Project 8: Strategy Evaluation Report

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Abstract—In this project I compare the performance of a manual strategy versus a machine learning strategy learner. It will help us look at the behavior of an AI learner and how it may differ from a human-developed strategy. I use technical analysis indicators to make prediction on how a stock may react to price and create BUY and SELL signals and evaluate the portfolio output.

1 INTRODUCTION

The goal of this project is to analyze and compare the performance of different stock trading strategies. First, I create a manual strategy that uses a set of technical indicators described below to help us make decision on when to buy or sell a stock. Then I create a strategy learner that uses that same technical indicators that I use for the manual strategy, but this time I use them as features and run them through a classification random tree learner inside of a Bag Learner to create a random forest learner. This ML technique is used to determine when to go long on a stock and when to go short. Both of these strategies were compared against a benchmark. The benchmark is a rule where I start with 1000 shares of a stock and I hold that position over the period of time and sell on the last day. The initial hypothesis for this project is the strategy learner will outperform the benchmark and manual strategy based on the chosen indicators.

2 INDICATOR OVERVIEW

2.1 Bollinger Band Percentage (BBP)

Bollinger Band Percentage (BBP) calculates the closing price as a percentage of the upper and lower Bollinger bands. The upper band is plotted 2 standard deviations above the simple moving average (SMA) and the lower band is plotted 2 standard deviations below the SMA. The Bolling Band percentage is calculated by: $\%B = \frac{(price - Lower\ Band)}{(Upper\ Band - Lower\ Band}$. The percentage falls between 0% and 100% or 0 and 1.0

where 0 would represent that the price is at the lower band, 0.5 means that the price is in the middle and 1.0 would mean that the price is at the upper band.

For the manual learner and strategy learner I have used a lookback window of 10 days. For a buy signal, I check that the percentage value is at or below 20% or 0.2 which signifies that the stock is oversold and that there is likely going to be a price reversal to make it go back up. Alternatively, if the percentage value is at or above 80% or 0.8, it signifies that the stock is overbought and there is likely going to be a price reversal to make it go back down.

2.2 Exponential Moving Average (EMA)

Exponential moving average is an indicator that takes the rolling mean of the stock price over a specified window and it assigns a weight that is higher for more recent data points. The EMA can be calculated using the following formula:

$$EMA_{today} = \left(Value_{today} * \left(\frac{Smoothing}{1 + Days}\right)\right) + EMA_{yesterday} * \left(1 - \left(\frac{smoothing}{1 + Days}\right)\right)$$

From the equation above, there is a "smoothing factor" that is used in the calculation, and the most common choice for this is 2. As the smoothing factor increases, the more recent observations have more influence over the overall EMA that is plotted. For the manual and strategy learners, I have used a lookback window of 10, and I return the value of price / ema ratio. When the ratio is at or less than 0.65, which would mean 65% of the exponential moving average price, it can be used a buy signal as it may reflect that the price will go back up towards the moving average. Alternatively, when the ratio is at or more than 1.2 or 20% higher than the moving average price, then it can be used as a sell signal as it may reflect that the price will go back down towards the moving average.

1.3 Relative Strength Index (RSI)

The Relative Strength Index is a momentum indicator that is used to measure the speed and magnitude of recent price changes for a stock. The value for RSI falls between 0 and 100, and a reading above 70 typically indicates an overbought situation and a reading below 30 typically indicates an oversold situation. These are the parameters that I had used for the manual learner to determine a buy and sell signal respectively. When the reading was at or below 30, it could signify that price may pull back up and warrant a buy signal, and alternatively a reading at or above 70 could signify the price may go back down and warrant a sell signal. I have also used a lookback window of 10 for this indicator. The RSI reading is calculated using the following formula:

$$RSI = 100 - \left[\frac{100}{1 + \frac{Average\ Gain}{Average\ Loss}} \right]$$

