Project 8: Strategy Evaluation
CS7646 Machine Learning for Trading

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1 INTRODUCTION

This project will introduce a strategy learner that is designed based on a supervised machine learning algorithm and a manual strategy trader which is manual rule-based to make decisions of trading and compare their performances by conducting experiments. Both methods use three indicators: price/SMA ratio, momentum and Bollinger Bands value, which I will explain in detail in later sections. In addition, in this report, I also explore how changing the value of impact should affect in-sample trading behavior in the strategy learner.

2 INDICATOR OVERVIEW

2.1 Price/SMA Ratio

Simple Moving Average or SMA calculates the average price over the previous n days, where n is referred to as the window of an SMA. SMA is calculated based on the adjusted closing price.

$$SMA(t) = \frac{\sum_{i=(t-n)}^{t} P_i}{n} \qquad \text{Eq. (1)}$$

Technicians usually take the SMA as a proxy for underlying value, in other words, the true value of the company. If we see a large excursion of prices from the SMA, we would expect the prices would eventually come towards the SMA. In this report, I use the ratio of closing prices to the value of SMA on the same day as the first indicator. That is, it is a buy signal when the ratio is smaller than 1 and it is a sell signal when the ratio is larger than 1.

2.2 Momentum

Momentum measures the rate of change in price from one period to the next. To calculate an n-day momentum on a particular day, we just take the prices of that day, divide it by the prices n days earlier and subtract 1. A positive momentum value means the price has gone up recently and a negative momentum value indicates a downward trend of price. In order to use the momentum value as an indicator, it is a buy signal when the momentum is transitioning from negative to positive and it is a sell signal when the momentum is transitioning from positive to negative.

2.3 Bollinger Bands (BB) Value

Bollinger Bands are volatility bands placed above and below a simple moving average. Volatility is calculated from the standard deviation, which changes as volatility increases and decreases. The upper band and lower band are usually set two standard deviations above and below the middle band. The bands are tighter for periods of low volatility and wider for periods of high volatility.

In order to use Bollinger Bands as an indicator for buy and sell signals, we need to look out for crosses from outside to inside. It would be a sell signal when the price is outside the upper band and is retreating back towards the simple moving average and it would be a buy signal when the price is moving below the lower back towards the simple moving average. To quantify this strategy, we can calculate the BB value by subtracting the simple moving average (SMA) from the price (P) on a particular day and dividing it by 2 times the standard deviation (std) as shown in Equation 2 below.

$$BB(t) = (P(t) - SMA(t)) / (2 * std(t)) \quad \text{Eq. (2)}$$

Therefore, if BB value is greater than and tending towards 1, it indicates a sell signal and if a BB value is smaller than and tending towards -1, it indicates a buy signal.

3 MANUAL STRATEGY

In order to combine all three indicators to create an overall buy signal, I made two criteria: 1) price/SMA ratio (ratio[t] < 1) is smaller than 1 and the momentum value is transitioning from negative to positive (momentum[t-1] < 0 and momentum[t+1] > 0); 2) bb value is smaller than -1 (bb[t] < -1). If at least one of these two criteria are met, day t is a long entry point, which means only when both the price/SMA ratio indicator and the momentum indicator indicates a buy signal or the bb value indicator itself indicates a buy signal, I will buy the stock.

Accordingly, the two criteria for a sell signal is: 1) price/SMA ratio (ratio[t] > 1) is greater than 1 and the momentum value is transitioning from positive to negative (momentum[t-1] > 0 and momentum[t+1] < 0); 2) bb value is greater than1 (bb[t] > 1). If at least one of these two criteria are met, day t is a short entry point, which means only when both the price/SMA ratio indicator and the momentum indicator indicates a sell signal or the bb value indicator itself indicates a sell signal, I will sell the stock.

There are three allowable positions: 1000 shares long, 1000 shares short and 0 shares. So a long entry point means that if I have 0 or -1000 shares, I will buy 1000 or 2000 shares respectively to reach but not exceed the portfolio size constraints. If I am already in a long position of 1000 shares, I will do nothing. Vice versa, a short entry point means that if I have 0 or 1000 shares, I will sell 1000 or 2000 shares respectively. If I am already in a short position of 1000 shares, I will do nothing.

