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University College London

Comp0051 - Algorithmic Trading

Coursework 2

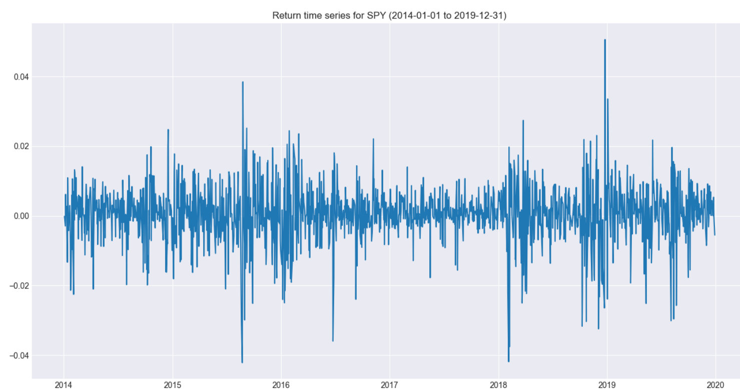
Candidate number:

ZWLD8

1 Introduction

Algorithmic trading involves the use of automated trading strategies to buy and sell stocks, bonds, or other types of securities. It can be used to reduce risk, increase profits, and improve the efficiency of trading decisions. In this coursework, we will look at developing three trading strategies on SPY, an ETF that tracks the S&P 500 index.

We begin by downloading SPY data from Yahoo!Finance for the period of time ranging between 1 January 2014 and 31 December 2019. We plot the return time series for this period below. We use adjusted closing price as our basis as SPY pays dividend, and using this figure instead of closing price accounts for price changes due to this.

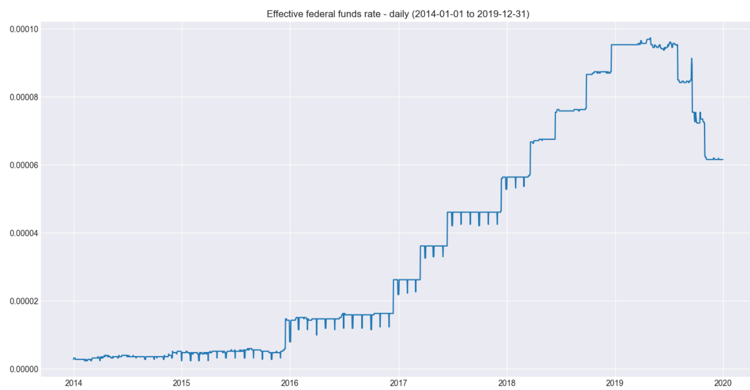


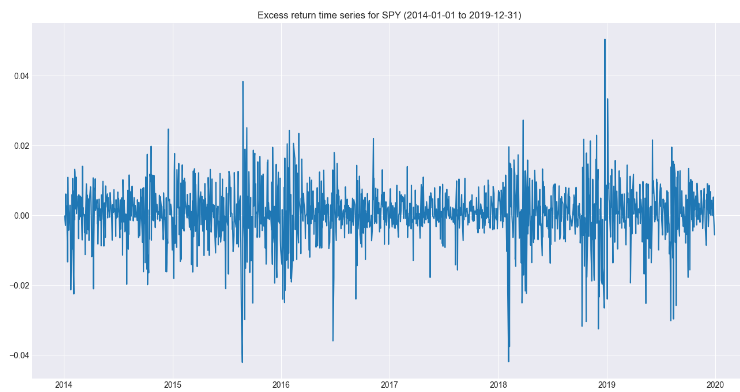
We then download data for the Effective Fed Funds Rate (EFFR) from the Federal Reserve Bank, which we will use as our risk-free interest rate throughout the coursework. This is not exactly correct as we will assume we can borrow money at this rate, while we would likely borrow at a premium in a real life trading scenario, but this is the approximation we will use. The interest rate, which is denominated annually when downloaded, is converted to daily by dividing it by the trading days (252 is the convention we will use).

Below we plot the SPDR return time series, the EFFR, and the excess return per unit of SPDR, starting from $t = 0$ (1 Jan 2014). The excess return is defined as follows:

$$r_t^e = \frac{\Delta p_t}{p_t} - r_t^f \tag{1}$$

where p_t is the price at time t and r_t^f is the risk-free interest rate at time t.





