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Part 1: Strategy Learner

To create a strategy learner, I created an implementation of the Bag Learner which used the Random Tree Learner created in the previous project in which we experimented with Bag Learners and Random Forests. Because decision trees are classifiers, the decisions to buy, sell, or hold stocks must be turned into numeric classifications. Therefore, three classifications were created: 1 = LONG, -1 = SHORT, and 0 = CASH. These classifications enable the learner to compare the training data (consisting of the indicators such as Bollinger Bands, Volatility, etc.) for the in-sample period with the assigned labels indicating which of the three positions is to be taken.

To train the Strategy Learner, I experimented with different parameters and different indicators. I settled on volatility, Bollinger Band Value, and the Relative Strength Index (RSI) based on a 20-day simple moving average. These three indicators were similar to my model in the Manual Strategy project and seemed to generate to the most valuable returns during the in-sample/training period of Jan. 1, 2008 - Dec. 31, 2009.

To determine when a LONG, SHORT or CASH position should be adopted, I calculated the return of the stock over the future N days, known as the N-day return. When this return exceeded certain thresholds, the training labels were assigned to different positions. After experimenting with different threshold values, I decided to use +/- 0.04 + the impact value. Therefore, if the N-day return was above 0.04 + impact for a particular day, the training label assigned was 1, meaning to purchase shares and adopt a LONG position. On the other hand, if the N-day return was below -(0.04 + impact), the training label of -1 was assigned, meaning to sell shares and adopt a SHORT position. If neither of these thresholds were reached, a zero was assigned to the label, instructing the model to adopt a CASH position.

After the indicator data and the associated labels are used to train the learner, it is tested against out-of-sample/testing data, in this case the period of Jan. 1, 2010 - Dec. 31, 2011. The model is used to simulate a hypothetical portfolio consisting of the stock "JPM" which is bought and sold on days indicated by the model's predicted labels. If the model's prediction for a particular date is a 1, then the portfolio adopts a LONG position by increasing its holdings to 1000 shares. If the model's predication is -1, the portfolio adopts SHORT position and shorts 1000 shares. If the model's prediction is 0, the portfolio reverts to a CASH position by either selling its shares (if it is currently LONG) or buying shares (if it is currently SHORT).

Outline of the Training and Testing Process

1) A Bag Learner is created with a leaf size of 5 and is set to 20 bags (meaning 20 instances of the Random Tree Learner).
2) Strategy Leaner gets the pricing data and, using indicators.py from the Manual Strategy project, calculates indicators such as Bollinger Bands, Volatility, Relative Strength Index, etc. using a 20-day moving window. The indicator data is concatenated into a single dataframe to serve as the training data for the learner.
3) The training labels are then assigned using N-day return where a value of 0.04 + impact results in a label of 1 (LONG) while a value of -(0.04 + impact) results in a label of -1 (SHORT) and returns reaching neither threshold are assigned a 0 (CASH).
4) The learner is then trained using the indicator data as its X dataset and the training labels as its Y dataset.
5) The learner is then tested with a hypothetical portfolio with a starting value of $100,000 and trading the stock "JPM".
    a) If the predicted values are 1, the portfolio adopts a LONG position of 1000 shares
    b) If the predicted value is -1, the portfolio adopts a SHORT position of 1000 shares.
    c) If the predicted value is 0, the portfolio reverts to a CASH position, selling shares currently held and buying shares currently short.

