Quantitative Monographs
Introduction to Deep Learning

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Expert call on machine learning

We are happy to have hosted a call with Matthew Dixon, Professor of Finance & Statistics at the Illinois Institute of Technology on the topic of deep learning in finance. This note is our edited transcript of the call where we have added in the contents of the slides.

Introducing deep learning

The key idea of deep learning is to build a multi-layer network and these hierarchical layers represent a very high dimensional input space. Deep learning doesn't make sense when you only have a small amount of input data. Even daily stock return data might not be enough.

Introduction[1]

This is a presentation on deep learning in finance. The main takeaway from this talk is going to be identifying and understanding where deep learning makes sense to apply within finance and, in some sense, that means untying some of the rhetoric which has been coming from Silicon Valley around this topic.

Machine learning is an algorithmic class (Breiman, 2001) of models that differ from the classical statistics models in that no assumptions about the data generating process are made. Unlike, for example, Brownian motion and other typical models that have come to be celebrated within finance, this class of model fitting or *learning* does not assume any (distributional) properties of the data that it is fitted to, thus giving rise to a much wider class of modelling capacity.

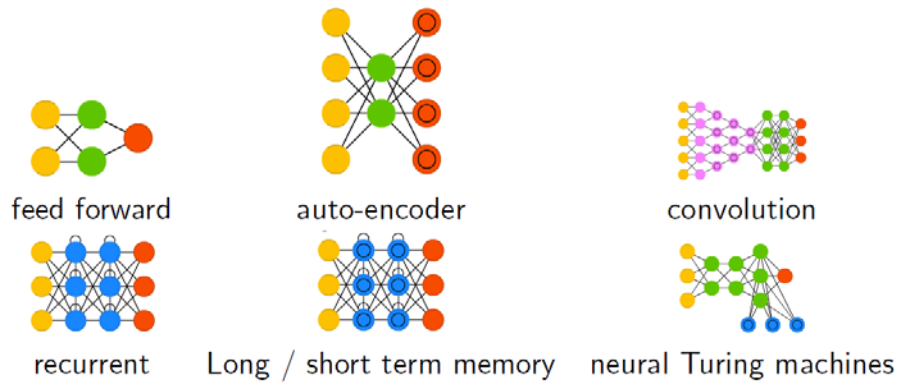
Deep learning requires lots of input variables

The key idea behind deep learning is the use of hierarchical layers to represent (usually) a very high-dimensional *input* space[2]. It really doesn't make sense to use deep learning if you have a small number of input variables (or *features*). I'm going to discuss and provide a little insight into how deep learning works as opposed to just presenting performance results (which will also be done towards the end of the presentation).

Traditional metrics fail in high dimensions

We're going to depart a little from the traditional statistical metrics such as R^2, *p*-values, *t*-values and the concept of statistical significance overall. These often fall short as a measure of out-of-sample forecasting accuracy, particularly for high dimensional problems. Instead we turn to a well-worn concept within pattern recognition and machine learning known as the *bias-variance trade-off*. The idea behind it is to control how well the model performs out-of-sample and also to control the difference in accuracy of the model in-sample and out-of-sample.

Figure 1: Deep Architectures in TensorFlow



Source: Matthew Dixon. Some of the most commonly used deep learning architectures for modelling.

Machine learning is good at avoiding overfitting

And that's really what machine learning does well – it enables us, through a framework which is based on information theory, to *avoid overfitting*. Of course, it does require some skill; there are some techniques that we'll just touch on during

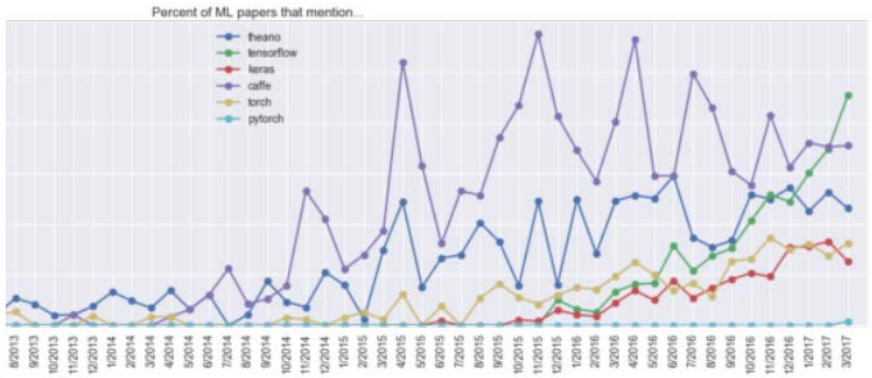
[1] This is our edited transcript of the Expert Call with Professor Matthew Dixon. Produced with his permission. We have edited some of the slide content and equations into the text for clarity.
[2] Input space is the set of all possible realisations of the input variables.

this presentation and as we go along I'll leave some pointers for anyone who is interested in learning more.

