© INTERNATIONAL JOURNAL FOR RESEARCH PUBLICATION & SEMINAR
ISSN: 2278-6848 | Volume: 12 Issue: 02 | April - June 2021
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Stock Portfolio Management using LSTM model based on a proprietary Stock Promise Factor comprising Technical & Fundamental indicators

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Abstract

Stock market predictions, be it prices or patterns, is a complex task that is both human intensive as well as computer intensive. The fact that the market is a dynamic and chaotic environment adds to the challenge. An intermittent rise or fall in a stock's price has an important role in determining the investors' gain because it affects the overall portfolio returns immensely. Due to this dynamic nature of the stock market, applying conventional batch processing methods is not a viable option. This leads us towards discovering a more actively managed portfolio as opposed to traditional methods like buying and holding value stocks or following the indices. While one can rely on stock market professionals, this paper proposes and reviews an artificial intelligence-based stock portfolio managing method. This paper proposes a LSTM and statistics-based technique to manage and restructure portfolios consisting of fundamental and technical indicators, in order to maximise the gains. The technique is tested for a portfolio of ten stocks over six months and the results are tabulated. A comparison with respect to final portfolio value is then performed against buying and holding stocks, Treasury Bills, and S&P 500 index.

Keywords: LSTM, Technical & Fundamental Indicators, S&P 500, Stock Portfolio

Introduction

An investor or traders' ultimate goal is to optimise some relevant measure of trading system performance such as profit, economic utility or risk-adjusted return. The most important aspect to be monitored for the stock investors is the continuous rise and fall of the stocks' price. The fluctuation of the stock market is tumultuous and heavily depends upon the multiple complicated financial indicators. It is an art to understand these indicators and put them to good use and earn a fortune. Majority of the people rely on luck to earn money from stock trading or holding index funds. A combination of machine learning along with financial indicators is an opportunity for the people to gain profits from the stock market as well as for experts to come up with revealing indicators.

Stock markets and the field of economics are intertwined with each other. The bull and bear of stock prices can be narrowed down to five indicators which are the opening stock price, closing stock price, intra-day maximum price, intra-day lowest price and volume of that particular stock traded on that day. This data is generally available as sequential data where at the end of the day, the entries for that day of that stock are added.

Recurrent Neural Networks (RNN) are one of the most strong and powerful methods of processing sequential data. Long-Short term Memory (LSTM) is a particular architecture type of RNNs and they enable RNNs to memorise their inputs over a stretch of time which is really helpful in stock portfolio management.

In this work, a framework for long-term stock portfolio management that aims at maximising the gains is being presented. The method suggested, makes use of deep learning mechanism LSTM model and financial indicators which comprises both fundamental and technical indicators. In this paper, the method suggested is then compared with buying and holding, S&P 500 index and treasury bills and shows an improved version.

Background and Related Works

Since the beginning of the stock markets, researchers have been working on predicting the stock market. The purpose for predicting the stock market is to beat the odds and gain profits. [1] presents the Efficient Market Hypothesis which believes that the stock market prices reflect all the information present at the moment. Thus, there is no way to effectively beat the market returns. But there exist living examples like Warren Buffett who achieved tremendous success in stock markets.

There are two types of Analysis performed on the stock markets to predict future prices, considering that Efficient Market Hypothesis is wrong, technical analysis and fundamental analysis. Technical Analysis is the study of the past price movements and patterns they form in order to predict the future prices. Fundamental Analysis is the study of the company's fundamentals whose stock price is being tried to determine.

While Fundamental Analysis chases the value of the stock, what price the stock 'should' be, technical analysis chases the trend, what stock prices are going to be according to past trends. Long Short-Term Memory (LSTM) works in a similar fashion, the difference being that technical analysis consists of simple mathematical operations on past data whereas LSTM is a deep and recurrent neural network [2] designed to predict the trend. Recurrent neural networks differ from the traditional feed-forward networks in the sense that they don’t only have neural connections on a single connection in a single direction, in other words, neurons can pass data to the previous or same layer.

The introduction of LSTM by [3], was to get improved performance by getting rid of the vanishing and exploding gradient issues that recurrent networks suffer from. This is made possible via special units called “gates” which allow for weights adjustments as well as truncation of the gradient when its information is not necessary.