Adjustment of parameters

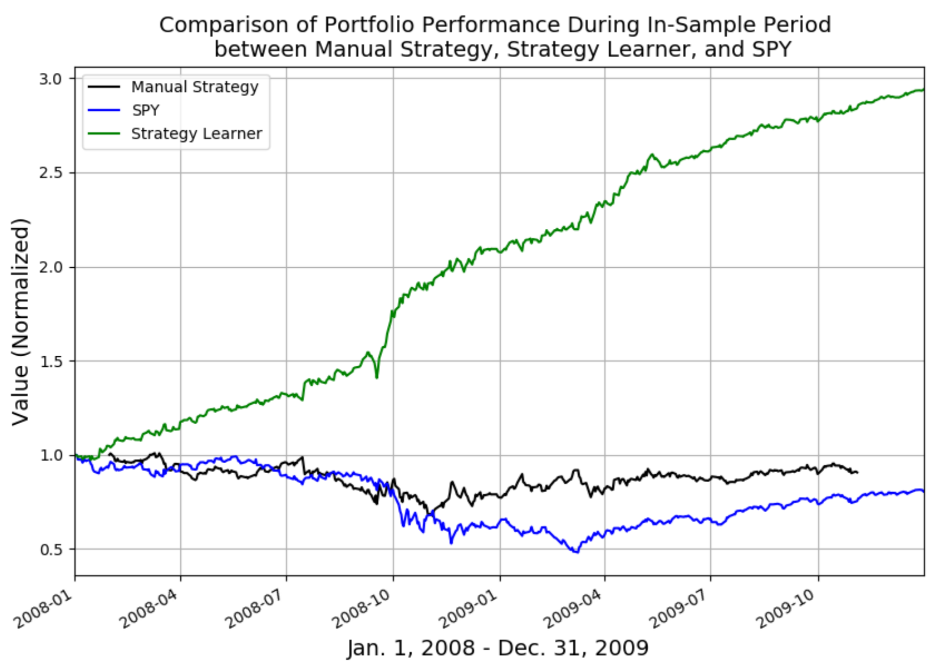
When developing the model I experimented with different parameter settings such as leaf size, number of bags, N-day return and the BUY/SELL thresholds for the training data. I found that increasing the leaf size beyond 5 and increasing the number of bags beyond 20 did not appear to have an appreciable difference in the model. I tried changing the values of the N-day return from 5 to 10 and 20, but this seemed to decrease the value of the portfolio when it came to the testing period. An N-day return of 5 seems appears to be optimal. In addition, I varied the BUY/SELL thresholds from +/- 0.1 + impact to +/- 0.5 + impact. I did not see a substantial difference in changing these thresholds except that increasing above 0.4 + impact resulted in the ML4T-220 test case failing due to the in-sample return not beating the benchmark.

Part 2: Experiments

Experiment 1:

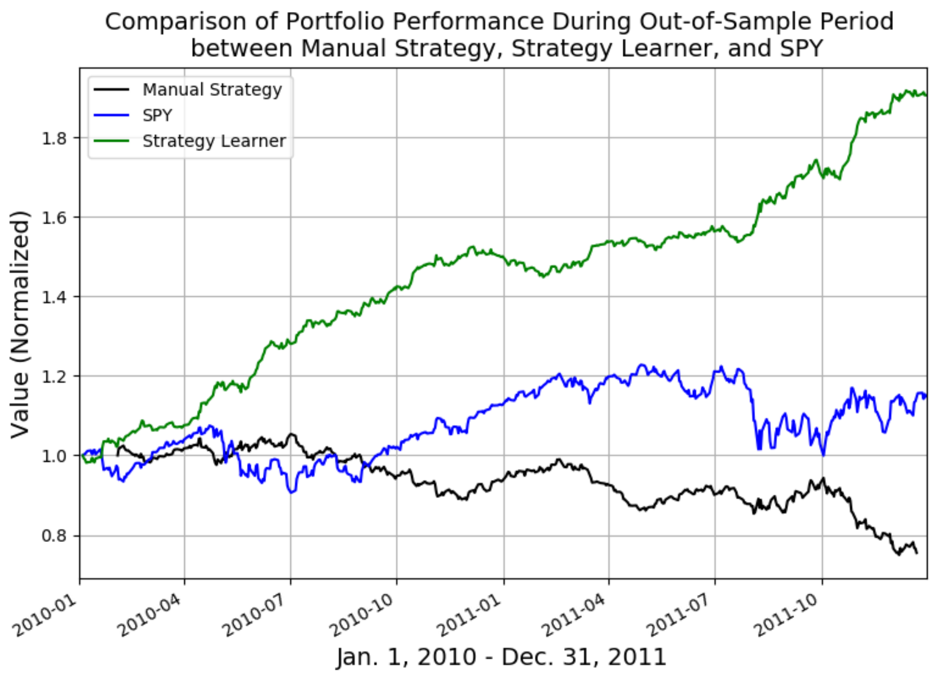
In experiment 1, I compared the performance of the Strategy Learner with the exact same indicators I used in the Manual Strategy project, namely Bollinger Band Value and the Relative Strength Index based on a 20-day moving average. In that project a portfolio trading JPM during the in-sample phase outperformed the SPY which lost approximately 25% of its value over the period of Jan. 1, 2008 - Dec. 31, 2009.