Why I'm giving this talk in part is because we've seen a surge of interest in machine learning algorithms (partly driven by the Googlization trend) and a number of these include various neural network architectures (some of which are illustrated in Figure 1). A lot of these architectures are now very much in place and used widely in practice: whether it's speech recognition on your phone; whether it's image recognition; whether it's self-driving cars. However, there are certain subsets of these architectures which are more relevant to finance, such as recurrent neural networks, which can handle time series data; more standard architectures (e.g. feed forward) might also be useful. All of these techniques can be regarded as a form of data compression, which is a way of taking fairly noisy data and compressing it down into several hundred parameters.

Google's TensorFlow, which is a software library for machine learning, has been growing rapidly (see Figure 2) and a number of deep learning researchers are reporting to be using this. We are seeing an age where the volume of data is large and it's also cheap to do large computation, which allows us to be a little bit more relaxed about our data assumptions. That's what machine learning really is: it is us bypassing any parametric assumptions for the data and instead jumping forth with all our heavy machinery, taking advantage of our multi-core computing era that we are now in.

Figure 2: Growth of TensorFlow



% of papers	framework	has been around for (months)
9.1	tensorflow	16
7.1	caffe	37
4.6	theano	54
3.3	torch	37
2.5	keras	19
1.7	matconvnet	26
1.2	lasagne	23
0.5	chainer	16
0.3	mxnet	17
0.3	cntk	13
0.2	pytorch	1
0.1	deeplearning4j	14

Source : Andrej Karpathy's arXiv-sanity database

Source: Matthew Dixon

Examples using an unfair coin

I'm going to use a coin tossing as a way to introduce some of the theory and terminology that we're going to use for deep learning. Of course, many will be familiar with the main ideas of machine learning, but it doesn't hurt to tie this back to probability theory in an intuitive way.

Let's walk through a couple of examples slowly building up the complexity before we get to machine learning, deep learning, and some of the key concepts that are

crucial to learning in general. Then I'll talk more about the architecture side and application within equity research.

Running example: coin tossing experiment

The running example through this presentation will be an experiment of tossing a coin that shows heads with probability $p \in [0,1]$. We introduce a random variable Y, defined on a sample space, which contains a head or a tail, $\Omega = \{H, T\}$. We therefore have that Y is a Bernoulli random variable with probability mass function, f, so that:

$$f(Y=1) = P\{H\} = p \;\; and \;\; f(Y=0) = P\{T\} = 1-p$$

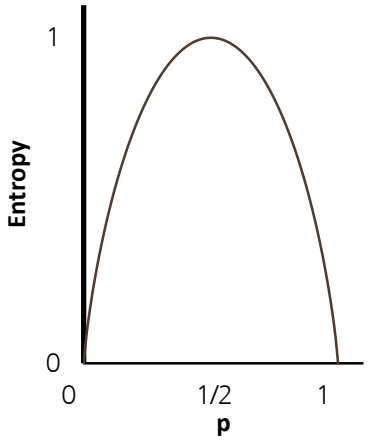
Entropy is a key concept underlying machine learning

The key concept underlying machine learning is the concept of entropy brought to us by Claude Shannon in his 1948 Bell System Journal paper. The idea is very simple: we want to understand how many bits of information we need. In this case we have a coin – which is a simple piece of binary information and we want to encode how much uncertainly there is about the experiment. The entropy of the binary variable Y under f is:

$$\mathcal{H}(f) = -p\log_2 p \; -(1-p)\log_2(1-p) \leq 1bit \; [3] \qquad (1)$$

Figure 3 plots the entropy of Y as a function of the probability of getting a head, p, showing that the entropy (or uncertainy) is maximum when we have a fair coin and decreases to zero when the coin always shows either a head or a tail.

Figure 3: Entropy as a measure of uncertainty



Source: UBS Quant. The figure illustrates the entropy of a binary random variable.

For an arbitrary density function f (i.e. not necessary a Bernoulli mass function), the entropy is defined as minus the expected value of the log density:

$$\mathcal{H}(f) = -\mathbb{E}_f(log_2 f).$$

In the simple case of a Bernoulli variable, it is easy to see that we recover our definition of binary entropy (see Equation 1), which, of course, is less than or equal to one bit (see Figure 3). In the general case of N states the entropy is less than or equal to $\log_2 N$.

We consider our random variable more formally as a map from the sample space Ω to some subset of the real line, $Y: \Omega \to \Upsilon \subset \mathbb{R}$ (although Y will only take on discrete values). We're going to assume that there's a density function for this random variable, which is parameterised by a parameter θ: $f(y|\theta) = P(\omega \in \Omega: \Upsilon(\omega) = y)$. The meaning of the parameterization will become very clear in a moment, when we look at machine learning, because the goal of machine learning is essentially to learn a set of parameters.

