Deep Learning Robot Trader 1.0

Applying Recurrent Neural Networks to Predict Optimal Portfolio Allocations

Hi Siri, how much should I trade?

We train deep neural networks to directly predict optimal portfolio allocations, with an objective to maximize strategy performance such as Sharpe ratios. Unlike traditional investment processes which firstly predict returns (alpha generation) and then control risk (portfolio construction), it could be more natural and efficient to directly predict optimal portfolio allocations that deliver good risk-adjusted returns.

Maximizing the Sharpe ratio of an Equity/Bond portfolio

We look at an architecture of recurrent neural network called the Long Short-Term Memory (LSTM) model, which is popular in modeling sequential data. We train the model to learn time-series patterns of asset returns: What are the important features to keep, and what is irrelevant noise to forget? We apply the model to predict optimal allocations on S&P 500 and US Treasury so as to maximize Sharpe ratios. Comparing with benchmarks like 60/40 and risk parity, the Deep Learning model exhibits decent performance, and successfully avoids massive drawdowns in 2018. The latest model allocations suggest slightly higher exposure to equities and significantly lower exposure to bonds, relative to that in a risk-parity portfolio.

Global Quantitative and Derivatives Strategy

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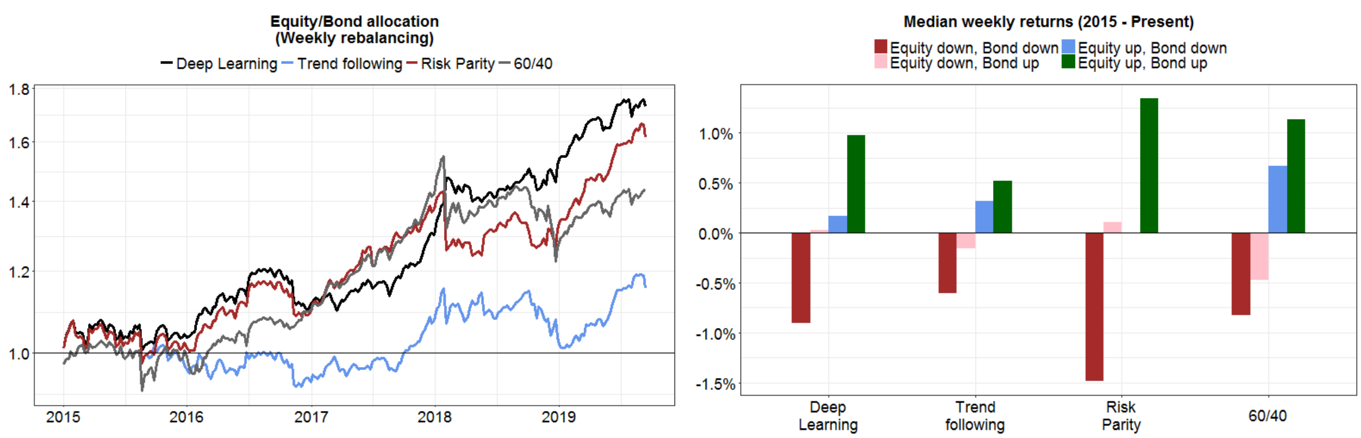
Deep Learning model applied to weekly allocation on S&P 500 and US Treasury



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg

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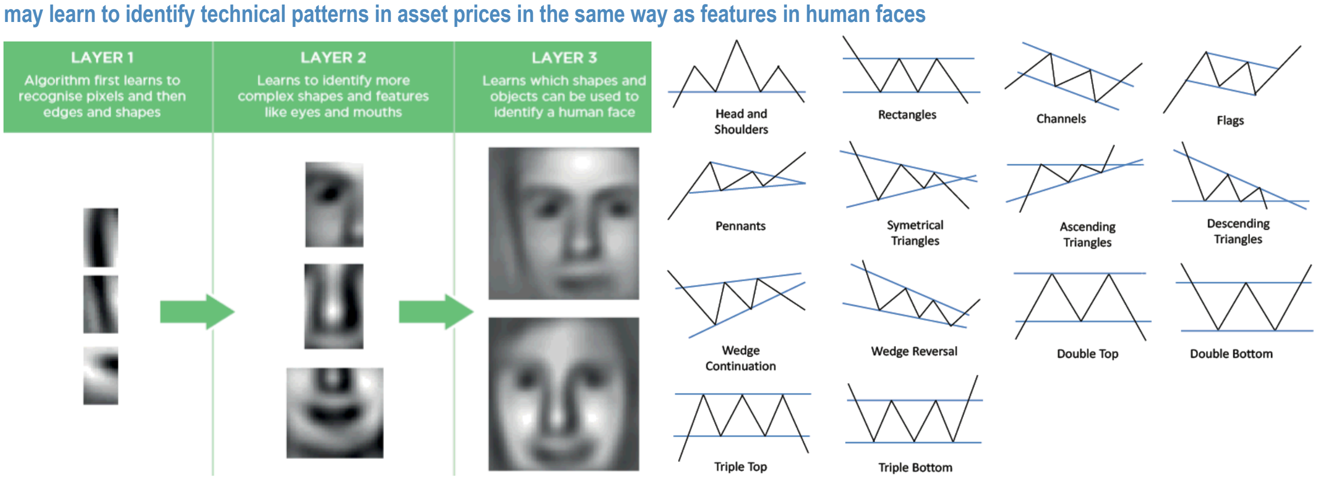
Why is Deep Learning so powerful?

Deep Learning refers to neural network models that consists of many layers, where each layer is made up of a number of "neurons" that process information via activation functions, analogous to how human brains work. As Deep Learning has been very successful in applications related to Artificial Intelligence (e.g. self-driving cars), we ask ourselves a question: can we train a robot via deep neural networks to learn how to trade a strategy successfully?

Deep Learning automatically extracts useful features

Deep Learning is capable of learning patterns (i.e. representations) in a hierarchy of concepts, from very coarse representations to finer details through layers of network (Bengio et al 2013). The classic example is to recognize a face: The first layer learns to identify edges, the next layer learns about more complex shapes like the eyes, and the next layer learns to combine complex shapes, and so on. An advantage of Deep Learning over traditional Machine Learning is that in many situations, we do not need to apply domain knowledge to extract features for model training. Instead, the deep neural network architecture handles feature extraction as one of its learning processes. In the above example of facial recognition, the algorithm automatically learns about useful features in the hidden layers, and applies these features to perform classification or regression where the results (e.g. is it a human face?) are output in the final layer. Similarly, it could be possible for a deep neural network to learn about patterns of asset prices via different levels of representations, e.g. short-term reversals, long-term trends, V-shape rebounds, etc. (Figure 1, Kolanovic et al (2017)).

Figure 1: Neural networks learn patterns in a hierarchy of concepts and automatically learn about useful representations. A neural network may learn to identify technical patterns in asset prices in the same way as features in human faces



Source: Mahapatra, S. Towards Data Science, J.P. Morgan Quantitative and Derivatives Strategy

Another advantage of Deep Learning is the availability of powerful open source libraries such as Google's TensorFlow. In TensorFlow, deep learning models are represented as network graphs where data (i.e. tensors/multidimensional arrays) flow through the edges and the nodes are computation units. An important feature in TensorFlow is the "Automatic Differentiation", meaning that it has a gradient operator at each node to calculate derivatives. During backpropagation, gradients with respect to the parameters are calculated automatically, without the need to explicitly define derivatives in advance. This enables us to optimize custom loss functions easily, for instance, the Sharpe ratio of the final strategy.

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Past Research on Neural Networks

To gain some perspectives, let us revisit a few interesting applications of neural networks in finance. Many of the studies are focused on using neural networks to learn textual relationships, whilst the usage in the context of time series is relatively limited:

- **Equity factor allocations:**
  Compare the use of neural networks and other machine learning models on equity factor allocation, and highlight pitfalls and challenges involved with deep learning in time series modelling (Hlavaty et al (2018))

- **NLP model to extract sentiment from news:**
  Neural networks based on Multilayer Perceptron (MLP) are trained to classify sentiment from J. P. Morgan analyst reports (Smith et al (2018))

- **Tracking themes in equities:**
  Train a neural network the relative context of words and phrases in J. P. Morgan analyst reports, and create an engine that automatically group phrases into related clusters and calculate a "smart buzz" score (Smith et al (2019))

- **Volatility forecasting:**
  Neural networks are applied to volatility time series forecasting, and the correspondence between different architectures of neural networks and traditional econometric models (ARCH, GARCH) is highlighted (Peng et al (2019))

For investors trying to get a quick grasp on Deep Learning, the primer Big Data and AI Strategies: Machine Learning and Alternative Data Approach to Investing (Kolanovic et al, 2017) would be a good starting point. We will go through some more background of neural networks in the next sections before discussing our model design.

Rationale of Our Study

As we see Deep Learning as a promising field in finance, we explore an application below in the context of portfolio allocation. Similar to smart home devices where robots assist us to manage electronics appliances, we investigate if it is ever possible to train robots to help us manage portfolios. In line with traditional investment process which involves alpha generation and portfolio risk management, we may ask the robot to predict asset returns and/or risk, and use these predictions to construct portfolios. On the other hand, it may be more natural and efficient to directly ask the robot to predict optimal portfolio allocations that would deliver good risk-adjusted returns such as Sharpe ratios. In this report, we look into the latter using an example of equity vs bond allocation, and train deep neural networks with the objective to maximize the Sharpe ratio of the portfolio. Whilst we look at a simple example with two assets, the framework is readily extensible to larger portfolios.

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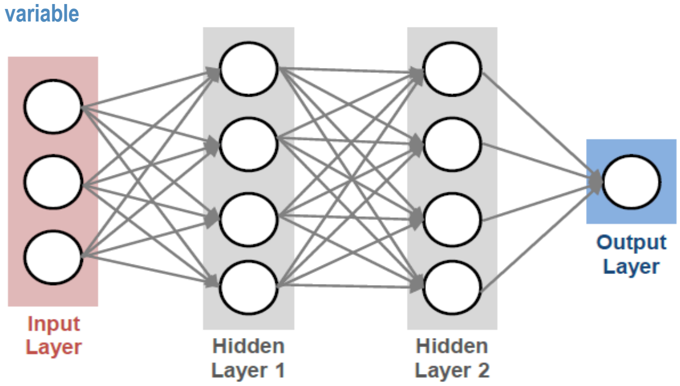
Recurrent Neural Network for Time Series Prediction

Deep neural networks are very successful for problems such as image classification and facial recognition. These tasks are typically quite easy for humans but difficult for machines, and neural networks inspired by models of neurons in human brains come naturally into play. A neural network consists of layers of neurons, as in Figure 2.

Figure 2: Example of a Neural Network with 2 hidden layers (4 neurons each), 3 input variables and 1 output variable

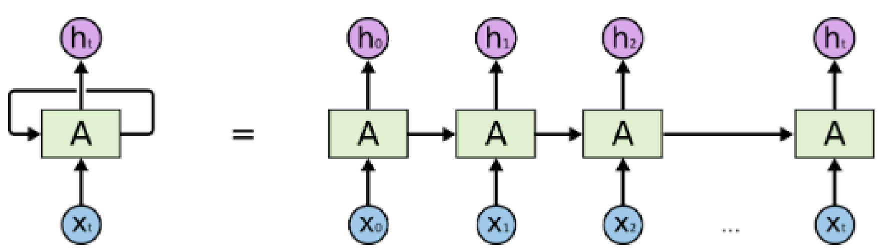


Source: J.P. Morgan Quantitative and Derivatives Strategy

Whilst deep learning has now become the powerful engines of self-driving cars and smart home products, application of deep neural networks on time series prediction is less successful due to several reasons, such as non-stationary distributions and time dependency of observations. Relationships between variables could change over time, and models need to take a balance between stability and adaptability.

To model the time dependency using neural networks, we need to consider a special form of architecture called Recurrent Neural Networks (RNN), which are developed to analyze sequential data, such as speeches. An RNN is similar to a usual feedforward neural network, except that it has a feedback loops to handle time dependencies. As such, it is able to "remember" information in the past. We can "unroll" an RNN into a chain of neurons (or cells) to explicitly see the time dependency (Figure 3):

Figure 3: Recurrent Neural Network (RNNs) can be unrolled across time. Each neuron is represented by a cell unit *A*, *x* are the inputs and *h* are the hidden states



Source: Olah, Christopher (2015) [Understanding LSTM Networks]

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Unfortunately, a vanilla RNN is impractical to model most time series data, because it is very bad at retaining long-term memory. The reason is due to the "vanishing gradient" in the Back-Propagation Through Time (BPTT) algorithm, i.e. an algorithm used to estimate the weights in the neural networks using gradient descent. As gradients propagated back in time tend to vanish, the weights do not get updated and past information becomes irrelevant (or even worse, in case the gradients do not vanish, they tend to blow up and the estimated weights will oscillate and diverge).

Better designs of RNNs that attempts to solve the above problem consist of various gates to control the flow of data across the network. It means that useful information in the past could be "remembered" when they pass through the RNN if deemed useful, or could be "forgotten" if they are no longer relevant. The most popular architectures include the Long Short-term Memory (LSTM) (Hochreiter et al (1997)) and the more recent Gated Recurrent Unit (GRU) (Cho et al (2014)).

Long Short-Term Memory (LSTM) Model

An LSTM model is made of a specially designed cell that manipulates the flow of data carefully with a few gates defined by *sigmoid* functions (Figure 4). Whilst the equations maybe intimidating (see Appendix on P.26), an LSTM cell essentially applies the following logic:

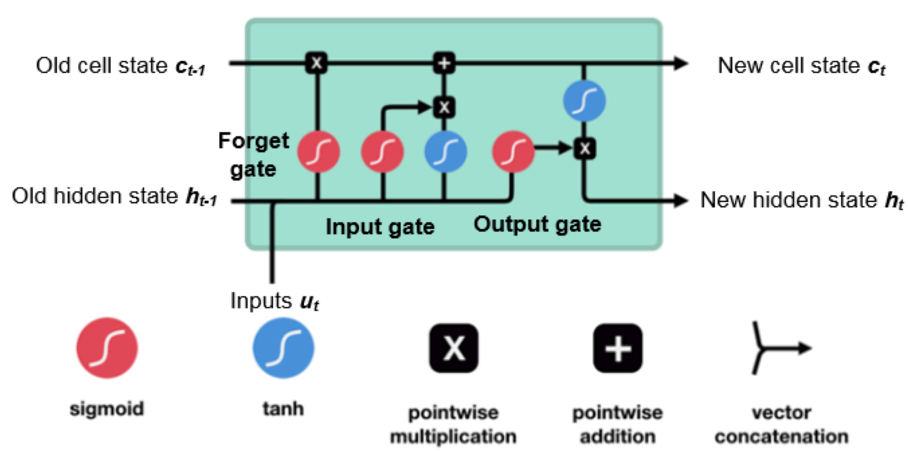
1. First, we have the **forget gate**, which decides how much information is to be forgotten in the cell state.

2. Then we use the **input gate** to prepare an input signal (using the *tanh* function to ensure the scale is from -1 to 1), and further use the *sigmoid* function (which maps to 0-1) to determine the importance of the input.

3. Next we update the cell state based on the results in (1) and (2). If we decide to remember more information (i.e. output in forget gate is closer to 1), then the new cell state will be closer to the old one.

4. Finally, we have the **output gate**, which decides the next hidden state. The predictions are based on the hidden states, and the exact output depends on the chosen activation function.

