CS7646 Spring 2022 Project 8 Strategy Evaluation

Fung Yi Yuen

fyuen3@gatech.edu

1 Introduction

This project is to implement and compare Manual Strategy and Strategy Learner. Both strategies use three indicators, Simple Moving Average (SMA), Bollinger Bands Percentage (BBP) and Momentum to determine buy/sell signals. A trades data frame is generated for each strategy by leveraging historical prices.

The initial hypothesis is that Strategy Learner would perform better than Manual Strategy. This hypothesis will be verified by comparing both strategies' cumulative return and daily returns with the benchmark strategy.

2 Indicator Overview

This project uses SMA, BBP and Momentum as indicators.

2.1 Simple Moving Average (SMA)

SMA is the average stock price in a fixed time period.

SMA = $\sum_{i=1}^{n} \frac{a_1 + a_2 + \ldots + a_n}{n}$ where a_i is the stock price at period n and n is the total periods

In this project:

- 21 days is used as the lookback window
- adjusted close is used as stock price to calculate the rolling means
- Price/SMA ratio is used to indicate a trading signal.

The 21-day lookback window is large enough to ignore the noise in daily price fluctuation while not too large (like 200-SMA) to reflect recent stock trends.

Thus SMA = Sum of 21 daily adjusted close stock prices / 21 days

Price/SMA ratio is implemented in both Manual Strategy and Strategy Learner to show how far the stock price deviates from the SMA.

2.2 Bollinger Band Percentage (BBP)

Bollinger Bands uses the SMA ± 2 rolling standard deviations to create an upper and a lower band:

Upper band = SMA + 2 * rolling standard deviation

Lower band = SMA - 2 * rolling standard deviation

Bollinger Band Percentage (BBP) = $\frac{(price - lower\ band)}{(upper\ band - lower\ band)}$ is used to indicate a buy / sell signal when the stock price deviates far from the SMA.

2.3 Momentum

Momentum measures how fast the stock price changed over a lookback period.

Momentum = $\frac{price\ of\ the\ day\ (t)}{price\ of\ the\ day\ (t-n)}$ - 1 , where **n** is the lookback period

This project uses 21 days as lookback period, i.e.

Momentum = prices / prices.shift(21 days) - 1

3 Manual Strategy

To create an overall buy/sell signal, the 3 indicators mentioned above are combined based on their signaling values and current stock holding position.

3.1 SMA

The reason for using Price/SMA ratio is that daily volatility of a stock price tends to follow the SMA line. SMA represents the trend of a stock. Daily ups and downs of a stock price will finally return to the SMA value.

- If "Price / SMA" < 0.6, current price is far below SMA value. The price is expected to go up and return to the SMA value. It is a buy signal.
- If "Price / SMA" > 1.1, current price is above SMA value. The price is expected to drop and return to the SMA value. It is a sell signal.

3.2 BBP

The reason for using BBP is that stock prices are usually moving within the Bollinger Bands. If the price is moving out of bands and away from the SMA line, this indicates a buy / sell signal.

- If BBP > 0.8, the stock price is near the upper band which means overbought is happening. The stock price is overestimated by the market. It is a sell signal.
- If BBP < 0.2, the stock price is near the lower band which means oversold is happening. The stock price is underestimated by the market. It is a buy signal.

3.3 Momentum

Positive momentum means the stock price is rising fast. Investors in the market tend to buy the stock thus the price rises. There is a higher chance of the stock being overbought. Negative momentum means the stock price is dropping. Investors in the market tend to sell the stock thus the price drops. There is a higher chance of the stock being oversold.

- If momentum > 0.1, the stock might probably be overbought and would soon drop. It is a sell signal.
- If momentum < -0.1, the stock might probably be oversold and would soon rise. It is a buy signal.

3.4 Implement Manual Strategy

This project uses signal 0, 1, -1 to represent zero holding, 1000 shares long, 1000 shares short respectively.

