# ML4T Report: Project 8

Aditya Bhushan
abhushan30@gatech.edu

## 1 INTRODUCTION

The report presents my approach and analysis on the Strategy Evaluation project. The project has multiple tasks but the key component is to determine if to buy, hold or sell a given stock. Broadly, this is required to be done using:

A. Manual Strategy – Using key indicators (3) to determine stock position

B. Strategy Learner – Using A Machine Learning Model, train and test model operation (dicisions)

This project helped me think through in depth when devising a trading algorithm (Machine Learning Model) that combines all the various techniques, tips and tricks we have learnt in the ML4T class. We are to utilize the ML model training the machine learning model on data from 2008 to 2009 and then test the model against data from 2010 to 2011.

## 2 INDICATOR OVERVIEW

I leveraged the following indicators in this project:

a. Simple Moving Average (SMA)

As the name suggests, we are taking a simple arithmetic mean of the stock price values over a specified time period **[1]**. Along with being a fantastic indicator of direction in which the stock is trending, it also smooth out the fluctuations in stock price. This indicator also forms basis of many other advance indicators such as MACD.

SMA is calculated by adding the closing price of the security for a number of time periods and then dividing this total by the number of time periods, which gives the average price of the security over the time period

In general, SMA = Mean of the Daily Returns of the stock

**Indication:** Buy signal when the stock price goes above SMA, Sell signal when the stock price goes below SMA line.

**For the purpose of computations in this project, I used 'Price per SMA'. Here, I divided the price (current date) with the SMA value in order to adjust SMA to be used as a signal for trading. Price per SMA < 1 implies that stock is likely to rise whereas Price per SMA >1, implies that the stock is likely to fall in price.**

**Parameters Optimized:** Sliding Lookback Window or slbWindow which is the lookbak period in order to stabilize the SMA fluctuations

b. Momentum

We can track the rate of change in price of a stock over a set number of days (lookback window) and that's how momentum comes into play. Momentum tracks the velocity of a price fluctuations of a stock. Positive momentum occurs when stock price on current day is higher than what it was on the set number of days (lookback window) before and negative momentum occurs when stock price is currently lower than what it was lookback days ago.

**Formula [2]:**

Momentum = (V – Vx)    , where:

V = Latest price
Vx = Closing price
x = Number of days ago

**Indication:** Buy signal when momentum shows uptrend, Sell signal when momentum shows downtrend

**Parameters Optimized:** Sliding Lookback Window or SLB (=20)

c. Bollinger Bands

Here, we use the SMA line and generate bands 'm' standard deviations above and below. I am considering m=2 i.e. twice * stddev and a 50-day rolling SMA.

This concept was introduced by John Bollinger. As the SMA, line diverges from these bands, we can make decision on whether to buy or sell. However, Bollinger bands alone should not be used as it could be riskier investment. These bands are great at determining overbought and oversold conditions **[5].**

**Formula:**

Upper Band = SMA(n) + $m*\sigma[n]$

Lower Band = SMA(n) − $m*\sigma[n]$ , where:

> SMA= Simple Moving average
> n=Number of days in smoothing period (I took n=50 for my project)
> $\sigma[n]$=Standard Deviation over last n periods
> m=Number of standard deviations (I took m=2 for my project)

**Indication:** Buy signal when stock price is above the upper band and moving towards region between the bands, Sell signal when stock price is below the lower band and moving towards region between the bands.

**For the purpose of computations in this project, I used Bollinger Bands Percentage or BBP. So, BBP > =1, implies stock is going above the top band whereas BBP <=0, implies stock is going lower than the lower band,**

**Parameters Optimized:** Sliding Lookback Window or SLB (20), SMA and Standard Deviation (Volatility).

## 3 MANUAL STRATEGY

For my manual strategy, I utilized a combination of all 3 technical indicators for making a buy, hold or sell decision.

