

Deep neural networks for FX prediction

Designing robust models for FX trade sizing and currency positioning

Using historical spot FX rates from 30 currency pairs dating back 16 years, Mesirow Currency's neural network models address the challenges that traditional machine learning techniques can face when trying to model financial time series.

Brief overview of classic machine learning pipelines

Traditional machine learning pipelines usually consist of four separate steps:

1. PRE-PROCESSING

Data is mapped from a noisy, irregular, and sometimes high dimensional space onto a cleaner, more regular, and lower dimensional space.

2. HANDCRAFT FEATURE EXTRACTION

Distinctive features (represented as vectors or tensors) are manually formulated and engineered from the input data. These features should be consistent, robust, and preserve information while simultaneously removing redundancy.

3. POST-PROCESSING

The features, which together form a feature space, are sometimes post-processed to achieve further dimensionality reduction or expansion.

4. CLASSIFICATION

The result of the first three steps is then given to a classification/regression algorithm. Input is mapped onto a discrete domain (class labels) and hyper-planes split the feature space into different regions, each belonging to different classes.

Some of the advantages of this traditional machine learning pipeline are as follows:

- they are (usually) fast to train and back test
- feature extraction can be robustly designed if the underlying physics from which the samples were generated is known (example: Mel-frequency cepstral coefficients (MFCC) features used in speech recognition¹)
- hand crafted feature extraction and engineering can sometimes help in understanding the failure of the system, thus facilitating *explainability*

This traditional approach does come with limitations, though, as the steps mentioned above are clearly not independent from each other.



Mehryar Emambakhsh
Vice President,
Senior Research Scientist



Richard Turner
Managing Director,
Head of Research

The information contained herein is intended for institutional clients, Qualified Eligible Persons, Eligible Contract Participants and Wholesale Clients, or the equivalent classification in the recipient's jurisdiction, and is for informational purposes only. Nothing contained herein constitutes an offer to sell an interest in any Mesirow Financial investment vehicle. It should not be assumed that any trading strategy incorporated herein will be profitable or will equal past performance. Please see the disclaimer at the end of the materials for important additional information.

A well performing machine learning model is dependent on strong classifiers (step 4), which requires a well-designed feature extraction (step 2). If either of these steps fail, it can deteriorate the overall performance. Therefore, to avoid this issue, steps 1 to 4 of any machine learning pipeline should be somehow simultaneously optimised.

Also, these models usually assume that the input samples are independent and identically distributed (IID)². When attempting to predict financial data trends, however, non-IID input samples prove difficult to structure and model, so the task of simultaneously designing a robust feature extraction algorithm and avoiding class over-representation is extremely difficult.

One solution to make the feature extraction step more robust would be to link outputs from several different algorithms. Unfortunately, this approach also leaves us with a potential problem: when the number of feature vectors is much higher than the number of samples, this concatenation can result in an extremely high dimensional space in which there will not be enough samples to represent each class. This is known as the *curse of dimensionality*³ and can result in poor predictive performance.

Deep neural networks

Neural networks belong to a category of machine learning algorithms that attempt to find structure and model input data by learning parameters embedded within a set of composite non-linear functions.

Neural networks are not totally new machine learning techniques, and most of their well-known architectures can be traced back to research in the 80s and 90s: recurrent neural networks (initiated) in 1982⁴, convolutional neural networks in 1995⁵ and long short-term memory networks (LSTM) in 1997⁶.

What makes these techniques widely popular in recent machine learning pipeline design are two key factors: availability of a large amount of open source data, and accessibility to fast and cheap parallelised computational power.

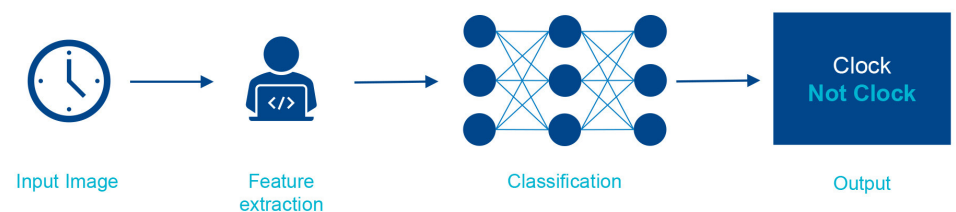
Neural networks superiority

Neural networks have many advantages when compared to other machine learning algorithms. One of the most important features of the neural network is their closed-form solution for feature extraction and classification. This resolves the difficult problem of first formulating a feature extraction algorithm and then optimising a compatible classifier for it. As Shown in Figure 1, neural networks do both tasks simultaneously, and these learned features can even be transferred to other (not necessarily similar) tasks, a process known as transfer learning⁷.