Figure 4: Component of an LSTM cell



Source: Nguyen, Michael (2018) Illustrated Guide to LSTM's and GRU's: A step by step explanation

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A Decision on Optimal Allocation

What do we want to achieve with the deep learning model? We formulate our problem in terms of an optimal allocation among N assets. First, we target the volatility of each asset to σ_{Target}, such that their returns are comparable. The position allocated to each asset at time t is denoted by $X_t^{(i)}$ with $|X_t^{(i)}| \leq 1$ and $i = 1\text{-}N$. The returns of the portfolio from t to $t+1$ is

$$R_{t,t+1} = \frac{1}{N}\sum_{i=1}^{N} X_t^{(i)} \frac{\sigma_{Target}}{\sigma_t^{(i)}} r_{t,t+1}^{(i)}$$

where N is the number of assets, $r_{t,t+1}$ is the returns of the corresponding asset from t to $t+1$, and σ_t is the estimated volatility of the asset at time t. Depending on the trading rules that determine $X_t^{(i)}$, we can have different strategies:

Long-only Risk Parity:
As we scale the asset volatility to σ_{Target}, risk parity always takes the unit positions:

$$X_t^{(i)} = 1$$

Trend following strategy (Long / Short):
For each asset, we estimate a trend signal, say, by looking at past 252-day returns. Then we assign the weights simply based on the sign of the trend:

$$X_t^{(i)} = sign(r_{t-252,t}^{(i)})$$

Deep Learning Model:
We predict the optimal position on each asset using our LSTM model. Our aim is to use some set of features $F^{(j)}$, feed them into the model and obtain the optimal weights to be held in a portfolio (say on the next day or next week). The model prediction is a vector of length N, corresponding to the weight on each asset, i.e. $X_t^{(i)}$. The LSTM model maps the features to our predictions via some non-linear functions:

$$\hat{X}_t^{(i)} = f^{LSTM}(F_t^{(j)})$$

With this set-up, we are interested in the returns of the strategy if we allocate such positions to our portfolio. To control the turnover of the model outputs, we assume a transaction cost of c, which acts like a hyperparameter (Lim, Zohren and Roberts (2019)). The strategy returns after costs from t to $t+1$ is:

$$R_{t,t+1} = \frac{\sigma_{Target}}{N}\sum_{i=1}^{N}\left(\frac{\hat{X}_t^{(i)}}{\sigma_t^{(i)}} r_{t,t+1}^{(i)} - c\left|\frac{\hat{X}_t^{(i)}}{\sigma_t^{(i)}} - \frac{\hat{X}_{t-1}^{(i)}}{\sigma_{t-1}^{(i)}}\right|\right)$$

Our objective function for training the model is directly defined as the strategy performance such as Sharpe ratio, which is a function of the returns:

$$Loss\ function = L(R_t) = -\frac{CAGR(R_t)}{\sigma(R_t)}$$

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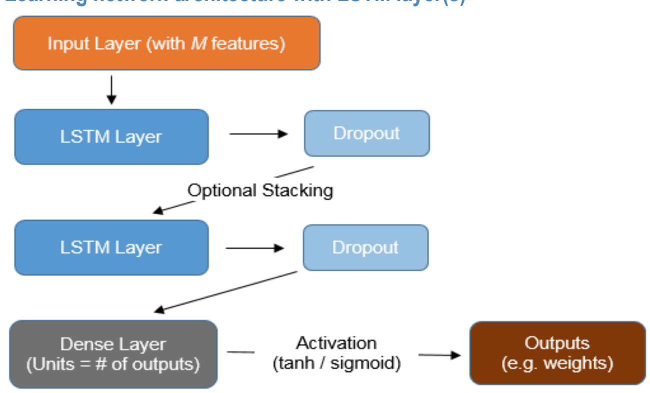
Model Design

Below, we provide details of the design of our LSTM model, as well as the estimation and prediction procedures. Readers who are interested in the applications and strategy backtests may directly move on to the case studies in the next sections.

Network Architecture

We build an LSTM model with M neurons in the input layer, representing the M features that we feed into the model. We use a "Stateful" LSTM layer, meaning that we do not reset the internal states of the LSTM units after each batch of training. Interestingly, we find that stacking two LSTM layers together may improve predictions significantly, especially for situations with more training data and higher output dimensions. Whist it is common to stack many layers in problems associated with image classifications and video captioning, this is a bit surprising to us in the case of financial time series which tend to be noisy and non-stationary. Figure 5 shows the model layers we build in Keras. Each LSTM layer represents a recurrent unit with components as shown in Figure 4. Dropout layers help to prevent overfitting (for details please refer to the Appendix).

Figure 5: Deep Learning network architecture with LSTM layer(s)



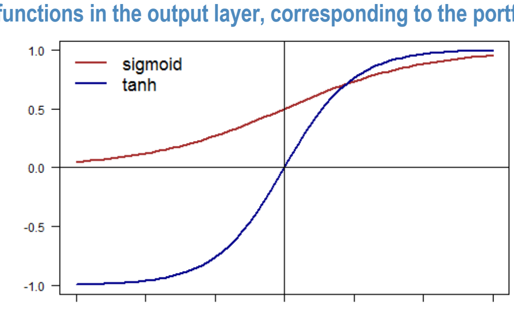
Source: J.P. Morgan Quantitative and Derivatives Strategy

Activation functions

The output from the LSTM layer is fed to a fully connected (a.k.a. Dense) layer with N neurons representing the outputs in $X_t^{(i)}$. Depending on the problem, we could apply different activation functions (Figure 6):

- Long-only or Short-only positions: ***sigmoid*** (outputs from 0 to 1)
- Long / Short positions: ***tanh*** (outputs from -1 to 1)

Figure 6: Activation functions in the output layer, corresponding to the portfolio allocations



Source: J.P. Morgan Quantitative and Derivatives Strategy

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Loss functions

Loss functions can be set according to our preferences. As described above, we pose the problem directly as a decision for optimal allocation, which means that our aim is not to have predicted returns with smallest errors (although we could have done this). Instead, our objective is to make the "optimal" allocations that would lead to the "best" strategy performance, such as highest average returns, Sharpe ratios or Calmer ratios[1]. Custom loss functions can be handled easily in TensorFlow, as it applies automatic differentiation during backpropagation to compute gradients using chain rules, without the need to explicitly define derivatives in advance.

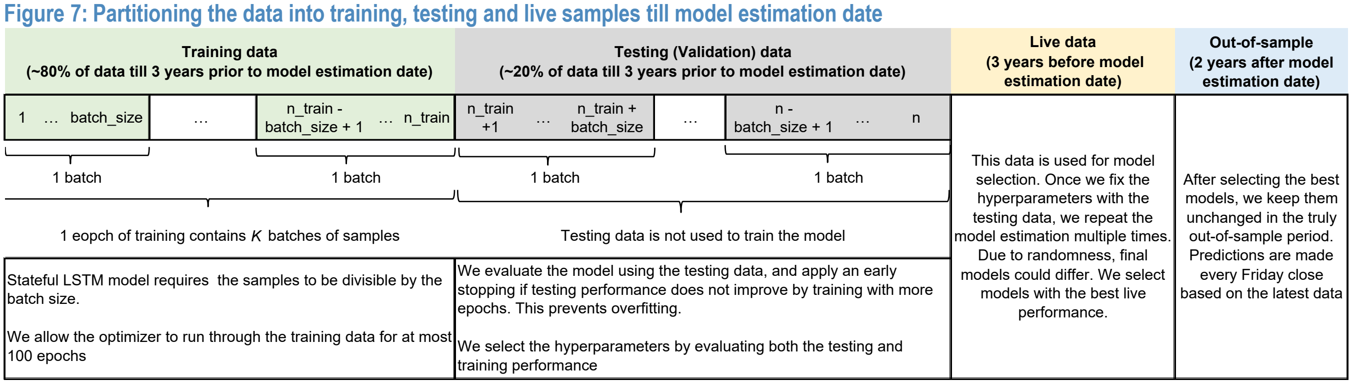
Data partition for training, validation and model selection

Deep Learning model training often comes along with jargon like batch size and number of epochs. Put simply, many algorithms find it more efficient (in terms of both memory usage and convergence) to train "batches" of samples and take the average gradient to descent, rather than training the whole set of training data at once. As such, we often determine a batch size to train each time, and when the network has seen all batches of training data, it has "completed an epoch". The process repeats and we determine the number of epochs to train the model, and set an early stopping criteria to prevent overfitting. Rather than using all data to estimate the model, we carefully divide the data into 3 portions, and we train the model only using the training data. Testing data is used to validate the model, prevent overfitting and help us to select the hyperparameters. The most recent 3 years of data is reserved as "live" data, where we analyze the strategy performance in this period and use the results for model selection (Figure 7). Model selection is done by comparing the model performance in the training, testing and live periods with a set of simple benchmarks: Risk Parity, Equity, Bond, 50/50, 60/40, 70/30 and 80/20:

- We require the model performance to be at least better than all the benchmarks in the training and testing data.
- We remove models which are more likely to be overfitted. We will see that models with extremely good training performance tend to underperform out-of-sample (Figure 13).

We keep the models that satisfy the above criteria, and select the best 20 models based on their live performance.

Figure 7: Partitioning the data into training, testing and live samples till model estimation date



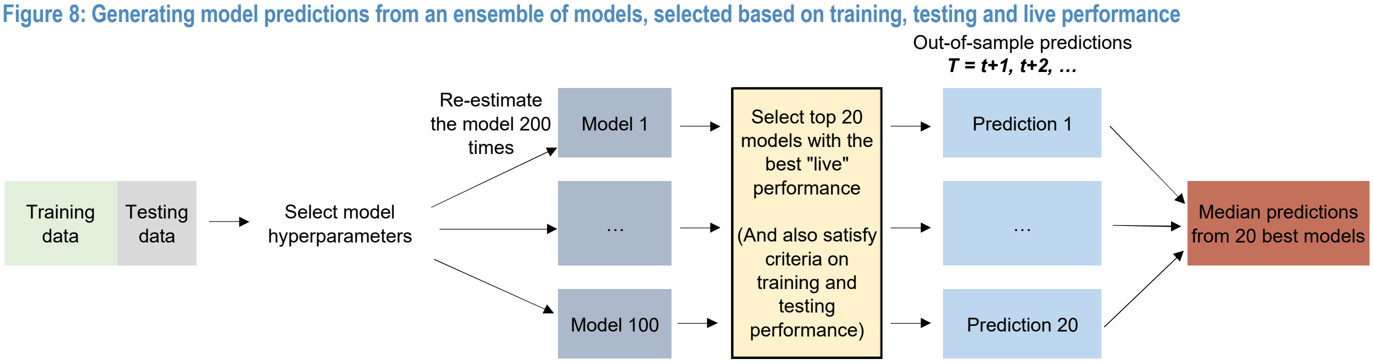
Source: J.P. Morgan Quantitative and Derivatives Strategy

[1] Many usual loss functions such as mean squared errors are implemented directly in Keras. However, for custom loss functions like the (negative) Sharpe ratios, we need to define explicitly.

Model Predictions

Many Machine Learning and Deep Learning models are inheritably random, and some of the algorithms (e.g. Random Forests) actually make use of random subsampling to reduce model variance. In some cases, setting a random seed could ensure reproducible results (which is useful in tutorials), but this would not apply for models trained on distributed CPUs or GPUs (Hlavaty (2018)). We do not recommend setting random seeds in models deployed in production. Our preferred approach is to collect an ensemble of trustworthy models (say 20) in the model selection process described above. Different results are expected due to the inherited randomness (e.g. weight initializations), but we expect (and confirm) that the average statistics to be relatively stable. We take the median predictions from the ensemble as the final model output (Figure 8).

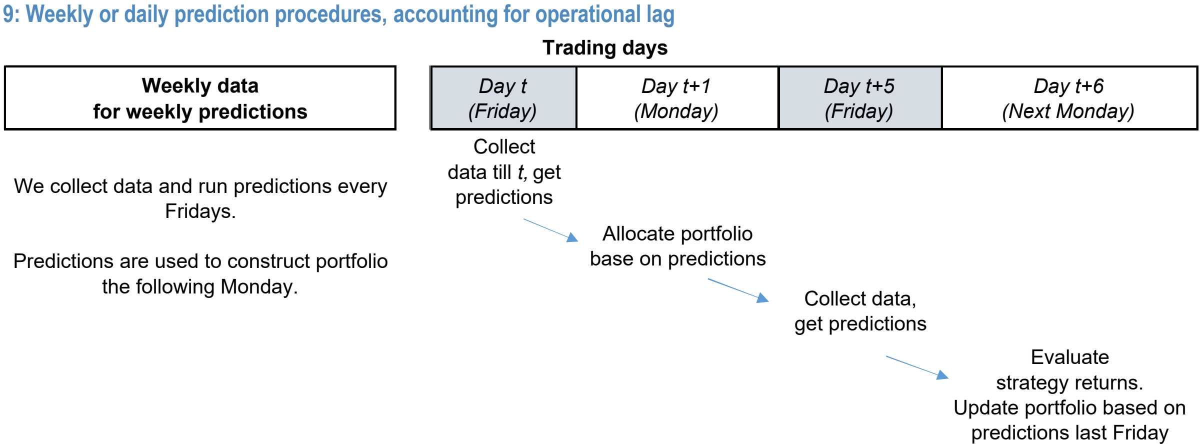
Figure 8: Generating model predictions from an ensemble of models, selected based on training, testing and live performance



Source: J.P. Morgan Quantitative and Derivatives Strategy

In the next section, we will use the framework to study an application on equity/bond allocation. With our model set-up, we consider training weekly data to generate weekly predictions. Based on weekly data, we generate predictions every Friday. The predictions correspond to optimal positions on the assets, and we allocate the portfolio based on the predictions at the close of next Monday, or the next trading day (Figure 9). Whilst we can run daily predictions with daily data, we hope to better dissect the model behavior based on predictions at lower frequencies. Discretionary portfolio managers may also use our signals to assist judgements in allocation decisions. For example, we may see meaningful changes in the model positions amid shifts in market regimes.

Figure 9: Weekly or daily prediction procedures, accounting for operational lag



Source: J.P. Morgan Quantitative and Derivatives Strategy

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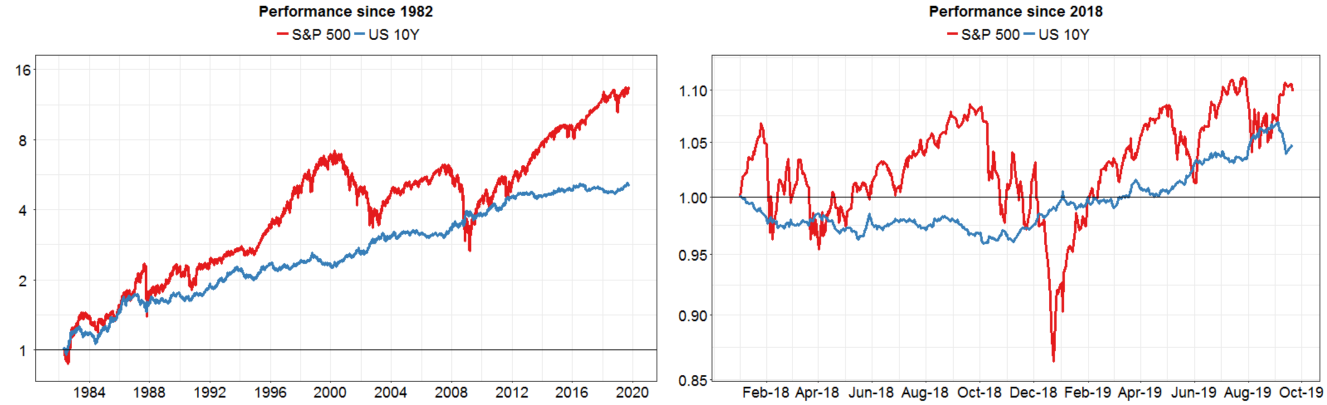
Allocating an Equity/Bond Portfolio

We apply the Deep Learning model in an asset allocation context, aiming to predict optimal positions in a portfolio. In this example, we construct a portfolio of S&P 500 and US 10-year treasury. The historical performances of S&P 500 and US 10-year are shown in Figure 10. We see that simply holding US treasuries over the long-term delivers a Sharpe ratio of 0.7, as yields have been declining in general since the 1980s.