**Criteria:**

| | BUY criteria | SELL criteria |
|---|---|---|
| Price per SMA | < 0.9 | > 0.9 |
| Momentum | < - 0.1 | > 0.1 |
| Bollinger Bands Percentage | < 0.2 | > 0.8 |

SHORT: All SELL criteria fulfilled, 1000 shares short

LONG: All BUY criteria fulfilled, 1000 shares long

HOLD: Anything else, other than the above conditions

**Additionally, I used the following:**

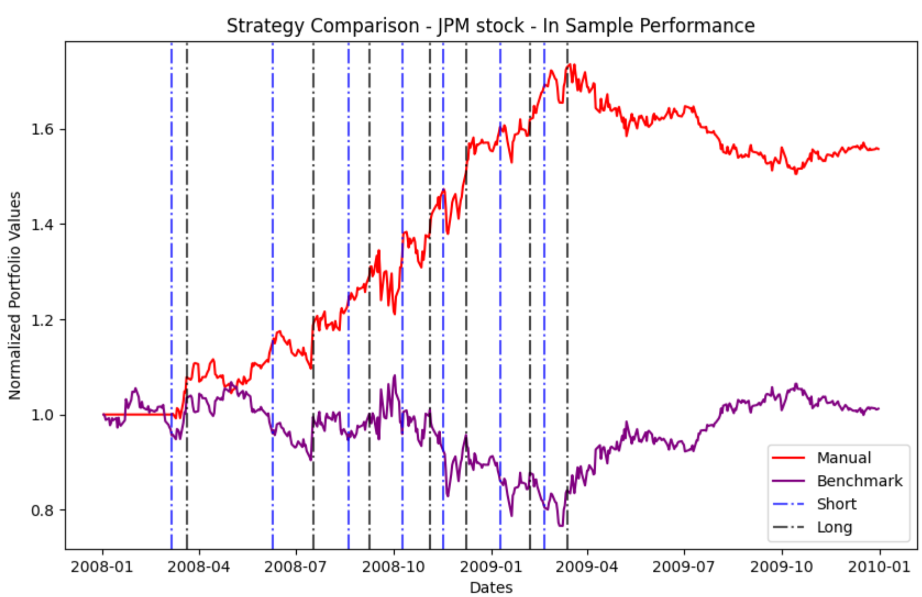
- **'JPM' share and its price**
- **Commission = 9.95**
- **Impact = 0.005**
- **slbWindow (loockbak) = 20**

**I believe that this is effective because I tuned the parameters and indicator values so that the cumulative returns are higheras compared to the bench mark, which I will discuss next.**

Benchmarking is done keeping in mind the first and last day of the trading period. Buying 100 shares on day 1 and hold till last day and sell all 1000 shares on last day.

Results: Manual Trader outsmarts the benchmark trader for 'JPM' shares as shown in figure 1.

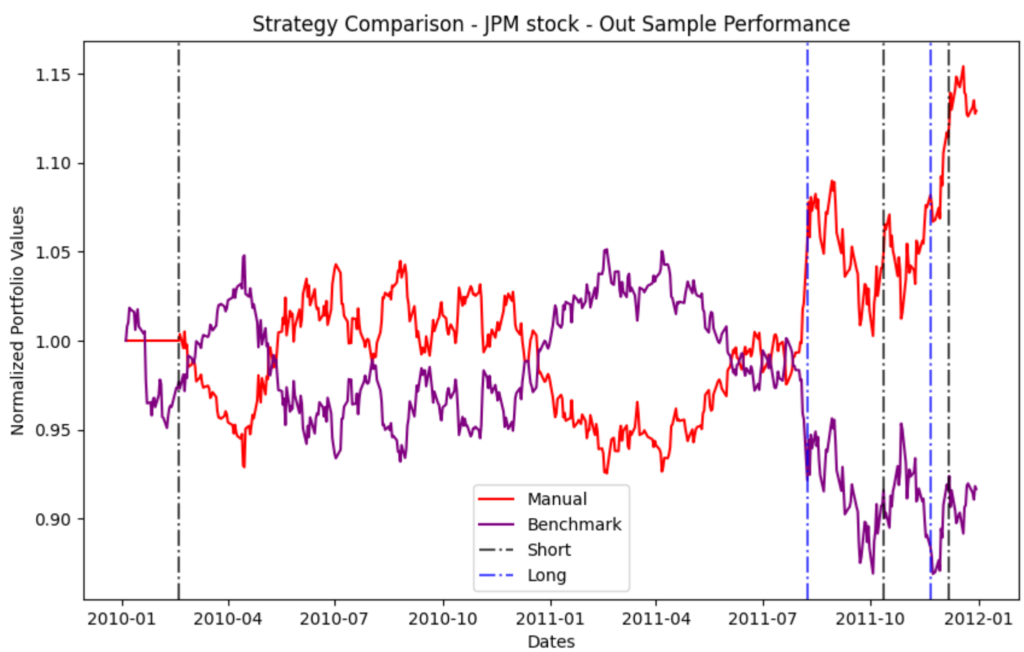
Figure 1 - In Sample Comparison:



As the time increases, the difference between normalized portfolio price of Benchmark VS Manual increases or widens. This implies that the returns in case of manual strategy are higher than benchmark strategy.

