CS 7646 Project 8 Report: Strategy Evaluation

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Abstract—This report involves the implement two strategies and compare their performance: Manual Strategy *vs.* Strategy Learner. Given the same specific stock, timeframe, and indicators, the differences and performance between the benchmark, manual strategy, and strategy learner will be compared and discussed.

1 INTRODUCTION

The main goal of this project is to compare performance of stock trading strategies. Firstly, **Benchmark** (baseline) refers to a rule that starting with $100,000 cash, investing in 1000 shares of JPM stock, and holding that position. Secondly, **Manual Strategy** is a manually created strategy based on three chosen technical indicators and their performance to determine when to buy (long) or sell (short). Finally, **Strategy Learner** uses a random tree with bag learner algorithm to determine a buy (long) or sell (short) based on the identical technical indicators results. An initial **hypothesis** is that strategy learner should significantly outperform both the manual and the baseline strategies. Below are three chosen technical indicators used in this project.

1.1 Indicator 1: Simple Moving Average (SMA)

SMA represents a rolling mean of the stock prices over a specified rolling window (days), its formula is below where "*n*" is number of periods and "*a*" indicate stock prices. The **parameters** to optimize is the moving window and a Price/SMA ratio. I have used a moving window of 20 days to capture the trends in price movements, if a *Price/SMA ratio < 0.6*, current price is 60% of the rolling price, meaning that the stock price is going to go up, this is a **BUY signal**; if a *Price/SMA ratio > 1.4*, current price is 1.4 times higher than the average price, meaning that the stock price is going to go down, this is a **SELL signal**.

$$SMA = \sum_{i=1}^{n} \frac{(a1 + a2 + \cdots + an)}{n}$$

1.2 Indicator 2: Bollinger Bands % (BBP)

BBP combines the upper and lower Bollinger band using SMA and rolling Standard Deviation, its formula is below. The **parameters** to optimize is the moving window and a BBP value. I have used a moving window of 20 days to capture the trends in price movements, if a *BBP < 0.2*, meaning the stock price nears the lower band, it shows "oversold" and suggests a **BUY signal**; if a *BBP > 0.8*, meaning the stock price nears the upper band, it shows "overbought" and suggests a **SELL signal**.

$$BBP\% = \frac{(sma - lower_{band})}{(upper_{band} - lower_{band})}$$

$$upper_{band} = sma + 2 * std$$

$$lower_{band} = sma - 2 * std$$

1.3 Indicator 3: Momentum

Momentum measures how much has the price of a stock changed over a period of the window. Its formula is shown below where n is the lookback period. The **parameters** to optimize is the moving window and a momentum value. I have used a moving window of 20 days to capture the trends in price movements, if a *momentum* < *-0.2*, it shows "oversold" and indicates the stock price is going to go up, it is a **BUY signal**; If a *momentum* > *0.2*, it shows "overbought" and indicates the price is going to go down, it is a **SELL signal**.

$$Momentum = \frac{price[t]}{price[t-n]} - 1$$

2 MANUAL STRATEGY

Assumptions**:**

- Symbol used is JPM and no limit on leverage.
- In sample time period used is Jan 1st, 2008 - Dec 31st, 2009.
- Out of sample time period used is Jan 1st, 2010 - Dec 31st, 2011.

- Starting cash is $100,000, commission is $9.95, impact is 0.005.
- Allowable positions are 1000 shares long, 1000 shares short, 0 shares trade.
- Benchmark: starting with $100,000 cash, investing in 1000 shares of JPM, and holding that position.

Strategies:

- Trading decisions are made by adjusting different combinations and thresholds of the above three indicators, parameters that could gave the best performance in In-Sample period were chosen as the manual strategy for the Out-of-sample trade.
- Long the stock: buy 1000 shares if Price/SMA < 0.6 or BBP < 0.2 or momentum < -0.2. Otherwise, hold the stock.
- Short the stock: sell 1000 shares if Price/SMA > 1.4 or BBP > 0.8 or momentum > 0.2. Otherwise, hold the stock.

It turned out that our manual strategy always outperforms the benchmark for the In-sample period (Figure 1), and in a half time, also performed better than the benchmark for the Out-of-sample period (Figure 2). A table that documents their performance metrics (cumulative return, mean of daily returns, and STDEV of daily returns) is also shown below (Figure 3). The differences occur was because this manual strategy was trained in In-sample period only, so it is expectable not always win in the Out-of-sample period. I believe it is achievable by training more data and more time.