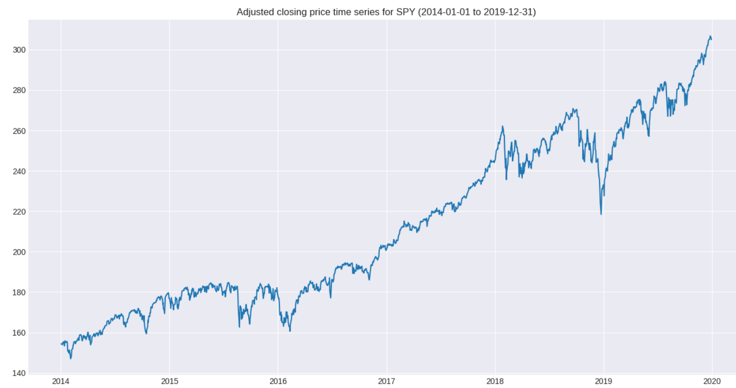
2 Methodology

We will develop a total of three trading strategy, plus a benchmark buy-and-hold strategy we will use to evaluate the others. The first strategy is a trend-following strategy, the second one will make use of technical anlysis indicators and the last strategy will use a machine learning approach.

2.1 Buy-and-Hold Strategy - Benchmark

This simple strategy consists of buying at time $t = 0$ and holding onto the stock over our analysed period. Given SPY mirrors the S&P 500, which is widely considered to be a relatively safe holding, especially over longer periods of time, this is a strategy that many individuals and entities indeed follow, while possibly diversifying their holdings with other ETFs, stocks, and corporate and government bonds.

We are trading with 5x leverage, therefore we will buy using \$200,000 of initial capital and \$800,000 of margin for a total worth of \$1 million.



As we can infer from the above image, our profit if we held over the entire period would be around \$1.4 million after paying back the money borrowed. This is a return of almost 700%, which is staggeringly high and will be very difficult to top. A more detailed discussion of this strategy which goes beyond the returns will be provided in the Results and Discussion sections.

2.2 Trend-Following Strategy

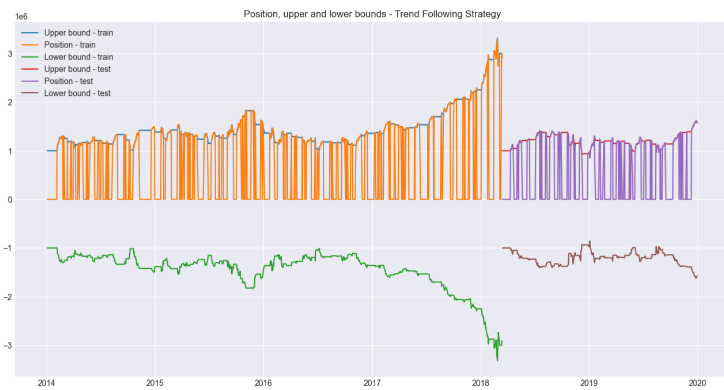
This strategy uses a combination of the long-term and short-term moving averages in order to establish whether to send a buy or sell signal. The moving average of the price is defined as follows, where p is the price and T is the time window used.

$$\bar{p}_t = \frac{1}{T} \sum_{t-T+1}^{t} p_t \tag{2}$$

In our case we will use two MA with different time windows T_S and T_L The signal s sent by the strategy at time t is designed in the following way, where L is the leverage used (5 in our case).

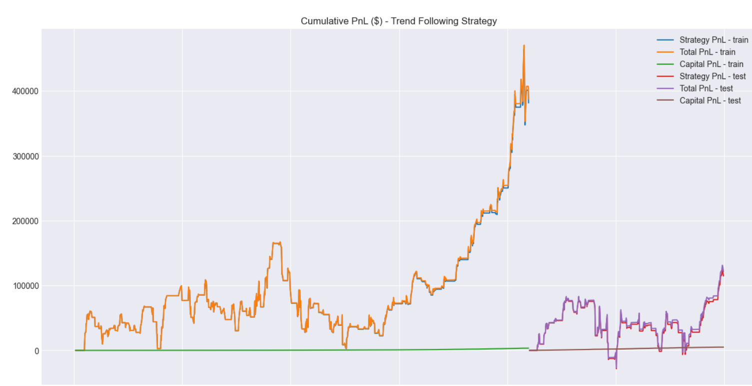
$$s_{TF} = L \text{ if } \frac{1}{T_S} \sum_{t-T_M+1}^{t} p_t > \gamma + \frac{1}{T_L} \sum_{t-T_L+1}^{t} p_t, 0 \text{ otherwise} \tag{3}$$

