

Machine Learning for Trading

Manual Strategy

1. Technical indicators

In this project, we consider the following technical indicators for determining our position on stocks in the stock market:

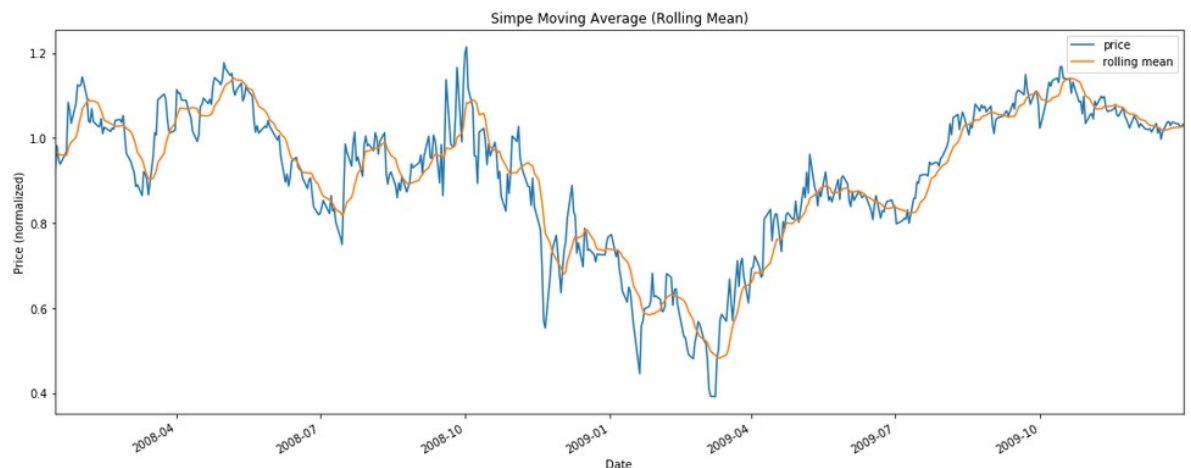
- A] Simple Moving Average (SMA)/ Rolling Mean
- B] Bollinger Bands and BB Value
- C] Volatility
- D] Commodity Index (CCI)

1.1 Simple Moving Average (SMA)/ Rolling Mean

A simple moving average (SMA) is an arithmetic moving average calculated by adding the closing price of the security for a number of time periods and then dividing this total by the number of time periods. It is an indicator that smoothens the price curve volatility and demonstrates the lagged characteristics of the stock price movement. The simple moving average formula is calculated by taking the average closing price of a stock over the last "x" periods. Many traders watch for short-term averages to cross above longer-term averages to signal the beginning of an uptrend. Short-term averages can act as levels of support when the price experiences a pullback.

$$SMA_t^{(n)} = \frac{1}{n} \sum_{i=0}^{n-1} Price_{t-i}$$

In this project, we will determine the 15-day SMA of the stock price and use its relative value from 5 days ago as an indicator of the price trend.



The above chart demonstrates how SMA can be used as an indicator.

1.2 Bollinger Bands and BB value

Bollinger Bands® are a highly popular technical analysis technique. It is plotted two standard deviations away from a simple moving average. Many traders believe the closer the prices move to the upper band, the more overbought the market, and the closer the prices move to the lower band, the more oversold the market.

The squeeze is the central concept of Bollinger Bands®. When the bands come close together, constricting the moving average, it is called a squeeze. A squeeze signals a period of low volatility and is considered by traders to be a potential sign of future increased volatility and possible trading opportunities. Conversely, the wider apart the bands move, the more likely the chance of a decrease in volatility and the greater the possibility of exiting a trade. However, these conditions are not trading signals. The bands give no indication when the change may take place or which direction price could move.

Bollinger Bands® are not a standalone trading system. They are simply one indicator designed to provide traders with information regarding price volatility. John Bollinger suggests using them with two or three other non-correlated indicators that provide more direct market signals. The bottom line is that Bollinger Bands® are designed to discover opportunities that give investors a higher probability of success.

