A Review of "Forecasting Directional Movements of Stock Prices for Intraday Trading Using LSTM and Random Forests"

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Background and Motivation

Short-term stock market forecasting is a common challenge but one that is tackled by many millions of analysts and investors daily. Stock market data is frequently non-linear and is influenced by not only financial drivers but also geopolitical and macroeconomic policies and events. Recently, new breakthroughs in machine learning have provided potential for modeling much of this complexity. Random Forest has demonstrated the ability to handle non-linear, heterogeneous features while being explainable and resistant to overfitting. Long Short-Term Memory networks are a form of recurrent neural network (RNN) have been developed to handle sequential learning bringing forward context from previous decisions making them a good tool for financial forecasting.

This study by Ghosh, Neufeld, and Sahoo (2022) employs these two algorithmic approaches and study the effect of multi-feature intraday pricing data and its effective use in predicting future prices. This expands on earlier work by Krauss and Fischer (Krauss et al., 2017; Fischer & Krauss, 2018) which focused on single-feature daily return data to predict next-day performance. This paper extends this to add previous closing price, the opening price, pricing movements during the trading day. The authors analyze if this additional data, which is more granular, provides better profitability after the cost of trading.

The authors' motivation is both academic and practical. From an academic perspective the authors want to study if their additional features and intraday granularity improve on the more commonly studied single-feature approaches in the literature. From a practical perspective the authors want to determine if they can devise a systematic approach that can deliver high risk adjusted returns consistently in real-world trading including the economic friction of trading cost.

Methods Used

The authors employ and compare two different modeling approaches, Random Forest and a GPU-accelerated LSTM network, CuDNN LSTM. The dataset analyzed contains all the stocks within the S&P 500 index from January 1990 to December 2018. The data included adjusted opening and closing prices and retrieved from Bloomberg. The team used the methodology of Krauss et al. (2017) and Fischer and Krauss (2018) dividing the 29-year dataset into 26 non-overlapping "study periods" each of which contained approximately three years of training data (one for feature creation and two for training) with one year of hold out data for test and validation. The data "study periods" were non-overlapping in the sense that a single year's data would not be used more than once for a phase (once for feature creation, once for training, once for testing).The time period selection was made to made epochs in the data that are slightly more granular than the entire 29-year dataset and allow for bucketing major market trends and events, such as the dot-com bubble.

The authors removed all data with zero trading volume. For the Random Forest (RF) model the authors used 93 features composed of intraday returns, returns relative to previous close, and returns relative to the opening price. These were calculated within the "study periods". The RF features were not scaled or centered whereas the LSTM used Robust Scalar standardization to mitigate the effects of outliers.

The prediction is a binary target variable with value of 1 if a stock's intraday return is expected to exceed the median of all other stocks in the S&P and 0 if not. This selection for the target variable is taken from Avellaneda and Lee (Avellaneda & Lee, 2010).

For training the Random Forest is configured to produce 1,000 trees with a maximum depth of 10 and to randomly select features at each split (Breiman, 2001; Ho, 1995). The LSTM architecture was composed of 25 CuDNNLSTM cells, a dropout layer (0.1), and a dense output layer with softmax activation. The LSTM training used RMSProp optimization, categorical cross-entropy loss, a batch size of 512, and early stopping based on validation loss.

The trading methodology required a decision each day wherein 10 stocks with the highest predicted probability of outperforming the median intraday return were bought and 10 with the lowest probability were sold short with equal monetary weighting. Calculating the cost of slippage the authors used Avellaneda & Lee's methodology of adding a total daily transaction cost of 0.2% (Avellaneda & Lee, 2010). Sharpe ratio and standard deviation were selected as risk-adjusted return metrics.

Significance of the Work

The study demonstrates that the group's multi-feature intraday setting outperforms the single-feature next-day setting used in prior studies. Before transaction costs the LSTM model achieves an average daily return of 0.64%, compared to 0.41% in Fischer and Krauss (2018). The Random Forest achieves 0.54% versus 0.39% in Krauss et al. (2017). After transaction costs the authors' multi-feature LSTM results in 0.44% daily returns with a Sharpe ratio of 4.32 and the RF yields 0.34% daily returns with a Sharpe ratio of 3.22. These returns are substantially greater than the single-feature models.

The authors demonstrate that multi-feature models also provide lower maximum drawdowns, higher Sortino ratios, and better Value-at-Risk (VaR) profiles. Positive daily returns were achieved 63.1% of the time for LSTM and 59.3% for RF after costs.

The results demonstrate that using multiple return-based features captures richer market dynamics than single-feature approaches and results in better risk-adjusted return. Also, LSTM networks outperform Random Forests in this context as RF is memory-free while LSTM provides sequential memory (Fischer & Krauss, 2018; Sezer & Ozbayoglu, 2018).

Connection to Other Work

This study relies heavily on previous work by Krauss et al. (2017) and Fischer and Krauss (2018) and extends their single-feature prediction framework by expanding the feature space and shifting the data from daily to intraday. This work also relies on previous work to determine the friction cost of trades (Avellaneda & Lee, 2010) and previous neural network architectures

for trading strategies (Huck, 2009; Takeuchi & Lee, 2013) . This study also relies on Random Forests to stock return prediction (Moritz & Zimmermann, 2014; Lohrmann & Luukka, 2019).

Good practices in financial machine learning gleaned from previous work include non-overlapping training/testing periods, binary classification targets, and performing both long- and short-side trades. Applying these standards allows the authors to demonstrate how multi-feature inputs can provide superior risk adjusted returns by providing an analytical approach consistent with other studies.

Relevance to Capstone Project

This paper is relevant to my capstone project in that I will study the application of Random Forest models to stock market index prediction. The multi-feature input approach leads me to expect I will need to add intraday metrics and not rely on open-last-close metrics for price prediction. I also know that scaling is likely not required for these data in an RF model..

The study's non-overlapping evaluation framework is directly relevant for my work to reduce model bias and to improve my model by splitting modeling into discrete time periods. I also have some good understanding of measures of success and comparison to previous works. The addition of a concrete cost of trading in a 0.2% daily penalty will make my results more realistic to real-world returns.

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