FIGURE 1: CLASSIC MACHINE LEARNING PIPELINES (TOP) VS. DEEP LEARNING-BASED APPROACHES

While classic machine learning relied on an independent handcrafted feature extraction and classification, deep learning paradigms encapsulate feature extraction and classification inside a simultaneous process.

Machine Learning



Deep Learning

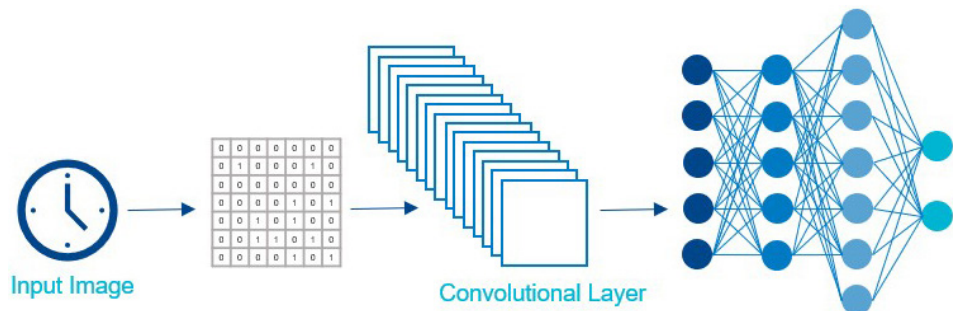


Source: Mesirow Financial

Thanks to their non-linearity, neural networks can learn more complex patterns from the data, and temporal dependencies between samples can also be learned via recurrent or convolutional architectures. As an example, Figure 2 shows a convolutional neural network which is capable of extracting spatial information from input images via learning various filters and, finally, performing classification through dense layers.

FIGURE 2: A SIMPLE CONVOLUTIONAL NEURAL NETWORK APPLIED FOR AN IMAGE CLASSIFICATION TASK

The input data is passed through several convolutional layers, which capture spatial information. Their output is then given to dense neural network layers to perform dimensionality reduction and classification.



Source: Mesirow Financial

General challenges in training neural networks

Neural networks require much more computational power to train than traditional machine learning algorithms. A neural network can very easily have thousands of trainable parameters, and to optimise these parameters over a high dimensional space, a substantial amount of data is usually needed.

Neural networks also have several hyper-parameters, which significantly influence their performance. These cover a wide range of parameters, from the number of hidden layers and neurons per layer, to learning rate and optimisation parameters.

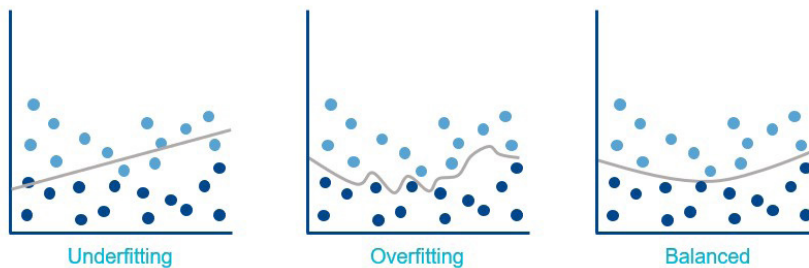
Neural network architecture search, a process that can automatically search for the best network architecture and hyper-parameter setting, can be a possible solution but is still an ongoing research problem.^{8,9,10}

Although underfitting is not often problematic, due to the high complexity of these networks, one problem that could result (and needs to be avoided) during model design is overfitting (Figure 3). This shows itself in a large gap between train, validation, and test performance and in drastic fluctuations in output (high variance) when there is any small alteration to the input data.

FIGURE 3: UNDERFITTING VS. OVERFITTING

Failure to properly model input data (due to low model complexity and sometimes, class over-representation within the training data) increases bias and results in underfitting.