- At the beginning of trades, I don't have any stock so signal is set to 0
- If Price/SMA < 0.6 or BBP < 0.2 or Momentum < -0.1,
    - Buy 1000 shares and set signal = 1 if current holding is zero
    - Buy 2000 shares and set signal = 1 if current holding is -1000
    - No action if current holding is 1000
- If Price/SMA > 1.1 or BBP > 0.8 or Momentum > 0.1,
    - Sell 1000 shares and set signal = -1 if current holding is zero
    - Sell 2000 shares and set signal = -1 if current holding is 1000
    - No action if current holding is -1000

3.5 Comparing Manual Strategy with benchmark

Figure 1 & 2 shows Manual Strategy performs better than benchmark most of the time, except for a few periods in out-of-sample periods. Table 1 shows Manual Strategy has higher cumulative return, higher daily return and smaller deviation of daily return than benchmark in both in-sample and out-of-sample periods. That means Manual Strategy earns more with less volatility.

Manual Strategy performs better because trades are made based on price trends and movements. Manual Strategy uses shorting positions instead of "buy and hold" (benchmark strategy) which earns more when the stock price is dropping.

However, Manual Strategy in out-of-sample performance is not always better than benchmark. Since the lookback window is set to be 21 days for all 3 indicators, there is time lag for Manual Strategy to execute a profitable trade at the right time. At the end of the period, Manual Strategy still performed better than benchmark. Another reason could be due to the tuning for in-sample data instead of out-of-sample data. So the trades are more favorable in the in-sample period than the out-of-sample period.

In-sample: Symbol=JPM, period=2008-01-01 - 2009-12-31, start_val=100000, commission=9.5, impact=0.005

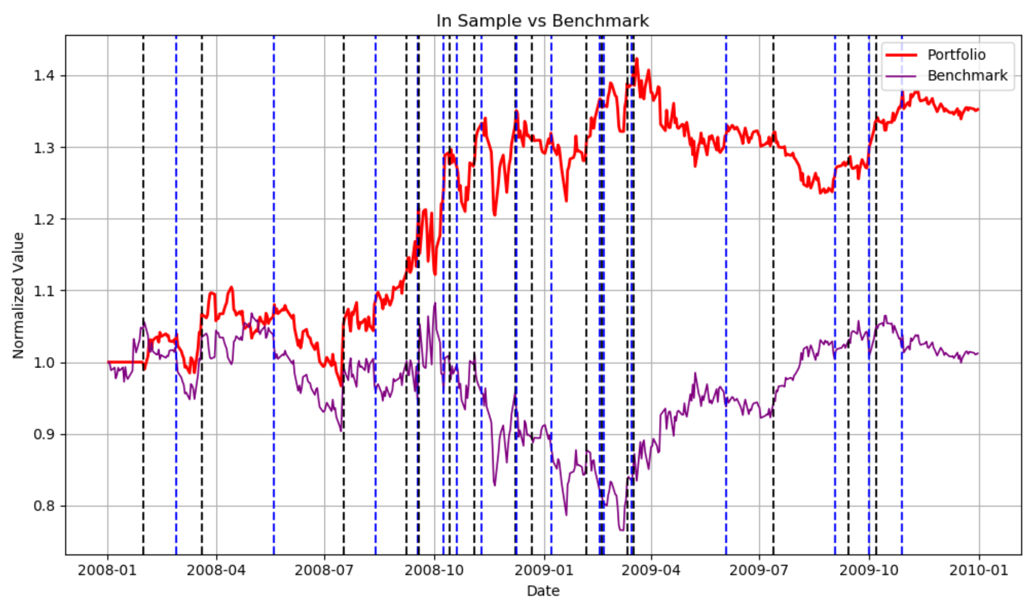

Figure 1 —Manual Strategy vs benchmark for in-sample (symbol: JPM)

Out-of-sample: Symbol=JPM, period=2010-01-01 - 2011-12-31, start_val=100000, commission=9.5, impact=0.005

