Project 8 Strategy Evaluation (Spring 2020)

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1 Indicator Overview

My Manual Strategy and Strategy Learner for this project are devised using the following three technical indicators: Bollinger Bands Percent, Price/Simple Moving Average (SMA) ratio, and Commodity Channel Index(CCI). Table 1 shows the parameters used for the indicators selected.

Bollinger Bands are a volatility indicator which creates a band of three lines which are plotted in relation to a security's price. The middle band is the Simple Moving Average and the upper and lower bands are two standard deviations away in their respective directions.

The SMA is the average stock of a price over a n-day period. The SMA provides insight into when the stock is overbought or oversold which in turn shows which way the price is moving.

Commodity Channel Index is another indicator that assists in identifying overbought and oversold by measuring an instrument's variations away from its statistical mean.

Table1: Parameters for selected indicators.

	Price/SMA ratio	Bollinger Bands® %(BBP)	Commodity Channel Index(CCI)
Parameters	SMA window =10	SMA window =10	SMA window = 10
			Constant = 0.015 (for scaling purposes)

2 MANUAL STRATEGY

2-1 Three indicators

Three indicators were combined together with below conditions.

1) Go long when:
   - Symbol is **oversold**, index is not.
   Price/SMA ratio < 0.95 **and**
   Bollinger Band % < 0 **and**
   CCI < -100
2) Go short when:
   - Symbol is **overbought**, index is not.
   Price/SMA ratio > 1.05 **and**
   Bollinger Band % > 1 **and**
   CCI > 100
3) Close positions when:
   - Symbol crosses through its SMA.

This manual strategy should work well because this trading result was determined by satisfying three different indicators' Buying signal or the Selling signal conditions.

2-2 Manual Strategy versus the Benchmark Comparison

The results of the in-sample time period showed that my Manual Strategy performed better than the benchmark for almost the entire time period except for a couple exceptions in the beginning. Then it drastically outperformed the benchmark as shown in Figure 1.

