Strategy Name: LSTM Volatility & Price Forecasting

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1 Introduction

Our goal is to produce a return that could at least double the benchmark's return. We plan on investing in the SP 500 Index with an active investing style that could achieve the goal. We thereby choose the SP 500 Index as our benchmark. With $10 million initial capitals, we would achieve this goal by deploying 70% of the capitals in the SP 500 Index ETF, 25% invested in 2-Year U.S. Treasury Note for risk management, and the remaining 5% as cash for emergency needs. Our invested period is from June 21, 2018, to January 10, 2020. We would buy-and-hold the Treasury Note and cash.

The investment in the SP 500 Index is directed by two-step quantitative procedures: a deep learning volatility forecasting model and a deep learning price forecasting one. The volatility model will deliver a first-stage "Buy" or "Sell" signal without indicating the price movement direction. Then, the deep learning algorithm will reveal where the price would move and instruct us to fill or liquidate a position. The active strategy would generate an annualized return of 44% during the invested period on the index ETF investment. Thus, we would achieve our goal because our portfolio would produce a weighted average total return of 46.6%, compared with the benchmark total return of 12.7%. The alpha would be 33.9%.

2 Economic Hypothesis

We expect that the economic cycle, which reflects in the SP 500 Index, does exist and will repeat itself, which means that our strategy might be applied multiple times. Our essential assumption is that the U.S. economy will grow. We present our rationales in four aspects.

2.1 Fundamental Values

The SP 500 Index constituents are often successful businesses, which not only meet the index listing qualifications but also maintain their seats in the index for a long period. The economies of scale, better access to resources, and effective governance support the listed companies' profitability and fundamental values. We believe that the index price based on current constituents will not outperform that on previous listed companies, but the listing criteria filter and retain relatively effective public companies. Moreover, profitable businesses result in a stable or growing EPS. Historically, the SP 500's EPS has been trended up, which would indicate a higher SP 500 Index if the P/E remains at a stable level.

2.2 Demand for the Index

Passive managers have driven the demand for the SP 500 Index due to its long-term return, manageable expenses, and sound economic rationale. The efficient market hypothesis might hold for the large-cap equities because of more analyst research on the large-cap equities to allow more information to be disclosed. The demand for transparency would increase the liquidity of the SP 500 Index investing. Additionally, the flight to "safer" equities, such as market-wide indexes, because of the market's awareness of liquidity risk, would also facilitate the liquidity and demand for index investing. We assume that the strong desire of the SP 500 Index could add a hidden information premium for investors to pay for transparency. There are not too many asset managers that can efficiently replicate the SP 500 Index with relatively low expense ratio and tracking errors. Given the demand and supply relationship, we expect the SP 500 Index could continue to go up.

2.3 Exchange Rates, Interest Rates, and Inflation Rates

We assume that the real interest rates across the global markets are the same. The interest rate difference between the U.S. and other developed markets is the inflation rate difference. Over the past 25 years, the inflation rate in the U.S. has been mostly greater than that in the European Union (EU). According to the international Fisher effect, the interest rate in the U.S. should be higher than the interest rate in the EU. However, on a global scale, the U.S. has a relatively lower inflation rate than the non-EU markets and a generally higher interest rate as a developed country. Hence, the U.S. equity market might be attractive to global investors due to the stable USD FX rates and lucrative investment returns. If this environment can persist, favorable inflation and interest rates would fuel the demand for investing in the U.S. equities.

2.4 Index Calculation and Composition

The weighted market capitalization method biases upward the companies with a greater market cap, which are usually valued at higher valuation multiples. For instance, the technology giants have obtained more weights in the SP 500 Index. The potential price raise led by huge RD expenses in these companies will attract more investors, which will cause the companies' market cap to rise. As a result, these companies collectively push up the SP 500 Index's P/E. The result of a higher P/E would be a higher index level.

