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Deep Dive

Searching for Alpha

Practical Considerations in Building Neural Networks for Stock Selection

CITI'S TAKE

Interest in more sophisticated Machine Learning models is growing in the finance industry. One Deep Learning model – Neural Network – is seen as having a wide application in forecasting returns. While this model is powerful, it can be prone to overfitting and difficult to fine-tune hyperparameters. In this research, we identify key hyperparameters in applying a Neural Network for stock selection and propose a practical solution to mitigate instability of model output.

Modelling Non Linearity — Financial markets generally do not price risks in a linear fashion and Neural Networks are well suited to studying complicated nonlinear relationships in data. However, they can be easily over fitted and result in poor out-of-sample forecasts. In addition, the large number of hyperparameters in a Neural Network based on noisy observations poses a particular challenge in its application in equity investing.

Sensitive to Hyperparameter Selection — Learning rate**,** Dropout and Batch Size are among the most sensitive hyperparameters needed to be fine tuned in order to build an effective Neural Network stock selection model. 'Deep' models are not necessarily required for this type of application - a shallow network of 2 or 3 hidden layers works reasonably well.

Ensembling Improves Stability — The basic idea of ensemble models is to reduce the generalization variance of single models by averaging many of them. This concept can be applied to Neural Networks to improve the stability/repeatability and instill confidence in the model output.

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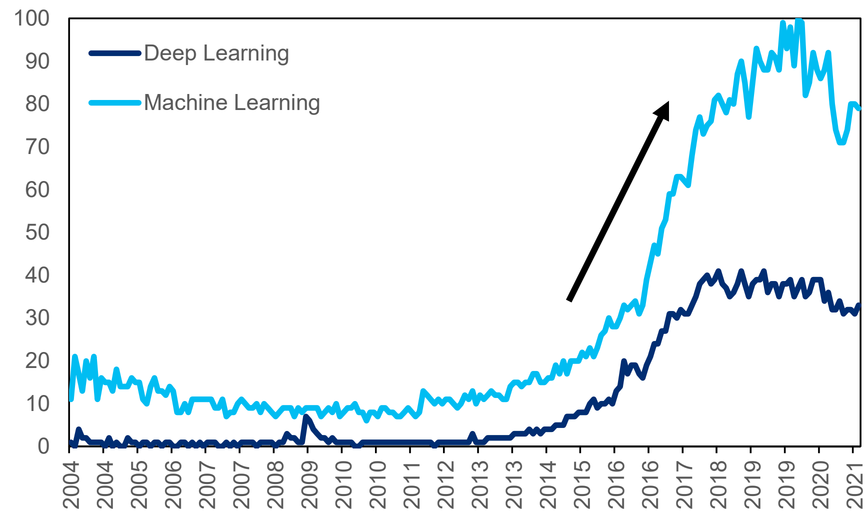
Investing with Deep Learning

Deep Learning (DL) has become a powerful and increasingly used toolset applied in various areas, largely as it has the ability to model complex nonlinear relationships without an assumption of a pre-specified underlying structure. Many of the DL algorithms have been developed initially for image recognition, audio and speech processing. The common aspects of what drives the application of DL to these areas of research is the large data sets, both in terms of observations and features, and largely stable or repeatable cross-sectional observations. Interestingly, even as the interest in broad machine learning has dropped during the Covid-19 pandemic, interest in Deep Learning algorithms have remained relatively stable (Figure 1).

Figure 1. Machine Learning Google Trends



Source: Citi Research, Google Trends

In our own research agenda, partly due to our experience in developing Decision Tree based models, we have published a series of research reports (Global Quantitative Research: Machine Learning Research Series) applying mostly tree-based ensemble learning techniques (Random Forests, XGBoost, etc.) in the context of equity investing. More importantly, we have focused on interpretation and attribution analysis of the ML models, which is critical for a better understanding and wider adoption of the approaches in the financial industry. One unique and more challenging part of applying ML algorithms in financial investing is the underlying data used in training models, specifically, cross-sectional and time-series data with arguably a dynamic or less stable system over time (Quantitative Factor Profile: Macro risk remains high in Price Momentum and Estimate Revision and Global Quantitative Insights: Look to Macro to get better exposure to Value).

Over time there has been increasing body of academic literature in the fields of finance and economics that have applied ML techniques. Recent research includes comparing various modeling techniques and suggest that some deep learning models (Neural Network, Long Short-Term Memory (LSTM), etc.) may produce better empirical results than the traditional linear, boosting or Random Forests models. (See Gu, et al. (2020), Messmer (2017) and Zhang, et al. (2020)). However, we believe there has not been enough focus on the practical aspects of applying DL models in published research and attribution analysis of these models is particularly sparse.

Via our own experience and discussion with clients, the large number of hyper-parameters and fine-tuning of DL models post special challenges when deploying these models, specifically when dealing with sparse time-series data sets, noisy observations (low signal-to-noise ratios) and a lack of relevant factors (features). Stability (i.e. repeatability) of the model output is of a particular concern for investment professionals as often the same model with fixed hyperparameters may generate quite different forecasts with different weight initialization. In this research, we focus on the 'workhorse' of NN models - the feedforward Neural Network - and empirically study the impact of individual key hyperparameters, the stability of the final model, and provide guidance on how these parameters impact the successful use of these types of models in a finance application.

The Structure and Model Building Process of Deep Learning

From a statistical perspective, the most common forecasting problem to solve in equity investing essentially comes down to the following general setup:

$$R_{t+1} = f(\boldsymbol{X_t}) + \epsilon$$

Where $\boldsymbol{X}$ is the predictors' matrix, ϵ is a vector of errors and $f(.)$ is a function describing the mapping from the predictors to the future returns, R_{t+1}. In other words, in any forecasting framework, the objective is to 'fit' a function of the predictors so that one can forecast the target variable (i.e. in this example, stock return) by examining the current level of the predictors.

The traditional linear models are undoubtedly appealing for practitioners: they are fast to estimate (with closed form solution in most cases), intuitive and easy to interpret. However, the relationship of financial variables are often nonlinear and the interaction between the factors can be complicated (higher order interactions, see Searching for Alpha: Machine Learning - Attributing Higher-Order Interactions: SHAP Value as Factor Selection Criterion).

In general, Machine Learning models allow more modelling flexibility and different techniques can be exploited to capture the complex relationship of financial data. Neural networks are the utmost flexible to some extent. In particular, it has been proven in theory that *any* function can be approximated by Neural Networks[1]. They are therefore appealing for learning complex patterns that characterize the relationships among data in finance.