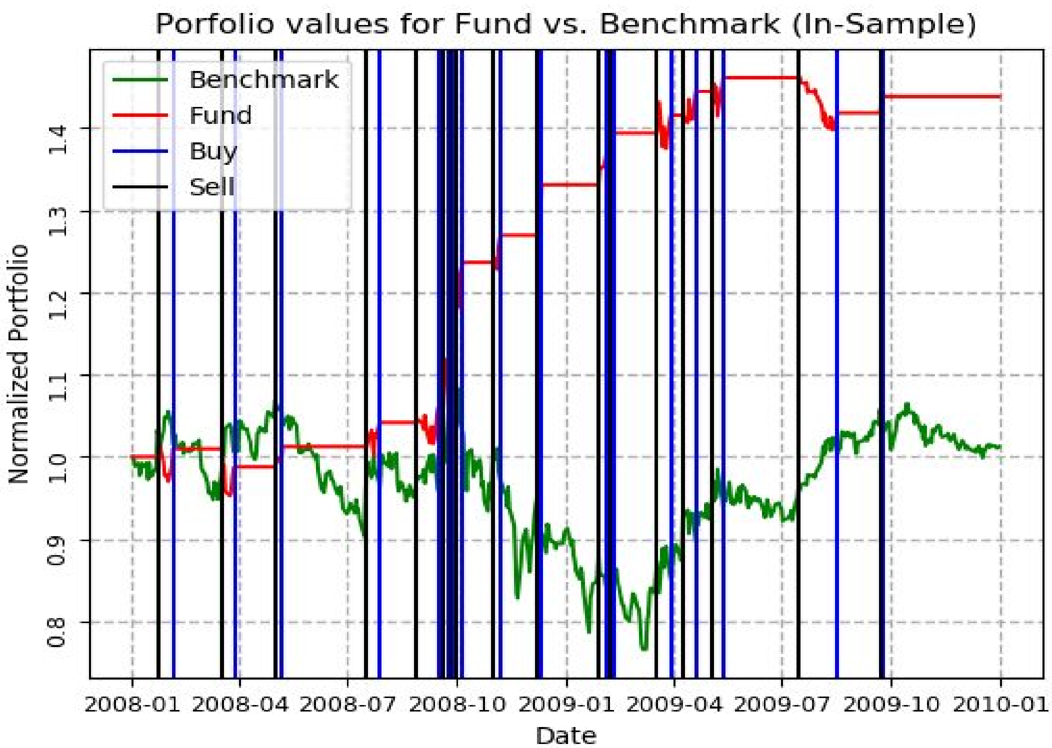

Figure 1: Benchmark vs Manual Strategy for the In-Sample

The results of the out-of-sample time period also showed better general performance than the benchmark. There were more fluctuations in this one when compared to the in-sample where the benchmark performed better but the overall result was still dramatically larger than the benchmark at the end of the time period. This result is shown in Figure 2.

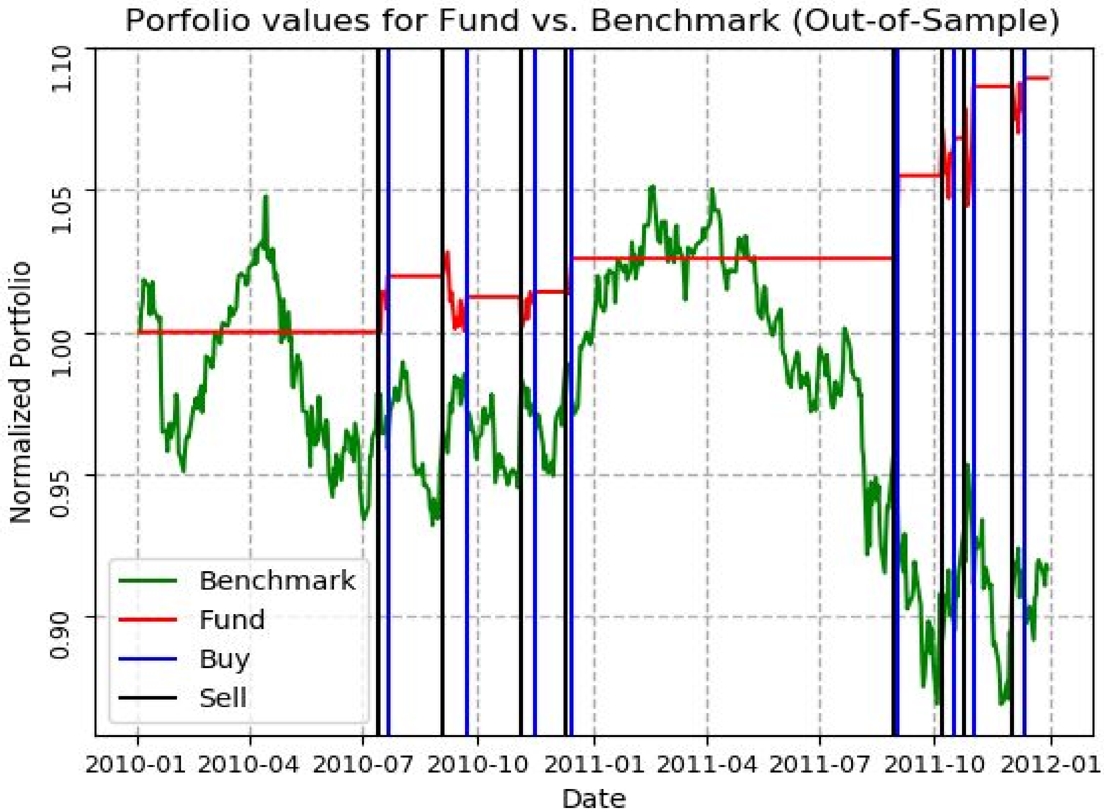

Figure 2: Benchmark vs Manual Strategy for the Out-of-Sample

2-3 Manual Strategy vs the Benchmark Out-of Sample Evaluation

My strategy in the out-of-sample time period was successful and had a fairly good performance result, however it probably could be improved by swapping one of my indicators for momentum. I used two trending indicators and one volatility indicator for my strategy. This strategy could be improved by removing one of the trending indicators and using a momentum indicator. This would pair with the trending indicator as it will look at speed and momentum of the price for a better result.

