Project 8 Report

Strategy Evaluations

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Abstract—In this project, Manual Strategy (MS) and Learner Strategy (LS) are implemented with three technical indicators: Price/SMA ratio, price rate of change, and Bollinger Bands®. Results show that MS outperforms Benchmark, and LS further beats MS. In both strategies, in-sample performance is better than out-of-sample. For in-sample LS, higher impacts lead to fewer trades and lower profits.

1 GENERAL SETTING

This project presents two strategies – **Manual Strategy (MS)** and **Learner Strategy (LS)**. Both strategies share the following settings.

1.1 Experiment design

1) Apply strategies to the adjusted closing price of JPM with starting cash of $ 100,000 and no limit on leverage (i.e., all trades can be executed without validating the availability of cash in the portfolio). The legal positions are 1000 shares long, 1000 shares short, and 0 shares.

2) Transaction costs include 1) commission, i.e., the fixed amount of charge for each transaction, both entry and exit; 2) impact, i.e., the amount the price moves against the trader compared to the historical data at each transaction[1]. **For MS and experiment 1, commission = $ 9.95, and impact = 0.005. For experiment 2, commission = $ 0, and impacts are 0, 0.008, and 0.01.**

3) The in-sample period is from January 1, 2008 to December 31, 2009, and the out-of-sample period is from January 1, 2010 to December 31, 2011.

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1 https://lucylabs.gatech.edu/ml4t/fall2022/project-5/

1.2 Indicators

Three indicators are selected to work with both strategies: Price/SMA ratio, price rate of change, and Bollinger Bands®. **Indicator parameters are determined by the in-sample MS performance to gain the possible highest profit.**

1.2.1 *Price/SMA Ratio*

Price/SMA Ratio (P/SMA) is the ratio of price to a simple moving average (SMA), which is a "moving" mean[2] calculated based on the length of the list and the window size (i.e., the number of days for a look-back period). It portrays the fluctuations of the trends represented by the moving average (Charles, 2011).

P/SMA_{10} (window size = 10) is used in both Manual and Learner Strategies. In Manual Strategy, $P/SMA_{10} < 1$ signals a buy, and $P/SMA_{10} > 1.105$ signals a sell.

1.2.2 *Price Rate of Change*

The price rate of change (ROC) measures the percentage change between the current price and the previous price.

$$ROC_t = \frac{Price_t - Price_{t-n}}{Price_{t-n}} \times 100$$

ROC > 0 implies an increase, and ROC < 0 confirms a drop, while ROC hovering near 0 indicates that the price is consolidating.[3]

ROC_9 (window size = 9) is used in both Manual and Learner Strategies. In Manual Strategy, ROC < 0 followed by ROC > 0 signals a buy, and ROC > 0 followed by ROC < 0 signals a sell.

1.2.3 *Bollinger Bands®*

Bollinger Bands® were developed by John Bollinger and contain three lines: an SMA line, an upper and a lower band. The upper/lower band is 2 times of standard deviations above/below the SMA line. When the price reaches the

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[2] https://www.investopedia.com/terms/s/sma.asp

[3] https://www.investopedia.com/terms/p/pricerateofchange.asp

upper band, it indicates a sell signal, and it's a buy signal when the price touches the lower band. A Bollinger Bands® value (Tucker, 2015) is calculated as:

$$BBV = \frac{Price - SMA}{2 \times Std}$$

Where Std is the standard deviation.

BBV_{14} (window size = 14) is used in both Manual and Learner Strategies. In Manual Strategy, $BBV_{14} < -1$ signals a buy, and $BBV_{14} > 1$ signals a sell.

2 MANUAL STRATEGY

2.1 Combination of indicators

The combination of indicators includes three steps: 1) BBV_{14} works solely to signal a buy/sell; 2) when BBV_{14} doesn't work (i.e., $-1 \leq BBV_{14} \leq 1$), P/SMA_{10} generates a buy/sell; 3) when neither BBV_{14} nor P/SMA_{10} returns a signal (i.e., $-1 \leq BBV_{14} \leq 1$ and $1 \leq P/SMA_{10} \leq 1.105$), ROC_9 plays a role. Execution of trades is based on the overall signals from BBV_{14}, P/SMA_{10}, and ROC_9.