In the beginning, we observe that the manual strategy is learning mainly because of the sliding window lookback period introduced which can cause lag. There are fluctuation due to volatility of the stock price movement.

Figure 2 - Out of Sample Comparison:




At the beginning, benchmark strategy is yielding higher returns as opposed to manual strategy but by the ending of the time period, we see that manual strategy is yielding far greater returns.

It appears that for out of sample, our manual strategy fails to execute trades at crucial points in time when returns could have been maximized but slowly and gradually it does end up performing better than benchmark. There is a tussle between both strategies in yielding better results.

It is important to note that the black and blue lines represents short and long positions along the way.

**Performance Metrics:**

| Benchmarking | Parameter | Manual Strategy |
|---|---|---|
| 0.012299 | **Cumulative Returns** | 0.55790 |
| 0.016987 | **Daily Return Std Deviation** | 0.011429 |
| 0.000167 | **Daily Return Mean** | 0.000943 |
| 101230 | **Final Portfolio Value** | 155790.0 |
| 0.156763 | **Sharpe Ratio** | 1.310201 |

We can clearly see a significatnt or considerable difference in the daily returns (Mean, Standard Deviation) and sharpe ratio, respectively.

## 4 STRATEGY LEARNER

For Strategy Learner, we are provided a few options, Classification Learner, Reinforcement Leaner and Optimization-based learner.

Out of these options, I chose to experiment with **Reinforcement Learning Algorithms, especially, Q-Learner**. This is because I think we can frame the problem as a reinforcement learning problem wherein we can define states, action, policy, rewards, etc.

Q-learning is a model-free reinforcement learning algorithm that seeks to find the best action to take given the current state.

**Actions are LONG, SHORT and CASH**

**Reward is easy to compute within the environment defined**

**Use of Dyna for making the training process least expensive of the 3 options provided for this assignment**

**Plus, DISCRETIZATION:** This is a really important concept as Q-Learning requires discretized states to function correctly as opposed to continuous values. Now, we are free to choose how many discrete levels we need to build. So I chose to go with the simplest way – Binary state i.e. 2 values for each indicator used and each position held (states). So, I picked total number of states = 96, Combination (indicator,state) must be (0,95). Moreover, rewards are adjusted depending on the state (cash,short,long). If algorithm was short previously (old state) and the share price has increased currently (now state), then reward will be negative and vice versa. For CASH state, reward will be zero until the state changes.

**Hyperparameters:** I tuned the following hyperparameter combination as follows:

**Rate of random action, rar = 0.9; Rate of decay, radr = 0.99; dyna = 0, alpha = 0.2, gamma = 0.9**

In summary, strategy leaner is fed the indicator values, lookback window and returms for everyday until it begins to learn the optimal combination. It eventually learns on its own to come up with a trading strategy by interacting with its environment and understands the reward-performance trade offs.

## 5 EXPERIMENT 1

This experiment is performed with a sole purpose of comparing performance, statistics and metrics between the Benchmark performance, Manual Strategy and the Strategy Learner using a Q-Learner.

Initial Hypothesis is that the strategy learner should outperform both the manual learner and the benchmark.

As per figure 3a in sample results, it appears like Strategy Learner is not able to catch up to returns of manual learner and strategy learner is struggling to beat manual learner. This implied that strategy learner with Q-learner needs more time frame to learn and come up with an optimized combination of reward-return framework that will yield a much higher return as initially thought. Also, the starting time period for strategy learner seems relatively flat with low volatility and it could also be because of lookback window.

However, looking at Figure 3B, it seems like the Manual and Strategy Learner are in tussle at the beginning and eventually Strategy Learner beats the manual learner in out of sample test data. This implied that strategy learner with Q-learner is able to yield better returns for JPM stock.

