CS7646 Fall 2022 - Project 8: Strategy Evaluation

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Abstract—This project is a culmination of this semester's assignments, combining ensemble decision tree learners and technical indicator heuristics to implement two stock trading strategies competing against each other and a benchmark. Some restrictions exist such as a capped holding amount and simplified short, out, or long positions. The benchmark, manual strategy, and ensemble learner are compared by their cumulative returns, average daily return, and standard deviation of daily return.

1 INDICATOR OVERVIEW

1.1 Simple Moving Average

Simple Moving Average (SMA) is calculated with the formula:

$$SMA = (Price_1 + Price_2 + Price_3 ... + Price_n) / n$$

Where n is the number of days prior in which prices are aggregated to find their mean. Smaller n values give a closer match to actual price data, while larger n values result in a line less sensitive to volatility though at a cost of more lag time. I chose a period of 14 days for this project. To apply this metric as an indicator, I used PSMA.

$$pSMA = Price / SMA$$

A pSMA of 1 represents no difference in the SMA and price while pSMA > 1 shows an upwards trend and pSMA < 1 shows downward trend.

1.2 Bollinger Bands

The Bollinger Bands are an indicator that expands on SMA and is calculated by adding and subtracting 2 rolling standard deviations to the SMA. I used a window of 14 days.

$$Top\ Band = SMA + 2 * StdDev[t]$$

$Bottom\ Band\ =\ SMA\ +\ 2 * StdDev[t]$

To implement this in my trading strategies, I used pBB.

$pBB\ =\ (Price\ -\ Bottom\ Band)\ /\ (Top\ Band\ -\ Bottom\ Band)$

pBB represents the price's position within 2 standard deviations with a number centered at 0.50. At pBB = 1.00, the price is trending up and has hit the Top Band, while pBB = 0.0 means the price is at the bottom band having trended down, making pBB an indicator of outlier trending.

1.3 Momentum

Momentum is calculated with the formula:

$Momentum\ =\ Price_t\ /\ Price_{t-n} - 1$

Where $Price_t$ is the stock price at 't' date and n is the lookback period for which I used 14. When prices rise, momentum is seen to be positive, indicating buying pressure. While prices drop, momentum moves towards the negative, indicating selling pressure. Deviant momentum spikes from negative to positive, such as the one in March of 2009, would be seen as a buying indicator. Momentum also reflects the volatility in price as lower volatility keeps momentum near the 0 line, as seen in the last several months of data.

2 MANUAL STRATEGY

2.1 Indicator Implementation

pSMA, pBB, and Momentum were considered each day to determine whether to take a long, short, or out position through buying, selling, or holding. For this project, we start with a portfolio value of $100,000, are limited to holding positions of 1000 , 0 , or -1000 shares, and can only trade up to 2000 shares at a time when flipping between positions. The values of pSMA, pBB, and momentum are all indicators of deviant trend and I allowed any one of them that exceeds the bounds I gave them to trigger a trading decision.

For pSMA, which is centered on 1, I chose values below 0.8 and above 1.2 to trigger a trading response as these values represent a 20% change in price over the lookback period. Values below 0.8 would indicate a downtrend and trigger a buy order, while above 1.2 indicates an upwards trend and sell order.

pBB, is centered on 0.5 and I chose values below 0 and above 1 to trigger buy and sell responses respectively. This is because pBB of 0 or 1 represent a price touching the Bollinger Band and being 2 standard deviations away from the SMA. 2 standard deviations is a reasonable limit for statistical deviance so I chose it to drive trading.

Momentum is centered at 0 and represents the % difference between current price and past price. I am not as confident in this metric to drive good decisions as I am in the other two, so I chose values of less than -0.2 to trigger buying and above 0.2 to trigger selling. Momentum leaves the bounds less frequently than the other indicators.

2.2 Manual Strategy vs. Benchmark

When any of the indicators above leave their bounds, the manual strategy triggers a buy, sell, or hold. The benchmark on the other hand is set to hold a position of 1000 shares from day 1 and sell it on the last day.