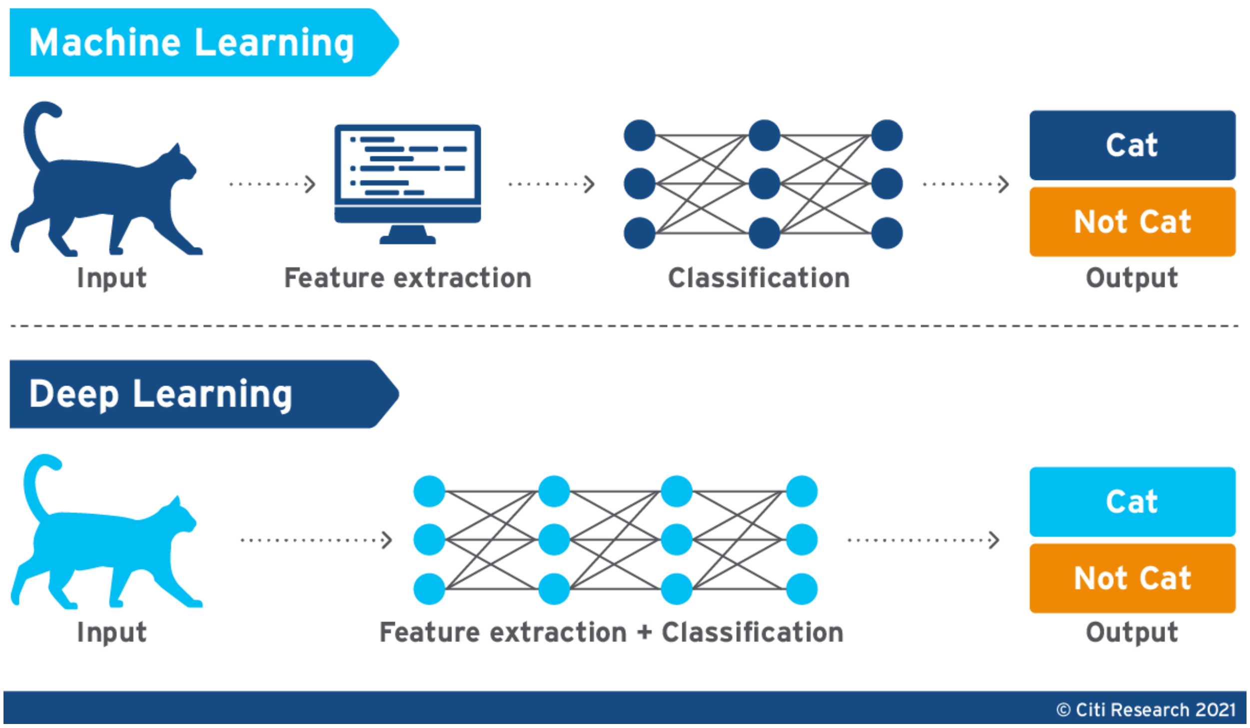
Examples of Neural Networks usage in financial literature are increasing, with authors exploiting the flexibility of Neural Networks in many ways, ranging from applying to momentum strategies (Lim, et al. (2019)), to forecasting the cross section of daily returns (Gu, et al. (2020)), and also in portfolio construction (Zhang, et al. (2020)).

How does Deep Learning work?

In general terms, Neural Networks are part of the unsupervised learning class of techniques, which requires minimum human discretionary input. What it means is that a Neural Network can directly deal with any form of raw data and it will transform the data (including extraction of features) in any non-linear fashion that allows a better fit. However, the downside of this, particularly in the field of Finance and investing, is that this flexibility may pose a challenge in understating the models and specifically in interpreting the results. Figure 2 provides an illustration of the basic difference in ML and DL. For the DL example, the combination of feature extraction and classification results in a true 'black box', potentially limiting the interpretation of how the model arrives at a given result/output. The flip side of this is that in addition to the flexibility that DL provides, depending on the problem setup and data, DL can discover a good set of features (feature extraction) in reasonable time in contrast to manually designing features which require a great deal of human effort of discretion and time.

[1] Hornik, K., et al. Multilayer feedforward networks are universal approximators. Neural Networks 2, 5 (1989), 359 – 366

Figure 2. Machine Learning versus Deep Learning.

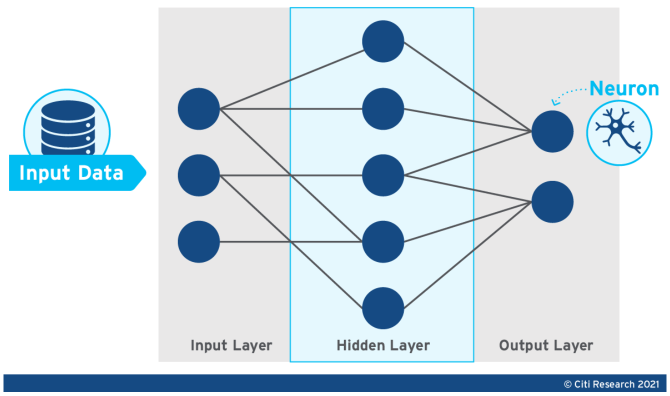


Source: Citi Research, Google

Figure 3 present the structure of a simple Neural Network. We can loosely define a Neural Network as a series of neurons connected together and organized into layers. A 'neuron' is the basic unit of a Neural Network. It simply takes the inputs, performs a linear transformation (i.e. multiplies the data by some weights), applies a nonlinear function and produces an output. The output is then 'fed' into the consecutive connected neuron and the process is iterated up until the output is generated. In Figure 3, data are fed (from the left hand side) into the model passing through three layers of neurons with the model output being generated from the output layer on the right hand side. Hence in this example, it's called *feedforward* Neural Networks.

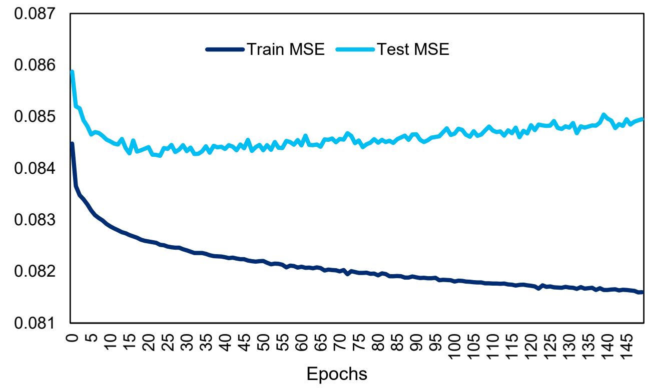
Once the output is produced, it is evaluated relative to the target variable and a measure of error (mean square error - MSE - as commonly used) is computed. Based on this error, the weights inside each neuron are adjusted in a way to reduce the MSE, in a process called backpropagation. This procedure is reiterated for a pre-determined number of times (epochs) and each time the weights within the neurons are adjusted to better fit the data. In other words, a Neural Network is really performing a trial and error process, with the model adjusting 'itself' based on the results as they are reiterated. Figure 4 provides an example of this process, by looking at the MSE obtained by a shallow neural network through 150 epochs. At any iteration, the model adjusts its weights so that the training MSE (dark blue line) is reduced, meaning that it is fitting (i.e. 'learning') more closely to the data. In addition it also shows the MSE of the test set (light blue line). This difference in these two lines is critical because given its optimization procedure, the Neural Network may fit very well the training set but it might then not be able to generalize well to the new observations out-of-sample. While not exclusive to the DL models, balancing the in-sample fit with the test generalization (validation of forecasts) is critical in Neural Network modeling.

Figure 3. Shallow Network



Source: Citi Research

Figure 4. Model Errors vs. Epochs



Source: Citi Research

In recent years, advances in optimization techniques and computing hardware has made it feasible to 'go deep' when using Neural Networks which translates to having the ability to add more hidden layers. It's worth emphasizing, however, that adding layers also increases (quickly!) the number of parameters. As the layers increase and in turn the number of parameters increases, the complexity of the model goes up exponentially, having a large amount of data is paramount for deep Neural Networks to be effective, which as we discussed previously can be an obstacle for many problems in the finance industry.

Building a Neural Network Deep Learning Model

With the complexity of numerous layers and neurons, a NN model can quickly turn into an in-sample data fitting exercise with potentially poor out-of-sample results. A central problem in machine learning, and NN in particular, is how to make an algorithm that will perform well not just on the training data, but also on new or future data. The technical answer is to adjust the model parameters (hyperparameters) with regularization and validation or testing on new data sets.

