STRATEGY EVALUATION

1 INDICATORS OVERVIEW

1.1 Simple Moving Average (SMA)

SMA is calculated as the rolling mean of a stock price. Below is the formula of SMA. N means the look back period (the number of the rolling days). A crossover of SMA and the price can be used to signal a change in trend and can be used to trigger a trade. I use N=20 days as the look back period in both Manual Strategy and Strategy Learner.

$$\mathrm{SMA} = \frac{A_1 + A_2 + ... + A_n}{n}$$

1.2 Moving Average Convergence Divergence (MACD)

MACD combines the strengths of EMA and momentum. There are two lines we should look at when using this indicator. One is the MACD line, the other is its Signal line. MACD is calculated by subtracting the 26-period EMA from the 12-period EMA. The 9-day EMA of the MACD is used as the "signal line. MACD triggers trade signals when it crosses above (to buy) or below (to sell) its signal line.

MACD = 12-Period EMA − 26-Period EMA

Signal = 9-day EMA of the MACD

The MACD indicator I use in Manual Strategy and Strategy Learner has been processed by subtracting MACD value from Signal value as below.

price_df['MACD'] = macd['Signal'] - macd['MACD']

1.3 Stochastic oscillator

Stochastic oscillator is a popular technical indicator for generating overbought and oversold signals. There are also two lines we need to look at when using the indicator. One is the indicator line, which is also known as %K, the other is the signal line, also known as %D. The formula is listed below. When the signal line is above the indicator line, which means the stock is overbought and might be a signal for selling the stock.

$$\%\mathrm{K} = \left(\frac{\mathrm{C} - \mathrm{L14}}{\mathrm{H14} - \mathrm{L14}} \right) \times 100$$

%D = 3-period moving average of %K

C = The most recent closing price

L14 = The lowest price traded of the 14 previous trading sessions

H14 = The highest price traded during the same 14-day period

%K = The current value of the stochastic indicator

The Stochastic oscillator indicator I use in Manual Strategy and Strategy Learner has been processed by subtracting %D from K% as below.

price_df['%KD'] = KD['%D'] - KD['%K']

2 Manual Strategy

2.1 Description and the logic

To determine the threshold of each indicator which would trigger a long or short position, I analyze SPY's data from 2008-1-1 to 2009-12-31 by taking the steps below and the manual strategy will be used to trade JPM in this project.

Step 1. Group the data points into two groups:

a) the data points of which the prices are higher than previous trading day

b) the data points of which the prices are lower than previous trading day

Step 2. For both of the groups, I divide the datasets into quartiles based on price changes (difference between the prices on a trading day and their prices on the previous trading day) and use the first quartile to compute the mean of the indicators. My reasoning is that since the rising and falling trends of the first quartile are most significant, the strategy would be more effective. Below is the mean of the indicators.

	Mean SMA	Mean MACD	Mean Stochastic oscillator
Top 25% of the rises	0.73093	0.00083	0.88187
Top 25% of the falls	0.75742	0.00060	-3.87106

Table 1— The mean of each indicators from the 1st quartile of rising and falling data points

Based on the analysis above, I devise the rule-based strategy with the buy/sell signals below:

Buy Signal - SMA < 0.730 & MACD > 0.0008 & Stochastic oscillator < -3.87

Sell Signal - SMA > 0.757 & MACD < 0.0006 & Stochastic oscillator > 0.88

2.2 Comparison between the performance of your Manual Strategy vs. the benchmark

2.2.1 In-sample time period

Figure 1— The portfolio value of in-sample benchmark and manul strategy from 2008-1-1 to 2009-12-31

	Cumulative return	STDEV of daily	Mean of daily returns

		returns	
Manual Strategy	0.18614	0.01442	0.00044
Benchmark	0.01232	0.01704	0.00016

Table 2 — The metrics of in-sample manual strategy and benchmark

According to figure 1 and table 3 above, we can see that the rule-based strategy outperforms the benchmark over the in-sample period. The cumulative return of the manual strategy is around 18 times more than benchmark's cumulative. As for the standard deviation of daily return and mean of daily return, manual strategy's performance is also better than benchmark.