Machine learning is really about minimising cross-entropy

Cross-entropy is the last key concept we need to introduce, which will allow us to quantify how different two probability distributions are. This is important in machine learning because our aim is to approximate the true (but unknown) distribution $f(y|\theta)$ with something we can estimate, $f' = f(y|\theta')$. More formally, we wish to minimise the cross-entropy between two probability distributions f and f', which is defined as the negative expected value of the logarithm of $f' = f(y|\theta')$, where the expectation is taken under the true distribution f:

$$\mathcal{H}(f,f') = -E_f[log_2 f'] \; = -\sum_y f(y|\theta) log_2 f(y|\theta') \geq \; \mathcal{H}(f)$$

[3] Entropy is usually measured in *bits* – this is the case when log-base 2 is used. One can also use a different base; common examples include the natural log (units of entropy are then called *nats*) or log base 10 (*bans*).

Notice that the cross-entropy of f with itself is simply the entropy: $\mathcal{H}(f,f) = \mathbb{E}_f(log_2 f) = \mathcal{H}(f)$.

Going back to our unfair coin example, we estimate $f(Y=1|\theta') = p_{\theta'}$ so that it matches the underlying true distribution, $f = f(y|\theta)$ as closely as possible. To this end, given a set of realisations $\boldsymbol{y} = \{y_1, \ldots, y_n\}$ of our random variable Y, we "learn" the best model $\hat{f} \coloneqq f(y|\hat{\theta})$ which minimises the cross-entropy:

$$\hat{\theta} \coloneqq \underset{\theta'}{\operatorname{argmin}}\, \mathcal{H}(f,f')$$

Log-likelihood as approximation of cross-entropy

It is very common in applications, and in particular for a lot of financial and econometrics modelling, to assume that the log-likelihood is a good approximation of the negative cross entropy[4]:

$$-\mathcal{H}(f,f') \approx l(\theta'|\boldsymbol{y}) = \frac{c}{n}\sum_{i=1}^{n} \ln f(y_i|\theta')$$

That's one of the reasons why the log-likelihood function is so heavily used in finance – for example, maximum likelihood methods are commonly used to estimate the parameters in various geometric Brownian motion models.

Back to our coin tossing experiment, suppose we have a sequence of ones and zeros, each of which is a realisation of Bernoulli trials (e.g. **y** = {1, 0, 1, 1, 1, 0, 1, 0}), then the log-likelihood becomes:

$$l(\theta|\boldsymbol{y}) = \ln\left(p_\theta^{y_1}(1-p_\theta)^{y_1} \times \ldots \times p_\theta^{y_n}(1-p_\theta)^{y_n}\right)$$

$$= \frac{1}{n}\sum_{i=1}^{n} y_i \ln p_\theta + (1-y_i)\ln(1-p_\theta)$$

Vanilla maximum likelihood often results in overfitting…

That is where regularisation comes into play

In many circumstances however the maximum likelihood approach is not a good approximation of the cross-entropy. Another problem associated with maximum likelihood is that it often leads to overfitting. Various **regularisation techniques** have been developed to try and overcome some of these problems, and this continues to be an active area of machine learning research. A simple example of regularisation is the well-known Akaike Information Criteria (AIC, a form of L2 regularisation), introduced in the 1970s.

Before we jump into machine learning, it is helpful to build up our coin tossing experiment one more level. This time we assume that we have two coins and let X and Y be two random variables that count the number of heads generated by each coin. Furthermore, the two coins are correlated[5] and we assume that there is conditional density function for Y given X: $f(y|x,\theta)$ with $f(y=1|x,\theta) = p_\theta(x)$ In other words, the number of heads generated by one coin is dependent on the number of heads generated by the other coin. This stylised example of correlated coins is useful for machine learning as it illustrates the concept of observing one variable and then making a statement about the other one.

Same as before, we can write the cross-entropy between the true density and some approximation of it, $f' \coloneqq f(y|x,\theta')$ as:

[4] c is a constant equal to the conversion from natural log to log base 2

[5] The UBS Quant Team has discussed how you can create correlated coins and we have to admit we've failed to come up with a suitable physical mechanism. It still works as a thought experiment though.

$$\mathcal{H}(f(\cdot\,|x), f(\cdot\,|x,\theta') = -p(x)\log_2 p_{\theta'}(x) - \big(1 - px(x)\big)\log_2(1 - p_{\theta'}(x)).$$

Given a set of realisations of X and Y, $D = \{x_i, y_i\}_{i=1,\dots n}$, the likelihood then becomes $l(\theta|D) = \frac{1}{n}\sum_{i=1}^{n} \ln f(y_i|x_i,\theta')$ and is maximised for a choice of $\theta = \hat{\theta}$.

What is machine learning…?