This means we will go long with 5x leverage whenever the short-term moving average is larger than the long-term moving average plus a small constant γ, and we will sell our holdings (or not buy) whenever this condition falls. This strategy will be a long-only strategy, so we will never be placing any shorts. The chart below plots the position of the strategy in the training and test set.



As we can see the strategy ends up trading quite often, and we can identify a profit is being made both in the training and test set over the lifetime of the strategy.

We then plot the daily trading PnL of the strategy along with the total PnL, which assumes we grow the capital at the risk-free rate while unused, and the capital PnL, which is the share of PnL given by the risk-free rate.



Due to the climate of overall low interest rates, the capital PnL ends up being a negligible share of the total PnL, therefore the strategy PnL line overlaps

the total PnL line quite closely. In total, the difference ends up being around \$6000 in the training set and \$7000 in the test set (due to higher interest rates in the testing period).
We calculate the turnover, which ends up being \$300,591,308 for a total of 1490267 units of SPY stock traded in the training set, and \$93,710,000 for a total of 334261 units in the test set.

2.3 Technical Analysis Strategy

This strategy will make use of three commonly used technical analysis indicators: MACD (Moving average convergence/divergence) , RSI (Relative Strength Index) and Bollinger Bands.
Let us first define these indicators, beginning with MACD. The MACD measures the difference between two moving averages. The 12- and 26-period EMAs are used as they are a short and long-term indicator of the trend of the price. If the 12-period EMA is greater than the 26-period EMA, then the MACD is positive, indicating that the short-term trend is stronger than the long-term trend. Conversely, if the 12-period EMA is less than the 26-period EMA, then the MACD is negative, indicating that the long-term trend is stronger than the short-term trend.

$$MACD = EMA_{12} - EMA_{26} \tag{4}$$

where EMA_{12} and EMA_{26} are the 12- and 26-period exponential moving averages, respectively.
The RSI is an indicator used to measure the relative strength of a stock or other asset. The RS (Relative Strength) is calculated by dividing the average gain of the asset over a certain period of time by the average loss of the asset over the same period of time. For our strategy, this period will be 14 days. By dividing the average gain by the average loss, we get a Relative Strength ratio. This ratio is then used to calculate the RSI. The higher the RSI, the more overbought the asset is, and the lower the RSI, the more oversold the asset is.

$$RSI = 100 - 100/(1 + RS) \tag{5}$$

Bollinger Bands are an indicator invented by John Bollinger in the 1980s. They consist of a moving average and two other bands, respectively two standard deviations above and below the moving average. In our strategy, our time window will be 20 days.

$$UB_t = MA_{20} + 2(s.d.) \tag{6}$$

$$LB_t = MA_{20} - 2(s.d.) \tag{7}$$

Bollinger Bands are used to identify periods of high and low volatility in a given time series. When the bands are close to each other, it indicates low volatility, when they are far apart, it indicates high volatility. When the price touches the upper band, it may indicate that the asset is overbought and likely to correct lower, while when the price touches the lower band, it may indicate that the asset is oversold and likely to correct higher.
The signals from these three indicators are as follows:

$$s_{MACD} = 1 \text{ if } MACD > EMA_9(MACD), 0 \text{ otherwise} \tag{8}$$

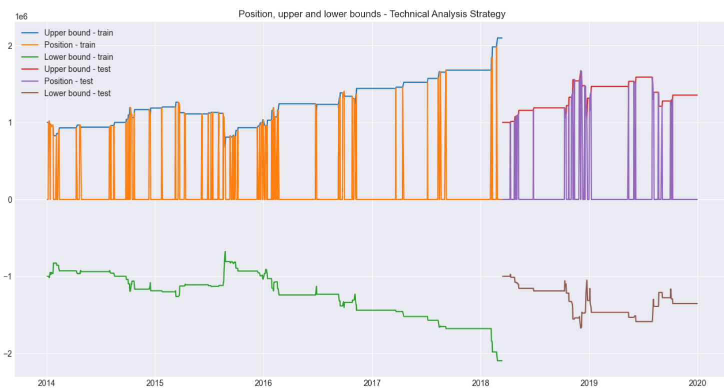
$$s_{RSI} = 1 \text{ if } RSI < 30, 0 \text{ otherwise} \tag{9}$$