2.2.2 *Out-sample time period*

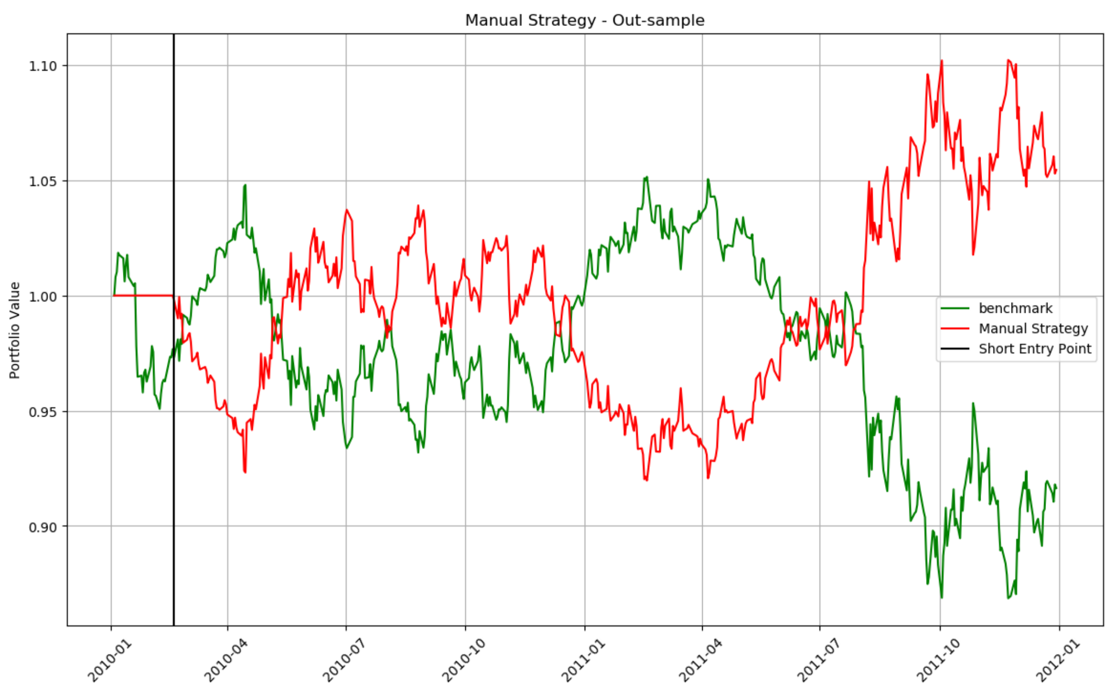

Figure 2— The portfolio value of benchmark and manul strategy from 2010-1-1 to 2011-12-31

	Cumulative return	**STDEV of daily returns**	**Mean of daily returns**

Manual Strategy	0.05449	0.00771	0.00013
Benchmark	-0.08357	0.00850	-0.00013

Table 3 — The metrics of out-of-sample manual strategy and benchmark

Based on figure 2 and table 3 above, we can manual strategy also outperform the benchmark over the out-sample period. However, compared with in-sample time periods, the gaps of manual strategy's metrics and benchmark's metrics are much narrower.

When I devise the manual strategy, I analyze SPY's in-sample time period data to determine the selling and buying signals. In other words, the strategy is tailored for the in-sample dataset. Thus, the manual strategy's performance on the in-sample dataset should be better than the performance on out-of-sample dataset.

3 Strategy Learner

3.1 Description

The strategy learner is a classification-based learner, which is built on RTLearner and BagLearner. The leaf_size of the learner is 10 and the number of the bags is 25, which I will provide more details in section 3.2 about how I determine the values for hyperparameters. Since it is a classification-based learner, I aslo convert the regression learner to use mode rather than mean in both RTLearner and BagLearner.

3.1.1 Features

The features are the same indicators used in the manual strategy: SMA, MACD and stochastic oscillator. As for the hyperparameters of the indicators, I also use the same ones used in manual strategy, like the window of SMA is 20 days, etc. I preprocessed the data and created three columns as features.

3.1.2 Labels

Based on instruction on *Classification Trader Hints*, the labels are classified as 3 types: +1(Long), -1(Short), 0(Cash). The transition costs, namely commission and impact, are taken into account when constructing the labels. To avoid excessive transition costs, I have raised the threshold for long/short positions instead of using the zero crossing rule. The definitions of the long and short positions are listed below.

