Project 8 – Strategy Learner

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1 INTRODUCTION

This project will compare performance of stock trading strategies. The first is referred as the baseline which consists of buying a single stock and holding until the end of the testing period. The second is a manually created strategy based on technical indicators and domain knowledge, where I have set the thresholds for the various indicators to determine a buy or sell. The final strategy uses a random forest to determine when to buy and sell stocks. I hypothesis that the random forest will significantly outperform both the manual and the baseline strategies. I also hypothesis that impact will determine the frequency at which trades are executed, a higher impact would correspond to less trades and conversely a lower impact to more trades. The in-sample date range used for this project will be from January 1, 2008 until December 31, 2009. The out of sample range used will be from January 1, 2010 until December 31, 2011. Commission is the cost of a trade and will be specified when used, impact is a trading penalty which is symbolic of a loss in profitability, typical value of 0.005 will be used. Valid number of stocks within a buy or sell are dependent of the current holdings but must be one of five values: -2000, -1000, 0, 1000, 2000. The portfolio has a starting value of $100,000, with a maximum stock holding of 1000 and minimum stock holding of -1000.

2 INDICATOR OVERVIEW

The technical indicators used in this project will be Relative Strength Index (RSI), Bollinger Band Percent (BBP), Moving Average Convergence Divergence (MACD). The strategy learner optimized the parameters for the various indicators as well as the threshold to buy or sell by iterating over a large combination of values. This was a very time-consuming process because training the random forest was not parallelized. The manual strategy was optimized by starting with commonly accepted values for one indicator such as the 0.3 and 0.7 for BBP and matching parameters of the other indicators based on signals. I crossed referenced the adjusted closing price with the signals of the indicators to validate changes. An example of this would be if setting a parameter which then causes that indicator to sell every time the stock is very low; this would be a mistake and should be changed to buy that stock instead.

The RSI indicator is typically used to indicate if a stock is oversold or overbought. When a stock is overbought, this may suggest a good time to sell a stock because there will be selling pressure; as in having more people selling the stock than are buying; and the stock price should begin to decrease. When a stock is oversold this may suggest a good time to buy as the buying pressure; which means having more people buying the stock then people selling; tends to move stock prices upward. The strategy learner found window of 2 to be optimal for RSI and the manual strategy used values greater than 75 as a selling signal and less than 57 as a buying signal.

The BBP indicator is derived from using the Bollinger band indicator which consists of multiple measurements. Bollinger bands are thresholds set by two standard deviations above or below a stock. When a stock exceeds those thresholds, it would indicate abnormally low or high stock prices and to make the appropriate trade. A BBP above 0.7 suggests the stock should be sold and under 0.3 should be bought. The commonly used values produced great results in the manual learner. Further optimization of the values for BBP found that a BBP of less than 0.39 for buying and above 0.63 for selling was best. The strategy learner found that a window of 3 was best for BBP.

The MACD indicator also uses multiple subcomponents to provide signals of when to buy or sell a stock. Since there are multiple subcomponents, I combined the MACD and its signal into a single indicator. This newly merged indicator is positive when the signal line is above the MACD and negative when the signal line is below the MACD. When the new indicator is positive it suggests times to sell a stock and when it is negative as times to buy. For the strategy learner the window size of 10 was found to be optimal for MACD. In the manual strategy a signal to buy was created when the merged MACD was less than 0.12 and to sell when greater than 0.77.

3 MANUAL STRATEGY

The manual strategy is created by looking at the technical indicators and determining when a buy or sell should occur. One of the advantages of the manual strategy is domain knowledge can be directly injected into the strategy. One of the draw backs would be having to do things manually. In many cases there may be patterns in the data which are not detected by the person creating the strategy. This is where a strategy learner would be more beneficial as those patterns are picked up and help to translate the data into better buy and sell signals. A manual strategy does allow for more granular decision making over the signals produced but does require someone knowledgeable enough to make those granular decision.

