CS 7646 Project 8: Strategy Evaluation

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1 INTRODUCTION

Our project aims to assess the efficacy of three technical indicators in predicting stock prices. We'll begin by constructing a manual strategy based on these indicators, comparing it against a benchmark. If these indicators genuinely signal optimal buy and sell times, our manual strategy should outperform the benchmark.

Additionally, we'll employ machine learning techniques to create a random forest-based learner using the same indicators. By testing its performance, we'll determine whether these indicators hold predictive power. Anticipating success, we expect the strategy learner to outperform the benchmark both in-sample and out-of-sample.

2 TECHNICAL INDICATORS

2.1 Overview

We will leverage three key technical indicators—Bollinger Band Percent (%B), Relative Strength Index (RSI), and Stochastic Oscillator (SO)—to construct both a manual trading strategy and a strategy learner. Subsequently, we will compare the investment portfolios generated by these approaches against the benchmark.

2.2 Bollinger Band Percent

Bollinger Band Percent (%B) is a popular indicator introduced by Jon Bollinger. We first calculate its upper band and lower band and use them to get Bollinger Band Percent. They can be implemented by their formulas (Guochiuan, 2023):

Upper band = 20-day moving average + standard deviation (n-day) x 2
Lower band = 20-day moving average – standard deviation (n-day) x 2
Bollinger Band Percent = (Price – Upper band) / (Upper band – Lower band)

We set the window to be 20 for both manual strategy and Strategy Learner, and 0.05 to be oversold, 0.95 to be overbought for the manual strategy.

2.3 Relative Strength Index

The Relative Strength Index (RSI) is to indicate price trend and it can be implemented by its formula (Guochiuan 2023)

RSI = 100 – 100/ (1 + average gain / average loss)

, where the window is set to be 20 for both manual strategy and Strategy Learner. Oversold is modified to be 33, and overbought is 67 for manual strategy compared with typical setting for oversold and overbought to be 30 and 70.

2.4 Stochastic Oscillator

The Stochastic Oscillator (SO) is to measure the relative location in price ranges. It has two parts: %K and %D, and can be implemented by its formula:

%K = (Price – Low) / (High – Low) * 100

%D is just a 3-period moving average of %K (Guochiuan 2023). For our manual strategy and strategy learner, we only look at %D. We set the oversold to be 20 and overbought to be 80 for manual strategy.

3 MANUAL STRATEGY

3.1 Overview

Our Manual Strategy relies on three key technical indicators: Bollinger Band Percent (%B), Relative Strength Index (RSI), and Stochastic Oscillator (SO). Within this framework:

- **Trading Positions**: We maintain three positions: 1 for long, 0 for holding, and -1 for short.
- **Trading Constraints**: We can hold a maximum of 1000 shares (long or short) per stock. Thus, each trade involves up to 2000 shares.
- **Signal Logic**:
    - Long Signal: All three indicators must indicate oversold conditions.
    - Short Signal: All three indicators must indicate overbought conditions.
    - Otherwise, we maintain our current positions.
- **Trading Frequency**: We execute trades once daily based on the given signals.
- **Hypothesis**: Combining these popular indicators enables effective stock price prediction.
- **Training and Testing Data**:
    - In-Sample Data: JPM stock prices from January 1, 2008, to December 31, 2009.
    - Out-of-Sample Data: JPM stock prices from January 1, 2010, to December 31, 2011.
- **Benchmark**: We start with $100,000 cash and purchase 1000 shares of JPM at the outset.
- **Transaction Costs**: Commission fee set at $9.95, with an impact of 0.005.

This rigorous experiment aims to validate our strategy's predictive power.

3.2 Results

To facilitate observations, we normalized the portfolio value, setting its initial value to 1. Our Manual Strategy portfolio exhibits superior performance compared to the benchmark using in-sample data (as depicted in Figure 1). While the benchmark briefly outperforms during an initial short period, the Manual Strategy consistently demonstrates stronger performance throughout the entire evaluation period.