3 Implementation

3.1 Trading Securities Selection

Our securities selection was driven by the goal of doubling the benchmark (SP 500 Index) return. We finalized our investment in the SP 500 Index by qualitative analysis, which was mentioned in the Economic Hypothesis section. The key rationale is that the SP 500 Index would closely track the U.S. economy, and the market will experience an economic uptrend and will repeat. Meanwhile, the SP 500 ETFs market provides high liquidity, which is ideal for hedge funds. Moreover, the SP 500 index has a much more stochastic movement than any individual stocks. Usually, stochastic processes are better modeled by statistical tools, i.e. quantitative apparatus, than qualitative indicators. It is then justified for us to introduce statistical models to research on the SP 500 Index, predict its movement, and generate trading signals.

In general, we plan on allocating 70% of the initial capitals to the SPDR SP 500 ETF Trust (SPY) because of its low gross expense ratio, low tracking error, and high liquidity. To manage our risk exposure and beat the inflation, we deploy 25% of the initial capitals to a 2-Year U.S. Treasury Note as a buy-and-hold fashion. We hope to reduce the portfolio's exposure to the equity market and safeguard the hedging capitals. By a direct investment in the Treasury Note, 25% of the capitals are immune to major market risks. We will keep the last 5% for emergency needs.

3.2 Trading Signals

There are two parts of the quantitative strategy. The first is the LSTM volatility prediction model, and the second is the LSTM price movement prediction model. The strategy will first predict if absolute price percentage change exceeds 0.5% on day two (today as day one), and if it is the case, the price movement prediction model will predict the direction of the price change on day two, i.e. whether price percentage change is positive or negative. The trading decision will then be made accordingly.

We started with an ambitious goal, trying to use a deep learning algorithm to predict the percentage change of price. However, this proved too difficult a task to accomplish. As a result, we broke the process into two procedures. Volatility is much easier to predict than price, and because the price move prediction model is trained only on trading days with price percentage change greater than 0.5%, it captures features that cause the change of stock prices better.

Specifically, we chose the SP 500 Index data from 2014 to 2020 as our whole data set (we assume that this data set is the same as the SPY's data). As mentioned, in order to better capture features that cause the change of stock prices, we selected days that have price percentage change greater than 0.5% in the first half of the data as our training set, and the second half as our testing set. For feature engineering, we produced 161 technical analysis indicators with Python TA-Lib, and imported external data includes agricultural data, bond index data, currency data, and energy and metals data. Principal Component Analysis was used to reduce dimensions and decrease model complexity, which resulted in 60 principal components that represented more than 95% variance of the original data set. In view of LSTM's good property for processing time series data, we used it as the last part of the model to predict the percentage change of price and took previously produced principal components as input.

In the fitting model, dimension reduction and dropout neural network layers are used to prevent overfitting. As a result, the model is not trying to perfectly fit the training set but to capture significant fluctuations during a period. Thus, we can see in Figure 1 that the model doesn't fit the training set very well but has a good generalization on the testing set in Figure 2.

For our strategy, we buy a fixed amount of SP 500 when the model predicts the price will go up in the next three days and sell all if the model predicts the price will go down in the next three days. Based on this, we ran a backtest from June 21, 2018, to January 10, 2020. The comparison of annualized returns between our trading strategy and holding the SP 500 for the long term is shown in Figure 3.

In Figure 3, we see that our model is very sensitive to volatility, especially price bouncing back, but performs not very well when the change in price is relatively stable. We think it is because we selected data with a price change percentage greater than 0.5% as the training set, which allowed the model to detect price percentage change.

Meanwhile, it is commonly believed that predicting volatility is a much easier task to accomplish than predicting price. Volatility tends to cluster, i.e. high volatile trading days are usually followed by high volatile trading days as well, whereas price movement is a much more stochastic process. However, there are multiple ways to denote volatility in financial literature; in our case, since our goal is to capture trading signals on days when absolute price change percentage is greater than 0.5%, we chose the absolute value of day return to denote volatility. Thus the predicted result of the volatility model is absolute price change percentage and can be used directly as signals to determine whether it makes sense to use a price prediction model to forecast the price movement tomorrow. We used 14-day rolling standard deviation as input data for the LSTM model to capture the lag effect of time series data. The prediction on test data is shown in Figure 4. Though the model does not make an exact prediction of volatility, it captures the general shape of volatility movement. Moreover, it matches with real volatility well when a threshold line of 0.5% is put on the plot. The model predicts most trading days accurately that have more than 0.5% volatility and thus enables the price prediction model to signal the direction of the market these days.