In sample testing is where we train on a set time period and then test on that same time period. I started by looking at the BBP and using a commonly accepted range of values 0.3 to 0.7 as my threshold. I validated these values by just looked at one indicator at a time and then comparing the actions of the strategy to what I would expect should happen. An example of this would be verifying that when a stocks BBP is above 0.7 it could be considered oversold and stock should go up from there due to the buying pressure. The optimized values used to indicate a buy were for BBP was less than 0.12, MACD was less than 0.12 and RSI was less than 57. The signal to sell is when the BBP was greater than 0.63, MACD greater than 0.77 and when RSI is greater than 0.75. Market impact takes the thresholds and either increases or lower that threshold by the impact value as a percent of the total. For example, if the threshold to buy with RSI was less than 57 and the impact was 0.005. I would then take 57 and multiple it by (1 – impact) which is 57 * 0.995, and the new threshold becomes 56.715. This method makes buying more frequent when impact is low and less frequent with higher impacts. This leaves me with three individual signals, to produce a single signal I added the three signals together. This can result in values of -3 and +3, I then binned the results if ≥ 2 the final signal would be a 1. If the result is ≤ -2, the final signal would be -1, otherwise the remaining were set to zero. The strategy looks at the indicators and where they correspond to low and high stock prices and I hypothesize this will be a good overall strategy. I would expect it to buy stock when the stock's price is low and is expected to increase. I also would expect it to sell when the price is high and expected to lower.

Figure 1 shows the manual strategy in red normalized to start at 1.0, the benchmark is show in green and normalized to start at 1.0. There are blue vertical lines which indicate long entry points and black lines which indicate short entry points. There are some instances where there are two or more of the same colors beside each other. This was due to the ability to trade in increments of 1000 if the maximum holding of 1000 shares held. How this can occur is if we are at a holding of either -1000 or +1000. This would allow for two consecutive trades of the same type to occur if they are in 1000 increments. If our holdings are at -1000 and I buy 1000 shares, my total holdings are now at 0 this means I can then buy another 1000 shares which would then put my total holdings to +1000.

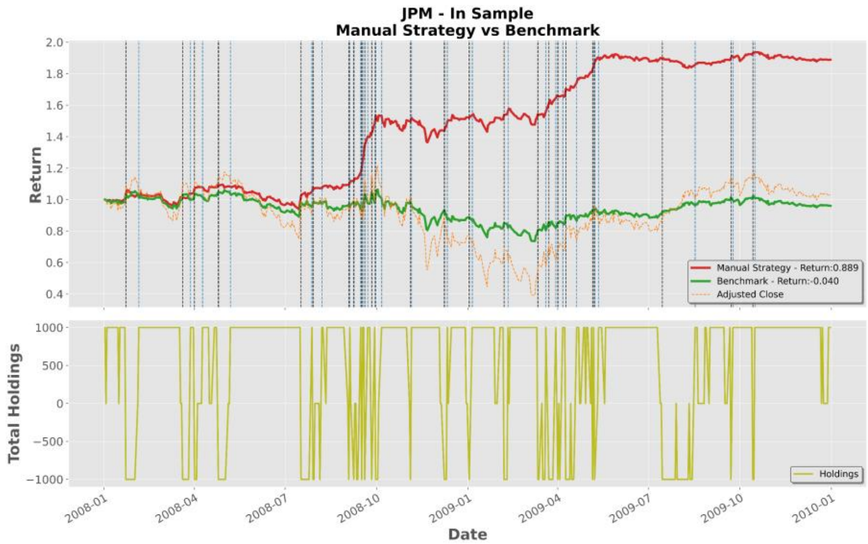

Figure 1—Manual strategy versus Benchmark on in-sample data.

As expected, the manual strategy performed better than the benchmark because we were able to capitalize on the stock change. This was due to being able to look at the data and make changes to the strategy as to perform better.

Out of sample testing is where we train on a certain time period, then test on a time period which was not used during training. The manual strategy performed much worse that I had expected. The reason was that the manual strategy was created using the in-sample data, this means it knows how to behave when it sees those examples. This being the out of sample test, the changes in the data was not adjusted for in the strategy. I was expecting the manual strategy to perform at least better than the benchmark.

