

Machine Learning Techniques for Pricing, Hedging and Statistical Arbitrage in Finance

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Certificate of original authorship

I, Prateek Samuel Daniels, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy in the UTS Business School at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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"I will be glad and rejoice in you; I will sing the praises of your name, O Most High."

- Psalm, 9:1-2

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Abstract

This thesis aims to evaluate the performance of deep learning artificial neural network (ANN) (multi-layer perceptron (MLP) and long short-term memory (LSTM)) models and parametric (Black–Scholes–Merton, Heston, Heston jump diffusion and finite moment log stable) models in the daily prediction of Standard and Poor’s (S&P) 500 call option prices and delta and optimally trading ETF pairs. We use multiple specifications of hidden layers and neurons for ANN models that reflect a more granular level of deep learning, aiming to provide insight into the efficacy of increasing granularity in improving performance. For comparison, we employ classical option parametric pricing models widely used in academia and practice to comprehensively assess the models’ performance based on their practical relevance.

In the first study, an extensive empirical assessment of the forecasting performance of daily S&P 500 call option prices/moneyness is performed, and we experiment with single, double, and triple hidden layers specifications of ANN and parametric models. Deep learning ANN models are trained on lagged and one-trading-day-ahead input variables. The numerical investigations reveal that the best-performing models for daily forecasts of call option prices and moneyness are LSTM models (with lagged input variables) and MLP models (with one-trading-day-ahead input variables) compared to parametric models. Moreover, most triple hidden layer ANN models outperform single and double hidden layer ANN models. These results have practical implications for pricing options without look-ahead bias and for network architectures that empirically demonstrate performance improvement from single to triple hidden layers ANN models.

In the second study, the empirical performance of triple hidden layer deep learning ANN and parametric models (with lagged and one-trading-day-ahead input variables) is assessed by predicting daily S&P500 call option delta and the corresponding replicating portfolio value. The delta is computed directly and may also be analytically inferred from option prices. We find that the Black–Scholes–Merton model and the LSTM models typically outperform the other parametric and ANN models. In particular, the LSTM models outperform when the delta is analytically inferred from option prices. The results of this chapter have practical relevance for short-term dynamic hedging applications of options portfolios.

The third study amalgamates the models discussed in the first and second studies by comparing model averaging predictions of prices, deltas and replicating portfolios from deep learning ANN and parametric models. It is shown that the average triple hidden layer MLP models tend to

perform the best in forecasting option prices, with the parametric models performing better in forecasting delta. For the replicating portfolio, the pricing forecasts seem to dominate the delta forecasts, revealing the superiority of the average triple hidden layer MLP models. These findings provide empirical evidence of the effectiveness of model averaging techniques for forecasting options prices and delta risks, which would be helpful in short-term risk management and derivatives evaluation.

The fourth study introduces a new methodology for pair trading equity ETFs, which is formulated by effectively applying commonly used technical indicators and machine learning algorithms (decision tree and deep learning MLP models) to the spreads generated by traditional approaches, thereby generating unique ways to enhance returns. We perform a comparative analysis based on actual PnL(Profit and Loss), returns, Sharpe ratios, and other performance indicators. Eight ETF pairs across three rolling windows (30 days, 50 days and 100 days) yield 3,084 pair trading strategies, which are back-tested. We find that there are alternate and profitable ways to trade pairs that provide a practitioner with many profitable opportunities, unlike traditional approaches in which one is confined to a limited number of opportunities. A pair of ETFs can be traded irrespective they are cointegrated or correlated, thereby enabling hedge funds, institutional investors and retail traders to deploy this strategy as a long/short equity investment tool.