

# CS 7646 ML4T Project 8 Strategy Evaluation

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**Abstract** – In this project I implemented 2 strategies: manual trading strategy using technical indicators, and strategy learning using random forest with technical indicators as x parameters. I compared the performance of the 2 trading strategies with benchmark trading. The indicator I selected is Momentum, SMA ratio and Bollinger percentage. The experiment also

## INDICATOR OVERVIEW:

In this part of the report, I describe the indicators that I use to develop my Manual strategy and strategy learning. The 3 indicators I chose are: Momentum, Price/SMA ratio, and Bollinger percentage.

### 1.1 Momentum

The formula of Momentum is below:

$$\text{Momentum}[t] = (\text{price}[t] / \text{price}[t - n]) - 1$$

Momentum neglects the volatility of the stock price changes, but shows an overall trend in the past n day's period. If momentum > 0, it means stock prices have been going higher, and we assume the trend will continue, and vice versa. In this project I use 15 day's momentum

### 1.2 Price/SMA ratio

The SMA (simple moving average) of the stock is the mean value of the stock's prices in the past several days. In this project, I chose 5 days SMA. The formula of 5 day's SMA is:

$$\text{SMA}(5) = \text{Sum}(\text{price in the last 5 days})/5$$

Price/SMA ratio shows how stock price comparing with SMA.

$$\text{Price/SMA ratio} = \text{stock price} / \text{SMA}(n)$$

If price/SMA ratio > 1.03, it means the stock is overbought. Thus we should decrease the holding or short the stock. When price/SMA ratio < 1.03, it often means oversold and we should signal buying to the stock.

### 1.3 Bollinger Percentage

Bollinger Band is implemented with SMA. We need to add/ take out 2 standard deviations of the prices from the original SMA line. The Formular of the upper and lower Bollinger Band is shown below:

Upper Bollinger band(n) =  $SMA(n) + 2 * std(n \text{ day's price})$

Lower Bollinger band(n) =  $SMA(n) - 2 * std(n \text{ day's price})$

The Bollinger Band percentage is a useful signal to see if the stock is overbought or over sold:

Bollinger Band Percentage =  $(\text{stock price} - \text{lower Bollinger Band}) / (\text{Upper Bollinger Band} - \text{Lower Bollinger band})$

In both manual strategy and strategy learner, I use these 3 indicators. In Manual strategy, I combine the 3 indicators to decide whether to long/short the stock. In strategy learning, I use random forest to train a model to decide whether we need to buy/hold/sell the stock. The 3 indicators are used as attributes.

#### MANUAL STRATEGY:

The manual strategy decides whether to long or short stock based on the three indicators that I described. I implement the below rules with technical indicators to build the training strategy:

Trigger a long when:

- Bollinger percentage < 0.2 and momentum > 0
- Or
- Price/SMA ratio < 0.97 and momentum > 0

Trigger a short when:

- Bollinger percentage > 0.8 and momentum < 0
- Or
- Price/SMA ratio > 1.03 and momentum < 0

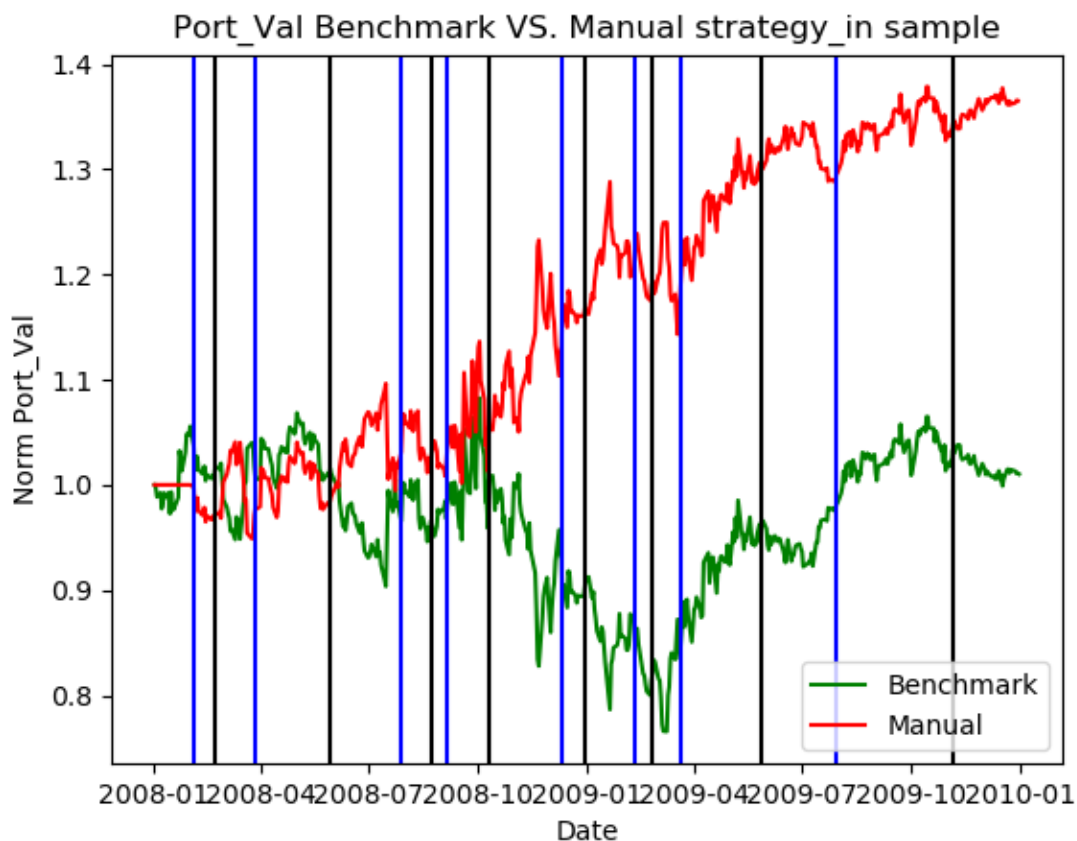
The reason I use this strategy: momentum shows the overall trend of a stock. I want to make sure when I long/short a stock when it's in a ascending/descending trend. Also I want to make sure either Bollinger percentage or price.SMA ratio is good enough to trigger a buy or sell.