By combining these two models, we filter out days with low volatility and choose the rest to decide whether to trade or not based on our strategy, which helps fully use the advantage of our model. The performance of this model will be discussed in the next section.

In summary, our final model for calculating trading signals includes two parts. One is LSTM-Volatility to predict volatility; the other is the PCA-LSTM model to predict price change. And the schematic diagram is shown in Figure 5.

3.3 Position Sizes

We would fill and liquidate everything in a position when trading the SPY, which means that we plan on moving every penny in and out for each trade. There are several reasons behind this. First, it is convenient to track the risk and return in terms of the cost basis. It would be likely to miscalculate the return and risks if we were to fill or realize a partial position. Second, our strategy aims to capture the upside as much as possible. Investing in the entire capitals would allow the fund to compound in large magnitude. By realizing a gain from a previous trade, we would have a larger invested capital for the subsequent periods if the market declined in the following day. Third, trading the SPY has become extremely cheap or even commission-free. The SPY's bid-ask spread might be relatively small due to its large size and high liquidity.

3.4 Timing and Execution of Trades

We used close prices to train our models and make predictions. However, we assume that the close prices are almost the same as the prices at 3:50 PM. We would fill or liquidate our trades between 3:50 PM and 4 PM if the signals appear.

4 Risks

4.1 Risk Exposures

Investment Risks: 30% of the initial capitals would remain as cash and be invested in the 2-Year Treasury Note, which are essentially risk free. Most of the investment risks derive from the U.S. large-cap equity markets. However, we would experience opportunity risks if there were better alternatives for the capitals in cash and the Treasury Note. The volatilises in the U.S. large-cap equity markets are closely associated with the domestic and global economy. The macro risks sources come from the interest rate, foreign exchange, unemployment, consumer strength, manufacturing, geopolitical disputes, and extreme events.

Liquidity Risks: Although the SPY is relatively liquid, our portfolio could still come across the liquidity issues in sudden market drops or extreme events. We might not redeem the SPY shares at a favorable price due to the market demand for liquidity. Not only can the wide bid-ask spread hinder our returns, but also our trades may only be partially filled.

Model Risks: Our training set is rigorously selected - we dropped those days with less fluctuation, which largely improved our model's reaction for volatility but decreased the model's ability to process stable periods. Thus, it is possible that this model will perform poorly during these periods.

4.2 Risk Control

We would maintain a low portfolio beta. 30% of the initial capitals are nearly zero beta assets. The rest of the assets are the SPY shares, meaning that this portion has a beta at 1. Even when the SPY shares appreciate, we would always maintain a portfolio beta below 1. Our deep learning algorithm provides us with two trading signals, "Buy" and "Sell", around the market close. If there is a "Sell" message, we would liquidate our current position in the last hour, or we would not buy in if we have not had a position yet. Thereby, the position's short duration limits the downside. Additionally, our strategy does not involve short trades or leverage, which improves the portfolio's liquidity and prevents the fund from suffering an unlimited loss to recover the initial position.

5 Liquidity and Capital

We present our liquidity concern earlier, but our strategy has good liquidity overall. It is easy to redeem our position, which has millions of dollars value, given the fact that the SPY has hundreds of billions of dollars of assets under management. The SPY's trading volume is hundreds of millions of shares each day. If we assume our trading value is $7 million, which only involves about 20,000 shares. Thus, our trade size is negligible compared to the SPY's total market size. Our strategy is also effective for a portfolio with $100 million AUM because the SP 500 Index market can easily absorb our trading volume. Moreover, there are other asset managers that provide the SP 500 Index ETFs, including BlackRock and Vanguard.

5.1 Analysis of Strategy Prospects - Back Test

The SPY Investment: We simulated our active equity investing strategy (excluded the Treasury Note and cash) on the testing period from June 21, 2018, to January 10, 2020.