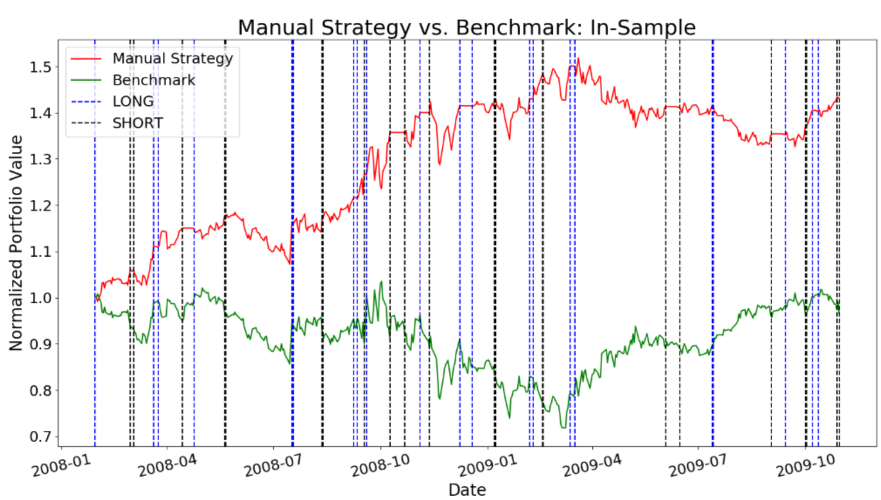

Figure 1— Normalized portfolio value comparison of the manual strategy versus the benchmark for the in-sample period.

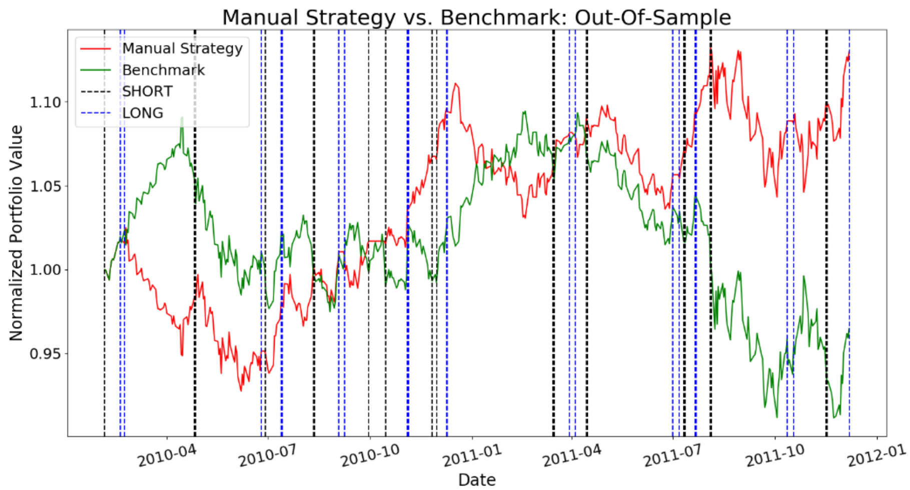

Figure 2— Normalized portfolio value comparison of the manual strategy versus the benchmark for the out-of-sample period.

	Manual Strategy (In-Sample)	Benchmark (In-Sample)	Manual Strategy (Out-of-Sample)	Benchmark (Out-of-Sample)
Cumulative Return	0.431028	-0.036071	0.129860	-0.035030
Mean of Daily Returns	0.000879	0.000092	0.000289	-0.000044
STDEV of Daily Returns	0.011856	0.018777	0.007301	0.008047

Figure 3— The comparative statistics of the manual strategy versus the benchmark for the in-sample period.

3 STRATEGY LEARNER

Assumptions: as same as manual strategy.

Strategy: a classification-based learner was employed by creating a strategy using a prior-designed random forest learner: RT Learner + Bag Learner. To avoid degenerate overfitting in-sample, the leaf_size for the learner was set to 5 and the number of bags was 20.

Training: add_evidence()

- The same indicator values as manual strategy used (Price/SMA, BBP, Momentum) were treated as the 'X_Train' data frame. 'Y_Train' is the future 10 days return. A market variance of 1.5% was added as a threshold.
- The learner then uses this data to learn a strategy.

Testing: testPolicy()

- The query method returns the 'Y_Test' data frame, then generate Trades data frame based on signal values.
- The learner then predicts for future price changes and actions to decide to long or short shares (1000 shares). It finally returns a trade data frame for the later use.

Discretization: this is not applied in my strategy learner as I used Classification Learner instead of the QLearner method.

4 EXPERIMENT 1

Experiment 1 compares the manual strategy, the strategy learner and the benchmark. As stated earlier, a **hypothesis** is that the machine learning strategy learner should significantly outperform both the empirical-based manual strategies and the benchmark. And it turned out to be true in the In-sample period (Figure 4): value of the manual strategy portfolio, value of the strategy learner portfolio, and value of the benchmark portfolio were all normalized to 1.0 at the start. A table that documents their performance metrics (cumulative return, mean of daily returns, and STDEV of daily returns) is also shown below (Figure 5).