Machine learning is all about finding the map between X and Y, where X, does not need to be the outcome of a coin, but some real input space, which we assume to be high dimensional. As a simple analogy one can think of the outcome of one coin as being dependent on hundreds or thousands of other coins. What we are then trying to do is to construct a nonlinear predictor, $\hat{Y}(X)$, of an output, Y given a high dimensional input matrix[6] X. Put differently, machine learning is just the study and the construction of an input/output map.

… A map from a high dimensional input space to an output space

The output variable Y can be continuous, discrete or mixed. If Y is discrete then we call this a *classification problem*; otherwise we call it a *regression problem*. We'll see later that in simple cases, this map reduces to an ordinary linear regression or a logistic regression (a type of semi-affine transformation).

Deep predictors use a sequence of hidden layers

What is a deep predictor? A deep predictor is trying to approximate this map between input data and some output using a sequence of *hidden layers*. We can assume that there are L layers and there's now a composition of some multivariate functions between the layers taking our input data and transforming them through some semi-affine function and composing them together to give us our sequence of layers.

Definition – Deep Predictor

A deep predictor is a particular class of multivariate function F(X) constructed using a sequence of L layers via a composite map

$$\hat{Y}(X) \coloneqq F_{W,b}(X) = \big(f^{L}_{W^L,b^L} \circ \cdots \circ f^{1}_{W^1,b^1}\big)(X)$$

$f^{l}_{W^l,b^l} \coloneqq f^{l}(W^l X + b^l)$ is a semi-affine function, where f^l is univariate and continuous.

$W = (W^1, \dots, W^L)$ and $b = (b^1, \dots, b^L)$ are weight matrices and offsets respectively.

The theory behind deep learning is now well understood

"bio analogy" is no longer necessary

There is a lot of theory behind deep learning and it's well understood why applying such transformations to the input space makes sense and works in practice (i.e. it's not a purely empirical result that has seen great success in applications). What we need to do is learn from observed data the weights, W, and biases, b, that link the nodes in the neural network from one layer to another. The analogy with neurons - the "bio analogy" - may have served us well in the past, but isn't needed now. I think we understand deep learning enough in mathematical terms that we needn't rely on biological analogies to explain things, which I think comes with some relief to those that have given up on genetic algorithms and that whole area of bio-inspired algorithms. There's no doubt in my mind that, really, these neurons are just transformations with some semi-affine function (whether the brain itself does that is questionable).

The structure of a deep prediction rule can be written as a hierarchy of $L-1$ unobserved hidden layers (and a final output layer, giving us a total of L layers), $\{Z^l\}_{l=1,\dots,L-1}$, given by:

[6] We are now using X as the data matrix, not as a random variable.

$$\hat{Y}(X) = f^L(Z^{L-1})$$
$$Z^0 = X,$$
$$Z^1 = f^1(W^1 Z^0 + b^1),$$
$$\ldots$$
$$Z^{L-1} = f^{L-1}(W^{L-1} Z^{L-2} + b^{L-1})$$

The functions $f(.)$ are known as *activation functions*. Depending on the application (classification vs regression), popular choices include rectified linear unit ($ReLU$), hyperbolic tangent ($\tanh(.)$), max and softmax (usually used in the final/output layer in classification problems).

There are a number of questions that come to mind: How many layers do I need in my application? How do I fit these weights and biases? The answers to such questions still remain a challenge in machine learning; however the availability of software, such as TensorFlow, provides us with a very efficient way to solve some of these problems.

Why does deep learning work? Let us consider the two-dimensional space as shown in Figure 4. We have two lines labelled one for the red line and zero for the blue. These are linked to coordinates in this two-dimensional space.

We want to separate the input space in order to distinguish between the blue line and the red line. If we were going to use a linear method such as logistic regression as shown in Figure 5, we would struggle to accurately classify these two lines.

Figure 4: Problem

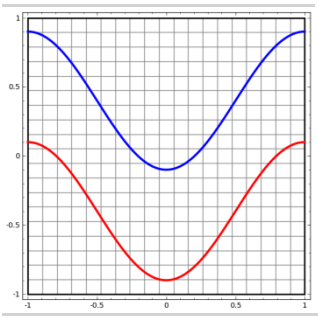


Figure 5: Linear method

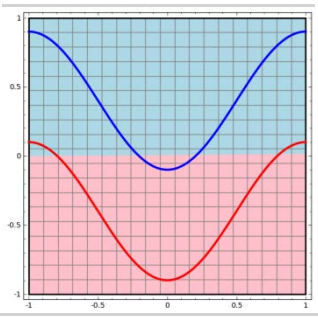


Figure 6: Transformation

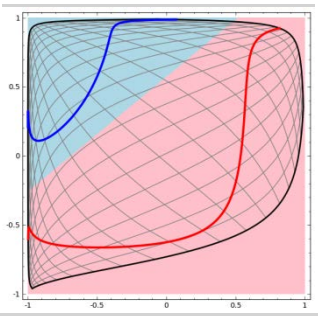
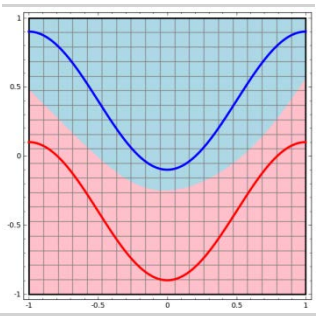


Figure 7: Final result



Source: Chris Olah. Used with permission

What do hidden layers do?

