Strategy Evaluation Report

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Abstract—The objective of this project is to implement and compare two different trading strategies – a manual strategy based on defined trading rules and an strategy learner that uses bagged Random Tree Learner to derive trading strategy.

INDICATORS

Bollinger Bands Percentage (BBP)

Bollinger Bands are comprised of three lines: a simple moving average, the upper band and the lower band. Using SMA_t (Simple Moving Average) and σ_t (Standard Deviation), the upper and lower band at any day t can be evaluated with equations given below.

$$upper_t = SMA_t + (2 * \sigma_t)$$

$$lower_t = SMA_t + (2 * \sigma_t)$$

BBP quantifies price of a stock relative to the upper and lower Bollinger Bands, and can be calculated with the equation given below.

$$BBP_t = \frac{Price_t - lower_t}{Upper_t - lower_t}$$

BBP is one of the indicator for this project. In the manual strategy, BBP has two parameters for optimization – moving window and threshold value for generating sell/buy signal. However, in the strategy learner, only moving window is optimized and trading signal is learned by the model itself.

Momentum

Momentum refers to relative change in price over a certain number of days. The n-day momentum at day t can be evaluated using equation shown below, where p_t is the prices for t^{th} day.

$$m_t = \frac{p_t}{p_{t-n+1}} - 1$$

In the manual strategy, Momentum has two parameters for optimization – moving window and threshold value for generating sell/buy signal. However, in the strategy learner, only moving window is optimized and trading signal is learned by the model itself.

Relative Strength Index (RSI)

Relative Strength Index (RSI) is a momentum indicator that measures the strength and speed of price movement.

The average gain and average loss between $t - n + 1$ to t days in evaluated first to calculate RSI. RSI at any day t can be evaluated using equation shown below where n is the look back period.

$$RSI_t = 100 - \left(\frac{100}{\frac{Average\ Gain\ between\ day\ t - n + 1\ to\ t}{Average\ Loss\ between\ day\ t - n + 1\ to\ t}} \right)$$

In the manual strategy, RSI has two parameters for optimization – moving window and threshold value for generating sell/buy signal. However, in the strategy learner, only moving window is optimized and trading signal is learned by the model itself.

MANUAL STRATEGY

In manual strategy, BBP, RSI, and Momentum were used to create a Buy/Sell signal. The moving widow and thresholds for these indicators were optimized. Table 1 below summarizes the final optimized parameters. The optimized moving window for BBP, Momentum, and RSI were 25, 25 and 25 respectively. The optimized buy strategy is to buy if BBP < 0 or Momentum < -0.2 or RSI < 30. On the other hand, the optimized sell strategy is to sell if BBP > 1 or Momentum > 0.2 or RSI > 70. If none of these conditions are met, no Buy/sell action is performed. These values were selected because they demonstrated stable trading performance during in-sample testing.

Table 1: Optimized parameters for manual strategy

Indicator	Moving Window	Buy Signal	Sell Signal
Bollinger Band Percentage (BBP)	25	BBP < 0	BBP > 1
Momentum	25	Momentum < -0.2	Momentum > 0.2
Relative Strength Index (RSI)	25	RSI < 30	RSI > 70

The manual strategy was tested on JPM for in-sample period between 2008 January 1 to 2009 December 31 and out-sample period between 2010 January 1 to 2011 December 31. The allowable positions were 1000 shares long, 1000 shares short or 0 shares. The strategy was allowed up to 2000 shares (short/long) as long as the current position was 1000 shares long or 1000 shares short. The commission was set to $9.95 and impact was set to 0.005. Another benchmark portfolio was created by buying 1000 shares of JPM on start date and selling 1000 shares on end date. Both benchmark and manual strategy were started with the initial cash of $100000. The portfolio with the manual strategy was then compared to benchmark portfolio.

The manual strategy beats the benchmark in both in-sample and out-sample period. Figure 1 and Figure 2 below shows the comparison of normalized portfolio value for in-sample and out-sample period respectively. The normalized value of for manual strategy can be clearly seen above the benchmark in these plots.

