Project 8: - Strategy Evaluation

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1 INTRODUCTION

In this assignment, we are dealing with trading problem by building portfolios based on two strategies that are implemented for making trade decisions and later compared with benchmark portfolio for their performance. The first strategy is manual strategy wherein we inspect the indicators, identify their best combinations and decide whether to long or short the trade. The second strategy is developed using machine learning algorithms namely Random Tree learner and Bag learner. Benchmark portfolio is the result of buying 1000 shares of a particular stock, holding throughout the analysis period and selling them entirely when the period is due. We perform all the experiments and analysis on JPM stock.

In the entire implementation, we expect that the strategy learner will beat manual strategy portfolio and benchmark during the in-sample period. The in-sample period is defined to be the training period for the strategy learner and the period for which we analyse indicators and create a strategy which would perform well for various unseen timeframes. This is implemented as experiment 1.

Finally, we visualize the influence of various impact rates on the portfolio performance for strategy learner. Experiment 2 is concerned with this visualisation.

1.1 Indicator overview

Indicators act as the tools that allows us to understand stock trends and make appropriate decisions for the trade. A single indicator may not be strong enough for predicting the future movement of the stock or providing a deeper insight of the stock. Hence, combinations of indicators are used for confirming the trend and thereby the trade decision. This strategy of aggregating various indicators works well as compared to single indicator as we have ample data from indicator that confirms the trading signal. In this assignment, we have used combination of four indicators that are as follows.

A) Percent B (Bollinger bands)
B) Momentum
C) MACD (Moving Average Convergence Divergence)
D) SMA (Simple Moving Average)

A. Percent B (Bollinger bands)

Percent B indicator provides the stock movement in the form of percentage. To calculate this percentage, it uses the Bollinger bands (Upper Bollinger band and Lower Bollinger band) wherein the percentage is 100% or 1.0 (normalized) when the stock price reaches Upper Bollinger band. Similarly, the percentage is 0% or 0.0 when the stock price touches the Lower Bollinger band. Negative percentage indicates the stock price exceeded the lower Bollinger band.

In our implementation, Percent B indicator is used to identify the overbought and oversold decisions. For identifying certain points, we define a threshold of 0.1 (10%). Whenever the price of the stock declines below the threshold, we BUY the stock i.e., we make long decision. Whereas, when the stock price exceeds 0.1, we SELL the stock i.e., we short the stock.

B. Momentum

Momentum indicator gives us the strength and weakness of the stock price. It provides the rate of change of stock price over a period. For getting a better performance than the benchmark portfolio, we adjusted the window size (number of lookback days) to 9 for both Manual strategy as well as Strategy learner. It is the single parameter that momentum indicator is based upon.

In our implementation, momentum provides as a supporting indicator that shows the strength in direction followed by the price trend. Now, for this indicator we have defined a threshold of 0.0. Whenever the momentum rises above the threshold, we short the stock and take the long position when the momentum falls below the threshold.

C. MACD (Moving Average Convergence Divergence)

Moving Average Convergence Divergence (MACD) is a trend following indicator which is calculated by subtracting Fast EMA (shorter lookback period) from Slow EMA (longer lookback period). MACD takes three window sizes for its implementation, where the first two are used for calculating Slow EMA and Fast EMA developing a MACD line, whereas third window size is used for calculating the MACD signal. Generally, a signal is considered BUY when the MACD line crosses MACD signal line from below; whereas, the signal is considered SELL when the MACD line declines and crosses MACD signal line from higher position.

For creating a strategy that returns higher cumulative returns in Manual strategy and Strategy learner, we set the lookback period as 26 days, 12 days and 9 days for Slow EMA, Fast EMA and EMA for MACD Signal respectively.

D. SMA (Simple Moving Average)

SMA commonly known as Simple Moving Average, illustrates the moving average of the stock price for a given window period (lookback period) where each day or time is given equal weight. This indicator helps us to determine the trend of the market and a potential change in the established trend.

Like Momentum indicator, SMA indicator is built upon single parameter window size which in our implementation is defined as 9 days. We have defined a threshold for SMA as 1.0. We assume the signal to be BUY when the SMA value is less than the threshold and SELL signal when the SMA value is more than the threshold.

