Project 8: Strategy Evaluation (CS7646)

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1. INTRODUCTION

In this project, we have developed a Manual Strategy and a Machine Learning based strategy learner to beat the stock market. We have picked up three stock market indicators namely, Simple Moving Average (SMA), Bollinger Bands, and Momentum. These three indicators are chosen from the list of indicators that we presented in project 6. We have analyzed these two strategies and compared their performance against a benchmark (JPM) using both in-sample and out-of sample data. To generate the charts and simulations results for this report, the random seed was set to 1481090000 (same as the grading script provided). Both manual rule based strategy and the strategy learner is expected to beat the market for in-sample data.

2. INDICATOR OVERVIEW:

I have picked up Simple Moving Average, Bollinger Bands, and Momentum as indicators for the Manual Strategy as well as the stagey learner implemented in this project. A certain threshold was set to each of the indicators to identify a 'BUY' or 'SELL' signal in the Manual Strategy Implementation. For the Strategy Learner, we have used the indicators over the entire trading period to form our feature matrix.

i. Simple Moving Average (SMA): The SMA (simple moving average) is calculated by adding recent prices and dividing that figure by the number of time periods (also known as window or look-back period) as shown in the equation 1. For this project, we have used the ratio of **Price/SMA** as our indicator. The look back window is set to 14 for all the simulations.

$$SMA[t] = (1/n)\sum_{i=0}^{n-1} price[t-i] \qquad (1)$$

ii. Bollinger Bands: Bollinger Bands are volatility bands placed 2* stdev (standard deviation) above (upper band) and below (lower band) the simple moving average (SMA) line (equation 2). For this project, we have calculated the Bollinger Bands Percentage (**bbp**) and used that as our indicator.

Similar to Price/SMA, the look back window is set to 14 for all the simulations.

$$upper\_band[t] = SMA[t] + (2 * stdev[t])$$

$$lower\_band[t] = SMA[t] - (2 * stdev[t]) \qquad (2)$$

$$bbp[t] = (price[t] - lower\_band[t])/(upper\_band[t] - lower\_band[t])$$

iii. Momentum: Momentum is a simple indicator which is the rate of acceleration of the price or the volume. It's considered as an oscillator and is used to identify trend lines. Momentum is calculated using equation 3. For this project we have used a look back window (N) of 14 days.

$$momentum[t] = (price[t]/price[t - N]) - 1 \qquad (3)$$

3. MANUAL STRATEGY:

We have implemented a manual rule based strategy using certain threshold limit for different indicators to identify BUY and SELL signals to conduct trade. We are given the following constraints to determine the optimal portfolio:

- we can be in one of the three states in-terms of holdings: -1000 shares, +1000 shares, 0 shares
- we can trade a maximum of 2000 shares at a time as long as we maintain the above requirement of holdings
- For trading, we have used 'JPM' shares (in-sample period: January 1, 2008 to December 31, 2009 and out-of-sample period: January 1, 2010 to December 31, 2011)
- Commission is $9.95, impact is 0.005, and the starting value is 100,000.
- Portfolio values were normalized to 1 at the start.

We have combined the three selected indicators (SMA, Bollinger Bands, and Momentum) to decide trading decisions and has the following steps:

- If the current holding 0 shares: We buy 1000 shares if: bbp[t]<0 and Price/SMA[t]<1 and momentum[t]<0. However, we sell 1000 shares if: bbp[t]>0 and Price/SMA[t]>1 and momentum[t]>0.

- If the current holding is -1000 shares: We buy 2000 shares if: bbp[t]<0 and Price/SMA[t]<1 and momentum[t]<0.
- If the current holding is +1000 shares: We sell 2000 shares if: bbp[t]>0 and Price/SMA[t]>1 and momentum[t]>0. Figure 1 and Table 1 show the comparison between Manual Strategy and Benchmark using 'JPM' stock.

