Project 8 Report

Xianci Tang
xtang307@gatech.edu

1 INTRODUCTION

The focus of this research project is to gain insights into the application of indicators in trading and compare the performance of two distinct trading strategies: a manual ruled-base strategy and a machine learning based strategy utilizing a Q Learner. The assessment of these strategies will be conducted both in-sample and out-of-sample. This project will be using previous developed projects including the implementation of indicators(indicators.py), a market simulator(marketsimcode.py), and my chosen Q Learner. Additionally, investigate the influence of order impact on trading behavior.

By exploring and analyzing these methodologies, it aims to uncover the strengths and limitations of each approach, shedding light on the significance of indicators in shaping trading decisions. The study's findings will contribute to a deeper understanding of how trading strategies can be optimized and the potential benefits of incorporating machine learning techniques in the trading domain.

2 INDICATORS

Three indicators are used in Manual Strategy and Strategy Learner:

Commodity Channel Index (CCI), Stochastic Oscillator (%D specifically), and Relative Strength Index (RSI)

CCI measures the current price level relative to an average price level over a given period. (3) the implementation of this involves the utilization of the formula below.

CCI = (Typical Price -20-period SMA of TP)/ (0.015 * Mean Deviation)

Typical Price (TP)= (High + Low +Close)/3

Stochastic Oscillator is a momentum indicator that shows the location of the close relative to the high-low range over a set number of periods. (2)

%D is a 3-day simple moving average of % K, the implementation of this involves the utilization of the formula below.

%K= (Current Close – Lowest Low)/ (Highest High – Lowest Low) *100

%D =3-day SMA of %K

The RSI measures the speed and change of price movements. It moves up and down (oscillates) between 0 and 100. (1) the implementation of this involves the utilization of the formula below.

RSI = 100 – 100 /(1+RS)

RS = Average Gain / Average Loss

The important parameter for these 3 indicators is lookback window.

Typical period for RSI is 14, for CCI is 20, for %D is 14.

To optimize the Learner's performance, various combination of three indicators' lookback periods is explored while keeping other hyperparameters constant. The most favorable configuration is found to be RSI with a 14-day lookback period, CCI with a 20-day lookback period, and %D with a 20-day lookback period.

3 MANUAL STRATEGY

A multi-indicator approach is employed to generate trading signals, focusing on identifying both oversold and overbought conditions in the market.

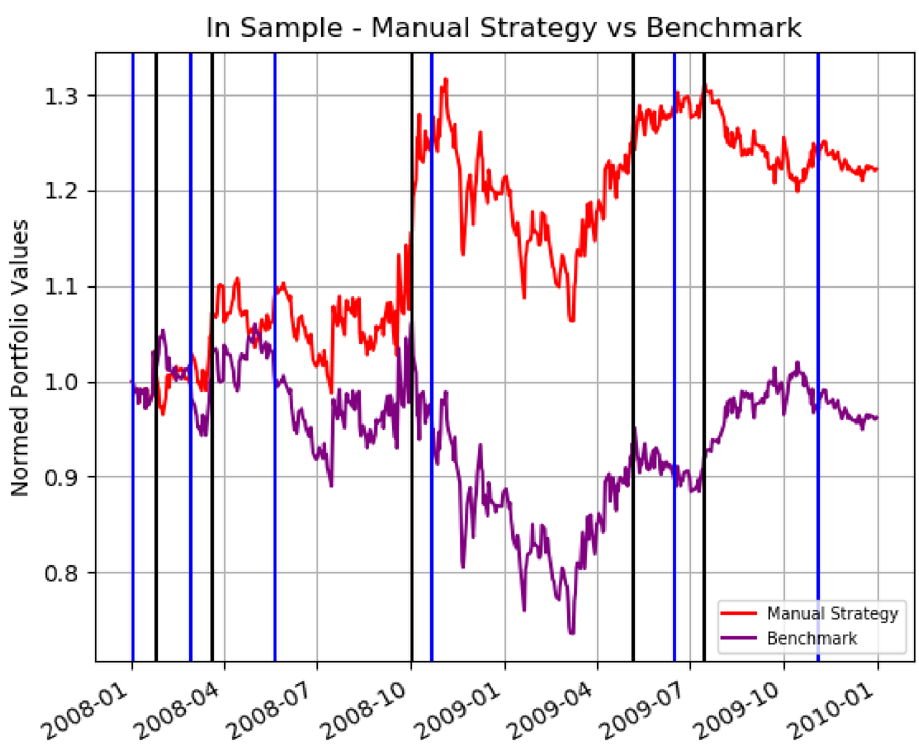
To achieve this, begin by creating two lists, a short value list and a long value list. The short value list contains three threshold range checks for each indicator, which indicate an overbought signal. On the other hand, the long value list contains three threshold range checks for each indicator, indicating an oversold signal.