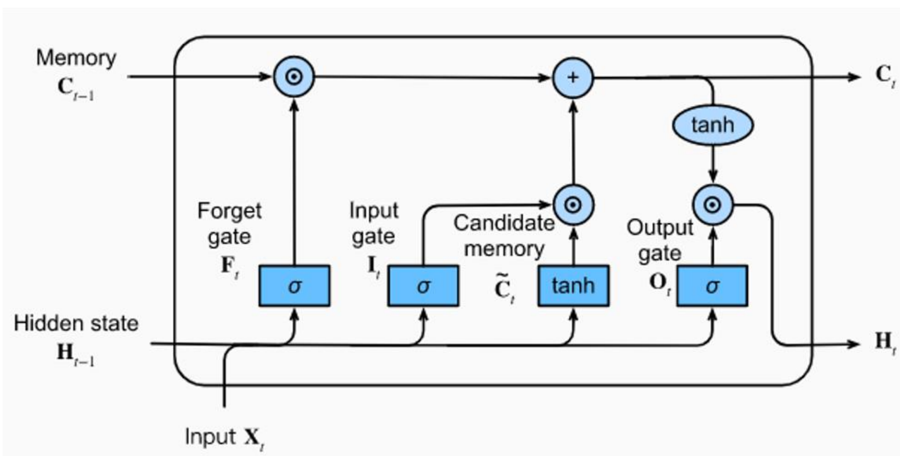

Fig. 1. Long Short-Term Memory Network

As can be seen in the figure 1, in an LSTM you have three gates: forget, input and output gate. These gates determine whether new input is allowed in or not (input gate), whether the information is important or should be deleted (forget gate), or should it have impact on the output in current step (output gate). The issue of vanishing gradients is solved through LSTM because it keeps the gradients steep enough and henceforth, the accuracy high and training short.

Predicting a future price is not an exact science; if it were, then somebody would have already figured it out. It is a combination of art and science and whilst it shows that a random strategy can produce good outcomes, bits from previous research are used in order to choose the indicators to be used alongside the LSTM model. In the paper published by [8] and [9], it has been noted that some indicators play an important role in determining the stock price. They have been mentioned in the Section III of the paper.

Hence, this paper proposes a method based on LSTM to predict price movements along with technical and fundamental indicators in order to restructure our portfolio.

Methodology

In this section, elaboration of method and introduction of a new parameter called, **Stock Promise Factor (SPF)**, which can be used for restructuring of stock portfolios, has been done.

Step 1: Create a portfolio of different stocks.

In this experiment, 10 stocks based on the following fundamental indicators were chosen:

1. Price-Earnings Ratio
2. Price/Sale Ratio
3. Price/Book Ratio
4. Earnings/Share
5. Dividend Yield

First, the values available for each of the 500 stocks in the S & P 500 index have been normalised for these ratios for the last financial year and give equal weightage to all. Then, the portfolio of 10 stocks has been created.

Step 2: Create a dynamic dataset of stock value, fundamental and technical indicators

A dataset that comprises dates, closing prices, and values of fundamental and technical indicators of the stocks at the beginning of each period is created.

Step 3: Predict future price movements based on the trend observed by LSTM model

Make use of the LSTM model to predict the future price movement direction and save it in an upward and downward movement counter which records the movements.

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Step 4: Create a counter for upward and downward movement predicted in the next period

On each run, the model predicts the stock values for the next 30 days based on the previous 220 days data. On each run, the dataset is shifted by a one month window. This step is repeated for making a prediction for each of the next six months. And this entire step is repeated for each of the chosen stocks. The predicted stock values are compared with actual stock values. And up-count and down-count is recorded based on the predicted values for each stock. The LSTM model has used the ADAM optimizer and mean squared error as the loss function.

Step 5: Calculate Stock Promise Factor (SPF) as

$$\mathbf{SPF = 0.5SPF_{(A)} + 0.5SPF_{(B)}}$$

Where:

$SPF_{(A)}$: Normalized LSTM values of up count and down count predictions

$SPF_{(B)}$: Value obtained using Fundamental and Technical Indicators

$$\mathbf{SPF_{(B)} = 0.4F + 0.6T}$$

Where:

F: Fundamental indicators weight-age, $\mathbf{F = 0.3*PE^{-1} + 0.3*(P/S)^{-1} + 0.2*(DY) + 0.2*(P/B)^{-1}}$