Generally, hyperparameters play a key role in the model specification as forecasting performance can be highly impacted by these choices. Broadly speaking, hyperparameters can be classified into four categories:

Architecture and Learning Capacity (*to reduce bias*)

This category refers to the overall structure of the network that includes the following decision parameters:

- Objective metric (MSE or R^2 are most commonly used, but we also explore alternatives);
- Number of hidden layers;
- Number of nodes in each layer;
- Choice of Activation function (e.g. rectified linear unit, ReLU is a common ridge activation function);
- Training set size.

Optimization (*to fit the data*)

This is akin to parameter estimation as in traditional structured statistical models where the parameters are determined endogenously to fit the data. Many optimization strategies can be considered when fitting a NN other than regularization techniques that can be part of the optimization procedure. The main choices in this category are as follows:

- Objective function (divergence or optimizing metric);
- Optimization algorithm;
- Learning rate;
- Learning rate decay;
- Momentum parameter;
- Weight initialization;
- Mini-batch size;
- Batch normalization;
- Number of epochs (how long we train; the number of updates/iterations used in the gradient descent).

For this research, we rely on 'ADAM' optimizer[2]. ADAM has proven to be very efficient and effective across diverse datasets, sample sizes and problems and it is considered today one of the more popular optimizers used in Neural Networks.

Regularization (*to reduce variance and control overfitting*)

Given the potentially very large number of parameters to be estimated in the optimization, regularization is a crucial step to reduce overfitting and produce more stable and consistent forecasts. Many strategies used in ML are explicitly designed to reduce the test error, possibly at the expense of increased training error. A great many forms of regularization are available to deep learning practitioners, which include:

- Dropout;
- L1 / L2 regularization;
- Early stopping;
- Deeper network architecture;
- Data augmentation (introducing noise to training data).

Validation (to finalize a more stable model)

In theory, validation and test data sets should come from the same distribution in order to produce a more reasonable forecasting model. In financial applications which involve forecasting next period returns, new data sets in the near-term future are often used for validation. Here the time-series feature of the data structure becomes a key dimension that needs to be taken into consideration for NN modeling. The main hyperparameters here are:

- Evaluation metric (MSE is most commonly used, but we also explore alternatives);

[2] Kingma, PD and Ba, J. (2014): Adam: A Method for Stochastic Optimization, *Proceedings of the 3rd International Conference on Learning Representations (ICLR)*

- Validation set size.

Tuning hyper-parameters is one of the main challenges in DL modeling. The theoretical link between one hyperparameter and its effect on the result/output is weak as many hyperparameters are often interconnected. Due to this, a grid search across hyperparameters is often needed in order to achieve a good empirical outcome. This process, however, can be very time consuming and potentially confusing.

In addition, data preprocessing can also be an important step to help produce a more stable and effective model. The most common practice of data preprocessing involves two parts: target (forecast variable) engineering and feature (explanatory variables) engineering. Target engineering most often defines the problem objective as whether we want to forecast a continuous output as in a regression setting, or a classification problem where output is discretized into bins. In this research, we use the regression setting in order to forecast the entire cross-section of stock returns for the MSCI World index. Note that some computer science experts suggest that when faced with a problem potentially requiring a regression where the forecast variable is continuous, first consider if it is absolutely necessary - they would argue that there should be a strong preference to discretizing outputs and perform a classification regression whenever possible.

Feature engineering relates to how the predictive variables are selected in the model and how they may be transformed before being used by the model. We have found that feature engineering, in particular feature pre-selection which is often ignored in ML modeling, is an important step in building a successful Random Forest stock selection model. (See Searching for Alpha: Machine Learning - Attributing Higher-Order Interactions: SHAP Value as Factor Selection Criterion).

Modelling and Testing of Stock Selection Neural Network Models

In this research, similar to the traditional factor based stock selection modeling, we use the stock level fundamental, risk characteristics and macro variables to forecast next month returns of stocks, based on the constituents of the MSCI standard index universe. The specific factors are listed in Figure 5. More specifically, we want to forecast the rankings of next month stock returns, as that is the most common form used in practice for various investment decisions. They are the same data sets we have used in previous research using Random Forest models such as Searching for Alpha: Machine Learning: Beyond Random Forest for Stock Selection, and a similar subset in our Pairs Trading model in Searching for Alpha: Pairs Trading: Applying Machine Learning to Pairs Trading.

Figure 5. Macro, Risk and Fundamental Factors

Macro / Technical Factors	Fundamental Factors	
Size Squared Returns	Earnings Yield (12 month Forward)	Earnings Yield (12 month Historical)
Price Mo Squared Returns	Cash Flow to Price	Dividend Yield
1M Returns	Book to Price	Sales to Price
RSI (14 days)	EBITDA to EV	Sales to EV
Volumes	Earnings Growth (12 month Forward)	S&P Growth-Value Score
Oil	1-Year Sales Growth	Long Term Earnings Growth
DXY	1-Year EPS Growth	1-Year DPS Growth
GSCI	3 Month Volatility Adj Price Trend	12 Month Volatility Adj Price Trend
JPY	First 11 Month Volatility Adj Price Trend	FCFY
VIX Index	1 Month Change in Earnigns Forecasts	Earnings Revision
Credit Spread	Sales Revision	Cash Revision
Correlation	Equity to Debt	Earnigns Stability
Dispersion	Beta against MSCI AC World	Beta against MSCI Country Index
	Earnings Certainty	ROE
	Net Profit Margin on Sales	Margin Growth
	Earnigns Quality (Accruals)	Balance Sheet Quality (NOA)
	Market Capitalization (log)	Illiquidity Ratio
	6M Price Volatility	

Source: Citi Research

Our investment universe is based on the point-in-time month-end constituents of MSCI World Index starting from the end of 1995. At the start of each month, using previous month-end data, we run the model and generate stock-level return forecasts for that month. We then rank all the index constituents based on their forecasted returns and group them into quintile portfolios. In terms of measuring performance, we calculate the subsequent monthly total returns of a long-short strategy (long portfolio based on top quintile, short portfolio on the bottom quintile) in US dollar terms and rebalance monthly. We weight stock constituents of the long/short portfolio on an equal weighted basis.

With respect to data pre-processing, all the stock level input variables are normalized as the percentile ranking of the variables across the MSCI universe of stocks each month. This approach is also taken for the output variable/forecast of next month stocks returns. The macro variables are based on the difference or percentage change depending on the variable, such that they are close to being stationary. Given our objective of forecasting the rank of stock return for the next month, we use the continuous regression form, same as we have done previously when building a random forest model.

Optimization and Hyperparameter Tuning

In this section, we discuss the details of our model building process with a focus on the hyperparameters that we believe are of most importance in a Neural Network stock selection model. Our approach has been inspired by the idea of 'orthogonalization' of hyperparameters, i.e. focusing on one hyperparameter at a time. To keep the comparison fair and relatively simple, we fix the training and test sets to 10 years of data so the model is initially built with monthly data from 1995 to 2005, and from here we use a 10-year rolling window to observe predictions from 2006 to 2020.