1.2 Manual strategy

Manual strategy is the strategy that we have devised by combining the indicators discussed in section 1.1. Here, we started by defining the in-sample period, the period for which we analyse the stock performance and develop a strategy that we expect to work for unseen period known as out-sample period. Then, we inspected the values of all the indicator and identified the key points that we assumed to be the turning point for the price trend in stock. Since, a single indicator did not provide the expected returns, we combined four indicators one by one. Even when a single indicator provides a BUY or SELL decision, those decisions do not provide expected results and hence, we make use of other indicators that will confirm the decision.

1.2.1 In-sample period

In this assignment, in-sample period is defined staring from 2008-01-01 to 2009-12-31. The stock chosen is JPM with the portfolio starting amount of 100,000 (normalised to 1.0). Impact and commission are set to 0.005 and 9.95 respectively. Trading during this period is visualised in figure 1 plotted in terms of daily returns.

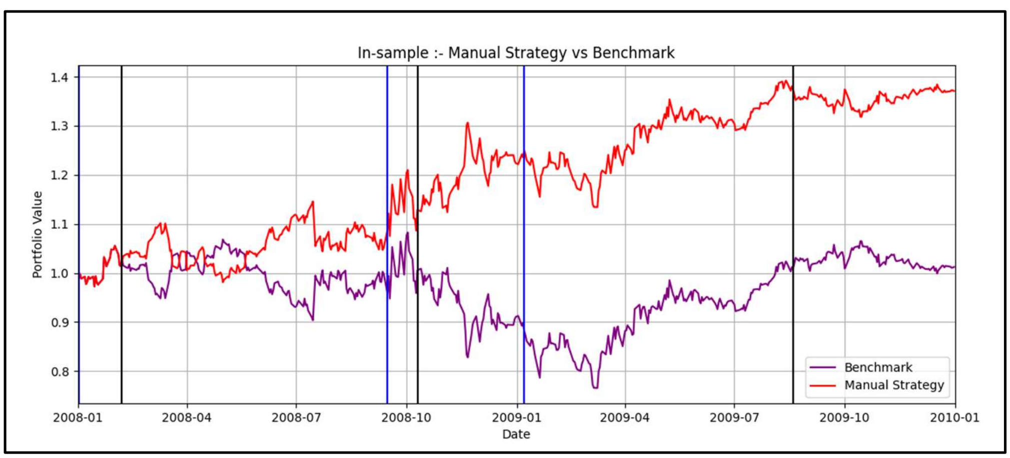

Figure 1 – Graph of comparison between In-sample Manual strategy portfolio performance and benchmark portfolio

For benchmark, we have purchased 1000 stocks of JPM on the first day of in-sample period and held the position for the entire in-sample period. In figure 1, comparison between portfolio returns from Manual strategy and benchmark portfolio is visualized. The vertical blue lines indicate entry position whereas vertical black lines indicate exit position. The entry position is where we increase our position from -1000 stocks to +1000 stocks and exit position being transformation from +1000 stocks to -1000 stocks. It is evident from figure 1 that the manual strategy we developed provides higher cumulative returns than benchmark. Further statistics are summarised in table 1.

Table 1 – In-sample performance statistics of Manual strategy portfolio and benchmark portfolio returns

Statistics	**Manual strategy**	**Benchmark**
Cumulative return	0.37	0.01
Mean daily return	1.19	0.97
Standard deviation of daily return	0.12	0.06

1.2.2 Out-sample

To back-test our manual strategy, we analyse it for an unseen period from 2010-01-01 to 2011-12-31 but for JPM stock. Commission and impact are same as in case of in-sample period i.e., 9.95 and 0.005 respectively. Starting cash is also set to 100,000 normalised to 1.0.