Indicators are tuned to achieve the best performance during in-sample MS. This process defines parameters (window sizes and signal thresholds discussed in 1.2) and the combination of indicators. These definitions are used throughout the project (both in-sample and out-of-sample MS and LS).

2.2 Enter and Exit Strategy

Theoretically, based on a confident prediction of a next-day uptrend/downtrend, the best strategy to gain as much profit as possible is 1) setting a maximum legal position long/short if the stock price begins to rise/drop; 2) holding the position until the price trend reverses; 3) repeating 1) and 2). **This is the most efficient strategy because it cumulates the profit (with the maximum position) at the beginning of an uptrend/downtrend and reduces transaction costs.**

Therefore, to achieve the possible highest profit, set the position to 1000 shares for a buy signal and set it to -1000 shares for a sell signal. Accordingly, the first trading volume is 1000 shares, and each trade afterward is 2000 shares.

2.3 Results

2.3.1 *In-sample*

During the in-sample period, an overall uptrend of JPM price ($ 38.47 at the beginning and $ 39.7 at the end) guarantees a positive gain for Benchmark. Meanwhile, MS works well and outperforms Benchmark by a 1.8-times higher final portfolio value than Benchmark (Fig.1).

In the beginning, MS and Benchmark share a similar trend, and MS gains a slight advantage over Benchmark after several trades from February to August 2008. After frequent trades in September 2008 and May 2009, MS portfolio value soars to 1.6 times and 1.8 times higher than Benchmark respectively. There are 45 in-sample trades: 23 buy and 22 sell.

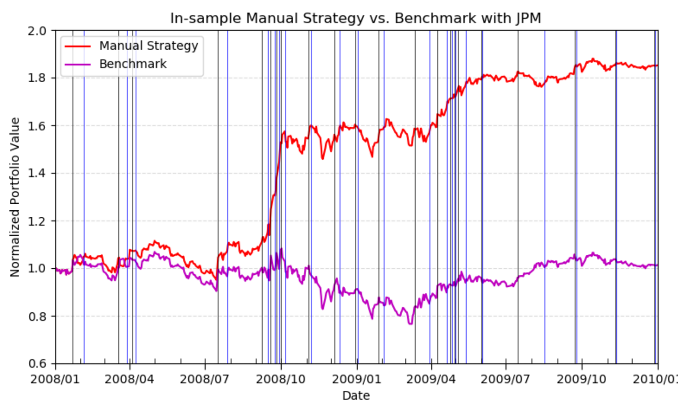

Figure 1—In-sample normalized portfolio value of Manual Strategy and Benchmark (Blue vertical lines indicate long entry points; black vertical lines indicate short entry points)

2.3.2 *Out-of-sample*

During the out-of-sample period, MS achieves a negative gain but is slightly better than Benchmark (Fig. 2) – the MS final portfolio value is $93570.5, while Benchmark ends up with $ 91445.7. The negative gain of Benchmark is due to the overall downtrend of JPM price, which starts at $ 40.87 and ends at $ 32.53.

Before April 2011, MS and Benchmark share a similar trend – Benchmark value is slightly higher than MS. Afterward, portfolio values of MS and Benchmark tend to converge, and MS finally outperforms Benchmark by a thin margin. There are 44 out-of-sample trades: 22 buy and 22 sell.

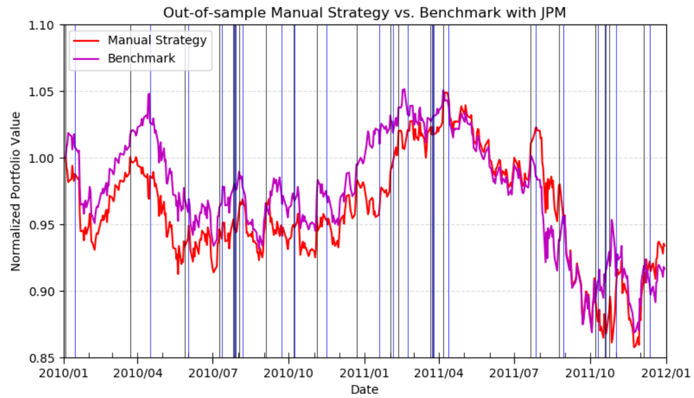

Figure 2—Out-of-sample normalized portfolio value of Manual Strategy and Benchmark (Blue vertical lines indicate long entry points; black vertical lines indicate short entry points)

