Strategy Evaluation

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1 INTRODUCTION

Can an AI agent build a better strategy than a human trader informed with technical indicators? This project evaluates the effectiveness of applying a QLearner agent to buying and selling stocks using technical indicators on the symbol JPM. In theory, the QLearner agent should out-perform a human crafted strategy ("Manual Strategy"). The QLearner can optimally learn the reward on each trading day and potentially detect unique level combinations of technical indicators that have predictive power compared to the Manual Strategy.

To gauge the effectiveness of the agent, several experiments are run to test the performance of the agent's strategy to a Manual Strategy and to a simple benchmark. But first, the details of the indicators, Manual Strategy, and QLearner derived strategy ("Strategy Learner") are explored.

2 INDICATORS

2.1 Overview

Generally, several indicators representing momentum are used for both strategies. Each strategy does not optimize the parameters within the indicator calculation. Rather the strategies pass pricing data to the indicator functions and either receive a long/hold/short signal or continuous data depending on the type of strategy.

2.2 RSI

The relative strength indicator ("RSI") is a momentum indicator that measures the magnitude of recent price changes. The metric falls between 0 and 100 with upper bounds of 70 and lower bounds of 30. This strategy behind relies on trend reversals. If the RSI breaches its upper limit, then this signifies that the stock is oversold and will trend downward. This indicates a strong case for selling the stock. (Fernando, 2021a) Specifically, the sell signal for RSI is when RSI breaches the upper limit and comes back to the upper limit. Similarly, the buy signal occurs when the RSI hits the lower limit and then reverses to that limit.

The RSI is calculated as $RSI = 100 - 100/(1 + (Average\ Gain/Average\ Loss))$. Average gain represents a rolling average of the last 14 days of positive returns omitting negative returns. Similarly, Average Loss is the rolling average of negative returns.

2.3 Golden Death Cross

The Golden Cross or Death Cross is an indicator seeking to capture underlying turns in the market price. The strategy leverages two simple moving averages ("SMA") representing short-term ("ST") 20 – day and long-term ("LT") 50-day average. SMA is calculated as $\sum_{d=0}^{n} Price_d\ / n$ with d representing days and n as the total number of days. A buy signal occurs when the ST trends upwards and surpasses the LT; this is referred to as a Golden Cross. Conversely, a Death Cross and sell signal happens when the ST trends downwards and then dips below the LT. (Li, 2021)

2.4 Moving Average Convergence Divergence

Like RSI, the intent of Moving Average Convergence Divergence ("MACD") indicator is to identify whether the market is over-sold or overbought. It is comprised of several exponential moving averages ("EMAs") whereas RSI is using the ratio of positive and negative returns.

The MACD is the difference between a short-term EMA of 12 days and a long-term EWA of 26 days. Further, an EMA of 9 days on the MACD itself determines the buy or sell signal once it crosses the MACD line. (Fernando, 2021b) In particular, if the signal line is below the MACD line and then surpasses the MACD, this generates a buy signal.

3 MANUAL STRATEGY

3.1 Description

The Manual Strategy leverages converting the continuous indicator data into individual long/hold/short trade signals representing the values 1, 0, and -1 respectfully and combining the signals. This aggregated signal determines when the strategy enters and exits a position. To get a combined indicator signal, the strategy sums all three individual indicator trade signals and normalizes this sum to values of 1,0, and -1. The normalization method used simply maps instances of values greater than 1 to 1 and values lessor than -1 to 1.

The combined signal effectively considers multiple confirmations of momentum signals while controlling for conflicting messages amongst the indicators. This property is due to how numerically dissenting indicators cancel each other out. For example, if RSI, Golden Cross, and MACD had values of -1, 1, and 1 respectfully, the sum of these indicators would still be 1. This depicts how the Manual Strategy democratizes the individual indicator trading signals.

In theory, the Manual Strategy should be effective in screening out dissonance in momentum indicators and could provide a "true" and hopefully, "leading" indication of where the stock price is headed.

3.2 Performance

As shown in Figure 1, the Manual Strategy portfolio shown in red outperforms the benchmark of simply holding the underlying JPM stock by the end of the in-sample window. The figure also indicates in blue when a long signal occurred and when a short signal occurred in black. Note that most of the portfolio's gains occurred when the strategy correctly identified a long signal around August 2009 and held until the sell signal in late September 2009.