The experiment consisted of re-running the code I wrote in the Manual Strategy project to generate returns for that hypothetical portfolio and also calling the Strategy Learner, training it on the same indicators, and generating a hypothetical portfolio based on its predications to compare with the portfolio of the Manual Strategy. The results shows that the Strategy Learner clearly outperformed both the Manual Strategy and SPY, which was used as a benchmark. The Strategy Learner produced a portfolio that nearly tripled its original value, which the Manual Strategy was close to break-even, and the SPY lost about 25% of its value.



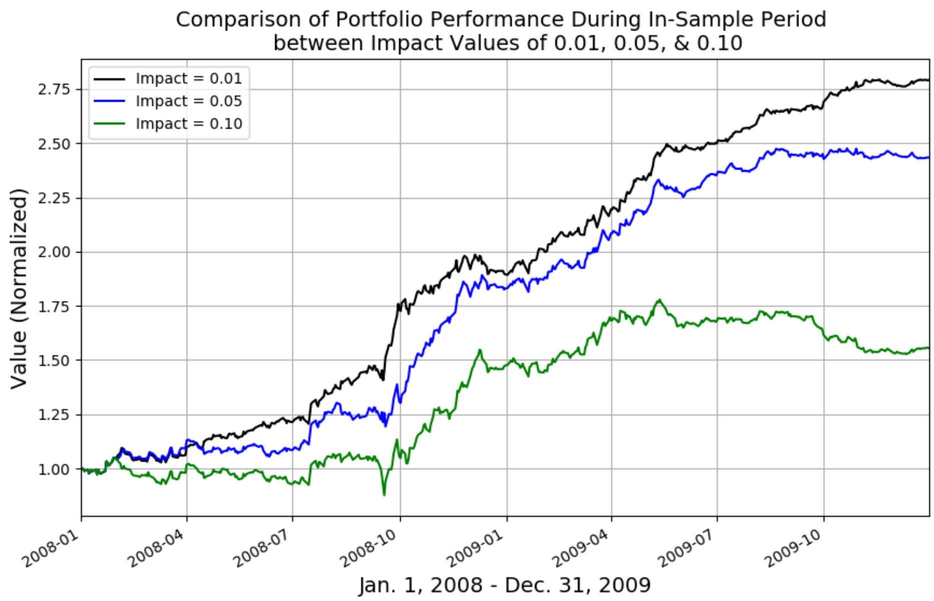
I then repeated the experiment using the out-of-sample period of Jan. 1, 2010 - Dec. 31, 2011. While the performance of the Strategy Learner was no as dramatic, it was still substantially better than either the Manual Strategy or the SPY. The Strategy Learner's portfolio almost doubled in value over this time, while SPY gained approximately 20% and the

Manual Strategy portfolio lost over 20%. The results show the Strategy Learner is clearly superior for both the in-sample and out-of-sample time periods.