2.3.3 *In-sample & out-of-sample*

Statistics also support that MS generally works better than Benchmark during both in-sample and out-of-sample periods (table 1). MS has a higher cumulative return (CR), average daily return (ADR), Sharpe Ratio (SR), and final portfolio value (FPV) than Benchmark. In-sample MS has less volatility, i.e., a smaller standard deviation of daily return (SDDR) than Benchmark, while out-of-sample MS has a slightly higher volatility than Benchmark. **In-sample MS is notably better than out-of-sample because the trading strategy is specifically tuned to fits in-sample data and fails to generalize to the testing data.**

Table 1—In-sample statistics of technical indicators.

Category	Name	CR	ADR	SR	FPV ($)	SDDR
In-sample	Manual Strategy	0.850828	0.001295	1.692207	184708.4	0.012152
	Benchmark	0.012325	0.000169	0.157205	101027.7	0.017041
Out-of-sample	Manual Strategy	-0.066110	-0.000098	-0.180270	93570.5	0.008669
	Benchmark	-0.083579	-0.000137	-0.256657	91445.7	0.008500

3 LEARNER STRATEGY

3.1 Trading problem & data discretization

A classification learner (Random Forest) is implemented as the core of the Learner Strategy (LS). **Hyperparameter tuning of different combinations determines the optimal setting of bag size = 20 and leaf size = 5.**

3.2 Trading problem frame & data discretization

Set the values of indicators (discussed in 1.2) as the X data, and the training Y data (Y_{train}) is derived from the N-day return of the stock:

$$R_N = \frac{Price_{today+N} - Price_{today}}{Price_{today}}$$

In a previous study, P6 (Juejing Han, 2022), the Theoretically Optimal Strategy (TOS) was built on the next-day price changes, which captures everyday variation and returns the possible highest profit. Experiments with different *N* values also support the result. Therefore, **set *N* = *1***.

For a typical day *m*, R_N depends on the stock prices of day *m* and day *m+N*, hence **in-sample LS peeks into the future to generate Y_{train}.** $R_N > 0$ means a buy; $R_N < 0$ implies a sell. Considering impact (*i*) and commission (*c*), the profit for a buy is:

$$(Price_{today+N} \times (1-i) \times S_s - c) - (Price_{today} \times (1+i) \times S_b + c)$$

Where S_s and S_b are the numbers of shares sold and bought respectively. According to the strategy in 2.2, each trading volume after the first trade is always 2000 shares, so generally, $S_b = S_s = S$. To guarantee a positive profit:

$$(Price_{today+N} \times (1-i) \times S - c) - (Price_{today} \times (1+i) \times S + c) > 0$$

Ultimately, to gain a positive return for a buy, $R_N > \frac{\varepsilon+2i}{1-i}$, where $\varepsilon = \frac{2c}{S \times Price_{today}}$, and $0 \le i < 1$. Similarly, to gain a positive return for a sell, $R_N < \frac{\varepsilon-2i}{1+i}$.

These thresholds for R_N guarantee the possible highest return in TOS. Nonetheless, LS is a classification learner based on the relationship between technical indicators and the discretized Y data. Therefore, modify R_N thresholds:

Y_{train} = 2 (signals a buy), when $R_N > \alpha \frac{\varepsilon+2i}{1-i}$

Y_{train} = 1 (signals a sell), when $R_N < \beta \frac{\varepsilon-2i}{1+i}$

Y_{train} = 0 (signals do nothing), when $\beta \frac{\varepsilon-2i}{1+i} \leq R_N \leq \alpha \frac{\varepsilon+2i}{1-i}$

Where $\varepsilon = \frac{2c}{S \times Price_{today}}$, $0 \leq i < 1$, $\alpha \geq 1$, and $\beta \geq 1$.