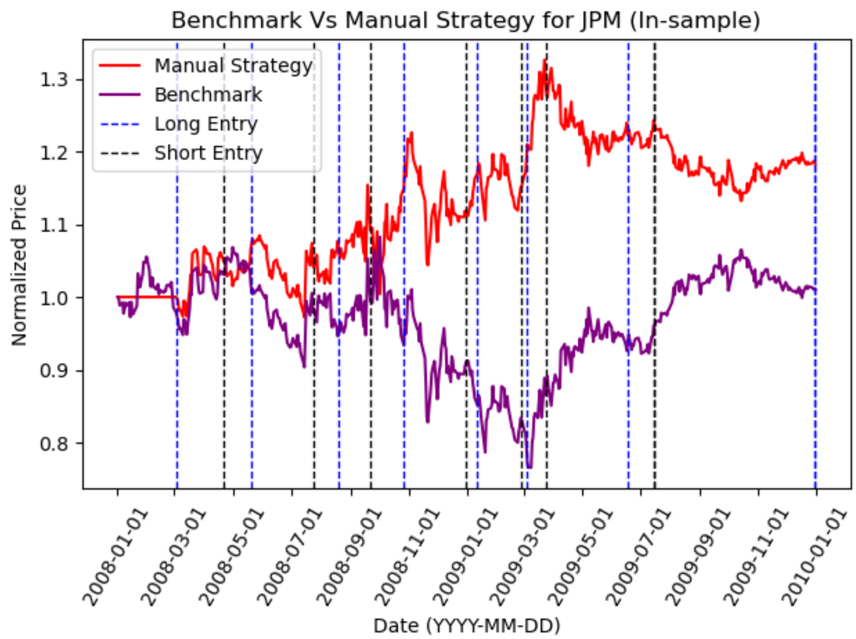

Figure 1: Comparison between Benchmark and Manual Strategy portfolio for in-sample period

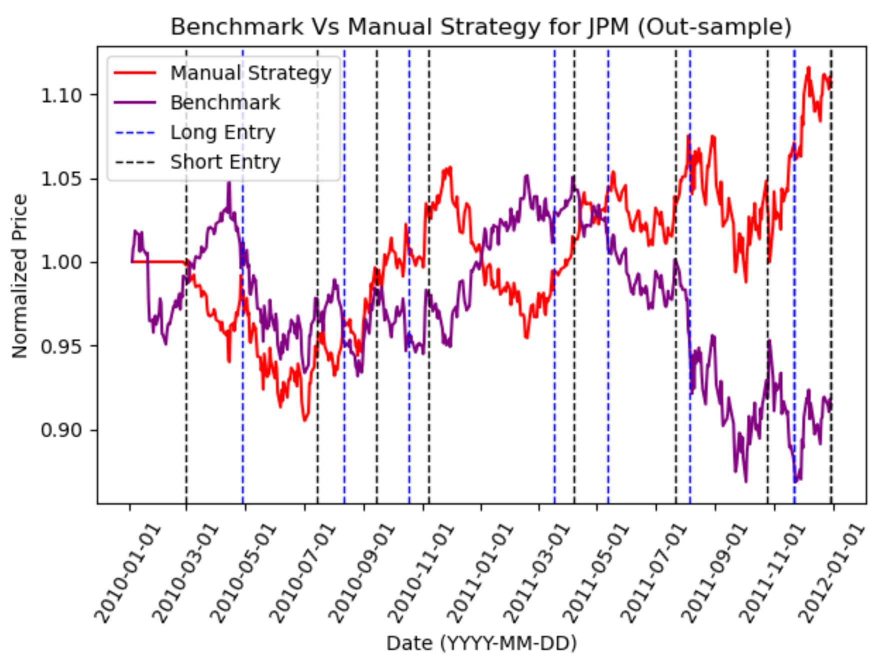

Figure 2: Comparison between Benchmark and Manual Strategy portfolio for out-sample period

Average daily return, standard deviation of daily return, and cumulative return were also calculated to compare the performance. Table 2 below shows the comparison of these performance metric between benchmark and manual strategy. For in-sample period, both benchmark and manual strategy yield positive average daily returns and cumulative returns and the manual strategy beats benchmark in both metric. On the other hand, in out-sample period, benchmark yield negative average daily returns and cumulative returns whereas manual strategy yields positive return. With the positive value, the manual strategy beats benchmark for out-sample testing as well. Also, the standard deviation of manual strategy is less than benchmark. This suggests that our manual strategy is less volatile than the benchmark. Overall, the manual strategy developed here is an effective strategy as it yields higher return with less volatility. The technical indicators were successfully utilized to analyze price movements and identify patterns such as overbought or oversold conditions, momentum shifts, and price volatility.

Table 2: Comparison of performance metric between benchmark and Manual strategy

Statistics	In-sample data		Out-sample data	
	Benchmark	Manual Strategy	Benchmark	Manual Strategy
Cumulative Returns	0.010236	0.182695	-0.085309	0.107043
Standard Deviation of daily returns	0.017041	0.014038	0.008501	0.00778
Mean of daily returns	0.000165	0.000431	-0.000141	0.000232

STRATEGY LEARNER

Strategy learner utilizes machine learning algorithm to generate trading signal. The problem of deciding when to buy, sell or hold a stock was first transformed into a classification problem. The first part is to create data to train the model. The feature vector is constructed using the same three technical indicators employed in the manual strategy – BBP, RSI, and Momentum. The moving windows for indicators are selected from Manual strategy to keep the result consistent. Table 2 below shows the moving window values for each indicators.