Figure 3A – In Sample Strategy Comparison:

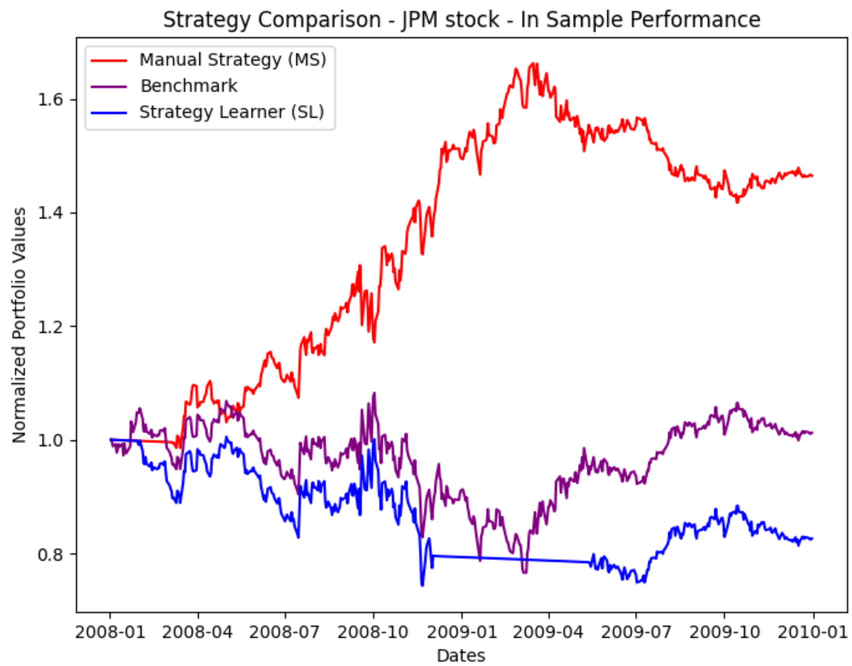
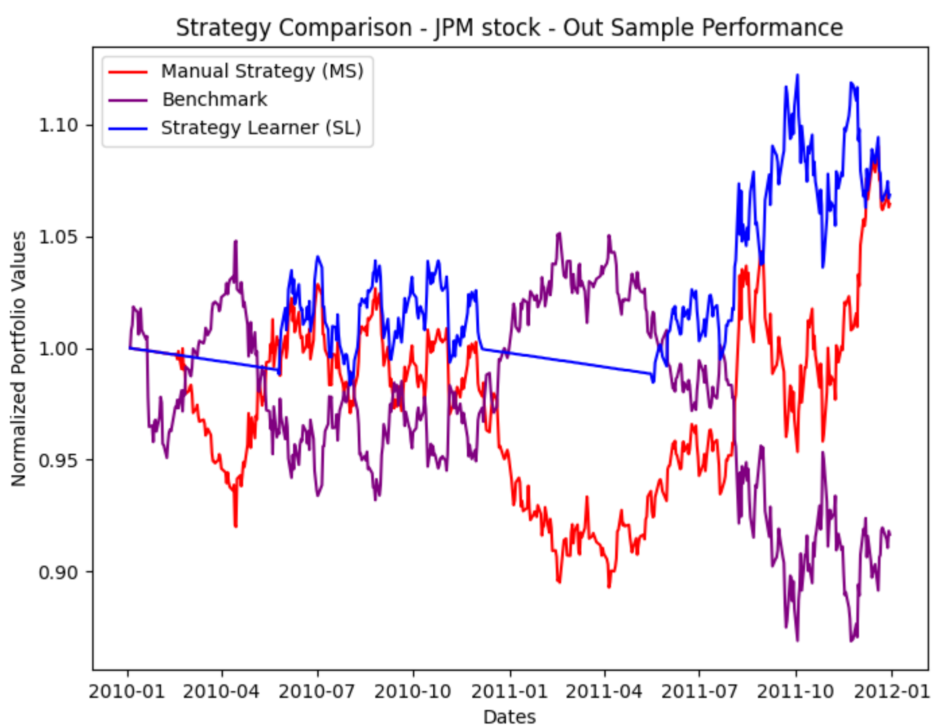



Figure 3B – Out Of Sample Strategy Comparison:



## 6 EXPERIMENT 2

This experiment is done to understand the effect of market 'Impact' parameter on the performance of strategy earner. Impact refer to how much trading of stocks affects the buyers and sellers. My initial hypothesis is that in order for the learner to perform better, the market impact needs to be low.

When the impact is high, our strategy learner is not penalized enough to make wrong trades which could result in poor cumulative returns and poor performance gains. Also, during high market impact, for meeting the YBUY,YSELL thresholds, our learner will have to make fewer trades whereas during low impact, learner is free to make many trades without being penalized.

