden layers can multiply, bringing many new interactions and relations into the model (as we see in more recent revivals of neural net as deep learning (Hinton and Salakhutdinov 2006)).

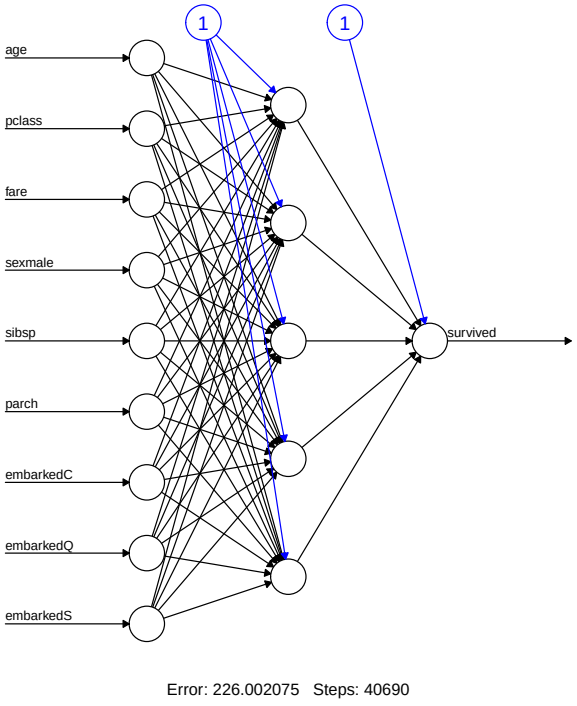

Figure 2: Neural network topology for ‘titanic‘ data

The subjects of a hidden operation

Given the diagrammatic forms of the basic model equations, the network diagram and the operational code comprising the privileged machine, how are subject positions assigned? In early 2002, while carrying out an ethnographic study of 'extreme programming,' a software development methodology popular at that time (Mackenzie and Monk 2004), I spent several months visiting a company in Manchester developing software for call centres. The purpose of the software was to manage 'knowledge' in call centres such that any query from a caller would be readily answered by call centre staff who would query a knowledge management system. This system was marketed on the promise of the neural net. It contained an artificial neural network that learned to match queries and responses over time. The taciturn neural network expert, Vlad, sat in a different part of the room from the developers working on the databases and the web interfaces of the knowledge management system. His work with the neural network was at the core of the knowledge management system yet outside the orbit of the software development team and its agile software development processes. They generally regarded Vlad and the neural net as an esoteric and temperamental yet powerful component, a hidden node we might say, of the knowledge management system. As we have already seen with `kittydar` , today the situation of neural networks has changed. They are no longer exotic or specialized, but both banal and occasionally spectacular.

How would we describe the figure of human machine learner in this setting? In *The Archaeology of Knowledge*, Michel Foucault refers to the 'position of the subject' as an anchor point for the power-laden, epistemically conditioning enunciative functions called 'statements.' When a subject position can be assigned, propositions, diagrams, numbers, models, calculations and data structures can come together in statements, as 'the specific forms of an accumulation' (Foucault 1972, 125). But this anchor point is not a unifying point grounded in interiority, in intentionality or even in single speaking position or voice (that of the machine learning expert, for instance). On the contrary, 'various enunciative modalities manifest his [sic] dispersion' (Foucault 1972, 54). In the mist of this dispersion (a dispersion that is the main focus of this chapter), the position of subject is linked to operations that determine statements that become a kind of law for the subject. As Foucault puts it, in a formulation that effectively anticipates accounts of performativity that gain currency elsewhere several decades later,

> in each case the position of the subject is linked to the existence of an operation that is both determined and present; in each case, the subject of the statement is also the subject of the operation (he who establishes the definition of a straight line is also he who states it; he who posits the existence of a finite series is also, and at the same time, he who states it) ; and in each case, the subject links, by means of this operation and the statement in which it is embodied, his future statements and operations (as an enunciating subject, he

> accepts this statement as his own law) (Foucault 1972, 94–95).

It is fitting that Foucault's examples here include subjects who say things like 'I call straight any series of points that …,' since these are just the kinds of sentences that operate in machine learning. The *operation*, however, is crucial, since the operation opens onto many different practices and techniques (function finding, optimisation, transformation of data into the common vector space, mobilisation of probability distributions as a kind of rule of existence for learnable situations, etc.) that accompany, ornament, armour and diagram the statement. But that choice of illustration is only coincidental. The more substantial point of connection here is the subject-positioning circularity that Foucault posits between the operation and accompanying statement: the subject of the statement is also the subject of the operation.