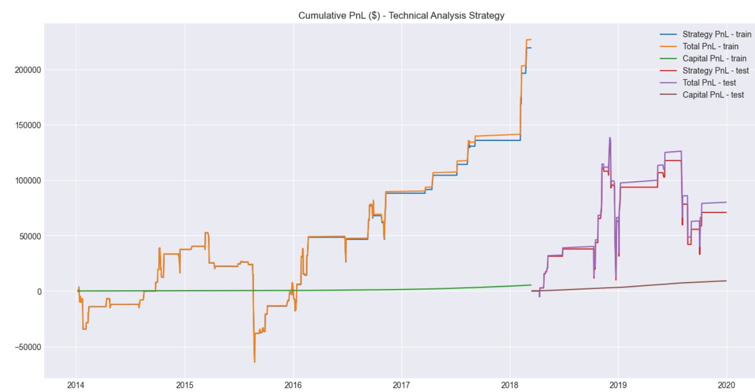
$$s_{BB} = 1 \text{ if } p_t < LB_t, 0 \text{ otherwise} \tag{10}$$

We could use short signals as well, but we will later explain their ineffectiveness, therefore this too will be a long-only strategy. We combine the three signals to obtain:

$$s_{TA} = L \text{ if } s_{MACD} + s_{RSI} + s_{BB} > 1, 0 \text{ otherwise} \tag{11}$$

Therefore we will go long with 5x leverage when at least two of the indicators are positive.
The first chart below plots the position of the strategy in the training and test set.
As we can see the strategy ends up trading much more rarely than the previous one, and seems to manage to achieve a decent profit.
We then plot the daily trading PnL, total PnL and capital PnL.
It seems to be substantially lower than for the previous strategy, both in the training and test set, and the capital PnL ends up being a larger share of the profit due to the lower trading frequency.
We calculate the turnover, which ends up being \$137,075,033 for a total of 757960 units of SPY stock traded in the training set, and \$59,977,554 for a total of 757960 units in the test set.





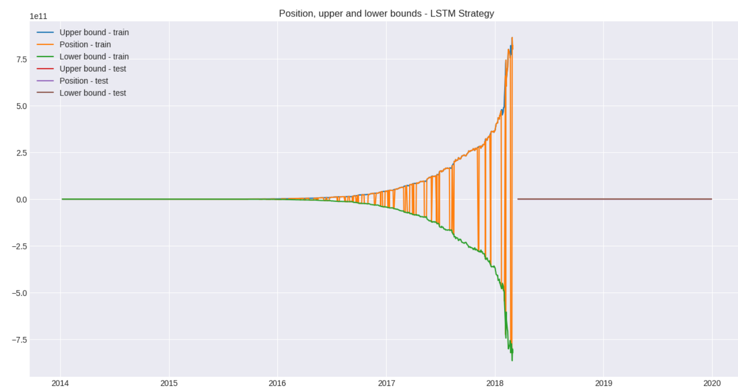
2.4 Neural Network Strategy

We now turn to a strategy which will use machine learning techniques, more specifically a neural network, in order to predict the price for the following day and execute a trade accordingly. The strategy is implemented in PyTorch, and our network architecture will be a simple LSTM. Long short-term memory (LSTM) is a recurrent neural network (RNN) architecture, which unlike traditional RNNs, which often remember only a limited amount of information, are capable of learning and remembering long-term dependencies. An LSTM consists of several layers of memory cells, each of which contains a forget gate, an input gate, and an output gate. The forget gate determines which information will be remembered and which will be discarded, while the input and output gates are used to control the flow of information into and out of the cells. The LSTM architecture is capable of learning complex patterns from sequential data and has been used previously in applications such as Natural Language Processing and time-series prediction.

