Developing a Machine-Learning based Stock Trading Strategy

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1 INTRODUCTION

We compare two strategies for trading stocks, the human-intuition-based strategy (or the manual strategy; Section 2) and machine-learning-algorithm-based strategy (or the learner-based strategy; Section 3). The data source is the historic prices of one particular stock ("JPM"). To implement each strategy, we first need to extract the so-called technical indicators from the stock price. The indicators can generate buy/sell signals and be used to inform both strategies. Our hypothesis is that the learner-based strategy should perform better than the intuition-based strategy.

2 TECHNICAL INDICATORS

The three technical indicators used for the manual and learner-based strategies are 1) the Price/SMA ratio, 2) the Community Channel Index **(**CCI) and 3) the Percentage Price Oscillator (PPO) Histogram, the formula of which were all described in the report for Project 6. When calculating each of the indicators, the stock price is first normalized by the first value in the selected date range (either in-sample or out-sample periods), and the parameters used are the same for the manual strategy and strategy learner. Below is an overview of the three indicators and the parameters used.

- The price/SMA ratio is simply the ratio of between the actual stock price and the Simple Moving Averaged (SMA) stock price. We use a lookback window of 14-days to calculate the SMA.
- The CCI measures the difference between the current stock price and the SMA, which is normalized by the moving Mean Deviation. Again, we use a lookback window of 14-days to calculate the SMA and the moving Mean Deviation.
- The PPO histogram indicator is obtained as follow. The PPO is first calculated by subtracting the 26-day-period Exponential Moving Average EMA from the 12-day-period EMA. Then the 9-day-period EMA of the

PPO is obtained as the "signal line". Finally, the PPO histogram is obtained as the difference between PPO and the signal line.

3 MANUAL STRATEGY

Each of three selected indicators can generate 'buy' or 'sell' signals on it own. So there are many possible combinations when making buying or selling decisions. We decide to implement the following principle in our manual strategy: **the buying or selling transactions can only be made when at least two out of the three indicators give consistent signals.**

We believe this is an effective strategy for two reasons. First, one indicator is not likely reliable all the time; therefore, we need to rely on at least two indicators when making decisions. Secondly, there are certain costs (commissions and market impacts) associated with each transaction. Therefore, we cannot make transactions liberally. Considering at least two indicators will limit the number of times we make transactions.

Next we describe the implementation of the manual strategy in details. First, we identify the potential 'buy' and 'sell' signals based on each of the indicators as follows.

The possible 'buy' criteria:

1) Price/SMA < 0.9, or
2) CCI < -100, or,
3) PPO Histogram < -1

The possible 'sell' criteria:

1) Price/SMA > 1.1, or
2) CCI > 100, or,
3) PPO Histogram > 1

Then, we make 'buy' or 'sell' decisions based on an algorithm that can be best described as the pseudo code in Figure 1.

Manual Strategy: Pseudo Code

```
if ( has 0 shares ):
    if (at least two of the buy criteria are meet):
        buy 1000 shares
    else if (at least two of the sell criteria are meet):
        sell 1000 shares
else if ( has 1000 shares / in long position):
    if (two of the sell criteria are meet):
        sell 1000 shares
    else if (three of the sell criteria are meet):
        sell 2000 shares
else if ( has -1000 shares / in short position):
    if (two of the criteria signals are meet):
        buy 1000 shares
    else if (three of the criteria signals are meet):
        buy 2000 shares
```

Figure 1— Pseudo code of the manual strategy.

We compare our manual strategy and a benchmark strategy during the in-sample (January 1, 2008 to December 31, 2009) and out-sample (January 1, 2010 to December 31, 2011) periods in Figures 2-3 and Table 1. We used the starting cash of $100,000 and assumed the commission fee of $9.95 and an impact factor of 0.005. The benchmark strategy simply holds 1000 shares of the stock from the beginning of each period. The main points are summarized below.