This might be loosely formalised for any machine learner as follows: the diagrammatic operations of the machine learner support the production of statements; these operations become a way of producing future statements to the extent that the subject of the operation is *also* the subject of the statement. The assignation of a subject position occurs in this forward and backward, feed-forwarding and back-propagating movement between operation and statement. Although the gap between what is done operationally and what is stated might seem small, there are many slippages and divergences in it. The specificity of seemingly minor statements such as 'we see that Net-5 does the best, having errors of only 1.6%, compared to 13% for the "vanilla" network Net-2' (Hastie, Tibshirani, and Friedman 2009, 407) bears within it, in its coupling to all the operations comprising 'Net-5,' a set of determinations and relations for variously positioned subjects. (These might include machine learners, such as Hinton or Lecun, but also U.S. Postal workers). In any concrete situation, in relation to any specific machine learner, the diagrammatic operations and statements will position subjects in specific ways. There is no simple referent here, no simple object facing a knowing or controlling subject, since on this account, the operations and statements in their dispersions, accumulations and distributions overflow any simple dyadic relation between a subject-object or human-machine/world.

Algorithms that propagate machine learning

The coincidence of the subject of the operation and the subject of the statement mobilises machine learners in the sense that it aligns future operations and statements. It puts them in movement but a form of movement propagated by specific operations. Neural nets, especially in their algorithmic operation, make this propagation between statement and operation more tangible. Take the back-propagation algorithm. In their initial publication, Rumelhart, Hinton and Williams conclude:

> The learning procedure, in its current form, is not a plausible model of learning in brains. However, applying the produced to various

> tasks shows that interesting internal representations can be constructed by gradient descent in weight-space, and this suggests that it is worth looking for more biologically plausible ways of doing gradient descent in neural networks (Rumelhart, Hinton, and Williams 1986, 536).

In some respects, this is the standard disclaimer: the brain has only analogical relevance to machine learning, although it can certainly be a source of novel mechanisms ('biologically plausible ways of doing gradient descent'). At the same time, if a machine learner can construct 'interesting internal representations … in weight-space,' then the process whereby these representations become interesting will be of great interest. That is, when the operations of the algorithm – in this case, back-propagation – become a focus of interest or perhaps a matter of concern (Stengers 2005, 161).

How could an algorithm such as back-propagation diagram the coincidence of subject of operation and subject of statement that defines machine learners? The pivotal point here is error. Errors, error rates, training error, test error, validation error: these are just some of the errors that criss-cross between human and machine learners. Errors move between operations and statements. While not all of these errors figure directly in the algorithms, the The automatic character of most machine learners derives from the way they update model parameters in the light of incoming data, and errors or differences between expected and actual outputs. Every machine learner makes different determinations in relation to model parameters and errors. The distinctive feature of neural nets, at least in their ordinary 'vanilla' forms, consists in their use of gradient descent to minimise errors by adjusting the weights (or parameters) of all the nodes (or linear models) comprising the machine learner. Adjusting the parameters of the nodes in the neural net hardly seems a striking achievement. If we, however, look more closely at the way in which the 'representations' are iteratively constructed in neural nets, something more interesting begins to emerge from the forwards and backwards movement of this algorithm. We have already seen something of the forward movement. It is defined by the equations 1 that move data through a succession of layers and their nodes. Conversely, the equations 3 specify the way in which the weights of various nodes in the output layer nodes and the hidden layer nodes in a neural net are updated during the back-propagation phase of the iteration:

$$\begin{aligned} \beta_{km}^{(r+1)} &= \beta_{km}^{(r)} - \gamma_r \sum_{i=1}^{N} \frac{\partial R_i}{\partial \beta_{km}^{(r)}} \\ \alpha_{ml}^{(r+1)} &= \alpha_{km}^{(r)} - \gamma_r \sum_{i=1}^{N} \frac{\partial R_i}{\partial \alpha_{km}^{(r)}} \end{aligned} \tag{3}$$

(Hastie, Tibshirani, and Friedman 2009, 396)

There are many different variables in the equations 3. They include measures of error (R), values of the weights or parameters in various layers of the models (β, α), variables that count the number of iterations the model has performed (r, $r + 1$) and the functional operators such as summation ($\sum$) and partial differentiation (∂). The usual indexical relations to data appear in N, the number of rows or observations, as well as K, the number of outputs and M, the number of nodes in the hidden layer. In the densely iconic and indexical diagram of equation 3, the interweaving of the subscripts in the two lines show that the ways in which values of the parameters in the models of the first two lines of equation 1 are varied as the model is trained on the input data. The two lines of equation 3 specify how first the values of the parameters of the K nodes of the output layer should be altered in the light of the difference between the actual and expected output values, and then how the weight of the M nodes of the hidden layer should be adjusted. Once these are adjusted, the forward movement defined by equations 1 begin again. In adjusting weights in the layers, back-propagation always starts at the outputs, and travels back into the net towards the input layer at the bottom (or left hand side in diagram 2. 'It is as if the error propagates from the output y back to the inputs and hence the name *back-propagation* was coined' writes Alpaydin (Alpaydin 2010, 250). As in any gradient descent operation (see chapter **??**), a rate parameter (here γ) regulates the speed of descent. If γ is too large, the gradient descent might jump over a valley that contains the absolute minimum error; if γ is too small, then the descent is too slow for fast machine learning. In some versions of neural net, the value of γ changes each at iteration r of the model.

