Project 8

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1 INTRODUCTION

In the following report we will discuss how to form a trading strategy using technical indicators via manual (Manual Strategy) and model based (Strategy Learner) methods. The goal is explore and evaluate both methods effectiveness against a benchmark and stress test them with changing factors. The benchmark here is going to be the scenario of purchasing 1000 shares of JPM holding it. Thus will evaluate both manual and strategy learner against this scenario and also test them outside of the in sample data.

2 INDICATORS OVERVIEW

In this paper we used three indicators to build our strategy: Simple Moving Average (SMA), Momentum (MOM) and Bollinger Bands Percentage (BBP). It is worth noting that those technical indicators were chosen and optimized on the stock data of JPM from the period of Jan, 1,2008 to Dec 31 2009.

Recall that simple moving average is a technical indicator that basically takes the arithmetic average of a time series (price in our case) with a provided rolling window. Simply put, SMA calculates the mean of the provided period rolling back each day. For example SMA(50) will calculate the mean of prices for 50 days for every day. This implies if you provide the prices for 100 days, the first 50 days will not have SMA to calculate but it will for the next subsequent days.

As a technical indicator, SMA helps us understand the current trend of a price of a security we can act on a stock if there is an uptrend or downtrend for the price at any given time.

In this report, I have used the lookback window of 50 days to calculate SMA for both Manual Strategy and Strategy Learner. The rational behind this choice of parameter was to capture no longer than 50 days price trend as the JPM stock seem to change more frequently.

The second indicator will be using is Momentum which is a indicator that measures the rate of change of security price in a number of past periods ago. Such indicator help us understand the rate of rise or fall of stock prices. The indicator values range between -1 and 1. As such, a stock with a momentum near zero means the price is consolidating while a momentum value above zero indicates an uptrend and below zero value signals a downtrend. Momentum is not used alone as a buy or sell signal, it is rather used to spot upcoming trends that are confirmed with other indicators such as SMA.

I have used the lookback window of 50 days to calculate MOM for both Manual Strategy and Strategy Learner. The rational behind this choice of parameter is similar to SMA as I wanted to use both indicators to confirm trends in the stock.

Lastly, will be using Bollinger Bands Percentage, which is a powerful indicators that measures how spread out the numbers from average value using standard deviation. Recall that there are two bands, upper and lower, both are corresponding to above and below mean standard deviation respectively. In practice, those bands can helps understand if a stock is overbought or oversold. Meaning when the price approaches an upper band, the stock is said to be overbought and when price approaches lower band, the stock is said to be oversold. Thus based on those signals it can help traders trigger buy/sell actions.

Similar to MOM and SMA, I have used the lookback window of 50 days to calculate for both Manual Strategy and Strategy Learner. Using the same lookback window on all indicators serves confirm trends in the stock such that long and short positions are guaranteed to generate a decent return.

3 MANUAL STRATEGY

The Manual strategy is composed of using technical indicators to generate buy, sell or hold signals. The Buy signal is composed of the following structure:

BUY IF SMA < 0.95 and BBP < 0 and MOM < -0.05
SELL IF SMA > 1.05 and BBP > 1 and MOM > 0.05

We use those signals to buy/sell/hold JPM shares with the constraint that we can maintain -1000,0 or 1000 shares at any given time in the in sample period of Jan,1,2008 to Dec,31,2009.

It is worth noting that this strategy's exact numbers were tuned using multiple trials and runs to see which numbers can generate return that beats the benchmark return (purchasing 1000 shares of JPM on Jan 1,2008 and holding it until Dec, 31, 2009) Looking at the values that were curated for this strategy it is no surprise that those indicators work together creating an effective strategy.

In the buy strategy, recall that BBP help us understand if a stock is overbought or oversold thus if the value of BBP < 0 then price is approaching the lower bands suggesting the stock can indicate that it is being oversold. The value of the BBP can also play in harmony with momentum or the rate of change of the price. If we see that the rate of change of the price is declining strongly, which is indicated by the MOM value <-0.05 then we expect that the stock is also being oversold as well. Similarly looking at the stock short term SMA when it crossed below 0.95 it was indicating an oversold signal (although looking back it would have been more accurate to use price/sma ratio) to make this strategy applicable to other stocks.