- Our manual strategy works very well during the in-sample period because we tweak the strategy to get the best performance. The manual-strategy portfolio has a much higher cumulative return and averaged daily return, and a smaller standard deviation of the daily return than the benchmark portfolio during the in-sample period.
- The manual strategy also works satisfactorily during the out-sample period. During the out-sample period, the benchmark portfolio has negative cumulative return and averaged daily return, but our manual-strategy portfolio was able to reach positive returns.
- The performance of the manual strategy during the out-sample period is not as good as the in-sample period. This is not surprising and mostly because we optimized our strategy only based on the data during the in-sample period. Because the stock price behaved quite differently in the out-

sample period than the in-sample period, our strategy misses many opportunities to gain profits in certain windows (Figure 3).

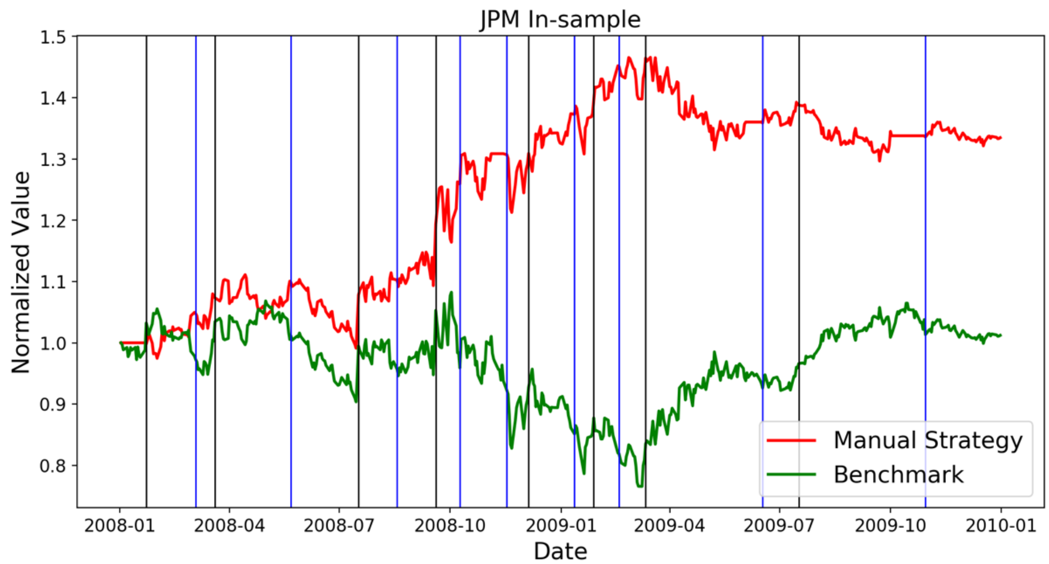

Figure 2 — The normalized values of the portfolio created based on the manual strategy (red line) and the benchmark strategy (green line) during the in-sample period. Vertical blue lines indicate 'long' entry points, while the vertical black lines indicate 'short' entry points.

