AI-Driven Strategy Learner for Stock Market Trading Optimization

Use Case: Predictive Modeling & Forecasting / Anomaly Detection

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***Abstract*—** In this project we have built a simplified AI based trading system and developed the technical indicator and the strategy learner along with manual learner. The technical indicator we developed gives a baseline and signal to help us to improve the strategies performance. Our result on JPM has indicated a slight outperformance of Strategy Learner than Manual Strategy and large improvement than Baseline. Moreover, our result indicated the impact factor has a strong impact on overall profit.

1 INTRODUCTION

In this project, we combined several earlier works from the semester to assemble and evaluate the performance of different models we developed. Specifically, we focused on finding a trading solution and creating policies with various indicators to build a trading system. We concluded this project by finding the optimal trading solution by comparing machine learning methods with mathematical technical strategies. In this research, our main work can be categorized as follows:

1. **Indicators**: Defining essential tools to help us analyze market trends.
2. **Manual Strategy**: Using a combination of indicators as signals for market trading.
3. **Strategy Learner:** Employing a decision tree with random forest theory for stock trading.
4. **Experiment 1**: Describing the experiments conducted on performance comparison.
5. **Experiment 2**: Evaluating the impact of commission fees on stock trading.
6. **Reference Section**

2 INDICATORS

Technical indicators are essential tools for Traders seeking to analyze the market trend and the final battle trading solution indicators used to identify the potential entry and the exit point which will be used to optimize the trading strategies. In this project we implemented 3 indicators that can be used to determine the best trading strategy including **MCAD, Bollinger Bands, RSI.** To implement these indicators into the trading strategies, we set the **MACD** short term window as 12 and long term window as 26, where signal window as 9 to generate if the buying or selling signal happened. Regarding the **bollinger bands**, we use window size as 20 and the upper band and lower band defined as 2 times the standard deviation. Regarding **RSI**, we have the window size seated as 14 as the previous research works recommended. For such indicators has been implemented into the Mannual Strategy and Strategy Learner as transaction signal and feature engineering. More details will be expanded in the respective sections.

2.1 MACD

Moving average convergence divergence (MACD) was introduced by Gerald Appel in late 1970s. It is a trend following momentum indicator that shows the relationship between two moving averages for security price. It quickly became the most popular technical indicator due to its Effectiveness in identifying Trend Direction. MACD can be expressed as:

$$MACD = EMA_{12} - EMA_{26}$$

$$Signal\ Line = EMA_{9}(MACD)$$

$$MACD\ Histogram = MACD - Signal\ Line$$

2.2 RSI

At the same period of time relative strengths indexed(RSI) was introduced by J. Welles Wilder Jr. in 1978. RSI is a momentum as seen later that measures the speed and the change of the price movements. It helps to identify the potential overbought (above 70) or oversold (below 30) conditions. when price makes a new high or low that isn't confirmed by the RSI it can be a signal for potential reversal. RSI defined as:

$$RSI = 100 - \left(\frac{100}{1 + \frac{Ave\ Gain}{AVe\ Loss}}\right)$$

Where Average Gain is the average of all gains over the last 14 periods and average loss is average of all losses over the last 14 periods.

2.3 Bollinger Bands

Bollinger Bands consist of a middle band, which is a simple moving average (SMA), and two outer bands that are standard deviations away from the SMA.

$$Middle\ Band\ =\ SMA_{20}$$

$$Upper\ Band\ =\ SMA_{20}\ +\ 2\ St.d_{20}$$

$$Lower\ Band\ =\ SMA_{20}\ -\ 2\ St.d_{20}$$

3 Manual Strategy

The first algorithm we used is called manual strategy where we implement the indicators as signals to decide the trading. During the training process we allowed your manual strategy to maximum treat 2000 bucks for either buying short or buying longs. when the agent did not buy anything you can decide to buy 2004 by 1,000 depending on the signal strengths. when a user has already bought a southern shears it can only buy a maximum 1000 more shears. When the agent buys 2000 shares of shorts, it can decide to sell the 2000, but cannot directly change to the stage of buying 2000 long.