What a hidden layer would do is apply a semi-affine function, transforming the input space into something that the output layer could use. As Figure 6 demonstrates, by doing this we are able to transform the input space so that it is easy for a linear separator to clearly discern between the red and the blue line. Translating back to the original space (Figure 7) we see that the boundary is no longer linear. The more layers we have, the more complex (and non-linear) a transformation you tend to do, especially when used in a much higher dimensional space.

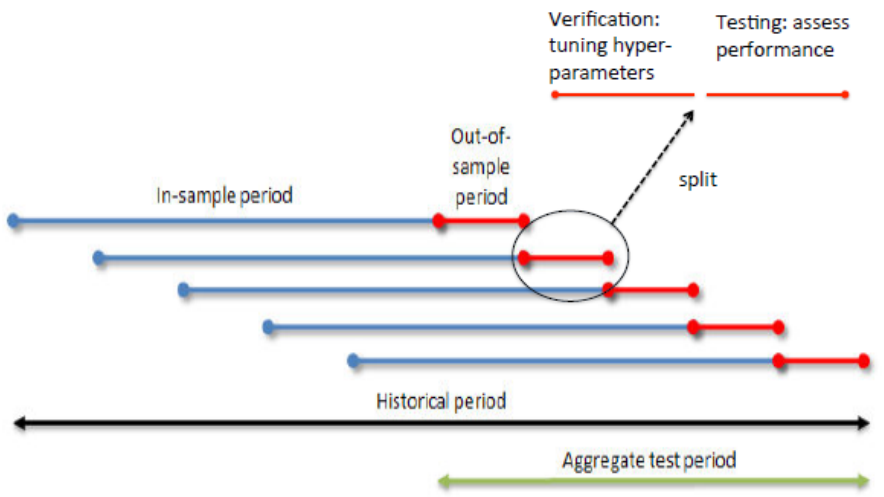
This simple example illustrates the role of hidden layers and therefore the main ideas of deep learning. Of course, different learning methods perform different types of transformations. There is still a lot of work to be done on exactly how these are done and in particular what types of transformations would be most useful for noisy financial data, which in most cases comes in the form of time series. What is special about time series modelling is that we can't simply apply the standard methods for choosing appropriate parameter values, such as (K-fold)

cross-validation or bootstrapping, as those will break the temporal structure of the data.

Cross validation for training time-series models

To train a time series model we are going to use a technique known as *time series cross-validation*, which is demonstrated in Figure 8. We will assume there's a period of historical data and on a rolling (or expanding) window basis, we use part of this historical data for **in-sample training** of out model; *this is known as the training set*. We have an out-of-sample period which the model has not seen that will be used for **tuning** the parameters of the neural network; *this is known as the validation set*. Ideally, we would like to keep some of the out-of-sample period datapoints to **test** the final (tuned) model; *this is known as the test set*. This will give us an unbiased view of how accurate the model will perform in the future (as the tuned architecture hasn't seen it before).

Figure 8: Time series cross validation



Source: Matthew Dixon, used with permission. Times series cross validation, also referred to as walk forward optimization, is used to avoid introducing look-ahead bias into the model.

We'll keep sliding the window forward. As with optimization there are variants on this. This approach I think is common to us and seen before in finance, although I have seen still an alarming number of research papers reporting in-sample model performance and not assessing over the moving time frame what is the real performance of a strategy.

Model training

Given some data, $D = \{Y_i, X_i\}_{i=1,\ldots,n}$ the first part of the process – model training, is simple – it is simply an optimisation problem that involves minimising some loss function $\mathcal{L}$, solving for the weights W and bias terms b:

$$\underset{\mathrm{W,b}}{\operatorname{argmin}} \sum_i \mathcal{L}\left(Y_i, \hat{Y}^{W,b}(X_i)\right)$$

When Y is categorical, we will use the negative log-likelihood as approximation of the cross-entropy.

$$\mathcal{L}\left(Y_i, \hat{Y}^{W,b}(X_i)\right) = -y_i \log \hat{Y}^{W,b}(X_i) + \phi(W, b)$$

When Y is continuous a popular choice of the loss function is the $L2$ norm an error metric, in which case the problems simplify to traditional least squares (with a penalisation term):

$$\mathcal{L}(Y_i, \hat{Y}^{W,b}(X_i)) = \left|\left|Y_i - \log \hat{Y}^{W,b}(X_i)\right|\right|_2^2 + \phi(W, b)$$