Figure 10: Performance of S&P 500 and US 10-year since 1982 (left) and since 2018 (right)



	Start date	End date	Annualized returns	Annualized Vol	Sharpe ratio	t-stat	Skewness	Kurtosis	Max Drawdown	Hit ratio	Sortino ratio	Calmer ratio
S&P 500	1982-05-05	2019-09-20	7.1%	18.8%	0.38	2.83	-1.08	51.99	62.9%	53.8%	0.04	0.11
US 10Y	1982-05-05	2019-09-20	4.4%	6.6%	0.67	4.25	0.11	3.50	16.1%	52.5%	0.06	0.28
					Since 2018							
S&P 500	2018-01-02	2019-09-20	6.0%	16.2%	0.37	0.58	-0.54	4.85	20.5%	55.2%	0.04	0.29
US 10Y	2018-01-02	2019-09-20	2.6%	3.9%	0.66	0.87	0.31	1.45	4.3%	52.1%	0.06	0.59

Source: J.P. Morgan Quantitative and Derivatives Strategy

We aim to generate weekly predictions on the optimal allocations on equities versus bonds. As an example, we use features based on historical returns, some CTA trend-following signals (Baz et al (2015), Lim et al (2019)) as well as levels and slope of the yield curve. Figure 11 summarizes the set-up of this study.

Figure 11: Deep Learning model for Equity/Bond allocation – Weekly rebalancing

	Details	Remarks
Asset	S&P 500 futures (SP1 Index) US 10 Yr futures (TY1 Comdty)	Returns are calculated based on the GFUT settings in Bloomberg, which rolls to the next future with highest liquidity
# of Features	28	
Features	SP1 and TY1 Standardized returns (5D, 1M, 3M, 6M, 12M)	Standardized returns are the raw returns divided by the corresponding realized volatility in the same lookback period
	CTA momentum signals for SP1 and TY1 at 3 different time scales	CTA momentum signals are based on Baz et al (2015): Dissecting Investment Strategies in the Cross Section and Time Series
	US 2Y yield, US 10Y yield and slope of yield curve (10Y-2Y)	z-scores of the levels over 4 lookback windows (1M, 3M, 6M, 12M)
Activation function (Output layer)	tanh	Possible positions from -1 to 1
Objective function	Sharpe ratio	Maximize the Sharpe ratio after t-costs assumptions
Data start	1983	Weekly data till close of Fridays
Model estimation dates	1st week in Jan on 2015, 2017, 2019	Expanding window. Most recent 3 years are reserved for model selection. The remaining 80% of data is for training, and 20% for testing / validation
Predictions	Weekly on Fridays, for the next 2 years after model estimation	We do not update the model weights when new data comes in. Portfolio construction is on the next Monday close

Source: J.P. Morgan Quantitative and Derivatives Strategy

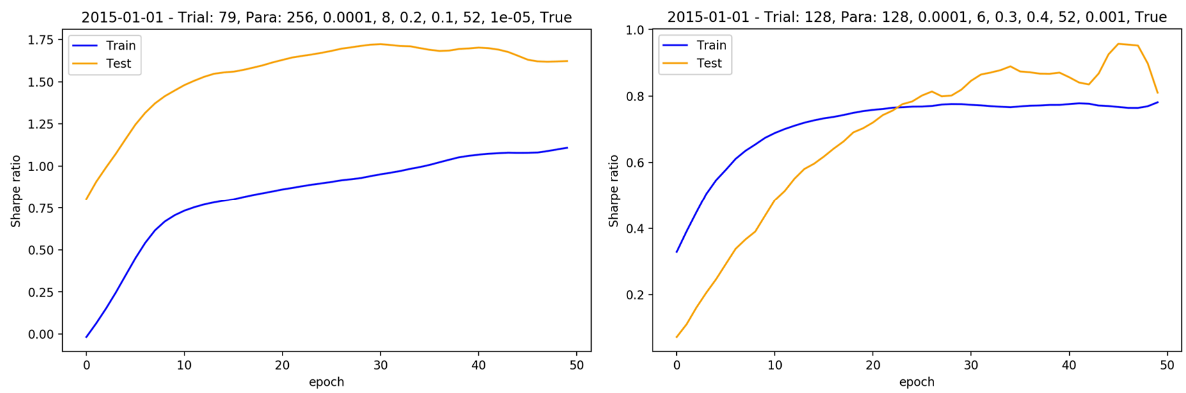
Details on Model Estimation

We highlight some major results on model training below, using the model estimated at the beginning of 2015 as an example. More details can be found in the Appendix. Readers who are more interested in the final model outputs and strategy backtests can move on to the results from Figure 16 onwards.

Using 1024 samples (four batches) from Jun 1986 to Feb 2006 for training and 256 samples (one batch) from Feb 2007 to Dec 2011 for validation (i.e. testing)[2], we select the hyperparameters as in Figure 12. Training over the epochs improves the in-sample Sharpe ratios, but the improvement in the testing data stops after about 30 epochs and starts to decrease, indicating overfitting. As a comparison, we show a less optimal model fit with another set of hyperparameters on the right, where the training Sharpe ratio stops to further increase at about 0.8, and the validation Sharpe ratio is around 1. To put things into perspectives, risk parity has a Sharpe of 0.58 and 1.2 in the same training and testing period respectively (Figure 12).

Figure 12: We select the best model with hyperparameters leading to the highest Sharpe ratio in the testing data (left). A less optimal model fit is shown in the right. The table shows the performance of some benchmark strategies in the training and testing period.

Learning rate	Batch size	Units	Dropout	Recurrent Dropout	Regularization lambda	Time step	Stack LSTM layer
1.00E-04	256	8	0.2	0.1	1.00E-05	52	TRUE



Benchmarks	Start date	End date	Annualized returns	Annualized Vol	Sharpe ratio	t-stat	Skewness	Kurtosis	Max Drawdown	Hit ratio	Sortino ratio	Calmer ratio
					Training data							
Risk Parity	1986-07-03	2006-02-10	7.6%	13.1%	0.58	2.78	-0.69	6.74	31.6%	55.5%	0.12	0.24
Equity	1986-07-03	2006-02-10	6.9%	19.0%	0.36	2.00	-2.31	34.51	52.3%	55.0%	0.09	0.13
Bond	1986-07-03	2006-02-10	3.0%	6.9%	0.43	2.05	0.48	7.39	15.7%	54.1%	0.10	0.19
50/50	1986-07-03	2006-02-10	5.4%	10.6%	0.52	2.47	-1.58	24.36	25.4%	54.1%	0.11	0.21
60/40	1986-07-03	2006-02-10	5.8%	12.1%	0.48	2.35	-1.87	28.15	29.3%	53.5%	0.10	0.20
70/30	1986-07-03	2006-02-10	6.2%	13.7%	0.45	2.25	-2.06	30.79	35.5%	54.1%	0.10	0.17
80/20	1986-07-03	2006-02-10	6.4%	15.4%	0.42	2.15	-2.18	32.56	41.6%	54.4%	0.09	0.15
					Testing data							
Risk Parity	2007-02-16	2012-01-06	10.1%	8.4%	1.20	2.63	-0.57	2.52	10.5%	59.4%	0.25	0.96
Equity	2007-02-16	2012-01-06	-2.3%	26.1%	-0.09	0.10	0.00	3.34	60.0%	52.3%	0.01	-0.04
Bond	2007-02-16	2012-01-06	8.8%	7.4%	1.20	2.63	-0.58	2.08	8.1%	57.4%	0.25	1.09
50/50	2007-02-16	2012-01-06	4.3%	11.9%	0.36	0.92	0.13	3.64	28.1%	53.5%	0.08	0.15
60/40	2007-02-16	2012-01-06	3.1%	14.6%	0.22	0.63	0.09	3.60	35.7%	54.3%	0.06	0.09
70/30	2007-02-16	2012-01-06	1.9%	17.4%	0.11	0.43	0.05	3.54	42.6%	54.3%	0.04	0.04
80/20	2007-02-16	2012-01-06	0.6%	20.3%	0.03	0.29	0.03	3.47	49.0%	53.5%	0.03	0.01

Source: J.P. Morgan Quantitative and Derivatives Strategy

[2] We do not deliberately remove samples in 2006. Our algorithm automatically trims the data sample to ensure it is divisible by the batch size, which is necessary for Stateful LSTMs.

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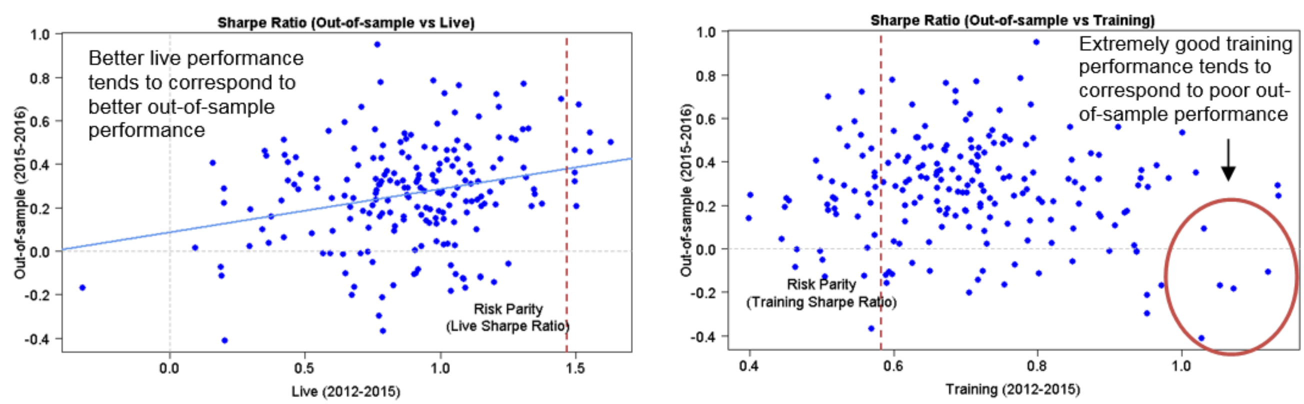
Model Selection

After fixing the hyperparameters, we re-run the model estimation multiple times and estimate an ensemble of models. We select the top 20 models out of the ensemble with the best live performance, since in general we see better out-of-sample performance for models with better live performance. On top of that, some criteria also help us to select good models:

- For models with poor training or testing performance, we do not have confidence that they are trained properly (although they could have good live performance, probably by chance). We require the training or testing Sharpe ratios to be above that of the best benchmark
- On the other hand, models with very superior training performance are likely to be overfitted, and this also apply for testing and live performance. Hence, we discard models with extremely good performance beyond three times that of the best benchmark in the training, testing or live period.

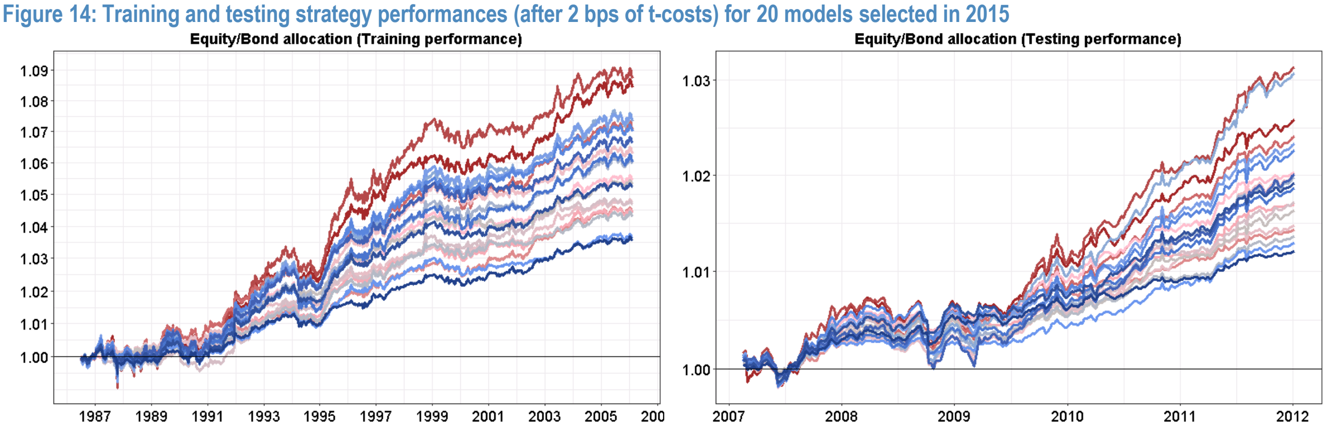
Figure 13: Model selection is based on performance in the live period (recent 3 years), and also training and testing performance relative to a set of benchmarks



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 14 shows the training and testing performance of the selected models. Volatility is extremely low in the raw output, but this is not surprising as we aim to maximize Sharpe ratios. Final strategies are leveraged to 10% portfolio volatility.

Figure 14: Training and testing strategy performances (after 2 bps of t-costs) for 20 models selected in 2015



Source: J.P. Morgan Quantitative and Derivatives Strategy

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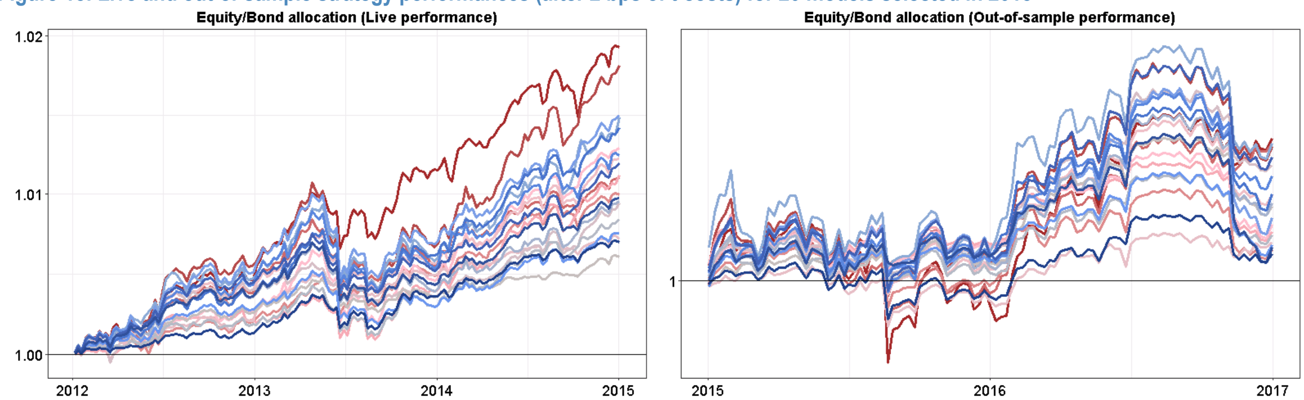
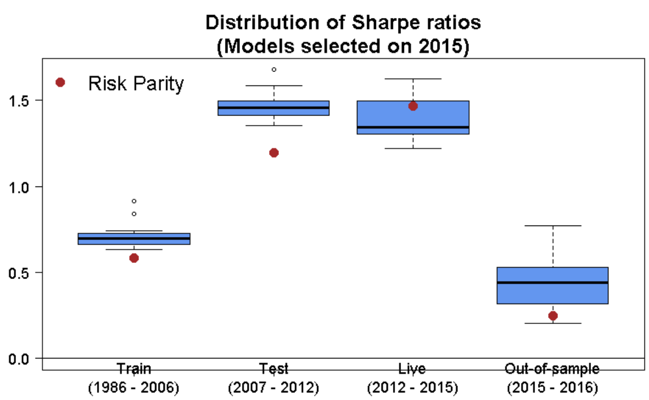
In Figure 15, we show the model performances in the live period, i.e. 3 years of data prior to model estimation date, which is unseen by the model. We select models which perform well in this live period. Nevertheless, it is clear that out-of-sample performance could still vary, especially when there are regime changes or political events which could not be learnt from historical patterns. For instance, the performance at the end of 2016 is quite poor, which corresponds to a surge in bond yields after the election of president Trump. Having said that, a risk parity benchmark also suffered in such period, where Sharpe ratio drops from 1.5 in 2012-2015 down to 0.25 in 2015-2016.