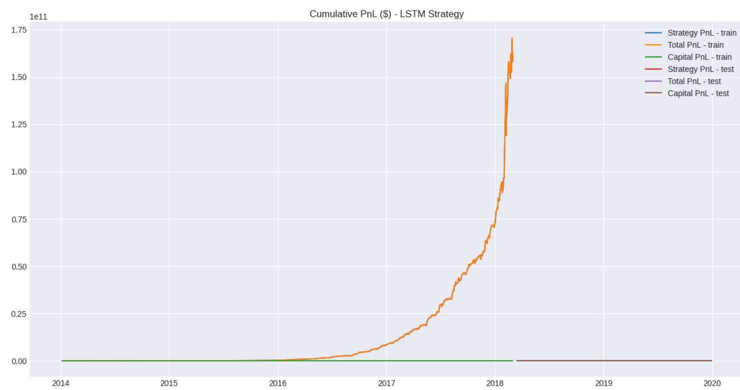
Given this strategy is supposed to predict a specific price, we should be able to trade every day, and the signal will be as follows:

$$s_{LSTM} = L \text{ if } p_{t+1pred} > p_t, -L \text{ otherwise} \quad (12)$$

Therefore we will go long with 5x leverage if the next predicted price is higher, otherwise we will go short with 5x leverage.
The chart below plots the position of the strategy in the training and test set.



This graph seems unusual initially, as it looks like the strategy is not trading for about 2 years, but notice the scale on the y axis. The strategy is indeed trading every day as expected, but the returns end up being so high (in the order of billions) that the initial position is squeezed and results close to zero. This is the case in the test set as well, where, interestingly, we do not see any evidence of skyrocketing returns.
We then plot the daily trading PnL, total PnL and capital PnL.
This graph is, as expected, as crazy as the last one, and further displays the staggering returns in the training set. In the test set, we do not see such results and in fact, by analysing the numbers, the strategy returns a loss of \$90,000 dollars. Capital PnL is zero as we are trading every day.
As one could imagine by now, the turnover is incredibly high and ends up being \$18,751,111,608,314 for a total of 78243263087 units of SPY stock traded in the training set, and \$169,872,866 for a total of 651673 units in the test set. Needless to say, there is clearly something wrong going on with this strategy, as none of the numbers we have been obtaining in the training set make any sense.



3 Results

We now move on to a comparative analysis of our strategies, where we employ a number of financial metrics to evaluate our strategies' performances. We first define these metrics.
The Sharpe ratio is a measure of risk-adjusted return, calculated as follows.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

Where R_p is the return of the strategy, R_f is the risk-free rate, and σ_p is the standard deviation of the returns.
The Sortino ratio is a modified version of the Sharpe ratio, which adds a penalty for downside risk.

$$Sortino\ Ratio = \frac{R_p - R_f}{\sigma_d}$$

Where R_p is the return of the strategy, R_f is the risk-free rate, and σ_d is the downside deviation of the strategy returns.
The Maximum Drawdown is a measure of the largest loss that the strategy has experienced over a given period of time.

$$Max\ Drawdown = V_{max} - V_t$$

Where V_{max} is the maximum historical peak value of the strategy, and V_t is the current value of the strategy.

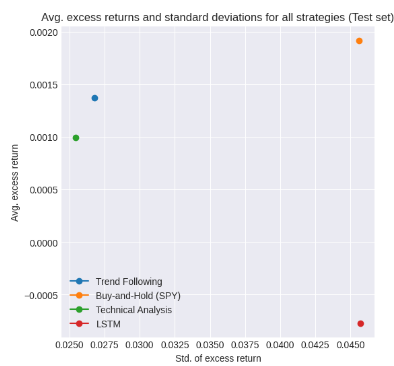
The Calmar ratio is a measure of risk-adjusted performance, which is calculated by dividing the strategy's annualized rate of return by its Maximum Drawdown.