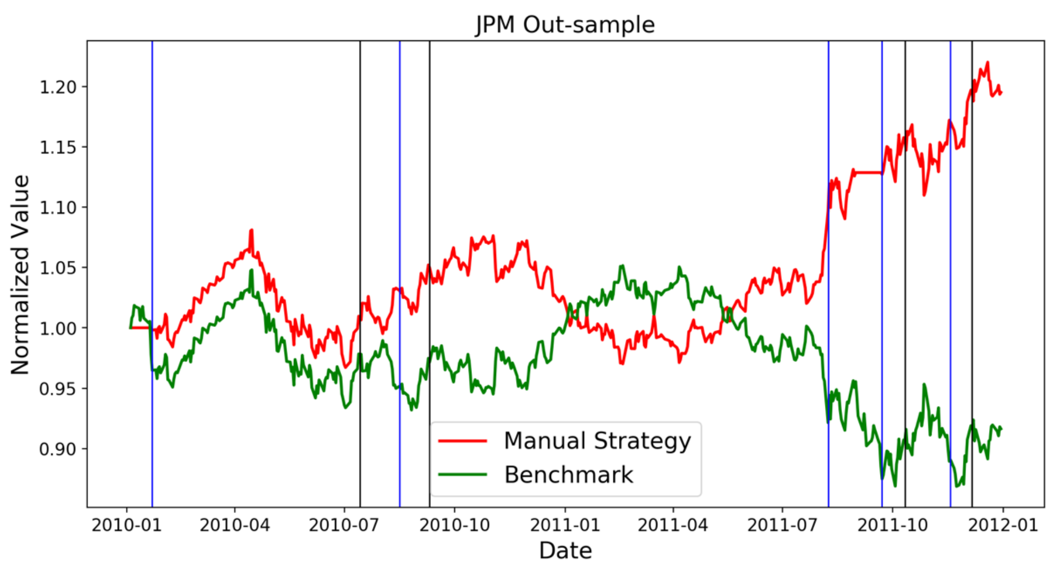

Figure 3 — The normalized values of the portfolio created based on the manual strategy (red line) and the benchmark strategy (green line) during the out-sample period. Vertical blue lines indicate 'long' entry points, while the vertical black lines indicate 'short' entry points.

Table 1— Comparison of the performance of the Manual Strategy and benchmark for both in-sample and out-of-sample periods.

Period	Portfolio	Cumulative return	Averaged daily return	Standard deviation of daily return
In-Sample	Manual Strategy	0.3347	0.00065	0.0125
	Benchmark	0.0122	0.00017	0.0170
Out-Sample	Manual Strategy	0.1950	0.00038	0.0072
	Benchmark	-0.0837	-0.00014	0.0089

4 STRATEGY LEARNER

4.1 Framing the problem

The problem in this assignment is a stock trading problem, which is about whether or not to trade a stock (either buy or sell) on a given day. We convert this trading problem into a machine learning problem. Here we use combine the Bag learner and the Random Forest learner to create a **classification** learner. Our ultimate goal here is that the trained learner can directly tell us the trade actions to be made based on the stock price data on the present day (and in the past). Below we give a summary of the steps taken to achieve this purpose.

Step 1. Data preparation

One essential piece is preparing the feature (X) and label (Y) data based on the historic stock prices that can be used to train the learner. We can use the selected technical indicators described in Section 2 as features (X). The tricky part is preparing the labels (Y) based on the in-sample dataset. The project material provides very helpful instructions that can be followed. In summary, the Y values need to reflect the three possible positions we can be in, which are "long the stock", "short the stock", or "only hold cash". We use three numerical values (1, -1 and 0) to represent the three positions, respectively. The Y value on a given day is determined by the trends in the next N days. The essential idea here is that if the stock price increases (declines) in the next N days, we long (short) the stock. The details on how to obtain the Y values will be given in Section 4.3.

Step 2. Create the learner

We use the bag learner to ensemble the random tree learner we created for project 6. The hyperparameters (bag size and leaf size) are described in Section 4.2. Since we are framing a classification problem in this project, we return "mode" rather than the "mean" from the bag and random tree learners.

Step 3. Train the learner

The training phase is relatively straightforward. Once the X and Y training datasets are prepared, we can them to train the learner using the "add_evidence" function.

Step 4. Test the policy

We can deploy or test the model after it is trained. For a given set of out-sample stock price data, we can prepare the indicators as X data, and get Y value (1,0, or -1) after the query step. Next we need to transform the Y values to trade actions. Figure 4 shows the pseudo code for this purpose. The trade actions are the desired final outputs from our strategy learner.

Strategy Learner: From Y value to trade action

```
if (current postion = = 'only hold cash'):
        if Y = 1, buy 1000 shares
        if Y = -1, sell 1000 shares
else if (current postion = = 'long the stock'):
        if Y = 0, sell 1000 shares
        if Y = -1, sell 2000 shares
else if (current postion = = 'short the stock'):
        if Y = 1, buy 2000 shares
        if Y = 0, buy 1000 shares
```

Figure 4 — Pseudo code for transforming Y values to trade actions.