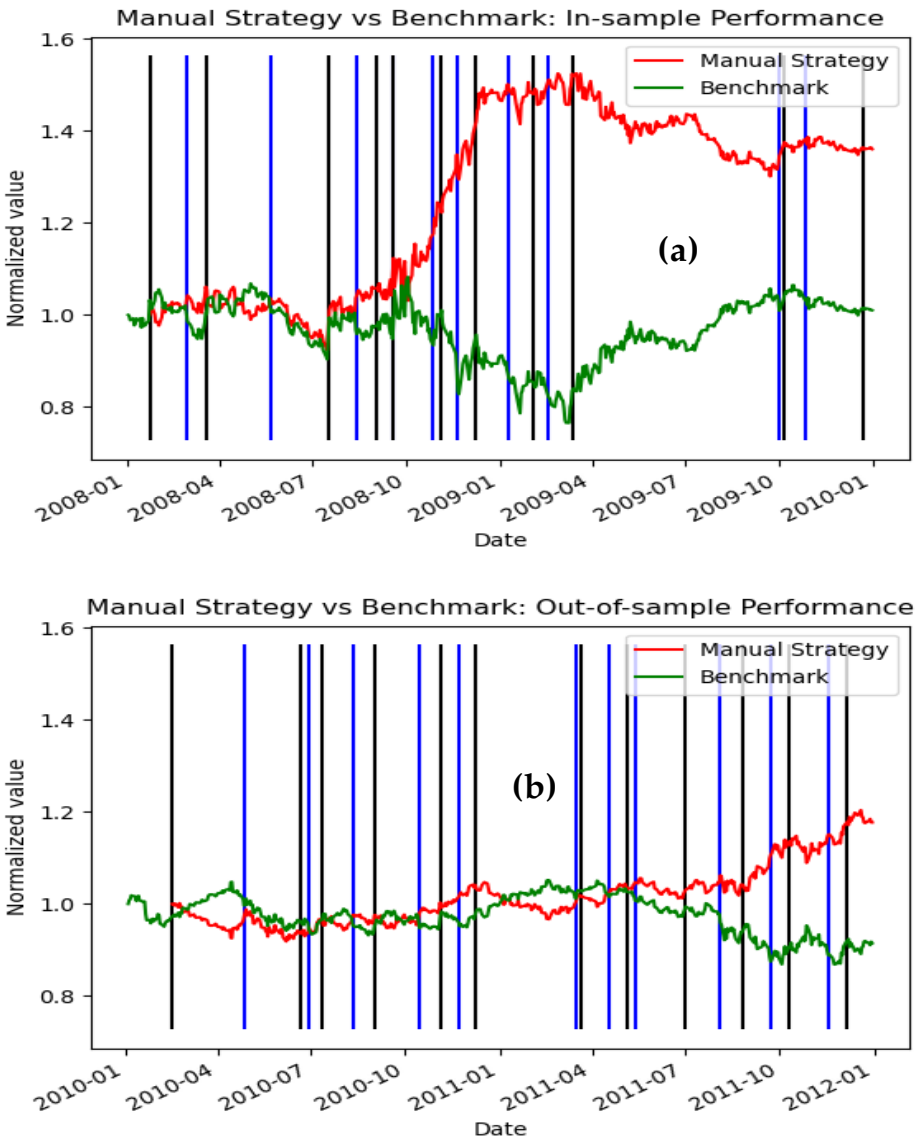

Figure 1—Manual Strategy vs Benchmark: (a) In-sample, (b) Out-of -sample

Why we picked up the above thresholds: When the Bollinger point is less than 0 (meaning price is below the lower band) and the Price/SMA is less than 1, this along with a negative momentum indicates a potential oversold scenario. Thats why we picked up this condition as a 'BUY' signal. Similarly, When the Bollinger point is greater than 0 (meaning price is above the lower band) and the Price/SMA is greater than 1, this along with a positive momentum indicates a potential overbought scenario. Thats why we picked up this condition as a 'SELL' signal.

Why is the strategy effective: The indicators I have picked up may or may not be very effective as a stand alone indicator. But each of them provides valuable information regarding the market volatility and momentum. Therefore, combining all three together provided us with a very strong strategy.

As we see in Figure 1 and Table 1, the Manual strategy out performs the benchmark in both in-sample and out of sample performance with higher cumulative portfolio, lower standard deviation (volatility) and higher mean of daily returns. This is because, manual strategy is carefully chosen by observing the various indicators from the previous 14 days (look back window) price where the benchmark strategy simply buys 1000 shares and holds that position regardless of how the market indicators behave. In addition, the manual strategy is optimized for the in-sample data. Thats why, the out of sample performance (although beats the benchmark) is relatively worse compared to the in-sample data.