3.1 Creation and Assumptions.

To create Manual strategy we made the following assumption and designs:

1. As mentioned above we only allowed a maximum 2000 shares a day on top of the 1000 shares in the previous day for either short or long.
2. So initial Capital we have including $100,000 cash matches the benchmark for portfolio.
3. For the benchmark situation we use a buy and hold strategy for JPM stock on the first day.
4. For the testing situation, we use JPM starting from 2010 January 1st until 2011 December 31st.

3.2 Implementation and Evaluation.

Specifically we use the indicator as below:

If no position is hold a long position is triggered if the RSI is below 30 baldinger band below 2 or MSD buying signal Pierce in contrast a short position is initiated if you are in size above 70 holding your band over 0.8 or macd cell signal appears but a short position happened is the RSI below 25 or bollinger band below .15 triggers such a trade for 2000 shares, and if RSI is 30 or Bollinger Bands is less than 0.2, we will buy 1000 shares. If the RSI exceeds 75 or Bollinger Bands exceed 0.85, a transaction will be triggered to sell 2000 shares and if RSI is larger than 70 but less than 75, or Bollinger Bands is larger than 0.8 but smaller than 0.85, we will sell 1000 shares. at the end of the testing. All open positions will be closed to prevent hold of the stock.

Position (Flag)	Condition	Transaction	Shares	Flag Change
No Position (0)	RSI < 30 or Bollinger Bands < 0.2 or MACD Buy	Enter Long Position	1000	1 (Long)
	RSI > 70 or Bollinger Bands > 0.8 or MACD Sell	Enter Short Position	-1000	-1 (Short)
	None of the above conditions met	Hold	0	0 (Neutral)
Short (-1)	RSI < 25 or Bollinger Bands < 0.15	Exit Short and Enter Long	2000	1 (Long)
	RSI < 30 or Bollinger Bands < 0.2 or MACD Buy	Exit Short to Neutral	1000	0 (Neutral)
	None of the above conditions met	Hold	0	-1 (Short)
Long (1)	RSI > 75 or Bollinger Bands > 0.85	Exit Long and Enter Short	-2000	-1 (Short)
	RSI > 70 or Bollinger Bands > 0.8 or MACD Sell	Exit Long to Neutral	-1000	0 (Neutral)
	None of the above conditions met	Hold	0	1 (Long)
End of Period	Any open position (Flag = 1 or -1)	Close Position	+-1000	0 (Neutral)

Table 1: Manual Trading Strategy

To evaluate the strategy:

1. Daily returns based on the position held and the actual price changes.
2. Cumulative returns, st.d of daily returns, and mean daily returns.
3. Compare these metrics to the benchmark portfolio of 1000 shares of JPM.

3.3 Results.

From the evaluation and normalization, we got the table below:

Metric	Manual (IN)	Benchmark (IN)	Manual (OUT)	Benchmark (OUT)
Cumulative Return	**0.731100**	0.012300	**0.233000**	-0.083400
St.d of Daily Returns	**0.010536**	0.017004	**0.006964**	0.008481
Average Daily Return	**0.001145**	0.000168	**0.000441**	-0.000137

Table 2: Performance result for Manual Strategy and Benchmark

In a manual strategy, there is no need to train a machine learning model to test performance. Most of the evaluation focuses on the strategy's performance across all samples. From the results shown, we observe that the cumulative reward from the manual strategy outperforms the benchmark in both the simple sample and the complete dataset. The standard deviation of daily returns for the manual strategy is significantly lower than that of the benchmark, while the daily average return is considerably higher. This indicates that our manual strategy, implemented using various indicators, strongly enhances trading performance. Compared to the benchmark, the difference between the manual strategy and the benchmark is attributed to the use of indicators, validating their effectiveness in stock trading.