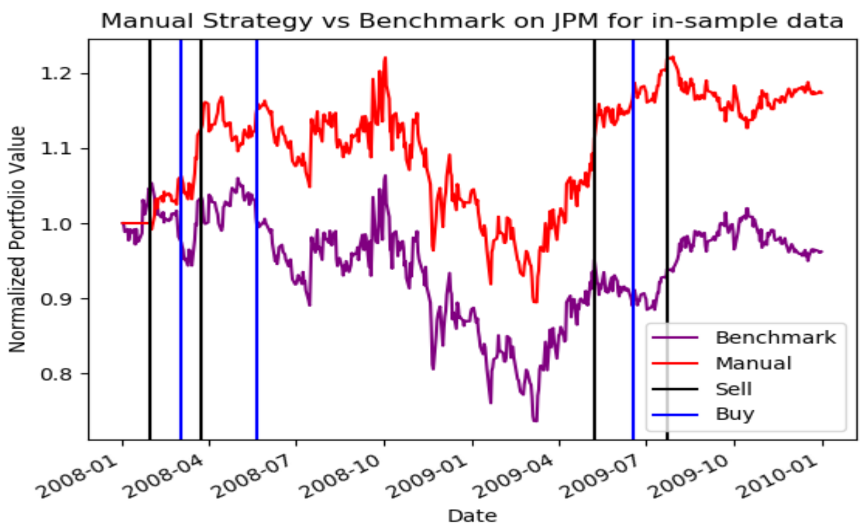

Figure 1 — In-sample normalized portfolio value comparison for manual strategy and benchmark.

While the Manual Strategy portfolio occasionally lags behind the benchmark in out-of-sample data (as illustrated in Figure 2), it consistently maintains a higher portfolio value overall. These three indicators demonstrate the ability to indicate stock price trends to some extent, although not infallibly accurate.

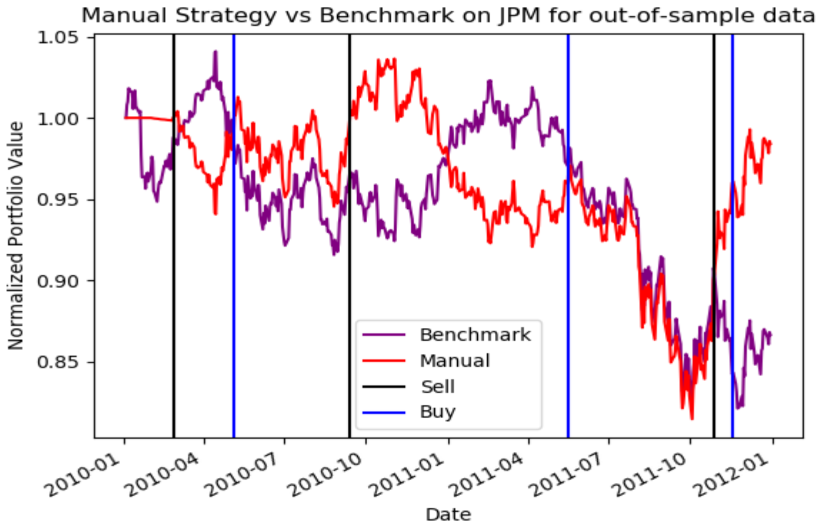

Figure 2 — Out-of-sample normalized value comparison for manual strategy and benchmark.

Comparing the in-sample and out-of-sample charts, we observe consistent outperformance of the manual strategy over the benchmark within the in-sample data (as depicted in Figure 1). However, this superiority does not always extend to the out-of-sample period. At times, the manual strategy fails to accurately predict stock price trends, resulting in suboptimal performance compared to the benchmark.

The reason behind this divergence lies in our training approach: we exclusively train the model using in-sample data, adjusting oversold and overbought thresholds accordingly. Consequently, while the manual strategy consistently excels within the training data, its effectiveness varies when tested against out-of-sample data—a true litmus test for its real-world viability.

	Cumulative Return	STD of Daily Returns	Mean of Daily Returns
Benchmark in-sample	-0.037925	0.017468	0.000075
Manual Strategy in-sample	0.173817	0.014625	0.000425
Benchmark out-of-sample	-0.133735	0.008781	-0.000247
Manual Strategy out-of-sample	-0.016018	0.008371	0.000003

Table 1 — Statistics for in-sample, out-of-sample, benchmark, and manual strategy are listed separately.

4 CLASSIFICATION-BASED STRATEGY LEARNER WITH RANDOM FOREST

Our strategy learner employs the powerful Random Forest algorithm. Here's how we prepare and evaluate it:

1. **Standardization of Indicators**:
   - We standardize our three calculated indicators, ensuring each has a mean of 0 and a standard deviation of 1.
   - This normalization allows our learner to treat each indicator equally, regardless of its original value range.
2. **7-Day Return Classification**:
   - For each trading day, we compute the 7-day return.
   - We classify these returns as follows:
     - 1: When the return exceeds 0.02 plus the impact.
     - -1: When the return falls below -0.02 minus the impact.
     - 0: Otherwise.
   - The impact represents the percentage of price movement against the trader.
3. **Training and Testing Data**:
   - In-Sample Data: We train our learner using JPM stock prices from January 1, 2008, to December 31, 2009.
   - Out-of-Sample Data: We evaluate performance using JPM stock prices from January 1, 2010, to December 31, 2011.