For each trading day, gather the values of all indicators. To identify a short signal, I require at least two out of three range checks from the short value list to be true. This means that if at least two indicators agree on an overbought condition, I consider it as a short signal. Before executing the trade, estimate the potential gain. If the gain is deemed favorable, proceed with the short move, updating the trade and position accordingly. However, if the estimated gain is not satisfactory refrain from taking any action.

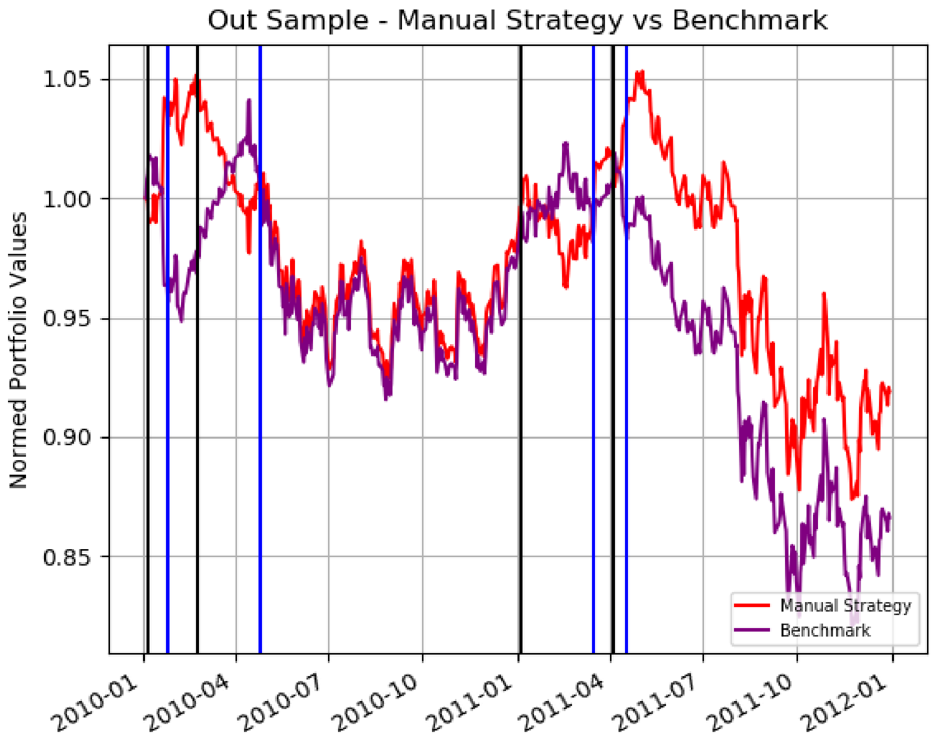
Similarly, for the buy signal, I need at least two out of three range checks from the long value list to be true. In this case, if at least two indicators agree on an oversold condition, I consider it a buy signal. Again, before executing the trade, estimate the potential gain. If the gain estimation meets criteria, proceed with the buy move, updating the trade and position as necessary. If the estimated gain is not met, refrain from making any changes.

The core concept of this strategy revolves around capitalizing on market fluctuations as much as possible, while ensuring profitability after accounting for commission and market impact. It involves buying when oversold signal are detected and selling when overbought signal appear, ensuring profitable opportunities are seized during these conditions.

The strategy is not perfect as trading signal vary under different market conditions and patterns. To accurately identify real trading signal, additional analysis is required.



Based on the presented chart, it is evident that during the in-sample period, the manual strategy performance exceeds the benchmark significantly.



Moreover, even in the out-of-sample period, there is slight outperformance compared to the benchmark.