On the other hand, models that are too complex can cause high variance, low generalisation capability, and can cause the model to overfit. Ideally, there should be a balance between bias and variance³, which is a fundamental challenge in machine learning.



Source: Mesirow Financial

Challenges in training neural networks over financial data

Non-stationary and non-IID inputs (e.g. financial time series) can be problematic for training. Non-stationarity causes significant statistical differences between the train, validation, and test sets. For complex models, which are already vulnerable to input variations this can, of course, cause a significant drop in performance during the live prediction.

One solution to this is to limit the number of training samples by using more recent data points (in the hopes of achieving higher stationarity while simultaneously capturing recent market trends), but this undermines the necessity of incorporating a substantial amount of data in order to effectively train the neural networks.

In short, using too many training samples can result in class over-representation, but using too few can cause the neural network model to overfit. Hence, the challenge of using neural networks to their highest potential over a complex task can sometimes force quantitative researchers to discard neural networks completely and utilise old-fashioned solutions instead.

Designing a classification model over financial data relies on first labelling the samples, which could be quite challenging. Such data labelling should perfectly represent immediate market trends for each sample. Only utilising immediate next samples for label assignment can result in high class overlap as in a short forward-looking window, financial series tend to act as random walk. However, a long-term forward-looking window for labelling can cause mid-term losses or a missing out on profit-making opportunities. Ideally, a financial data labelling strategy should consider all of these.

Our neural network-based solution

The neural network models used in Mesirow Currency Management’s alpha strategies use historical daily spot FX rates from 30 currency pairs as the only input to the network; implemented as a binary classifier, the models learn to label each sample into going long or short. All the models are back tested over a period of 16 years.

During model development, we considered the limitations of classic machine learning techniques and challenges in utilising neural networks over financial time series and addressed those issues (overfitting, hyper-parameter optimisation, stationarity) in the design of our deep neural network strategy.

Network architectures

Our networks are based on three main architectures:

1. Convolutional
2. Recurrent
3. Convolutional Recurrent (or Mixture)

Convolutional networks model the temporal dependencies by learning filters which are convolved with the input data. An example of this approach is shown in Figure 4.

The financial data samples are intrinsically temporally dependent. Such dependency can be modelled through defining a (hidden) state

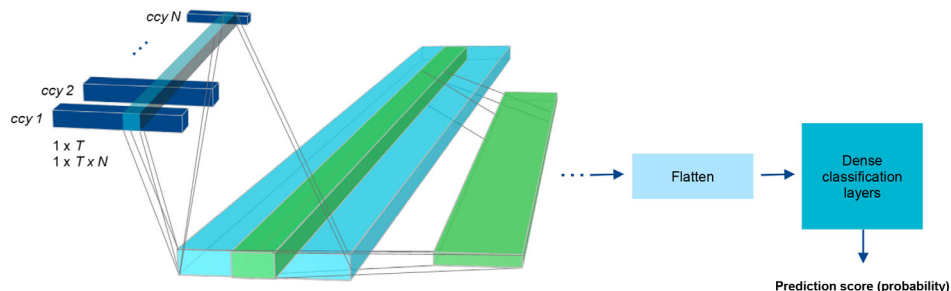
space, which stores information about previous samples (observations). As shown in Figure 5, recurrent neural networks can learn from past data samples and generate this state space during their training process.

The recurrent architecture models the underlying temporal dependencies between the samples by propagating the neural hidden states. The recurrent units are implemented as simple recurrent layers, long short-term memory networks (LSTM)⁶ and gated recurrent units (GRUs)¹¹. The choice of recurrent layers is determined fully automatically from a separate optimisation procedure.

Finally, the Mixture architecture utilises the convolutional filters to smooth out, denoise, and simplify the input data by making important features more prominent; the outputs of these convolutional layers are then given to a recurrent neural network to capture the temporal trends, as depicted in Figure 6.