We also introduce benchmark trading, to evaluate how good is the manual strategy. The benchmark strategy is the performance of the portfolio starting with \$100,000 cash, investing in 1000 shares of JPM on the first trading day, and holding that position.

To compare manual strategy with the bench-mark, we introduce below rules:

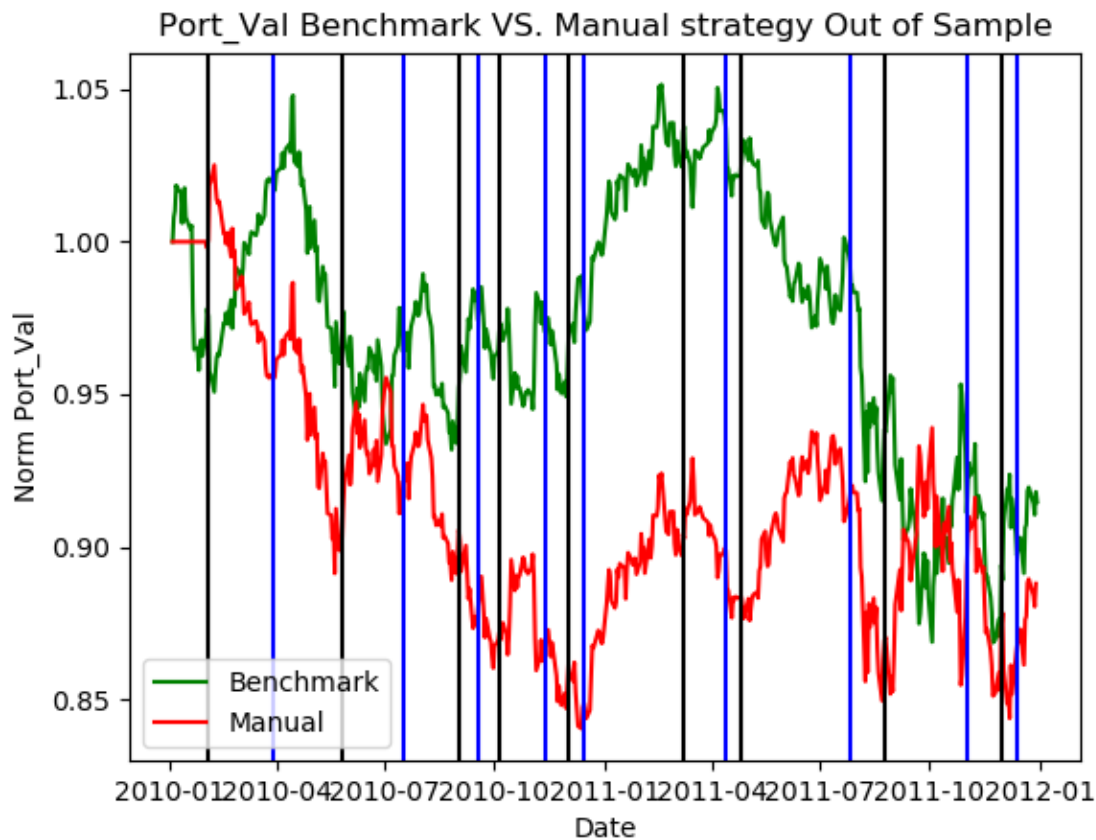
- In-sample period is Jan 1 2008 to Dec 31 2009
- Out-of-sample period is Jan 1 2010 to Dec 31 2011
- Stating case is 100,000
- Only allow 1000 shares long, 1000 shares short, 0 shares as positions
- Transaction costs: commission: \$9.95, impact: 0.005