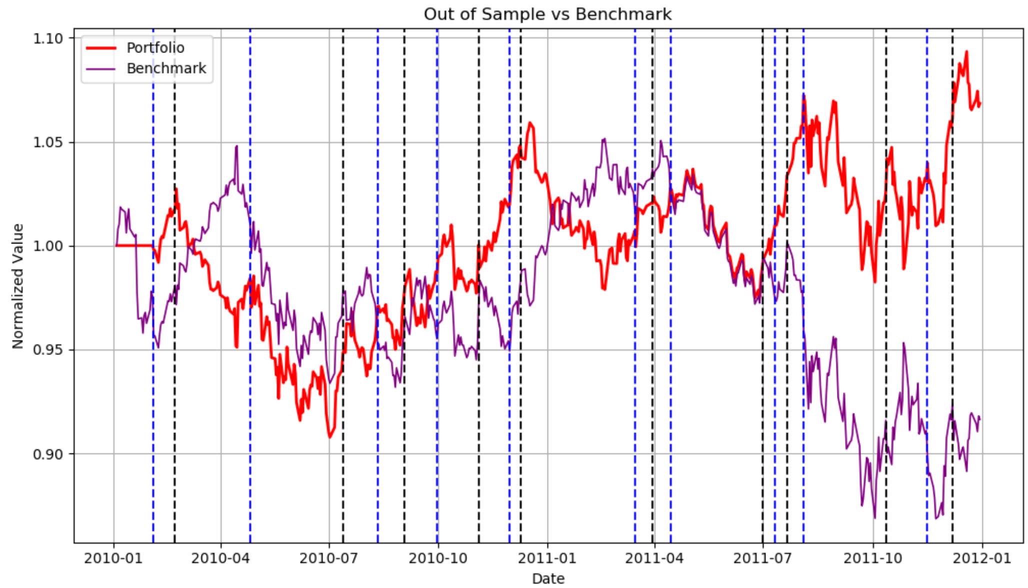

Figure 2 —Manual Strategy vs benchmark for out-of-sample (symbol: JPM)

Periods	Type	Cumulative return	Std dev of daily returns	Mean of daily returns
In-sample	Benchmark	0.012324	0.017041	0.000168
	Manual	0.352235	0.012931	0.000682
Out-of-sample	Benchmark	-0.08357	0.008500	-0.000137
	Manual	0.068366	0.007680	0.000160

Table 1— Manual Strategy & benchmark performance for In-sample & out-of-sample

4 Strategy Learner

4.1 Steps to frame the trading problem

Strategy Learner is created using Random Forest learner (RT Learner). An ensemble Bag Learner calls RT Learner to train 20 models (20 bags) with leaf_size=5.

- Define stock symbol (e.g. IBM), start date (2008, 1, 1) and end date (2009, 1, 1). Get a data frame of the stock prices within this date range for the 3 indicators (SMA, BBP and Momentum)'s calculation.

- Define X and Y values to train the model. X values are 3 indicators (SMA, BBP and Momentum) mentioned above. They are factors used to train the model.
- Import the 3 indicators (SMA, BBP, Momentum) into the Strategy Learner. Set lookback window = 2. The "add_evidence()" will call these 3 indicators and put them into Xtrain to train the model.
- Define YBuy, YSell and Returns. This project sets
  - YBuy = 0.015 + impact
  - YSell = -0.015 - impact
  - Returns = future 10 days return = price (t+10)/price(t) - 1
  - Note that the "0.015" is 1.5% increase / decrease in stock price. Impact is a user defined variable how less profitable a trade can be.
- Define Ytrain. It is a value of +1 (Long), -1 (short) or 0 (cash), depending on N day returns. In this project, N = 10 and
  - If returns > YBuy, Ytrain = +1 (go long)
  - If returns < YSell, Ytrain = -1 (go short)
  - Otherwise, Ytrain = 0 (cash)
- Strategy Learner will use the Xtrain and Ytrain values to learn the pattern and predict future trading actions.