4.2 Hyperparameters

We set the leaf size to 5 for the random tree learner. A smaller leaf size would cause overfitting. We also found that using a larger leaf size (for example, 10) causes larger fluctuations in the daily portfolio value and smaller cumulative return in the in-sample period.

We use a bag size of 30 for the bag learner. We learned from Project 3 that even a small value of bag size can reduce over fitting. Here we find that the exact value of the bag size does not seem to matter much as long as the bag size is large enough (larger than 10).

4.3 Data preparation and adjustment

For feature data (X) on any given day (either during in-sample or out-sample periods), we use the three technical indicators described in Section 2. The parameters used are the same as the manual strategy. To have a fair comparison with the manual strategy, we did not optimize the lookback windows for the strategy leaner.

To obtain the label data (Y) during the in-sample period, we do the following. The specific value of Y on a given day should be determined based the return of the stock prices N days from the present day.

- Y = 1 ("long the stock"), if the N-day return is above a threshold (YBUY)
- Y = -1 ("short the stock"), if the N-day return is below a threshold (YSELL)
- Y = 0 ("only hold cash"), if the N-day return is between YBUY and YSELL.

For this project, we choose to use the stock price 5 days ahead of the present day (N = 5) to determine the Y values. When determining the values of YBUY and YSELL, we consider the impact factor as follows.

- YBUY = 0.02 (selected critical 5-day return) + impact factor
- YSELL = -0.02 (selected critical 5-day return) - impact factor

5 EXPERIMENT 1

Here we compare the performance of the manual strategy (Section 3) and the strategy learner (Section 4) in trading the stock "JPM" only during the in-sample period (January 1, 2008 to December 31, 2009). For a fair comparison, we use the same three technical indicators described in Section 2 for both strategies and the parameters (e.g., the lookback windows) are kept the same (see Section 2 for the exact values). The two strategies are described in Sections 3 and 4, respectively. We used the starting cash of $100,000 and assumed the commission fee of $9.95 and an impact factor of 0.005. Additional, the benchmark strategy is created, in which we simply hold 1000 shares of the stock from the beginning.

The performance of the three strategies are summarized in Figure 5 and Table 2. Not surprisingly, the strategy learner creates the best outcome, and significantly outperforms the manual strategy during the in-sample period. The cumulative return from the learner-based strategy is about 4 times of that from the manual strategy during the in-sample period.

We expect this relative result every time with **in-sample** data. This is because the strategy learner seeks to maximize the return during the in-sample period by design. The learner can capture opportunities that cannot be seen by our intuition-based manual strategy during the in-sample period. However, this may not be true for the out-sample period.

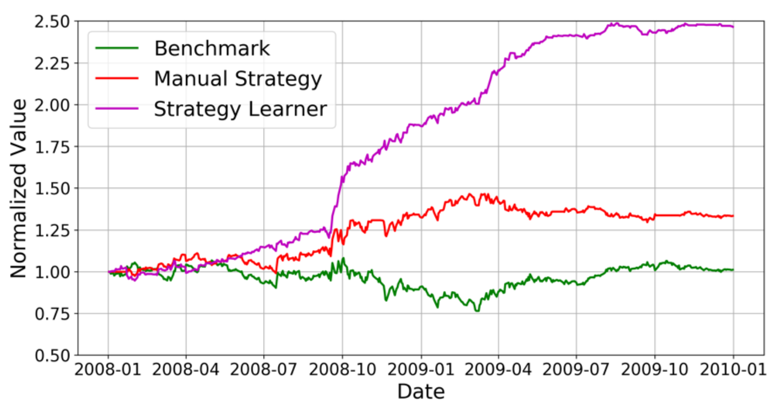

Figure 5— The normalized values of the portfolio created based on the manual strategy, the strategy leaner, and the benchmark strategy during the in-sample period.

Table 2— Comparison of the performance of the manual strategy, strategy learner and benchmark during the in-sample period.