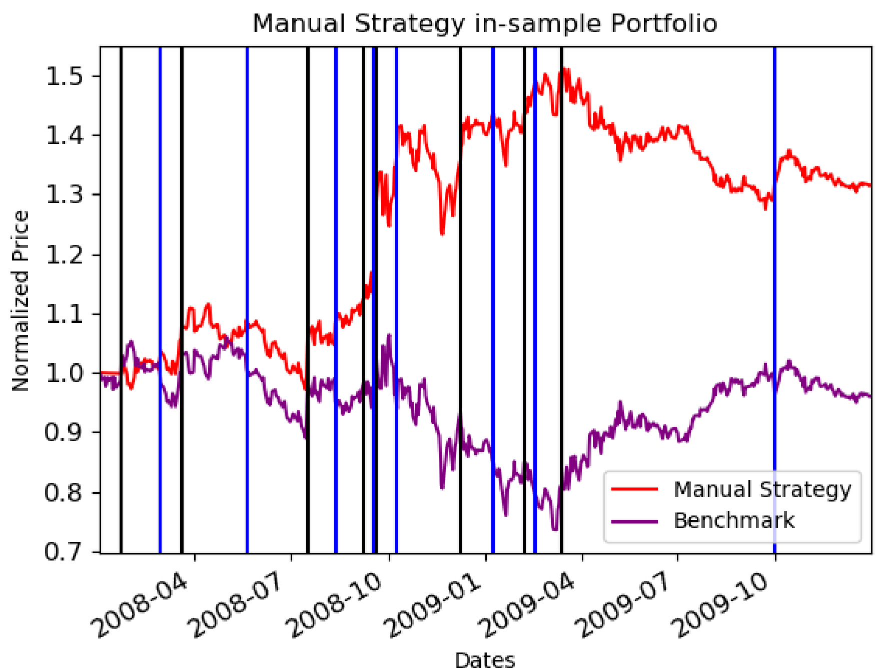

***Figure** 1—Manual vs Benchmark in-sample normalized portfolio value.*

As seen in *figure 1*, the manual strategy outperforms the benchmark on in-sample data between 2008/1/1 and 2009/12/31 on stock data for JPM. The bluelines represent times when the manual strategy chose long positions and the black lines represent short positions. The manual strategy did well with a +31.58% return on investment compared to the benchmark's -4% return. The manual strategy of course had a higher average daily return at 0.06% but also boasts a lower standard deviation of average return at 0.012 compared to benchmark's 0.017.

