Strategy Evaluation Report:

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***Abstract*—** The objective of this assignment is to develop two trading strategies, one manual and one using artificial intelligence, and compare their performance. Three technical indicators were used in both strategies to determine when to buy or sell stocks in JPMorgan Chase ('JPM'). Both strategies were able to outperform a 'benchmark' strategy on both in-sample and out-of-sample periods. Additionally, the effect of varying impact value on the StrategyLearner was found to reduce cumulative returns and the number of trades.

1 INTRODUCTION

Algorithmic trading strategies allow trades to be generated and placed automatically by software systems. The advantage of these systems is the speed at which large volumes of data can be analyzed in order to find profitable trading opportunities. Algorithmic strategies can be implemented with pre-determined heuristics, utilizing signals generated by the stock price and volume. These strategies must be devised by a human before implementing them in a computer program and so require some level of domain knowledge about trading stocks.

Machine learning based strategies involve a data-driven approach to generating trading strategies. These strategies will usually involve technical indicators as well, however, the algorithm will learn the optimal thresholds and signals to execute trades based on the training data provided.

This assignment will compare the performance of these two strategies, Manual and Learner, against a benchmark case. As these strategies will be trained on a period of price data, it is expected that both strategies will result in higher returns than the benchmark case within the in-sample period. It is possible that the strategies developed are over-fit to the training data and may not perform as well to different, out-of-sample, data as well as other stocks.

2 Indicator Overview

The indicators used in both the Manual and Learner strategy were Bollinger Band Percent, Momentum and RSI. Both strategies used these indicators to find profitable trading opportunities, particularly when the stock is oversold or undersold compared to its intrinsic value.

2.1 Bollinger Band Percent

Bollinger Bands represent two 'bands' which are a number of standard deviations, σ, away from the simple moving average of stock price (Investopedia, 2022). A more accessible indicator is the Bollinger Band Percent (BBP), which represents the position of the stock price relative to the upper and lower band:

$$Upper\ Band = Moving\ Average + 2\sigma, \qquad Lower\ Band = Moving\ Average - 2\sigma$$

$$Bollinger\ Band\ Percent = \frac{Price - Lower\ Band}{Upper\ Band - Lower\ Band}$$

The indicator was generated in this assignment using a 20-day lookback period and 2 standard deviations. Trading signals are generated when the indicator is greater than 1, generating a 'SELL' signal as the stock is likely overbought, and when the indicator is less than 0, generating a 'BUY' signal as the stock is likely oversold.

2.2 Momentum

Momentum is a technical indicator used to show the rate of change in the stock price, which can then be used to estimate the strength/weakness in stock price change (Investopedia, 2022). The Momentum is calculated as the ratio between the current price and the price n periods ago:

$$Momentum_t = \frac{Price_t}{Price_{t-n}} - 1$$

The indicator will be positive if the price is increasing and negative if the price is decreasing. The time period used in this assignment was 10 days, which will result in an indicator able to quickly react to changes in price.

2.3 Relative Strength Index

Relative Strength Index (RSI) is used to determine when a stock is overbought or oversold by assessing recent price changes (Investopedia, 2022). The RSI is determined by first calculating the average gain and loss over a time period, 14 days in this assignment. Once the average gain and loss is calculated, the formula below is used to calculate the RSI:

$$RSI = 100 - \left[\frac{100}{1 + \frac{Average\ Gain}{Average\ Loss}}\right]$$

The indicator is bound between 0 and 100 and will classify a stock as over-valued when above 70 and under-valued when below 30.

3 MANUAL STRATEGY

3.1 Strategy

The Manual strategy was comprised of using all three indicators together to find profitable opportunities for trading shares in JPM. The use of multiple indicators allows the benefits of all three to create what is likely a more effective overall indicator than using any one indicator in isolation (Investopedia, 2022).

To create the strategy, a number of technical indicators were calculated over the entire in-sample period, 1st January 2008 to 31st December 2009, and their values were reviewed at points where large changes in stock price were identified. These changes in price could be either positive or negative, where profits would be generated from a long or short position respectively.