2-4 Results the performance of the stock, and the Manual Strategy for both in-sample and out-of-sample periods.

	Manual Strategy		Benchmark	
	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample
Cumulative return	0.4380	0.0894	0.0123	-0.0834
STDEV of daily returns	0.0.0071	0.0031	0.0170	0.0085
Mean of daily returns	0.0007	0.0002	0.0002	-0.0001
Sharpe Ratio	1.6747	0.9015	0.1569	-0.2568

3 Strategy Learner

In order to create a classification learner, I used a combination of the Random Tree Learner. The technical indicators from Project 6 were loaded to indicators dataframe and calculated the daily returns using the normalized prices. From there, I determined if the daily returns were the classifications of LONG(1), HOLD(0), or SHORT(-1). If the daily return was greater than YBUY(0.02) +2* impact, then it was classified as LONG. If the daily return was less than YSELL(-0.02) +2*impact, then it was classified as SHORT. After the above training the model, a data frame was created using out of sample data to represent trades for each day.

The optimization was preceded by adjusting the model parameter to gain better results.

4 Experiment 1 (Manual Strategy / Strategy Learner)

This experiment 1 was focused on comparing your Manual Strategy with the Strategy Learner that I have implemented.

Parameters that were used for this experiment are as the below.

```
Symbol="JPM"
StartDate= in sample : 2008,1,1 , out-of-sample: 2010, 1, 1
EndDate= in sample : 2009,12,31 , out-of-sample: 2011, 12, 31
```

StartValue=100000
commission=0.0
impact=0.000

Both StrategyLearner and ManualStrategy showed very good results in-sample data. However, the results of the Out-of-Sample data from Strategy Learner was very poor. The reason is that overfitting occurred during training of the Random Forest Learner model. I tried to reduce the overfitting of the model in various directions, but at this moment, I could not achieve much better results.

However, I can assure that better results can be obtained through parameter optimization such as for the number of bags or leaf_size of the Random Forest Learner.