As Figure 6 showed, the active equity trading strategy would deliver an annualized return of 43.88%, while the benchmark, the SP 500 Index, produced an annualized return of 9.82%. In terms of risk measurements, the annualized standard deviation of the active SPY investment is 0.425, compared to the benchmark's annualized standard deviation of 0.123. The return skewness is -0.478 and the kurtosis is 4.655, which means the return is negatively skewed and does not have a normal distribution. It is inappropriate to use the Sharpe ratio on an abnormal distributed return pattern. Alternatively, we measured the Sortino ratio, which accounts for only the downside deviation. The Sortino ratio is 1.463. One unit of downside risk would be compensated by 1.463 unit of an excess return over the benchmark. We also implemented several methods to evaluate the risks during extreme events. The return over the maximum drawdown is 0.969, indicating that 1% of the maximum drawdown would be rewarded by 0.97% of return. The 5% VaR is -4.14%, denoting that there is a 5% probability that the SPY investment would lose more than 4.14%. Expected shortfall, or CVaR, is -5.86%, with a 99% confidence interval of [-8.41%, -4.69%]. If the loss exceeds the VaR threshold, the average loss would be 5.86%.

Total Portfolio: The total return of the SPY investment would be 58.89% between June 21, 2018, and January 10, 2020. We assume that the 2-Year Treasury Note would generate a total return of 2%. At the end of the invested period, the weights of the SPY, Treasury Note, and cash in the portfolio would be around 78.5%, 18%, and 3.5%. Our portfolio's weighted average total return would be 46.6%, compared with the benchmark's total return of 12.7%. The alpha would be 33.9%.

6 Additional Thoughts

We didn't consider using leverage to multiply our buying power to enhance the overall return. The leverage would magnify both gains and losses. Combining the equity exposures with put options expiring near the end of the invested period would be a feasible strategy to protect from downside risks. Moreover, the quantitative strategy is sensitive to volatile markets, and further leveraging positions might undermine the strategy's efficacy, especially during volatile periods. The utilization of short positions against the SP 500, however, shall be further analyzed with the purpose of downside protection if assuming a day with the occurrence of downside volatility. Additionally, our prediction models restrict the trades at the end of a trading day, which means that we might forgo the opportunities during the other trading hours. When the SPY's price rises higher than the price implied by the estimated volatility, we could fill or liquidate the positions immediately. If we had hourly data, our strategy could be modified to execute trades more frequently.

The sole utilization of close prices sheds light on the volatility level near the next day's market close. To realize the optimization of next day's intra-day volatility, further trading improvement is to integrate the data set of historical opening prices into our volatility forecasting model, so as to obtain a volatility prediction towards the next day's market open. For example, the point of prediction in our current strategy is near the end of Day t; an additional point of prediction can be set at the beginning of Day t. Therefore, if the projected directional volatility at the market open on t+1 is downward against upward projected volatility near the market close on t+1, we can open a long position at market open on t+1 and liquidate by the end of the day to capture the profit, and vice versa. In this way, the after-market price volatility can be reasonably hedged.

References

[1] Chen, K., Zhou, Y., Dai, F. (2015, October). A LSTM-based method for stock returns prediction: A case study of China stock market. In 2015 IEEE international conference on big data (big data) (pp. 2823-2824). IEEE.

[2] Cizeau, P., Liu, Y., Meyer, M., Peng, C. K., Stanley, H. E. (1997). Volatility distribution in the SP500 stock index. arXiv preprint cond-mat/9708143.

[3] Fischer, T., Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research, 270(2), 654-669.

[4] Frino, A., Gallagher, D. R. (2001). Tracking SP 500 index funds. The Journal of Portfolio Management, 28(1), 44-55.

[5] Hamid, S. A., Iqbal, Z. (2004). Using neural networks for forecasting volatility of SP 500 Index futures prices. Journal of Business Research, 57(10), 1116-1125.

[6] Harris, L. (1989). SP 500 cash stock price volatilities. The Journal of Finance, 44(5), 1155-1175.

[7] Kim, H. Y., Won, C. H. (2018). Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models. Expert Systems with Applications, 103, 25-37.

[8] Kong, W., Dong, Z. Y., Jia, Y., Hill, D. J., Xu, Y., Zhang, Y. (2017). Short-term residential load forecasting based on LSTM recurrent neural network. IEEE Transactions on Smart Grid, 10(1), 841-851.