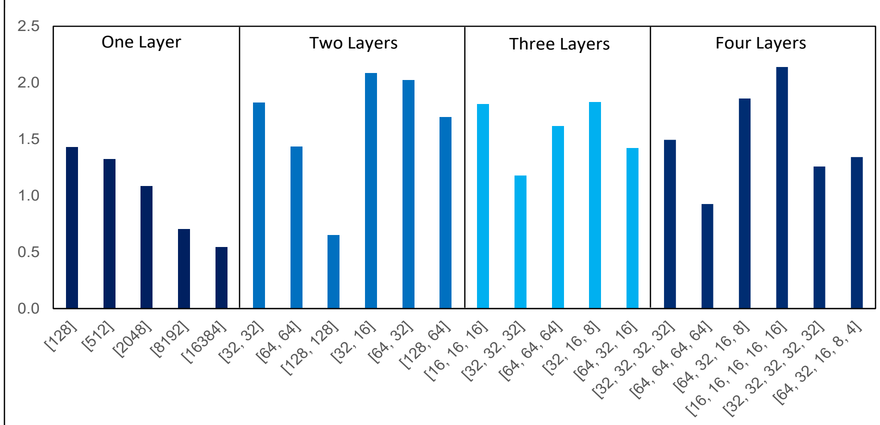
Architecture

In chain-based architectures, the main architectural consideration is to choose the depth of the network (number of hidden layers) and the width of each layer (number of neurons). As documented in some academic studies (Gu, et al. (2020)), a network with even one or two hidden layers is sufficient to fit the training set. Deeper networks are often able to use far fewer units per layer and far fewer parameters, as well as frequently generalizing to the test set, but they also tend to be harder to optimize. The ideal network architecture for a task can be found via experimentation guided by monitoring the validation set error.

The Gu, et al. (2020) study, which uses a similar dataset as ours, shows that out-of-sample R^2's for all ML models they studied are very small and sometimes negative. This is broadly consistent with our own experiences in building multi-factor linear factor models and tree-based ensemble learning models. In this case, we use the information coefficient (IC) as the objective metric, which we think is better suited for forecasting the whole cross-section of stock returns.

With the 'orthogonalization' approach in mind, we start by fixing all hyperparameters to default values and test different model architectures. Here we focus on both the number of layers and number of neurons simultaneously and test both equal-sizing or pyramid sizing rules[3]. Figure 6 shows the normalized IC delivered by each model architecture without regularization based on out-of-sample forecasts. The chart below suggests that given our dataset, going too deep does not necessarily payoff - the additional layers do not significantly improve the performance but do add computational costs and model parameters. In the end, we heuristically select the [32, 16] architecture – i.e. we use a Neural Network made of two hidden layers, with 32 and 16 neurons respectively. This is consistent with the NN models selected in Gu, et al. (2020).

Figure 6. Model Performance with Different Layers



Source: Citi Research

[3] Starting from a simple mode, increasing the complexity should at first improve the validation results up to a 'maximum' and then start to reduce due to overfitting (i.e. pyramid shape).

Learning Rate and Epochs

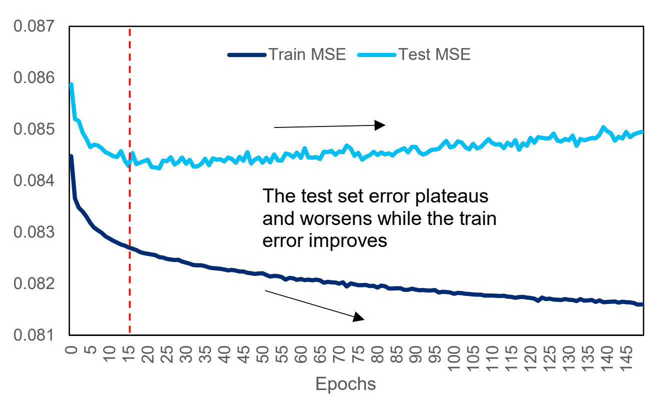
As briefly discussed in the previous section, Neural Networks are trained using a recursive optimization approach: given the error that the model produces, the parameters are updated accordingly and the process reiterates for a number of pre-specified times (epochs) or until certain criteria are met.

The learning rate is a hyperparameter that controls how much the model is changed (i.e. the weights) in response to the estimation error. Many consider it as the single most important hyperparameter and it should be re-tuned after all others are determined. Choosing the learning rate is challenging as a value too small may result in a long training process, whereas a value too large may result in a sub-optimal solution and leading to an unstable training process.

Figure 7 shows the training and testing MSE with the default learning rate (3e-4 – is widely seen as the 'best' learning rate for ADAM) iterating the optimization through up to 150 epochs. The chart shows that after the first few iterations, the model learns weights that improve the MSE both in training and in testing. After approximately 15 epochs, however, the test error plateaus and eventually worsens, while the training error continues to decrease, that is, the model starts to overfit the training set.

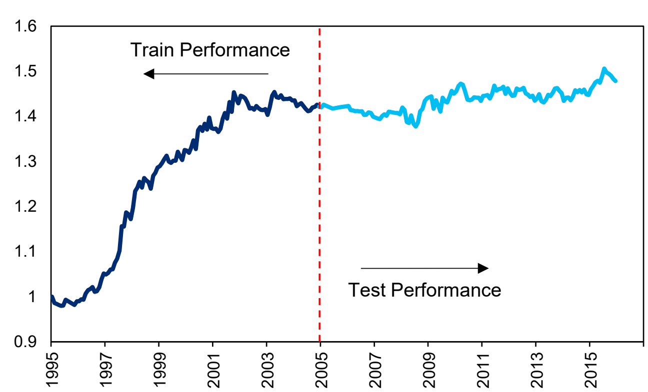
The overfitting intuition is confirmed by looking at the performances of the model prediction in training and in testing shown in Figure 8. The model is clearly very good at modelling the observations in-sample, but generates a poor out-of-sample performance.

Figure 7. Training /Testing Error



Source: Citi Research

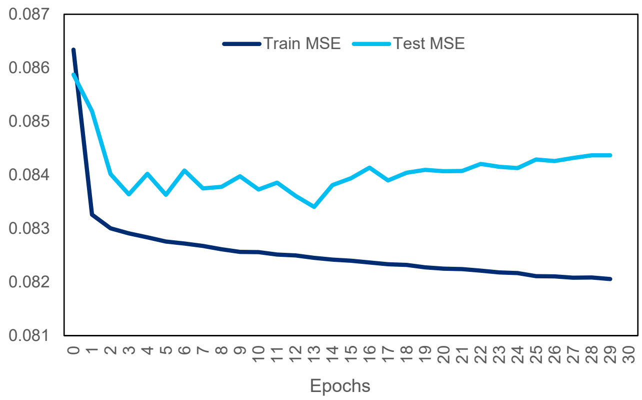
Figure 8. Training/Testing Period Performance



Source: Citi Research

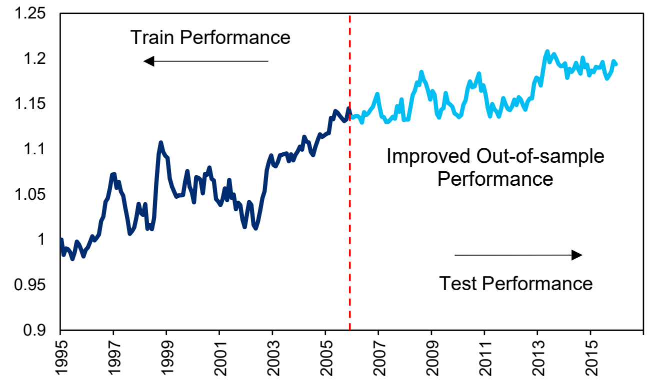
To deal with this outcome, we test smaller learning rates and iterate the optimization through a smaller number of epochs. Figure 9 and Figure 10 present the training and testing MSE and corresponding performances using a lower learning rate (3e-7) and iterating through 30 epochs only. This leads to more balanced training/testing performances.