4.2 Testing Strategy Learner

The "testPolicy()" uses out-of-sample data to see the performance of Strategy Learner. Testing steps are similar to training steps:

- Define stock symbol (e.g. IBM), start date (2009, 1, 1) and end date (2010, 1, 1). Get a data frame of the stock prices within this date range for the 3 indicators (SMA, BBP and Momentum)'s calculation.
- Xtest is the 3 indicators input to the trained model to predict Y i.e. trade signal
- Ytest is the trade signal +1 (Long), -1 (short) or 0 (cash) query from the model
- A trade table is generated according to Ytest and holding positions
  - If Ytest > 0,
    - buy 1000 shares if current holding is zero
    - buy 2000 shares if current holding is -1000
  - If Ytest < 0,

- sell 1000 shares if current holding is zero
- Sell 2000 shares if current holding is 1000

4.3 Discretization

No discretization of data is required since RT Learner is used instead of Q-Learner. But to convert my ensemble Bag Learner into a classification learner, mode instead of mean is used to get the predicted result Y.

5 Experiment 1 (Manual Strategy / Strategy Learner)

This experiment compares the performance of Manual Strategy, Strategy Learner and benchmark for both in-sample and out-of-sample data.

To plot a graph for comparison, 3 portfolios are needed to represent 3 strategies (Manual Strategy, Strategy Learner and benchmark).

- Create 3 data frames to store the trades of the 3 strategies (by calling ms.testPolicy, learner.testPolicy and a benchmark function)
- ms.testPolicy is the method from Manual Strategy, learner.testPolicy is from Strategy Learner (run "add_evidence()" to train up a model before using testPolicy()), benchmark function is constructed according to the buy and hold 1000 shares conditions.
- Use the trade data frames to compute the daily portfolio value of the 3 strategies.
- Normalize the 3 portfolios (i.e. portfolio value / portfolio value[0])
- Plot the 3 normalized portfolios in one graph for comparison
- Both in-sample and out-of-sample use the above same steps. Only the start date and the end date parameters are different (see below).

5.1 In-sample performance

Assumption: no limit on leverage

Hypothesis: Strategy Learner outperform > Manual Strategy > benchmark

Parameter: symbol=JPM, start date=(2008, 1, 1), end date=(2009, 12, 31), in_sample=True, start value=100000, commission=9.95, impact=0.005