If back-propagation was formulated in the 1980s (and indeed, was already known in 1960), what do we learn from its current re-iterations? Given the effort that went into crafting neural nets to recognise handwritten digits during the 1980s and 1990s, what does the revival of neural nets suggest about machine learning? From the early publications such as (Rumelhart, Hinton, and Williams 1985) on, the layered composition of the model has been linked to architectural considerations. As Hastie and co-authors write:

> The advantages of back-propagation are its simple, local nature. In the back propagation algorithm, each hidden unit passes and receives information only to and from units that share a connection. Hence it can be implemented efficiently on a parallel architecture computer (Hastie, Tibshirani, and Friedman 2009, 397).

These practical considerations have different significance in different settings. Some of the current iterations of neural nets in deep learning rely on massively parallel computing architectures (for instance, Andrew Ng's GoogleX Youtube video project). Yet the information sharing that happens during back-propagation might also encompass the human others of neural nets. The efficient parallel implementation in computing architecture affects, I would suggest, human and non-human machine learners in different ways. Given that equations

1 and 3 seem to function automatically, without any hand in their movement, how could humans fit here?

The competitions as examination

Again, the treatment of errors provides a useful thread to follow here. At almost step of its development as a field, and in almost every aspect of its operation, competitions conducted through forms of examination of error rates lie at the intersection of human and machine learners. The learning of machine learning seems to incarnate learning through examination. We saw above that competitions to recognise handwritten digits constituted a focal point for neural nets during the 1990s. Much of the discussion of neural net in *Elements of Statistical Learning* revolves around a competition conducted in 2003. As we will soon see, machine learning competitions more generally form one of the principal ways in which people and machines come together. What can we learn from such competitions about subject positions in machine learning?

If we take a typical contemporary machine learning competition, something of the backwards and forwards movement between human and machine machine learners starts to appear. In

> Predict if an online bid is made by a machine or a human

> Ever wonder what it's like to work at Facebook? Facebook and Kaggle are launching an Engineering competition for 2015. Trail blaze your way to the top of the leader board to earn an opportunity at interviewing for a role as a software engineer, working on world class Machine Learning problems (**???**)

The competitions all take the form of examinations that set a problem, define some limits or constraints on its solution, and create a space that qualifies, ranks and displays the work of individuals or groups in relation to the problem. Machine learning competitions furnish a contemporary instance of the practices of examination that Foucault described in *Discipline and Punish*:

> The examination combines the techniques of an observing hierarchy and those of a normalizing judgement. It is a normalizing gaze, a surveillance that makes it possible to qualify, to classify and to punish. It establishes over individuals a visibility through which one differentiates them and judges them. That is why, in all the mechanisms of discipline, the examination is highly ritualized. In it are combined the ceremony of power and the form of the experiment, the deployment of force and the establishment of truth. At the heart of the procedures of discipline, it manifests the subjection of those

> who are perceived as objects and the objectification of those who are subjected. The superimposition of the power relations and knowledge relations assumes in the examination all its visible brilliance (Foucault 1977, 183–185).

In this formulation, Foucault links epistemic and operational aspects of examination. Examinations combine ceremony, ritual, experiment, force and truth, as well as processes of subjectification and objectification. If, as already been suggested above, the pack-ice of machine learning formed around neural nets during the 1990s, we might say that the re-solidification of neural nets today in high profile deep learning projects can be understood in terms of a much more pervasive practice of examining and testing occurring through machine learning training and competitions. How would such a process be legible? The forms of visibility created by competitions, the ways in which they individualize and document machine learners (often by proper names), and that maximise extractions of force, time, propensities and aptitudes.

In competitive examinations, we might see attempts to construct 'parallel architectures' for people doing machine learning. Machine learning competitions effectively implement a parallel architecture for machine learners with limited communication.