Figure 9. Train /Test MSE Error



Source: Citi Research

Figure 10. Train/Test Performance



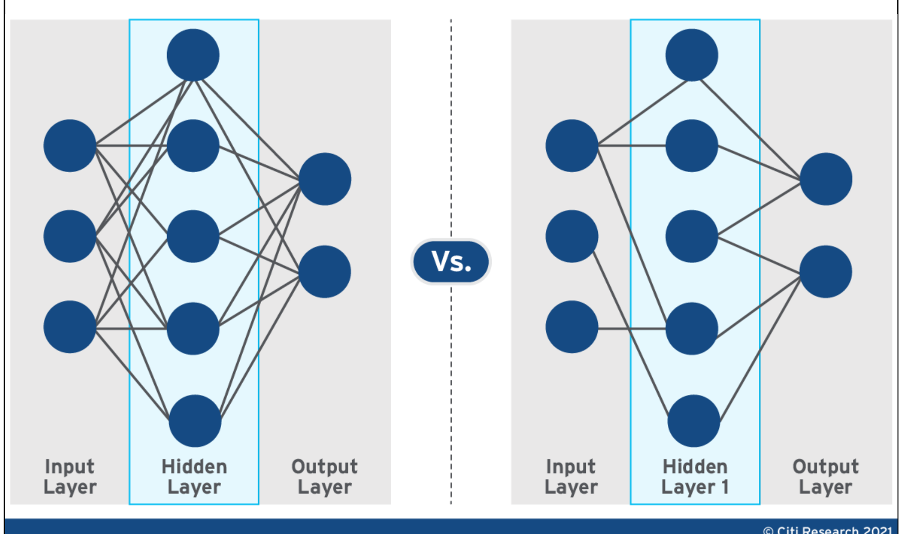
Source: Citi Research

Dropout

Dropout is a regularization technique introduced by Srivastava et al. (2014) which has been widely used in deep learning practice due to its efficacy and intuitiveness. It is designed to mitigate the in-sample overfitting problem.

In a fully connected neural network, all neurons in one layer are connected to all neurons in the next layer. With the Dropout parameter, some links between neurons are randomly ignored or 'dropped out'. In other words, some neuron output is not used in the next layer. The Dropout rate is expressed as a number from 0 to 1, indicating the percentage of randomly selected outputs to be dropped. (Figure 11).

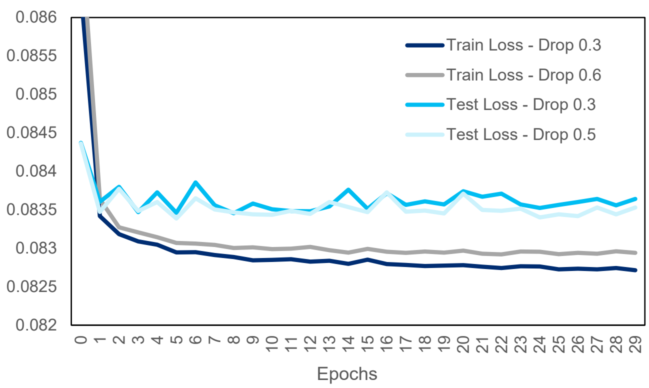
Figure 11. Neural Network without/with Dropped Connections



Source: Citi Research

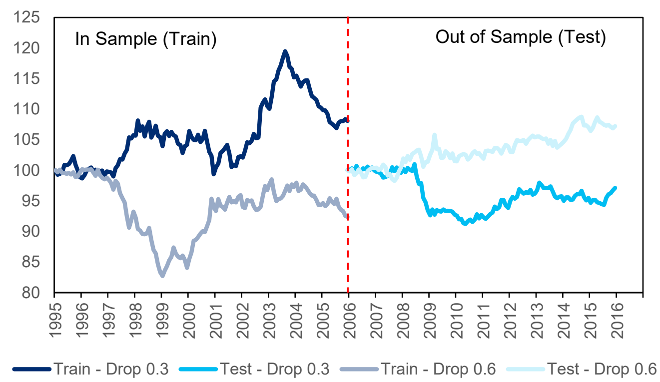
Figure 12 and Figure 13 present the train and test MSE and corresponding performances with Dropout of 30% and 60%. The effect of Dropout is essentially to prevent the Neural Network from fitting too many details of the observed training data. As a result, the model can be trained for more epochs to avoid overfitting. The example below shows that the higher Dropout actually lead to better out-of-sample results despite the in-sample fitting being worse.

Figure 12. Train/Test Errors – Comparing Dropouts



Source: Citi Research

Figure 13. Train/Test Performance



Source: Citi Research

Batch Size

The batch size defines the number of observations that will be propagated through the network in the optimization process - it is an important consideration in the optimization process.

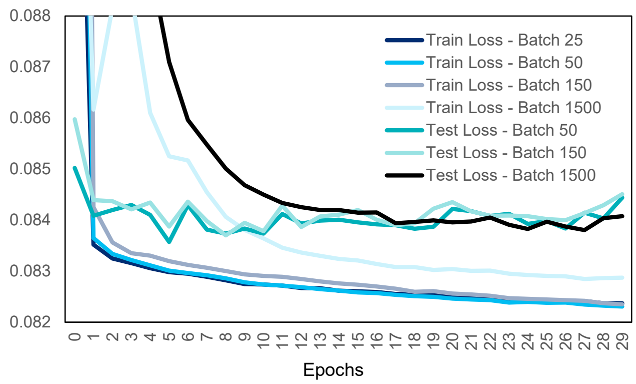
For instance, in our setup we have approximately 1500 stocks by 10 years of monthly data which yields over 180,000 observations. We can utilize all of the observations within the network, compute the corresponding loss function, and adjust the weights of each neuron based on the gradient and reiterate for the selected epochs. However, when the training set is very large, evaluating the sums of gradients becomes computationally very expensive. To economize the computational cost at every iteration, we can group the observations together to create mini-batches.

For example, suppose we set up a batch size equal to 100. The algorithm takes the first 100 observations in the training set and trains the network. Next, it takes the second 100 samples and trains the network again. We can keep doing this procedure until we have propagated all samples through the network. This significantly increases computational efficiency and requires far less memory in training the model. On the other hand, the smaller the mini-batch, the less accurate the estimation of the gradient may be.

Figure 14 and Figure 15 report the train and test MSE and corresponding performance with batch sizes of 25, 50, 150 and 1500. The first important observation of this analysis is that the better the model performs in-sample, the worse it performs out-of-sample. This is consistent with what we previously discussed on Dropouts, showing that the model is very prone to overfitting. A second observation is that there is not a clear pattern in performance for different batch sizes. In particular, batches of 25 and 150 observations lead to worse in-sample/better out-of-sample performances, while batches of 50 and 1500 lead to better in-sample/worse out-of-sample performance. This implies that the model may be quite unstable and that the randomness intrinsic in the model (weight initialization, optimization, etc.) outweighs the effect of different batches.

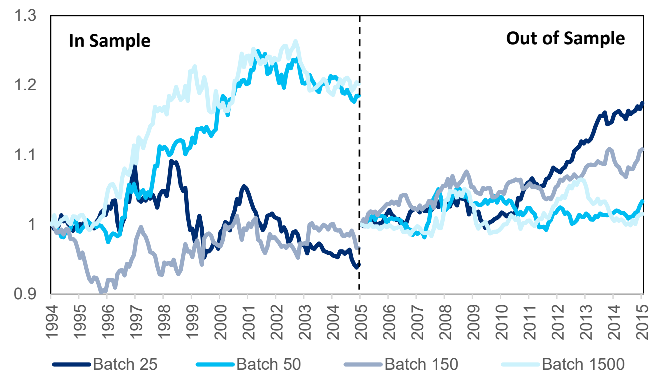
Given the special properties of our financial data consisting both time series and cross-sectional observations, one could think of creating batches from both cross-sectional data at one time point or across multiple time periods to take advantage of the time dimension of the data. It is partly the reason we also test the batch size of 1500, which is roughly the number of stocks in each time period. Interestingly, larger batch size in our setup, does not help produce better out-of-sample performance. This is consistent to what Messmer (2017) found. However, Gu, et al. (2020) selected the batch size of 10,000, which is slightly bigger than the number of stocks at a time point in their model.