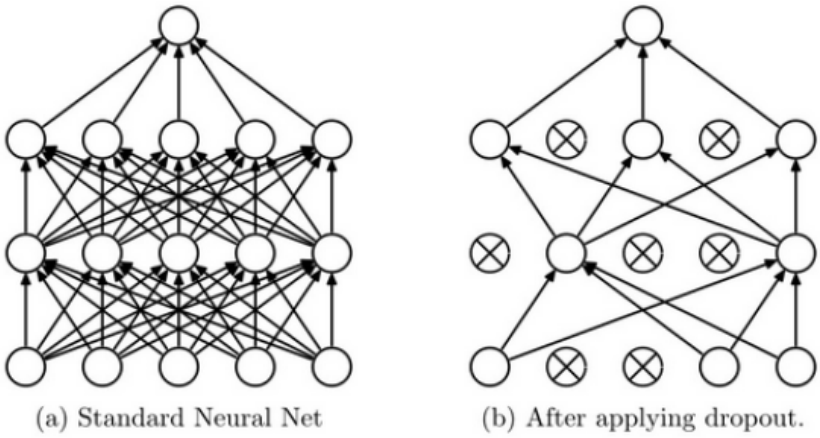
TensorFlow to estimate the weights and bias terms

Regardless of the choice of a loss function, to be able to find a minimum, we need to compute its gradient and this is where make use of the power of Google TensorFlow.

Dropout: regularisation technique to prevent overfitting

I'll tie that in with a technique which is called *dropout*, illustrated in Figure 9, where we're now trying to take an average of sub-dimensional models. We're dropping out some of the nodes, we're measuring accuracy of the model, and essentially we're repeating this over and over again like an ensemble approach with some reduced model and trying to assess the performance under various different randomly eliminated nodes. This is a technique which has been very effective in reducing the dimension of the network and variable selection, and it leads to improved performance out of sample.

Figure 9: Dropout



Source: Matthew Dixon. Used with permission.

Dropout can be combined with stochastic type of search:

$$D_i^l \sim Ber(\theta)$$
$$\tilde{Z}^l = D^l \times Z^l, \quad 1 \leq l \leq L$$
$$Z^l = f^l(W^l \tilde{Z}^{l-1} + b^l) \,,$$

and can be thought of as a ridge regression with a g-prior. In other words, there is a Bayesian of interpretation to this technique, details of which can be found in a paper by Polson and Sokolov (2017)[7].

An example: portfolio returns

Predicting the direction of the return of a portfolio

As an example we are going to consider a portfolio with a position in n stocks. We want to make an investment decision every day based on using a large number of stocks over history. We are going to attempt to apply deep learning to the problem capturing directional changes in the portfolio returns. Specifically, we're trying to make a decision on whether to long or short the entire portfolio based on our prediction of the next-day portfolio return.

[7] Polson, N & Sokolov V. (2017). Deep Learning: A Bayesian Perspective. Available at https://arxiv.org/abs/1706.00473

We calculate the portfolio returns using equal weighting. The data we are going to use is daily data. What we want to do is use the deep network to maximize the capacity to predict the next day portfolio returns given our cross-sectional market data. So, given the returns across all the stocks, what can we say about the overall portfolio return in the future?

Deep learning is very data hungry

It is worth stopping to mention here, with this notion of horses for courses, deep learning does very well when there's a high-dimensional input space and there's a lot of data, a lot of historical data. Now, we're stretching it a bit with daily data, and I've actually been working a lot more with intraday data and the reality is that deep learning is very data hungry and to avoid over-fitting we really need to train on the large samples.

It doesn't make sense to apply deep learning as a predictor where we might use an autoregressive, ARIMA or GARCH-type model; a univariate type of model. It makes sense to use it in a highly multi-variate model, in this case a classification model based on a large number of inputs. And large here is hundreds, ideally thousands or tens of thousands.

We define our stock returns as $r_i(t)$ and hence our portfolio return is

$$r_P(t) = \sum_{i=1}^{n} w_{i,t} r_i(t), \quad w_{i,t} = \frac{1}{n}$$

The observed data consists of the historical return of all the stocks, and then we are going to label the data with a categorical variable

$$Y_t = \begin{cases} 1, & r_p(t+1) > \epsilon \\ 0, & |r_p(t+1)| \leq \epsilon \\ -1, & r_p(t+1) < -\epsilon \end{cases}$$

The goal will be to learn the map $\hat{Y}_t = F_{W,b}(X_t)$. ϵ is a threshold chosen from the training data to avoid an imbalance of the labels.

Hence we are going to design a simple strategy $S(Y_t)$ which choses whether to hold a long, neutral or short position in all the stocks over the next period.

$$w_{i,t+1} = S(Y_t) = \begin{cases} \frac{1}{n}, & Y_t = 1 \\ 0, & Y_t = 0 \\ -\frac{1}{n}, & Y_t = -1 \end{cases}$$

This example is trying to exploit the high dimensions in our data set.