From this perspective, it should come as no surprise that machine learning itself as a predictive practice has become a matter of prediction and optimisation. In machine learning and data mining, as in many other domains, competitions are one way that highly technical challenges are addressed. Often these competition are associated with academic events such as conferences. Sometimes they are associated with programmer recruitment, as in the 'Google Code jam' (**???**) that each year attracts tens of thousands of programmers. Increasingly, programming work is also allocated through competitive outsourcing sites such as Topcoder, 'the world's largest competitive commmunity for software development and digital creation' (**???**). A social media platform called 'Kaggle' stages machine learning competitions (**???**). The list of competitions on Kaggle provides a general snapshot of anticipatory projects in the world of big data. Kaggle sponsors data-mining or statistical analysis competitions ranging across health data, chess ratings, tourism, grant application outcomes, dark matter, essay scoring and the progression of HIV infections. Like bitly.com's Hilary Mason, Kaggle's founder and CEO, Anthony Goldbloom, attracts media attention. In 2012, he was one of *Forbes* magazines '30 under 30' leading technology entrepreneurs (**???**).

In 2011, the data blog Dataist.com sponsored a Kaggle machine learning competition called 'R Package Recommendation Engine.' In the case of the 'R Package Recommendation Engine' competition, competitors were supplied with metadata from the R CRAN repository describing which of the several thousand R packages available there were installed by 52 R users. Competitors were tasked to use this so-called 'training data' to build a predictive model of what program-

mers would do with R. Having modelled this sample population, competitors were meant to predict what packages would be installed by another a much larger group of R users, describing in the 'test data.' The underlying idea here is that a 'recommendation engine' suggest to new users of R what R packages they should install. The predictions produced by the 'R Package Recommendation Engine' would in some ways, however modestly, address an object - machine learning - that is problematically multiple and open-ended. In this competition, what programmers do as they install - and perhaps use - R packages become features or predictors for a machine learning problem. It seems then that one response to the newly acquired popularity of R in the regime of anticipation is an attempt to re-anchor it in the stabilizing form of a machine learning model. In other words, the possibility of the divergent, free-associating play of methods in R is reorganised by machine learning to predict what programmers will want. Predictive practice can be applied to the agents of anticipation themselves.

Winners of Kaggle competitions often write statements describing what they did to win. The winner of the 'R Package Recommendation Engine' competition, under the name 'OneOldDog,' describes himself as 'a computer scientist with over 48 years of programming experience and more than 25 years doing machine learning and predictive analytics. Now that I am retired from full-time employment, I have endeavored to keep my skills sharp by participating in machine learning and data mining contests' (**???**). OneOldDog goes onto to describe how he used the 'same core forecasting technology that I've employed in other contests.' The third placed competitor, 'lib-GUNDAM,' is in a very different situation: 'I recently got my Bachelor degree from National Taiwan University (NTU). … Noticing that the machine learning society lacks software on various kinds of algorithms that may be beneficial to our daily life, I am now developing pieces of tools that compile various state-of-the-art algorithms performing well in many data or contests. One of these pieces is lib-GUNDAM' (**???**). Using his software lib-GUNDAM, lib-GUNDAM managed to develop a successful model to predict what software packages other programmers should use. The contrast between OneOldDog and lib-GUNDAM is marked by differences in age, differences in software production (old vs fresh code), reasons for participation (keep skills sharp vs the needs of 'the machine learning society'). If OneOldDog's enthusiastic participation (he made 55 different models) seems to be a return to a familiar scene (more than 25 years of machine learning), lib-GUNDAM he/she writes code 'beneficial to our daily life' because it is 'state-of-the-art.'

There are other examples of this recursive application of predictive practice to agents of anticipation. For instance, a later competition at Kaggle was sponsored by Facebook, under the banner 'Facebook Recruiting Competition: Show Them Your Talent Not Your Resume' (**???**). Given a dataset of describing friend-relations between the people ('a directed social graph'), the challenge is 'to make ranked predictions for each user in the test set of which other users they would want to follow' (**???**). The prize for this competition is not money, but a job interview at Facebook. This is another case where the agents of anticipation, those who implement predictivity, show how they are in turn subjectified

through their own attachments. In both cases - the package recommendation competition or the Facebook recruitment competition - there is a striking symmetry between the situation faced by Facebook users, and R programmers, the 'useRs'. Once the practices of programming are also processed in a predictive analytics recommendation engine, unruly predictive practices can be brought into the regime of anticipation itself. This is both stultifying and exciting since it places programmers themselves in the same impasse as all the other inhabitants of regimes of anticipation. UseRs become more like users with calculable response rates and retention ratios. Self-abductively, useR!s become users.

Who is a machine learner?

Competition and the work of optimisation

Programming back-propagation

$$z_h = \frac{1}{1 + exp[-(\sum_{j=1}^{d} w_{hj} x_j + w_{h0})]}, h = 1..., H \tag{4}$$

(Alpaydin 2010, 246)

$$y_t = \frac{1}{1 + exp([-(\sum_{h=1}^{H} v_h z_h^t + v + 0]} \tag{5}$$

(Alpaydin 2010, 252)

The privilege of machine learning

Conclusion

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