Figure 14. Train/Test Errors - Comparing Batch Sizes



Source: Citi Research

Figure 15. Train/Test Performances vs. Batch Size



Source: Citi Research

Summary of Hyperparameter Tuning

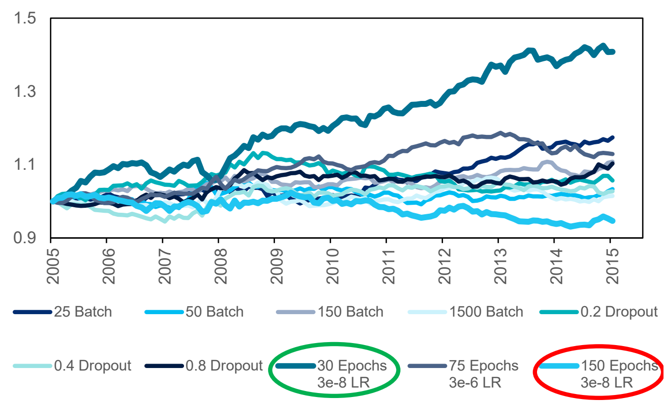
In this section, we empirically assess the impact of tuning many of the key hyperparameters in a Neural Network stock selection model, given that little theoretical guidance is available in the general computer science literature.

Following the concept of 'orthogonalization' discussed before, we have test hyperparameter values individually, while keeping all of the other parameters to their default values.

Figure 16 and Figure 17 show the performance of the out-of-sample backtests. The most important aspect to highlight here is that there is not a clear pattern emerging in performance across the different hyperparameter settings. Having said that, there is a notable benefit from regularization and reducing the overfit of the model, particularly by limiting the number of training epochs and using a smaller learning rate. One main takeaway from this is that our model tends to overfit very quickly and we need, therefore, to be careful in making sure that the test set can generalize to the validation set.

Given the complexity and potential interactions between the hyperparameters, many research papers (Messmer (2017), for example) have suggested the use of 'brute-force' grid search or random search (Bergstra and Bengio (2012)) to find an optimal set of hyper-parameters based on out-of-sample performance results. This additional layer of decision analysis complicates the modeling process further and may lead to more criticism of data-snooping and other issues.

Figure 16. Wealth Curves for Various Hyperparameters



Source: Citi Research

Figure 17. Performance of Hyperparameter Settings

	Ann. Avg Return	Ann. Volatility	IR	Hit Rate	Min	Max
25 Batch	1.6%	2.1%	0.79	60%	-1.8%	1.9%
50 Batch	0.4%	2.2%	0.16	52%	-1.9%	2.5%
150 Batch	1.0%	2.1%	0.50	54%	-1.4%	1.6%
1500 Batch	0.2%	2.3%	0.08	54%	-2.5%	2.6%
0.2 Dropout	0.6%	2.5%	0.24	51%	-1.8%	2.5%
0.4 Dropout	0.3%	2.4%	0.12	45%	-1.6%	2.4%
0.8 Dropout	1.0%	2.3%	0.45	57%	-1.3%	2.1%
30 Epochs, 3e-8 LR	**5.4%**	**3.8%**	**1.42**	**65%**	**-3.1%**	**4.2%**
75 Epochs, 3e-6 LR	1.2%	2.3%	0.55	53%	-1.9%	1.8%
150 Epochs, 3e-8 LR	**-0.5%**	**2.5%**	**-0.21**	**44%**	**-1.6%**	**2.5%**

Source: Citi Research

In addition, since our training and testing data sets are coming from different time periods, as the market inevitably evolves and the relationship among variables changes (i.e. non-stationarity), it poses an additional challenge to hyperparameter tuning. Via the empirical analysis, our research has found that a fixed set of hyperparameters can deliver large variation of performance in different periods. We conclude, therefore, for our financial dataset, Neural Networks need to be re-trained as new observation come through. More specifically, we use a rolling window of 10-years of monthly data to train the networks, and each year we re-train a new model with updated hyperparameters.

Building a Stable Neural Network Model

As shown in the previous section, the performance of Neural Network models can be very sensitive to hyperparameter selection, particularly when fed with low signal-to-noise ratio data such as the traditional equity investment related data set we are utilizing in this report.

It has been documented in the computer science literature that random seeds used to initialize Neural Network estimation from different runs of the same model with fixed hyperparameters can lead to quite different outcomes. Within the finance industry, this technical issue may pose compliance and credibility risks when deploying models in that results may not be replicable.

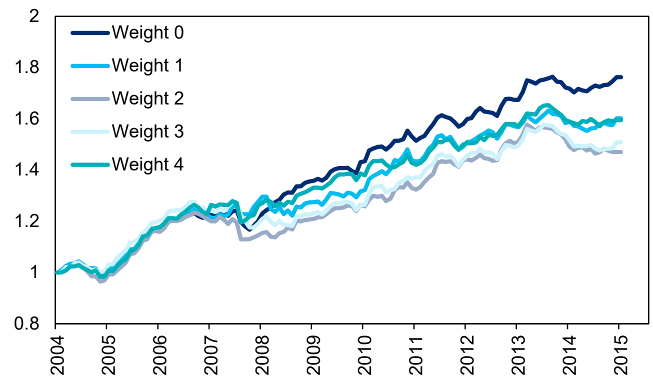
To get a grasp of how unstable these models can be with our financial data, we first train five Neural Networks with the same architecture and same hyperparameters, but with different random weight initializations (W0 to W4), then compare their predictions. Figure 18 shows the cross-sectional rank correlation between the return predictions of each of the five runs. The level of correlation is quite low, ranging from 0.55 to 0.6. This means that each of the five identical model delivered quite different rankings of return forecasts. More importantly, the out-of-sample performance from the five models in Figure 19 are markedly different. This demonstrates that the Neural Network model in the initial setup is quite unstable, making it difficult to have high confidence in the final return forecasts.

Figure 18. Cross-sectional Correlation of Return Forecasts from Five Weight Initializations

	W0	W1	W2	W3	W4
W0	1	0.56	0.58	0.57	0.58
W1		1	0.58	0.55	0.56
W2			1	0.59	0.60
W3				1	0.57
W4					1

Source: Citi Research

Figure 19. Backtest Performance of the NN Model with Five Weight Initializations



Source: Citi Research

Ensemble…Once again

The basic idea of ensemble models is to reduce the generalization variance of single models by averaging many of them. This technique is certainly not new and is still a very active area of research. For example, the Random Forest modeling approach specifically relies on ensembling to mitigate the weaker 'learners' in individual Decision Trees. Ensemble models have proven particularly effective in financial predictions. In Beyond Random Forest for Stock Selection, we show that ensemble regression and classification predictions significantly improved results. Krauss et al. (2017) use deep Neural Networks, gradient-boosted trees and Random Forests to forecast one-day-ahead stock returns for the S&P 500 constituents, and similarly Abe and Nakayama (2020) ensemble three different ML models to forecast the cross section of daily returns. Both Gu, et al. (2020) and Messmer (2017) suggest to take the average of the return forecasts from the same NN model with different weight initializations to reduce variations.