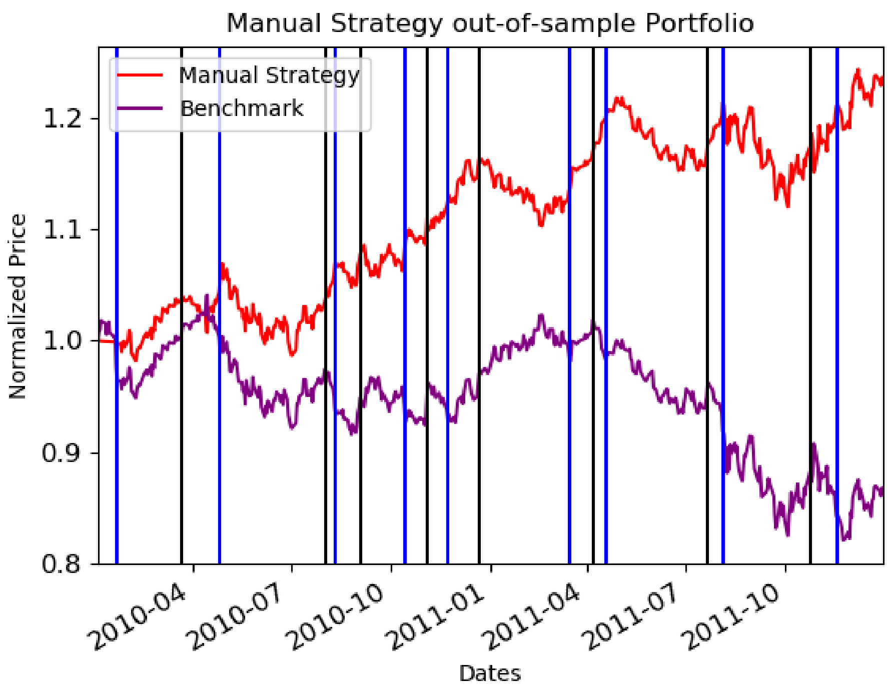

***Figure** 2— Manual vs Benchmark out-of-sample normalized portfolio value.*

Figure 2 shows the performance of these strategies on the testing out-of-sample data between 2010/1/1 and 2011/12/31. Again the manual strategy outperforms benchmark with a 23.47% return on investment compared to -13.54%. A lower standard deviation of daily returns is also seen in the manual strategy in 0.007 compared to 0.009.

In Sample: 2008-01-01 - 2009-12-31 for JPM	Out Of Sample: 2010-01-01 - 2011-12-31 for JPM
Manual Strategy - In Sample	Manual Strategy - Out Of Sample
Cumulative Return: 0.3157854206493309	Cumulative Return: 0.23468635129194437
Standard Deviation: 0.012461464265651943	Standard Deviation: 0.006941735095089588
Average Daily Return: 0.0006218446280199613	Average Daily Return: 0.00044325081275167815
Benchmark Strategy - In Sample	Benchmark Strategy - Out Of Sample
Cumulative Return: -0.039913745507146325	Cumulative Return: -0.13536508738224562
Standard Deviation: 0.017468249019795736	Standard Deviation: 0.008781865133658723
Average Daily Return: 7.09716619623517e-05	Average Daily Return: -0.00025061167508665436

***Figure** 3—Manual vs Benchmark statistics for in and out-of-sample performance.*

As typically expected, the manual strategy does not perform as well on the out-of-sample data as in training, however the results are still impressive. The trading heuristics chosen in training proved efficacy in outperforming the passive benchmark, winning advantages by reacting accordingly in periods of price volatility like 2010-07 and 2010-11 and after 2011-10.

3 STRATEGY LEARNER

3.1 Strategy Learner Implementation

The strategy learner is a random tree ensemble learner with 25 bags and leaf size of 5. The x training data comes from the pSMa, pBB, and momentum of the normalized JPM stock data from 2008-1-1 to 2009-12-31, while y training data is generated by looking at normalized price data 14 days ahead and recording the optimal holding position. Normalizing the price data makes for easier interpretation later on.

BagLearner and RTLearner's add_evidence and build_tree methods are called to train the random forest. A minimum 5 leaf size is used to help overfitting the training data and 25 trees or bags are used to build the forest.

The indicator values of JPM price data from 2010-1-1 to 2011-12-31 is the x test data. Query methods are called to bag the trees, using modes of each tree's classifications to enforce the majority vote mechanism and build a y test set. This y_data is a set of instructions on whether to buy, sell, or take no action that will act on the price data.

Because holdings are limited to 1000, -1000, or 0 shares at any one time, a flag is used to reflect our current holdings and determine what trades are valid. A flag equal to 0, means we can buy or sell 1000 shares, while a flag of -1 or 1 allows us to buy or sell 2000 shares. After the flag is identified, we test the y value for being greater than or less than 0 and trade accordingly. These trades are applied to the price data through the market simulator.

4 EXPERIMENT 1

4.1 Experiment 1 Implementation

Experiment 1 simply applies the strategy learner on the JPM price data to be compared with the manual strategy and benchmark. The benchmark is produced with a function that buys and holds 1000 shares until the end of the date range. The manual strategy trades from indicator heuristics are determined with the ManualStrategy.testPolicy() method and the random forest's trades are made with StrategyLearner.add_evidence() and StrategyLearner.testPolicy() methods. All of these trades are then passed through the marketsimcode.compute_portvals() function to return the portfolio values and other statistics. The portfolio values are normalized and plotted.

In this experiment all market sims are done with a starting value of $100,000, impact of 0.005, and commission of $9.95. In-sample data is JPM price data from 2008-1-1 to 2009-12-31 and out-of-sample data is 2010-1-1 to 2011-12-31.