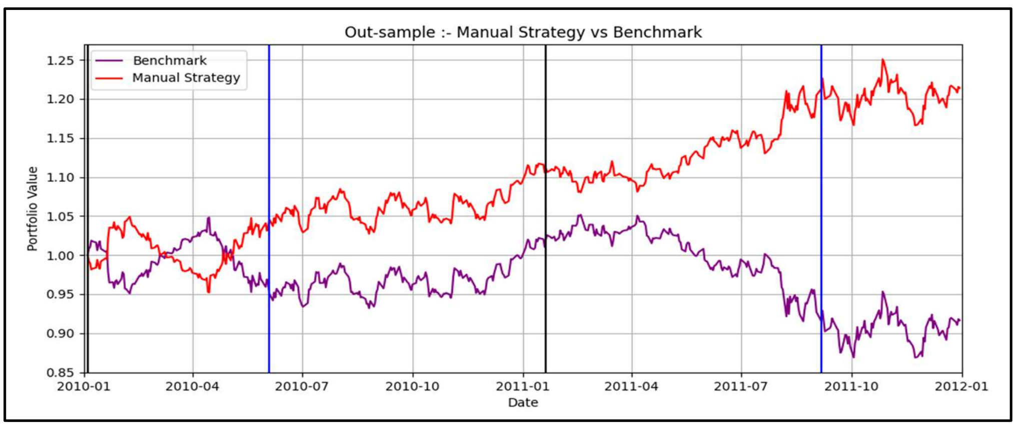

Figure 2 – Graph of Out-sample Manual strategy portfolio and benchmark portfolio

From figure 2, it is evident that the strategy that we devised during the in-sample period works well for out-sample period also. A gradual increase in portfolio value can be seen when traded using Manual strategy. The decisions as in case of in-sample period is taken using the four indicators simultaneously. The performance metrics can be further analysed in table 2 as shown below.

Table 2 – Out-sample performance statistics of Manual strategy portfolio and benchmark portfolio returns

Statistics	**Manual strategy**	**Benchmark**
Cumulative return	0.21	-0.08
Mean daily return	1.09	0.97
Standard deviation of daily return	0.06	0.04

From both the in-sample as well as out-sample period statistics and visualization, it can be concluded that the strategy we created by combining various indicators (from section 1.2) performed great and beat benchmark portfolio performance though the out-sample manual strategy providing slightly lower but positive returns than the in-sample manual strategy learner. The performance metric for the manual strategy from in-sample and out-sample period shows minute divergence which is due to the fact that the indicators are analysed and back-tested on in-sample period.

1.3 Strategy learner

Strategy learner is developed using Random tree learner and Bag learner algorithms. In this strategy we train our model based on an in-sample period (2008-01-01 to 2009-12-31) where we provide the indicator values for the entire period, perform operation and derive classification label as +1 (long position), 0 (cash) and -1 (short position).

In this assignment, we are implementing strategy to solve the trading problem which is, generate trading signal such as BUY (+1), SALE (-1) or HOLD (0) indicating long position, short position or hold position which can assist us in making effective decisions providing us better portfolio cumulative returns than the Manual strategy that we developed earlier. To derive the trading signals, we implement the problem as classification problem wherein classification labels are generated indicating the trading signals. To do this, we use future prices of the stock for a certain window size (30) and define a threshold value (maximum of 0.02 and impact rate). Cumulative return for the window size is calculated and compared with the threshold value. If the cumulative return is greater than the threshold, we generate a BUY (+1) signal, else if the cumulative return is lower than the threshold, a SELL (-1) signal is generated. For the case when the threshold value is equal to the cumulative return, we consider it as HOLD (0) signal.

Now, the generated data called as in-sample data, is provided to Random Forest learner for training in form of Dataframe. The classification labels are then appended to a dataframe consisting of trading days, stock symbol and the number of stocks exchanged. Finally, the resulting dataframe is provided to portfolio computer which generate portfolio performance. The portfolio is then analysed for various performance metrics same as in case of Manual strategy learner. For testing phase, we queried against out-sample data is done.

Since machine learning is utilised for developing strategy learner, we use Random Forest learner specifically. The learner takes one hyper-parameter for its implementation i.e., leaf size. For our system, we set it to 5 as lower leaf-size would cause overfitting issues. Also, Bag learner is used for boosting our learner which in turn provide better results. The bag learner also takes hyper-parameter as the number of bags, defined as 20; since lower values would cause overfitting issues and larger values will lower the time performance of our learner.

Data adjustment is not required as Random Forest learner needs only the features with data in nominal or ordinal form along with the classification labels with the same form is required. If the choice of learner was different such as a QLearner, data would have needed discretization since that learner performs best with discretized data.

2 Experiments

2.1 Experiment 1

In experiment 1, we compare Strategy learner, Manual learner and benchmark strategy for various performance metrics. In this experiment, we propose the hypothesis that Strategy learner would beat Manual learner strategy and benchmark strategy during the in-sample period.

To begin with, we execute all the three strategies for the same in-sample period from 2008-01-01 to 2009-12-31, with impact of 0.05 and commission of 9.95 and a staring cash of 100,000 for JPM stock. The results from the experiment are visualised as follows in figure 3.