Here we test how ensemble results can improve the stability and repeatability of the model when the same model is run multiple times. All models are trained based using the same parameters and data. We leave the architecture fixed and do not use any other form of regularization.

First, to assess the increased stability of the ensemble model, we construct ensembles of 5 and 10 models and replicate the correlation analysis highlighted in Figure 18. In particular, first we train five Neural Networks with model setup but with different initial random weights and average their predictions. We then replicate the same experiment with 10 Neural Networks.

Figure 20 and Figure 21 report the cross-sectional rank correlation in the predictions among the ensemble models based on five and ten of the NN models respectively. It is clear from the table that with five underlying models the resulting predictions are more stable and with ten model ensembling the correlation of the predictions are very close to 1 – in essence by averaging across models we manage to neutralize the randomness of Neural Networks which arises due to initial neuron weights when fitting our dataset.

Figure 20. Cross-Sectional Rank Correlation – Ensemble of 5 Runs

	W0	W1	W2	W3	W4
W0	1	0.89	0.90	0.90	0.91
W1		1	0.91	0.90	0.90
W2			1	0.90	0.90
W3				1	0.91
W4					1

Source: Citi Research

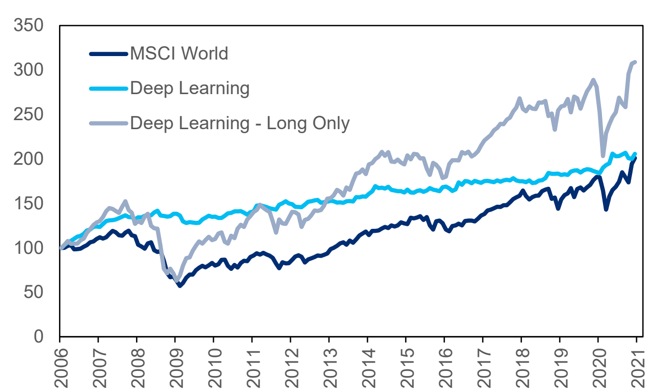
Figure 21. Cross-Sectional Rank Correlation - Ensemble of 10 Runs

	W0	W1	W2	W3	W4
W0	1	0.95	0.95	0.95	0.94
W1		1.00	0.95	0.95	0.96
W2			1.00	0.95	0.95
W3				1.00	0.95
W4					1.00

Source: Citi Research

Figure 22 and Figure 23 provide the out-of-sample performance statistics of the final ensemble model which is comparable to the results we have observed in our previous Random Forest models. Figure 24 to Figure 26 shows more details of the performance analysis where we find the performance of the final ensemble model did suffer more during the GFC and the 2015/2016 slowdown period.

Figure 22. Final Ensemble Model Backtest Performance



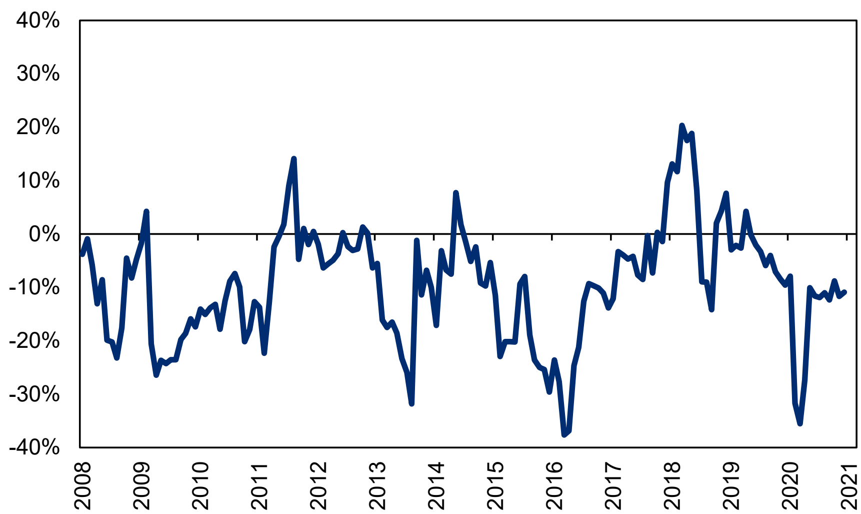
Source: Citi Research

Figure 23. Performance Metrics of Final Ensemble Model

	MSCI World	Deep Learning Long Short	Deep Learning Long Only
Annualised Avg Return	5.7%	5.0%	9.3%
Annualised Volatility	14.4%	5.3%	18.5%
IR	0.40	**0.94**	0.51
Hit Rate	64%	68%	61%
Min	-16.5%	-4.9%	-24.8%
Max	11.8%	5.5%	16.4%

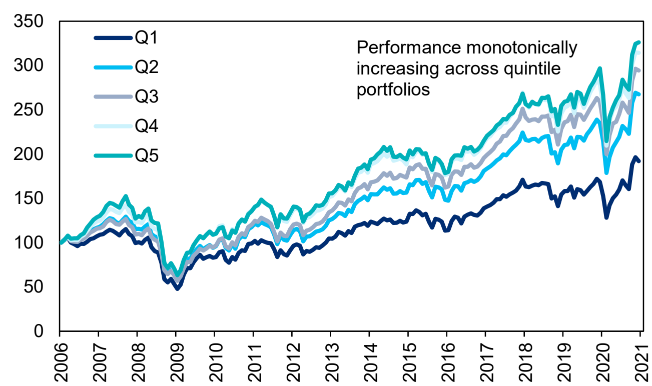
Source: Citi Research

Figure 24. Final Ensemble Model: Two Year Rolling Correlation vs MSCI World



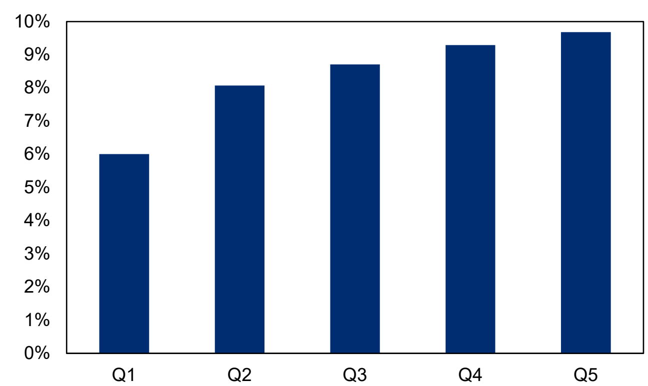
Source: Citi Research

Figure 25. Final Ensemble Model Quintile Performance



Source: Citi Research

Figure 26. Final Ensemble Model Quintile Average Return



Source: Citi Research

Conclusions

In this research, we investigate an application of the Neural Network deep learning model on stock selection based on the traditional monthly factor dataset. In particular, our aim to present the challenges and difficulties in building a relatively simple feedforward Neural Network. Most importantly, we have highlighted the key hyperparameters which have a significant influence on the final model predictions and in turn provide a practical solution for finding a more stable model. These practical suggestions include:

- The use of Deep Learning (at least in the case of simple feed-forward Neural Networks for predicting stock returns) is more of a practical and empirical endeavor with little theoretical guidance on aspects such as the setting of hyperparameters.

- The theoretical link between hyperparameters and their effect is weak. Applying a concept of Orthogonalization in hyperparameter tuning may help. Grid searching for the optimal setting of hyperparameters may be needed in order to achieve a reasonable/good result. Given the dynamic nature of financial markets over time, Neural Network models may need to be frequently tuned/optimized.

- Experience or heuristic suggestions from Computer Science applications are not always transferable into the financial market realm due to the nature of Financial market dynamics and the relative sparsity of data.
- Ensembling of Neural Network models may help produce more stable forecasts and instill confidence in the use of output from NN models.