I believe the Strategy Learner will perform best on insample data because tree based models are prone to overfitting. A leaf size of 5 and 25 bags will help, but it will still overfit more than simple manual heuristics. I expect the bagger to do better on out-of-sample data as well, however, as the random trees should do a better job generalizing.

4.2 Experiment 1 Outcome

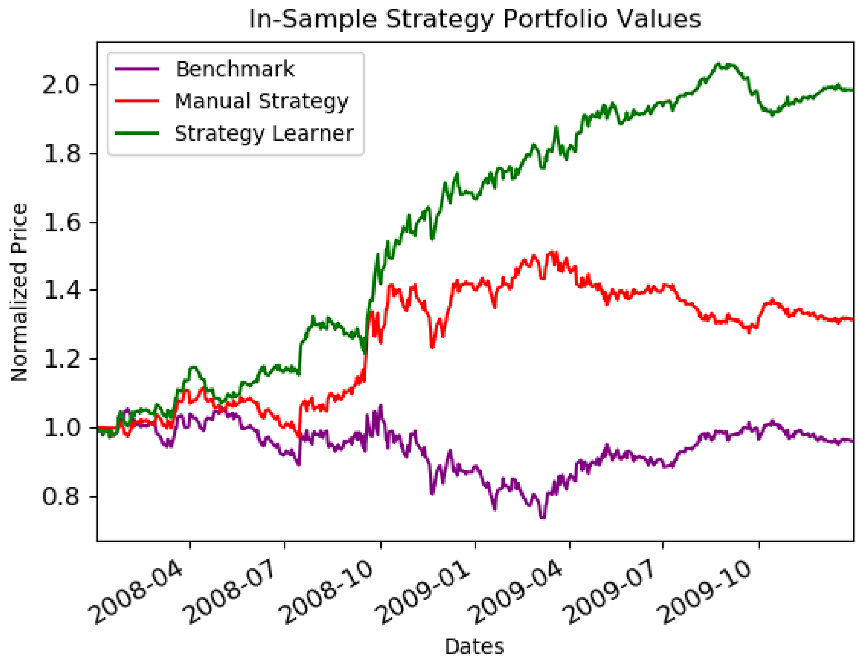

Figure 4*—Strategy vs. Manual vs Benchmark in-sample performance.*

Here we see the strategy learner performing well on the in-sample data, finishing with a return of +98.46% compared to manual strategy's +31.58%. This is to be expected from the forest model because of its relatively low leaf and bag size.