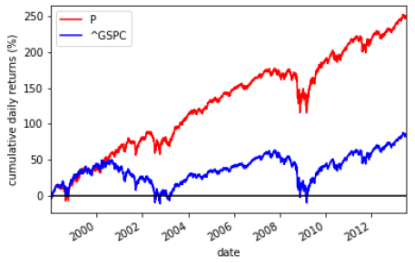
The returns of the portfolio, P, are shown in Figure 10. It's a subset of around 385 stocks from the S&P where we have a history over a 15-year period.

The experiment is set up to use a training horizon of 3,840 days, a test horizon of 30 days and then retraining the model every 30 days over 300 test observations. We avoid look-ahead bias by normalizing the data based on means and standard deviations from the training data. This is a common mistake we often see as we tend to normalize based on the full data, not just on the training data. If we use the full data set then we have a look-ahead bias.

In order to benchmark our deep learning model we will use logistic regression with regularization (to deal with multicollinearity) as a baseline classifier. Our neural network has three hidden layers with a "tapered" feed-forward architecture (with 200, 100, 50 neurons in each layer). This is a well-known successful configuration. This example does not consider how to capture auto-correlation within the data; it is cross-sectional only.

We show the performance of the logistic regression in Figure 11 and the neural network in Figure 12. We use a number of common measures of performance: precision, recall and the f1-score.

Figure 10: Portfolio return



Source: Matthew Dixon, used with permission.

Results

Figure 11: Performance of logistic regression

	in-sample				out-of-sample			
label	precision	recall	f1-score	support	precision	recall	f1-score	support
-1	0.91	0.88	0.89	1222	0.26	0.32	0.29	82
0	0.90	0.90	0.90	1347	0.38	0.35	0.36	121
1	0.89	0.92	0.91	1271	0.37	0.34	0.35	97
avg / total	0.90	0.90	0.90	3840	0.34	0.34	0.34	300

Source: Matthew Dixon, used with permission. The bias-variance trade-off is characterized by the difference between the in-sample and out-of-sample performance.

We can compare the in-sample logistic regression performance with the out-of-sample and we see a very big drop off. This is a very large variance and is very common with noisy data in finance. Our baseline is to beat this out-of-sample performance, the 0.34 for both the recall and the f1-score.

Figure 12: Performance of deep neural networks

	in-sample				out-of-sample			
label	precision	recall	f1-score	support	precision	recall	f1-score	support
-1	0.94	0.95	0.94	1222	0.35	0.35	0.35	82
0	0.97	0.93	0.95	1347	0.44	0.52	0.48	121
1	0.93	0.94	0.93	1271	0.41	0.32	0.36	97
avg / total	0.95	0.94	0.94	3840	0.41	0.41	0.41	300

Source: Matthew Dixon, used with permission. The bias-variance trade-off is characterized by the difference between the in-sample and out-of-sample performance.

When we look at the deep network, it is performing better in-sample than the logistic regression. More importantly, it's performing better out-of-sample. There is still a very big difference. It could be that we don't have enough data to fully represent our problem; it could be that we haven't got enough variables that is or enough training periods and there are more diagnostics than needed here. The deep network is also outperforming the simple logistic regression.

We're retraining the model every 30 days. You could of course train more frequently to improve performance more, especially if there's been some market

dislocation. It seems to me that we can certainly do better and outperform it and also reduce our risk. And certainly there's no question of the deep network outperforming a linear method. Several experiments show how well it can perform against other machine learning and so it does better there, too.

In passing that these types of approaches are very useful for high frequency trading, training the model on the data of the limit order book; there's a lot of information there.

In summary, deep learning is a form of machine learning for non-linear high-dimensional data. Regularization is really the key part here. The link between the log likelihood and the cross entropy, and that is really essential to how the learning approach works. I think there are many interesting applications to explore predicting the returns of portfolios, EFTs, where we are trying to model the entire all but constituent components as opposed to the aggregate result.

Clearly with so much information available there, why discard it? And there are obviously many other sources of data from exchange fundamentals and in equities and of course we could look across multiple exchanges and there are of course textual data in the form of news that can be encoded into this high-dimensional input space.

Questions[8]

How do you deal with liquidity? Or how do you model the impact of your trades on both prices and other people in the market?

I think my answer to that is you have to separate out the prediction from the rest of the problem. So make your prediction and then analyse how this translates into P&L.

My approach is to separate those out and to build your highly-predictive classifier and then to assess the impact of classification error under various different probabilities of fills, various other sort of trade fill constraints so that it becomes clear what the implications of error in the model are on the P&L.

There are other approaches which have tried to combine everything together. Reinforcement learning is an example. Michael Kearns at the University of Penn State wrote a paper about this some time ago. The outcome of the model is the trading position. There you can incorporate liquidity considerations and so on. That's not proven in any research to have worked well or any better than separating out the problem.