FIGURE 4: A CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE OVER FX DATA

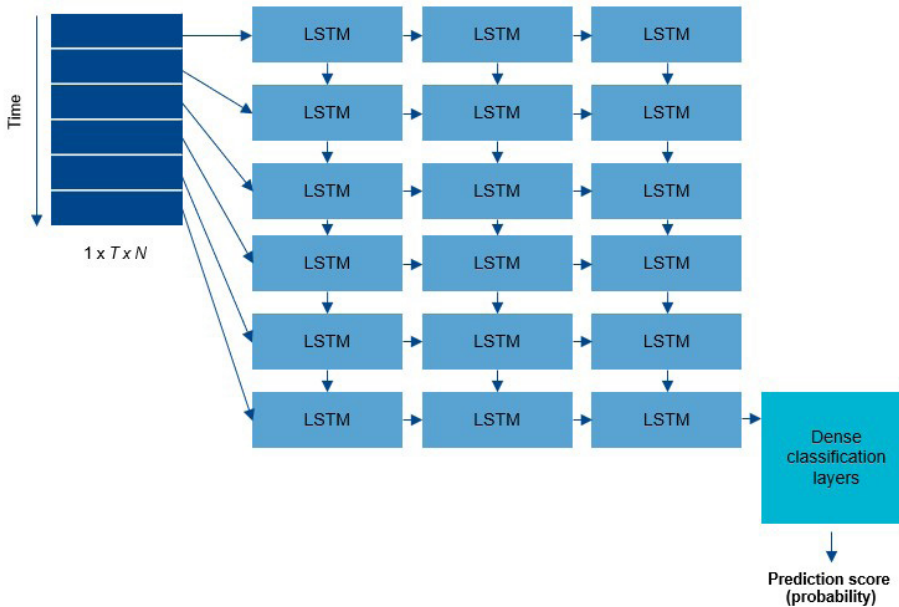
Given a look-back window size T , data from multiple N currencies can be arranged as tensors, which are given to several convolutional layers to capture temporal dependencies. After flattening their outputs, the filtered data is fed into several dense layers for dimensionality reduction and final classification. The output probability score is used to determine the label.



Source: Mesirow Financial

FIGURE 5: A RECURRENT NEURAL NETWORK USING LSTM RECURRENT BLOCKS

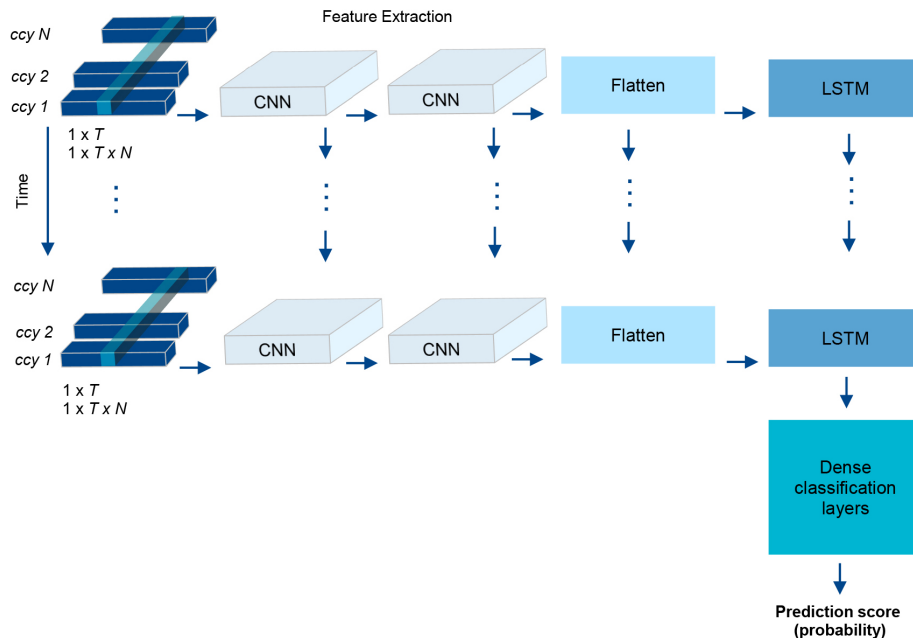
Given a look-back window size, the data is chronologically ordered and is given to a deep recurrent neural network. This model learns the temporal dependencies within the data samples by conveying the network’s latent state.



Source: Mesirow Financial

FIGURE 6: A CONVOLUTIONAL RECURRENT (MIXTURE) ARCHITECTURE.

During its training phase, the networks learn filters to smooth the data and extract features, while the outputs are given to a recurrent neural network (here shown as LSTM blocks) to learn temporal dependencies.



