Project 8: Strategy Evaluation

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Abstract—The objectives of this project are to divided in twofold: 1) the implementation of two strategies: a manual strategy and a strategy learner, and 2) the comparison of their performance.

1 INTRODUCTION

A trading strategy is a structured methodology to exchange securities in the equity market. Nowadays, with the large amount of markets data and computational power developments, about 60-75% of the overall trading volume is performed through a pre-programmed strategy.

To develop a successful strategy, it is required to have a solid understanding of technical indicators, trading actions, and investing. Moreover, this knowledge can be leveraged with machine learning. This project integrates these concepts to implement two trading strategies:

- Manual rule-based strategy: predefined rules using technical indicators to enter and exit stock positions.
- Strategy learner: trading policy based on a reinforcement-based learner using the same indicators.

Once implemented, the strategies are compared considering the following rules:

- Trades only using the symbol 'JPM' for J.P. Morgan Chase & Co.
- In-sample period from January 1, 2008 to December 31, 2009.
- Out-of-sample period from January 1, 2010 to December 31, 2011.
- Starting cash of $100,000, where the only allowable positions are 1,000 shares long, 1,000 shares short, or 0 shares. Only buy/sell actions are allowed.
- Transaction cots of $9.95 for commission and 0.005 for impact, except for experiment 2 (Refer to section 6 of the report)

The strategies are also compared to a benchmark of buying 1,000 shares of 'JPM'.

2 INDICATOR OVERVIEW

The selection of technical indicators is crucial for an effective trading strategy. Their combination mitigates individual indicator weaknesses and can lead to profitable trading signals. For this project, the following 4 indicators are chosen: 50-day 'JPM' Price/EMA, 20-day 'JPM' Percent B (%B), 12-day 'JPM' ROC, and 50-day 'SPY' Price/EMA.

The 'JPM' Price/EMA is selected because the exponential moving average (EMA) is a weighted average that is quicker to update for the most recent 'JPM' prices. This indicator is implemented with a the 50-day window to avoid executing actions for short-term variations – the objective is to identify medium-term time periods in the 'JPM' stock for price to have a more defined trend. This indicator divides the price over the EMA, which is calculated with the following formula:

$$EMA = \left(Adj.Close\ Price - \ EMA(previous\ day)\right) \times Factor + EMA(previous\ day)$$

The 'JPM' Percent B is chosen, as it is a great indicator to capture the volatility in any stock – when the standard deviation increases, the Bollinger bands® get broader, and vice versa. In the in-sample period, there is not a significant variability in the 'JPM' price, however, it is not possible to predict the future and it would be erroneous to assume this trend would be the same for out-of-sample periods. The indicator is implemented by calculating the top and bottom Bollinger bands ® with 2 standard deviations of the 20-day simple moving average (SMA). This 20-day window also aims for medium-term signals for actions to be triggered. Once the bands are obtained, the %B is computed as follows:

$$\%B = (Adjusted\ Price - Bottom\ Band)/\ (Top\ Band - Bottom\ Band)$$

For this project, the addition of a momentum indicator is considered convenient for the group of indicators – it is important to measure the speed at which the 'JPM' stock is changing. The rate of change (ROC) was found to be more successful than the relative strength of index (RSI) for the in-sample period and is selected for the trading strategies. The rate of change is implemented with a 12-day time window, and it is calculated with this equation:

$$ROC = (Adj.Close - Adj.Close\ N\ periods\ ago)/(Adj.Close\ N\ periods\ ago) \times 100$$

Finally, it is considered appropriate to have an indicator directly associated to the market, for this reason the 50-day 'SPY' Price/EMA is included. Even though

J.P. Morgan Chase & Co. was part of the S&P500 for the in-sample and out-of-sample periods, the 'SPY' is an excellent ETF that captures the influence of other large corporations in the market. For consistency, the 50-day window matches the 'JPM' Price/EMA indicator.

3 MANUAL STRATEGY

The manual strategy is a rule-based approach implemented using a trial-and-error to maximize the return in the in-sample period. After tweaking the indicators, the following rules were successful compared to the benchmark:

- 'Long' position of +1,000 shares when all these conditions are applicable:

'JPM' Price/EMA < 0.95, 'JPM' %B < 0.0, 'JPM' ROC < -5 & 'SPY' Price/EMA < 0.95

- 'Short' position of -1,000 shares when all these conditions are applicable:

'JPM' Price/EMA > 1.05, 'JPM' %B > 1.0, 'JPM' ROC > 5 & 'SPY' Price/EMA > 1.05

- 'Out' position with 0 shares when this condition is applicable:

'JPM' Price/EMA crosses value of 1.0 , i.e. when stock price is equal to EMA.