Similarly, the sell strategy follows that when the rate of change of stock is going up with 5% increase, this could indicate a spike in buy and thus overbought signal before a correction coming. The BBP is also increasing and approaching upper bands and the JPM SMA 50 days average is above 1.05, which based on the stock of JPM happens to be where the stock rebounds back after, as noted looking back this strategy will only work during the in sample period for JPM and not expandable beyond other periods for other stocks, I would be using price/sma ratio to make it more applicable to other periods. As we can see below in figure 1, the manual strategy beats the benchmark in the total portfolio value being higher than the benchmark by 30%.

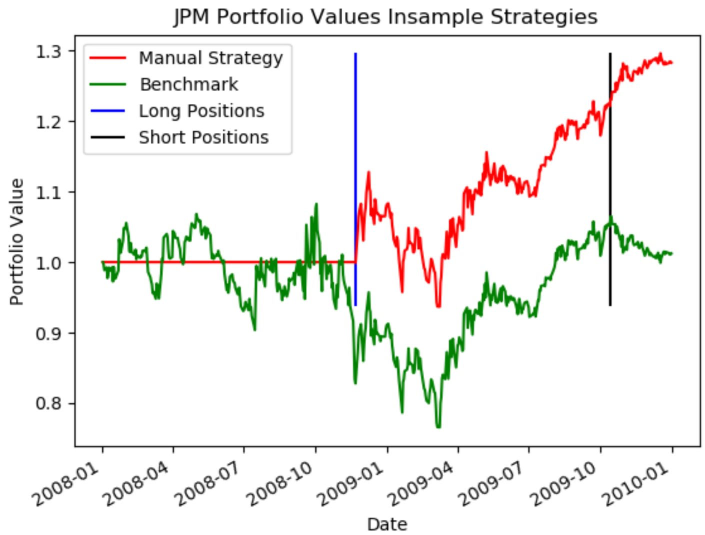

Figure 1—In Sample Manual Strategy

We take the strategy we created above and apply it to the out-of-sample strategy, which is the period of Jan, 2010 to Dec 2011 and compare it to the benchmark in the same period. As we can see in figure 2, the strategy still beat the benchmark but it only generated a 8% return, which is lower return than the in-sample. This is not surprising given that SMA strategy was customized to in-sample along with BBP and MOM may have not been able to capture the stock trends in the out-sample period. Interestingly, when we look at the benchmark in figure 2, we can see that the stock looks very different from the in-sample period where we have a rise in price around mid 2011 and crash in end of 2011.

As we can see the table below, the performance of our strategy declines significantly when we compare out-sample vs in-sample **cumulative return** and **mean of daily returns**. This is expected as one of our major indicators SMA was curated specifically based on the in sample moving averages thus it was not effective outside of the in-sample range. Similarly, BBP and MOM may have been impacted by the SMA inflexibility but also could have failed to capture trends as specified by the parameters is set to since the stock can act differently in the out-sample period which can be seen through the benchmark time series, the stock is deflecting to unstable downward trends in the late 2011. Additionally, we can see that there is a difference in **SDEV** of in-sample and out-of sample.

This can suggest that the stock had different volatility which a manual strategy is not going to be able to effective with the stock in a different price trends.

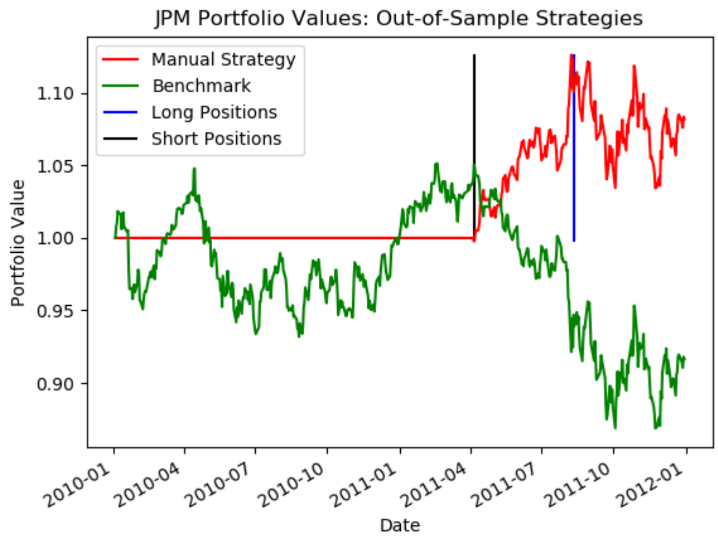

Figure 2—Out of Sample Manual Strategy

	In Sample	
	Benchmark	Manual Strategy
Cumilative Return	1.2%	28.3%
SDEV	1.7%	1.0%
Mean of Daily Return	0.02%	0.05%
	Out of sample	
	Benchmark	Manual Strategy
Cumilative Return	-8.4%	8.2%
SDEV	0.9%	0.5%
Mean of Daily Return	-0.01%	0.02%