Source: Mesirow Financial

Stationarity vs. memory preservation

One approach to provide stationary input data is to compute the first order differencing. This, however, can completely remove the temporal dependencies (or memory) between the input samples, which is extremely informative when designing predictive models. Therefore, there should be a trade-off between stationarity and memory preservation.

For our models, stationarity is maintained using a controlled adaptive fractional differencing procedure¹² and memorisation is achieved by incorporating recurrent and convolutional neural architectures.

Underfitting vs. overfitting

While underfitting is easily avoided by discarding models with low train accuracy, extra care has been taken to reduce the risk of overfitting. Each of our models can easily have tens of thousands of parameters, and a robust validation step is embedded within the network training process in order to avoid overfitting. This is achieved by incorporating regularisation methods, adding spatial and temporal dropout layers, early stopping procedures, and automated evaluation of validation loss and accuracy.

Data labelling and training one model per currency pair

Data labelling is performed in such a way to capture immediate data trends. To detect possible cross-currency correlations, the network inputs are tensors containing data from all 30 of the currency pairs traded. Each model performs prediction for one currency pair. Therefore, for each re-tuning interval we will have 30 deep neural networks optimised for the prediction task.

Temporal sample weighting and model selection

The class over-representation vs. lack of data dilemma is addressed via a temporal sample weighting procedure. The sample weighting is also used during the model execution: the models only generate signals if they perform better than a minimal threshold when their inputs are temporally weighted. This step significantly improves the robustness of the system by avoiding trading when the market is very volatile.

Hyper-parameter optimisation and implementation for back testing and live signalling

The model architectures are implemented in a decoupled way in our machine learning pipeline. This facilitates the utilisation of a separate hyper-parameter optimisation and neural architecture search. In other words, the model architecture constantly evolves based on the most recent FX rates.

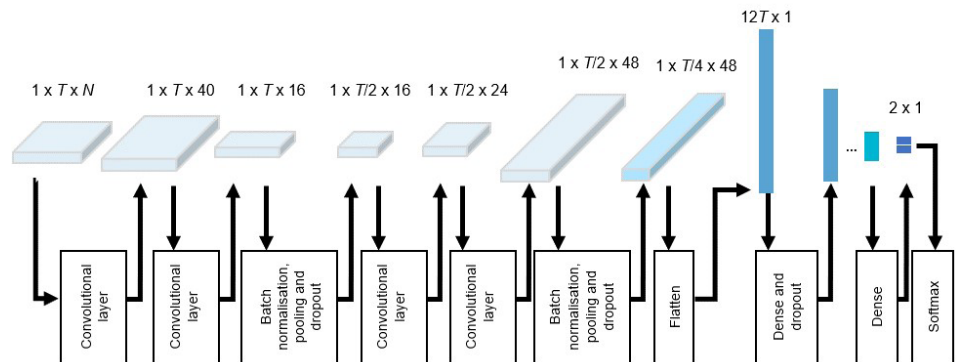
All the computations are performed over our in-house GPU servers. The models are extensively back tested over a period of 16 years. To speed up these highly computationally demanding back testing operations, the process is parallelised. This reduces the tuning time (including architecture search and training) to less than 5 hours over all 30 currencies and enables daily model re-calibration.

The generated signals are post-processed further to reduce the effects of carry and transaction costs, while reducing the absolute drawdown. The signal generated by our neural network model shows very low correlation with our other models, indicating it is a novel source of alpha and so improving the overall return of the system per unit of risk.

We have used TensorFlow v2.0 as our machine learning pipeline framework. An example of the trained convolutional architectures to predict for one of our currency pairs is shown in Figure 7. Depending on the number of filters, the convolutional layers generate tensors with different dimensionalities. While the stability of these layers is controlled using the batch normalisation layers, the average and max pooling layers extract the most prominent features from the input tensors. The dropout layers are used to improve the networks' generalisation and to reduce the risk of overfitting. The final layer applies the SoftMax function, which generates class dependency probabilities.

FIGURE 7: ONE OF OUR TRAINED DEEP CONVOLUTIONAL NEURAL NETWORK ARCHITECTURES

T and N are the number of look-back days and number of input currencies, respectively. The input data is passed through several convolutional, batch normalisation, pooling, dropout and dense fully connected layers, while the final decision making is performed over the output of the last layer (the SoftMax layer).