Table 3: Indicator parameters for Strategy Learner

Indicator	Moving Window
Bollinger Band Percentage (BBP)	25
Momentum	25
Relative Strength Index (RSI)	25

The target labels are generated based on future returns after 5 days which is listed below.

- If return after 5 days is ≥ (0.035 + impact), set label to +1
- If return after 5 days is ≤ (-0.035 + impact), set label to -1
- Otherwise, set label to 0

The strategy learner is implemented using a Bagging ensemble of Random Tree Learners. The hyperparameters optimized for the model are listed below.

- Leaf Size = 5
- Bags = 20

These values are selected because they demonstrated stable trading performance during in-sample testing on JPM data between 2008 January 1 to 2009 December 31. The knowledge learnt in the class about bagging and overfitting were also utilized while selecting these hyperparameters. Leaf size is not very small which could cause overfitting and is not very large which could oversimplify the trading signals. Bags size was selected to ensure a stable ensemble prediction.

Once the model is trained, it could be queried to predict trading signal for next day. This feature vector is passed to the model which outputs the Buy/sell prediction for the next day. The output is then processed to create Buy/sell signals. The logic is described below:

- If output > 0, Buy the next day
- If output < 0, Sell the next day

The allowable positions are 1000 shares long, 1000 shares short or 0 shares. The strategy is allowed up to 2000 shares (short/long) as long as the current position is 1000 shares long or 1000 shares short.

The discretization is not necessary because strategy learner is implemented with the classification learner rather than a Q-learner. Random tree learner is capable of directly handling continuous inputs.

EXPERIMENT 1

This experiment compares Manual Strategy, Strategy learner, and benchmark on JPM for in-sample period between 2008 January 1 to 2009 December 31 and out-sample period between 2010 January 1 to 2011 December 31. The starting cash is $100000, commission is $9.95, and impact is 0.005. The moving window and threshold used in manual strategy is explained in the Manual Strategy section of this report. Similarly, the hyperparameters and moving window used in Strategy learner is explained in the Strategy learner section of this report. Benchmark portfolio was created by buying 1000 shares of JPM on start date and selling 1000 shares on end date. The primary goal is to analyze whether the ML-based strategy can outperform or match the manual strategy using same set of technical indicators. It was hypothesized that strategy learner would either outperform or produce similar results compared to manual strategy on both in-sample and out-sample data because of its data-driven learning process. Figure 3 and Figure 4 below shows the normalized portfolio value for in-sample and out-sample data respectively. This data clearly indicates that performance of strategy learner is better than both benchmark and manual strategy. The performance with in-sample data on strategy learner is comparatively very high. This could be due to the fact that random tree is built with the in-sample data and there is some overfitting.

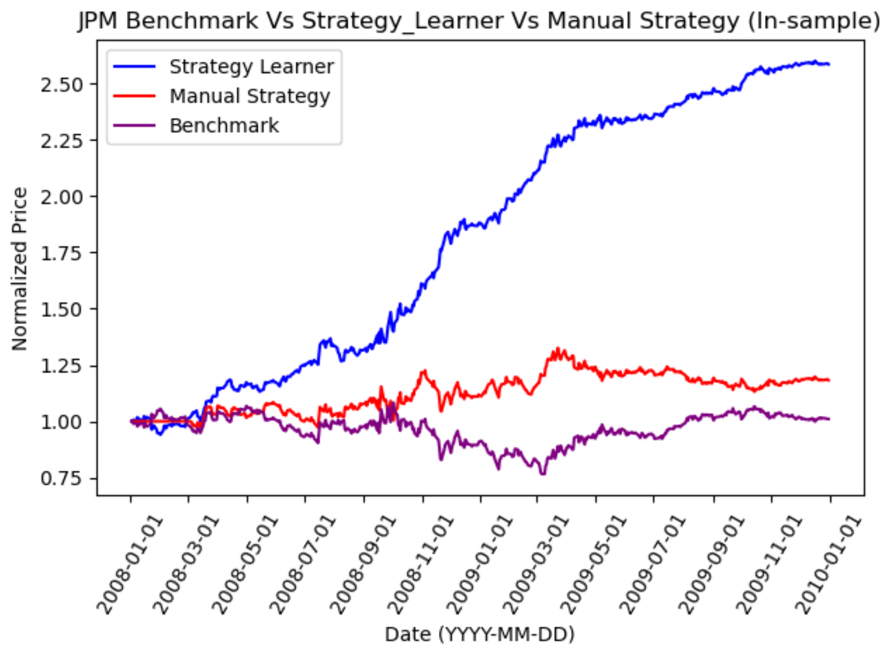

Figure 3: Comparison between Strategy learner, Manual learner and benchmark for in-sample data