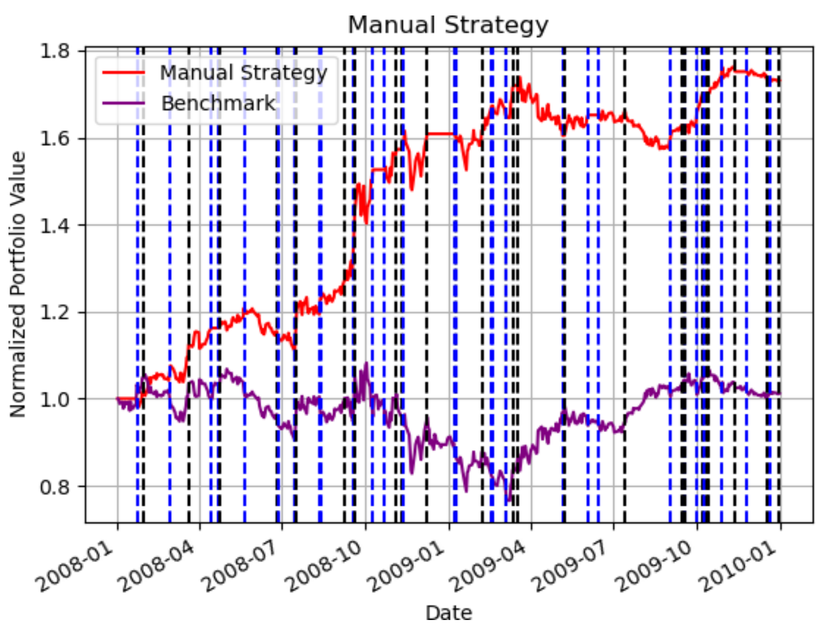

Figure 1: Manual Strategy vs Benchmark for JPM from 2008,1,1 to 2009,12,31

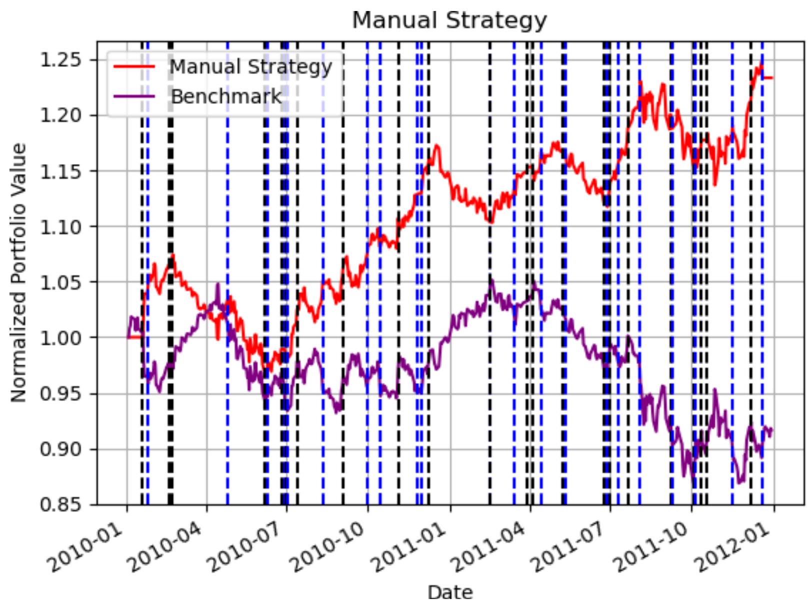

Figure 2: Manual Strategy vs Benchmark for JPM from 2010,1,1 to 2011,12,31

4 Strategy Learner

For the strategy learner, we use the instance of the bag learner with Leaf size as 5 and the bag size as 20. The bag learner contains 20 RTLearner putting together.

As the input to train the model we use all the indicators from RSI, Bollinger Bands or the MACD histogram which include a long term price changes search information to predict the selling or buying points for stock. The model output will predict the percentage of change in price and the signal will be transferred later in representing 1, -1, 0 for buy, sell or hold.. The Strategy here is when we have no stock on hand, we can buy or sell 1000 shares. if we have stock on hand, we can sell 2000 shares or buy another 1000 shares or back to 0 shares. if we have a short position, we can buy 2000 shares or sell another 1000 shares or back to 0 shares on the last day, we need to close the position. For the strategy learner, between the model based on the date of from 2008 to 2009 for the test policy we use the JPM data from 2010 to 2011. In order to backtest the models performance.

Result: the experiment resolved for strategy learners will be included in the next section for experiment 1 to get more details.

5 Experiment 1(Manual Strategy / Strategy Learner)

In experiment 1, we compared the results of manual strategy and the strategy learner from cumulative reward, St.d , and average daily return. And the result is shown below. In our hypothesis we believe the machine learning model will have a better performance than traditional manual learner. That's all parameters setting as mentioned above. Noticeably, we have the commission fee and impact factor kept as 0.0 for this experience. We collected the results as shown in the table and figures below.

