GEORGIA INSTITUTE OF TECHNOLOGY

CS7646: FALL 2019 PROJECT 8

STRATEGY LEARNER

Grace Park
GT User ID: gpark83, GT ID: 903474899

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Introduction

In this project, I developed a strategic trading strategy using a classification learner. The three indicators chosen and implemented were the same three I used to create a manual strategy – Simple Moving Average, Bollinger Band %B, and Stochastic Oscillator. The strategy was tested using a market simulator that I developed against the JPM stock.

1. Part 1: Technical Indicators

For my project, I chose three indicators: Simple Moving Average, Bollinger Band %B, and Stochastic Oscillator for my strategy learner. I have described each indicator, their calculations, how it can be reproduced, and a chart displaying when the indicator signals a buy or sell for JPM within the In-Sample period (January 1st, 2008 to December 31st, 2009).

1.1 Simple Moving Average (SMA)

SMA is essentially the average of a stock price over a n-day period. I chose this indicator because it is a strong technical indicator that looks at the average price of a company's stock over a certain period of time, which can represent the actual value of the company. As mentioned in Lecture 02-06: Technical Analysis, when there is a significant digression from that price, it is expected that the price will come down to the average, and reveal overbought and oversold conditions to trade when there's a large diversion from the SMA. The direction of the SMA gives a basic idea of which way the price is moving.

The SMA is calculated by designating a lookback period (14 days in my example), and calculating the stock's adjusted closing price average over the lookback period from the start date to the end date.

$$SMA = (P_1 + P_2 + P_3 + . . . P_n) \div n$$

P_n is the price and n is the number of total periods.

1.2 Bollinger Band (%B)

My second volatility indicator is the Bollinger Band %B, which is derived from the Bollinger Band indicator. We take the SMA as the middle band and add upper and lower bands that are two standard deviations away in both directions. In order to show what the price is within the upper and lower bands, we use the %B. This way, we can distinguish the trading signals to buy or sell. I chose this indicator because this is a strong indicator it quantifies exactly where the price is in terms of value.

We can calculate the %B as follows:

$$\%B = (P_C - \text{Lower Band}) / (\text{Upper Band} - \text{Lower Band})$$

P_C is the current price value.

1.3 Stochastic Oscillator

My third and final indicator is a price momentum indicator that indicates whether there are overbought and oversold circumstances by following the momentum of the price. It compares the recent closing price to a range of its prices over a period of time and the readings range from 0 to 100 indicating momentum, where 0 is the lowest point of trading range and 100 is the highest. I chose this indicator because I wanted to pair this along with the SMA indicator as this looks at the speed and momentum of the price. Having this confirm price trends is valuable in my strategy.

The Stochastic Oscillator can be calculated as follows:

$$\%K \text{ (Current Value of Stochastic Oscillator)} = \left(\frac{P_{closing} - N\ Day\ Low}{N\ Day\ High - N\ Day\ Low}\right) * 100$$

$P_{closing}$ is the recent closing price and N Day Low is the lowest price in the last N days, and N Day High is the highest price in the last N days. Typically, N is 14 days, but that can be adjusted to fit specific needs. If the N is smaller it will generate an oscillator that is more spastic with more readings that are overbought and oversold. A larger N period will generate a flatter oscillator with less overbought and oversold conditions.

%D is the 3 day SMA of %K, and that is used to determine buy or sell signals. If the reading is over 80, that will indicate an overbought condition and the price is near its high for the N period of days. This will signal a sell situation. If the reading is below 20, that will indicate an oversell condition and the price is near its low for the N period of days, signaling a buy.

1.4 Data Adjustment

In order to create a classification learner, I used a combination of the Random Tree Learner and implemented Bootstrap Aggregating. Under the addEvidence() function, I populated the prices for the stock(s) and calculated all three indicators using the indicators functionality from Project

6. I then calculated the daily returns using the normalized prices. From there, I determined if the daily returns for the prices within the date range fit into the classifications:

- +1: LONG
- 0: CASH
- -1: SHORT

If the daily return was greater than a value declared as YBUY plus double the impact, then it was classified as LONG. If the daily return was less than a value declared as double the YSELL plus the impact, then it was classified as SHORT. Lastly, if none fit, I returned 0. I trained the data on this model, and mode was used rather than the mean to learn the strategy.

Then, in the testing phase, all learning was turned off and the query function from the BagLearner was used to get the predicted Y. From there, the orders were created based on the similar creation within the Manual Strategy. Based on the positions above, the current holdings remain at 0, 1000, or -1000.

2. Part 2: Experiments

2.1 Experiment 1

In this experiment, I used the same exact indicators in the Manual Strategy to trade the stock: JPM. I compared this strategy with the in-sample strategy of my Strategy Learner.

2.1.1 Assumptions

Ahead of the experiment, I assumed that my strategy learner would perform exceedingly well against the benchmark, and would perform better than my manual strategy due to the ability to train and learn from my data.