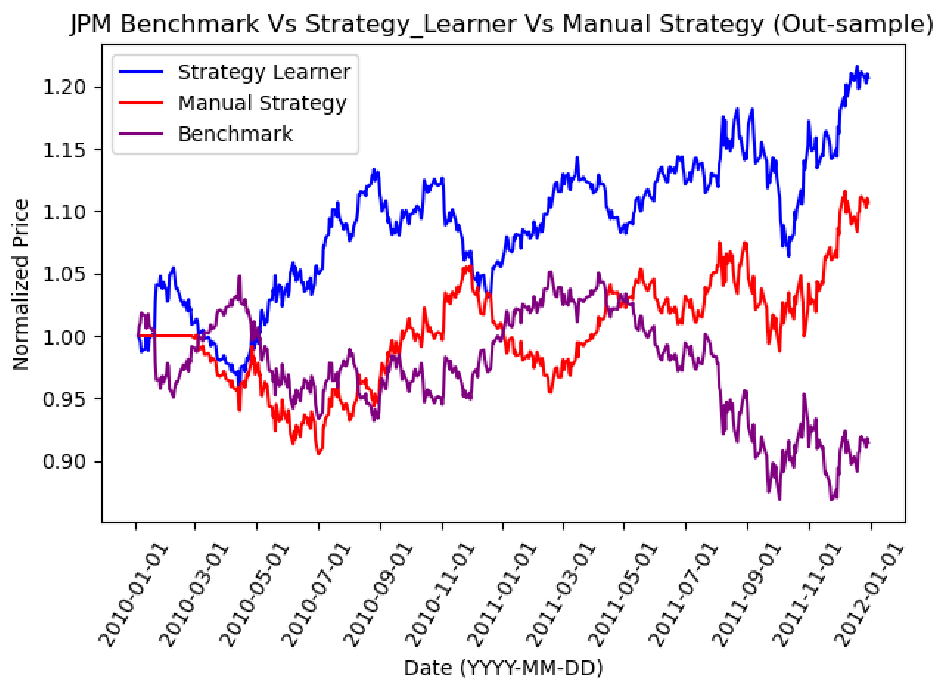

Figure 4: Comparison between Strategy learner, Manual learner and benchmark for out-sample data

The performance metric were also calculated. Figure 5 below shows the average daily return and cumulative return for all three strategies. These metric are also better for strategy learner compared to both manual strategy and benchmark in both in-sample and out-sample testing. It can also be seen that performance on in-sample data is superior to that of out-sample data. These values suggest that implementation of Machine learning algorithm in trading could improve the performance of the portfolio which supports initial hypothesis.

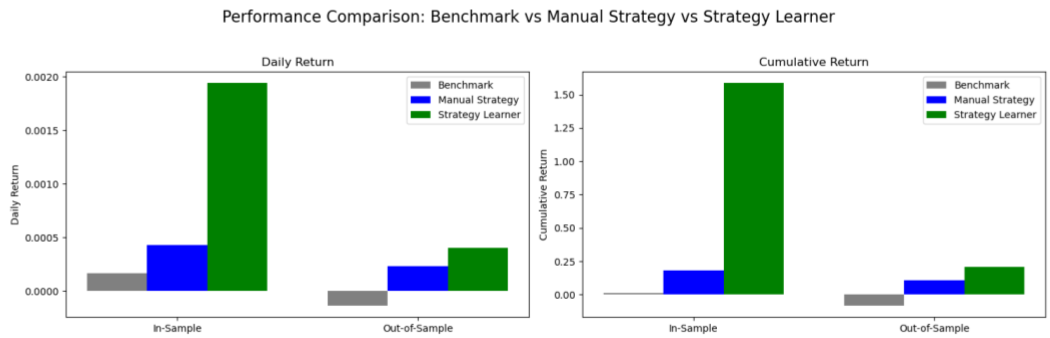

Figure 5: Comparison of performance metric between Strategy Learner, Manual Learner and benchmark

EXPERIMENT 2

This experiment compares Strategy learner with different impact on JPM for in-sample period between 2008 January 1 to 2009 December 31. The starting cash is $100000 and commission is $0. Three different impact values were run: 0.0, 0.01, 0.02. The hyperparameters and moving window used in Strategy learner are explained in Strategy learner section of this report. The primary goal of this experiment is to analyze the effect of impact. It was hypothesized that increasing the value of impact would make the portfolio performance worse because it would cause less trades and for each trade higher fees is paid. Figure 6 below shows the normalized portfolio value for different impact. It can be seen clearly that as the impact is increased the portfolio performance gets worse.