To summarize, we see the importance of taking an ensemble of models. Even all of the models have decent Sharpe ratios in the training, testing and live periods, truly out-of-sample performances could still vary. Similar results for models estimated at the beginning of 2017 and 2019 are shown in the Appendix.

Figure 15: Live and out-of-sample strategy performances (after 2 bps of t-costs) for 20 models selected in 2015





Benchmark Sharpe Ratios

	Training	Testing	Live	Out-of-sample
	1986 - 2006	2007 - 2012	2012 - 2015	2015 - 2016
Risk Parity	0.58	1.20	1.47	0.25
Equity	0.36	-0.09	1.95	0.44
Bond	0.43	1.20	0.31	0.23
50/50	0.52	0.36	2.16	0.62
60/40	0.48	0.22	2.12	0.57
70/30	0.45	0.11	2.07	0.53
80/20	0.42	0.03	2.03	0.49

Source: J.P. Morgan Quantitative and Derivatives Strategy

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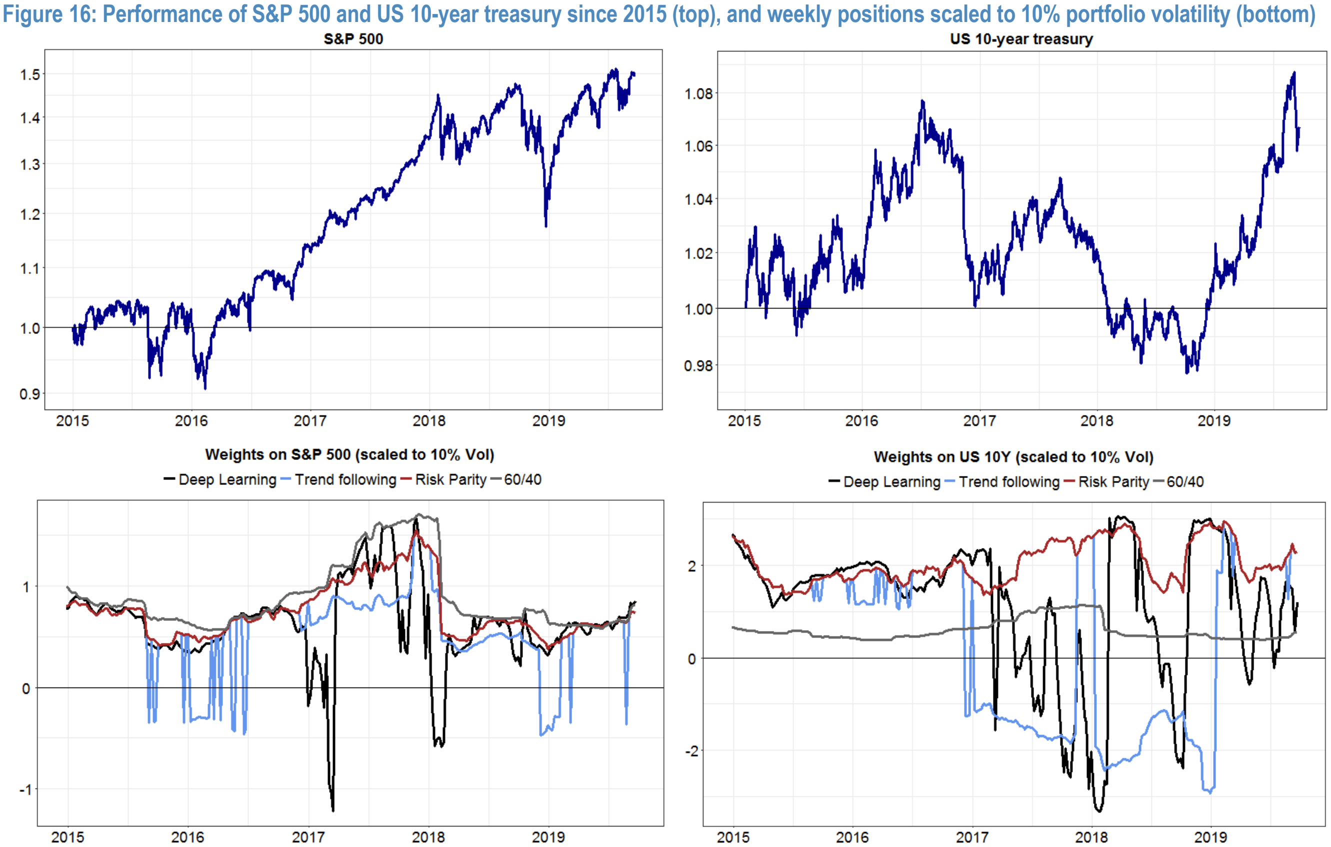
Strategy Backtests

Model predictions

Figure 16 shows the performance of S&P 500 and US 10-year since 2015, and the portfolio weights based on different models. The trend following and risk parity benchmarks follow the allocation rule discussed on page 7, and the Deep Learning model allocations are based on the LSTM outputs. All the weights are scaled to target at 10% portfolio volatility[3].

We find the Deep Learning model to be pretty cautious on equities when it detects some worrying signals, whilst behaving quite similar to risk parity during normal markets. We will further analyze the portfolio positions in the next sections.

Figure 16: Performance of S&P 500 and US 10-year treasury since 2015 (top), and weekly positions scaled to 10% portfolio volatility (bottom)



Source: J.P. Morgan Quantitative and Derivatives Strategy

[3] We use a lookback of 252 days to estimate portfolio volatility, and scale the raw positions to match the 10% vol target at the portfolio level and cap the maximum leverage to 4

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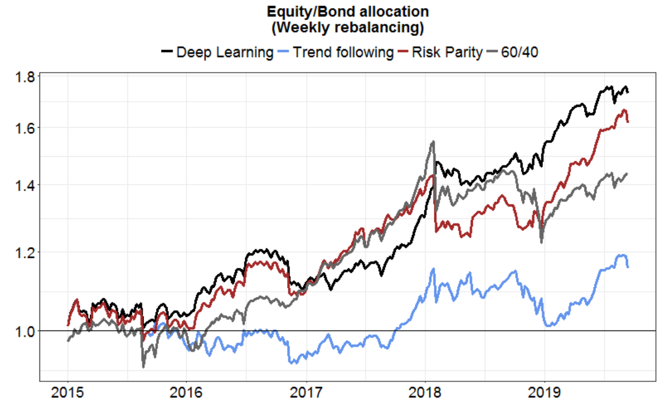
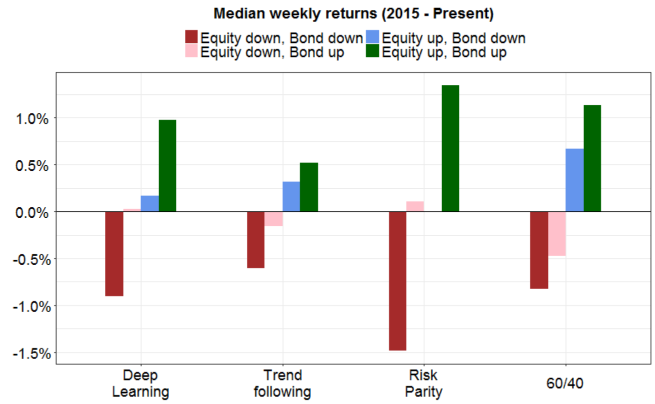
Model performance compared with benchmarks

Figure 17 shows the out-of-sample backtests of the weekly-rebalanced portfolios, assuming 2 bps of transaction costs. The Deep Learning model achieves the highest Sharpe ratio of 1.28, although risk parity is also very competitive and delivers a Sharpe ratio close to 1. The Deep Learning model also has the lowest drawdown amongst all.

Figure 17: Weekly strategy backtests on Equity/Bond allocation, assuming 2 bps of transaction costs





	Start date	End date	Annualized returns	Annualized Vol	Sharpe ratio	t-stat	Skewness	Kurtosis	Max Drawdown	Hit ratio	Sortino ratio	Calmer ratio
Deep Learning	2015-01-02	2019-09-20	12.3%	9.6%	1.28	2.74	-0.30	3.10	8.9%	61.5%	0.27	1.38
Trend following	2015-01-02	2019-09-20	3.4%	10.8%	0.32	0.80	-1.24	4.08	13.7%	57.5%	0.07	0.25
Risk Parity	2015-01-02	2019-09-20	11.0%	11.6%	0.95	2.09	-2.26	15.29	13.2%	60.3%	0.18	0.83
60/40	2015-01-02	2019-09-20	8.0%	12.5%	0.63	1.47	-3.34	24.16	20.9%	61.9%	0.12	0.38

Source: J.P. Morgan Quantitative and Derivatives Strategy

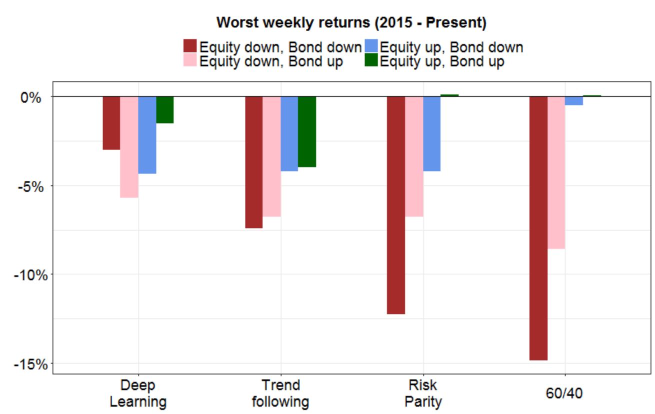
Looking at returns across market regimes, the Deep Learning model is relatively defensive: It suffers the smallest loss when both equities and bonds are down, whilst risk parity and 60/40 had large drawdowns. Trend following, as expected, was more defensive as well but the worst weekly returns are still more negative than the model (Figure 18).

Figure 18: The model suffers the smallest loss when both equities and bonds are down

Equity down, Bond down

Weekly returns (Monday to Monday)

	Deep Learning	Trend Following	Risk Parity	60/40	S&P 500	US 10Y
2018						
2018-02-05	5.8%	-7.4%	-12.3%	-14.9%	-8.6%	-0.4%
2018-03-05	-1.4%	-0.7%	-1.7%	-2.2%	-2.4%	-0.2%
2018-04-23	-3.0%	1.9%	-2.9%	-0.7%	-0.4%	-0.9%
2018-07-30	-0.3%	-0.1%	-0.4%	-0.3%	-0.3%	-0.1%
2018-09-03	0.0%	0.3%	-0.4%	-0.1%	0.0%	-0.3%
2018-09-10	-0.1%	0.3%	-1.4%	-0.7%	-0.8%	-0.5%
2018-10-08	1.4%	0.4%	-2.1%	-1.2%	-1.2%	-0.8%
2018-11-26	-1.2%	-1.0%	-1.5%	-2.0%	-2.7%	0.0%
2018-12-17	-1.4%	1.6%	-1.6%	-2.6%	-3.5%	0.0%
Average	0.0%	-0.5%	-2.7%	-2.7%	-2.2%	-0.4%
2019						
2019-03-04	-1.1%	-1.2%	-1.2%	-0.3%	-0.2%	-0.4%



Source: J.P. Morgan Quantitative and Derivatives Strategy

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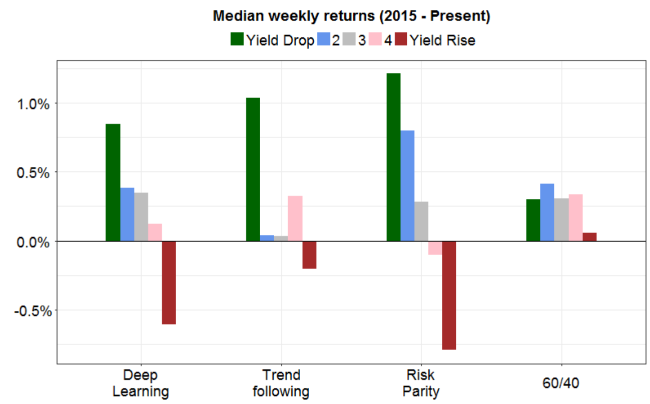
Sensitivity to yield changes

Another interesting point to note is that the strategy returns are in general inversely proportional to changes in yield, similar to the case of risk parity. When there is a large jump in yield, the model tends to suffer, but risk parity has even more negative returns. The most recent example occurs in the first two weeks of September 2019, when the yield on US 10Y surged by over 12%. In that case, the Deep Learning model suffered a smaller loss (almost half of that of risk parity) due to a trimmed exposure to bonds. On the other hand, large drops in yields tend to favor risk parity, but the model also delivers the best returns in such a scenario.

Figure 19: Returns tend to get hurt when there is a jump in yields, but the model in general suffers smaller loss than risk parity in such scenario.

	Weekly returns (Monday to Monday)					
	Deep Learning	Trend Following	Risk Parity	60/40	10Y Yield (%)	Weekly Change
2018-01-08	3.3%	2.5%	2.5%	3.9%	2.48	3.6%
2018-01-22	1.9%	2.8%	0.4%	2.0%	2.65	6.9%
2018-02-12	0.0%	2.2%	0.9%	2.3%	2.86	5.7%
2018-04-23	-3.0%	1.9%	-2.9%	-0.7%	2.98	5.3%
2018-07-23	0.0%	1.0%	-0.6%	0.1%	2.95	3.4%
2018-09-24	1.2%	1.1%	-0.1%	0.5%	3.09	3.4%
2018-10-08	1.4%	0.4%	-2.1%	-1.2%	3.23	4.8%
2018-11-05	0.3%	2.8%	0.5%	2.4%	3.20	3.8%
Average	**0.6%**	**1.8%**	**-0.2%**	**1.2%**		**4.6%**
2019-04-01	0.7%	-0.1%	-0.1%	1.1%	2.50	4.3%
2019-06-10	2.4%	2.3%	2.3%	2.8%	2.15	3.7%
2019-09-09	0.3%	-0.3%	-0.3%	0.9%	1.64	7.1%
2019-09-16	-1.5%	-2.8%	-2.8%	-0.2%	1.85	12.3%
Average	**0.5%**	**-0.3%**	**-0.2%**	**1.2%**		**6.9%**



Source: J.P. Morgan Quantitative and Derivatives Strategy

Dissecting Model Allocations and Performance

In the below, we examine a few episodes when the Deep Learning model behaves quite differently from risk parity and other benchmarks. It typically entails periods when the Deep Learning model decreases exposure in equities and/or bonds, or when positions switch from long to short. Whilst the model does not always outperform the benchmarks within certain periods, we think it may shed some light on the behavior of the model.