$$Calmar\ Ratio = \frac{R_p}{Max\ Drawdown}$$

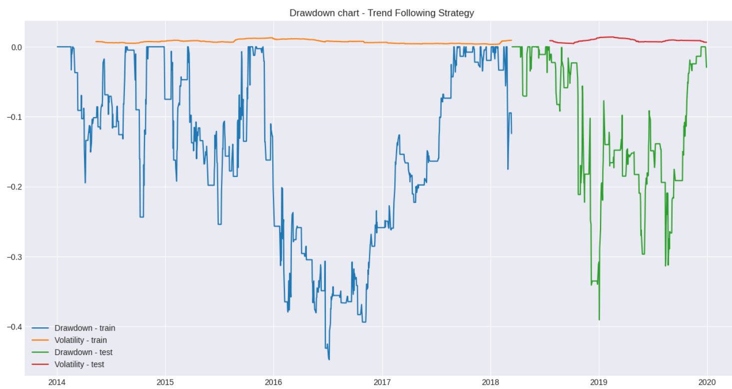
Where R_p is the return of the strategy.
Results for all strategies are displayed in the table below, where first value is in training set and second value is in test set.

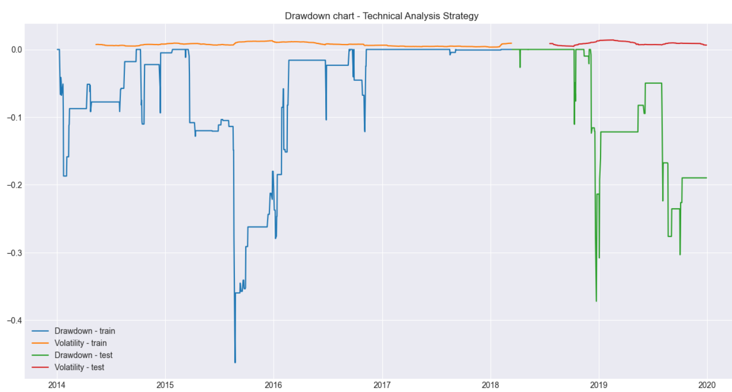
	Buy-And-Hold	Trend-Following	Technical Analysis	LSTM
Sharpe Ratio	0.97 / 0.66	0.88 / 0.81	0.77 / 0.62	5.95 / -0.20
Sortino Ratio	1.21 / 0.83	0.80 / 0.59	0.32 / 0.29	9.54 / -0.32
Max Drawdown	-0.61 / -0.71	-0.44 / -0.39	-0.46 / -0.37	-0.18 / -0.78
Calmar Ratio	0.99 / 0.68	0.72 / 0.88	0.46 / 0.67	18.55 / -0.19

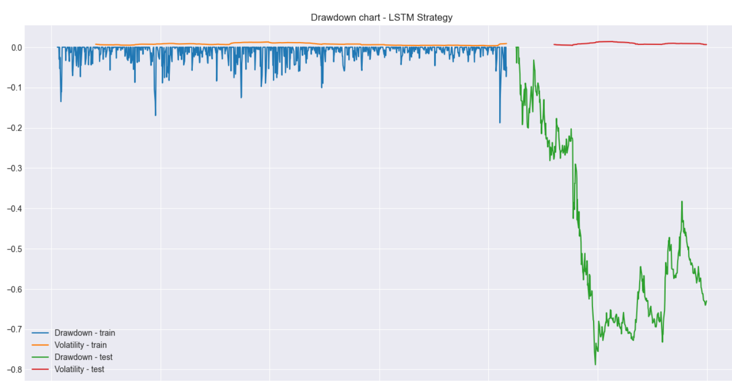
We plot the average excess returns of the strategies in the test set versus their standard deviations (in the test set, otherwise data will be biased).



By combining the Buy-and-Hold and TF strategies, there is a chance we can increase the Sharpe ratio, by finding the linear combination that maximises the return while minimising the standard deviation. The Kelly Criterion suggests that the allocation to each strategy should be proportional to the average return over the variance, according to which in this case we would allocate slightly less of the total portfolio (0.48) to the Buy-and-Hold strategy and the rest to the TF strategy. Both other strategy are always dominated. Plotting more strategies along with the Efficient Frontier would help us investigate this issue further. We now proceed to plot three Drawdown Charts for the different strategies, which we will discuss in the next section along with the above results. The chart display drawdowns along with the rolling 90-day volatility both in training and test set.