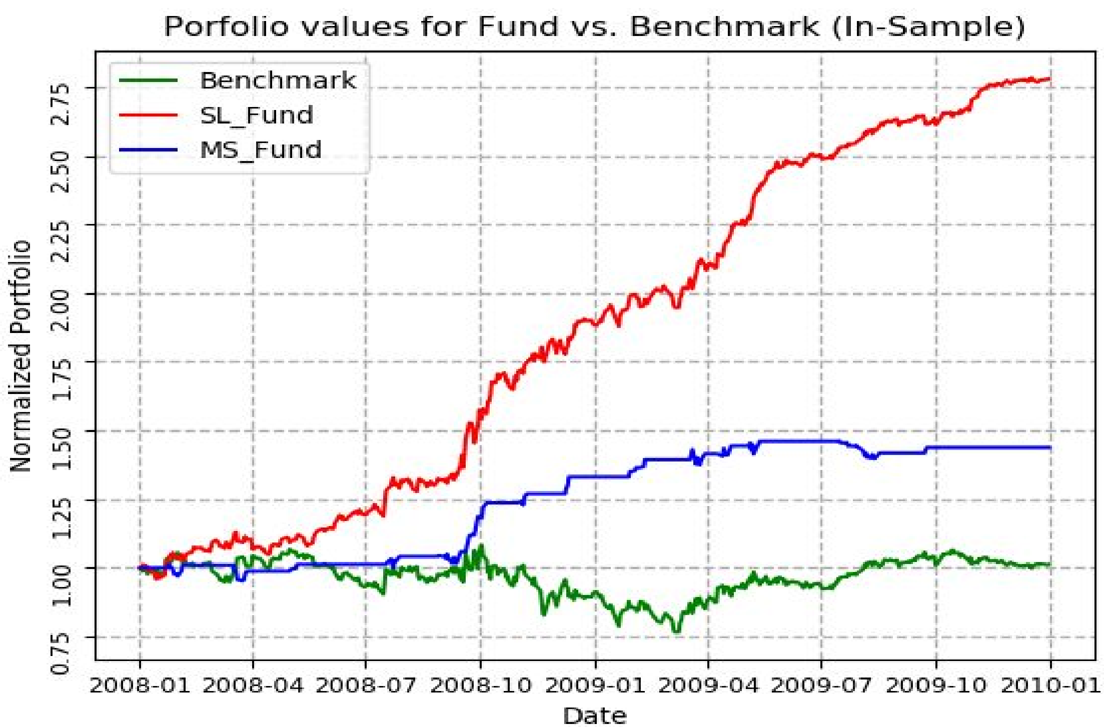

Figure 3: Benchmark vs Manual Strategy vs Strategy Learner for the In-Sample

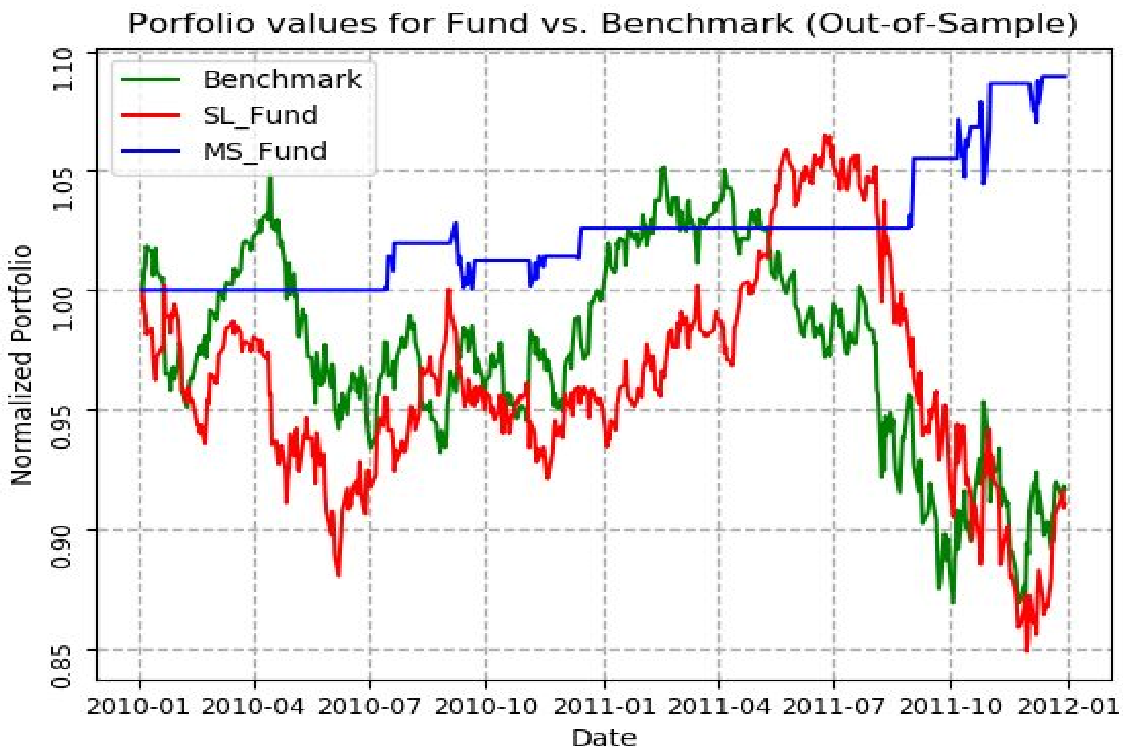

Figure 4: Benchmark vs Manual Strategy vs Strategy Learner for the Out-of-Sample

5 Experiment 2 (Strategy Learner)

5-1 Hypothesis

My hypothesis is the following:

By increasing the value of impact, the in-sample trading behavior will decrease over time compared to keeping it constant for the Average Daily Return and the Cumulative Return.