Table 1. Manual Strategy vs Benchmark using 'JPM' stock

Period	Metric	Manual Strategy	Benchmark
In-sample (January 1, 2008 to December 31, 2009)	Cumulative Return	0.35988266	0.01023621
	Stdev (daily Return)	0.01334012	0.0170243
	Mean (Daily Return)	0.000716325	0.00016466
Out-of-sample (January 1, 2010 to December 31, 2011)	Cumulative Return	0.17700286	-0.0853088
	Stdev (daily Return)	0.007696144	0.008492829
	Mean (Daily Return)	0.00037348	-0.000141175

4. STRATEGY LEARNER:

The same basic assumptions from the Manual Strategy regarding the minimum and maximum number of stock holdings as well as minimum and maximum number of stock trading are applied here. In addition, we have used the same in-sample and out-of-sample data to assess performance of the strategy learner. Steps Taken to implement the strategy are as follows:

- First step is to pick up the model for this strategy. I have chosen an ensemble technique (Bag Learner) with Random Tree (RT) Learner as the estimator. I used mode rather than mean to convert the regression based BagLearner from project 3 to a classification based learner. I have used a total number of bags of 50 with a leaf size of 5 for the estimators.

- Next step is to prepare the training data using the same three indicators (Price/SMA, Bollinger Bands point, and Momentum) used to implement the Manual Strategy. Each of the indicators is treated a feature to form the training data (train_x) with respect to the date. Similar to the Manual Strategy, I have used a look back window of 14 for all the indicators.

- We classified the y_train using N-day return. N was set to 2 for all the simulations. In addition to that we have introduced two other parameters: YBUY and YSELL to classify the outputs from the Bag Learner. If on a particular trading date, previous N-day return is greater than (YBUY+impact), the classification was set to +1 (Long). If its less than (YSELL-impact), the classification was set to -1 (Short). In all other cases, the sample was classified as 0 (Cash).

- Using the train_x and train_y from the previous two steps, I have trained my Bag Learner model.

- For testing purposes, I have extracted the same three indicators for the test sample data and formed test_x data in a similar way and predicted test_y from the trained model. Finally we determined the trading on a particular day using test_y as described below:

    - If the current holding is 0 shares: if test_y>0, we buy 1000 shares, else we sell 1000 shares.

- If the current holding is 1000 shares: if test_y<0, we sell 2000 stocks. else if test_y==0, we sell 1000 shares.
- If the current holding is -1000 shares: if test_y>0, we buy 2000 stocks. else if test_y==0, we buy 1000 shares.

Hyper-parameters tuning: We have chosen 50 bags since that gives us a very stable results for the repeated run of the same experiment. The leaf_size was set to 5 since that gave us the best in-sample accuracy. In addition, I have used both YBUY and YSELL values as 0 and N=2 for N-day return. These parameters were adjusted to get the best in-sample performances without any significant overfitting..

Data Adjustment: I did not have to adjust the data to implement the strategy learner. This is because, I have chosen the BagLearner with Random Tree Learner (RTLearner). Data standardization or normalization is not necessary in a tree based learner since it splits the tree based on one feature at a time (Randomly chosen in this case) and always reaches a leaf to get a decision. Data adjustment becomes more important in a learner like Q-Learner where data discretization is necessary to train the model.

5. EXPERIMENT 1: MANUAL STRATEGY VS STRATEGY LEARNER

Assumptions and constraints followed for this experiment are as follows:

- we can be in one of the three states in-terms of holdings: -1000 shares, +1000 shares, 0 shares
- we can trade a maximum of 2000 shares at a time as long as we maintain the first requirement of holdings
- There is no limit on leverage, commission = $9.5 and impact = 0.005, and the starting value is 100,000
- Number of bags and leaf size in the strategy learner are 50 and 5, respectively.
- Trading stock used is 'JPM' for both in-sample (January 1, 2008 to December 31, 2009) and out-of sample (January 1, 2010 to December 31, 2011) performance assessment.