[9] Lam, M. (2004). Neural network techniques for financial performance prediction: integrating fundamental and technical analysis. Decision support systems, 37(4), 567-581.

[10] Leigh, W., Purvis, R., Ragusa, J. M. (2002). Forecasting the NYSE composite index with technical analysis, pattern recognizer, neural network, and genetic algorithm: a case study in romantic decision support. Decision support systems, 32(4), 361-377.

[11] Malkiel, B. G. (2003). The efficient market hypothesis and its critics. Journal of economic perspectives, 17(1), 59-82.

[12] Nelson, D. M., Pereira, A. C., de Oliveira, R. A. (2017, May). Stock market's price movement prediction with LSTM neural networks. In 2017 International joint conference on neural networks (IJCNN) (pp. 1419-1426). IEEE.

[13] Nandi, S. (1998). How important is the correlation between returns and volatility in a stochastic volatility model? Empirical evidence from pricing and hedging in the SP 500 index options market. Journal of Banking Finance, 22(5), 589-610.

[14] Park, C. H., Irwin, S. H. (2007). What do we know about the profitability of technical analysis?. Journal of Economic Surveys, 21(4), 786-826.

A Figures

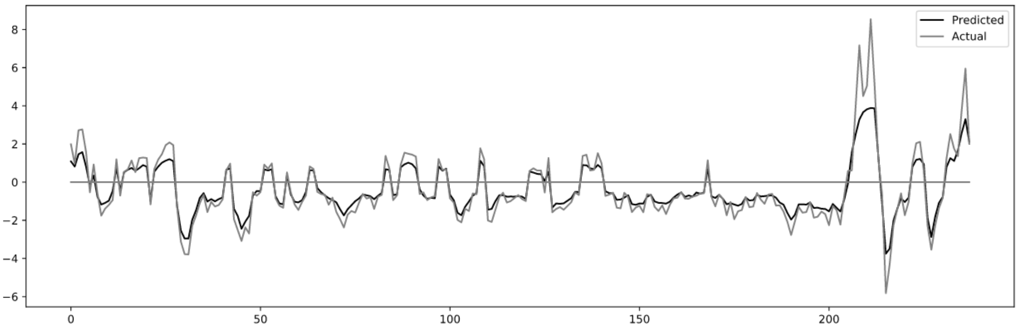

Figure 1: Predicted Percentage Change in Price (Training Set)

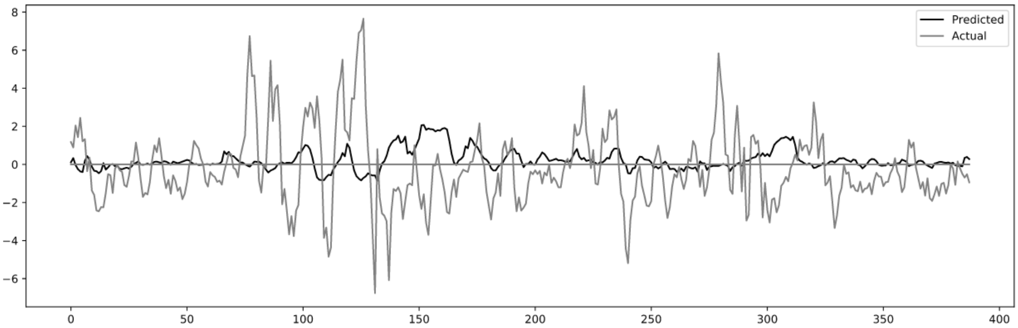

Figure 2: Predicted Percentage Change in Price (Testing Set)

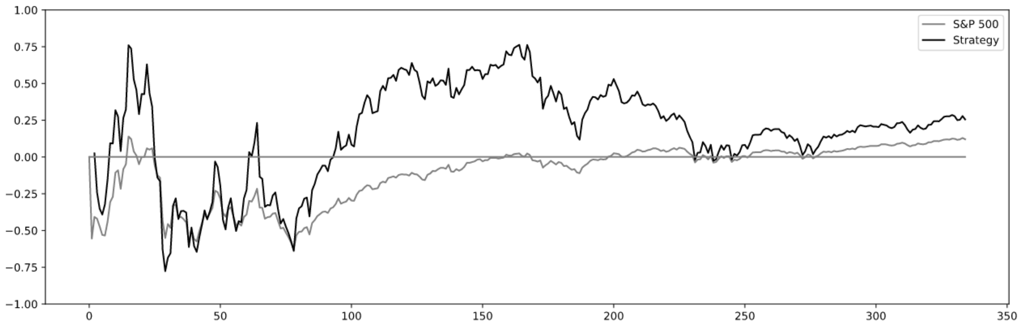

Figure 3: Back Test (ignoring volatility)