We highlight good performances of the model around 2017 to 2018:

- **Late 2017 to early 2018:** Trimming and shorting equities before market crash
- **Late 2018:** Navigating through market corrections
- **2018 Full Year:** Defensive positions have paid off well

But we find that allocations turn out to be sub-optimal in other periods. It may due to more policy driven dynamics that are unseen historically:

- **Late 2016 to early 2017:** Following Trump election, lower equities positions hurt performances
- **2019 YTD:** Performance hurt by lower bond positions amid bond rally

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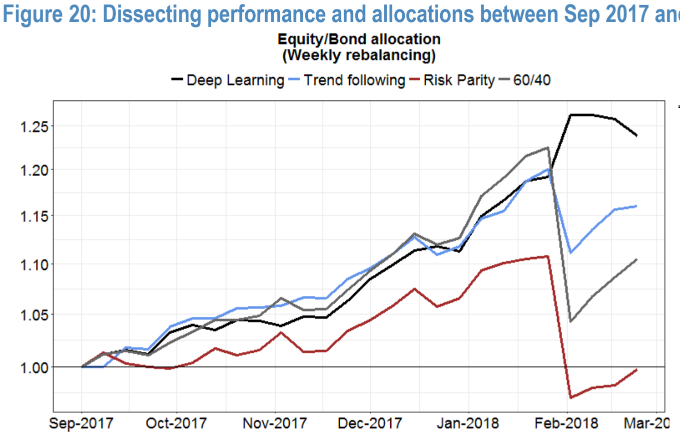
Late 2017 to early 2018: Trimming and shorting equities before market crash

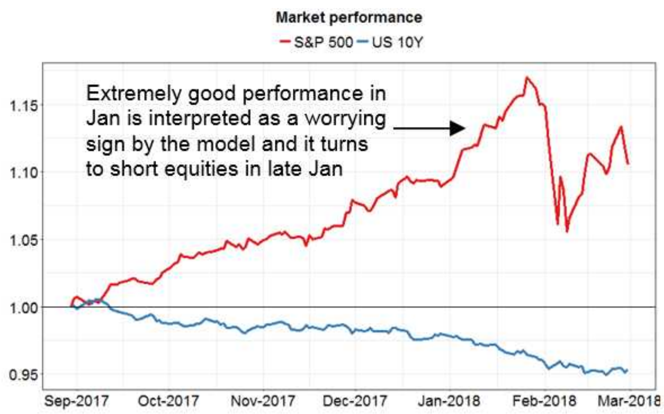
The model starts to decrease equity positions in Sep 2017, following a rather long streak of bullish market. The extremely strong equity performance in Jan 2018 seems to give a warning signal to the model, where it starts to decrease equity positions and turns to short the S&P 500 in late January. This contributes to its positive performance in Feb 2018 whilst other benchmarks suffer massive drawdowns during the market crash. For bonds, the model is mostly shorting the treasury as yields keep rising over the period.

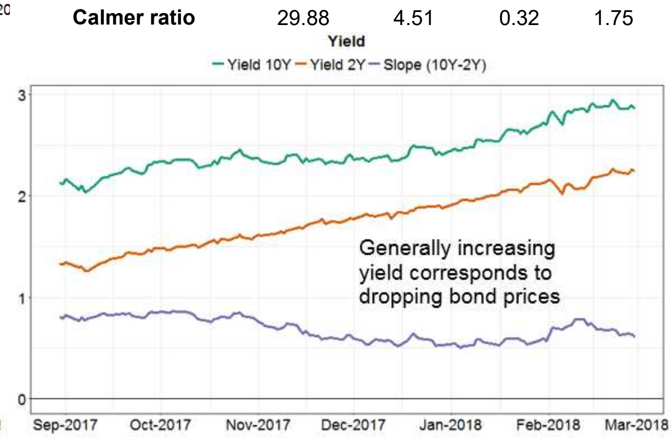
Figure 20: Dissecting performance and allocations between Sep 2017 and Feb 2018

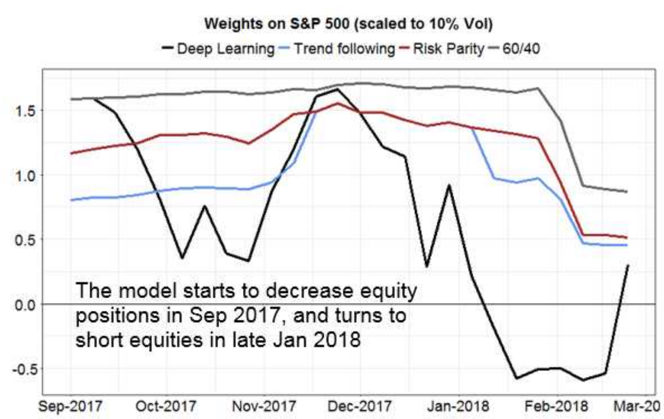


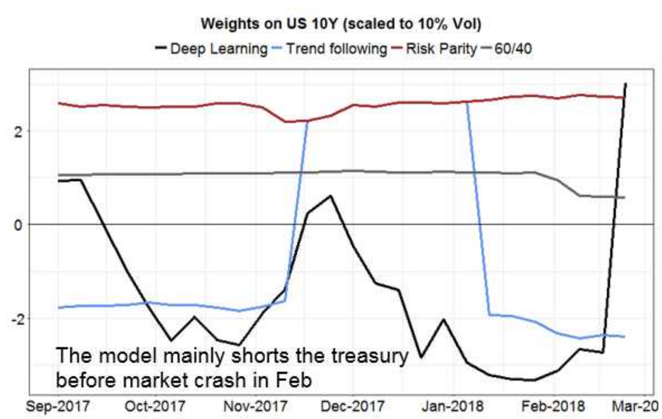
Sep 2017 - Feb 2018

	Deep Learning	Trend Following	Risk Parity	60/40
Annualized Returns	58.5%	33.5%	3.9%	26.0%
Annualized Vol	10.6%	13.9%	19.8%	23.9%
Sharpe ratio	5.52	2.40	0.19	1.09
t-stat	3.12	1.52	0.21	0.77
Skewness	1.59	-3.14	-4.12	-4.51
Kurtosis	3.13	9.57	14.13	16.31
Max Drawdown	2.0%	7.4%	12.3%	14.9%
Hit ratio	69.2%	73.1%	73.1%	84.6%
Sortino ratio	2.50	0.38	0.05	0.17
Calmer ratio	29.88	4.51	0.32	1.75









Source: J.P. Morgan Quantitative and Derivatives Strategy

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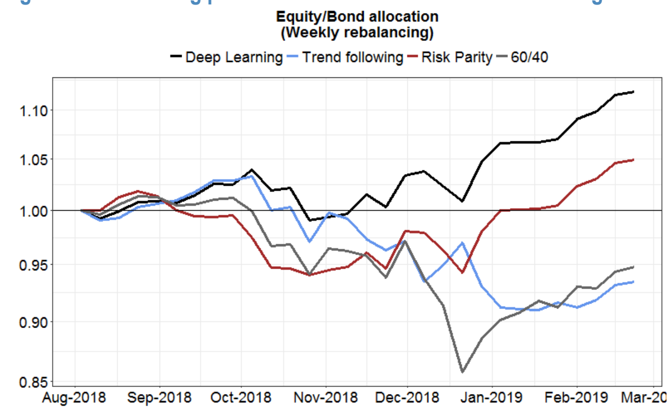
Late 2018: Navigating through market corrections

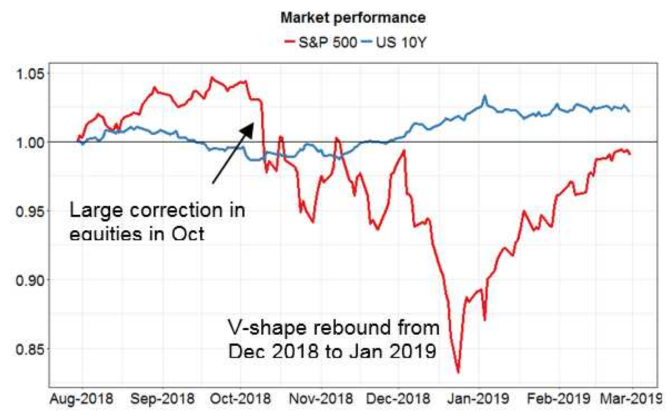
Trimming equity positions in late Sep 2018 has saved the model portfolio from another large corrections in Oct. The model does not short equities during the December meltdown, which actually may not be bad as otherwise it would likely miss the rally in January, just like the trend-following portfolio. For bonds, the model correctly shorts treasuries during Sep to Oct 2018, as yields start to rise. The equity market correction in Oct 2018 has likely led to higher bond positions in the model. The long positions since then have proved to be correct as yields start to drop and bonds begin to rally.

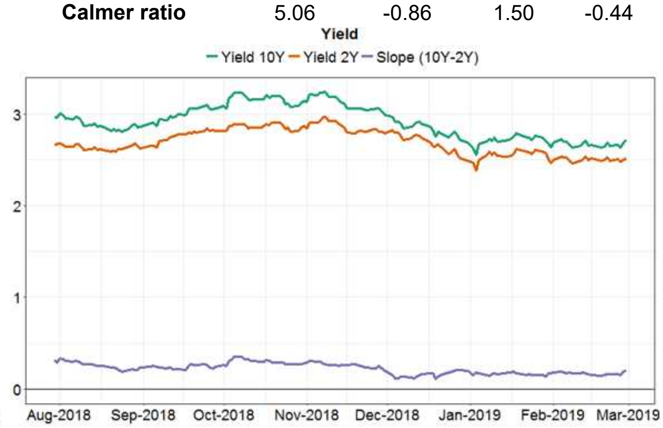
Figure 21: Dissecting performance and allocations between Aug 2018 and Feb 2019

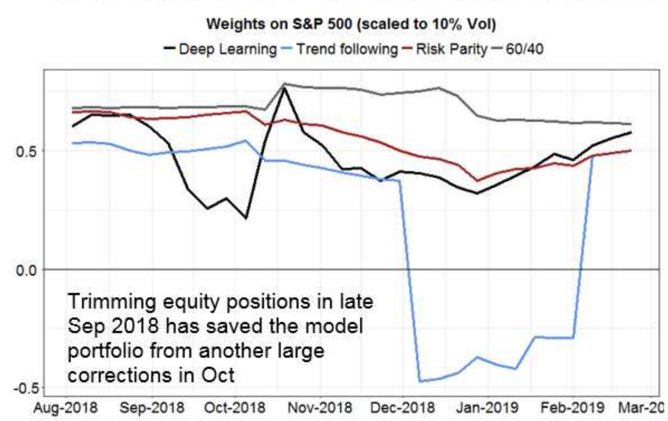


Aug 2018 - Feb 2019

	Deep Learning	Trend Following	Risk Parity	60/40
Annualized Returns	23.7%	-10.3%	11.6%	-6.8%
Annualized Vol	10.2%	12.2%	11.2%	15.0%
Sharpe ratio	2.34	-0.84	1.03	-0.46
t-stat	1.63	-0.63	0.79	-0.30
Skewness	-0.05	-0.89	0.43	-0.84
Kurtosis	0.53	0.08	0.37	0.83
Max Drawdown	4.7%	11.9%	7.7%	15.4%
Hit ratio	70.0%	60.0%	60.0%	53.3%
Sortino ratio	0.53	-0.14	0.24	-0.07
Calmer ratio	5.06	-0.86	1.50	-0.44







Source: J.P. Morgan Quantitative and Derivatives Strategy

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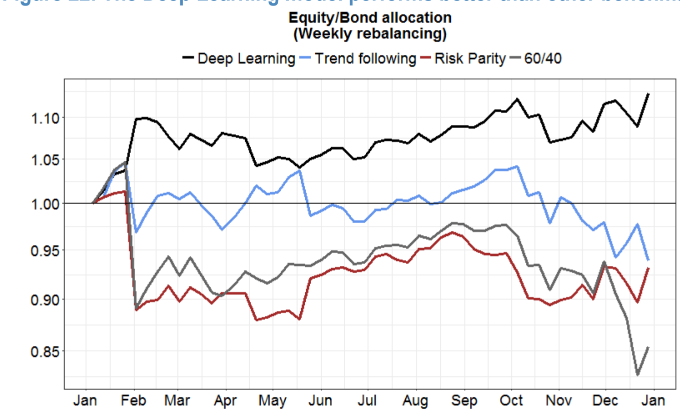
2018 Full Year: Defensive positions have paid off well

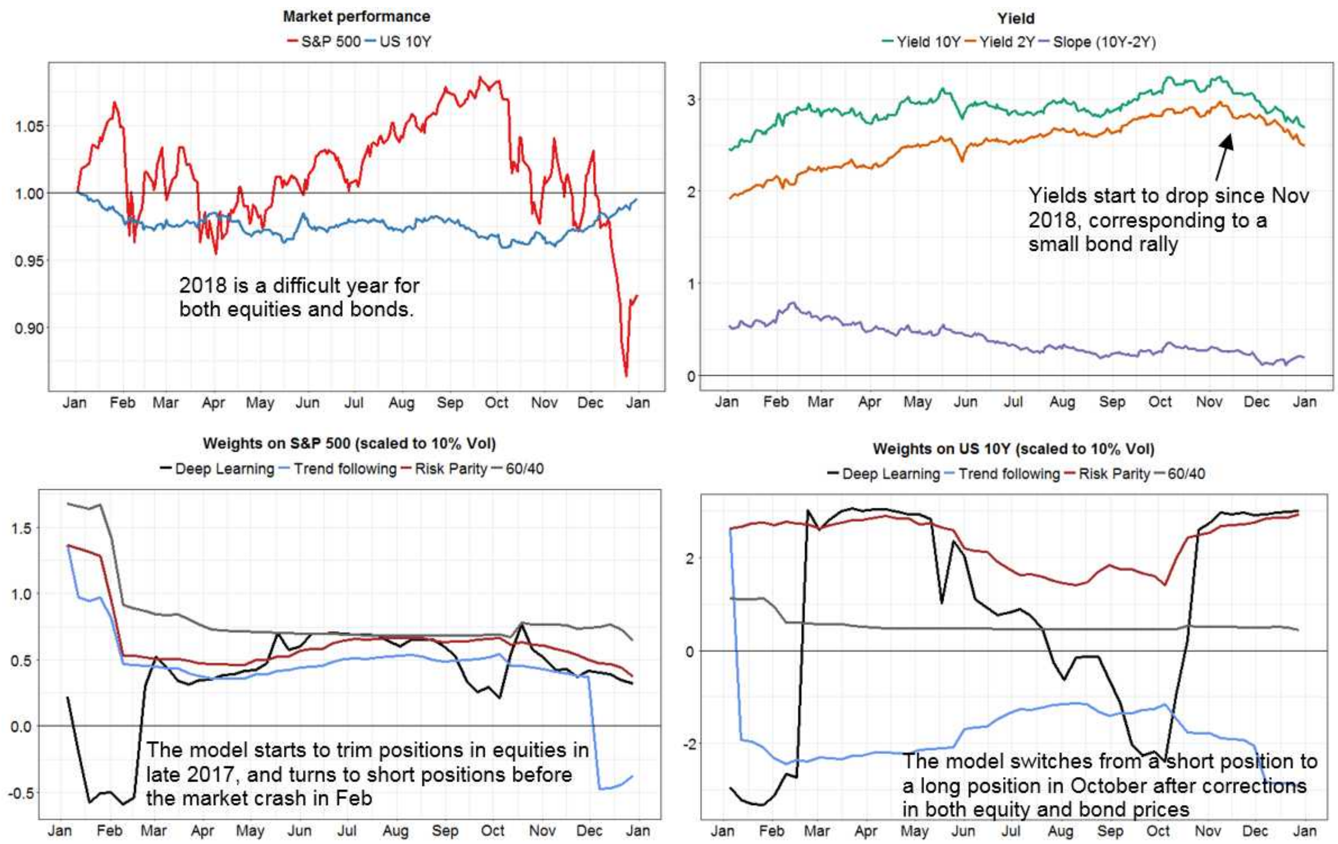
2018 is a year where the Deep Learning model behaves differently from other benchmarks, as we have seen above focusing on its performance around Feb and Oct. The Deep Learning model starts to trim positions in S&P 500 in late 2017, and turns to short positions before the market crash in Feb. As such, the model avoids massive drawdowns. For treasuries, the Deep Learning model switches from a short position to a long position in October after corrections in both equity and bond prices, enabling it to capture the bond rally since November 2018.