- As performance metrics, I have listed Cumulative portfolio value as well as the standard deviation and mean values of the daily returns.
- Portfolio values were normalized to 1 at the start for all strategies

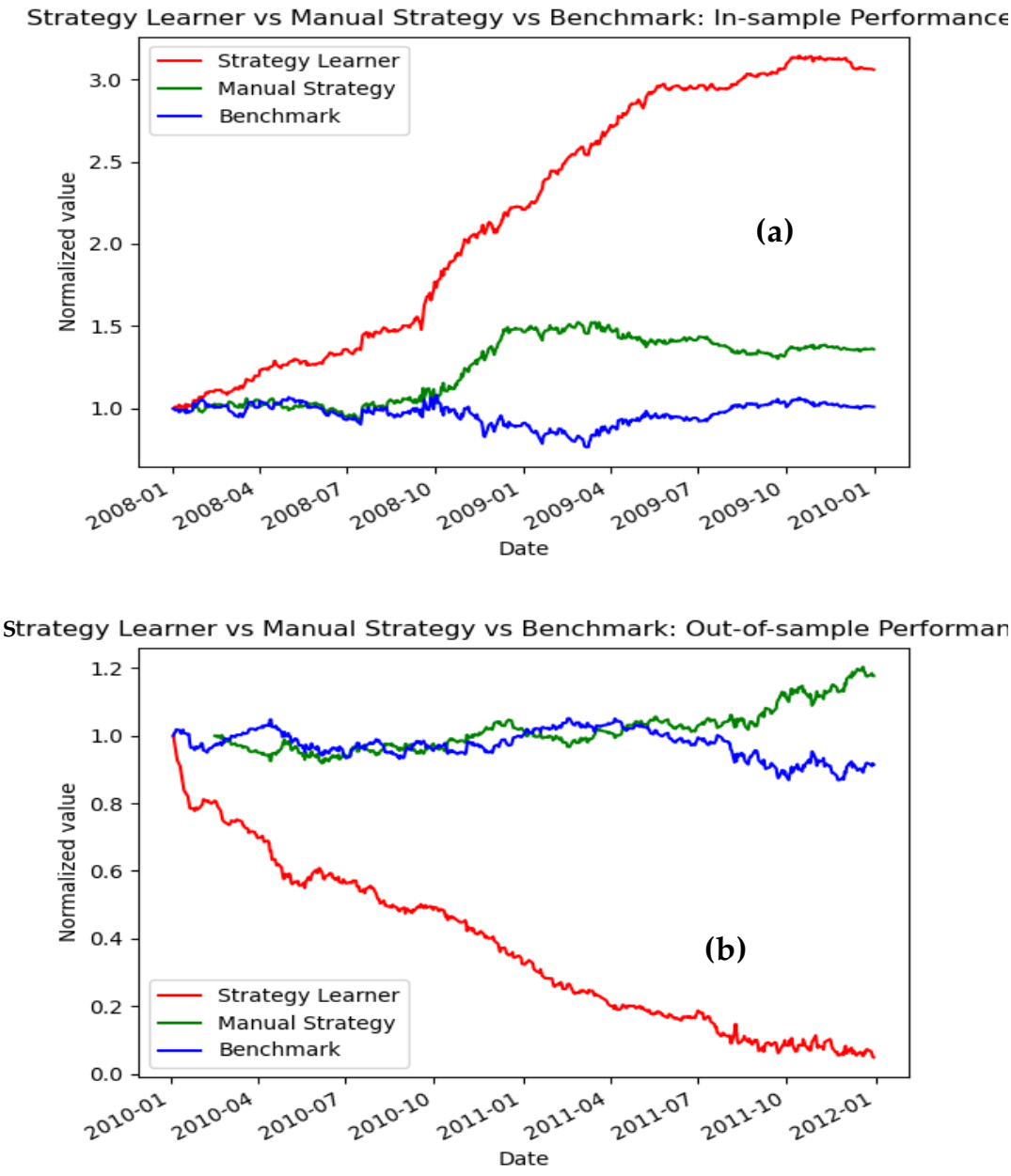

Figure 2—Strategy Learner vs Manual Strategy vs Benchmark: (a) In-sample, (b) Out-of -sample

The strategy learner comfortably beats the Manual strategy and benchmark for the in-sample performance. However, the out-of sample performance is worse for 'JPM' trading. We observe from Figure 2 that the strategy learner beats both manual strategy and the benchmark in in-sample performance, while it performs worst in the out of sample performance. The manual strategy performs best in the out of sample performance while performs worse than the strategy learner and better than the benchmark in in-sample performance. I have listed the cumulative portfolio value, the mean and standard deviation of the daily returns in Table 2 for both in-sample and out-of sample trading performance. We can expect the strategy learner to always perform better with in-sample data compared to that of the out of-sample data since the in-sample data is what we used to train this model. In general, most of the machine learning models performs better on in-sample or training data compared to that of the out-of sample or test data. However, further tuning of the parameters is still possible which can lead to a model that performs better on the out-of-sample data as well.