I believe it is an effective strategy because bb value is a relatively "strict" indicator and it only exceeds -1 or 1 occasionally. If I set the rule to be only when all three indicators say it is a buy signal then I would buy the stock, there would be very few trades. On the other hand, if I set a loose rule that when any of the three indicators indicates a buy/sell signal I would buy/sell the stock, there would be too many trades which may negatively impact the overall performance because of the existence of transaction costs.

Figure 1 compares the normalized portfolio values for the stock JPM for the in-sample period (Jan 1st 2008 to December 31st 2009) using the manual strategy versus the benchmark normalized portfolio values in which I start with $100,000 cash and buy 1000 shares of JPM and hold that position for the same period of time. Commission is $9.95 and Impact is 0.005. We can see that the portfolio values using manual strategy obviously beat the benchmark.

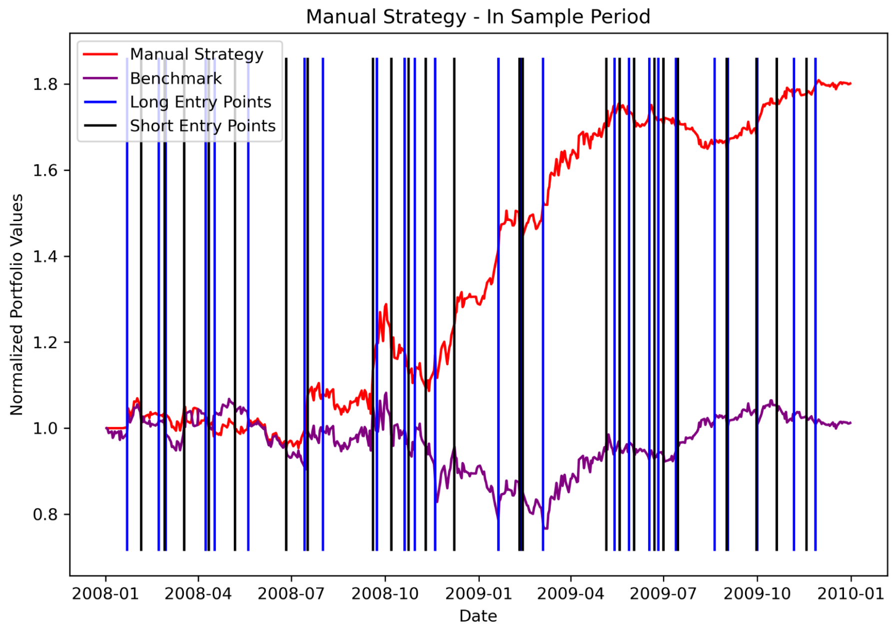

Figure 1—Normalized portfolio values using the manual strategy (red line) versus the benchmark normalized portfolio values (purple line) when trading JPM for the in-sample period. Vertical blue and black lines represent long and short entry points.

Table 1 also confirms this by providing metrics for the manual strategy and the benchmark. I calculated the cumulative returns, standard deviation (stdev) of daily returns and mean of daily returns for these two portfolios. The cumulative return and mean of daily returns of the manual strategy are much higher than the benchmark and the volatility (standard deviation) is lower for the manual strategy.

Table 1—Statistics for the benchmark and Manual Strategy for the in-sample period.

Strategy	**Cumulative return**	**Stdev of daily returns**	**Mean of daily returns**
Benchmark	0.012275	0.01693	0.000167
Manual Strategy	0.801169	0.013008	0.001250

Figure 2 compares the normalized portfolio values for the stock JPM for the out-of-sample period (Jan 1st 2010 to December 31st 2011) using the manual strategy versus the benchmark normalized portfolio values. For the out-of-sample period, manual strategy still outperforms the benchmark, which proves that this is an effective strategy. The cumulative return and mean of daily returns of the manual strategy are also much higher than the benchmark and the volatility (standard deviation) is lower for the manual strategy.