Source: Mesirow Financial

Conclusions

In this paper, we briefly discussed the limitations of classic machine learning-based techniques and challenges in utilising neural networks over financial time series. We then explained how we addressed those issues to design our deep neural network strategy for FX trade sizing. Our fast parallelised re-tuning framework enables even daily model re-calibration, preparing the networks to learn from the latest data and market trends.

In addition to FX trade sizing, our model design paradigm can be applied to other applications: asset allocation, market volatility analysis, regression, outlier detection, and portfolio management – some of which we have already started research and algorithm development. Our implemented framework facilitates straightforward integration and back testing for these applications. As our approach is completely data driven, capable of detecting underlying correlations between various data modalities, we believe it can also be applied to other types of financial time series (e.g. stock market data) and allows other data sources, for example textual news data, to be easily incorporated.

While this strategy has been part of our live trading platform since July 2020, we continuously inspect and analyse the performance of our models and actively research more advanced neural architectures and machine learning models. Our decoupled implementation facilitates fast historical back testing, replacing models with improved versions and immediate usage of any new model for live trading.

References

1. Steven Davis and Paul Mermelstein. "Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences." *IEEE Transactions on Acoustics, Speech, and Signal Processing* 28.4 (1980): 357-366.
2. Marcos Lopez De Prado. *Advances in Financial Machine Learning*. John Wiley & Sons, 2018.
3. Christopher M. Bishop. *Pattern Recognition and Machine Learning*. Springer, 2006.
4. John J. Hopfield. "Neural networks and physical systems with emergent collective computational abilities." *Proceedings of the National Academy of Sciences* 79.8 (1982): 2554-2558.
5. Yann LeCun and Yoshua Bengio. "Convolutional networks for images, speech, and time series." *The Handbook of Brain Theory and Neural Networks* 3361.10 (1995): 1995.
6. Sepp Hochreiter and Jürgen Schmidhuber. "Long short-term memory." *Neural Computation* 9.8 (1997): 1735-1780.
7. Michael J. Prince and Richard M. Felder. "Inductive teaching and learning methods: Definitions, comparisons, and research bases." *Journal of Engineering Education* 95.2 (2006): 123-138.
8. Liu, Chenxi, et al. "Progressive neural architecture search." *Proceedings of the European Conference on Computer Vision (ECCV)*. 2018.
9. Pham, Hieu, et al. "Efficient neural architecture search via parameter sharing." *International Conference on Machine Learning* (2018).
10. B. Zoph and Q. V. Le. "Neural architecture search with reinforcement learning." *International Conference on Learning Representations* (2017).

About Mesirow

Mesirow is an independent, employee-owned financial services firm founded in 1937. Headquartered in Chicago, with locations around the world, we serve clients through a personal, custom approach to reaching financial goals and acting as a force for social good. With capabilities spanning Global Investment Management, Capital Markets & Investment Banking, and Advisory Services, we invest in what matters: our clients, our communities and our culture. To learn more, visit mesirow.com and follow us on [LinkedIn](#).

11. Cho, Kyunghyun, et al. "On the properties of neural machine translation: Encoder-decoder approaches." arXiv preprint arXiv:1409.1259 (2014).

12. Clive WJ Granger and Roselyne Joyeux. "An introduction to long-memory time series models and fractional differencing." *Journal of Time Series Analysis* 1.1 (1980): 15-29.

Mesirow Currency Management ("MCM") is a division of Mesirow Financial Investment Management, Inc. ("MFIM") a SEC registered investment advisor. The information contained herein is intended for institutional clients, Qualified Eligible Persons and Eligible Contract Participants and is for informational purposes only. This information has been obtained from sources believed to be reliable but is not necessarily complete and its accuracy cannot be guaranteed. Any opinions expressed are subject to change without notice. It should not be assumed that any recommendations incorporated herein will be profitable or will equal past performance. Mesirow Financial does not render tax or legal advice. Nothing contained herein constitutes an offer to sell or a solicitation of an offer to buy an interest in any Mesirow Financial investment vehicle(s). Any offer can only be made through the appropriate Offering Memorandum. The Memorandum contains important information concerning risk factors and other material aspects of the investment and should be read carefully before an investment decision is made.