Long position: return > 0.02 + impact

Short position: return < 0.0 - impact

In addition, the learner classifies based on 5 day change in price, reflecting the 5 day change and aligning with the current date.

3.2 Hyperparameters

To find the optimal leaf size and the number of the bag, I've trained and tested the learner with several different pairs of the hyperparameter values. When tuning the hyperparameter, I trained the learner with JPM's in-sample data, and tested the learner on JPM's out-sample data, and the impact 0.005 was also applied to the data. The metrics are normalized to 1.0 at the start.

Leaf Size	# of Bags	Cumulative return	STDEV of daily returns	Mean of daily returns
10	25	**0.07141**	**0.00817**	**0.00017**
10	20	-0.13613	0.00900	-0.00025
10	30	-0.06237	0.00884	-8.9e-05
10	40	-0.07880	0.00861	-0.00012
5	10	-0.21031	0.00924	-0.0004
5	20	0.01734	0.00770	6.37e-05
5	30	-0.15409	0.00893	-0.00029

Table 4 — The results of tuning hyperparameters

Above are the seven pairs of the hyperparameters I've tried. Based on the cumulative return and the average of daily returns, I determined that the leaf size of 10 and 25 bags are the optimal hyperparameters for my strategy learner.

4 Experiment 1

In experiment 1, I compare the manual strategy with the strategy learner in-sample trading JPM. The in-sample period is January 1, 2008 to December 31, 2009, and the starting cash is $100,000. As for the transition costs, I set $9.95 as the commission fee and 0.005 as the impact.

In addition to the manual strategy with the strategy learner, there is also a benchmark portfolio with $100,000 cash, investing in 1000 shares of the symbol in use on the first trading day, and holding that position.

There are also some restrictions on trading. There are only three allowable positions, 1000 shares long, 1000 shares short, 0 shares. Below is the outcome of experiment 1.

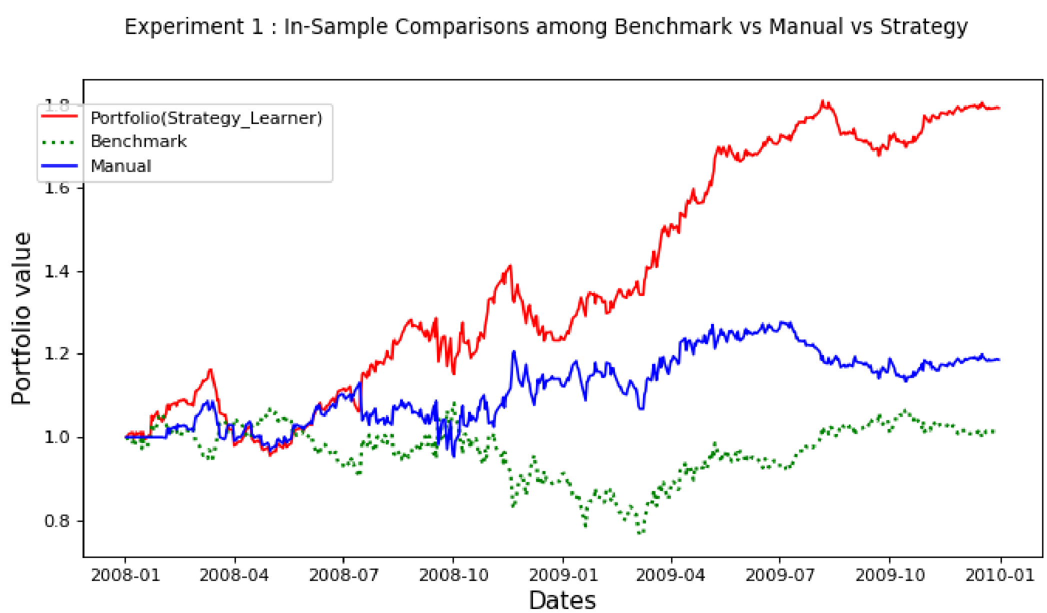

Figure 3— The portfolio value of benchmark, manul strategy and strategy learner from 2008-1-1 to 2009-12-31