T: Technical indicators weight-age, $\mathbf{T = 0.05*ROC + 0.4*MACD + 0.05*OBV + 0.05*VIX + 0.4*RSI + 0.05*ESP}$

The acronyms used along with their brief descriptions are given below:

a. PE: Price/Earnings ratio – It is the ratio for valuing a company that measures its current share price relative to its per-share earnings.
b. P/S: Price/Sale ratio - It is a valuation ratio that compares a company's stock price to its revenues.
c. DY: Dividend Yield - Forward dividend yield is calculated by dividing a year's worth of future dividend payments by a stock's current share price.
d. P/B: Price/Book ratio – It is used by companies to compare a firm's market to book value by dividing price per share by book value per share.
e. ROC: Rate of change – It is a technical indicator of momentum that measures the percentage change in price between the current price and the price 9 days in the past.

f. MACD: Moving average convergence divergence - It is a trend-following momentum indicator that shows the relationship between two moving averages of a security's price.
g. OBV: On-balance volume - It is a momentum indicator that uses volume flow to predict changes in stock price.
h. VIX: Relative Volatility Index - It is an indicator that measures the general direction of volatility. The volatility is being measured by the 10-days standard deviation of the closing prices.
i. RSI: Relative Strength Index – It is a momentum indicator that measures the magnitude of recent price changes to evaluate overbought or oversold conditions in the price of a stock or other asset. The time period used in the experiments is 14 days.
j. ESP: Earnings Surprise – It occurs when a company's reported quarterly or annual profits are above or below analysts' expectations.

The SPF values for each stock for each month are calculated.

Step 6: Perform Quartile Analysis on the held portfolio based on SPF values

After this, quartile analysis is performed on the SPF values of stocks calculated in the last step, for a particular value to find out the values of Q1 and Q3.

Step 7: Restructure the Portfolio

The following technique is to be followed to restructure the portfolio:

a. For stocks having SPF values less than Q1, sell 10% of the number of stocks of that particular stock or the nearest whole numbered value.
b. For stocks having SPF values greater than Q1 but less than Q3 are the stocks which are in the HOLD category and must not be bought or sold in the current month.
c. The amount received by selling the stocks is equally divided into the number of stocks having values greater than Q3 for that month.
d. Now, buy new stocks for the greater than Q3 companies. In case, the amount of the money allocated to each stock is not enough to buy even a single stock, then allocate the whole amount first to the highest SPF valued stocks and then trickle down the rest to buy the other till the threshold of Q3 is reached.

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e. After buying new stocks, calculate the new value of the portfolio and save it each month.
f. After that compare it with the portfolio value of the previous month and that of the day when the portfolio was created.

Empirical Testing

A. Dataset and Evaluation Metrics:

The dataset for the stock prices has been obtained from Yahoo Finance. The dynamic dataset for the indicators of the stocks has been created on a monthly basis from tradingview.com and macrotrends.com. The evaluation basis of the proposed methodology is the profit percentage as well as the final value of the stock portfolio.

B. Baselines:

Mainly three different baselines have been used for comparison to this proposed model.

a. Buying and Holding: The model has been compared to a scenario in which the number of stocks before and after the six-month period on which the implementation of this model remains the same, that is, there is no restructuring across six months.
b. S&P500: Index Stocks of any country act as the benchmark return for the market rate of return and thus this model was compared with investing the same amount in these S&P 500 index.
c. Treasury Bills: Treasury Bills of any country act as the benchmark return for the risk-free rate of return and thus the comparison of this model with holding treasury bills of the same amount.

C. Empirical Results:

Experiments were carried out to restructure the portfolio according to the proposed method for the months of April to October 2018 for the stocks as mentioned in Table I(Appendix I) in the following manner.

a. Initiation was done with an investment of $100000 divided equally into 10 parts among the following 10 stocks. Then, depending upon the price of the stock on 2nd April, 2018, stocks are bought. The remaining of the $10000 is kept in savings.

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b. The LSTM models use the data for the past 220 days on which the market was open to predict the next 30 days. Since, the number of days in each month differ and the experiment is actually only concerned regarding the upward or downward trends in a month, the values were normalised. Similarly, the values for fundamental and technical indicators are first normalised before calculation of SPF values. Table II(Appendix I) presents an example of the normalised data for three indicators for calculation of SPF(B) values for each stock for restructuring in April end.

c. Then as mentioned in the methodology section, the values for SPF(A), SPF(B) and SPF are calculated for all the 10 stocks in all the months, in this case, April to October 2018 and BUY/SELL/HOLD signals are generated. The resultant signals obtained are shown in Table III(Appendix II).

d. At the end of the six-month period, the results obtained are described below. The number of stocks at the beginning and at the end is described in Table IV(Appendix II). The portfolio value and the profit percentage are mentioned in Table V(Appendix II).