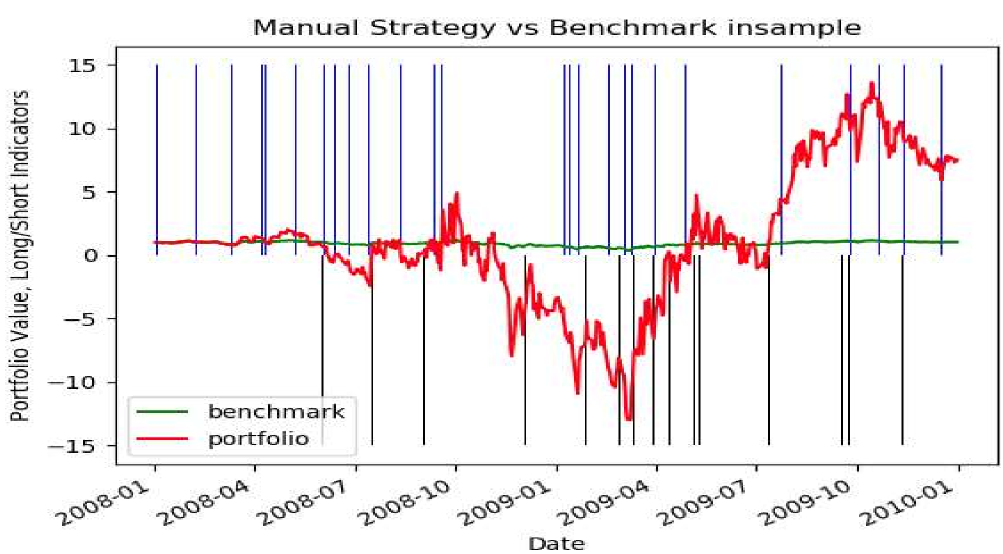

Figure 1—Normalized performance of portfolio and benchmark data with trade signal indicators for in-sample data.

Given the in-sample performance, one may think it's a confirmation of a successful strategy. However, this strategy would not fair well in practice as the out-of-sample performance shown in Figure 2 would have cancelled all previous gains from the in-sample window. It appears there is some increase in portfolio value during the first two quarters of 2011. Yet, the strategy misidentifies a series of strong buy signals in September or August area of 2011 and losses all gains and dives into the negative by the end of the out-of-sample window.

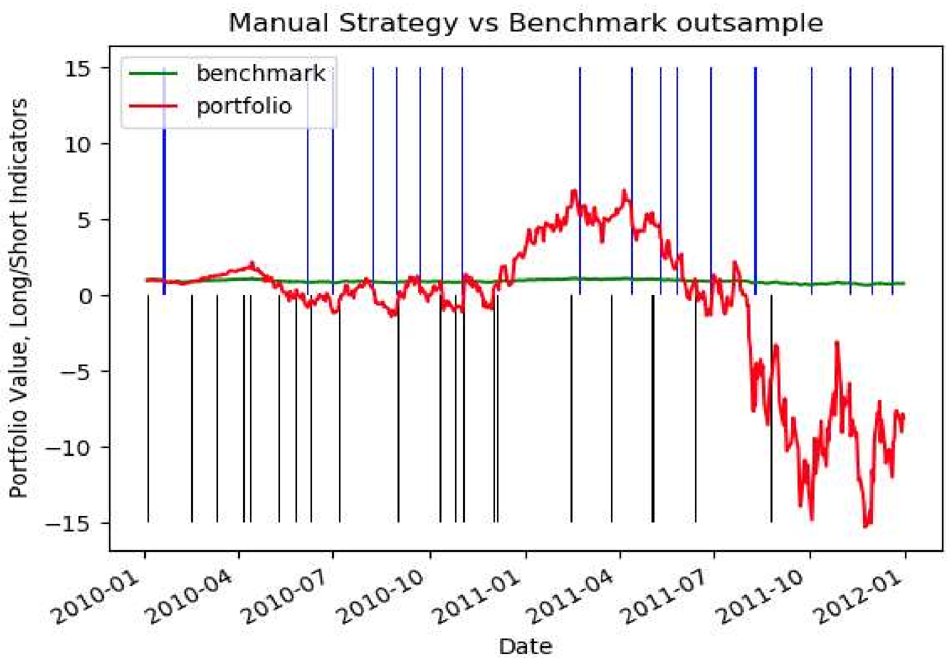

Figure 2— Normalized performance of portfolio and benchmark data with trade signal indicators for out-of-sample data.