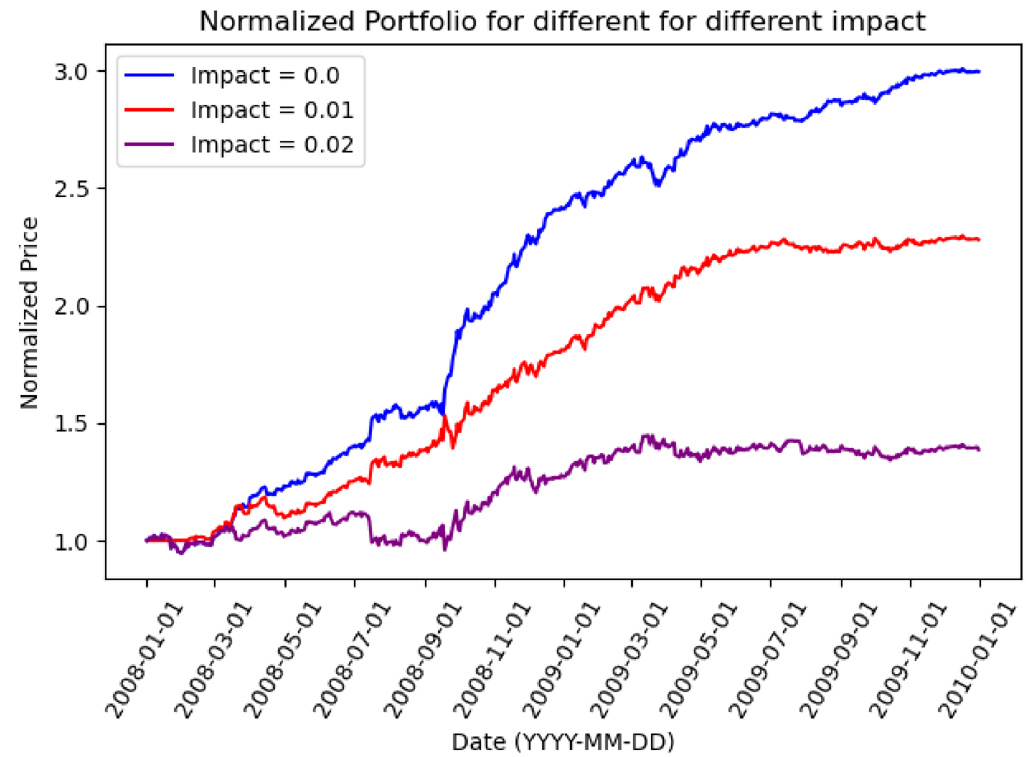

Figure 6: Comparison of Strategy Learner with different impact

Performance metric were also calculated for each impact. Figure 7 shows the daily return, Sharpe ratio, and cumulative return for each impact value. Both average daily return and cumulative return drop as the impact is increased. On the other hand, the Sharpe ratio increases with the increase in impact which means higher risk. This supports our initial hypothesis that increasing impact value makes performance of portfolio worse.

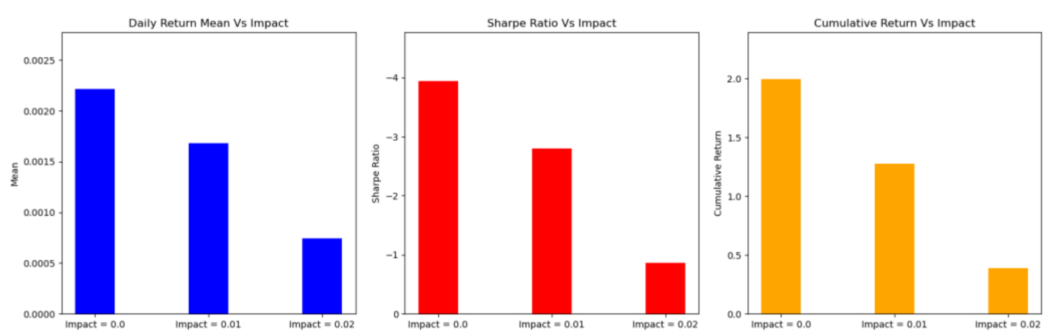

Figure 7: Performance metric for different impact values