The profit percent are also shown in figure 3.

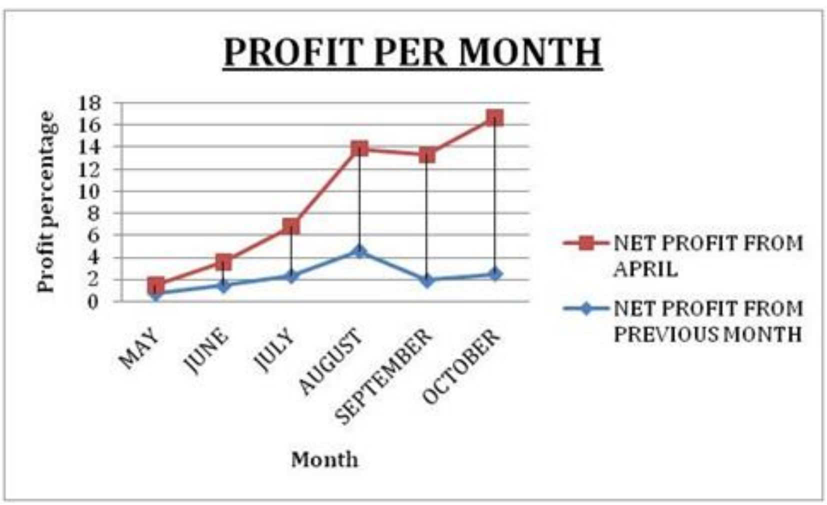

Fig. 3. Profit Per Month

Conclusion

The experiment was performed on S&P 500 Index for a six-month period with monthly restructuring of the portfolio. The period chosen for this experiment was from April 2,2018 till October 1, 2018. The ten stocks chosen based on the values of fundamental indicators on April 2,

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2018. The initial hypothetical investment amount was $100000. The stocks bought and sold were in indivisible units and the change amount was deposited/ withdrawn from a hypothetical current account with no interest on savings. The dividend distributed was added to the account for the shares held during the distribution. For ease of experimentation, the buying and selling brokerage/commission was assumed to be zero.

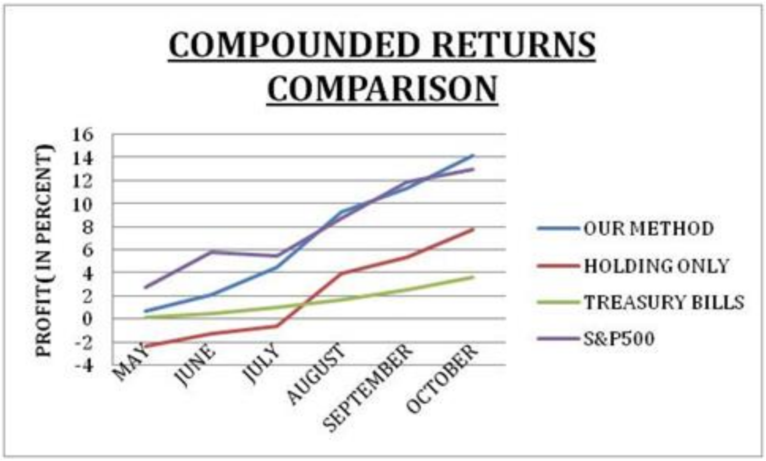

Fig. 4. Compounded Returns Comparison

At the end of the experiment, the balance amount was $114156.47 giving an absolute return of 14.15647% in the six-month period and a 30.3170% per annum annualised return. The resultant return is higher compared to U.S Treasury Bills (2.55% per annum), considered as risk free return and S&P 500 index (26.9512% per annum, annualised for the investment horizon) which is a benchmark for US stock market performance. It was observed that the returns were higher compared to holding the 10 stocks selected for the six-month time period without restructuring which would have generated a return of 17.3037% per annum, annualised for the investment horizon. This observation removes the doubt of "lucky guess" factor involvement in the results. Thus, it can be concluded that the proposed method is an efficient active portfolio manager and can be used to replace the professional portfolio managers with more advancements in the technique.