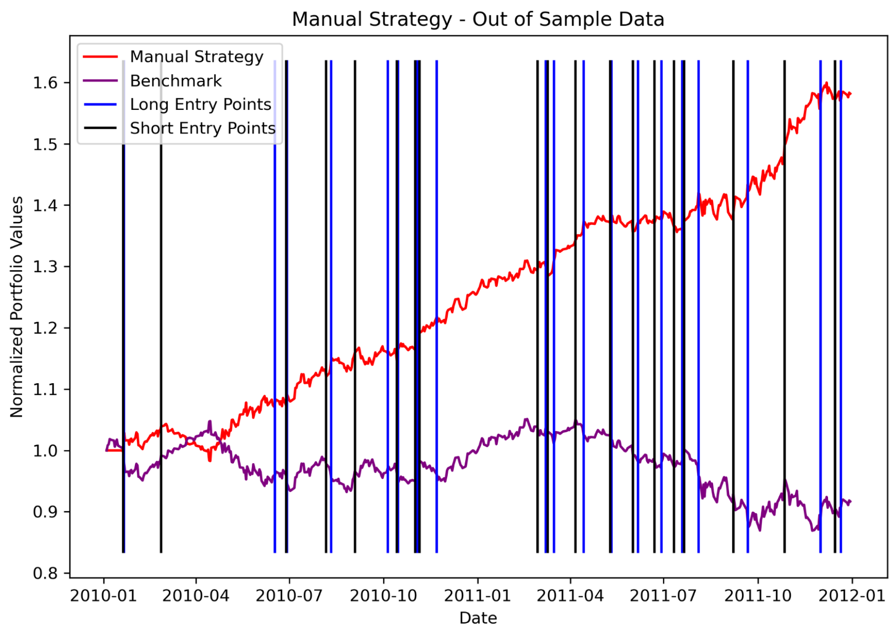

Figure 2—Normalized portfolio values using the manual strategy (red line) versus the benchmark normalized portfolio values (purple line) when trading JPM for the out-of-sample period. Vertical blue and black lines represent long and short entry points.

Manual strategy performs better during the in-sample period with a cumulative return of 0.8 compared to the out-of-sample period (cumulative return is 0.58). The differences occur because those hyperparameters (window size and the way to combine three indicators) are chosen in the way the policy of the manual strategy is best learned during the in-sample period. And I didn't train or tweak my approach again for the out-of-sample data.

Table 2—Statistics for the benchmark and Manual Strategy for the out-of-sample period.

Strategy	Cumulative return	Stdev of daily returns	Mean of daily returns
Benchmark	0.083222	0.008445	-0.000137
Manual Strategy	0.581612	0.006498	0.000931

4 STRATEGY LEARNER

In this section, I will explain how I implement a strategy learner using a random forest algorithm to determine the trading strategy. To convert a trading problem to a learning problem, I first need to separate the training data (in-sample) and testing data (out-of-sample). Then I convert my random tree regression learner into a classification learner and classify the actions in a trading problem (buy, sell or do nothing) to the Y data (labels; +1, -1, 0) in a learning problem. The X data (features) in this case are the values of my three indicators used in the manual strategy. Then I train the BagLearner which includes 10 bags RTLearner using the data during the in-sample period (Jan 1st 2008 to December 31st 2009) and test the strategy learner using out-of-sample data (Jan 1st 2010 to December 31st 2011). The step-by-step description of how I implement the strategy learner are as follows:

4.1 Setting Up Learning Environment

The strategy learner is essentially a BagLearner which includes 10 bags RTLearner (random tree learner) with leaf size of 5. BagLearner is a way to combine the outputs of multiple instances of a single random tree learner, to provide a composite prediction based on the mode of the results. Each random tree learner will randomly select one of the three indicators and use the median to split the dataset. The terminal node is called a leaf and leaf size defines the maximum number of samples to be aggregated at a leaf. The leaf will finally be marked by the mode of the values of these samples.

4.2 Training

To create the training data, I first read in the adjusted close prices of JPM during the in-sample period. Then I calculated the values of three indicators and concatenated them together to form an x_train dataframe. The Y data (or classifications) are based on a 2-day return. I chose 2-day because I tried several parameters and the 2-day return gave me the best performance. If the 2-day return exceeds a certain value (YBUY), it is classified as a buy decision and is labeled as +1. If the 2-day return is below a certain value (YSELL), it is classified as a buy decision and is labeled as +1. In all other cases it is classified as a 0 or "do nothing". I set the value of YBUY to be "*0.01+impact*" and the value of YSELL to be "*-0.01 - impact*" because I want to take the impact into account. If the impact is higher, I would reduce the number of tradings by setting a higher bar of YBUY/YSELL. If the impact is lower, I would do more trading by setting a lower bar of YBUY/YSELL.

4.3 Testing

In the testing phase, I kept all the hyperparameters the same and used both the in-sample and out-of-sample data to query the predicted Y value to create the trade dataframe. If the predicted Y value is +1, it means that it is a long entry point and if the predicted Y value is -1, it means that it is a short entry point. The strategy to perform trades based on the long/short entry point is the same as those described in Section 3.