These are the 3 different values on which strategy learner is tested and its performance is plotted as shown in Figure 4.

I have used commission 0.0, to check Impact effects only.

Impact 1: 0.005

Sharpe Ratio - Impact1 on SL: -0.368881

Cumulative Return - Impact1 on SL: -0.227446

Standard Deviation - Impact1 on SL: 0.016277

Average Daily Return - Impact1 on SL: -0.000378240765473842l5

Final Portfolio Value - Impact1 on SL: 77255.4

Impact 2: 0.25

Sharpe Ratio - Impact1 on SL: -0.742387

Cumulative Return - Impact1 on SL: -0.49875

Standard Deviation - Impact1 on SL: 0.023192

Average Daily Return - Impact1 on SL: -0.00108

Final Portfolio Value - Impact1 on SL: 50124.999999

Impact 3: 0.0

Sharpe Ratio - Impact3 on SL: -0.14750778066141107

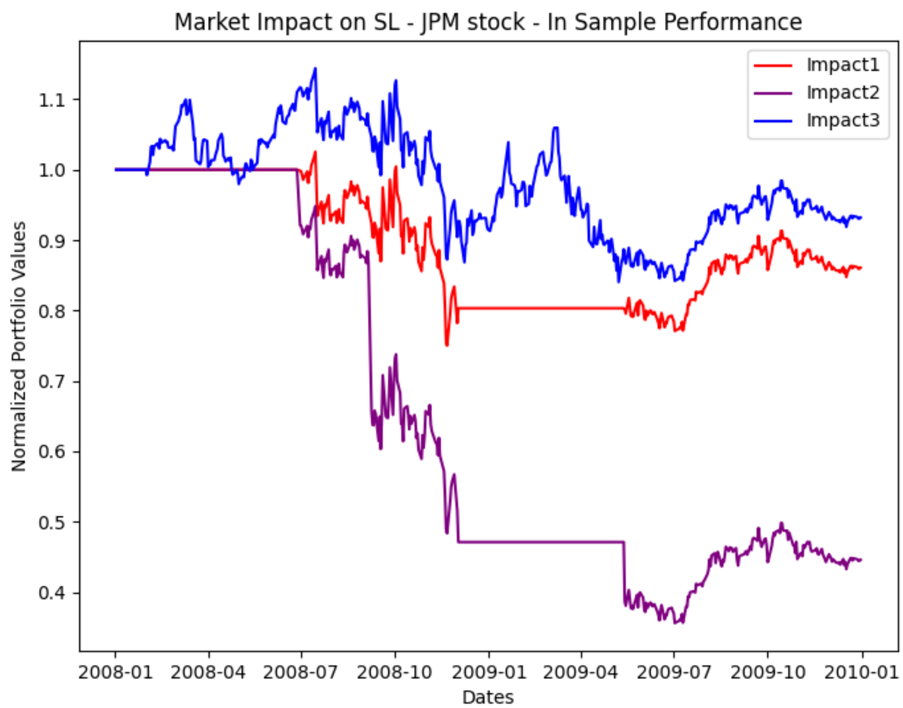
Cumulative Return - Impact3 on SL: -0.1159

Standard Deviation - Impact3 on SL: 0.014686533790130242

Average Daily Return - Impact3 on SL: -0.00013646898683252 99

Final Portfolio Value - Impact3 on SL: 88410.0

Figure 4 –Market Impact VS Strategy Learner:




**Statistics for** Date Range: 2008-01-01 00:00:00 to 2009-12-31 00:00:00

From the above graph and statistics, we clearly see how market impact affects the performance (portfolio values normalized) of our strategy learner. As the impact value increases, our learner performance lowers. This confirms our original hypothesis to be true.

## 7 REFERENCES


1. Hayes, A. (2019). Simple Moving Average - SMA. Investopedia. https://www.investopedia.com/terms/s/sma.asp
2. Momentum Indicates Stock Price Strength. (n.d.). Investopedia. Retrieved March 13, 2022, from https://www.investopedia.com/articles/technical/081501.asp#:~:text=Momen-tum%20is%20the%20speed%20or.
3. Using Bollinger Bands to Gauge Trends. (2019). Investopedia. https://www.investopedia.com/trading/using-bollinger-bands-to-gauge-trends/