Figure 22: The Deep Learning model performs better than other benchmarks in 2018 and avoids the massive drawdowns during February



Jan 2018 - Dec 2018

	Deep Learning	Trend Following	Risk Parity	60/40
Annualized Returns	16.7%	-3.7%	-4.4%	-11.2%
Annualized Vol	11.2%	14.4%	16.4%	20.1%
Sharpe ratio	1.49	-0.26	-0.27	-0.56
t-stat	1.43	-0.19	-0.19	-0.49
Skewness	0.87	-1.51	-2.92	-3.12
Kurtosis	2.28	2.53	14.48	13.15
Max Drawdown	5.2%	10.3%	13.2%	20.9%
Hit ratio	57.7%	65.4%	57.7%	53.8%
Sortino ratio	0.38	-0.03	-0.03	-0.08
Calmer ratio	3.21	-0.36	-0.33	-0.54



Source: J.P. Morgan Quantitative and Derivatives Strategy

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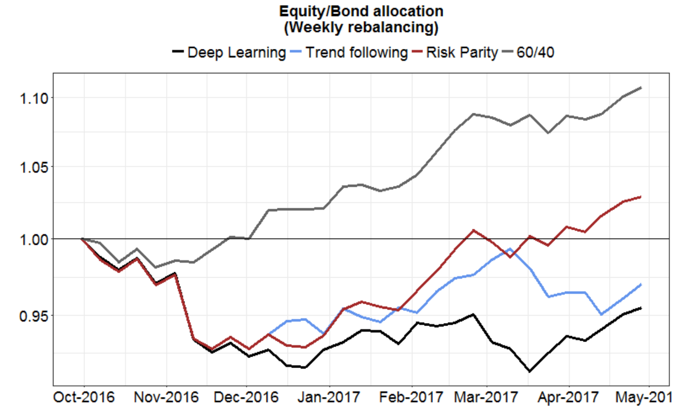
Late 2016 to early 2017: Following Trump election, lower equities positions hurt performances

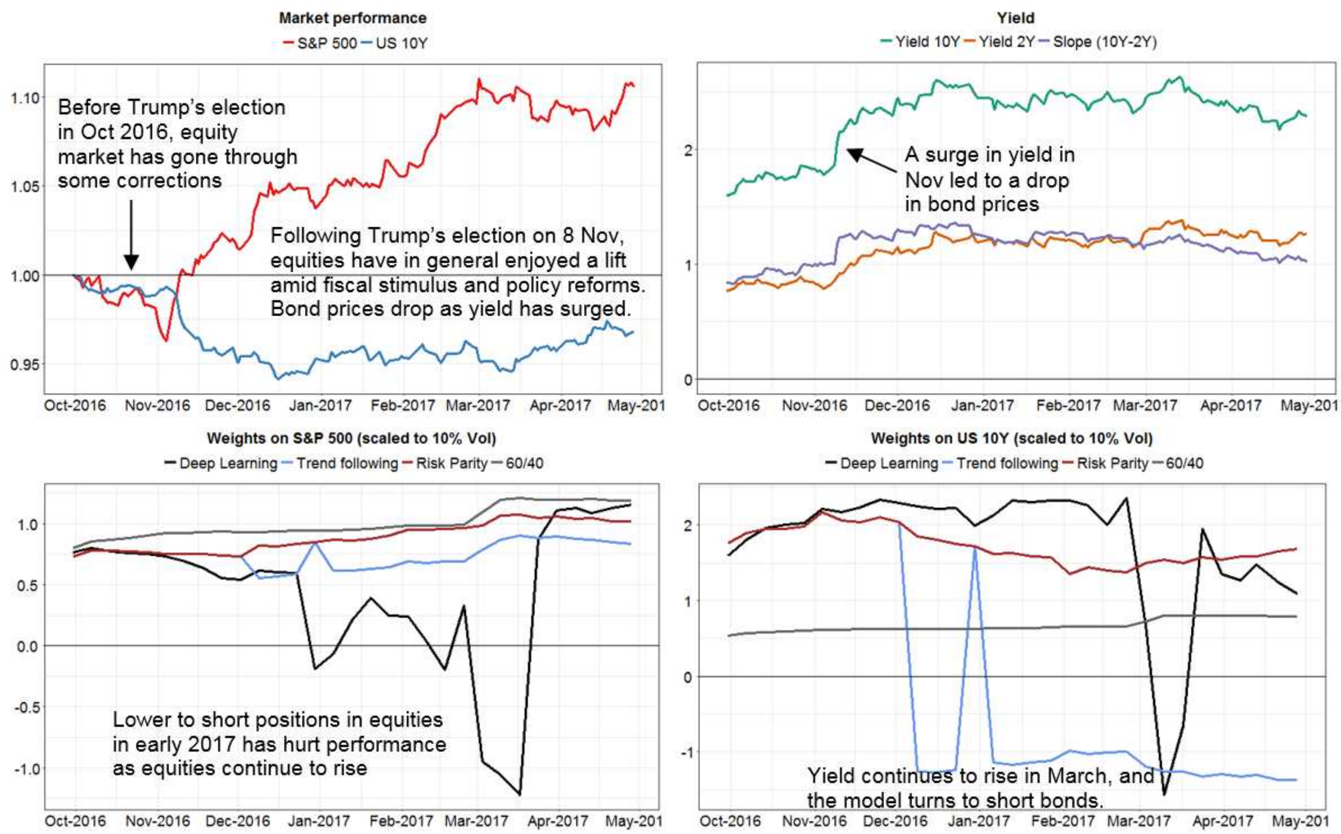
Following Trump's election on 8 Nov 2016, equities have in general enjoyed a lift amid fiscal stimulus and policy reforms. However, rapid gains in equities together with a surge in yield in Nov may have led the model to cautious positions with lower exposure on equities since early 2017. Unfortunately, equities continue to rise through the period and model performance is hurt. Overall, the model misses some of the equity rally during such a policy-driven period.

Figure 23: Dissecting performance and allocations between Oct 2016 and Apr 2017



Oct 2016 - Apr 2017

	Deep Learning	Trend Following	Risk Parity	60/40
Annualized Returns	-7.3%	-5.0%	4.8%	19.4%
Annualized Vol	8.8%	9.0%	9.0%	6.0%
Sharpe ratio	-0.84	-0.56	0.54	3.26
t-stat	-0.64	-0.41	0.44	2.33
Skewness	-1.53	-1.30	-1.43	-0.21
Kurtosis	2.75	1.86	2.57	-0.50
Max Drawdown	8.5%	7.1%	7.1%	1.9%
Hit ratio	51.6%	51.6%	51.6%	67.7%
Sortino ratio	-0.13	-0.09	0.11	0.84
Calmer ratio	-0.86	-0.70	0.68	10.24

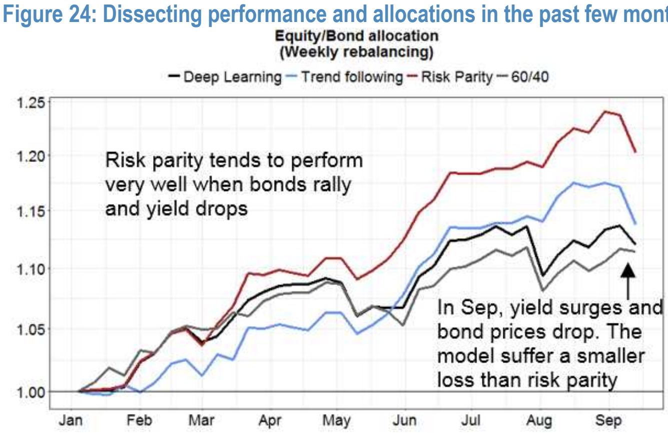


Source: J.P. Morgan Quantitative and Derivatives Strategy

2019 YTD: Performance hurt by lower bond positions amid bond rally

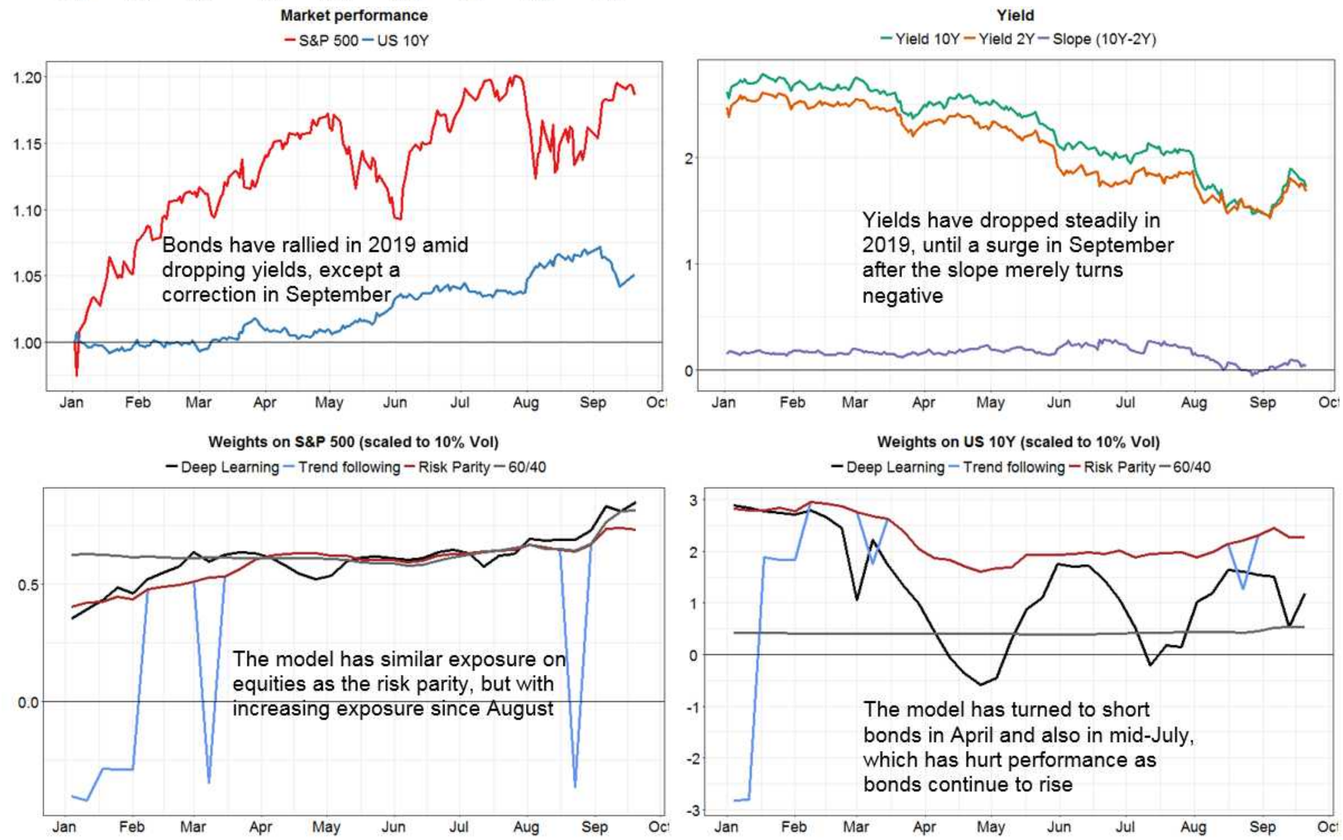
Since the beginning of the year, yields have been dropping in general and bonds have rallied. Risk parity tends to perform the best in such occasion, as we have seen in Figure 19. The Deep Learning model turned to short bonds in April and mid-July, which has hurt some performance as bonds are up. Nevertheless, after a long streak of declining yields, we see a surge in yields in the first 2 weeks of September, leading to large drops in bonds (down 2.4%). As such, the Deep Learning model has a much smaller drawdown than risk parity due to its lower exposure to bonds.