Experimental results with α = 1.2025, and β = 1.2020 return the most desirable outcome. Optimization (SciPy minimizer function) has also been applied to determine α and β. However, experiments show that the initial guess is vital to optimal results and different data sets with different noises might lead to a running-out-of-time issue and subsequently cause the script to fail. Therefore, the optimization process is not included in this report or its corresponding scripts.

4 EXPERIMENT 1

4.1 Hypothesis

Random Forest is an ensemble learning method for the classification task in this project. It is supposed to be better than MS and Benchmark.

4.2 Results

4.2.1 *In-sample*

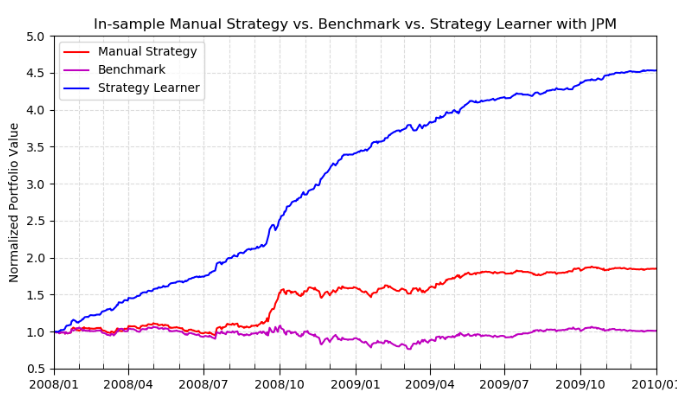

Figure 3— In-sample normalized portfolio value of Manual Strategy, Benchmark, and Strategy Learner

During the in-sample period, LS has the best performance (Fig. 3). Statistics align with the chart – Final portfolio value $ 452923.4, Sharpe Ratio 7.43, and standard deviation 0.0065 – outperforming MS and Benchmark (table 1). **When the parameters are appropriately tuned, the relative result is most likely to happen every time with in-sample data because LS has the peeking-into-the-future advantage over MS and Benchmark when generating the training Y data.**

4.2.2 *Out-of-sample*

During the out-of-sample period, LS is more volatile than in-sample and underperforms MS and Benchmark most of the time, but ultimately, LS outperforms MS and Benchmark (Fig. 4).

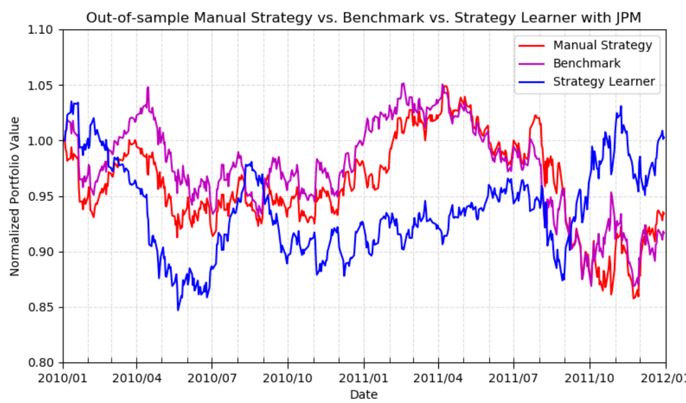

Figure 4— Out-of-sample normalized portfolio value of Manual Strategy, Benchmark, and Strategy Learner

Overall, LS beats the other two by returning a positive profit ($ 100070.7). LS combines ensemble techniques of the supervised learning approach with technical indicators, so it outperforms MS (which solely utilizes technical indicators) and Benchmark (which implements only one trade in the whole timeframe).

5 EXPERIMENT 2

During the in-sample period, three impact values (0, 0.008, 0.01) with LS are compared using the same settings in section 1, except for commission = $ 0.

5.1 Hypothesis

Since the impact moves against the trader, higher impacts lead to fewer trades and lower profits.