The overall theme of the Manual strategy was to identify periods where the stock price had deviated significantly away from its intrinsic value. Both the Bollinger Band Percent and RSI identify when the stock is either overbought and likely to fall in price, as well as when the stock is oversold and likely to rise in price.

Momentum will capture recent changes in trajectory of the stock price, helping to identify periods where the stock price has moved away from its true value. A large positive Momentum would indicate a recent significant increase in stock price and support an overbought price, and conversely a large negative Momentum would indicate a stock which has recently dropped in price and is oversold.

The rules and specific thresholds at which to generate the 'BUY' or 'SELL' signal were tuned on the in-sample data in order to maximise the cumulative returns and were as follows:

If BBP > 0.98 & Momentum > 0.09 & RSI > 0.68, SELL

If BBP < 0 & Momentum < -0.12 & RSI < 0.3, BUY

3.2 Implementation

This strategy was implemented by first calculating these indicators over the entire trading period. When all three conditions were met for either a BUY or SELL condition, a long/short position was entered depending on BUY/SELL respectively using the maximum amount of shares possible. This meant that all trades were either +2000 or -2000, apart from the first trade which was either +1000 or -1000. This ensured that the amount of shared held was never greater than +/- 1000. No logic was implemented to exit a position.

3.3 Results

To validate the Manual strategy, it will be compared to a benchmark strategy which involves buying 1000 shares of 'JPM' and holding for the entire trading period. The performance of the Manual Strategy in the in-sample period is shown in Figure 1 and highlights greater returns compared to the benchmark strategy. The Manual Strategy uses only 5 trades, depicted with the vertical blue and black lines for long and short positions respectively, and highlight the strategy of trading on less frequent but significant changes in price.

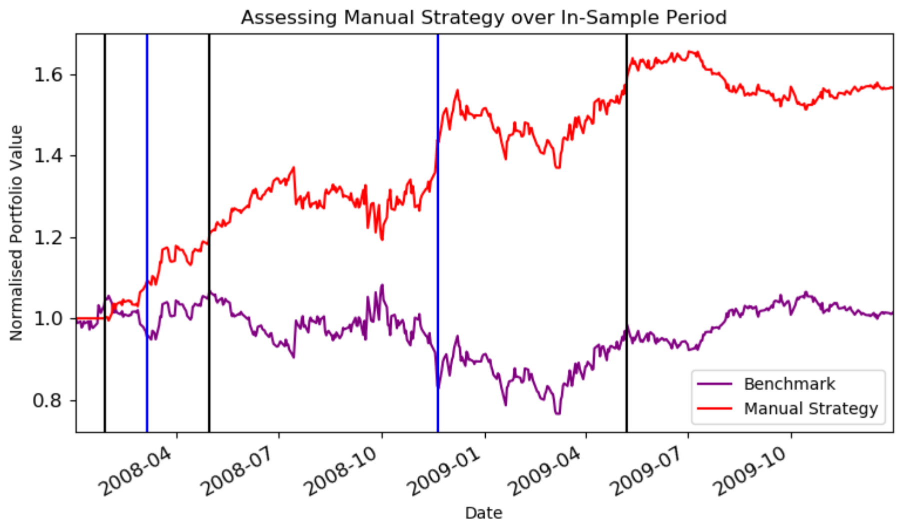

Figure 1 - Results of Manual Strategy on In-sample data

The results of the Manual Strategy over the out-of-sample period, 1st January 2010 to 31st December 2011, are shown in Figure 2. This depicts again a better return than the benchmark strategy over the trading period. In addition, the strategic theme remains similar with few trades but done on significant changes in price.