For this random-tree based strategy learner, I didn't need to adjust the data. RTLearner works just by learning from the training data to classify the Y data based on the mode of the values, so there is no need to discretize or standardized data before they could be trained or tested.

5 EXPERIMENT 1 (MANUAL STRATEGY / STRATEGY LEARNER)

In this experiment, I test the performance of my Manual Strategy and my Strategy Learner using both in-sample and out-of-sample data and compare their performance when trading JPM. The in-sample period is Jan 1st 2008 to Dec 31st 2009 and the out-of-sample period is Jan 1st 2010 to Dec 31st 2011. The parameter values in these two trading strategies are detailed in the previous two sections. My initial hypothesis is that Strategy Learner will definitely beat the Manual Strategy during the in-sample period because this is the time period in which training data are fed to the learner to learn a strategy but not necessarily during the out-of-sample period. Commission is $9.95 and Impact is 0.005 in all of the trading strategies in this experiment.

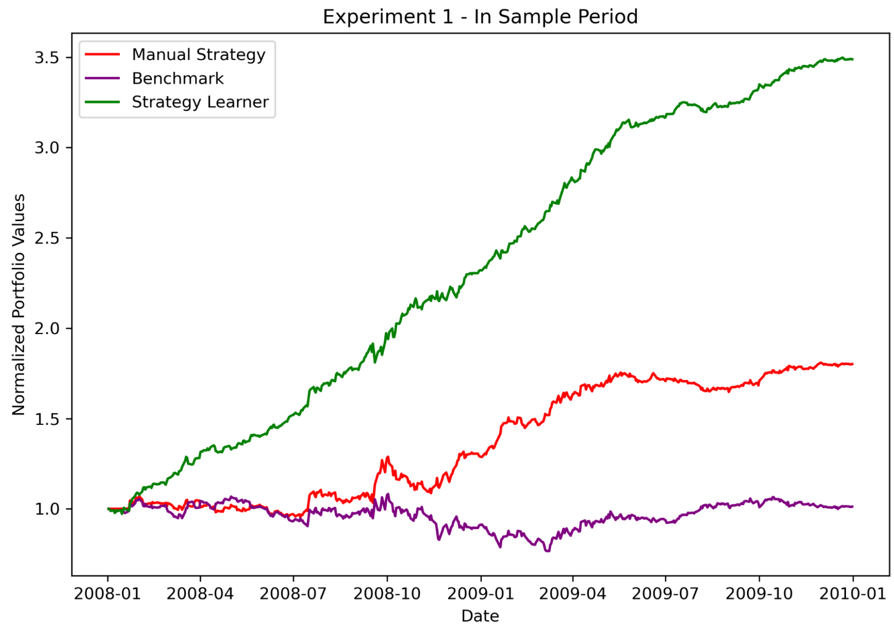

Figure 3—Normalized portfolio values using the strategy learner (green line) versus the manual strategy (red line) versus the benchmark normalized portfolio values (purple line) when trading JPM for the in-sample period.

Figure 3 confirms that Strategy Learner obviously outperforms the Manual Strategy and the benchmark a lot. However, during the out-of-sample period, Manual Strategy actually performs the best. This could be due to the fact that the prices of JPM behave so much differently during the out-of-sample period which makes the trading policy learned by the strategy learner less efficient in making trading decisions during the out-of-sample period. I believe that Strategy Learner will always beat the Manual Strategy with in-sample data because the random-tree based Strategy Learner is more complicated and tries to learn the best policy from training data while the Manual Strategy is to simply follow the indications of those three indicators.