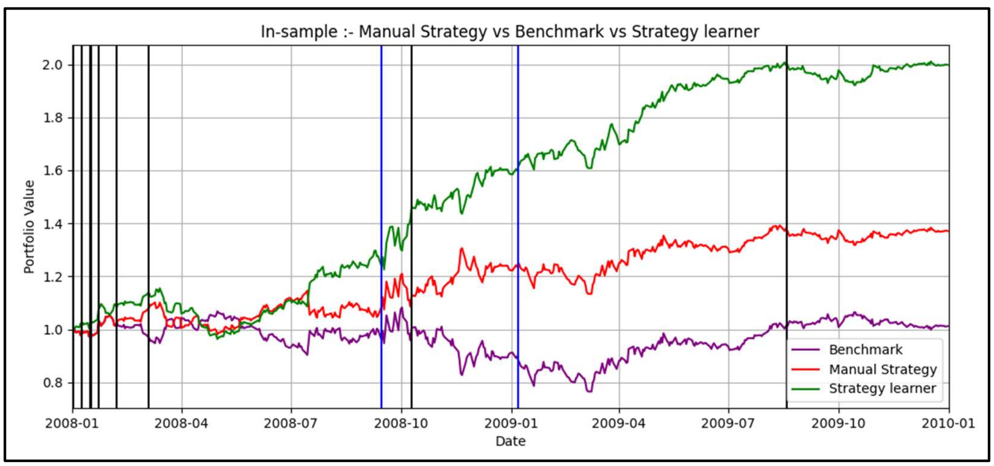

Figure 3 – Graph of in-sample comparison between Strategy learner, Manual strategy and benchmark

In figure 3, a comparative analysis between Strategy learner, Manual learner and benchmark is done. A significant performance difference can be seen between Strategy Learner and Manual strategy mainly. It is clearly evident that the strategy learner beats other two strategies tremendously. After a slow and steady increase in return, an exponential rise can be seen from 2008-05 to 2009-05 followed by a linear growth until the end. The Manual strategy and benchmark follow a similar trend initially being showing opposite trend up to 2008-09. The performance metrics are summarised in table 3.

Table 3 – In-sample performance statistics of Strategy learner portfolio, Manual strategy portfolio and benchmark portfolio returns

Statistics	Manual strategy	Benchmark	Strategy learner
Cumulative return	0.39	0.01	0.99
Mean daily return	1.21	0.97	1.54
Standard deviation of daily return	0.13	0.06	0.37

The results that we visualized in figure 3 are quantified in table 3. We can see that strategy learner shows a significant increase in cumulative portfolio returns of 1.38 (normalised) for in-sample period than Manual strategy and benchmark with 0.39 and 0.01 respectively. In terms of daily mean returns and standard deviation of daily returns, similar rise can be witnessed in strategy learner.

For out-sample period, all the three learners are queried and tested on period of 2009-01-01 to 2011-12-31; keeping other input parameters same as that of the in-sample period. The out-sample performance for the three strategies can be visualised in figure 4. From the figure, we can witness an opposite outcome, where strategy learner is defeated drastically by manual strategy as well as benchmark strategy. A gradual decline in performance of strategy learner can be seen in spite of the steep spike during 2011-08. Whereas, manual strategy earning better returns than the benchmark. Statistics for the out-sample strategies comparison can be interpreted from table 4.

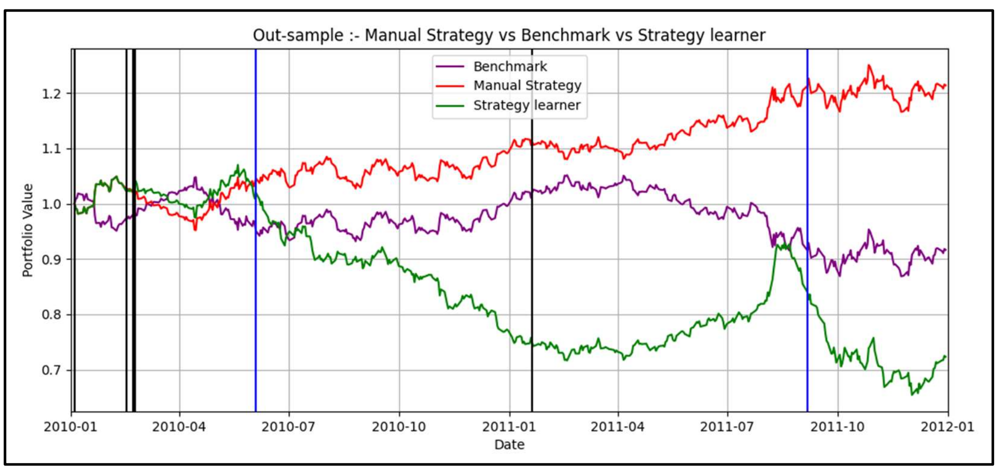

Figure 4 – Graph of out-sample comparison between Strategy learner, Manual strategy and benchmark