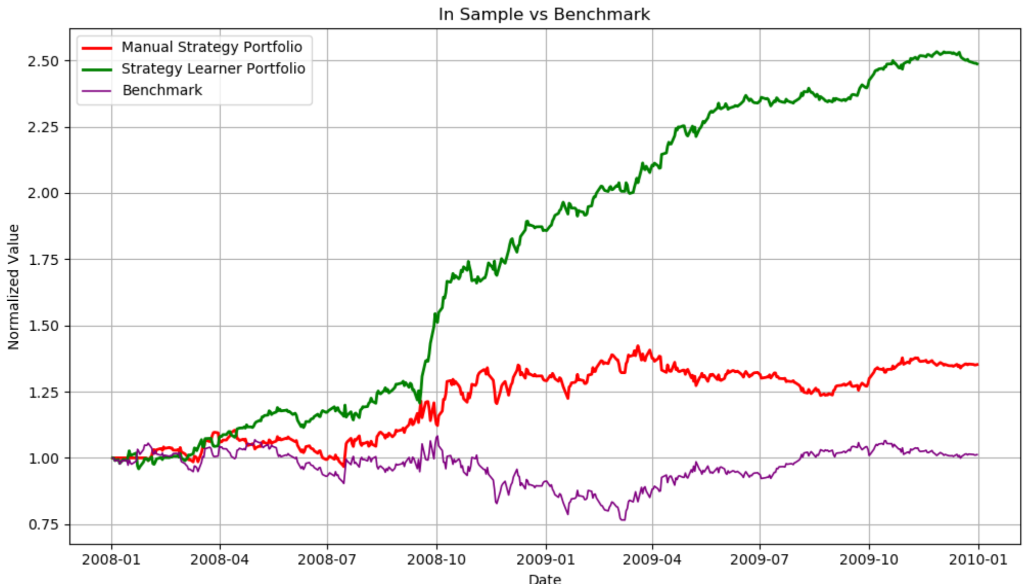

Figure 3—Manual Strategy vs Strategy Learner vs benchmark for in-sample data

5.2 Out-of-sample performance

Assumption: no limit on leverage

Hypothesis: Strategy Learner outperform > Manual Strategy > benchmark

Parameter: symbol=JPM, start date=(2010, 1, 1), end date=(2011, 12, 31), in_sample=False, start value=100000, commission=9.95, impact=0.005

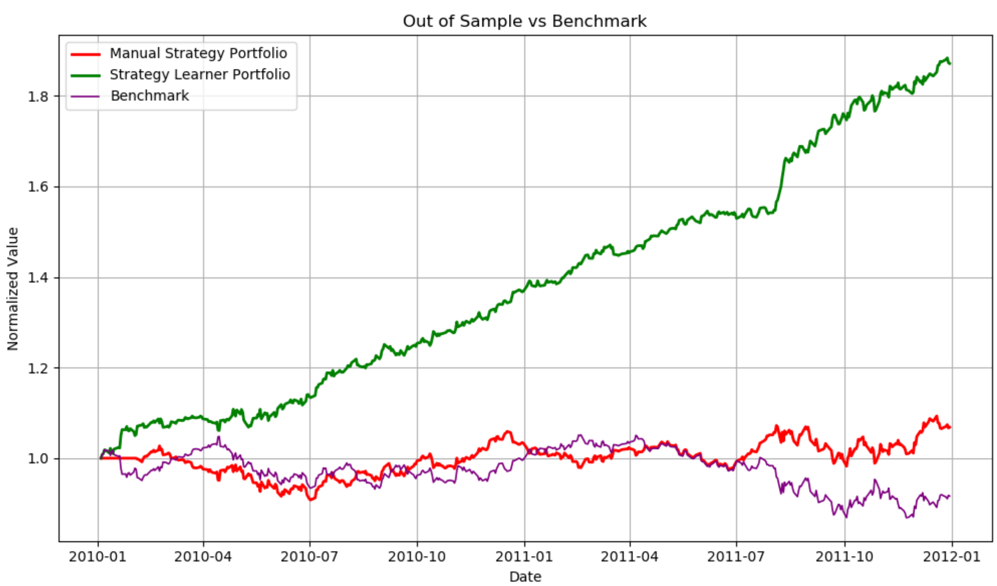

Figure 4—Manual Strategy vs Strategy Learner vs benchmark for out-of-sample data

5.3 Results

Table 2 summarizes the 3 Strategies performance.

In terms of cumulative returns and daily returns:
Strategy Learner > Manual Strategy > benchmark

In terms of standard deviation (smaller std dev means less volatile),
Strategy Learner < Manual Strategy < benchmark

I would **NOT** expect Strategy Learner to always perform better than Manual Strategy because RT learner introduces randomness in choosing split features and such randomness could cause the decision (Y values) being suboptimal.

Periods	Type	Cumulative return	Std dev of daily returns	Mean of daily returns
In-sample	Benchmark	0.012324	0.017041	0.000168
	Manual	0.352091	0.012932	0.000681
	Strategy	1.486634	0.010284	0.001861
Out-of-sample	Benchmark	-0.08357	0.008500	-0.000137
	Manual	0.068276	0.007680	0.000160
	Strategy	0.871258	0.005562	0.001261

Table 2—Strategy Learner vs Manual Strategy vc benchmark performance for In-sample & out-of-sample

6 EXPERIMENT 2 (STRATEGY LEARNER)

This experiment compares the Strategy learner's performance with different impact values.