In this implementation, my graph has 3 curves:

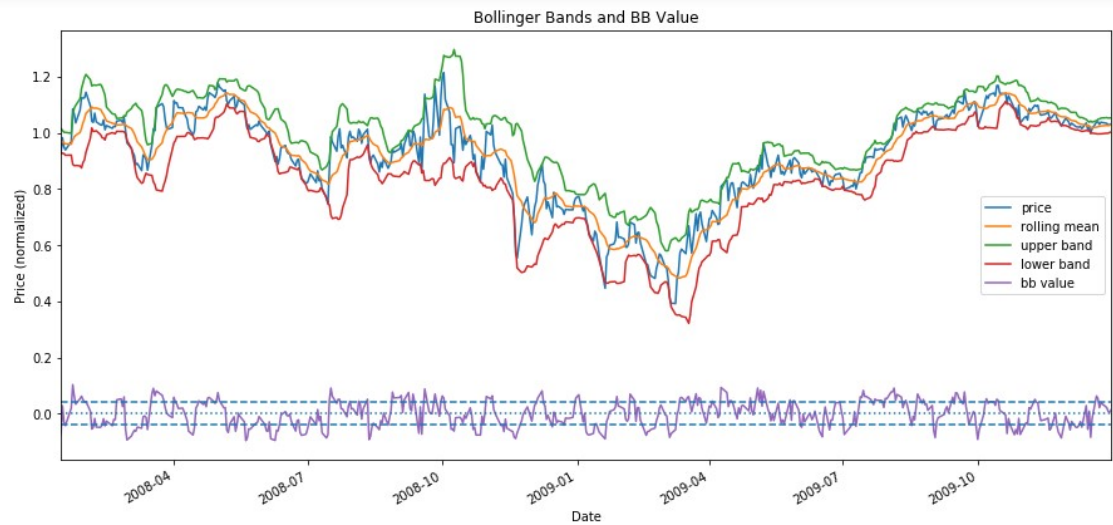
- i) Upper band (2 standard deviations above SMA)
- ii) Middle band (SMA)
- iii) Lower band (2 standard deviations below SMA)

The upper and lower bands signify the extent of current volatility about the SMA, and the prices are said to be high at the upper band, and low at the lower band. We will derive an indicator for trading strategy from these signals by computing the Bollinger Band Value (BB Value), which gives a relative position of the current price with regards to the bands. It is calculated as follows:

$$Upper - band = rolling - mean + (2 * \sigma(prices))$$

$$Lower - band = rolling - mean - (2 * \sigma(prices))$$

$$BBvalue = \frac{prices - rollingmean}{2 * \sigma(prices)}$$



The above chart demonstrates how Bollinger Band and BB value can be used as an indicator.

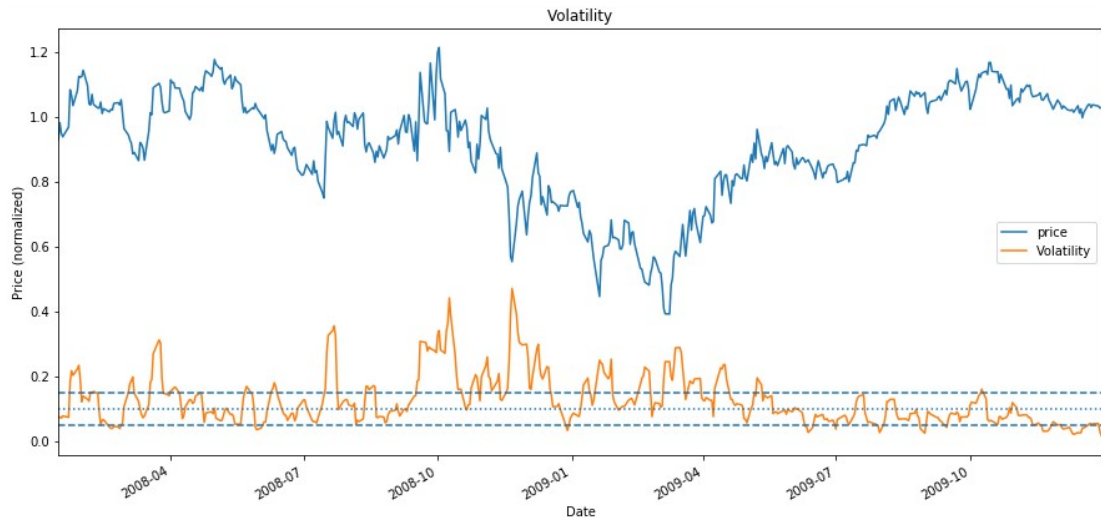
1.3 Volatility

Volatility is a statistical measure of the dispersion of returns for a given security or market index. Volatility can either be measured by using the standard deviation or variance between returns from that same security or market index. Commonly, the higher the volatility, the riskier the security.

Volatility refers to the amount of uncertainty or risk about the size of changes in a security's value. A higher volatility means that a security's value can potentially be spread out over a larger range of values. This means that the price of the security can change dramatically over a short time period in either direction. A lower volatility means that a security's value does not fluctuate dramatically, but changes in value at a steady pace over a period of time.