2.1.2 Parameters

I used the same parameters across the board for both strategies:

- Stock: JPM
- Starting Value: $100,000
- Start Date: January 1st, 2008
- End Date: December 31st, 2009
- Commission: $9.95
- Impact: 0.005

2.1.3 Outcome

As expected, my strategy learner performed better than both the benchmark and my manual strategy as seen in Table 1 below:

The final portfolio value of my Strategy Learner was $243,067.75 as opposed to $101,230 and $165,604.15 of my Benchmark and Manual Strategy, respectively.

Table 1: Statistics Benchmark vs Manual Strategy vs Strategy Learner of In-Sample Period

Statistics	Benchmark	Manual Strategy	Strategy Learner
Cumulative Return	0.012299999999999978	0.6562062925260748	1.4309193764779309
Standard Deviation of Daily Returns	0.017004366271213767	0.015693162339816564	0.010115931764095996
Mean of Daily Returns	0.00016808697819094035	0.0011224580281719934	0.0018147838150339162
Sharpe Ratio	0.15691840642403027	1.135428820021653	2.847864202662816
Final Portfolio Value	$101,230.00	$165,604.15	$243,067.75

As seen in Figure 1, the final portfolio value for the Strategy Learner was exceedingly higher than the Manual Strategy and Benchmark.

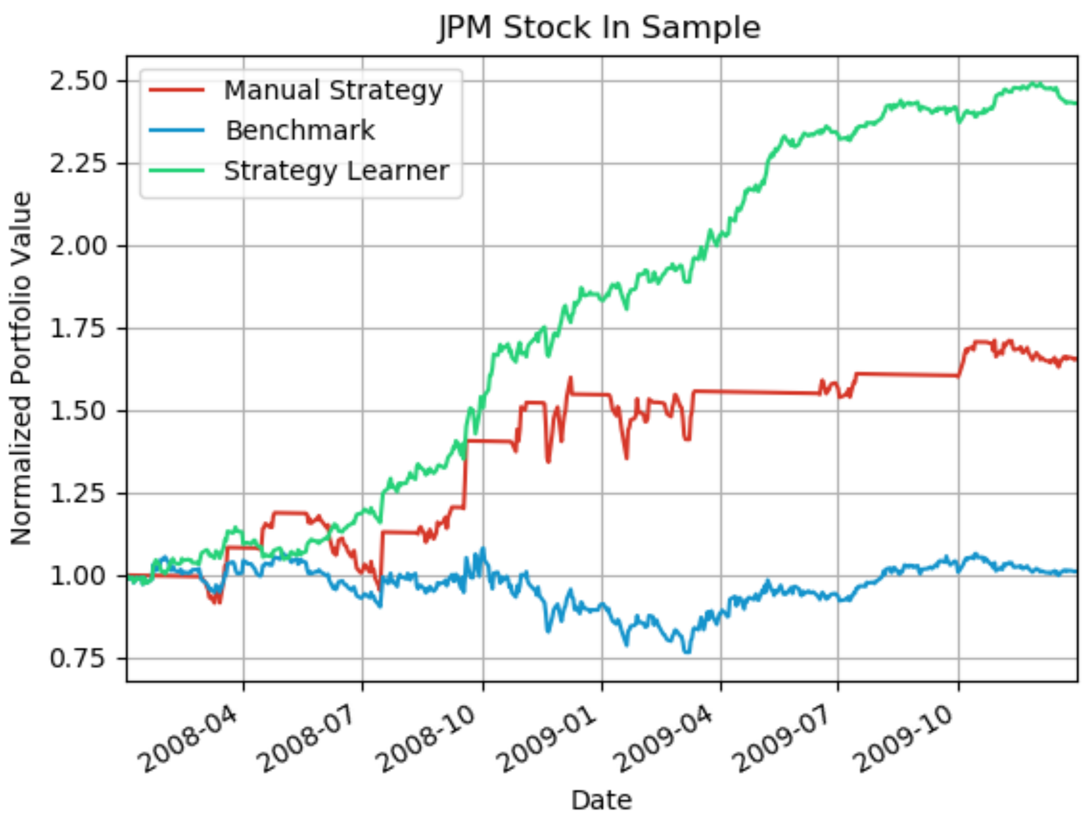

Figure 1: Benchmark vs Manual Strategy vs Strategy Learner of In-Sample Period - 2008-01-01 to 2009-12-31

2.1.4 Expectations

I do not expect the same results every time as the choice of feature to split on is made randomly every time. While I do expect the final portfolio value to be higher than the benchmark and Manual Strategy, the actual amount that would be the difference would vary.

2.2 Experiment 2

In this experiment, I looked at how higher impact affects in sampling trading behavior, specifically on the final portfolio value and the sharpe ratio. I increased the impact from 0.005 to 0.015 to see how a higher impact value can affect the statistics seen in Experiment 1.

