Machine Learning Algorithms for Financial Asset Price Forecasting: A Review

Flavius A. Nuta
MSc Data Science
Department of Mathematical Sciences
University of Essex
fanuta@essex.ac.uk

***Index Terms*—Machine Learning, Deep Learning, Asset Pricing, Neural Networks, Finance, Gradient Boosting**

I. Background

Within the field of computational finance, much attention has been given to the performance of machine learning prediction algorithms in forecasting financial assets prices. Existing literature on the matter comprises a large number of studies that aim to demonstrate the empirical performance of Machine Learning algorithms for asset price forecasting as opposed to traditional, linear financial models.

II. Thesis and Claims

In "Machine Learning Algorithms for Financial Asset Price Forecasting", Ndikum [4] looks at how institutional and private investors can estimate the annual returns of US equities using a range of Machine Learning algorithms and traditional finance models, such as the Capital Asset Pricing Model (CAPM). The author claims that machine learning prediction algorithms have a significant advantage over traditional finance models due to their ability to account for "alternative data" and large numbers of features. The paper compares a traditional CAPM model against a series of gradient boosting frameworks and neural networks.

III. Methodology

The author starts by explaining the assumptions and theoretical constraints behind the models implemented, as follows:

A. CAPM

The paper first dives into the CAPM and the assumptions behind it, as well as existing criticism. Despite this, the study does not present any specific technical limitations of the CAPM. Two limitations that could have been explored by the author, and could have made the argument even stronger for discarding the CAPM in favour of modern machine learning models, are:

- The model does not account for low volatility in order to maximise an investor's returns [5]; and
- The model assumes a one-period time horizon, therefore it does not allow for a repeated rebalance of portfolios over time.

B. Machine Learning - Theoretical Framework

The author presents the processing of data as a supervised learning task that requires two steps:

- A classification step where the algorithm is required to classify the occurrence probability of volatility-causing events, such as economic recessions; and
- A regression step that predicts the desired output; in this case, the annual return of a stock at a specific time in the future.

The paper outlines the task as an optimisation problem by iteratively minimising a loss function, and addresses the issue of overfitting. From a financial point of view, overfitting can lead to an algorithm performing well on historical data, but when faced with real-time data feeds the outcomes are not as accurate. The study accounts for this issue by adding a regularisation term to the loss function, in order to reduce overfitting and to increase the likelihood of a forecast being accurate [1].

When evaluating the empirical performance of the machine learning models employed throughout this study, the author makes use of AutoML to fine tune hyperparameters for each of the models. The optimisation algorithms used in this study are GridSearch and a Tree of Parzen Algorithm [2]. GridSearch has certain limitation as it is completely uninformed by past results and thus it can evaluate less performant hyperparameters. The author does not provide an explanation as to why this method is used, even though GridSearch can lead to a reduction in accuracy when compared to Bayesian optimisation algorithms such as Tree of Parzen.

C. Regulatory Contstraints

Aside from being concerned with accurate forecasts of asset prices, investors are also constrained by a number of regulations. A relevant example is the Markets in Financial Instruments Directive (MiFID) II, which requires an investment firm to provide a description of its algorithmic strategies, including parameters and any limitations that the system faces. The author provides two solutions from existing literature on how to address these regulatory requirements, such as LIME [6] and SHAP [3].

Apart from addressing legislation designed to limit risk, the paper also provides a solution on how to account for macroeconomic policy decisions that may lead to systematic risk. A set of Bayesian techniques is employed in order to account for risk [3]. This is a robust approach, as it showcases how advanced modern machine learning techniques are as opposed to traditional finance models, which are still widely employed in the industry.

D. Data

The author conducts a large scale empirical analysis using US equities data for 782 stocks, spanning from 1983 until 2019. A positive aspect of this study is that it only includes stocks that have existed throughout the entire 36-year time frame, which prevent any additional bias in the analysis. While the study could have included a more detailed list of data points extracted, some of the examples presented include:

- Monthly and annual asset prices
- Financial statements
- Consumer price indices
- Bond rates
- Gross domestic product
- Monthly unemployment rates
- Monthly LIBOR

Interestingly, there is no specific mention of market sentiment data in the study. Market sentiment could provide a more accurate understanding of subjective considerations in the model. For example, market participants may dwell on a particular piece of news over a set period of time; this could ultimately translates into a stock price remaining artificially high or low.

IV. Results

To evaluate the performance of the models, the paper employs the Mean Squared Error (MSE) as a performance metric to evaluate the predicted annual return (denoted Y) against the actual annual return (denoted y).

$$MSE(Y - y) = \frac{1}{n}\sum_{i=1}^{n}(Y_i - y_i)^2$$

One major disadvantage of using the Mean Squared Error is that the metric is not robust to outliers. In the event a sample y has an associated error that is significantly larger than that of other samples, the square error will be even larger. As a result, MSE is more prone to outliers as the measurement calculates the average of all errors. A more appropriate measurement could be the Mean Absolute Percentage Error (MAPE), which calculates the error between actual and forecasted values as a percentage.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - Y_i}{y_i}\right|$$

MAPE can provide a better understanding of how far off the predictions are in relative terms. This is particularly important because stocks are priced differently. For example, an error of \$10 made with respect to a stock priced at \$3,300 per share can be said to be accurate; in relative terms, the prediction error is 0.3%. However, if the error was obtained on a stock priced at \$40 per share, that would give an error of 25%. It could be argued, that in the case of financial asset pricing, MAPE provides a more accurate representation of the error as opposed to MSE.

V. Conclusion

The results obtained by Ndikum [4] are strong evidence that machine learning methods provide a significant performance improvement over classical financial models such as CAPM, and can be of great benefit to financial institutions and private investors. Given the flexibility of the machine learning models used, it was expected that the algorithms would be able to cater for a large number of features to accurately predict returns, as opposed to CAPM. The paper addresses the task from different angles including regulatory and financial constraints, as well as technical decisions required to set-up the machine learning models. While arguments are outlined in a concise manner, certain decisions or model limitations are not always explained. Future avenues for research include analysing how the framework developed in this study would perform when forecasting other asset classes such as currencies or commodities.

References

[1] David H. Bailey, Jonathan Borwein, Marcos López de Prado, Amir Salehipour, and Qiji Jim Zhu. Backtest overfitting in financial markets, 2016.

[2] James Bergstra, Brent Komer, Chris Eliasmith, Dan Yamins, and David D Cox. Hyperopt: a python library for model selection and hyperparameter optimization, 2015.

[3] Scott Lundberg and Su-In Lee. A unified approach to interpreting model predictions, 2017.

[4] Philip Ndikum. Machine learning algorithms for financial asset price forecasting, 2020.

[5] Sujin Pyo and Jaewook Lee. Exploiting the low-risk anomaly using machine learning to enhance the black–litterman framework: Evidence from south korea. *Pacific-Basin Finance Journal*, 51:1–12, 2018.

[6] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. "why should i trust you?": Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '16, page 1135–1144, New York, NY, USA, 2016. Association for Computing Machinery.