Below is the chart, showing how manual strategy comparing with benchmark trading strategy with in-sample data:



	Cumulative return	Mean daily return	Std daily return
Manual strategy	0.0102	0.000165	0.0139
Bench-mark	0.365	0.000715	0.0170

Below is the chart, showing how manual strategy comparing with benchmark trading strategy with out-of-sample data:



	Cumulative return	Mean daily return	Std daily return
Manual strategy	-0.112	-0.000141	0.00861
Bench-mark	-0.0853	-0.0002	0.00850

The Manual strategy beats the bench-mark with in-sample periods. However, it fails in the out-of-sample period. Being said that, the manual strategy could work in trading, but it still has a risk to underperform the market itself.

### STRATEGY LEARNER:

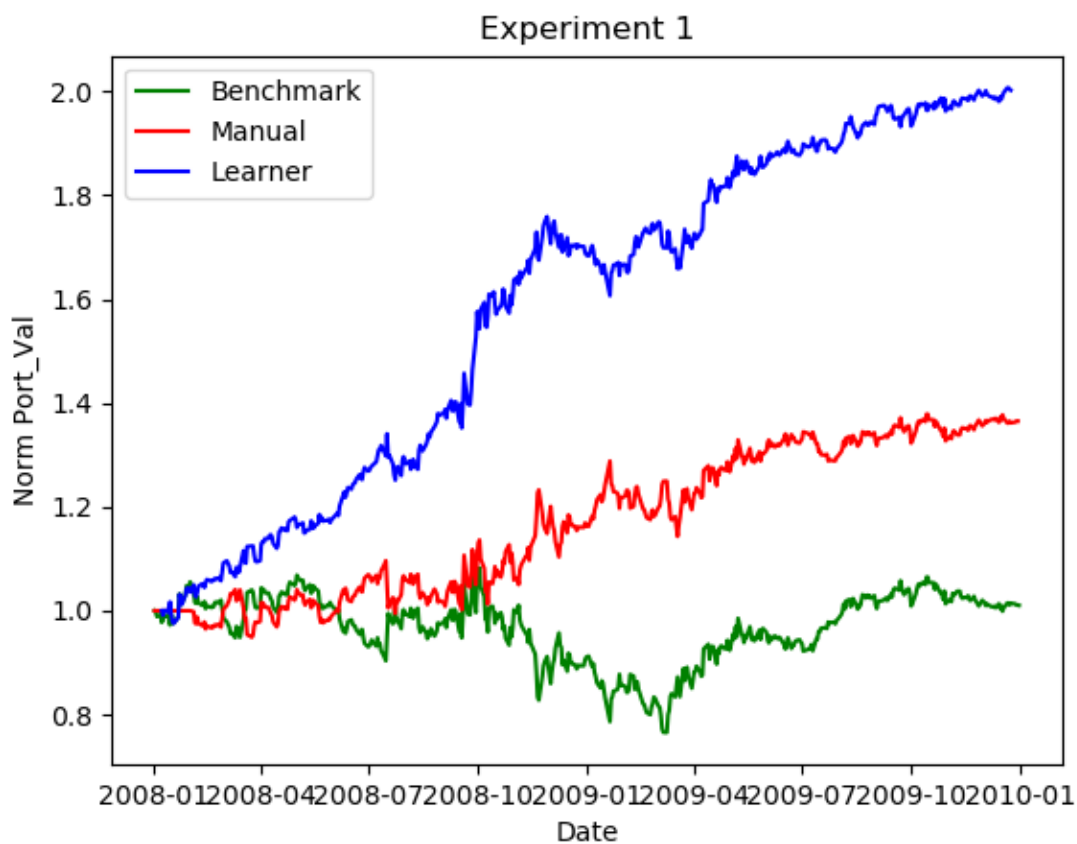
- In this trading problem, I use random forest as machine learning based model. Random forest groups certain number of random trees to minimize the random effects in each random forest model.
- The random forest model groups 15 random trees, each tree has a leaf size of 5. The random forest uses the mode of each random tree as output.
- The parameters are the indicators that I chose above: momentum, price/SMA ratio and Bollinger %. These are all numerical variables. We have this information for each trading day. The y is categorical. Is either we buy stock, sell stock or hold the position in that trading day.
- Since this is not q learning problem, there's no need to discretize data.

- To train the model, I use 10 day's return of the stock in the in-sample period to decide the strategy, if after 10 days the stock price is higher, we should buy, if lower, sell or if no change, hold the position. I assume today's momentum, Price/SMA ratio and Bollinger % can be used to forecast after 10 day's stock price change.

