

Intraday Algorithmic Trading using Momentum and Long Short-Term Memory Network Strategies

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Abstract

Intraday stock trading is an infamously difficult and risky strategy. Momentum and reversal strategies and long short-term memory (LSTM) neural networks have been shown to be effective for selecting stocks to buy and sell over time periods of multiple days. To explore whether these strategies can be effective for intraday trading, their implementations were simulated using intraday price data for stocks in the S&P 500 index, collected at 1-second intervals between February 11, 2021 and March 9, 2021 inclusive. The study tested 160 variations of momentum and reversal strategies for profitability in long, short, and market-neutral portfolios, totaling 480 portfolios. Long and short portfolios for each strategy were also compared to the market to observe excess returns. Eight reversal portfolios yielded statistically significant profits, and 16 yielded significant excess returns. Tests of these strategies on another set of 16 days failed to yield statistically significant returns, though average returns remained profitable. Four LSTM network configurations were tested on the same original set of days, with no strategy yielding statistically significant returns. Close examination of the stocks chosen by LSTM networks suggests that the networks expect stocks to exhibit a momentum effect. Further studies may explore whether an intraday reversal effect can be observed over time during different market conditions and whether different configurations of LSTM networks can generate significant returns.

Data and Methodology

For 16 trading days in February-March 2021, an updated list of tickers in the S&P 500 was retrieved from Wikipedia. For each second in the market hours of each day, bid and ask prices were retrieved for each of 505 stocks in the list of tickers through the Robinhood API, using the robin_stocks Python package. In instances where prices could not be retrieved for a given timestamp (e.g., network delay or failure, Robinhood credentials timeout) the timestamp was skipped and later forward-filled. On average, 10.5 seconds of data were forward filled per day (about 0.045% of rows). The midpoint of the bid-ask prices for each stock at each timestamp was computed and used as the price of the stock at that time. The resulting dataset was a 23,401 x 505 table for each day, with rows corresponding to timestamps and columns corresponding to stock tickers.

- Formation Period – the timeframe over which price movements are observed and used to choose the set of stocks to purchase
- Holding Period – the timeframe over which stocks are bought and held
- Each strategy observed stocks over a formation period, selecting stocks to buy and sell. After a delay of 5 minutes, positions were entered and held over the holding period after which they were exited.
- Returns and excess returns were calculated for multiple study periods over the days of study.

Momentum

- Momentum strategy – buys stocks that perform the best, expecting them to continue to outperform other stocks (ex. Jegadeesh & Titman)
- Reversal strategy – opposite of momentum; expects the worst-performing stocks to change course and outperform others (ex. De Bondt & Thaler)

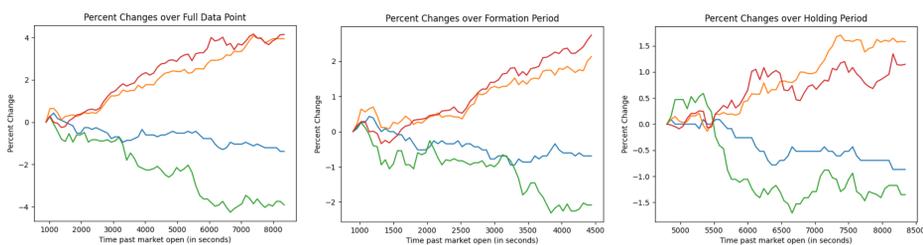


Fig. 1. Example of a successful momentum strategy. The lengths of the formation and holding periods are 60 minutes, meaning the full data point spans 2 hours 5 minutes. The red and orange stocks perform best over the formation period, so a momentum strategy would buy and hold them over the holding period.

Combinations of formation and holding periods with lengths of 30, 60, 90, and 120 minutes were used to test momentum and reversal strategies, totaling 32 different strategies. For a single formation-holding period combination, the returns on each of the 505 stocks were calculated for both periods. The stocks were then sorted by the formation period returns, and the top and flop k stocks were selected. The average returns over the holding period on the top and flop stocks were computed. Returns on longing winners, shorting losers, and doing both at once were recorded to show the momentum strategy's effectiveness. Returns on the reverse of each strategy (shorting winners, longing losers, and doing both) were also recorded to show the reversal strategy's effectiveness.