Figure 24: Dissecting performance and allocations in the past few months



Jan 2019 - Sep 2019

	Deep Learning	Trend Following	Risk Parity	60/40
Annualized Returns	20.2%	18.7%	35.2%	19.4%
Annualized Vol	8.6%	8.3%	8.2%	8.1%
Sharpe ratio	2.34	2.26	4.32	2.40
t-stat	1.86	1.80	3.21	1.91
Skewness	-1.34	-0.43	-0.65	-0.99
Kurtosis	2.64	0.46	0.71	2.29
Max Drawdown	3.7%	3.2%	3.1%	3.3%
Hit ratio	73.7%	60.5%	73.7%	65.8%
Sortino ratio	0.45	0.50	1.03	0.49
Calmer ratio	5.42	5.89	11.31	5.82



Source: J.P. Morgan Quantitative and Derivatives Strategy

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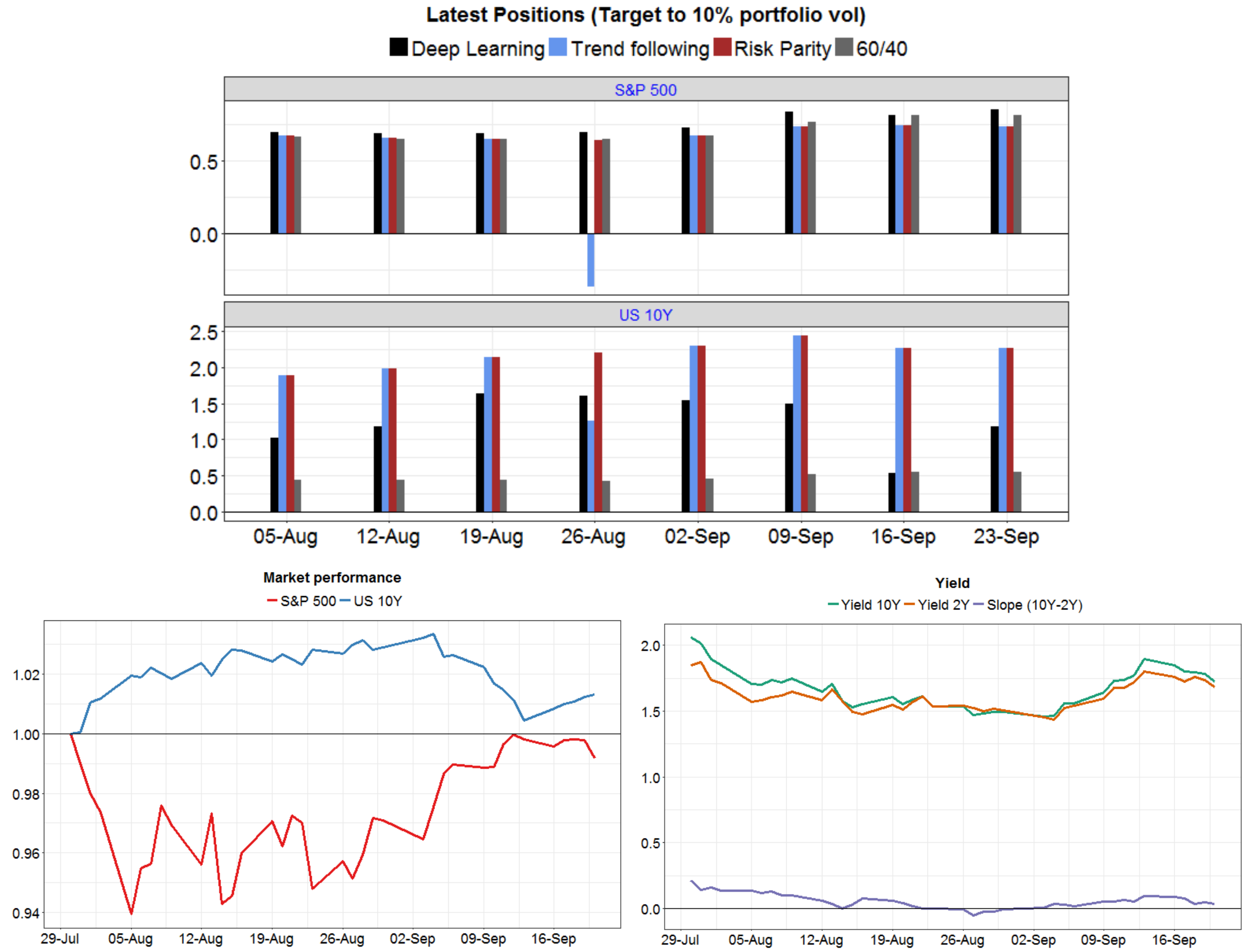
Latest Allocations

Figure 25 shows the recent allocations on equities and bonds for the Deep Learning model compared with other benchmarks. All strategies have increasing exposures on equities, and the Deep Learning model has higher allocation than risk parity. For treasuries, the model suggests a trimmed position, and exposure to US 10Y is about half of that in risk parity.

Figure 25: Latest positions on equities and bonds for different models (top), and recent market performances (bottom)



Source: J.P. Morgan Quantitative and Derivatives Strategy

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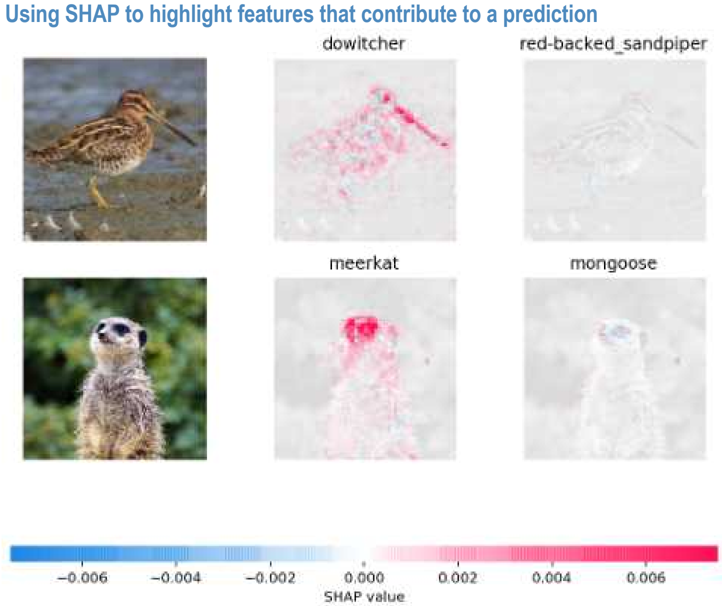
Can We Rely on Robots?

Whilst we see encouraging results in our Deep Learning models, we think that more research needs to be done before we fully deploy the task of trading to robots. As our robots have taken on many “lessons” to learn about trading, we think that there is still a lot to improve on:

1. The success of Deep Learning models rely on good hyperparameter selection. In our problems related to financial time series, it is not trivial to define the “best” model performance. Should we just pick the model with the best validation performance? But what about training performance? We find it a bit dangerous to simply automate the model tuning and selection procedure. As we pointed out in Figure 13, models with very high Sharpe ratios in the training period tend to perform poorly in the out-of-sample period. We need to spend time to check the training, validation and live performance before selecting a model.

2. We need to better understand what drives the model outputs. For example, is it the 1M or 12M momentum that mainly contributes to a short position in equities? It is possible to use algorithms such as LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive exPlanations) to analyze model behavior, and we have applied LIME to explain our Machine Learning predictions in A Quantitative Framework for Cross Asset Style Timing. Explanatory analysis is popular in models for image classification. For textual analysis, LSTMVis is a tool that helps to visualize hidden states in LSTM models. Similar analysis on financial time series would be necessary for us to better understand our robot traders.

Figure 26: Using SHAP to highlight features that contribute to a prediction



Source: SHAP (SHapley Additive exPlanations)

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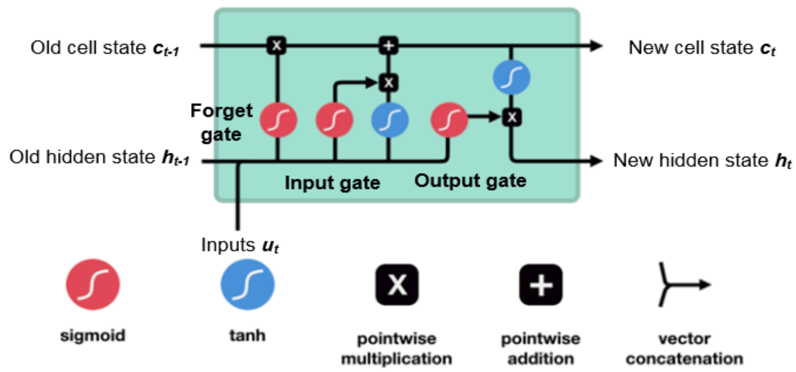
Appendix

LSTM Model Equations

We described the components of an LSTM unit in the main text, which consists of different gates to control the flow of information.

Figure 27: Component of an LSTM cell



Source: J.P. Morgan Quantitative and Derivatives Strategy

Here we provide the set of equations describing the logic of the LSTM unit, showing how the predictions are generated from the hidden states via an activation function:

$$Forget\ gate:\quad \boldsymbol{f_t} = \text{sigmoid}\left(\boldsymbol{W_f u_t} + \boldsymbol{V_f h_{t-1}} + \boldsymbol{b_f}\right)$$

$$Input\ gate:\quad \boldsymbol{i_t} = \text{sigmoid}(\boldsymbol{W_i u_t} + \boldsymbol{V_i h_{t-1}} + \boldsymbol{b_i})$$

$$Output\ gate:\quad \boldsymbol{o_t} = \text{sigmoid}(\boldsymbol{W_o u_t} + \boldsymbol{V_o h_{t-1}} + \boldsymbol{b_o})$$

$$Cell\ state:\quad \boldsymbol{c_t} = \boldsymbol{f_t} \odot \boldsymbol{c_{t-1}} + \boldsymbol{i_t} \odot \tanh(\boldsymbol{W_c u_t} + \boldsymbol{V_c h_{t-1}} + \boldsymbol{b_c})$$

$$Hidden\ state:\quad \boldsymbol{h_t} = \boldsymbol{o_t} \odot \tanh(\boldsymbol{c_t})$$

$$Predictions:\quad \boldsymbol{X_t} = g(\boldsymbol{Wh} + \boldsymbol{b})$$

where $\odot$ is the Hadamard operator for element-wise product, $\boldsymbol{W}$ and $\boldsymbol{V}$ are the model weight matrices, $\boldsymbol{b}$ is the bias (i.e. constant term), $\boldsymbol{u}$ is the input, and g is any chosen activation function. $\boldsymbol{W}$, $\boldsymbol{V}$ and $\boldsymbol{b}$ are model parameters to be estimated. The *sigmoid* function maps inputs to [0, 1], and the *tanh* function maps inputs to [-1, 1].

Deep Learning Implementation in Keras

Infrastructure

We build and train our LSTM model using Keras, which is a high-level neural network API written in Python. We use TensorFlow as the backend engine for Keras. Since our data and models are not huge, we are able to train the networks using a Xeon workstation with an E5-1650 processor (instead of relying on GPUs or cloud computing). We speed up the performance using Intel Distribution for Python, and training over an epoch (say with 15 years of daily data) takes less than a second.

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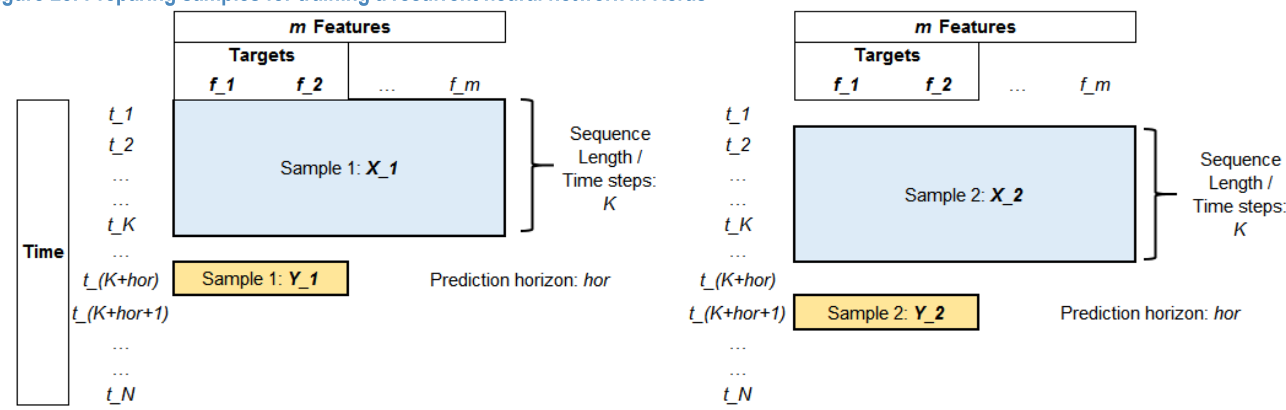
Data preparation

In Keras, inputs for an LSTM model must be preprocessed into the correct format, which is a tuple with dimensions of (*n_samples*, *sequence_length*, *n_features*). Referring to the diagram in Figure 28, we consider using m features to predict two targets, which we choose to be the first two features in a horizon *hor*. If we choose to use a time step of K in our LSTM model, we need to prepare S samples of the form

$$Input = \begin{pmatrix} (X_1, Y_1), \\ \vdots \\ (X_{n\_samples}, Y_{n\_samples}) \end{pmatrix}$$

At a fixed model estimation date t, we fit the model with about 80% of training data, and evaluate model performance with the testing data up to time t (Figure 28).

Figure 28: Preparing samples for training a recurrent neural network in Keras



Source: J.P. Morgan Quantitative and Derivatives Strategy

Hyperparameter Tuning

There are many tunable knobs in a deep neural network, and most of the effort in obtaining a good model is actually spent on searching for the best configuration. We use a grid search to look for the best hyperparameters, which is the most straightforward way (but Bayesian Optimization could be more efficient). We search over hyperparameters as shown in Figure 29.

Figure 29: Hyperparameter grid search

Hyperparameter	Values	Remarks
Learning rate	1e-1, 1e-2, 1e-3, 1e-4, 1e-5	Learning rate multiplied by the gradient is the change of the weights in each backpropagation loop. Smaller training rates with larger number of epochs may sometimes be better.
Batch size	64, 128, 256	Training size of each batch, divisible by the number of samples in training data
Number of epochs	50	Early stopping if validation performance do not improve after 20 epochs
Units (in LSTM layer)	4, 6, 8, 10, 12	# of neurons
Dropout	0.1, 0.2, 0.3, 0.4	Proportion of neurons dropped on the inputs/outputs
Recurrent Dropout	0.1, 0.2, 0.3, 0.4	Proportion of neurons dropped between the recurrent units in the LSTM layer
Regularization lambda	1e-1, 1e-2, 1e-3, 1e-4, 1e-5	L1 and L2 penalities on the magnitude of the weights
Time step	52	Sequence length when the RNN is unrolled (52 weeks of data)
Model Architecture	Ture, False	True: We use a stacked LSTM model, i.e. stacking 2 LSTM layers together

Source: J.P. Morgan Quantitative and Derivatives Strategy

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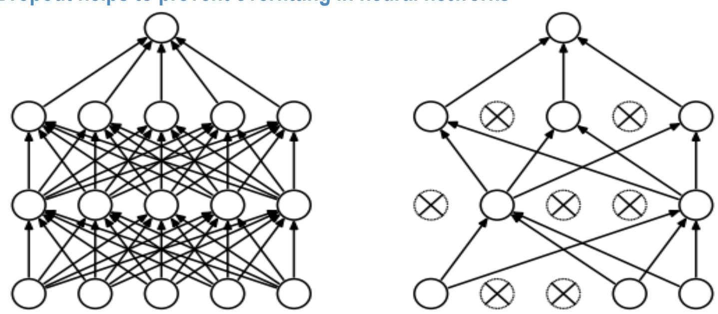
Regularization and Dropout

Dropout is a popular regularization technique for deep neural networks, where a random proportion of units are "dropped" during training. Dropout "masks" a proportion of neurons during training, resulting in a "thinned" network (Figure 30). During testing and prediction, the original network without dropout is used, but the weights are scaled down based on the probability that the neuron is retained. This helps to prevent overfitting

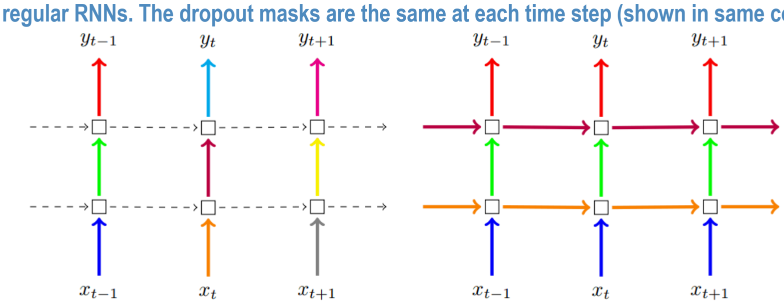
Figure 30: Dropout helps to prevent overfitting in neural networks



Source: Srivastava, N. et al (2014) Dropout: A Simple Way to Prevent Neural Networks from Overfitting

However, Gal and Ghahramani (2016) show that such naïve dropout do not work well for recurrent layers. Instead, recurrent dropout helps to better regular RNNs, in which the dropout masks are the same at each time step (Figure 31).