Metric	Manual (IN)	Strategy (IN)	Benchmark (IN)	Manual (OUT)	Strategy (OUT)	Benchmark (OUT)
Cumulative Return	0.731100	**2.277500**	0.012300	0.233000	**0.328400**	-0.083400
St.d of Daily Returns	**0.010536**	0.008667	0.017004	**0.006964**	0.007196	0.008481
Average Daily Return	0.001145	**0.002395**	0.000168	0.000441	**0.000590**	-0.000137

Table3: Manual Strategy, Strategy Learner, Benchmark comparison for In/Out Sample

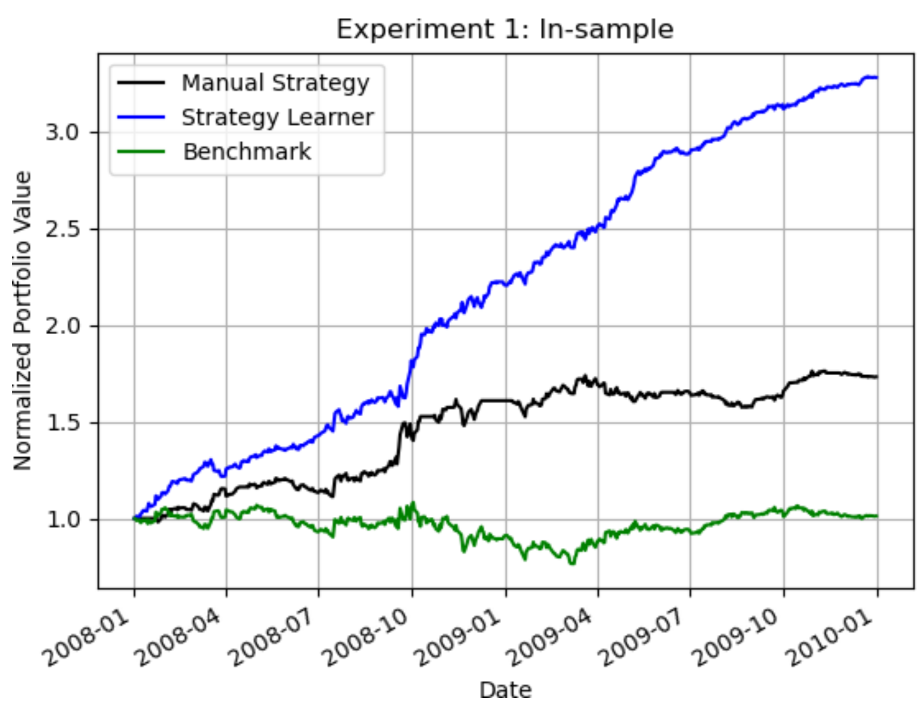

Figure 3: In-Sample comparisons for JPM from 2008,1,1 to 2009,12,31

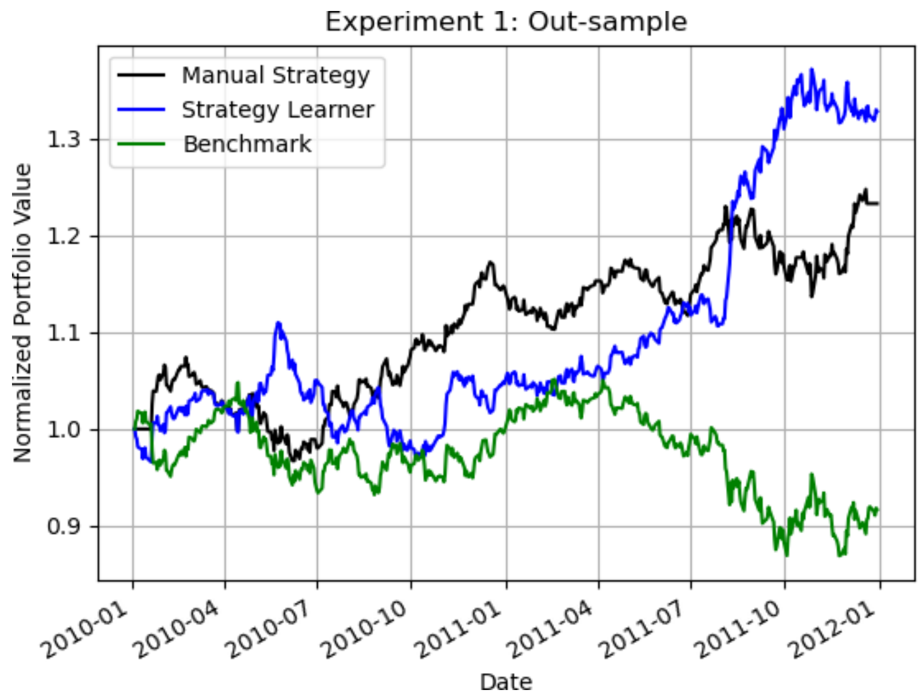

Figure 4: In-Sample comparisons for JPM from 2008,1,1 to 2009,12,31

From the experiment shown in the table above, the strategy learner has the best performance and cumulative reward for any sample for 2.27, meanwhile the manual learning only has 0.73 and The Benchmark only has 0.01. did indicate a significant Improvement on the In-Sample state. However, strategy learners have a significant drop on performance for out-sample prediction. Strategy learner indicated .32 cumulative return and manual learner remained 0.23 while benchmark lost money.

6 Experiment 2 (Strategy Learner):

An experiment to conduct an experiment where the strategy learner and show how to change the value of the impact should the fact that any simple training behavior. Our hypothesis indicates the higher impact factor will have a more significant change on the profit. As required from the project we're using the In-sample with the commercial pay weighs $0 to conduct this experiment. To evaluate the performance for social conditions we use cumulative reward standard deviation and daily return as our metric to evaluate the performance under each impact factor level. As shown in Table 4 and Figure 5 below, Our **hypothesis goes along** with the experimental results.

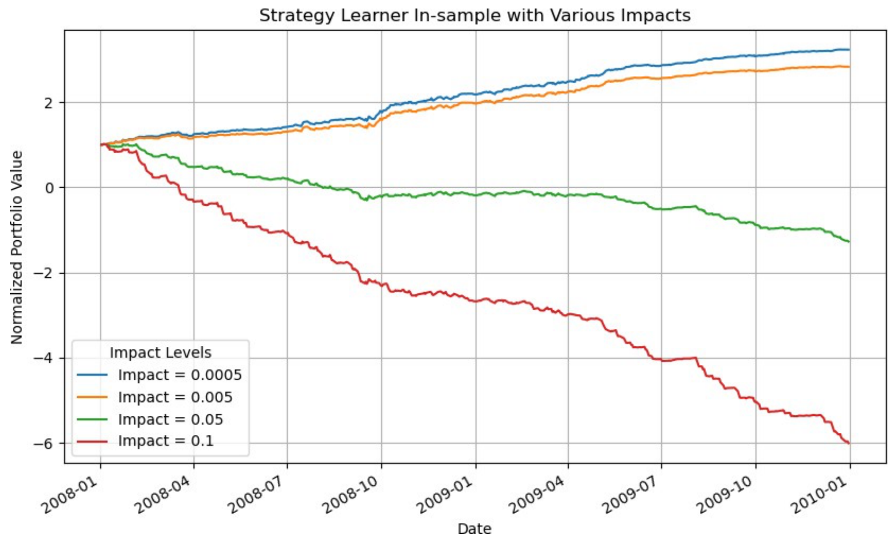

Figure 5: In-Sample comparisons for impact factor diff for JPM from 2008,1,1 to 2009,12,31

Metric	0.0005	0.005	0.05	0.1
Cum Return of Strategy Learner	2.232845	1.830176	-2.274694	-7.009017
St.D of Strategy Learner	0.008718	0.009297	3.792713	0.127162
Ave Daily Return of Strategy Learner	0.002369	0.002109	0.157399	0.002107

Table 4, Impact factor on performance of Strategy Learner.

As we can summarize from the table above the impact factor I have a linear relationship for average daily return as the impact factor gets larger and larger the daily return will be less, which goes along with our hypothesis. In addition it is also worth mentioning that the performance for In-Sample strategy learners is very good but when we are back testing that in Out-Sample, it has a significant decrease in performance for ROI.

7 Conclusion

In conclusion, from this experiment we conducted the comparison for strategy learner and the manual learner by indicators and our result indicated the strategy learner has outperformed the manual learner and the way much improved from the benchmark.

8 References ~0.25

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