2.2.1 Assumptions

Ahead of the experiment, I assumed that final portfolio value would decrease for my Manual Strategy and Strategy Learner, and the sharpe ratio would both decrease for my Strategy Learner and my Manual Strategy as well. For my benchmark, it should stay exactly the same as impact should not affect the benchmark (as nothing is being traded in between the date range).

I think that the portfolio value would decrease because impact value increases the classifications, and I believe it would bring about larger variety of sells/buys that may not be as accurate, particularly for the Strategy Learner (as this has more spontaneity due to the randomness of the feature it splits on). For the sharpe ratio I think the decrease would be larger for my Strategy Learner as the risk may be higher than my Strategy Learner due to the randomness.

2.2.2 Parameters

I used the same parameters across the board for both strategies:

- Stock: JPM
- Starting Value: $100,000
- Start Date: January 1st, 2008
- End Date: December 31st, 2009
- Commission: $9.95
- Impact: 0.015

2.2.3 Outcome

As expected, my strategy learner performed better than both the benchmark and my manual strategy as seen in Table 2 below:

The final portfolio value of my Strategy Learner was $156,331.95 as opposed to $101,230 and $149,381.95 of my Benchmark and Manual Strategy, respectively.

Table 2: Impact Change Statistics Benchmark vs Manual Strategy vs Strategy Learner of In-Sample Period

Statistics	Benchmark	Manual Strategy	Strategy Learner
Cumulative Return	0.012299999999999978	0.4939681498308788	0.5634750657690268
Standard Deviation of Daily Returns	0.017004366271213767	0.016396356381165805	0.013153997845648795
Mean of Daily Returns	0.00016808697819094035	0.0009289926120756183	0.0009732085278529389
Sharpe Ratio	0.15691840642403027	0.8994254690115342	1.174487529367154
Final Portfolio Value	$101,230.00	$149,381.95	$156,331.95

As seen in Figure 2, the final portfolio value did go down, and it is fairly comparable throughout the date range. It looks as though an increase in impact can heavily affect the final portfolio value based on this experiment.

In addition, both sharpe ratios also decreased as seen in the tables. What is interesting is that the degree of the decrease was much higher for the Strategy Learner than the Manual Strategy.

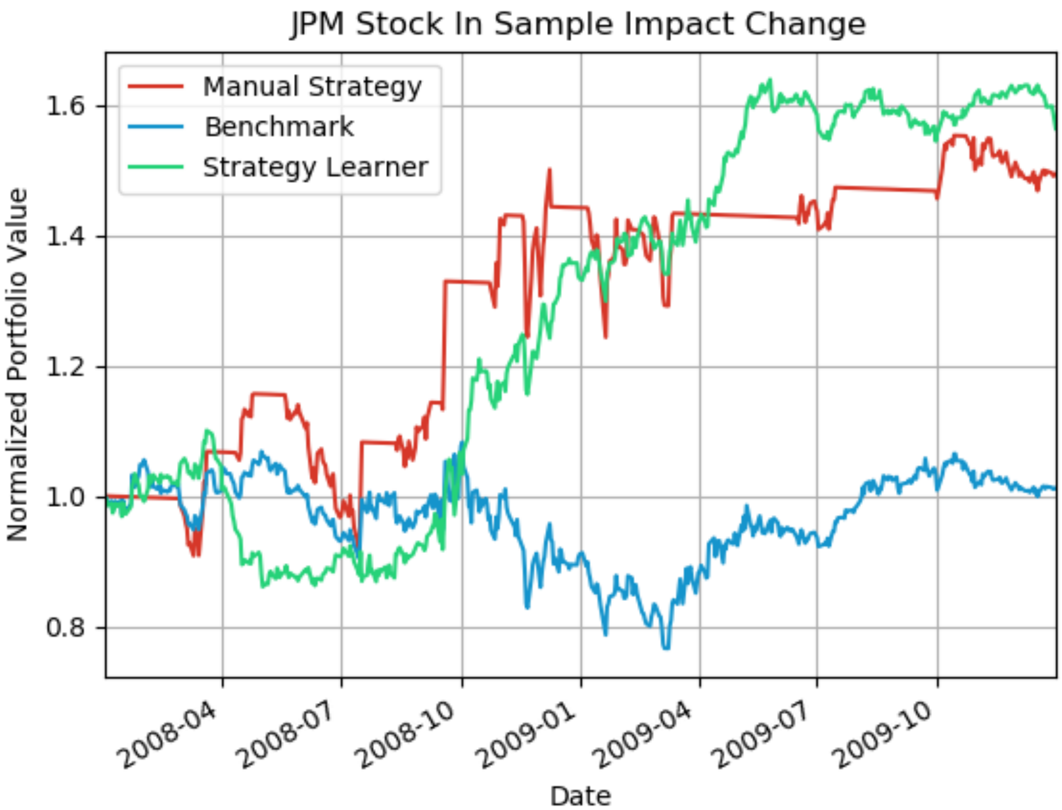

Figure 2: Impact Change on Benchmark vs Manual Strategy vs Strategy Learner of In Sample Period 2008-01-01 to 2009-12-31