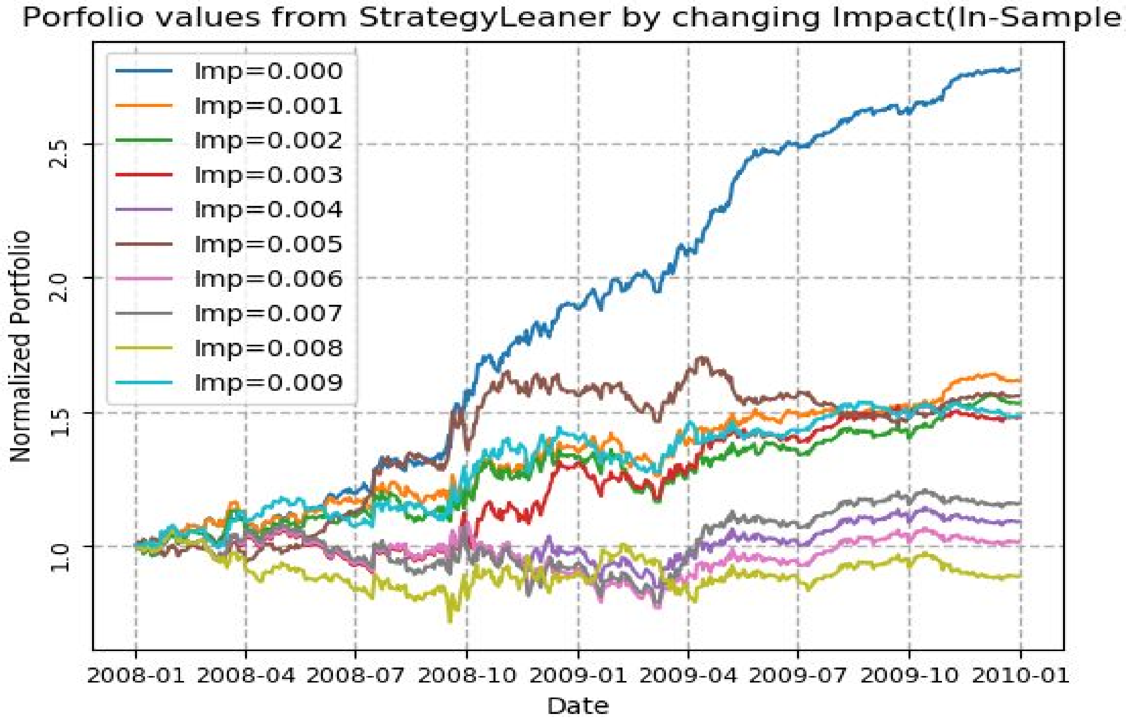

Figure 5: Value of Impact effects for the In-Sample

In this experiment, it is the result of observing the portfolio value by changing the Impact value from 0.000 to 0.009 under the same conditions as in Experiment 1. It is to observe how the Impact variable affects the final value of Portfolio. As mentioned, it was expected that the value of the portfolio would decrease as the impact value increased, but few impact data such as impact 0.004, 0.006, 0.007, 0.008 did not follow the trend. At this moment, it is not clear the reason for the observation.

REFERENCES

1. Mitchell, T. M. (2017). Machine learning. New York: McGraw Hill.
2. Retrieved from https://www.tradingview.com/wiki/