The out-of-sample performance of manual rule-based strategy is not as robust as during the in-sample period due to its limitation in its inability to adapt effectively to new data. Such strategies are developed based on observations from specific sample data, but data patterns tend to vary across different datasets and over time. Consequently, a rule that performs well in one dataset might not necessarily yield favorable results in another dataset or in future data instances. This lack of adaptability poses a significant challenge for rule-based approaches when encountering diverse and dynamic market conditions.

4 STRATEGY LEANRER

In the context of the market environment, I represent the state using a set of three chosen indicators. Trading types are actions can be taken, either buying or selling, and the reward is determined by the daily return percentage relative to the holding position. The learner engages with the market by trading actions with a degree of randomness and record past state, reward exploration history in its Q Table.

The process of learning begins with sufficient exploration, during which the Q Table keep updating, capturing numerous potential combinations of states and corresponding rewards. Once exploration is complete, the Q Table becomes a valuable reference for decision-making when encountering new market environments.

Here's a detailed implementation of this learning approach: on each trading day, the learner obtains the state for that day by calculating the values of the three indicators, and the previous day's action's reward. The learner then generates a new move by querying the Q Table, which considers past exploration history while incorporating a certain level of randomness. Concurrently, the learner updates the existing Q Table. Finally, the learner proceeds to implement the chosen action.

The learning process iterates through the sample data multiple times until the cumulative return shows no further improvement. This iterative approach allows the learner to adapt and refine its decision-making.

The essential hyperparameters for this learning approach are the number of states, number of actions, alpha, gamma, and rar.

For the number of states, different experiments were conducted with various bin numbers for the indicators, such as 5, 8 and 10, to adjust states space. Among these, 10 bins provided the best outcome. A smaller value like 5 resulted in a decrease in out-of-sample performance as each bucket becomes larger, potentially leading to less accuracy state representation.

The data discretization process follows a method inspired by the class lecture video. Initially, the step size is calculated by dividing the data size by number of bins chosen. Subsequently, the data is sorted in ascending order. Next, a loop is executed through the defined buckets, during which the threshold value for each bucket is identified and determined. This approach effectively segments the data into distinct intervals.

Regarding the number of actions available (buy, sell or do nothing), it remains fixed, and there is no need for adjustment.

The learning rate alpha, utilized in the update rule, was explored with values like 0.1, 0.2, and 0.3. Among these, 0.3 yielded the most favorable results.

As for the discount rate gamma, used in update-rule, values such as 0.8, 0.9, 0.95, and 0.99 were tested. The value great than 0.9, particularly 0.99, demonstrated excellent performance.

The random action rate(rar), representing the probability of selecting a random action at each step, was experimented with values like 0.5, 0.8, 0.88, 0.9, 0.95, and 0.99. Out of these, 0.9 provided the most optimal output.

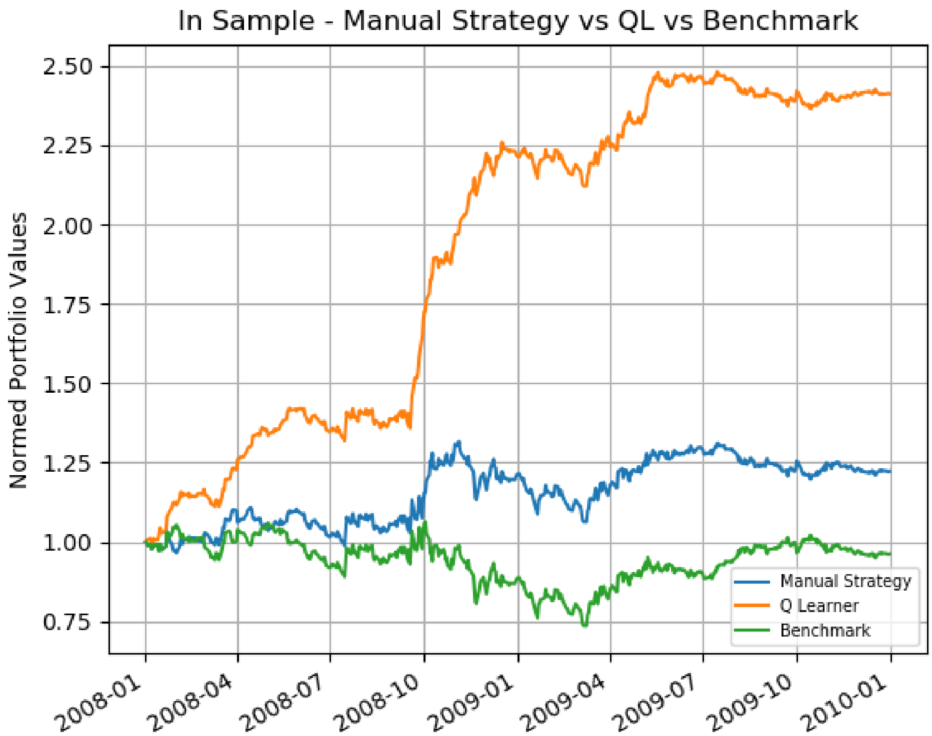
By meticulously exploring and tuning these hyperparameters, the learner can be optimized to achieve superior performance.