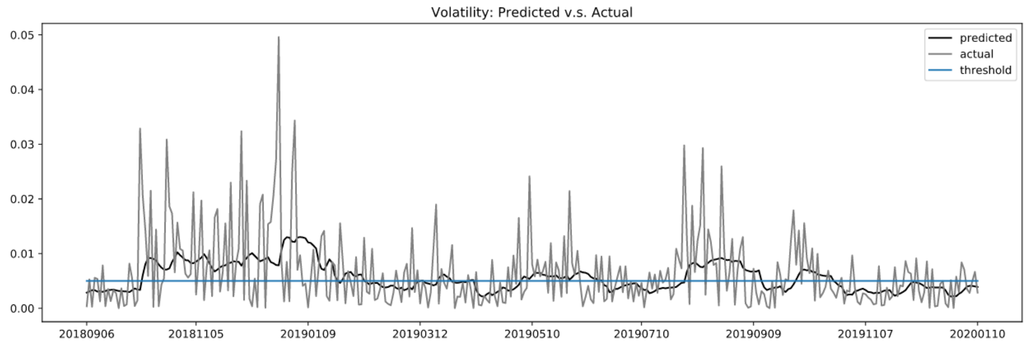

Figure 4: Volatility (Predicted v.s. Actual)

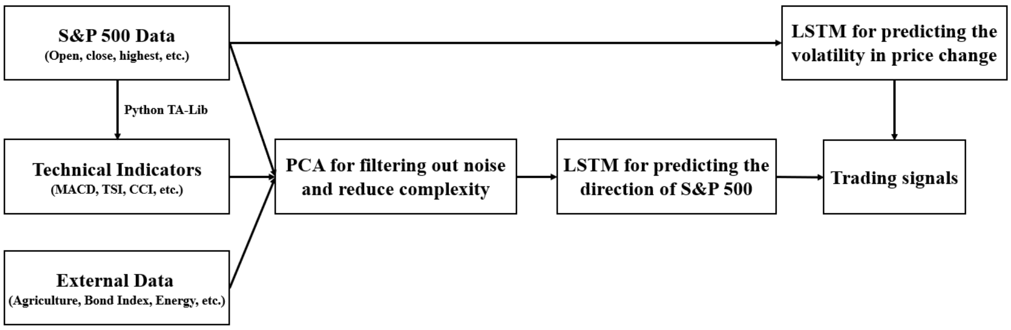

Figure 5: Schematic Diagram

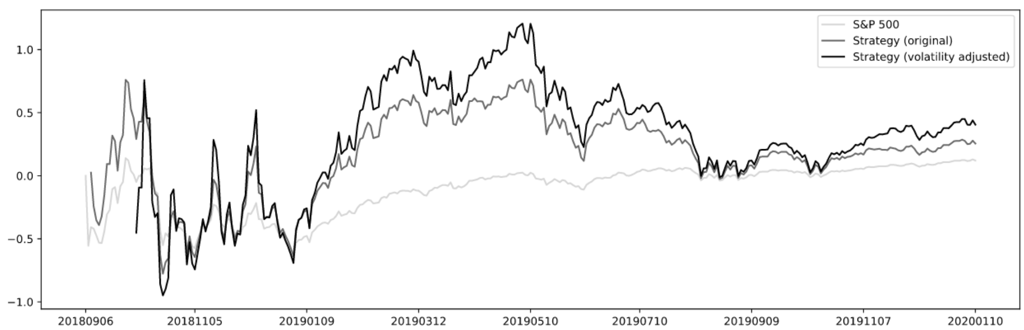

Figure 6: Back Test (adjusted by volatility)