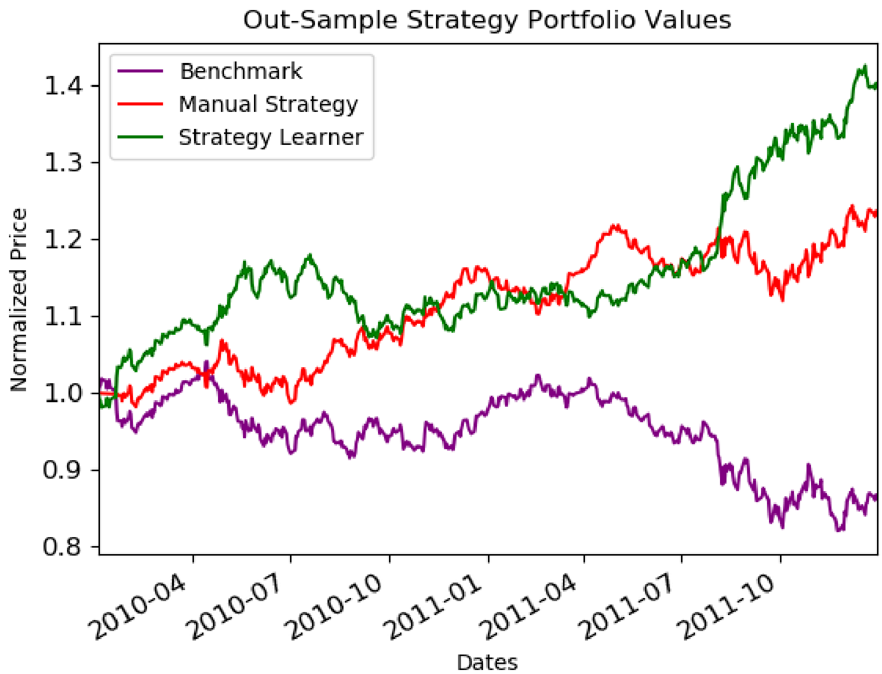

***Figure** 5—Strategy vs. Manual vs Benchmark out-sample performance*

The strategy learner also performs the best on out-of-sample data with a cumulative return of +40.08% compared to the manual strategy's +23.47%. Despite some overfitting concerns, the bagger managed to generalize fairly well. Interestingly it seems to slightly inverse the manual strategy returns, causing them to intersect multiple times as they increase. Both these strategies have very similar std deviations on their average returns.

In Sample: 2008-01-01 - 2009-12-31 for JPM
with commission = 9.95 & impact = 0.005

Benchmark - In Sample
Cumulative Return: -0.039913745507146325
Average Daily Return: 7.09716619623517e-05
Standard Deviation: 0.017468249019795736
Final Portfolio Value: 95814.40000000148

Manual Strategy - In Sample
Cumulative Return: 0.3157854206493309
Average Daily Return: 0.0006218446280199613
Standard Deviation: 0.006941735095089588
Final Portfolio Value: 131565.44999999763

Strategy Learner - In Sample
Cumulative Return: 0.9845517481865422
Average Daily Return: 0.0014191108780415333
Standard Deviation: 0.010835021598547646
Final Portfolio Value: 198053.6999999961

Out Of Sample: 2010-01-01 - 2011-12-31 for JPM
with commission = 9.95 & impact = 0.005

Benchmark - Out Sample
Cumulative Return: -0.13536508738224562
Average Daily Return: -0.00025061167508665436
Standard Deviation: 0.008781865133658723
Final Portfolio Value: 86278.20000000147

Manual Strategy - Out Sample
Cumulative Return: 0.23468635129194437
Average Daily Return: 0.00044325081275167815
Standard Deviation: 0.006941735095089588
Final Portfolio Value: 123456.34999999909

Strategy Learner - Out Sample
Cumulative Return: 0.40079540455193174
Average Daily Return: 0.0006929355593084777
Standard Deviation: 0.006743761805928274
Final Portfolio Value: 139779.3499999977

***Figure** 6—Strategy vs. Manual vs Benchmark statistics for in and out-of-sample performance.*

5 EXPERIMENT 2

5.1 Experiment 2 Implementation

For experiment 1 we used a market impact of 0.005, which is a measure of how strongly our trades shift the price of the stock against us. In experiment 2, we look to observe the effect that various market impacts have on the strategy learner's in-sample performance. This is done by simply running the strategy learner multiple times and changing the impact parameter. We keep commission at 0 for this experiment. I expect impact to lower in-sample performance as it increases, as the concept of impact counteracts returns.