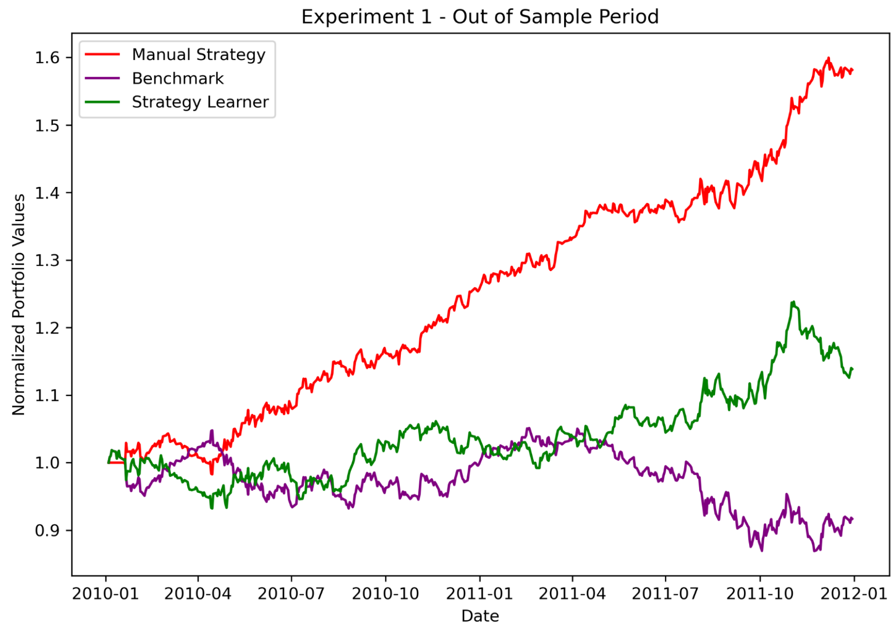

Figure 4—Normalized portfolio values using the strategy learner (green line) versus the manual strategy (red line) versus the benchmark normalized portfolio values (purple line) when trading JPM for the out-of-sample period.

6 EXPERIMENT 2 (STRATEGY LEARNER)

In this experiment, I explored how changing the value of impact would affect in-sample Strategy Learner trading behavior. Commission is kept the same as $9.95. Impact is a "penalty" parameter and it is the extent the price moves against the trader compared to the historical data at each transaction, i.e., upward when buying and downward when selling. The initial hypothesis is that when the impact increases, the total portfolio values will decrease.

Figure 4 shows the normalized portfolio values with four different values of Impact and this confirms my hypothesis. Table 3 also provides two metrics to measure the portfolio performance when trading with four different values of Impact. We can see that both cumulative return and mean of daily returns decreased as Impact increases. So we can conclude that the Strategy Learner performs poorer for larger values of Impact.

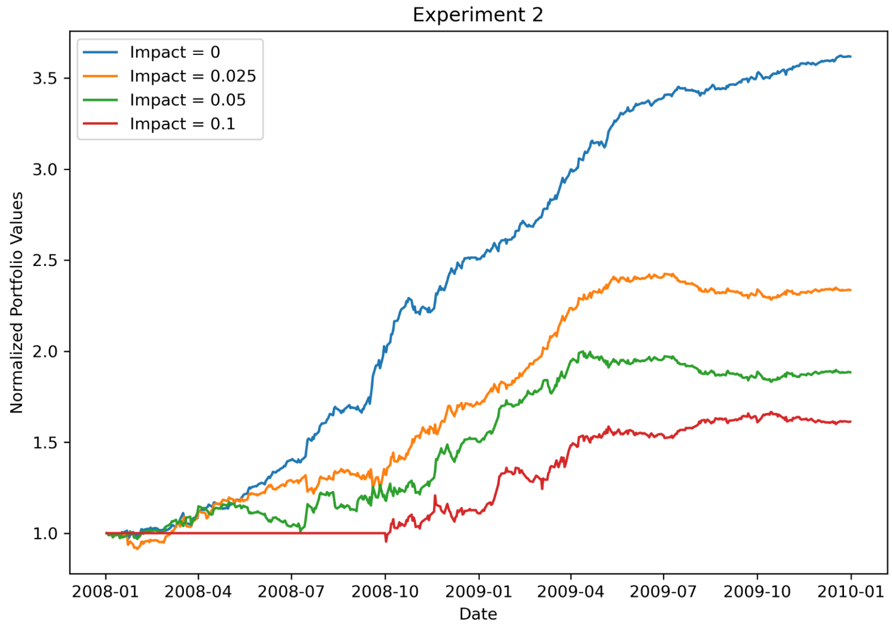

Figure 5—Normalized portfolio values using different values of Impact when trading JPM for the in-sample period.

Table 3—Statistics for the Strategy Learner with different values of Impact when trading JPM for the in-sample period.

Impact	Cumulative return	Mean of daily returns
0	2.618854	0.002585
0.025	1.336079	0.001744
0.05	0.883877	0.001335
0.1	0.612805	0.001008