Table 2. Strategy Learner vs Manual Strategy vs Benchmark using 'JPM' stock

Period	Metric	Strategy Learner	Manual Strategy	Benchmark
In-sample (January 1, 2008 to December 31, 2009)	Cumulative Return	2.05833902	0.35988266	0.01023621
	Stdev (daily Return)	0.00836271	0.01334018	0.01702431
	Mean (Daily Return)	0.002255188	0.000716325	0.00016466
Out-of-sample (January 1, 2010 to December 31, 2011)	Cumulative Return	-0.9517834	0.177002864	-0.085308817
	Stdev (daily Return)	0.0670917	0.007696147	0.00849283
	Mean (Daily Return)	-0.00379127	0.0003734791	-0.000141175

6. EXPERIMENT 2: STRATEGY LEARNER (EFFECT OF IMPACT VALUE)

For this experiment, we have analyzed the effect of changing impact values (for four different impact values: 0.0, 0.005, 0.010, 0.015). We have used the in-sample 'JPM' stock data (January 1, 2008 to December 31, 2009). Commission =0.0 and the starting value of 100,000 are used in this experiment. We observe

from Figure 3, that the strategy learner performs worse with the increase in impact value. The metrics I have used (listed in Table 3) are cumulative return, mean and the standard deviation of the daily returns. We observe from the table that the performance goes down with the increase in impact value. In other words, the cumulative return and the mean daily return decreases, while the standard deviation (volatility) increases with the increase in the impact value. Portfolio values were normalized to 1 at the start.

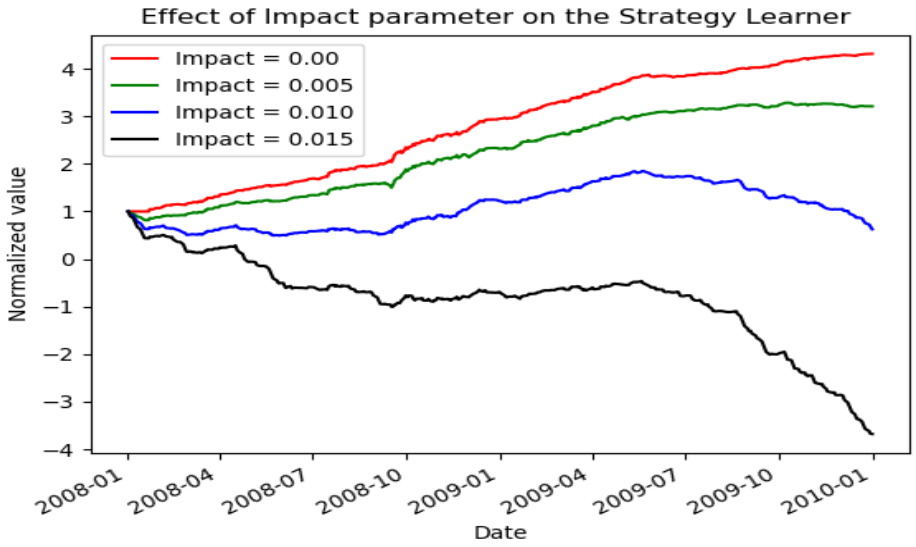

Figure 3—Effect of increasing impact on the strategy learner

My Theory: After analyzing the trading data from the simulations, I have observed that the number of trading decreases with the increase in the impact value. Since the impact is the effect a market participant has when it buys or sells an asset, the number of trades determined by the learner goes down in order to make each of the trading more impactful on the portfolio value. As a result, the portfolio becomes more volatile.

Table 3. Effect of changing impact value using 'JPM' stock in Strategy Learner

Performance Metrics	Impact=0.0	Impact=0.005	Impact=0.010	Impact=0.015
Cumulative Return	3.3157	2.21213	-0.37329	-4.67935
Stdev (daily Return)	0.006807	0.0088867	0.0213779	5.04295
Mean (Daily Return)	0.0029285	0.0023572	-0.000699	-0.2221211

7. REFERENCES

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