4. **Benchmark and Transaction Costs**:
   - Our benchmark starts with $100,000 cash and purchases 1000 shares of JPM at the outset.
   - We set commission fees at $9.95 and an impact of 0.005.
5. **Implementation Details**:
   - We utilize the add_evidence method to train our learner with in-sample data.
   - The testPolicy method provides trade recommendations based on the Strategy Learner's predictions.

This rigorous approach ensures robust performance assessment.

5 EXPERIMENT1

In this experiment, we meticulously compare the normalized portfolio values of three distinct strategies: Manual Strategy, Strategy Learner (based on the Random Forest algorithm), and the benchmark.

Hypothesis: My hypothesis posits that the Strategy Learner, leveraging the well-established Random Forest algorithm, will outperform both the Manual Strategy and the benchmark. Given Random Forest's widespread adoption in classification tasks, this expectation aligns with industry best practices.

Experimental Parameters:

- **Leaf Size**: Set to 5.
- **Bag Number**: Configured at 50.
- **Transaction Costs**:
  - Commission Fee: $9.95.
  - Impact: 0.005.

Results:

- Figures 3 and 4 reveal compelling evidence:
  - Within both in-sample and out-of-sample data, the Strategy Learner consistently surpasses both the Manual Strategy and the benchmark by a substantial margin.
  - This alignment with our initial hypothesis underscores the efficacy of the Random Forest-based approach.
  - Notably, the Strategy Learner's relative performance remains reproducible across various in-sample datasets.

Insight: While the Manual Strategy necessitates manual adjustments of oversold and overbought thresholds for each indicator, the Random Forest algorithm autonomously selects features and determines optimal modes for data separation. This adaptability, especially evident in in-sample data, underscores the algorithm's robust classification capabilities.

This rigorous analysis underscores the Strategy Learner's prowess in stock price prediction.

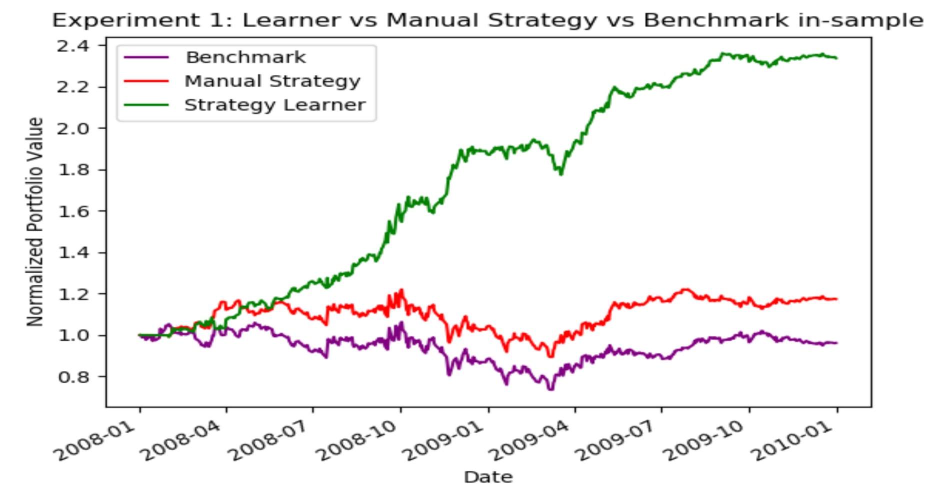

Figure 3 — Normalized portfolio value comparison for in-sample on JPM stock.