3 MANUAL STRATEGY

For the manual strategy, I use the 3 indicators described above to create a strategy of when to go long on a stock and when to go short on a stock based on indicator values at a given time. Using the signals that I get I then decide whether to hold, sell, or buy at a given time depending on whether I already have a position in the stock or not. We set a restriction that we may only have 1000 shares long, 1000 shares short or 0 shares at any given point in time. The strategy that I for the manual strategy is if the Bollinger band percentage is below 0.2 and relative strength index is below 30 or the exponential moving average is less than 0.65, then that warrants a buy signal. And vice versa, for a sell signal I say if the Bollinger band percentage is above 0.8 and relative strength index is above 80 or the exponential moving average is more than 1.2 then the criteria in met. I linked the Bollinger band percentage and the relative strength index together since they both look at whether a stock is oversold or overbought, and then since ema is a moving average indicator I didn't group it with the others. I think the strategy could be better in that the indicators could be more linked together when making a decision of whether to buy or sell, but it worked out for JPM stock for the in-sample data (Jan 1st 2008 to Dec 31st 2009) and out-of-sample data (Jan 1st 2010 to Dec 31st 2011) as shown in the results below by comparing it to a benchmark. The benchmark is the performance of a portfolio starting with $100,000, investing in JPM stock on the first day and then holding that position.

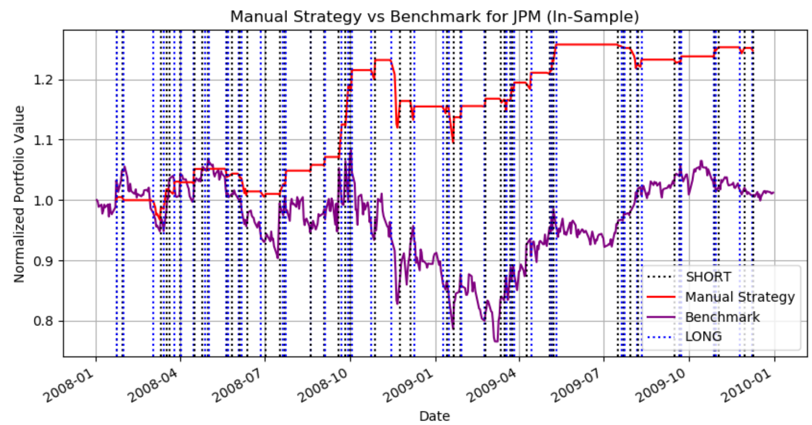

Figure 1— Graph of Manual Strategy portfolio normalized value plotted alongside Benchmark portfolio value for JPM stock for in-sample period along with long and short signals

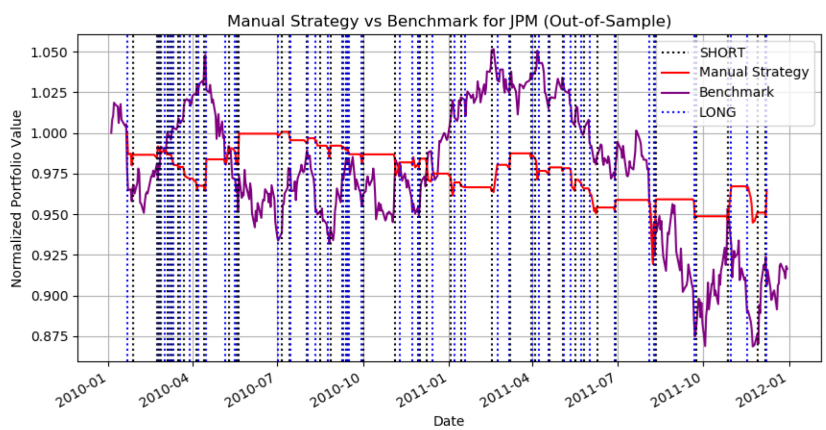

Figure 2— Graph of Manual Strategy portfolio normalized value plotted alongside Benchmark portfolio value for JPM stock for out-of-sample period along with long and short signals

Table 1—Performance metrics for JPM stock portfolio for in sample and out of sample data compared to the benchmark

	Benchmark (in sample)	**Manual Strategy (in sample)**	**Benchmark (out of sample)**	**Manual Strategy (out of sample)**
Cumulative Returns	0.0122252	0.2474190	-0.0836788	-0.0350648

Standard Deviation Daily Return	0.0170243	0.0072285	0.0084917	0.0036435
Average Daily Return	0.0001682	0.0004903	-0.0001374	0.0000682

As seen above, for the in-sample data, the manual strategy out-performed the benchmark for almost the entire duration, but only about half the time for the out-of-sample data. This difference occurs because the strategy was tweaked and trained with the in-sample data only and the out-of-sample data may not always result in the best outcome for the strategy.