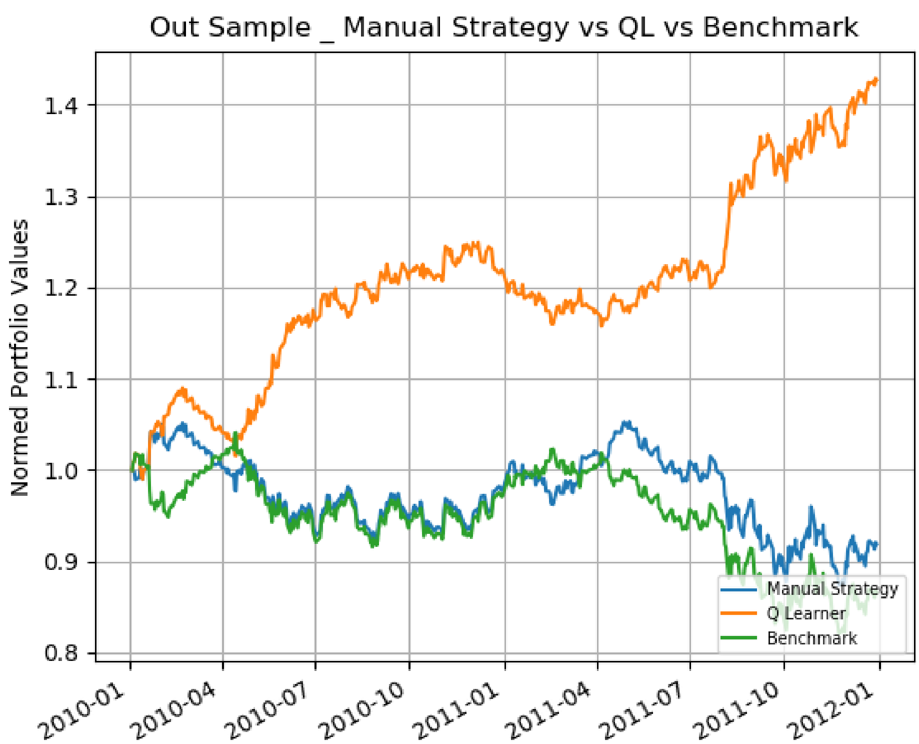
5 EXPERIEMNT 1

Assumption: assume that the market state remains the same, by using a consistent set of indicators and same data for all strategies. Additionally, assume the trade executions from manual strategy, strategy learner, and benchmark have equal impact and commissions in the market and regardless of trade amount. Finally, each strategy is optimized by tunning its hyperparameters if applicable.

Parameters: commission is set at 9.95, and market impact is at 0.005. The indicators used remain consistent, and the data('JPM') for both training and testing are same.

Hypothesis: strategy learner will perform the best, followed by manual strategy, with benchmark performing lowest.





The chart above depicts the normalized portfolio value of manual strategy, strategy learner and benchmark during in-sample trading of JPM. Notably, the performance ranking indicates that Strategy Learner outperforms Manual Strategy and benchmark overall, particularly during in-sample period. The Strategy learners demonstrates significantly superior performance compared to the other two approaches.

Even during the out-of-sample period, strategy learner remains strong in performance, while the manual strategy performs slightly better than benchmark. This outcome is expected since manual strategy lacks the ability to adapt to new conditions.

The Strategy learner, on the other hand, learns and evolves as it progresses, continuously exploring new states and leveraging exploration history to make decision. This adaptability renders it more effective in dealing with changes in market conditions, leading to its remarkable performance throughout.