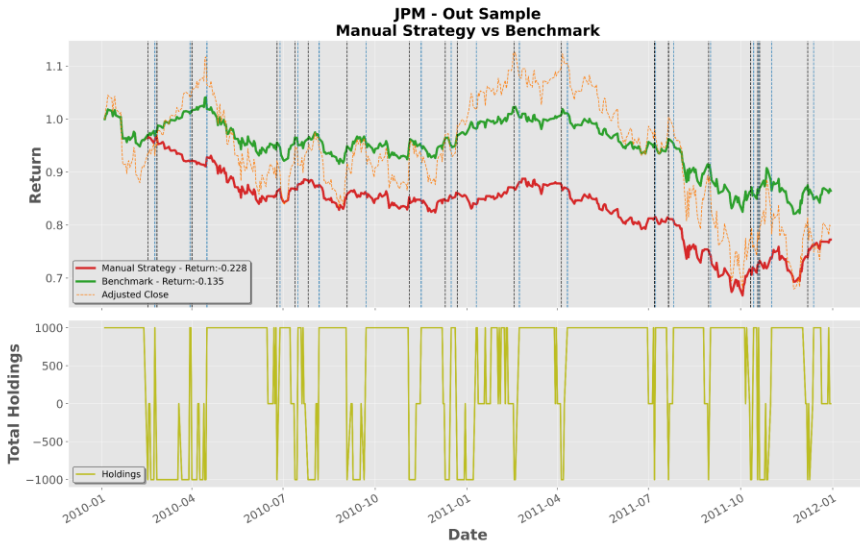

Figure 2 — Manual strategy versus Benchmark on out of sample data

The table below shows the cumulative return, the standard deviation of daily returns and the average of daily returns for the manual strategy and benchmark for both in sample and out of sample data. The manual strategy performed much better than the benchmark for in sample data, having a cumulative return of 0.892. The manual strategy performed worse than the benchmark in out of sample data and I was not expecting this result. I expected the out of sample performance to be much lower than the in sample of the manual strategy, but I had not expected it to perform worse than even the benchmark.

Table 1 — Manual strategy and Benchmark results.

	In Sample		Out Sample	
Name	Manual	Benchmark	Manual	Benchmark
Cumulative Return	0.889	-0.040	-0.228	-0.135
Standard Deviation of Daily Returns	0.011	0.017	0.009	0.009
Mean of Daily Returns	0.001	0.000	0.000	0.000

4 STRATEGY LEARNER

The strategy learner takes advantage of a random forest to predict the signal for a buy or sell of the stock. It does this by training many random decision trees on the technical indicators and the provided labels. The first thing was to generate labels for the training set. This was completed by looking at N day returns and setting the corresponding label as a buy or sell based on whether the return was greater than or less than set values for Y_Buy and Y_Sell. BBP, RSI and MACD were the technical indicators used. If I were to use the OBV and Vortex indicators it would have provided more information to the random forest and likely would have produced better results. Being that we are comparing the performance of the manual strategy with the random forest, it would not be an accurate comparison if I allowed one strategy to have more information than the other. To be able to use the random forest then data would need to be augmented and scaled. I implemented a Min/Max scaling which takes the dataframe and divides it by the mean and then is divided by the standard deviation of the dataframe. The reason I did this was to reduce the overall scale of the indicators and make it easier for the decision tree to split the data. All hyper parameters were determined through exhaustive searching. This was a very time-consuming process. The final hyper parameters used in the strategy learner was a one day return, Y_Buy of and a Y_Sell of , I used a window of three for BBP, two for RSI, and ten for MACD, I used 100 learners in the forest and each had a leaf size of 5, the Y_Buy was 0.001 and the Y_Sell was -0.001.

The in-sample results for the strategy learner were not as good as I had expected but I was able to beat the benchmark. It is clear the strategy learner made many more entries into LONG and SHORT positions when compared to the manual strategy.