4 STRATEGY LEARNER

The Strategy Learner uses the same indicators and the same assumptions as the manual learner, however this time instead of creating a strategy ourselves, we provide the indicator data to a random forest classification learner and let it determine the buy and sell signals. A random forest learner is a combination of a random tree learner combined with a bag learner that contains many instances of random tree learners and takes the mode from the results. Since we are using a classification learner, the strategy learner will not give us discretized signals of 1, 0, and -1 which represents buy, do nothing, and sell respectively.

So, the features that are input into the random tree learners are the indicator values, and the target value for each feature during the training phase was determined after performing some discretization. For each day, we would forward look 5 days at calculate the percentage return (could be positive or negative depending on how the price changed in the 5 days). A threshold of 0.027 and -0.027 was determined from fine tuning and if the return was greater than that value, we would append a buy signal (1) and if the value was less than the negative threshold, we would append a sell signal (-1) and 0 otherwise. Furthermore, some other hyperparameters that were fine tuned were the leaf size, bag size, lookback window and forward-looking window to determine that best values when training with the in-sample data. After thorough testing, I settled on the values of leaf size of 7, bag size of 20, lookback window of 10, and forward-window of 5. Once these values were determined, I train the model so that the learner could learn the data and then I run the same in-sample training data to verify its performance. Once I was satisfied, I could then run the same model that was trained with out-of-sample data and see how it performs.

5 EXPERIMENT 1

In this experiment, I compare the results and performance of manual strategy and strategy learner as well as comparing it against a benchmark for JPM stock. I use the same data and rules and described for each strategy above, and I compare the results by testing on both in-sample and out-of-sample data. Our initial hypothesis was that the strategy learner should out perform the benchmark as well as the manual learner since the ML algorithm could potentially correlate the information from the indicators better than what I was doing manually.

The parameters that were used for this experiment are as follows:

- $100,000 starting cash with no limit on leverage and any trade can be executed without having to validate cash. $9.95 commission fee and 0.005 impact will also be applied to each transaction.
- Only allowable positions are 1000 shares long, 1000 shares short, 0 shares.
- In – Sample date range is Jan 1st 2008 to Dec 31st 2009.
- Out – of – sample data range is Jan 1st 2010 to Dec 31st 2011.

Figure 3— Graph of Manual Strategy vs Strategy Learner vs Benchmark portfolio normalized values for JPM stock in-sample period

Table 2—Performance metrics for JPM stock portfolio using in-sample data for the different strategies

	Benchmark	Manual Strategy	Strategy Learner
Cumulative Returns	0.0122252	0.2474190	0.1144284
Standard Deviation Daily Return	0.0170243	0.0072285	0.0138879
Average Daily Return	0.0001682	0.0004903	0.00031113

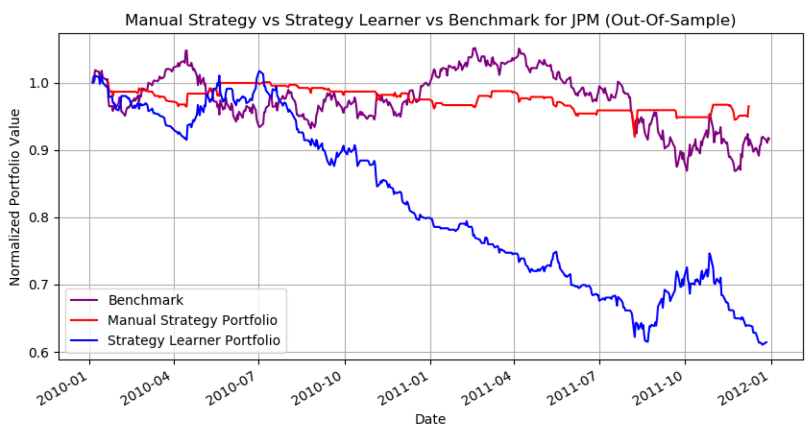

Figure 4— Graph of Manual Strategy vs Strategy Learner vs Benchmark portfolio normalized values for JPM stock out-of-sample period