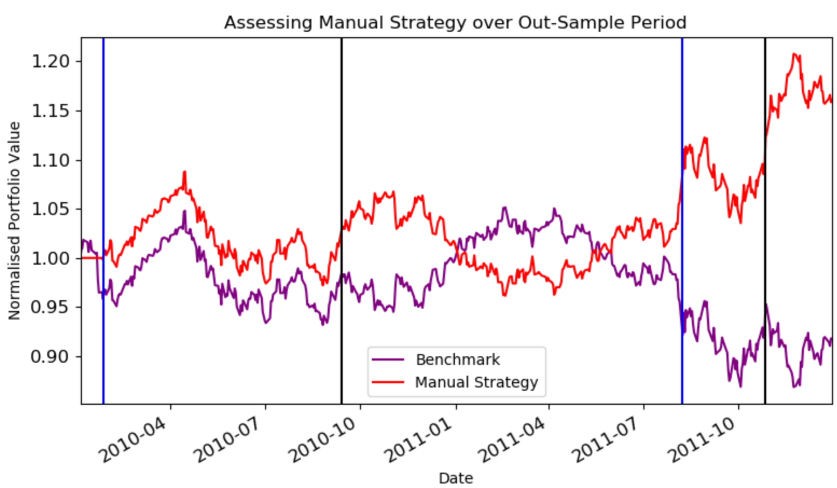

Figure 2 - Results of Manual Strategy on Out-of-sample data

The Manual Strategy is not as successful during the out-of-sample period compared to the in-sample, where it actually returns less than the benchmark for a portion of the trading period. As mentioned in Section 1, it is expected that the strategy would perform better on the in-sample period than on the out-of-sample.

The specific thresholds for the overall trading signals were tuned to perform well on the in-sample data. As these hyper-parameters were not tuned on out-of-sample data, they may not perform well during other time periods (i.e. out-of-sample) or even other stocks.

More quantitative results of the Manual Strategy over both the in-sample and out-sample period are shown in Table 1.

Metric	Benchmark – In-Sample	Benchmark – Out-of-Sample	Manual Strategy – In-Sample	Manual Strategy– Out-Of-Sample
Cumulative Returns	0.0142142	-0.0820488	0.5658954	0.1600185
Standard Deviation of Daily Returns	0.0170079	0.0084829	0.0116560	0.0075223
Mean Daily Returns	0.0001721	-0.0001338	0.0009562	0.0003228

Table 1 – Performance Results between Manual Strategy and Benchmark

4 STRATEGY LEARNER

4.1 Problem Formulation

The second strategy was developed using an area of machine learning known as reinforcement learning. This technique involves training an agent to perform a series of actions in an environment to maximise its reward. The agent can observe the 'state' of the environment and how that state changes after actions are performed. Through it's experiences interacting with the environment, it will learn a policy which governs which actions it will take to maximise its reward (deepsense.ai, 2022).

We can use reinforcement learning in the trading problem faced to find a profitable trading strategy. The agent will be the trader who can buy or sell stocks (i.e. perform actions) within the market (i.e. environment) in order to maximise portfolio returns (i.e. reward). The agent can observe the state of market through signals such as stock price, trading indicators and holdings. The trader can develop a trading strategy (i.e. policy) by learning which trades provide the highest returns depending on the state of the market.

In order to determine the best action to take, the agent needs some understanding of what rewards it can expect after performing actions as well as how the environment will change. As our agent does not have a perfect understanding of exactly how the market will change, it can use a technique called Q-Learning to build an understanding experientially of what action will return the greatest reward when in a given state (Mitchell, 1997).

Our agent will develop this understanding of the market by repeatedly observing technical indicators, choosing actions (i.e. Buy, Sell or Hold), observing the portfolio daily return and how the indicators change. Our reward function will also incorporate an impact and commission on each trade.

4.2 Hyper-parameter selection

The Strategy learning agent used two main hyper-parameters, alpha and gamma. Alpha represents the learning rate, or weighting that the learner puts on new information compared to older information. The learning rate which resulted in the best in-sample performance was 0.001, indicating a very high weighting on older information and very low weighting on new information. This could be due to the noisy, stochastic nature of daily stock price data.

Gamma represents the discount rate, or how much weight is placed on future rewards compared to immediate rewards. The gamma value found to provide the best performance was 0.9, indicating higher weight on future rewards than immediate.