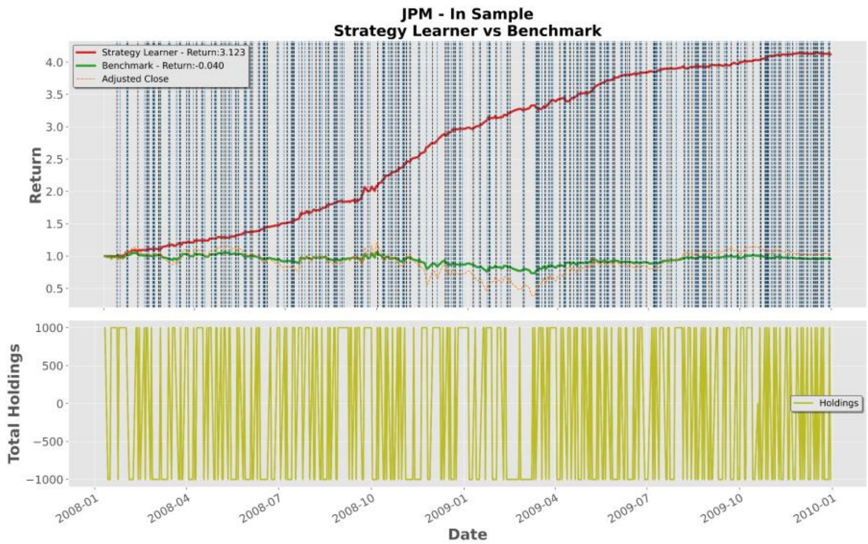

Figure 3—Strategy learner versus Benchmark on in-sample data.

The out of sample results were much worse than I had anticipated. I expected the learner to underperform when compared to the in-sample test, but I had not expected the cumulative returns for the learner on out of sample data to be -0.706.

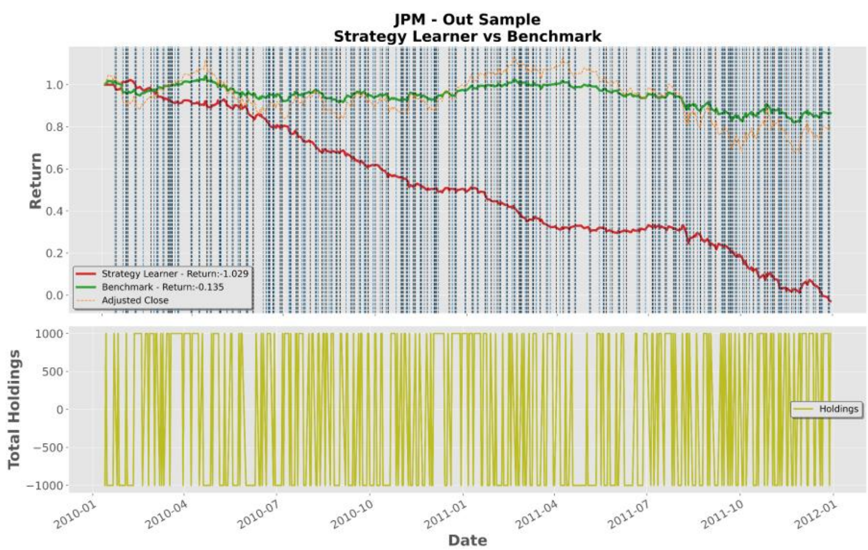

Figure 4—Strategy learner versus Benchmark on out of sample data

Figure 4 shows a clear negative trend line for the Strategy learner on out of sample data. The out of sample data testing could have been improved by increasing the number of days used for return calculation as well as increasing the leaf size in the trees and increasing the number of learners used.

5 EXPERIMENT ONE

Experiment one compares the manual strategy, the strategy learner and the benchmark. My original hypothesis was that the strategy learner would significantly outperform both the manual and the benchmark on in-sample data. Figure 5 clearly shows that my original hypothesis was correct. The reason I believe it was able to perform better than the manual strategy was due to fact, I was making the decisions about how the strategy should behave and I am not a stock expert. The next reason and arguable the most important one, was that my learners with a leaf size of five and having 100 learners to work with, were able to capture much information that I could process manually. This allowed my learners to overfit the in-sample training data which evident when you look at the out of sample data and performing so poorly using the strategy learner.