All strategies have somewhat significant drawdowns, although only the LSTM has such a large one in the test set. In the TA strategy, the two large drawdowns seem to be clearly correlated with an increase in volatility, therefore it could be beneficial to reduce the leverage in situations of high volatility in order to limit the potential losses. In the TF strategy, there are quite a few of medium to large drawdowns, and while some are again correlated with volatility, others are not. Adjusting the leverage could help in this case as well and possibly reduce the standard deviation of the strategy returns, but could also result in lower profits overall. The LSTM sinks in the test set, and although this drawdown is correlated with high volatility, it is likely adjusting the leverage would not do much to make the strategy better, apart from making it lose slightly less money.

4 Discussion

Now that we have all the data available, we can analyse the strategies and see what worked well and what did not.

First of all, we could note that the period over which trading would have taken place was quite peculiar, in that the market was incredibly bullish and interest rates were very low due to QE and expansionary monetary policy which took place in the US and EU until the past year's inflationary pressures. Making money in this market, at least until the Covid pandemic, would not have been difficult and the SPY chart shows that apart from a couple small hiccups, the Covid-fueled drop in price was the only significant one, and the market recovered rather quickly.

That said, with regards to profitability, the Buy-And-Hold strategy was unrivalled, and while the returns for the TF and TA strategies were positive in the test set, they were still not as good as they could have been. The LSTM strategy was unbelievably profitable in the training set, but ended up losing half of the money during testing. The TA strategy traded less often than the TF strategy, so although being quite similar in terms of returns, if we consider fees and slippage the former may come out on top. The LSTM traded every day, but fees and slippage are the least of this strategy's issues. Buy-and-hold is certainly the most cost-effective strategy.

One of the reasons chosen to make the first two strategies long only is that otherwise they tended to short too often and at the wrong times, while in fact there were few profitable shorts to make over this period, one of which was

Covid related and could not possibly be predicted from price data. In the bullish environment, there were truly few reasons to be placing shorts without additional data, which would be available if we were trading manually based on a variety of information.

We can have a look at the metrics computed to compare the strategies. All the strategies apart from LSTM end up producing sub-par Sharpe Ratios in any scenario, with Buy-and-hold being the closest to 1. Given a good Sharpe Ratio should be over 1, this results are fairly disheartening and show the risk took on in order to obtain these results was unjustifiably high, as SPY was too volatile. In the test set, the TF strategy ends up losing the lowest amount of Sharpe showing its resiliency to different scenarios, on the other hand SR for Buy-and-Hold drops significantly. When we use the Sortino Ratio the story does not change much, but Buy-and-Hold displays better performance than the other strategies, meaning the negative variance in TF and TA was higher. With regards to Maximum Drawdown, the TF and TA strategies achieve better results than Buy-and-Hold both in training and testing, meaning they manage to stay out of the market in the most bearish moments. Nevertheless the Buy-and-hold strategy makes up for the drawdowns with higher returns, at least in the training set, as conveyed by a much higher Calmar Ratio (which still remains higher for TF in the test set and similar for TA). We now move on to a discussion of LSTM, which has been purposefully left out because of its outlandish results. In the training set, the strategy looks great: all the metrics are incredibly positive, and any investor would have wanted to make these trades. In the test set the results are terrible, with sub-zero Sharpe and Sortino Ratios (meaning collecting risk-free interest rate would have been better) and this is indeed the case as the strategy loses about half the capital. The LSTM has been an interesting experiment which shows the dangers of extrapolating performance in the training set to a testing environment. During training, we grossly overfit the training set with near-perfect accuracy. During testing, all the weaknesses of this strategy come out. Although machine learning has many usages, using a RNN to predict the price using price data alone was clearly a bad idea. This was expected from the beginning, as if it was this easy it is safe to say everyone would be a billionaire by now. But as it is often the case, if something seems too good to be true, it is not.

Overall, if we had to pick a winner it would likely be the Buy-and-hold strategy. It has the best metrics, lowest costs and highest returns. It is simple, does not need any maintenance, and anyone can follow it, possibly by applying Dollar Cost Averaging and buying a set amount periodically. Nevertheless, the TF and TA strategies are not entirely bad, and may have worked better in a different market environment, where there were more short-term negative and positive trends, instead of a long-lasting profitable run.

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