4 STRATEGY LEARNER

4.1 Data and Model Build

The strategy learner is a model that used random forest and bag learners to generate buy and sell signals. The main structure of the model is using a class strategy learner with the following methods

```
class StrategyLearner: input are impact value and commission values
```

add_evidence : our training method that takes stock symbol start_date , end_date and start_value of portfolio and returns a model build with BagLearners that calls random forest models.
testPolicy: our testing method where it takes the same input as add_evidence returns a dataframe with values that indicate position of stock constrained to −1000,0 or 1000

The strategy was framed as a classification learning problem. As such, we needed features and a target variable. Our features in this problem are the value indicators (all normalized) that were chosen in the manual strategy, and our target variable Y was build however using multiple parameters. To determine Y, we need the following parameters:

N= Number of days to calculate the next date to determine a return
YBUY: Threshold we set to buy if return on a trade exceed this value
YSELL: Threshold we set to short if return on a trade exceed this value

Impact: A parameter that is provided which raises/lowers the stock price

Delta: This is the delta of two prices with Commission Adjusted:
absolute value of (Price on day i+N −Price on Day i) − Commission

Return: The price of a stock on day i + N divided by the price on day i minus 1

Therefore based on the parameters above, we use them to determine the value of Y (our target variable) following this logic:

```
If return value on a trade > YBUY + impact and Delta >0:
    Y= 1 -> Buy the stock
If return value on a trade < YSELL + impact and Delta >0
    Y= -1 -> sell the stock
else Y=0
```

The training (in-sample) data is to be generated from the JPM stock data from Jan,1,2008 to Dec,31, 2009. The testing data is generated for the same stock JPM from Jan,1,2010 to Dec,31, 2011. Once we calculate the value of the indicators and our target variable as shown above, we can start working on approaching the classification model. In this approach we build a random forest classifier that returns the mode of the values in the terminal leafs, and we build a bag learner that wraps around the random forest models and returns the average of the random forest models it runs using the following logic:

```
IF  average result of x random forest values >0.5: classify as buy
IF average result of x random forest values <-0.5: classify as sell
ELSE 0 -> HOLD
```

The rational behind the choice of the logic above was to only capture strong signals that are clear where the majority of the bag learner results are skewed strongly.

4.2 Hyperparameter selection

All parameters below were selected using the JPM in sample data as defined earlier. With many trial runs on the in sample data, the goal was to see which combination of those trades were resulted in a cumulative return that beats the benchmark return (not RMSE) so this parameter selection may not perform well for out of sample data.

YBUY and YSELL were set to 0.001 –> this was set to generate enough trades in our in sample data. If we set YBUY and YSELL to higher values, the trainning data generated very few trades.

N= Number of Days to calculate the N+current day price was set to 30, this was done based on looking at the JPM stock price and seeing major trends change drastically across roughly every month and also it happened to generate a decent number of trades in our in sample training dataset.

Leaf size: the number of data points for the terminal leafs was set to 5 as it generated the highest cumulative return on the training dataset. Although this could backfire on out of sample dataset since this number is small enough to cause overfitting but since we are tuning only using in sample data this value of leaf size was optimal.

Number of Bags: The number of models to generate in bag learner was set to 50 as it seems to produce the same results every time we run the model with a decent cumulative return.

4.3 Experiment 1

The purpose of this experiment is to compare the manual strategy and learner and see how they perform against each other and the benchmark. To generate this experiment, we follow the steps below:

```
Run Manual Strategy with the in sample data of JPM
Run Strategy Learner with in sample data of JPM
Run the benchmark strategy which is the purchase of the 1000
 shares JPM stock on Jan 1, 2008 and holding it.
```

With the three results above, calculate the cumulative return from each strategy and plot them as below in figure 3.