5.2 Results

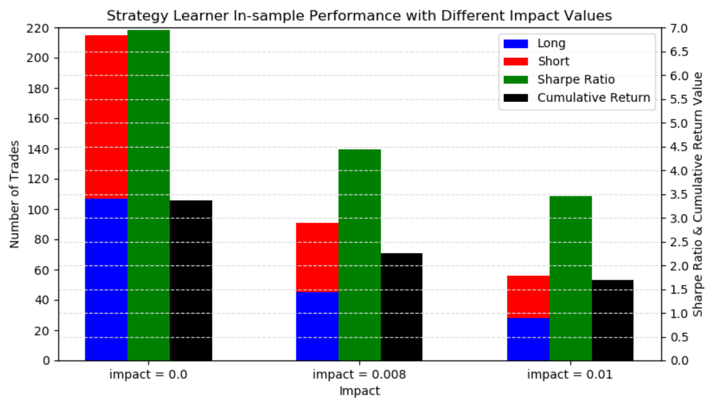

Figure 5—Strategy Learner in-sample performance with different impact values

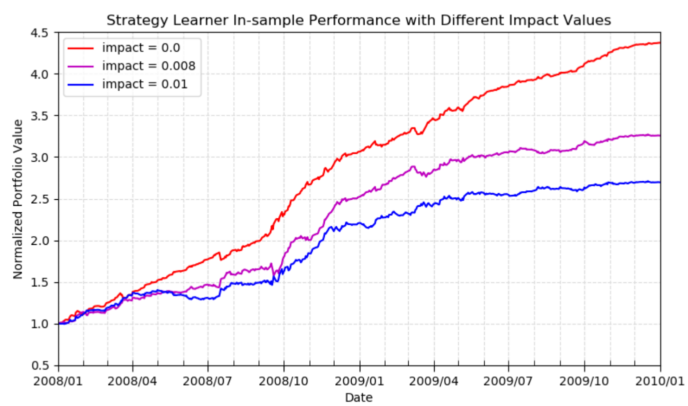

Figure 6— In-sample normalized portfolio value of Strategy Learner with different impact values

As the impact increases from 0 to 0.01, trades decrease (blue and red bars) from 215 to 56 (Fig. 5). Meanwhile, Sharpe Ratio (green bar) and cumulative return (black bar) also decrease from 6.94 to 3.46 and from 3.37 to 1.70 respectively.

Fig. 6 further demonstrates that lower impacts account for higher profits, while higher impacts correspond to lower gains. The final portfolio values are $ 436990 (impact = 0), $ 325726.6 (impact = 0.008), and $ 269693.2 (impact = 0.01).

6 CONCLUSION

Three technical indicators – Price/SMA ratio, price rate of change, and Bollinger Bands® – are implemented in both Manual Strategy (MS) and Random-Forest-based (Random Forest with 20 bags and leaf size of 5) Learner Strategy (LS). Overall, MS and LS are better than Benchmark, and LS outperforms MS.

During the training period, LS and MS have 4.8- and 1.8-times higher returns than Benchmark. In this project, the outstanding in-sample performance of LS is partly due to its peeking-into-the-future strategy of generating training Y data. However, for testing, LS proves its outperformance by a positive return, while MS and Benchmark correspond to a negative gain – this demonstrates the positive influence of ensemble techniques used in LS to reduce overfitting.

Regardless of strategy category (either MS or LS), in-sample performance is always better than out-of-sample because the parameters are specifically tuned for in-sample features and may fail to fit out-of-sample data.

Impact plays a role in trading behaviors and further affects the outcome. In general, higher impacts cause higher transaction costs, leading to fewer trades and less profit.

Experiments also support the statement in P6 that "Each indicator has its downsides… However, more indicators do not guarantee a more beneficial prediction." The indicator combination in 2.1 assigns different importance to each indicator. Besides, only three of the five indicators which were studied in P6 are used in this project because the combination of five indicators doesn't return a desirable result.

7 REFERENCES

1. Charles D. Kirkpatrick (2011). Time the Markets: Using Technical Analysis to Interpret Economic Data. Revised Edition. Pearson Education, United Kingdom.

2. T. Balch (2005). A Few Indicators: Bollinger Bands. Lecture of Technical Analysis, Georgie Institute of Technology. Georgie, United States of America.
3. Juejing Han (2022). Project 6 Report: Theoretically Optimal Strategy and Technical Indicators. Class Assignment Report of Machine Learning for Trading, Georgie Institute of Technology. Georgie, United States of America.