This communication may contain privileged and/or confidential information. It is intended solely for the use of the addressee. If this information was received in error, you are strictly prohibited from disclosing, copying, distributing or using any of this information and are requested to contact the sender immediately and destroy the material in its entirety, whether electronic or hardcopy.

Certain strategies discussed throughout the document are based on proprietary models of MFIM's or its affiliates. No representation is being made that any account will or is likely to achieve profits or losses similar to those referenced.

Australian Investors: The information contained herein is intended for Wholesale Clients only and is for informational purposes only. This document is not a prospectus or product disclosure statement under the Corporations Act 2001 (Cth) (Corporations Act) and does not constitute a recommendation to acquire, an invitation to apply for, an offer to apply for or buy, an offer to arrange the issue or sale of, or an offer for issue or sale of, any securities or investment service in Australia, except as set out below. The strategy has not authorised nor taken any action to prepare or lodge with the Australian Securities & Investments Commission an Australian law compliant prospectus or product disclosure statement. Accordingly, this strategy and document may not be issued or distributed in Australia other than by way of or pursuant to an offer or invitation that does not need disclosure to investors under Part 6D.2 or Part 7.9 of the Corporations Act, whether by reason of the investor being a 'wholesale client' (as defined in section 761G of the Corporations Act and applicable regulations) or otherwise. This document does not constitute or involve a recommendation to acquire, an offer or invitation for issue or sale, an offer or invitation to arrange the issue or sale, or an issue or sale, of any strategy or investment service to a 'retail client' (as defined in section 761G of the Corporations Act and applicable regulations) in Australia.

Canadian Investors: The information contained herein is intended for Permitted Clients only and is for informational purposes only. This confidential material pertains to the offering of the currency strategies described herein only in those jurisdictions and to those persons where and to whom they may be lawfully offered for sale, and only by persons permitted to sell such strategies. This material is not, and under no circumstances is to be construed as, an advertisement or a public offering of the strategies described herein in Canada. No securities commission or similar authority in Canada has reviewed or in any way passed upon this document or the merits of the strategies described herein, and any representation to the contrary is an offence.

EU Investors: The information contained herein is intended for Professional Clients as the term is defined by MiFID II and is for informational purposes only. Recipients that are classified under MiFID II as retail clients must opt up to Professional Clients before receiving any services from Mesirow Currency Management.

Japanese Investors: Mesirow Currency Management provides discretionary investment management services to managed accounts held on behalf of qualified investors only. MCM will not act as agent or intermediary in respect of the execution of a discretionary investment management agreement. Please note that this presentation is intended for educational purposes and solely for the addressee and may not be distributed.

Hong Kong Investors: The contents of this document have not been reviewed by any regulatory authority in Hong Kong. You are advised to exercise caution in relation to the contents of this document. You should obtain independent professional advice prior to considering or making any investment. The investment is not authorized under Section 104 of the Securities and Futures Ordinance of Hong Kong by the Securities and Futures Commission of Hong Kong. Accordingly, the distribution of this Presentation Material and discretionary management services in Hong Kong are restricted. This Presentation Material is only for the use of the addressee and may not be distributed, circulated or issued to any other person or entity.

South Korean Investors: Upon attaining a client, Mesirow Financial Investment Management, Inc. ("MFIM") will apply for the appropriate licenses and retain the services of a local licensed intermediary (a Korean financial investment company). In the interim, MFIM will rely on and sub-delegate to Mesirow Advanced Strategies, Inc. ("MAS").

This material is not intended for investment nor distribution purposes, but is being provided to the addressee for educational purposes only. This book may contain privileged and/or confidential information and is intended solely for the use of the addressee. If this information was received in error, you are strictly prohibited from disclosing, copying, distributing or using any of this information and are requested to contact the sender immediately and destroy the material in its entirety, whether electronic or hardcopy. Nothing contained herein constitutes an offer to sell or a solicitation of an offer to buy an interest in any Mesirow investment vehicle or to invest in any strategy. Any offer can only be made to Qualified Professional Investors through the appropriate Investment Management Agreement or Offering Memorandum, which contains important information concerning risk factors and other material aspects of the investment and should be read carefully before an investment decision is made.