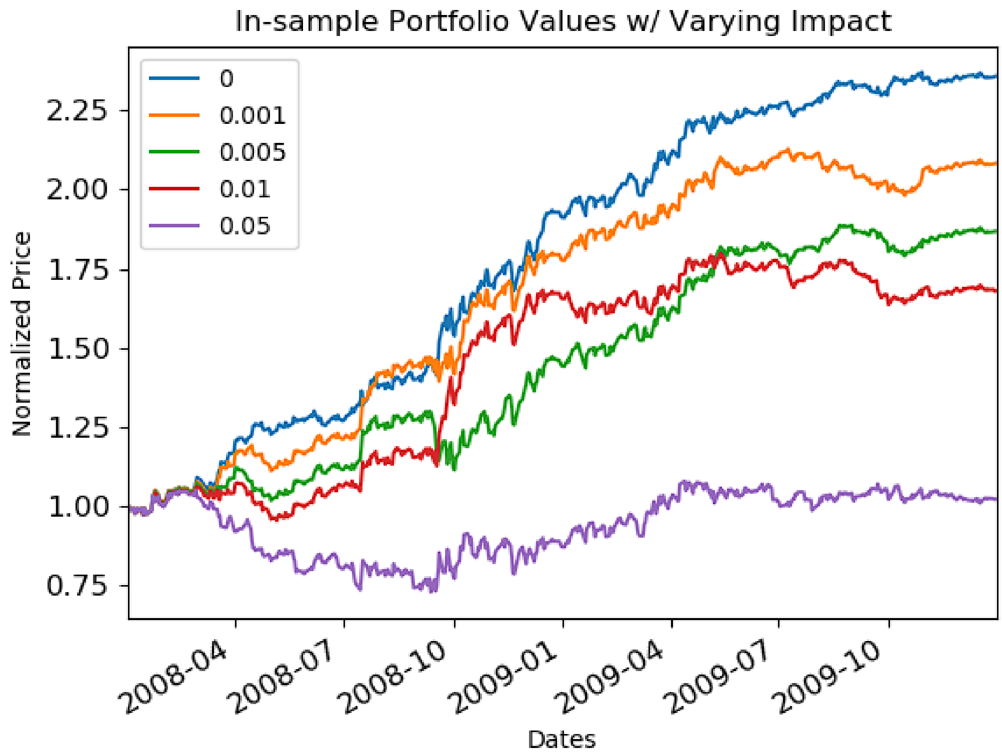

***Figure** 6—StrategyLearner in-sample portfolio values with varying Impact values*

As expected, greater impacts do appear to negatively affect in-sample performance, with impact=0 having +135.93% return and impact=0.05 having +2.32%.

However, it is interesting to note that there are intersections before the ending date. Most notably, in impact values of 0.01 and 0.005, the larger impact value 0.01 intersects and outperforms the latter for an extended period of time before coming back down to end with a cumulative return of + 68.10%, underneath impact=0.005 at +86.68%.

The impact=0.01 performance also has a lower standard deviation of daily returns at 0.01156 compared to impact=0.005 having a std dev of 0.01215. This makes me hypothesize there is more at play than simply an inverse relationship between impact and cumulative returns. A moderate impact may be beneficial at moderating the strategy learner's decision making by demanding higher expected value out of trades.

This inspired me to add in a count of the number of trades made by each learner. The count reveals that the impact=0.001 learner made 93 trades, the most contrary to my assumption. It is followed by impact=0 making 87, impact=0.005 making 85, impact = 0.01 making 82, and impact = 0.05 making 43.

In Sample: 2008-01-01 - 2009-12-31 for JPM with commission = 0.0 & varying impacts

Strategy Learner - Impact = 0
Cumulative Return: 1.2585000000000002
Average Daily Return: 0.0016732769803707007
Standard Deviation: 0.010564269709978613
Final Portfolio Value: 225850.0
Total # of Trades: 87

Strategy Learner - Impact = 0.001
Cumulative Return: 1.3719519899305275
Average Daily Return: 0.001764143340730933
Standard Deviation: 0.009927033726347744
Final Portfolio Value: 237103.95000000013
Total # of Trades: 93

Strategy Learner - Impact = 0.005
Cumulative Return: 1.150721412637207
Average Daily Return: 0.0015723813640663306
Standard Deviation: 0.01021106075804103
Final Portfolio Value: 214658.4499999999
Total # of Trades: 85

Strategy Learner - Impact = 0.01
Cumulative Return: 0.6718506092939542
Average Daily Return: 0.0011052170242050754
Standard Deviation: 0.013059949688485261
Final Portfolio Value: 166541.90000000002
Total # of Trades: 82

Strategy Learner - Impact = 0.05
Cumulative Return: -0.5001809811728601
Average Daily Return: -0.0010430847550165644
Standard Deviation: 0.025615922436908807
Final Portfolio Value: 49020.499999999985
Total # of Trades: 43

***Figure** 7—StrategyLearner in-sample stats with varying Impact values*