This strategy is deemed effective because it includes both the 'JPM' and 'SPY' (market) Price/EMA indicators – the stock market is closely interconnected, and the variations in other companies that are part of the S&P500, represented by 'SPY', are correlated to the stock in study, The %B addresses the volatility in the market by bounding the 'JPM' stock price in the Bollinger bands®. Lastly, the ROC is a simple yet insightful momentum indicator to determine the stocks' rate of price change.

Figure 1 illustrates a better performance of the Manual Strategy compared to the benchmark for the in-sample period. Figure 2 shows the performance in the out-of-sample period with the same rule-based strategy, and it is successful – it also beats the benchmark by having a higher cumulative return. It is important to note that the out-of-sample period dataset is not used to tweak the trading rules, as this would be 'peeking' into the future and is not allowed when developing trading strategies.

In Figures 1 and 2, the red line shows the manual strategy normalized portfolio value, and the purple line shows the benchmark normalized portfolio value. The blue vertical lines indicate 'long' entry points, the black vertical lines indicate 'short' entry points, and the light pink vertical lines (not required for the report) indicate 'out' positions.

Figures 1 and 2 can be visually checked by identifying how the portfolio value of the Manual Strategy mimics the benchmark in the same direction after 'long' positions (blue lines), in opposite direction after 'short' positions (black lines), and does not change after 'out' positions (light pink lines).

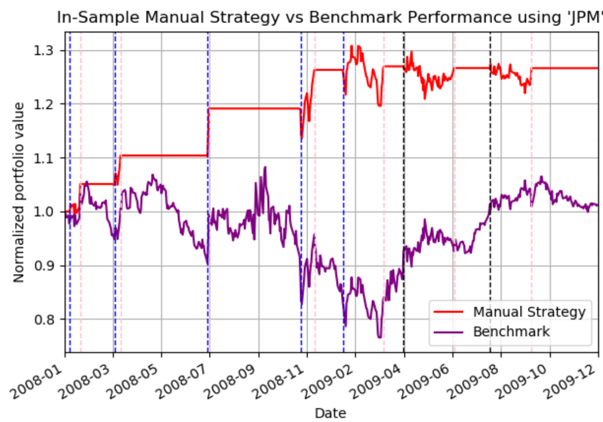

Figure 1 — In-sample Manual Strategy vs Benchmark Performance using 'JPM'

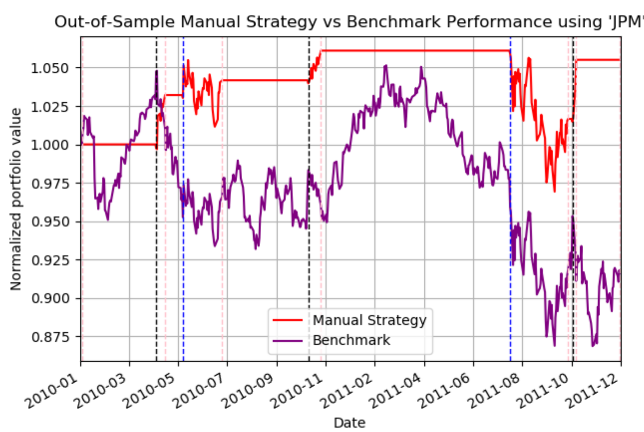

Figure 2 — Out-of-sample Manual Strategy vs Benchmark Performance using 'JPM'

Table 1 compares the Manual Strategy to the Benchmark for both the in-sample and out-of-sample periods using different metrics. In general, the Manual

Strategy is better than the benchmark results. For both in-sample and out-of-sample periods, the values for the Manual Strategy cumulative return, mean of daily returns, Sharpe ratio and final value are higher, whereas the values for standard deviation of daily returns values (volatility) are lower. For the in-sample period, the Manual Strategy cumulative return has a 20.6% increase. For the out-of-sample period, the Manual Strategy cumulative return has a 1.66% increase.

The difference in metrics occurs because the trading strategy was developed using the in-sample data with the intent of maximizing the return in this period. Thus, the cumulative return (and other associated metrics, such as daily returns and Sharpe ratio) is significantly higher than the out-of-sample values.