Hypothesis: Strategy Learner performs better when impact is smaller. Impact is a measure of how less profitable a trade can be. It means the stock prices move in a direction against the buyer or seller i.e. the price goes up when you want to buy. While the price drops when you want to sell. If the impact is low, a trade would be more profitable. Thus Strategy Learner would perform better.

Parameters: symbol=JPM, start date=(2008, 1, 1), end date=(2009, 12, 31), start value=100000, commission=0

For each impact value:

- Run "add_evidence()" in Strategy Learner to train up a model.

- Run testPolicy() to generate a trade data frame for the defined period stated in parameters above
- Use the buy/sell signals in trade data frame to compute a portfolio values
- Normalized the portfolio values (portfolio value / portfolio value[0])
- Repeat above steps for different impact values

Results support the hypothesis (figure 5 and table 3). Cumulative return, daily returns and Sharpe ratio are higher when impact is zero. Standard deviation is lower when impact is zero i.e. lower volatility when impact is low.

Impact	Cumulative return	Std dev of daily returns	Average daily returns	Sharpe ratio
0	2.0597	0.008484	0.002257	4.223150
0.002	1.404036	0.009679	0.001788	2.933172
0.05	0.082194	0.015173	0.000271	0.284089
0.1	0.240829	0.014380	0.000531	0.586574

Table 3— Strategy Learner with different impact values for in-sample data

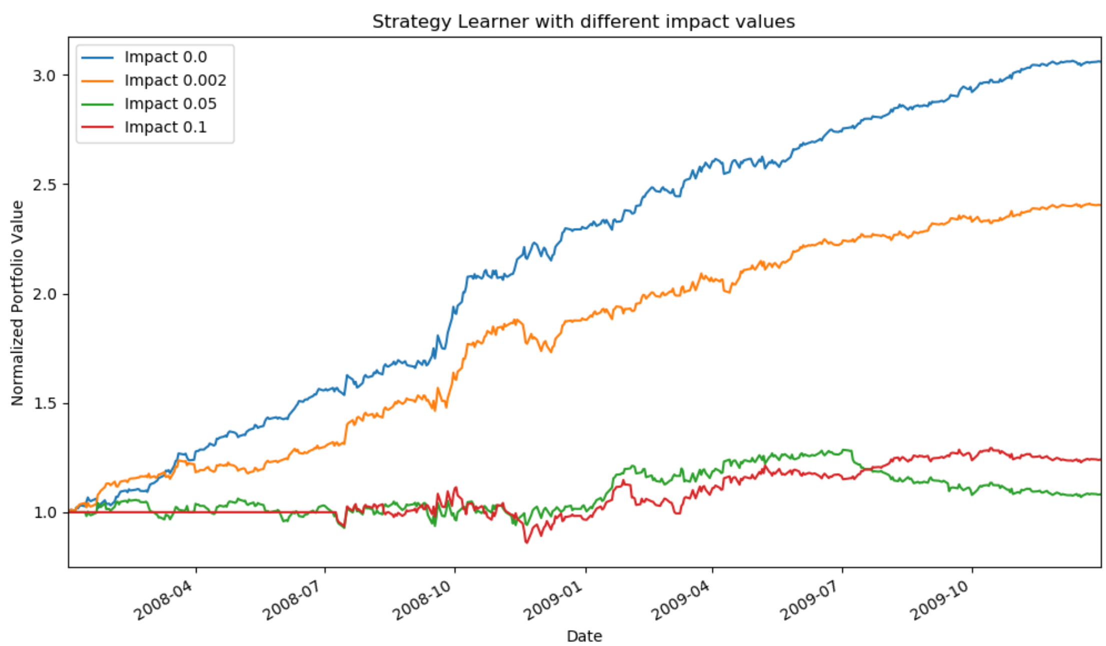

Figure 5—Strategy Learner with different impact values for in-sample data