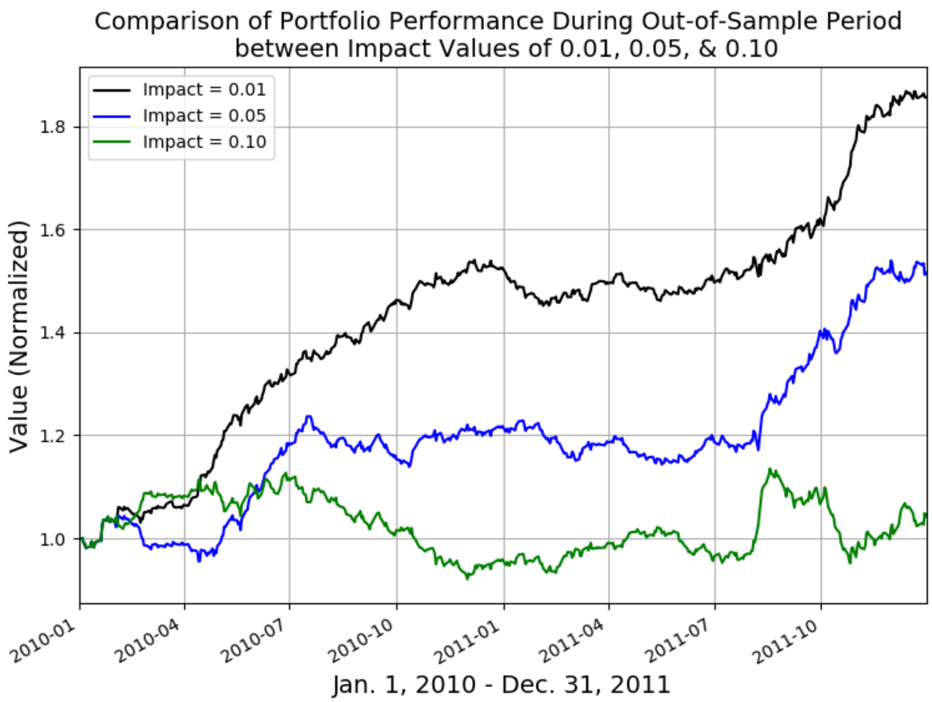
Experiment 2:

For experiment 2, I hypothesized that increasing the impact level would negatively affect the portfolio's performance. To test this, I created three versions of the Strategy Learner, with impact levels of 0.01, 0.05, and 0.10 respectively. I then trained and tested them using the same indicators as in Experiment 1. The results show a relationship between a higher impact value and a lesser performance of the portfolio. While the portfolio with an impact of 0.01 increased to over 2.75 times, the portfolio with an impact of 0.10 increased only about 1.5 times, and even appears to decrease towards the end of the time period.



I also compared the different impact levels on the out-of-sample period and found more dramatic results. The portfolio with the impact level of 0.01 increased by 1.9 times, practically the same performance as in experiment 1 where the impact level was zero. For impact levels of 0.05 and 0.10, however, the portfolios were substantially lower in value. An impact level of 0.05 led to the portfolio gaining approximately 1.5 times its value while an impact level of 0.10 led to the portfolio barely rising above its starting value.

Interestingly, the impact values do not show a correlation in the first 6 months or so of the time period. The portfolio with impact of 0.10 outperforms the other two impact levels for approximately the first four months of the period. The portfolio with impact of 0.05 substantially underperforms the other two during this same time period, losing value while the other two steadily gain value. Over entire time period, however, the lower impact level clearly performs the best.


Comparison of Portfolio Performance During Out-of-Sample Period
between Impact Values of 0.01, 0.05, & 0.10
Impact = 0.01
Impact = 0.05
Impact = 0.10
Value (Normalized)
1.8
1.6
1.4
1.2
1.0
2010-01
2010-04
2010-07
2010-10
2011-01
2011-04
2011-07
2011-10
Jan. 1, 2010 - Dec. 31, 2011