Table 1 — Manual Strategy vs Benchmark Metrics using 'JPM'

In-Sample Manual Strategy vs Benchmark Metrics using 'JPM'

	Benchmark	Manual Strategy
Cumulative Return	0.012325	0.266141
Std. Deviation of Daily Returns	0.017041	0.007950
Mean of Daily Returns	0.000169	0.000500
Sharpe Ratio	0.157205	0.997883
Final Value	101027.70	126614.05

Out-of-Sample Manual Strategy vs Benchmark Metrics using 'JPM'

	Benchmark	Manual Strategy
Cumulative Return	-0.083579	0.055063
Std. Deviation of Daily Returns	0.008500	0.004954
Mean of Daily Returns	-0.000137	0.000119
Sharpe Ratio	-0.256657	0.380672
Final Value	91445.70	105506.30

4 STRATEGY LEARNER

The strategy is a reinforcement-based learner, where a Q-learner is trained to develop a trading policy using the same indicators as the Manual Strategy.

The Q-matrix considers the following items for rows and columns, respectively:

- 30,000 states: one digit representing holdings, and the other 4 for indicators.
- 3 actions: 'long', 'out' and 'short' positions.

The hyperparameters for the strategy learners includes alpha = 0.2, gamma = 0.9, random action rate, rar = 0.98, and random action decay rate, radr = 0.999. Dyna is not employed as it compromised the running time of the strategy. These values were determined by considering an acceptable time for the learner to run, and the learning the strategy had after every iteration during the in-sample period.

The following pseudo-code describes the steps taken to frame the trading problem as a learning problem. No optimization is performed for time windows:

```
1. Initialize learner with impact, commission, and the Q-learner
2. Add evidence:
```

- `Identify start and end date as trading dates`
- `Get prices for in-sample period and indicators`
- `Identify threshold 10x4 matrix, which creates 10 bins or upper limits for each one of the 4 indicators`
- `While the total return is different than previous return and iteration < 35:`
  - `Get indicators for first trading day`
  - `State=discretization of action (between 0 and 1) and each indicator (values between 0 and 9 for each) using threshold`
  - `Action=querysetstate(state)`
  - `Based on action, get trade and position`
  - `For each date in in-sample period:`

```
Reward=(cumulative return / previous cumulative return)-1
Action=query(State, Reward)
Based on action, get trade and position
Calculate available cash considering impact and commission
Calculate portfolio value of holdings
Calculate cumulative return = cash + holdings
Get indicators
State= discretization of action (between 0 and 1) and each
indicator (values between 0 and 9 for each) using threshold
Repeat until convergence or iteration limit is reached
```

```
3. Test policy:
```

- `Same code as 'Add evidence', however, there is no learning anymore. Thus, there is no iteration and all the actions are queried as Action=querysetstate(state)`
- `Method returns trades for each as a pandas dataframe`

5 EXPERIMENT 1

Experiment 1 compares the Strategy Learner, the Manual Strategy and the benchmark. The rules described in the introduction are applicable for this experiment. Figures 3 and 4 show the normalized portfolio values for these strategies in the in-sample and out-of-sample period, respectively.

Figure 3 indicates how the Strategy Learner outperforms the other approaches, leading to an effective machine learning in the in-sample period. For this run, the normalized portfolio value for the Q learner is greater than the Manual Strategy and benchmark by approximately factors of 2 and 2.4, respectively. On the other hand, Figure 4 shows a poor performance of the Strategy Learner, indicating a possible overfitting of the data for the in-sample period that hinders the performance of the strategy. In general, these results have variations every run, but the pattern is expected to be the same, the Q-learner outperforms the others in the in-sample period and underperforms in the out-of-sample period.

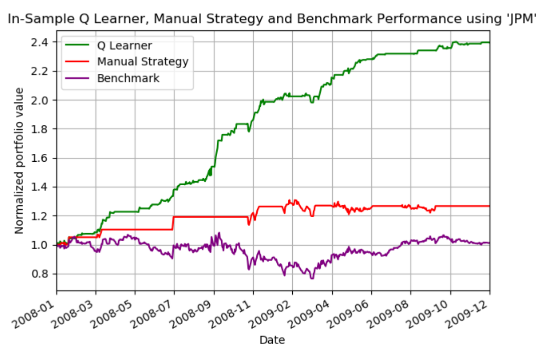

Figure 3 — In-sample strategy comparison for 'JPM'