Mesirow Financial Investment Management, Inc. ("MFIM") is not making any representation with respect to the eligibility of any potential investors or recipients of this material to invest in or acquire any interests therein under the laws of Korea, including but without limitation the Foreign Exchange Transaction Act and Regulations thereunder. The investment or interests may only be offered to Qualified Professional Investors, as such term is defined under the Financial Investment Services and Capital Markets Act, and no investment or any of the interests may be offered, sold or delivered, or offered or sold to any person for re-offering or resale, directly or indirectly, in Korea or to any resident of Korea except pursuant to applicable laws and regulations of Korea.

Singapore Investors: Mesirow Currency Management provides discretionary investment management services to managed accounts held on behalf of qualified investors only. MCM will not act as agent or intermediary in respect of the execution of a discretionary investment management agreement. Please note that this presentation is intended for educational purposes and solely for the addressee and may not be distributed.

Swiss Investors: Services are only offered to Regulated Qualified Investors, as defined in Article 10 of the Swiss Collective Investment Scheme Act. There can be no guarantee investment advice will be profitable or meet its investment objectives.

United Kingdom Investors: In the United Kingdom, this communication is directed only at persons who fall within the definition of: (i) "investment professionals" as defined in COBS 4.12 and Article 14 of the Financial Services and Markets Act 2000 (Promotion of Collective Investment Schemes) (Exemptions) Order 2001 (the "PCISE Order"); or (ii) "high net worth companies, unincorporated associations etc" as defined in COBS 4.12 and Article 22(2)(a) to (d) of the PCISE Order (all such persons together being referred to as "Relevant Persons"). This communication must not be acted on or relied on by persons who are not Relevant Persons. Any investment or investment activity to which this communication relates is available only to Relevant Persons and will be engaged in only with Relevant Persons.

Additional Information: Currency strategies are only suitable and appropriate for sophisticated investors that are able to lose all of their capital investment. This communication may contain privileged and/or confidential information. It is intended solely for the use of the addressee. If this information was received in error, you are strictly prohibited from disclosing, copying, distributing or using any of this information and are requested to contact the sender immediately and destroy the material in its entirety, whether electronic or hardcopy.

Certain strategies discussed throughout the document are based on proprietary models of MCM's or its affiliates. No representation is being made that any account will or is likely to achieve profits or losses similar to those referenced.

Performance pertaining to the Currency Alpha and Macro strategies may be stated gross of fees or net of fees. Performance information that is provided net of fees reflects the deduction of implied management and performance fees. Performance information that is provided gross of fees does not reflect the deduction of advisory fees. Client returns will be reduced by such fees and other expenses that may be incurred in the management of the account. Advisory fees are described in Part II of Form ADV of Mesirow Financial Investment Management, Inc. Simulated model performance information and results do not reflect actual trading or asset or fund advisory management and the results may not reflect the impact that material economic and market factors may have had, and can reflect the benefit of hindsight, on MCM's decision-making if MCM were actually managing client's money in the same manner. Performance referenced herein for Currency Alpha and Macro strategies prior to October 1, 2018, the date that the Currency Alpha and Macro Strategies team joined Mesirow, occurred at prior firms. Any chart, graph, or formula should not be used by itself to make any trading or investment decision. Any currency selections referenced herein have been included to illustrate the market impact of certain currencies over specific time frames. The inclusion of these is not designed to convey that any past specific currency management decision by MCM would have been profitable to any person. It should not be assumed that currency market movements in the future will repeat such patterns and/or be profitable or reflect the currency movements illustrated above.

Comparisons to any indices referenced herein are for illustrative purposes only and are not meant to imply that a strategy's returns or volatility will be similar to the indices. The strategy is compared to the indices because they are widely used performance benchmarks.

Mesirow refers to Mesirow Financial Holdings, Inc. and its divisions, subsidiaries and affiliates. The Mesirow name and logo are registered service marks of Mesirow Financial Holdings, Inc., © 2020, Mesirow Financial Holdings, Inc. All rights reserved. Investment management services provided through Mesirow Financial Investment Management, Inc., a SEC registered investment advisor, a CFTC registered commodity trading advisor and member of the NFA, or Mesirow Financial International UK, Ltd. ("MFI-UK"), authorized and regulated by the FCA, depending on the jurisdiction.