Portfolio	**Cumulative return**	**Averaged daily return**	**Standard deviation of daily return**
Manual Strategy	0.3347	0.00065	0.0125
Strategy Learner	1.4662	0.00184	0.0093
Benchmark	0.0122	0.00017	0.0170

6 EXPERIMENT 2

Here we conduct experiments to examine how the impact factor affects in-sample trading behavior and results. We hypothesize that a larger value of the impact factor has negative impact on the portfolio performance. Note that the impact factor was considered at two places. First, when preparing the label data (Y) for the strategy learner, we consider the impact factors in YBUY and YSELL (Section 4.3). If a larger impact factor is used, we should expect less trading opportunities. Secondly, the impact factor is considered in the market simulator as a transaction cost. We need to pay more cost each time we make a transaction with a larger impact factor.

We consider five values of the impact factor in our experiments, which are 0, 0.005, 0.015, 0.025 and 0.05, respectively. For each value, we train a strategy learner, and then obtain the portfolio during the in-sample period using the market simulator. We use the "JPM" during the in-sample period (January 1, 2008 to December 31, 2009). The commission is set to $0.00.

We use 1) cumulative return and 2) averaged daily return as the metrics to measure the performance of the portfolios created based on the varying impact factors. Figures 6-7 summarize the results from the experiments. The results confirm our hypothesis: with increasing impact factor, the performance of the portfolios becomes worse during the in-sample period. When the impact factor becomes large enough (approximately larger than 0.025), the cumulative return and the averaged daily return even become negative.

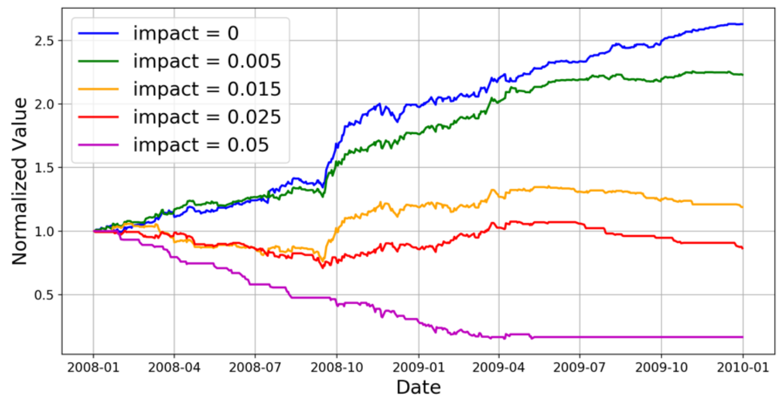

Figure 6— The normalized values of the portfolio created based on the strategy leaner with varying impact factors.

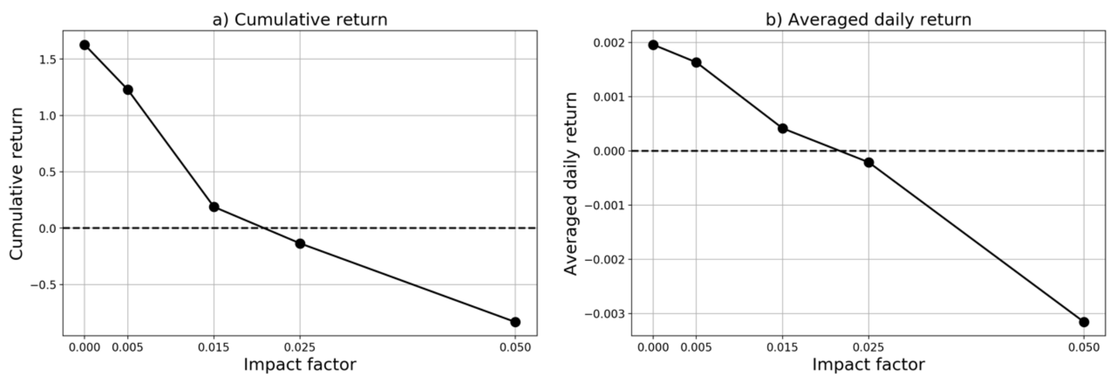

Figure 7— a) Cumulative return and b) the averaged daily return as functions of the impact factor.