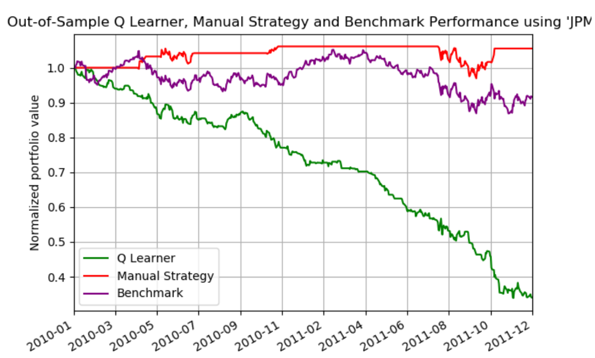

Figure 4 — Out-of-sample strategy comparison for 'JPM'

Table 2 presents different metrics for the benchmark, Strategy Learner and the Manual Strategy. Similar to Figures 3 and 4, the Strategy Learner has the best results in the in-sample period (maximum return and low volatility), and it is the worst strategy in the out-of-sample period (minimum return and high volatility). For the in-sample period, the Strategy learner cumulative return has a 112.1% increase. For the out-of-sample period, the Strategy learner cumulative return has a 689% decrease.

Table 2 — Metrics Comparison of Strategies using 'JPM'

In-Sample Q-Learner, Manual Strategy and Benchmark Metrics using 'JPM'

	Benchmark	Q Learner	Manual Strategy
Cumulative Return	0.012325	1.394037	0.266141
Std. Deviation of Daily Returns	0.017041	0.007548	0.007950
Mean of Daily Returns	0.000169	0.001762	0.000500
Sharpe Ratio	0.157205	3.705074	0.997883
Final Value	101027.70	238919.40	126614.05

Out-of-Sample Q-Learner, Manual Strategy and Benchmark Metrics using 'JPM'

	Benchmark	Q Learner	Manual Strategy
Cumulative Return	-0.083579	-0.659540	0.055063
Std. Deviation of Daily Returns	0.008500	0.012078	0.004954
Mean of Daily Returns	-0.000137	-0.002066	0.000119
Sharpe Ratio	-0.256657	-2.715890	0.380672
Final Value	91445.70	33973.00	105506.30

6 EXPERIMENT 2

Experiment 2 consists of using the Strategy Learner with different impact values to observe its effect in the in-sample period. As an extension of experiment 2, results are also presented for the out-of-sample period. The commission is set as $0.00 for all the cases, and the impact values vary from 0.015 to 0.00.

Figure 5 shows the effect of impact of the in-sample period, and it is evident how as the impact approaches zero, the Q-learner obtains a higher cumulative return. Compare for instance the normalized portfolio value of over 3.0 when impact is zero, against the value of around 1.5 when impact is 0.01.

This behavior is also explained considering the reward in the Q-learner. The reward is reduced when the impact comes into play, which directly affects the cumulative return. For this project, it can be said that the impact has an adverse effect on the trading strategy. The difference for a small impact can be appreciated by comparing the red and green lines in Figure 2, where the impact of 0.0025 significantly reduces the final portfolio value when compared to impact of zero.

Figure 6 shows similar trends for the out-of-sample period, where the normalized portfolio value gets worse as the impact increases.

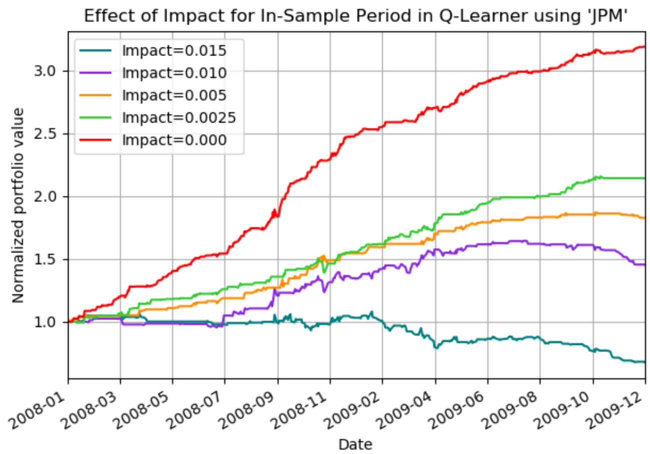

Figure 5— Effect of impact for in-sample period in Strategy Learner using 'JPM'