Looking at the portfolio statistics for both in and out-of-sample performance in table 1, confirms the lack of gains and shows a large risk appetite for this strategy. In-sample standard deviations of returns are above 16 and out of sample are about 7! Compared to the benchmark standard deviation, this is hundreds of times larger. This is exceptionally large and shows the volatile nature of this strategy. Further, the average returns for both the in and out-of-sample are negative. This indicates that some returns are very profitable, but others almost completely or completely offset the gains. Likely, the underlying indicators are not generating predictive data which is why out-of-sample cumulative returns are exceptionally negative. The in-sample performance is merely confirmation bias and not an indication of how useful the strategy actually is.

Table 1 — In and out-of-sample portfolio statistics for Benchmark and Manual Strategy.

Sample	Portfolio	Cumulative Returns	Standard Deviation of Returns	Average Returns
In-sample (1/01/2008 – 12/31/2009)				
	Benchmark	1230.00	0.0521	0.0014
	Manual Strategy	652089.30	16.1200	-0.8125
Out-of-Sample (1/01/2010 – 12/31/2011)				
	Benchmark	-8340.00	0.0226	-0.0002
	Manual Strategy	-906165.95	7.4807	-0.5793

4 STRATEGY LEARNER - QLEARNER

A QLearning algorithm is particularly useful for solving navigation problems in robotics. The QLearner robot takes in states and rewards to determine the next action. A typical navigation problem might have obstacles that inhibit transitioning the bot into a new position (“state). Or the problem could have “sand traps” that punish the bot with severe negative rewards. However, to solve for an optimal trading strategy, several adjustments had to be made to frame the iteration with the QLearner agent in an appropriate and constructive manner.

For purposes of trading, the action taken by the agent was converted into a series of numbers representing hold, long and short which are 0, 1 and 2 respectfully. These correspond to the columns in the Q-Table. The reward is not a punishment of hitting a wall or running into the sand trap but is the percentage of returns from taking an investment action less transaction fees like impact fees. Further, the state had to be converted from a number representing a coordinate system pegged to physical addresses to a system portraying the unique combination of discretized index states.

Discretization is performed by splitting continuous indicator data into 10 roughly equivalent segments. Each segment maps a portion of the data to a number between 0 and 9. This number depends on if the number range within the segment contains a given indicator value. Ultimately, each discretized indicator value is concatenated to values between 0 and 999, for a total of 1000 states.

5 EXPERIMENT1

This experiment seeks to compare the performance of the Manual Strategy and the QLearner generated strategy ("Strategy Learner"). The Strategy Learner should outperform the Manual Strategy in theory as it may be able to extract more useful information from the indicators. However, as shown in Figure 3, the performance of the learner portfolio does not beat the Manual Strategy portfolio. Yet, the learner portfolio appears to be less volatile compared to the Manual Strategy. This is likely because the QLearner is minimizing the negative returns.

Table 2 — Parameter values for QLearner, experiment1, and experiement2.