My bet is on classifying first with the data, taking a predictive signal and then having a separate model which then tries to assess the effect of liquidity constraints etc. This could be by back testing, or running a simulation of the market.

How does the size / frequency of the data effect the calculation time? Does this increase the latency of the algorithm?

There is a misconception around the implementation of these types of algorithms and the practicality of their deployment in a low-latency environment, or an environment where latency is a critical factor.

It is the training of the model which is computationally intensive, and that needn't be done on that frequently. I've done studies where I found surprisingly once I trained the model—this is from micro structural data—even with events that disrupt the market, the model remains fairly stable and does not to be retrained that often. I've seen the same also looking at daily data. Retraining is also computationally expensive. We would never want to do that in real time or near real time.

You can encode the trained network in C++ for example, and this can run the very fast.

I think the real problem is to have enough data to avoid over-fitting, because with machine learning one is trying not to impose a data generation process. If you do impose one, then this reduces the amount of data you require: with a parametric distribution you need less data.

When you relax all of that you need much more data – and that is the main challenge within finance. The latency is a much smaller problem. A network can be very efficiently implemented, especially with all the expertise that we have from the HFT quant community.

[8] Here we have edited the questions and answers quite significantly, but tried to keep the important points that were made.

How should one normalise the data when it isn't stationary? Should one make it stationary?

In the example above I'm not assuming any stationarity. The data is being normalised simply to ensure that the data is well-scaled. Deep Learning networks are remarkably resilient to different choices of scaling. The network and some of the algorithms which are performing the back propagation are quite robust.

What choice of network did you fit to the data? Did you use long / short memory networks or recurrent neural networks as the inputs are time series?

It's possible to actually encode lagged input variables into a feed-forward architecture. We have say P input variables and then you lag N times, you would then end up with P times N input variables. This then creates a much more difficult problem to solve because you need in a feed-forward architecture with many more neurons.

Of course if you use recurrent neural networks (RNNs), the more natural choice for capturing memory, then this reduces the number of neurons you need. You don't need to embed lagged variables in your input space. Hence your input space is a little smaller and generally you need fewer neurons and fewer hidden layers.

When I've experimented with long/short-term memory networks (LSTM), I've not seen any gain from using them. The idea is you would capture longer-term market movements and shorter-term movements. They are motivated in by work in say text completion where you're trying to close in a parenthesis on a sequence of characters where you've observed an opening parenthesis. There it is a well understood problem.

For finance it's not clear to me whether there is a benefit. It may well be they could capture some sort of market regime; similar to a Markov switching process. I've never found it to be that useful, and it doesn't seem to be well-suited to identifying these sort of longer-term effects with very noisy data. There is quite a bit of work to be done on this.

What are the input and output variables in your example?

The input variables are the daily log returns of each stock in the index where we have a complete history of prices. The output is driven by the direction of the return of an equally weighted portfolio on the next day [as detailed above].

As discussed above there are various considerations such as transaction costs which need to be considered, but the idea here is simply to illustrate how high-dimensional data can translate into decision-making at some aggregate level.

The model is trained over a rolling window, which is important. If you don't retrain you will see a downward drift in performance. How frequently you retrain is an open question. It is difficult when you have knowledge of the market's history not to bias your data gathering in some way.

What was the network architecture you used?

This was a very simple architecture with three hidden layers.

Given deep learning is very "data-greedy", is there any hope that this could be applied over a longer-term horizon?

There is a problem with longer-term prediction. Generally I have found that the performance of this classifier (i.e. is the market going to move up/down or remain stationary), has an exponential decay in the accuracy with increased time horizon. This, of course, probably comes as no surprise. It's why, for example, weather prediction tends to be pretty bad a week ahead as opposed to being good in the near future.

Another aspect is if you want to predict at weekly intervals is the granularity of your data. Do you fit using weekly data if you are trying to predict one week ahead? This would push you away from deep learning as you would have too little data.

One could keep all the daily data, but still make a weekly forecast. The timeframe of the prediction is different from the granularity of the data: this is a possibility. This returns to the first point: prediction accuracy. One might want to include variables to indicate day of the week for example. There would need to more to the input feature space than just prices.

One can explore quite aggressively with deep learning a range of ideas of how to augment the input space in a way that it makes sense. There could be seasonality factors; there might be a variable which encodes the number of days before an earnings announcement or something else more qualitative in its style.

Are there any analogues in deep learning architectures with principal components (PCA) or partial least squares (PLS) which are more traditional approaches to dimensionality reduction?

We are starting to realize that a lot of techniques that are used in finance, speaking generally, such as linear regression, PCA or PLS are just shallow learners: learners with a single layer. And they have served us well in many applications.

The advantage of deep learners is that by adding more layers we increase the expressability of the model. The theory has not been worked out yet, but it does seem that deep learning is at least a hierarchal version of factor models and various other types of models that we already use.

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