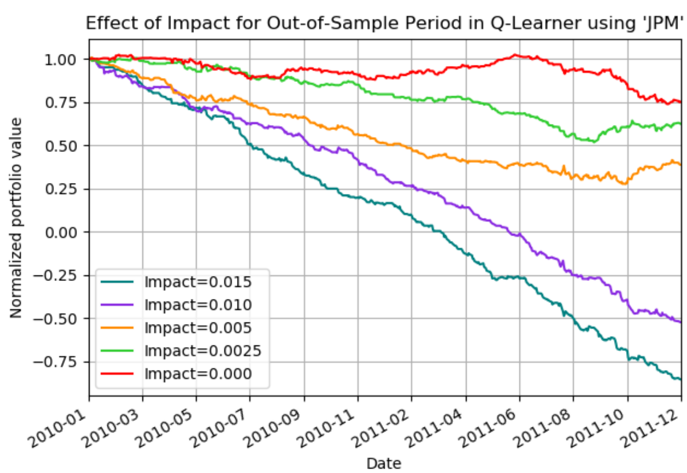

Figure 6— Effect of impact for out-of-sample period in Strategy Learner using 'JPM'

Two metrics are selected for main points of comparison to assess the effect of impact: Sharpe Ratio (shown in Table 3), and number of trades (shown in Figure 7). More metric comparisons can be derived from these two charts, however, these two are selected due to their importance.

The Sharpe ratio for in-sample period in Table 3 increases as the impact tends to zero. This is due to an increase of mean daily returns and a decrease of volatility. For these specific results in this run and considering impact = 0.00 as the baseline, the Sharpe ratio reduces to 65.2% when impact is 0.0025, and reduces to 0.228% when impact is 0.010.

Table 3 — Metrics Comparison of Impact in Q-learner for 'JPM'

In-Sample Q-Learner Metrics for Different Impact Values using 'JPM'

	Impact=0.015	Impact=0.010	Impact=0.005	Impact=0.0025	Impact=0.000
Cumulative Return	-0.323978	0.451826	0.827810	1.142395	2.190400
Std. Deviation of Daily Returns	0.011946	0.009155	0.006588	0.006286	0.006216
Mean of Daily Returns	-0.000705	0.000782	0.001219	0.001532	0.002324
Sharpe Ratio	-0.937330	1.355204	2.936879	3.869909	5.933894
Final Value	67602.20	145182.60	182429.45	214239.45	319040.00

Out-of-Sample Q-Learner Metrics for Different Impact Values using 'JPM'

	Impact=0.015	Impact=0.010	Impact=0.005	Impact=0.0025	Impact=0.000
Cumulative Return	-1.854682	-1.523325	-0.611998	-0.375032	-0.249542
Std. Deviation of Daily Returns	0.184072	0.317309	0.016860	0.008610	0.007260
Mean of Daily Returns	0.004651	-0.004584	-0.001739	-0.000897	-0.000544
Sharpe Ratio	0.401087	-0.229356	-1.637760	-1.653880	-1.189749
Final Value	-85468.25	-52113.45	38717.05	62426.77	75045.80

In Figure 7, it is observed that when impact is zero in the in-sample period, the maximum number of trades occur, which is around 280. As the impact increases, there is a tendency to reduce the number of trades by approximately half. For the out-of-sample period, on the other hand, the number of trades is not necessarily as sensitive, and it decreases in a more gradual manner. These trends are expected to be present even for different results after new runs.

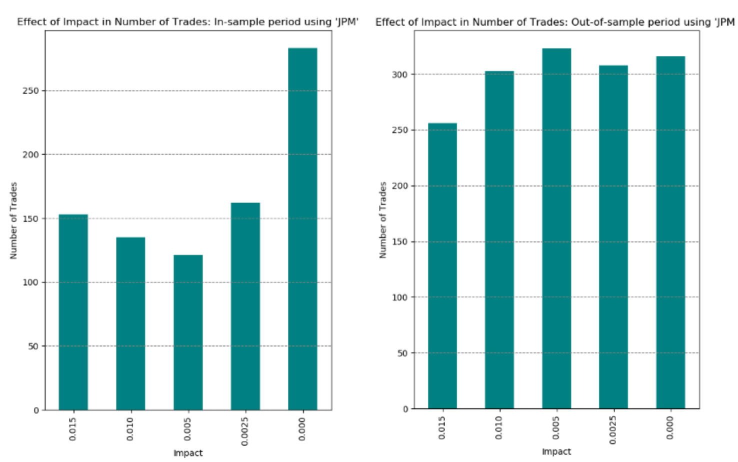

Figure 7 — Effect of impact in number of trades: in-sample period (left) and out-of-sample period (right) using 'JPM'

7 REFERENCES

1. https://www.investopedia.com/terms/t/trading-strategy.asp
2. https://www.quantifiedstrategies.com/what-percentage-of-trading-is-algorithmic/#What_is_algorithmic_trading