Parameter	Value
alpha	0.2
gamma	0.9
rar	0.9
radr	0.99

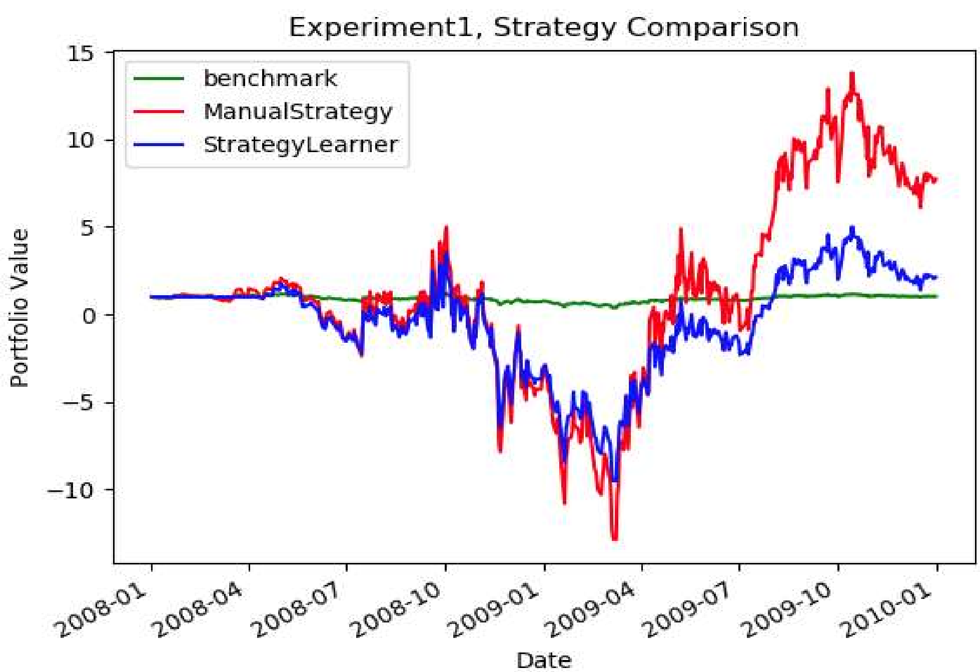

Figure 3 — Normalized performance of Manual Strategy, Strategy Learner, and benchmark data with trade signal indicators for in-sample data.

6 EXPERIEMENT 2

In experiment 2, the learner should react to having more impact fees. To test this, the impact fee is set to values of 0.0, 0.05, and .5 to observe how these values affect average returns and the number of trades performed by the strategy. As fees continue to increase, the expectation is that the number of trades and average returns from these trades decreases. As shown in Figures 4 and 5, both of these metrics decline likely due to a decreasing reward for each trade.

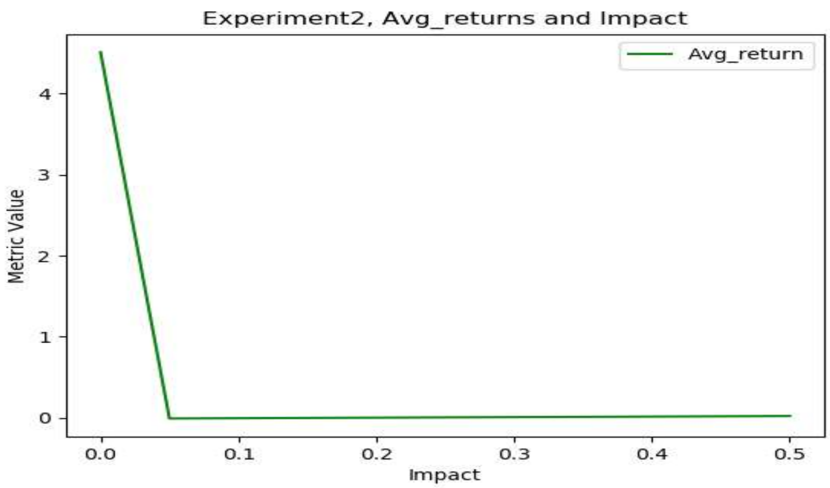

Figure 4— Average returns for impact at 0.0, 0.05, and 0.5.

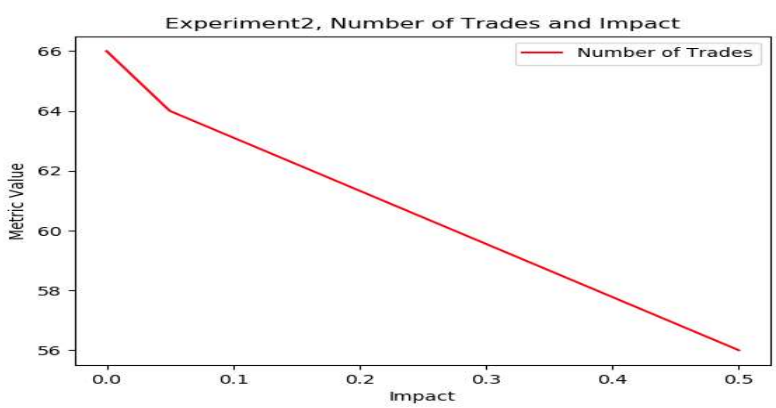

Figure 5— Total number of trades for impact at 0.0, 0.05, and 0.5.

7 REFERENCES

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