## EXPERIMENT 1:

In experiment1, I compare the performance of the strategy learner and the manual strategy. The same assumption in the manual strategy still applies.

Below is the chart: how strategy learning comparing with Manual strategy using in-sample data:



	Cumulative return	Mean daily return	Std daily return
Strategy learner	1.002	0.00146	0.0105
Manual strategy	0.365	0.000715	0.0139

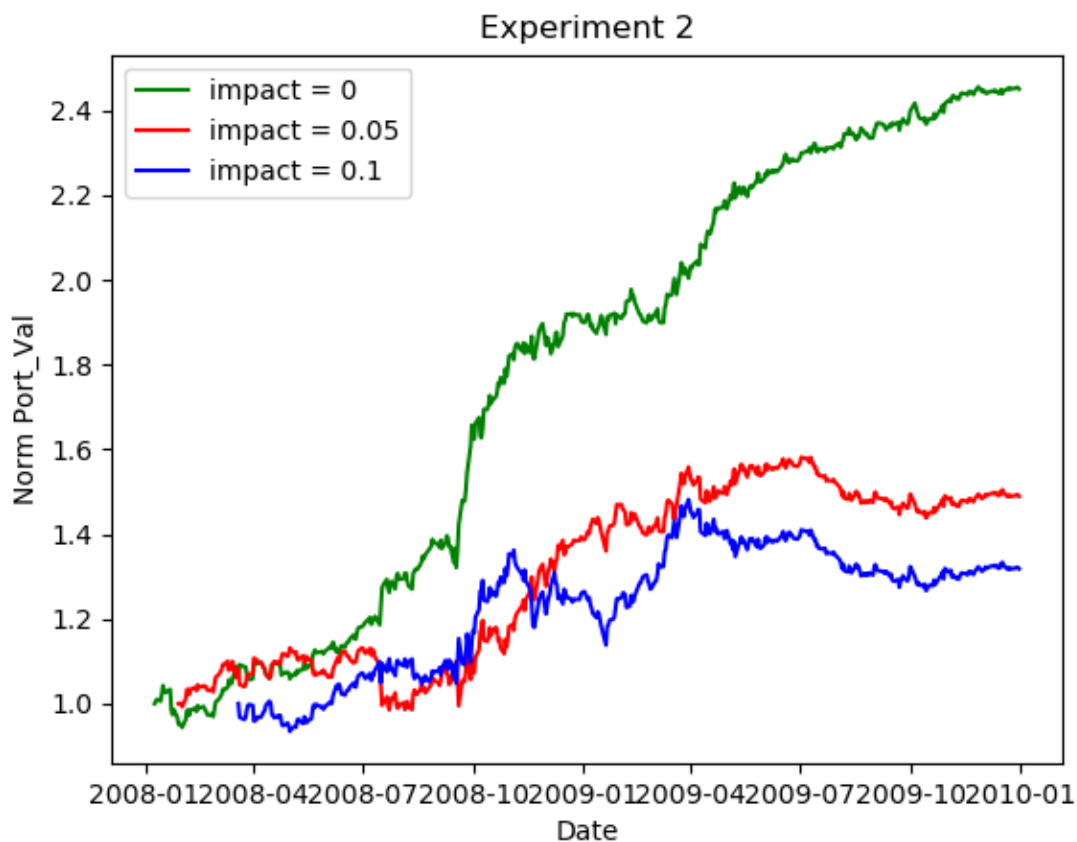
The strategy learner out-performs the manual strategy significantly. Not only the mean of the return, but also the standard deviation of the daily return, meaning the volatility is also small. This result is expected, as the comparison is only in-sample period. The model is trained in this

period so it is supposed to capture both real pattern and random pattern of this data set. So the strategy learner should perform better.

## EXPERIMENT 2:

In experiment 2, I compare different value of impact, and see how impact can affect in sample trading behavior.

I use 3 different value of impact: 0, 0.05, 0.1. Below chart shows the performance of different impact with in-sample period:



	Cumulative return	Mean daily return	Std daily return	Times of trading
Impact = 0	1.451	0.0018	0.0018	155
Impact = 0.05	0.489	0.0009	0.0009	34
Impact = 0.01	0.318	0.0007	0.0007	8

From the chart we can tell, the higher the impact, the cumulative return& standard deviation of return gets lower. The times of trading though each period also gets lowers.

Because we expect higher impact of each trading in the market, the harder we reach threshold to trigger a trade. Thus if one's trading has higher impact of the market, he tends to trade less and makes it hard to make profit. For someone like Warren Buffett, he needs to be very careful at each trading and it becomes more and more difficult to earn money when the amount of money he manages gets larger.