Parameters: JPM stock, 1/1/2008 – 12/31/2009, $100,000 starting cash, Commission = 9.95 & Impact = 0.005. For Strategy Learner, Leaf size of 5 & Bag Size of 20 is used.

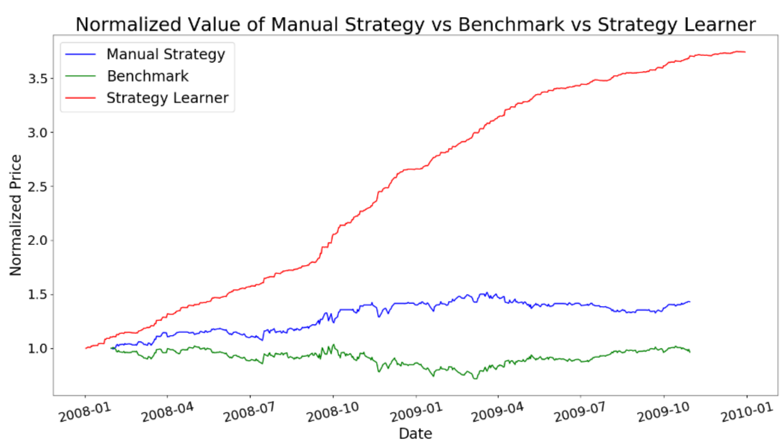

Figure 4 — Normalized portfolio value comparison of the manual strategy versus the strategy learner and the benchmark for the in-sample period.

	Manual Strategy	Benchmark	Strategy Learner
Cumulative Return	0.431028	-0.036071	2.741254
Mean of Daily Returns	0.000879	0.000092	0.002641
STDEV of Daily Returns	0.011856	0.018777	0.005394

Figure 5— The comparative statistics of the manual strategy versus the strategy learner and the benchmark for the in-sample period.

5 EXPERIMENT 2

Experiment 2 explores the way impact value changes in-sample trading behavior. I **hypothesize** that as impact value increases there will be less trades executed, since a cost of executing a transaction raise, which ultimately results in worse performance: lower cumulative return, mean of daily returns, and STDEV of daily returns. Experiment 2 was conducted by treating the Strategy Learner with different impact values of $0, $0.005 (same as the experiment 1 used), and $0.01 respectively. Then comparing their performances within the in-sample time frame. As expected, all the outcomes (Figure 6 and Figure 7) shown that the higher of the impact value, the lower in-sample trading performance the Strategy Learner will have.

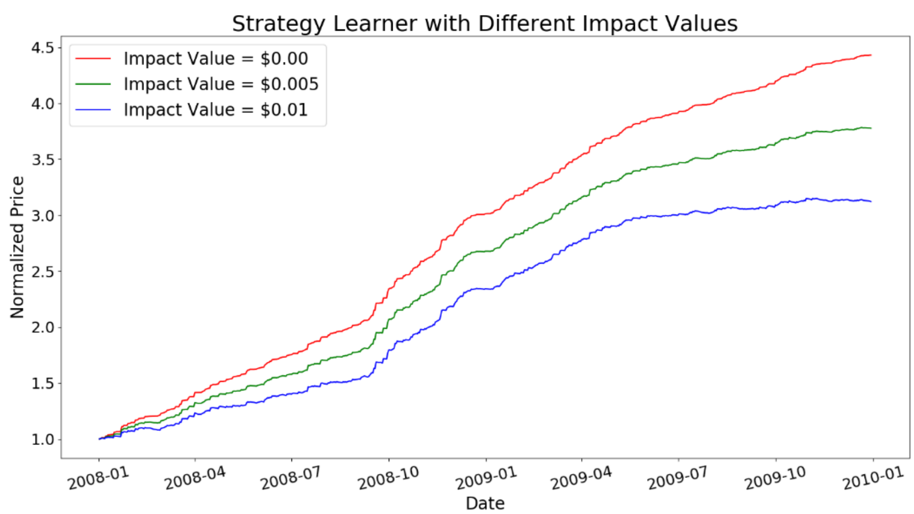

Figure 6— Normalized portfolio value comparison of the strategy learner with different impact values in the in-sample period.

	Impact Value of $0.00	Impact Value of $0.005	Impact Value of $0.01
Cumulative Return	3.431000	2.777667	2.121811
Mean of Daily Returns	0.002976	0.002660	0.002284
STDEV of Daily Returns	0.004885	0.005363	0.006067

Figure 7— The comparative statistics of the strategy learner with different impact values in the in-sample period.

6 REFERENCES

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