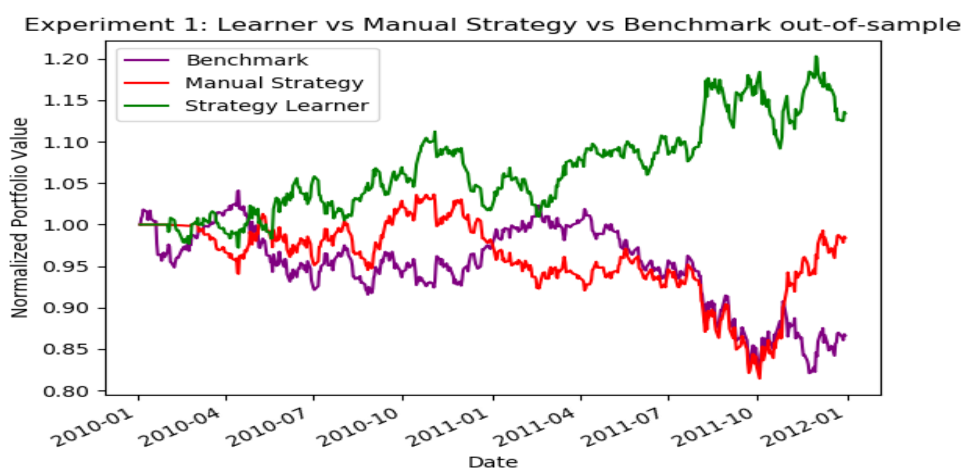

Figure 4 — Normalized portfolio value comparison for out-of-sample on JPM stock.

6 EXPERIEMENT 2

In Experiment 2, we meticulously investigate the impact value's influence on our Strategy Learner's performance. Key observations include:

1. **Hypothesis**:
    - Given that impact represents the percentage of price movement against the trader, we initially hypothesized that higher impact values would adversely affect our Strategy Learner.
    - Specifically, we expected increased impact to:
        - Reduce the portfolio's cumulative return.
        - Increase the standard deviation of daily returns.
        - Introduce greater risk, which is detrimental for traders.
2. **Experimental Setup**:
    - We deliberately set the commission fee to 0 (disregarding transaction costs).
    - Impact values were systematically varied: 0.001, 0.005, and 0.025.
3. **Performance Metrics**:
    - Our focus centered on two critical metrics:
        - **Cumulative Return**: Reflects overall portfolio growth.
        - **Standard Deviation of Daily Returns**: Indicates risk and volatility.
4. **Surprising Results**:
    - Contrary to our initial hypothesis, Figure 5 and Table 2 reveal that an impact value of 0.005 yields the highest cumulative return and the lowest standard deviation of daily returns.
    - Unexpectedly, the lowest impact value (0.001) does not yield optimal performance.
5. **Insight**:
    - The Strategy Learner adeptly considers impact value, offsetting its negative effects through more conservative trading.
    - Specifically, it takes long positions when the 7-day return exceeds the sum of 0.02 and the additional impact value. Conversely, it takes short positions when the 7-day return falls below the sum of -0.02 minus the extra impact value.
    - Conservative trading, as demonstrated here, can be advantageous.
    - These results underscore the need for robust testing and adaptability in real-world trading scenarios.

This unexpected outcome prompts further exploration, emphasizing the importance of considering impact in algorithmic trading strategies.

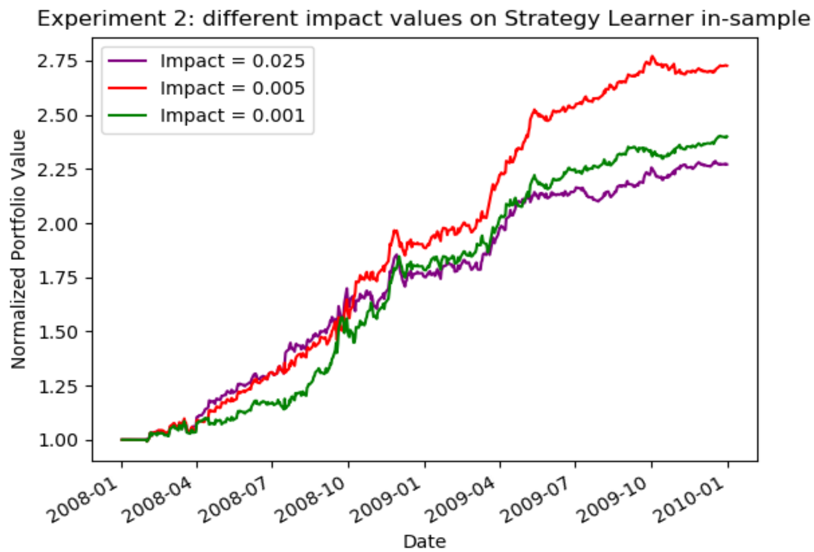

Figure 5 — Normalized portfolio values with respect to different impact values: 0.001, 0.005, 0.025

	Cumulative Return	STD of Daily Returns
Impact = 0.001	1.399603	0.010277
Impact = 0.005	1.726560	0.009519
Impact = 0.025	1.271057	0.00977

Table 2 — Cumulative returns and standard deviation of daily returns with different impact values.

7 REFERENCES

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