4.3 Indicator Discretisation

The three technical indicators (BBP, Momentum & RSI) need to be translated from individual indicators into a single representation of state. This is done by discretising each one into a digit between 0 and 9. An expected minimum and maximum threshold was used to bound the indicator, i.e. for BBP it was -0.5 and 1.5. The result was then multiplied by 10 and rounded to the nearest whole number, as shown below:

$$Discretised\ BBP = \left(\frac{BBP - (-0.5)}{1.5 - (-0.5)} * 10\right)$$

Each of the three indicator was then combined to create a single, three-digit representation of the market state.

5 EXPERIMENT 1

The aim of Experiment 1 is to compare the performance of the Manual and Strategy learner against the benchmark. The experiment was conducted by trading shares of '$JPM' with each trade carrying a commission of $9.95 and a market impact of 0.005. It is assumed that the strategies cannot 'peak' into the future and only know current stock price and indicator values.

Both the Manual and Strategy Learner were provided with the same three technical indicators. Both strategies used the same indicator lookback periods, described in Section 2, as these returned sufficient rewards over the in-sample period. Both strategies were only able to hold at most +1000 or -1000 shares at any point in time.

The results of the strategies over the in-sample period are shown in Figure 3, showing both the Manual and Strategy Learner were able to out perform the benchmark over the trading period. This is as expected, as both strategies were tuned/trained over this period.

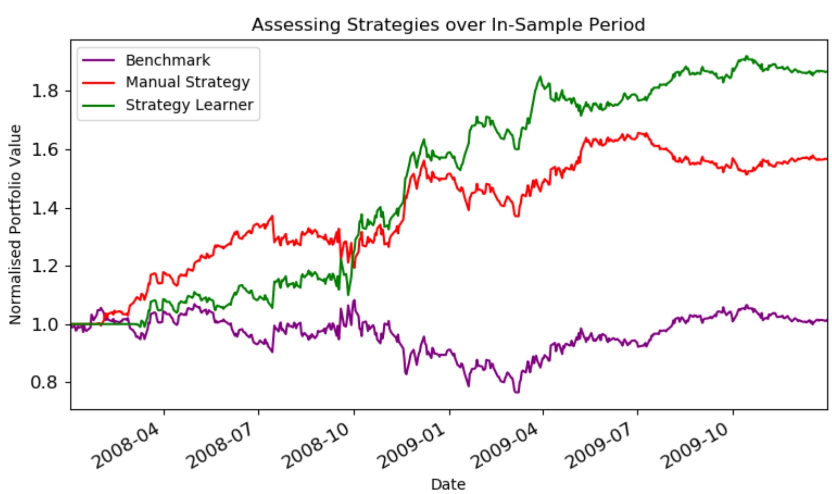

Figure 3 - In-sample performance of Manual and Strategy Learner compared to benchmark

The out-of-sample performance is shown in Figure 4, showing both strategies providing higher returns than the benchmark, which could be indicative of strong trading policies, however, this would need to be verified against other time periods and other stocks. Both the Manual Strategy and Strategy Learner do not perform as well as over the in-sample period, which is expected as the hyper-parameters were tuned on the performance of the in-sample data.

Four technical indicators were initially used in the strategy, however, that led to better performance in the in-sample period but worse performance than benchmark in out-of-sample. This is likely a symptom over-fitting, providing the strategies with too many degrees of freedom, and so three indicators were used.