Results

- Buy, sell, and market neutral portfolios from each strategy were tested for profitability using a t-test. Additionally, excess returns on buy and sell portfolios were tested to see if they outperformed or underperformed the market.
- No momentum strategies or LSTM strategies had statistically significant profitability, but some reversal strategies were statistically significantly profitable in both returns and excess returns.
- Significant reversal strategies were employed and tested on a second set of 16 days from March-April 2021. The strategies were not statistically significantly profitable. However, all strategies remained profitable on average.
- These findings suggest that certain reversal strategies derived from the results of the first set of days could remain profitable over the second set of days. However, the lack of statistical significance calls the consistency of these strategies into question. Further research could be done on a larger sample of days to see if intraday reversal strategies are profitable during different market conditions.

LSTM Neural Network

- LSTM Neural Network – A neural network designed to recognize patterns in sequences for use in time series prediction.

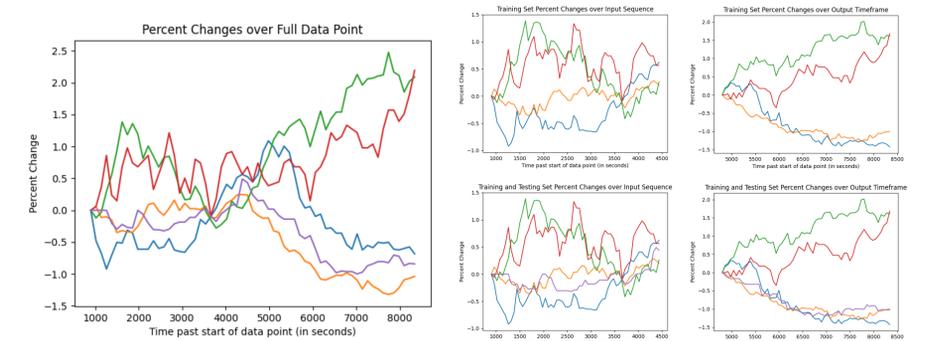


Fig. 2. Example of a successful LSTM prediction. The training set contains the green, red, orange, and blue stocks, and the testing set contains the purple stock. An LSTM network trained on this training set would expect stocks that follow input sequence patterns like green and red to perform well, and stocks with patterns like orange and blue to perform poorly. Because the purple pattern is closer to orange and blue, the network would correctly predict purple's price to fall.

- Four LSTM network configurations were used (shown in Table 1), with variable input sequence lengths, output timeframes, study period lengths, and training period lengths.
- The input sequence for the LSTM network was a stock's standardized returns over the input timeframe. The output was 1 if the stock outperformed the median during the output timeframe, and 0 otherwise.
- Each day of data was split into multiple study periods. For each study period, networks were trained on stock data from the training period, and used to predict profitable trades during the testing period.
- Stocks in the testing period were ordered by their predicted probability to outperform the median. The top and flop k stocks were selected to form long, short, and market-neutral portfolios. Returns and excess returns on each portfolio were calculated and recorded.

| Strategy | LSTM Network Details | Number Model Parameters | Number Training/Testing Examples | Number holding periods |
|----------|---|-------------------------|----------------------------------|------------------------|
| A | Input Sequence: 60 1-min Output Timeframe: 30 min Study period length: 3 hr Train period length: 2 hr 10 min | 8652 | 212605 training, 91405 testing | 80 |
| B | Input Sequence: 60 1-min Output Timeframe: 60 min Study period length: 3 hr 30 min Train period length: 2 hr 20 min | 8652 | 91405 training, 30805 testing | 48 |
| C | Input Sequence: 120 1-min Output Timeframe: 30 min Study period length: 4 hr Train period length: 3 hr 10 min | 14652 | 212605 training, 91405 testing | 48 |
| D | Input Sequence: 120 1-min Output Timeframe: 60 min Study period length: 4 hr 30 min Train period length: 3 hr 20 min | 14652 | 91405 training, 30805 testing | 32 |

Fig. 3. Average percent changes for top and flop stocks in LSTM strategies. Top stocks are shown in green, flop stocks in red, and all stocks in blue. Average percent changes for $k = 10$ top and flop stocks are used. Price movements across full data points are shown, meaning the output timeframe in which strategies hold positions is shown in the rightmost portion of each graph. For example, the output timeframe starts at $t = 3900$ for strategy A.

Plotting the average percent changes for each strategy reveals that strategies A and C buy stocks that perform well and sell stocks that perform poorly. Strategies B and D seem to be overfitted on training data, resulting in a lack of distinction between top stocks, flop stocks, and all stocks.