	Cumulative	STDEV of	Mean of daily	Sharpe Ratio	Final portfolio

	return	daily returns	returns		value
Strategy Learner	0.79149	0.01232	0.00123	1.58838	178,787
Manual Strategy	0.18614	0.01442	0.00044	0.48700	118,614
Benchmark	0.01232	0.01704	0.00016	0.15720	101,027

Table 5 — The outcome of experiment 1

Based on figure 3 above, we can see the performance differences among strategy learner, manual strategy and the benchmark are very significant. Since it is the comparison with in-sample data, it is expected that strategy learner outperforms manual strategy and manual strategy outperforms the benchmark. The manual strategy's performance should be better than benchmark because the rule-based strategy is developed with in-sample SPY data and human interpretation. In addition, the strategy learner is trained by JPM's data, so I do expect it will outperform manual strategy.

5 Experiment 2

In experiment 2, I conducted an experiment with the strategy learner that shows how changing the value of impact (impact = 0 / 0.05 / 0.005) should affect in-sample trading behavior .The in-sample period is January 1, 2008 to December 31, 2009, and the starting cash is $100,000 and the commission fee is $0.00.

In addition to the manual strategy with the strategy learner, there is also a benchmark portfolio with $100,000 cash, investing in 1000 shares of the symbol in use on the first trading day, and holding that position.

There are also some restrictions on trading. There are only three allowable positions, 1000 shares long, 1000 shares short, 0 shares.

Below is the outcome of experiment 2.

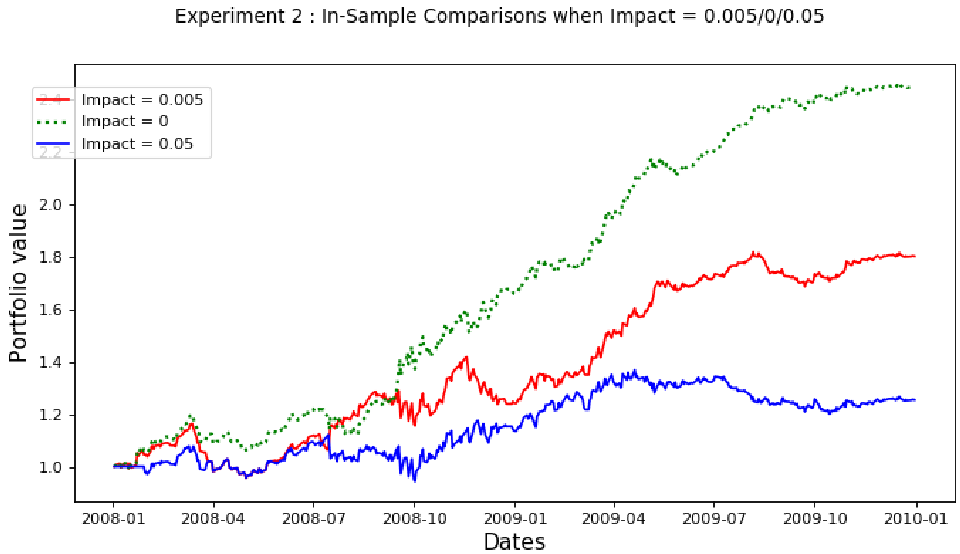

Figure 4— The portfolio value of strategy learner with different values of impact from 2008-1-1 to 2009-12-31

Impact	Cumulative return	STDEV of daily returns	Mean of daily returns	Sharpe Ratio	Final portfolio value
0.00	1.44830	0.01089	0.00183	2.67741	244,830
0.005	0.80278	0.01228	0.00124	1.60872	179,931
0.05	0.25399	0.01426	0.00055	0.61310	125,399

Table 6 — The outcome of experiment 2

Based on figure 4 and table 6 above, we can see that there is a negative correlation between the portfolio performance and the values of impact. When the value of impact increases, the cumulative return, the sharpe ratio, the average of daily return and the final portfolio would decrease.

Since the value of impact is a part of transition costs, it is expected that when the cost is higher, the return will be lower.

6 REFERENCES

1. Investopedia.com (2020). Stochastics Oscillator: An Accurate Buy and Sell Indicator
2. Investopedia.com (2020). Moving Average Convergence Divergence (MACD)
3. Investopedia.com (2020). Simple Moving Average (SMA)