Figure 31: Naïve dropout (left) do not apply to recurrent layers. Recurrent dropout (right) helps to better regular RNNs. The dropout masks are the same at each time step (shown in same colour)



Source: Gal, Y. and Ghahramani, Z. (2016) A Theoretically Grounded Application of Dropout in Recurrent Neural Networks

Optimizers

To look for the best model weights that minimize our loss function (or maximize our objective function), the gradient descent methodology is used:

$$\omega_{new} = \omega_{old} - (learning\ \ rate) \times \nabla_{\omega} Loss(\omega)$$

We test a few optimizers and find that the Adam optimizer (an optimizer with adaptive learning rate, see Kingma and Ba (2014)) tends to converge the fastest, but sometimes the vanilla SGD optimizer may find better solutions. The latest development is the Rectified Adam (RAdam) optimizer, which finds that the adaptive learning rate has large variance in the early stage of training, and rectifying the variance helps to improve convergence (Liu et al (2019)). Another new idea from the G. Hinton's team is the Lookahead Optimizer (Zhang et al (2019)). We tried both but did not find very different performances, except that RAdam seems to converge better for smaller data sets (e.g. weekly data).

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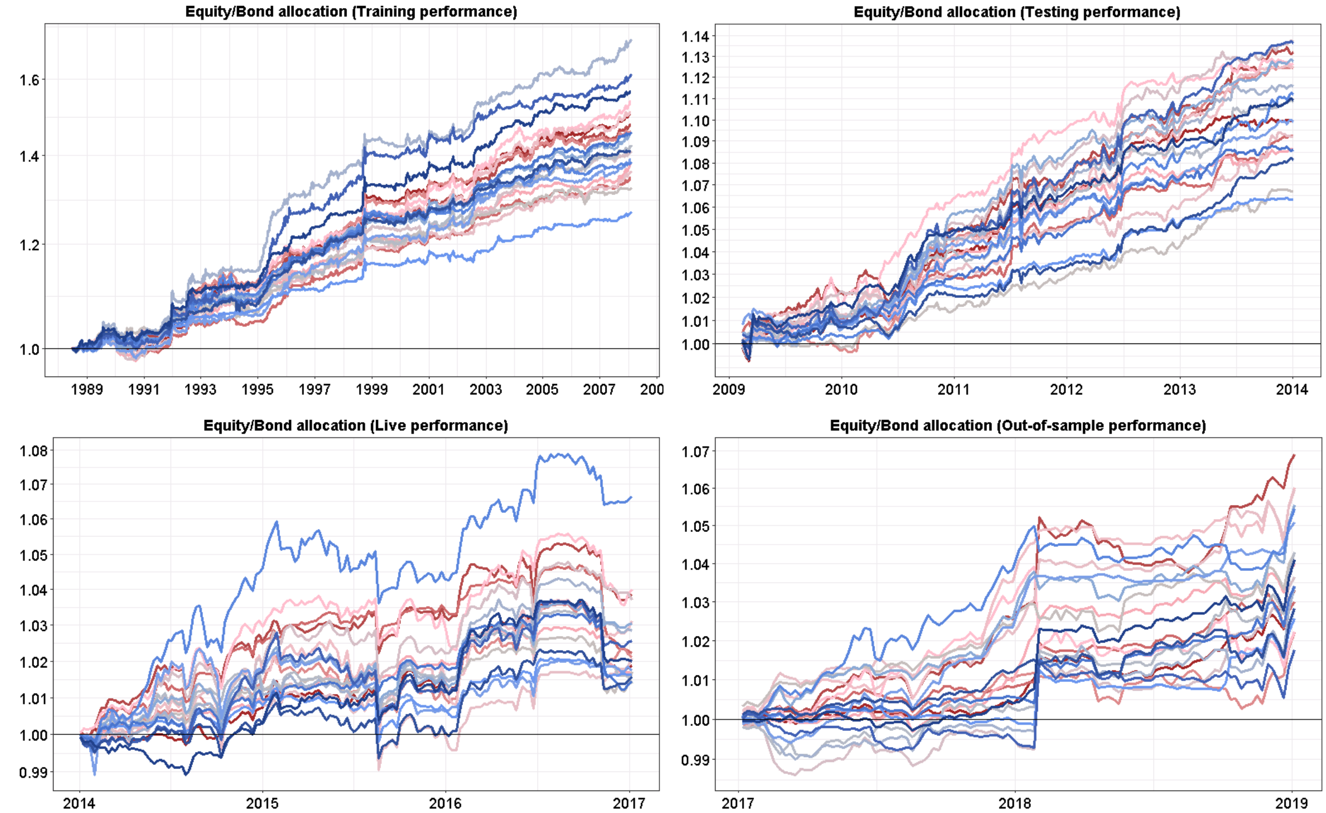
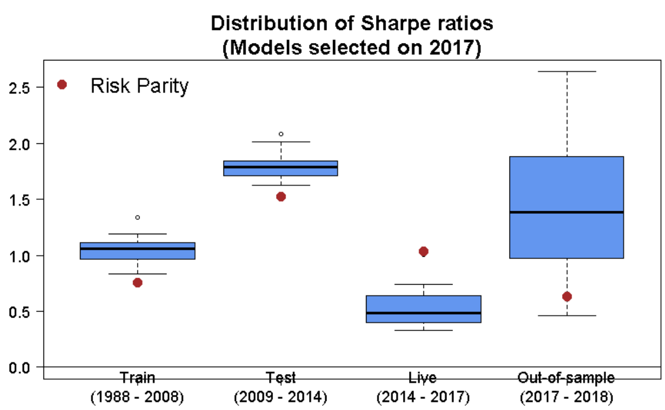
Training and Testing Performances

Below we show the training, testing, live and out-of-sample performances of our selected models in 2017 and 2019, similar to what we discuss in the main text for the model selected in 2015 in Figure 14 and Figure 15.

Figure 32: Models estimated and selected on the first week of 2017





Benchmark Sharpe Ratios

	Training 1988 - 2008	Testing 2009 - 2014	Live 2014 - 2017	Out-of-sample 2017 - 2019
Risk Parity	0.76	1.52	1.03	0.63
Equity	0.40	0.99	0.73	0.25
Bond	0.61	0.69	0.62	0.25
50/50	0.62	1.33	1.09	0.36
60/40	0.56	1.23	0.98	0.33
70/30	0.51	1.15	0.90	0.31
80/20	0.47	1.09	0.83	0.29

Source: J.P. Morgan Quantitative and Derivatives Strategy

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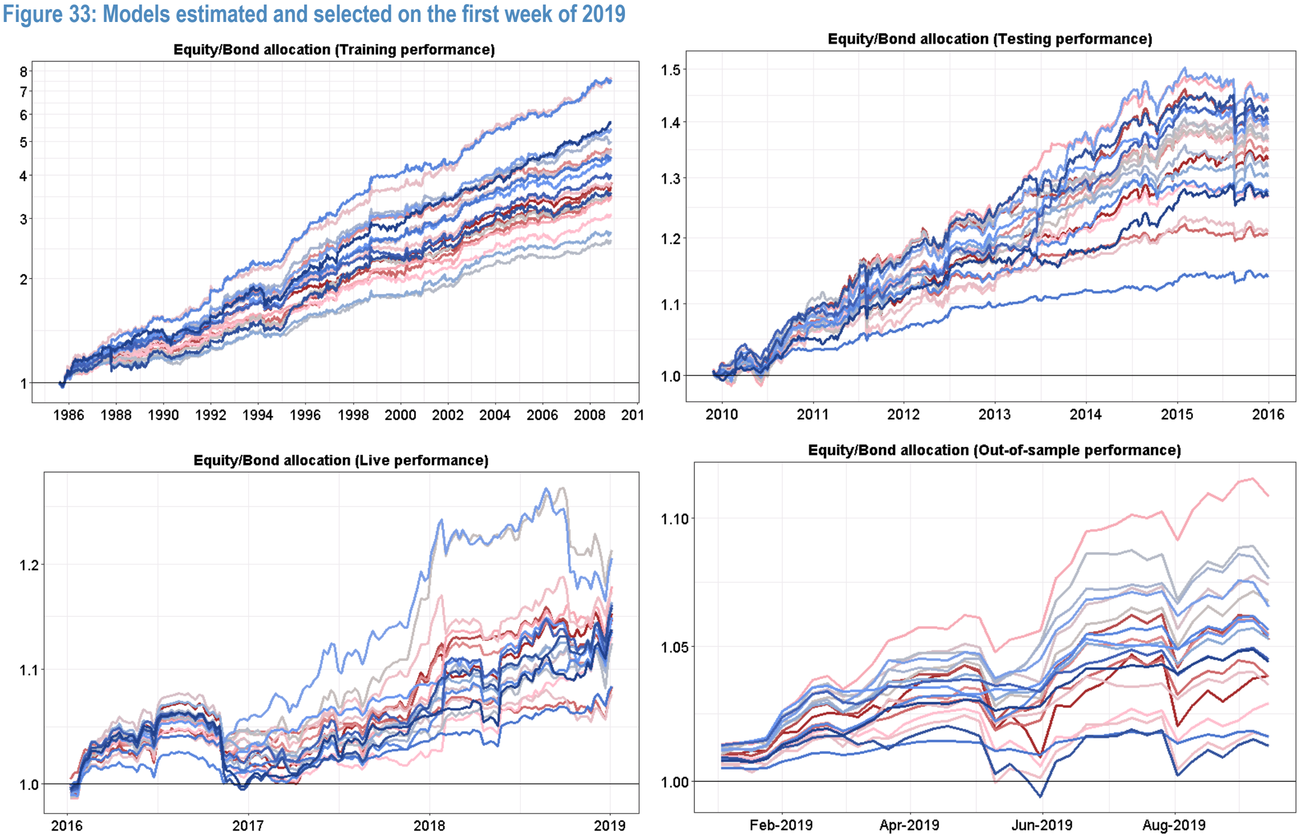
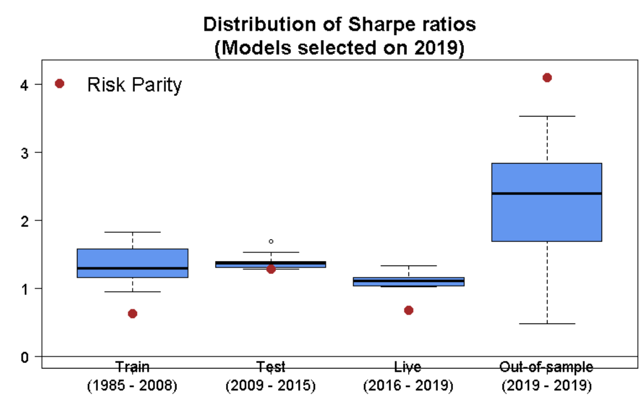
Figure 33 shows the performance of the models selected at the beginning of 2019. In this case, models with better live performance during 2016-2018 seem to underperform in the first nine months of 2019. A possible reason is due to some regime changes: Models that have survived the difficult year of 2018 may be too conservative, and are not aggressive enough for a generally bullish market till Sep 2019.

Figure 33: Models estimated and selected on the first week of 2019





Benchmark Sharpe Ratios	Training 1985 - 2008	Testing 2009 - 2015	Live 2016 - 2019	Out-of-sample 2019 till Sep
Risk Parity	0.64	1.29	0.68	4.10
Equity	0.24	0.84	0.60	1.71
Bond	0.60	0.76	0.21	1.97
50/50	0.48	1.24	0.73	2.77
60/40	0.42	1.11	0.70	2.40
70/30	0.36	1.02	0.67	2.14
80/20	0.32	0.95	0.64	1.96

Source: J.P. Morgan Quantitative and Derivatives Strategy

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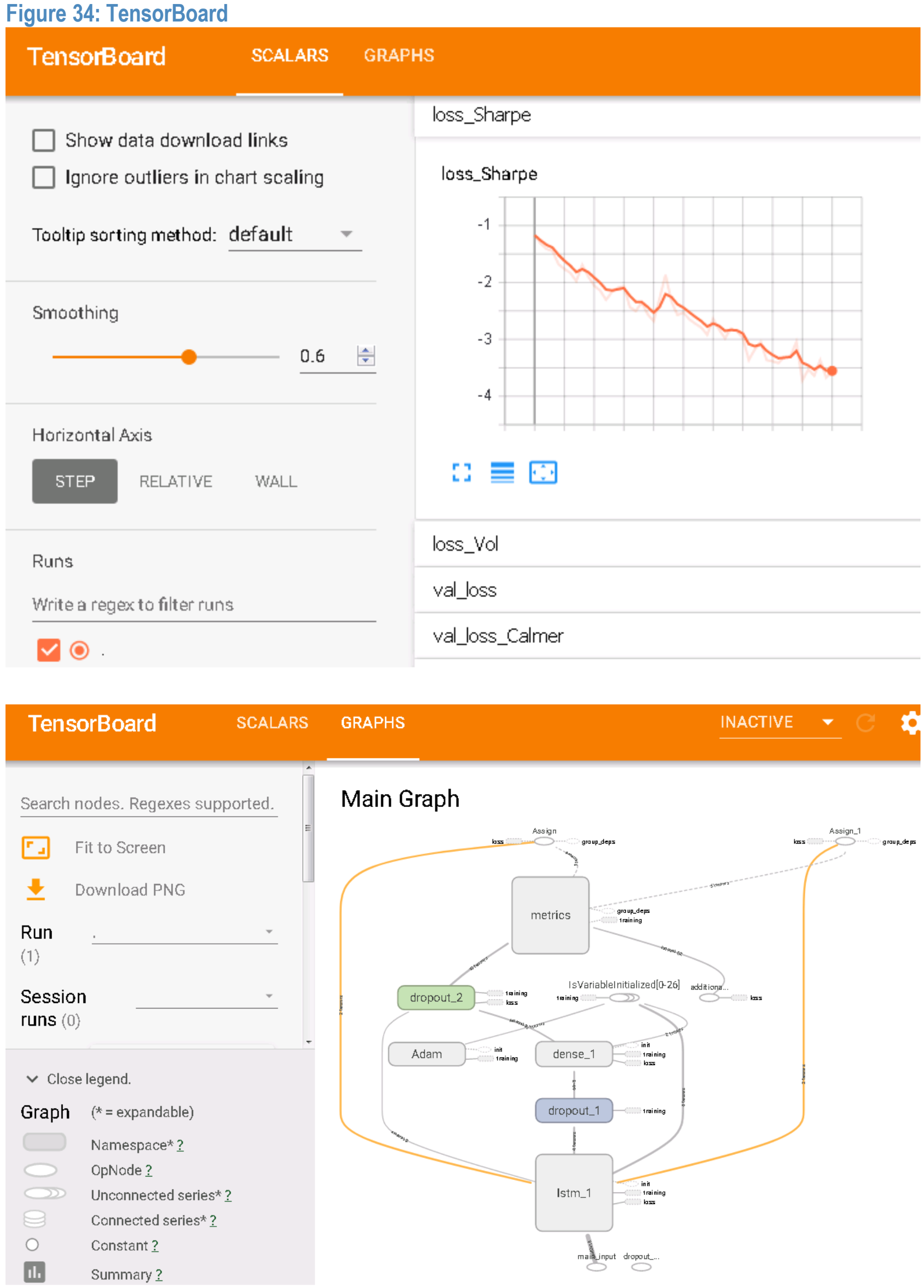
TensorBoard Visualization

TensorBoard is a useful tool to visualize the model training, which helps to debug and examine the training and validation process over epochs. It can also plot the model graph, showing how data flow between nodes.

Figure 34: TensorBoard



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