Table 3—Performance metrics for JPM stock portfolio using out-of-sample data for the different strategies

	Benchmark	Manual Strategy	Strategy Learner
Cumulative Returns	-0.0836788	-0.0350648	-0.3857346
Standard Deviation Daily Return	0.0084917	0.0036435	0.0086437

Average Daily Return	-0.0001374	0.0000682	-0.0009368

From the results, I notice that the strategy learner did out-perform the benchmark in the in-sample test but it did not beat the manual strategy. Adding more indicators, additional bags to the random forest learner, or fine tuning the leaf size parameter could all contribute to generating a better performance for the strategy learner. If I were to train the data every time, I would expect to see slightly varying results based on the random features chosen by the random tree learner, but the outcome should be relatively similar in the case for the in-sample data. However, in the case of the out-of-sample data, the strategy learner unfortunately performed the worst of the 3. This could be due to the hyperparameters being tuned for the in-sample testing case, but with further testing and optimization the strategy learner could do better in the long run.

6 EXPERIMENT 2

In this experiment, I look at the results of changing the market impact value on the strategy learner and how the portfolio is affected. The impact value is the affect of a trade on the overall price of a stock. When executing a large trade, the price of a stock may move against the trader, and to account for this change I use market impact value in our calculation of expected return. An initial hypothesis by changing the impact value is that as the value increases, the performance of the trader will decrease. This hypothesis is made because the as the impact increases, the adjusted expected return decreases and so fewer trades may be executed.

For this experiment, I use varying impact values of 0.0005 (0.05%), 0.005 (0.5%), and 0.010 (1%). The results of the experiment are plotted below:

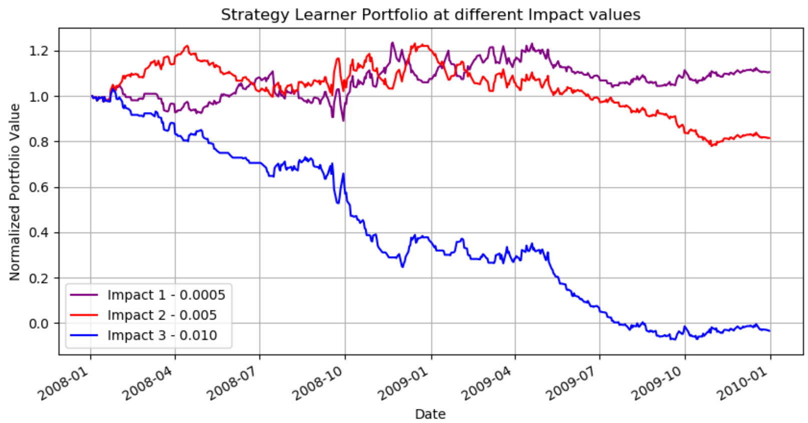

Figure 5 — Graph of Strategy Learner portfolio normalized value plotted with different impact values

From the graph above, I notice that when the impact goes from 0.5% to 1%, the portfolio value significantly decreases and from 0.05% to 0.5% there is also better performance when the impact is lower. Our hypothesis is confirmed based on the results. The metrics of cumulative return, average daily return, and standard deviation of daily return are also shown below.

Table 4 —Performance metrics for JPM stock portfolio at different impact values

Impact Value	**Cumulative Returns**	**Standard Deviation**	**Average**
0.000	*0.*1055697	0.0145930	0.0003054
0.005	-*0.*1847318	0.0144983	-0.0003003
0.010	-*1.*0339929	0.6556280	0.02797599

7 REFERENCES

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