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Previously Published Research

Figure 27. Research Reports (since 2009)

Date	Research Theme	Report Link
22-Jul-21	ESG	ESG Insights: Indexed ESG Funds – A Widespread Implementation Choice
22-Jun-21	Factor	Searching for Alpha: Go with the Stock Connect Flow, for a Sharpe of 4
18-Jun-21	Factor	Searching for Alpha: Overlaying Price Mo. and Short Interest to avoid drawdowns and improve returns
15-Jun-21	ESG	ESG Insights: ESG Fundamental Characteristics
13-Apr-21	ESG	ESG Insights: Following the ESG Herd: Has ESG become a Crowded Trade?
29-Mar-21	Machine Learning	Searching for Alpha: Pairs Trading: Applying Machine Learning to Pairs Trading
09-Mar-21	Positioning	Regime Modelling using Futures Positioning: Futures vs. Cash – A Distant but Meaningful Relationship
18-Feb-21	ESG	ESG Insights: The ESG 'Premium': How does ESG compare to other Factors?
01-Feb-21	Event	Searching for Alpha: Asia Earnings Surprise: Predicting Asia Earnings Surprises
14-Jan-21	ESG	ESG Insights: Where Machines do it Better: Inferred ESG Ratings Data
30-Oct-20	Factor	Searching for Alpha: China A Alpha – Smoothing Price Momentum
16-Oct-20	Factor	Under the Microscope: Overlapping Momentum
14-Sep-20	Positioning	Equity Markets Positioning Model: Introducing the EMP
11-Sep-20	Factor	Searching for Alpha: Combining ESG and Risk Premia Investment: A Double Screen Approach
08-Sep-20	Factor	Searching for Alpha: Factoring Short Interest: Measuring and Profiting from Information in Shorts
28-May-20	Machine Learning	Searching for Alpha: Machine Learning - SHAP Value as Factor Selection Criterion
28-Feb-20	Machine Learning	Searching for Alpha: Machine Learning: Leveraging Return Forecasts
21-Feb-20	Factor	Searching for Alpha: China A Alpha – Sector-rel. Value Is Powerful, Choose Sector Mappings Wisely
03-Oct-19	Machine Learning	Searching for Alpha: Machine Learning: Beyond Random Forest for Stock Selection
23-Sep-19	Event	Searching for Alpha: Earnings Surprise: Managing Expectations
05-Mar-19	Machine Learning	Searching For Alpha: Machine Learning: Interpreting Machine Learning Predictions
07-Feb-19	Misc	Searching for Alpha: GAAP vs. Non-GAAP: Which Earnings does the Market Price?
21-Nov-18	Positioning	Searching for Alpha: Style Crowding in Asia: Getting Ahead of the Crowd
17-Sep-18	Event	Searching for Alpha: Earnings Surprise: Using ML to Forecast Earnings Surprises & Returns
13-Sep-18	ESG	Searching for Alpha: The ESG Edge: ESG Investing – A Step Forward
03-Sep-18	Machine Learning	Searching For Alpha: Machine Learning: Interacting Machine Learning and Factors
03-May-18	Positioning	Measuring the Crowded Trade: Introduction to our Crowding Composite for individual stocks
14-Mar-18	Factor	Searching for Alpha: Profiting from Capex: Look To Capex Announcements
07-Sep-17	Rotation	Searching for Alpha: Tactical Style Rotation: Using Risk and Return to Manage Style Exposure
10-Mar-17	Misc	Searching for Alpha: Big Data: Navigating New Alternative Datasets
13-Feb-17	Factor	Searching for Alpha: Betting Against (Accurate) Beta
19-Sep-16	Factor	Searching for Alpha: Competitive Advantage: Survival of the Fittest
09-Sep-16	Factor	Searching for Alpha: Financial Strength Redux
14-Apr-16	Rotation	Searching for Alpha: Dynamic Style Weighting: Risk-Based Equity Style Allocation
04-Mar-16	Smart Beta	Long-Only Pure Style Portfolios: No Shorts Please
18-Feb-16	Factor	Industry Alpha Insights: Banks: One Size Does Not Fit All
21-Sep-15	Factor	Under the Microscope: Stock Momentum Conflation
15-Sep-15	Allocation	Searching for Alpha: Macro Moves Markets: Economic Data, Expectations and Market Pricing
23-Mar-15	Rotation	Searching for Alpha: Style Timing: Style Performance, Trading Volumes and Investor Agreement
13-Mar-15	Misc	World Radar Screen: Refining Our Global Search for Alpha
18-Feb-15	Factor	Searching for Alpha: Networking with Analysts: Modelling Analyst Forecast Dependence
01-Oct-14	Smart Beta	The Rise of Low Risk Investing: Is It Getting Crowded Out There?
27-Mar-14	Factor	Under the Microscope: Five Innovations In Momentum Investing
07-Mar-14	Factor	Searching for Alpha: Timing Price Momentum: When Does Momentum Move?
27-Nov-13	Smart Beta	Equity Risk Premia Investing: A New Methodology for Monitoring Style Performance
23-Jul-13	Allocation	Stock Market Country Selection: Changes to a Well-Established Model
02-Jul-13	Factor	Searching For Alpha: Digging For Dividends: QUARI - QUality with A Reliable Income
24-Jun-13	Misc	Global Theme Machine: An Objective Way of Identifying Attractive Investment Themes
25-Mar-13	Factor	Searching for Alpha: Purifying Analyst Recommendations: Removing Beta to get to the Alpha
06-Nov-12	Factor	Searching for Alpha: Tangible Benefits of Intangibles: Brand, Respect & Intellectual Capital
09-Mar-12	Smart Beta	Low-Risk Portfolio Strategies: Sharpe Ratio Maximisation and Multi-Asset Applications
28-Feb-12	Rotation	Macro Risk and Style Rotation: A Guide Rather than a Prescription
14-Sep-11	Factor	Searching for Alpha: Accruals Volatility - A New Approach to Quality Investing
24-Aug-11	Allocation	Industry Alpha Insights: Four Approaches to Tactical Industry Selection
17-Mar-11	Misc	Industry Alpha Insights: Quantifying Industry-Specific Fundamentals
18-Nov-10	Smart Beta	Low-Risk Equity Portfolios: More than just Minimum Variance
15-Nov-10	Allocation	Under the Microscope: Measuring Systemic Risk - The Absorption Ratio
14-Jun-10	Factor	Under the Microscope: Optionality in Valuation
31-Mar-10	Event	Searching for Alpha: Earnings Surprise: Still Profiting from Surprises
29-Jan-10	Factor	Momentum in Japan: Looking at Price, Trading Values and Earnings
15-Oct-09	Rotation	Searching for Alpha: Style Rotation: Optimising Style Rotation Strategies

Source: Citi Research

Citi Quant Research Team

Figure 28. Citi Quantitative Research Teams

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Appendix A-1

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% of companies in each rating category that are investment banking clients	65%	66%	55%	68%	63%	71%
Citi Research Quantitative World Radar Screen Model Coverage	30%	40%	30%			
% of companies in each rating category that are investment banking clients	43%	34%	29%			
Citi Research Quantitative Latam Radar Screen Model Coverage	20%	61%	20%			
% of companies in each rating category that are investment banking clients	81%	71%	62%			
Citi Research Quantitative Asia Radar Screen Model Coverage	20%	60%	20%			
% of companies in each rating category that are investment banking clients	46%	26%	20%			
Citi Research Quantitative Australia Radar Screen Model Coverage	57%	0%	43%			
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