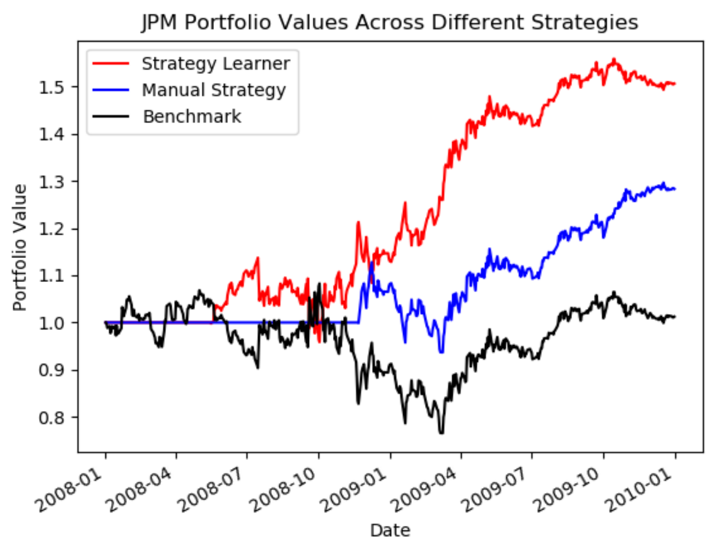

Figure 3—Experiment 1 Portfolio Values

The results above of the experiment shows that the value of the portfolio across the three different strategies vary greatly. The strategy learner beats the manual strategy at cumulative return of 50% compared the manual return of 28%. This is due the manual strategy being very hardcoded method while the strategy learner is based on the relationship of the indicator values and the target variable was able to detect more opportunities to go long or short in positions where the manual strategy was too hardcoded to capture. As for the benchmark, holding the 1000 shares of JPM does not generate a greater return, in fact it resulted in cumulative return of 1% since the stock fluctuates and not acting on the those fluctuations resulted in cash gain opportunities that other strategies were able to capitalize on.

4.4 Experiment 2

The purpose of this experiment is to stress test the strategy learner with three different impact values and assess the results using two metrics chosen: Sharp ratio and average daily return. *The hypothesis here is that as impact value goes up, the average daily return and sharp ratio go down.* This experiment was done on the in sample trading data of JPM and assumes that the strategy learner is tuned only using in sample trading data as well.

To generate this experiment, we need to call the strategy learner as defined in section 4.1 and 4.2 three times with the three different parameters (0.001,0.01,0.5) for each run. Then the resulted dataframe from those three runs will we calculate the portfolio statistics of resulted from the portfolio of those trades. From there, we then calculate the sharp ratio and average daily return of each run.

The three impact values were chosen for this experiment were: 0.001, 0.01 and 0.05. Then we use those data to feed our strategy learner and obtain the following results:

Impact of 0.05
Sharpe Ratio : 0.36773941688885127
Average Daily Return : 0.00036674659463388893

Impact = 0.01
Sharpe Ratio : 1.2692076702904085
Average Daily Return : 0.0009759907431414201

Impact of 0.001
Sharpe Ratio : 2.0240785412459663
Average Daily Return : 0.0013744504583303237

As we can see that from the results above the sharp ratio and average daily return decreases significantly as we increase the impact value. That can be attributed to the fact that the higher the impact value, the less our learner is allowed to trade since we defined in our target variable the threshold to trade to be contingent on the impact value. Thus when trading less, it allowed the learner to act less on possible trading opportunities. To illustrate the variation of the impact on the cumulative return, the figure showing the cumulative return of the three different impact values, as we can see it is no surprise that the impact value of 0.0001 preformed the best.

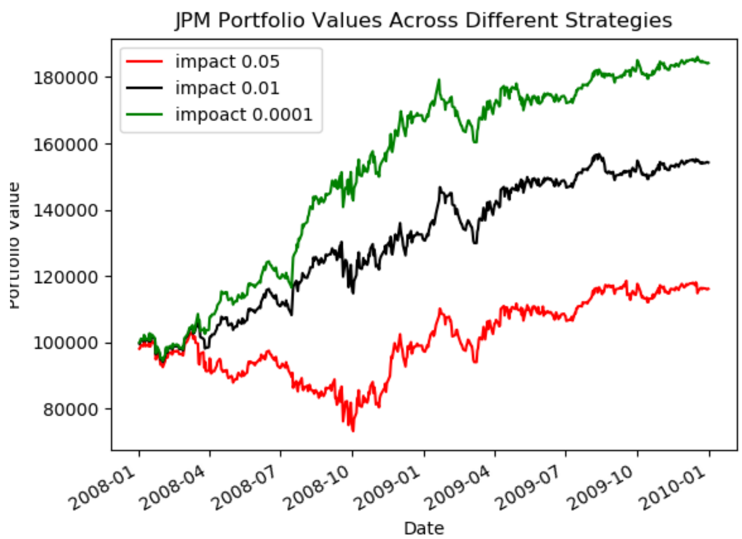

Figure 4—Experiment 2 Portfolio Values