**GEORGIA INSTITUTE OF TECHNOLOGY**

CS7646: FALL 2019 PROJECT 8

STRATEGY LEARNER

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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. 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 = (P1 + P2 + P3 + . . . P*n*) ÷ *n*

P*n* is the price and *n* is the number of total periods.

In order to reproduce this, you would essentially loop through the entire date range that you are looking for. From within that loop, you would then loop over the lookback period to the day in question and calculate the average of that lookback period.

Since we are looking for overbought and oversold conditions to determine when to buy and sell, we use the Price/SMA ratio, where we divide P*n* by the SMA(*n*). This is ideal because we can now determine that if the Price/SMA ratio is greater than 1, we should sell as the price is higher than the SMA, and if the Price/SMA ratio is less than 1, we should buy as the price is lower than the SMA. If the Price/SMA ratio is 1, it is at the current price, so we should do nothing. This can be seen in Figure 1 below:

A close up of a map

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Figure 1: Price, SMA, Price/SMA of In-Sample Period - 2008-01-01 to 2009-12-31

* 1. 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 = (PC – Lower Band) / (Upper Band – Lower Band)

PC is the current price value.

In order to reproduce this, you would loop through the date range and for each day you would loop through the lookback period to calculate the standard deviation. Once that is determined, you can derive the upper and lower bands, which then allows you to calculate the %B as seen above.

The %B identifies when there are overbought and oversold circumstances. When %B is greater than 1, the price is above the upper band, and if %B is 1, the price is at the upper band. When %B is below 0, the price is below the lower band, and if it is at 0, this shows the price is at the lower band. This means that when %B goes above 1 or below 0, it signals when to buy or sell. When %B goes above 1, and the trend is moving down, this signals a sell. Vice versa, when %B goes below 0 and the trend is moving up, this signals a buy.

As seen in Figure 2 below, when the %B breaks above 1 or below 0, the price will break the upper and lower bands as well.

A close up of a map

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Figure 2: Bollinger Band %B of In-Sample Period - 2008-01-01 to 2009-12-31

* 1. 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 (Current Value of Stochastic Oscillator) = (

Pclosing 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.

In order to reproduce this, you would loop through the date period, and for each day you would loop through the N day period to find the minimum and maximum. Then, you would calculate %K by getting the recent Close price, subtract the minimum and divide that by difference between the maximum and minimum. Lastly, multiply that value by 100. %D can be calculated using the SMA as mentioned above for a lookback period of 3 days.

As seen in Figure 3, when %K and %D intersect, this signals that a change in momentum is about to occur. The change in price can be seen in Close price below.

A screenshot of a cell phone

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Figure 3: Stochastic Oscillator of In-Sample Period - 2008-01-01 to 2009-12-31

* 1. 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.

1. **Part 2: Experiments**
   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.

* + 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.

* + 1. 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
  + 1. 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 4, the final portfolio value for the Strategy Learner was exceedingly higher than the Manual Strategy and Benchmark.

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Figure 4: Benchmark vs Manual Strategy vs Strategy Learner of In-Sample Period - 2008-01-01 to 2009-12-31

* + 1. 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.

* 1. 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.

* + 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.

* + 1. 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
  + 1. 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: 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 5, 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.

A close up of a map

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Figure 5: Impact Change on Benchmark vs Manual Strategy vs Strategy Learner of In Sample Period 2008-01-01 to 2009-12-31