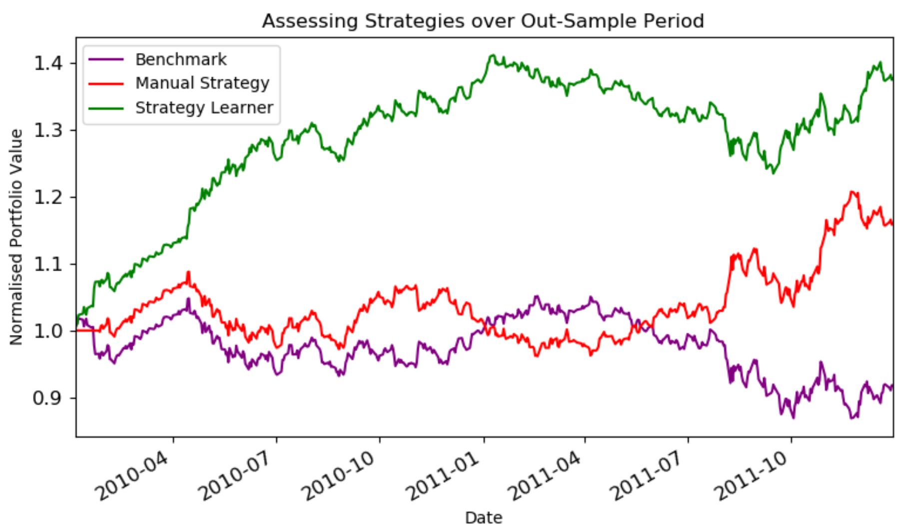

Figure 4 - Out-of-sample performance of Manual and Strategy Learner compared to benchmark

6 EXPERIMENT 2

The aim of Experiment 2 is to observe how changing the impact value will affect in-sample trading behaviour on the Strategy Learner. The impact value represents the extent at which buying or selling a stock moves the price against the trader (Wikipedia, 2022). As the impact will move the price against the trader and thereby reduce the reward from a trade, it is expected that as the impact value increases, the learner will perform trades less frequently. In addition, it is expected that as impact increases, the cumulative returns will reduce as the change in price is less profitable.

To assess this hypothesis, the impact was varied between 0.02, 0.04 and 0.08. The two metrics selected were cumulative returns and number of trades. For each impact value, a Strategy Learner was instantiated and trained over the in-sample period for the stock 'JPM'.

The results of the experiment are shown in Figure 5 and Table 2, showing that as impact value is increased, the Strategy Learner returns lower cumulative returns and performs less trades over the in-sample period. This highlights how important market impact can be for trading strategies.

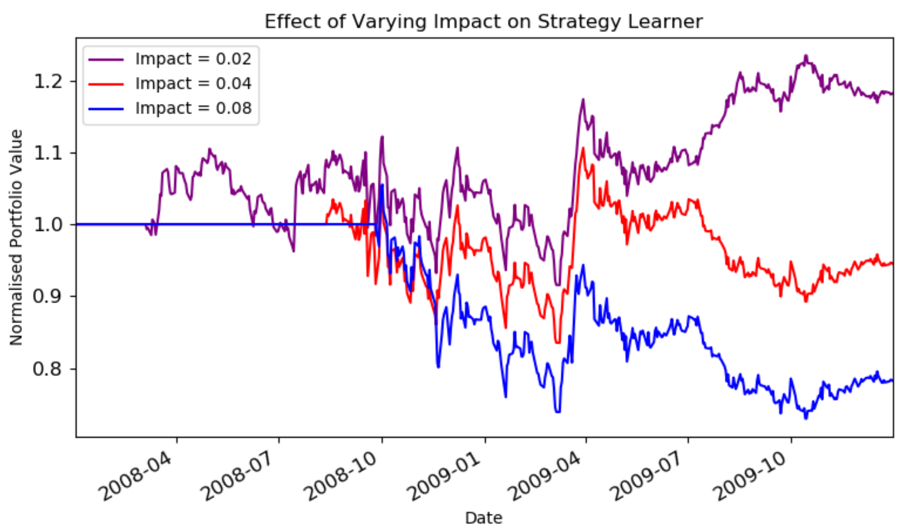

Figure 5 - Effect of varying impact on Strategy Learner over in-sample period data

Impact	Cumulative Returns	Number of Trades
0.02	0.1822255	15
0.04	-0.0551114	9
0.08	-0.2178110	2

Table 2 - Strategy Learner results after varying Impact

8 REFERENCES

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