Future Prospects

The Indian stock markets are booming at the fastest pace today. In this light, personal optimisation of personal portfolio can free individuals from the clutches of huge mutual fund corporate houses.

The Pareto optimization techniques can be applied to the proposed SPF model for maximising the profit to the highest limit possible and minimising the risk to the lowest levels possible.

When it comes to stock markets, perception and behaviour plays the major role. According to researchers, 90% of the price movements take place within three days of the outbreak of news of mergers, acquisitions, restructuring, bankruptcy, etc., thus making it time sensitive. If these opportunities are tapped in time, they can lead to maximum profits. Thus, behavioural aspects related to particular stocks can be incorporated in the system from news analysis from various sources such as Reuters, Twitter, etc.

For the optimum utilisation of unused cash, short term trading prospects and intraday trading routines can be incorporated. With several amendments over the years, India provides a good opportunity for short term and intraday traders to use online automatic funds allocation systems due to a number of factors such as co-location facilities and sophisticated technology at both the major exchanges; a smart order routing system; and stock exchanges that are well-established and liquid.

For users with lesser experience and knowledge in the field, GUI based interfaces can be created where technical financial indicators can be chosen by experts to be used in the Stock Performance Factoring System.

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Appendix I: Initial Portfolio and Indicator

Table I: Initial Portfolio

Symbol	Name	Number of stocks bought
AZO	AutoZone Inc	15
BKNG	Booking Holdings Inc.	4
AGN	Allergan, Plc	59
CHTR	Charter Communications	32
BLK	BlackRock	18
MCK	McKesson Corp.	71
RE	Everest Re Group Ltd.	38
GOOGL	Alphabet Inc Class A	9
NSC	Norfolk Southern Corp.	73
SHW	Sherwin-Williams	25

Table II: Sample of Indicators Used

Symbol	Price/Earning	Dividend Yield	Price/Sales
AZO	0.496458924	0	0.085365854
BKNG	0.167623147	0	0.001798099
AGN	0	0.838917585	0.040229885
CHTR	0.810404624	0	0.071428571
BLK	0.413081909	0.90981396	0.020588235
MCK	0.010973872	0.387164602	1

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RE	0.251976995	1	0.092105263
GOOGL	0.159245797	0	0.021084337
NSC	1	0.814599808	0.038567493
SHW	0.320383912	0.418933126	0.060869565

Appendix II: Resultant Data From Empirical Testing

Table III: Resultant BUY/SELL/HOLD Signals (Monthwise)

Symbol	April End	May End	June End	July End	August End	September End
AZO	HOLD	BUY	HOLD	HOLD	SELL	BUY
BKNG	HOLD	HOLD	SELL	HOLD	BUY	HOLD
AGN	BUY	HOLD	HOLD	BUY	HOLD	HOLD
CHTR	BUY	HOLD	HOLD	BUY	BUY	HOLD
BLK	SELL	SELL	SELL	SELL	SELL	SELL
MCK	SELL	SELL	SELL	SELL	HOLD	HOLD
RE	BUY	BUY	BUY	SELL	HOLD	HOLD
GOOGL	HOLD	BUY	HOLD	HOLD	SELL	BUY
NSC	SELL	HOLD	BUY	BUY	HOLD	SELL
SHW	HOLD	HOLD	BUY	HOLD	BUY	SELL

Table IV: Stock Composition Comparison

Symbol	Stocks Before	Stocks After
AZO	15	16
BKNG	4	5
AGN	59	80

CHTR	32	46
BLK	18	8
MCK	71	45
RE	38	49
GOOGL	9	14
NSC	73	71
SHW	25	27

Table V: Portfolio Valuation and Profits

Month	Portfolio Value	Savings	Total Value	Net Profit from Previous Month (Percent)	Net Profit from April (Percent)
APR	95986.78	4013.22	100000	NA	NA
MAY	100474.06	229.06	100703.12	0.70312	0.70312
JUN	102043.44	90.98	102134.42	1.42130651	2.13442
JUL	104097.42	391.61	104489.03	2.305403017	4.48903
AUG	109015.74	261.13	109276.87	4.582146087	9.27687
SEPT	111177.43	181.26	111358.69	1.905087508	11.35869
OCT	114115.75	40.72	114156.47	2.512403837	14.15647