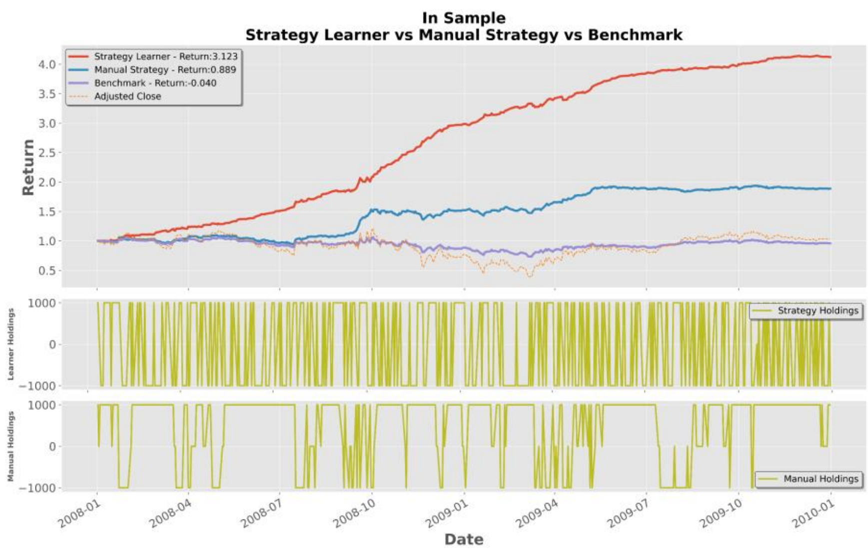

Figure 5 — Experiment one, Strategy Learner versus Manual Strategy versus Benchmark on in-sample data.

6 EXPERIMENT TWO

Experiment two explores the way impact changes in-sample trading behavior. I hypothesize that as impact increases there will be less and less trades executed, and I would expect the cumulative return to lower with higher impact.

I reduced the number of bags used in the random forest from 100 to 50 due to time constraints.

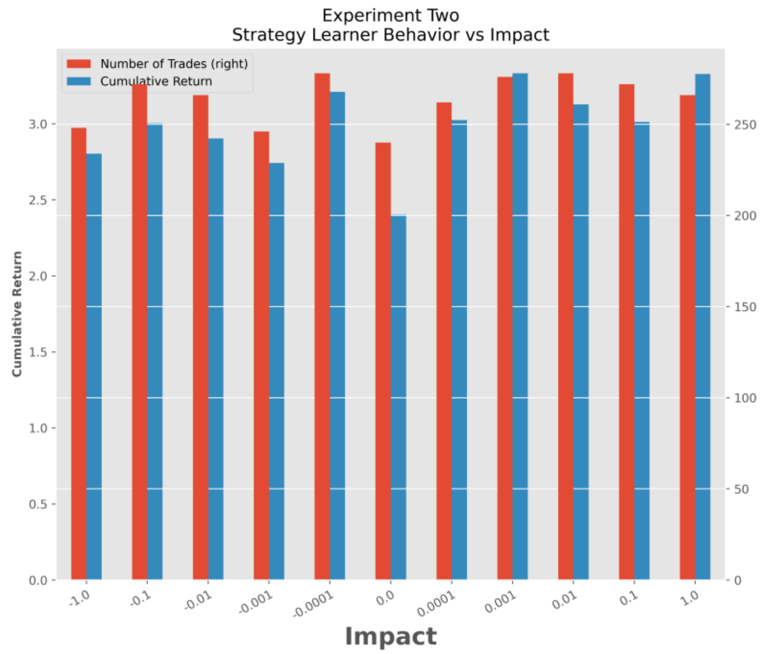

Figure 6—Manual strategy versus Benchmark on in-sample data.

Figure 6 shows the results from varying the impact from -1 to +1 and it shows that my hypothesis was wrong. The way impact is used is that it reduces the multiplier applied to the Y_Buy and Y_Sell. The formula being $return > | < (Y_{Buy}|Y_{Sell}) * (1.0 \pm impact)$. When impact is -1.0 this would essentially multiple the Y_Buy or Y_Sell by 2, and this would make trading much harder. Conversely when impact is 1.0 it will essentially turn Y_Buy or Y_Sell into 0 and this makes any positive returns sell and negative returns buy, which would translate into many more transactions and possibly more return. It appears that as impact is increased my cumulative return is going up as well as the number of trades. The way impact is used in my strategy learner uses impact as a multiplier of the Y_Buy or Y_Sell. This was the reason I thought a higher impact would produce lower results overall and less trades.

7 REFERENCES

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