Based on above discussion, I would expect obtaining similar relative result consistently when using in-sample data.

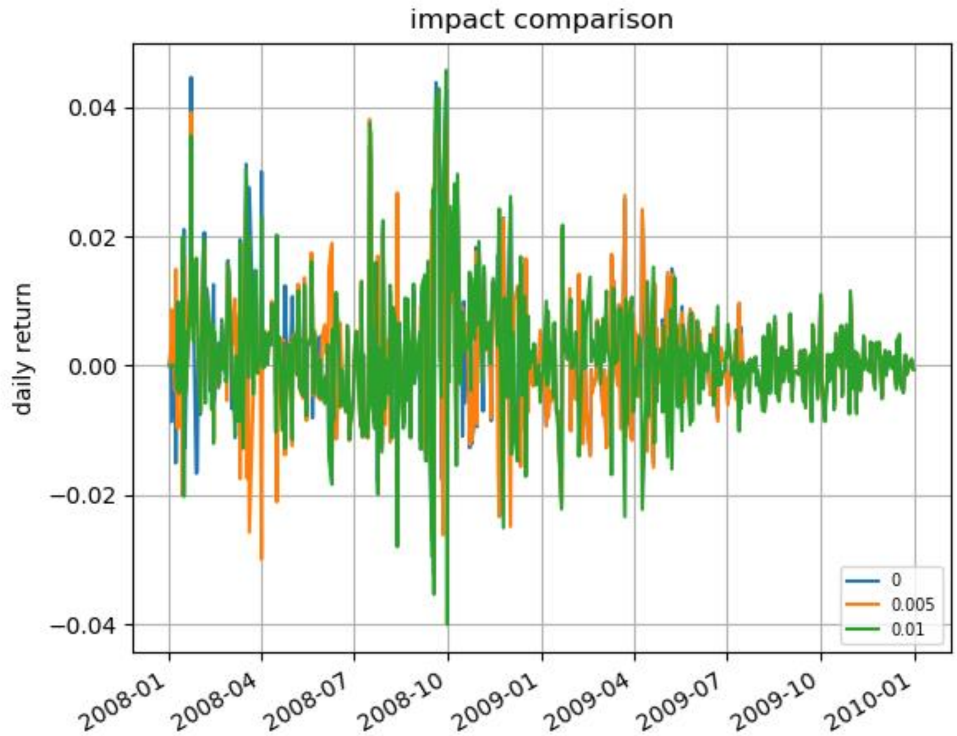
6 EXPERIMENT 2

Assumption: assuming all other parameters remain constant, the commission cost and other factors will not be affected by the impact, and the impact remain same regardless of trading amount. The only variable will cause a change in portfolio performance is the impact itself.

Parameters: commission is set at 0.0, and the Q Learner's parameters remain the same. We conduct tests using impact value of 0, 0.005 and 0.1.

Hypothesis: changing the market impact will influence in-sample trading behavior.

Two metrics are used to analyze the data: daily return and Sharp ratio.



The chart above illustrates the daily return for three market impact values. Notably, with an impact 0.01, the daily return fluctuates more frequently compared to other two values. With an impact 0.005, daily return fluctuates less. The line representing the absence of market impact is almost obscured by the fluctuation of the other two, indicating it has the most stable daily return.

<anonymous>	cumulative return	standard deviation	mean	sharpe ratio
impact 0.0	1.448900	0.009551	0.001820	3.025532
impact 0.005	1.312315	0.009221	0.001703	2.932735
impact 0.01	1.140402	0.009812	0.001556	2.517217

The data in table indicates as the market impact value increases, the Sharpe ratio decrease. This implies higher impact values result in lower risk-adjusted return for portfolio, which is a crucial consideration in real-life trading. It is essential to take this factor into account when making trading decisions.

7 REFERENCES

1. "Relative Strength Index (RSI) [ChartSchool]." https://school.stockcharts.com/doku.php?id=technical_indicators:relative_strength_index_rsi.
2. "Stochastic Oscillator [ChartSchool] - StockCharts.com." https://school.stockcharts.com/doku.php?id=technical_indicators:stochastic_oscillator_fast_slow_and_full.
3. "Commodity Channel Index (CCI) [ChartSchool]" https://school.stockcharts.com/doku.php?id=technical_indicators:commodity_channel_index_cci.