Table 4 – Out-sample performance statistics of Strategy learner portfolio, Manual strategy portfolio and benchmark portfolio returns

Statistics	Manual strategy	Benchmark	Strategy learner
Cumulative return	0.2	-0.08	-0.28
Mean daily return	1.1	0.97	0.85
Standard deviation of daily return	0.07	0.04	0.11

Discussing upon the outcomes, we can expect the in-sample strategy learner to win over the manual learner and benchmark learner most of the times since we are building a strategy based upon the in-sample data and querying on the same. But the fact that Random Forest learner used as the base algorithm for training or model, it cannot be denied that the strategy learner may not be able to provide expected results and may perform worser than manual strategy and possibly the benchmark strategy because of the inherent randomized behaviour of Random Forest learner.

2.2 Experiment 2

In experiment 2, we analyse the influence of various impact rates on the performance of strategy learner. To implement this experiment, we define three impact rates of 0.005, 0.05 and 0.0025 while keeping the commission of 0.0 constant for all the three impact rates. The hypothesis we propose is that lower impact rates will provide higher portfolio returns than the larger impact rates. That is, impact is inversely proportional to the portfolio returns (performance metrics).

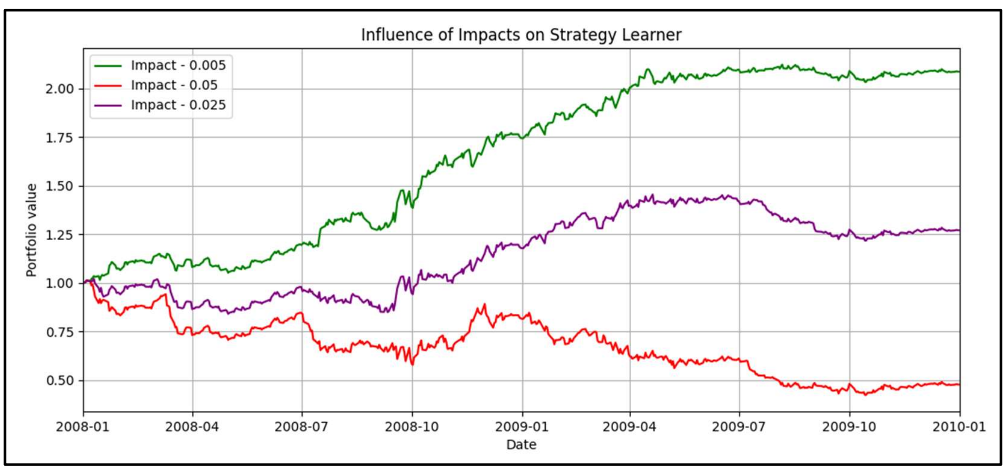

Figure 5 – Graph comparing the influence of various impact rates on the portfolio returns

For verifying the hypothesis, we inspect the visualization from figure 5 and analyse it. The graphical representation illustrates the data for in-sample period from 2008-01-01 to 2009-12-31 with the starting cash kept as 100,000. From the graph, it is interpreted that the impact rate of 0.005 performs better than the portfolio having impact rate of 0.05, which in turn outperforms the portfolio with impact rate of 0.025. In mathematical terms, we can say that Impact (0.0005) > Impact (0.025) > Impact (0.05). For the detailed analysis, refer table 5, where various performance metrics are compared.

Table 5 – Tabular comparison of influence of various impact rates on the portfolio returns

Statistics	**Impact = 0.005**	**Impact = 0.025**	**Impact = 0.05**
Cumulative returns	1.09	-0.52	0.27
Mean of Daily returns	0.001	-0.001	0.0005
Standard deviation of Daily returns	0.01	0.02	0.014

From table 5, it is interpreted as the impact of 0.005 provides higher cumulative returns than impact of 0.05 and 0.025 and hence being the best among three impacts while impact of 0.05 being the worst. This tabular comparison further provides confirmation towards the hypothesis we made earlier as lower impact rates performs better than the higher impact rates. Thus, we can conclude that impact is inversely proportional to portfolio returns.