Standard deviation is the most common way of calculating volatility. In my implementation, I have considered volatility to be the standard deviation of prices over a window of 1 week i.e. 7 days.

$$Volatility = \sigma = \sqrt{prices}$$



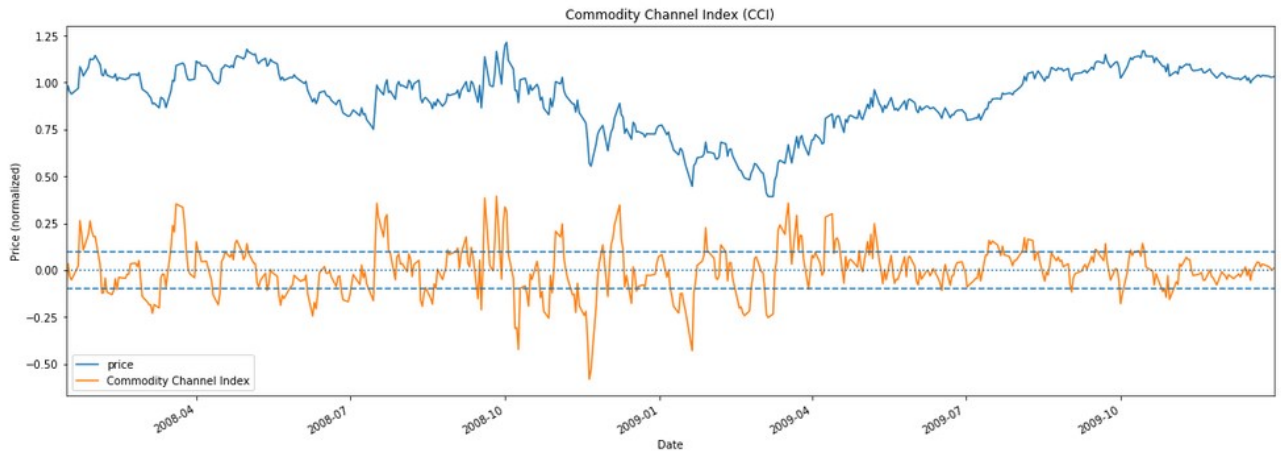
The above chart demonstrates how volatility can be used as an indicator.

1.4 Commodity Channel Index (CCI)

The Commodity Channel Index (CCI) is a versatile indicator that can be used to identify a new trend or warn of extreme conditions. CCI measures the current price level relative to an average price level over a given period of time. CCI is relatively high when prices are far above their average. CCI is relatively low when prices are far below their average. In this manner, CCI can be used to identify overbought and oversold levels.

CCI measures the difference between a security's price change and its average price change. High positive readings indicate that prices are well above their average, which is a show of strength. Low negative readings indicate that prices are well below their average, which is a show of weakness. The Commodity Channel Index (CCI) can be used as either a coincident or leading indicator.

The definition of overbought or oversold varies for the Commodity Channel Index (CCI). Theoretically, there are no upside or downside limits. This makes an overbought or oversold assessment subjective. Second, securities can continue moving higher after an indicator becomes overbought. Likewise, securities can continue moving lower after an indicator becomes oversold.



The above chart demonstrates how CCI value can be used as an indicator.

$$CCI = \frac{(prices - rm)}{\sigma(prices)}$$

2. Best Possible Strategy

2.1 Methodology

A] Portfolio

In the best possible strategy, we assume that we can peek into the future. However we are constrained by the portfolio size and order limits. We are allowed to be in one of the three states: -1000 shares, +1000 shares, 0 shares. We consider \$0.00 for commissions and 0.0 for impact in case of best possible strategy.

I have implemented best possible strategy such that I look 1 day ahead and decide my position based on a comparison of the stock price today and tomorrow. If the today's price is lesser than what it would be tomorrow, I will BUY 1000 shares of JPM today and sell 1000 shares of JPM tomorrow, thus making profit in the trade. On the other hand, if I see that today's price is greater than what it would be tomorrow, I will SELL 1000 shares of JPM today and buy 1000 shares of JPM tomorrow. Thus based on one comparison, my BUY and SELL strategies go hand-in-hand. Thus except for the first and last days, everyday there will be 2 transactions of either BUY or SELL (1 transaction that was a result of comparison with previous day's price and another which is a result of comparison with next day's price.)

To implement this logic, I first read in data from prices for JPM and decide what my action for today is. Then I use that same dataframe and shift it by 1day before replacing the values with opposite actions (i.e. BUY with SELL and SELL with BUY) denoting that BUY and SELL actions work in pairs.

These values are then populated into the dataframe that is passed to `compute_portvals()` function that was implemented in market simulator. This function processed the data and reports the following statistics:

- Cumulative return of the portfolio
- Standard-deviation of daily returns of portfolio
- Average daily returns of portfolio

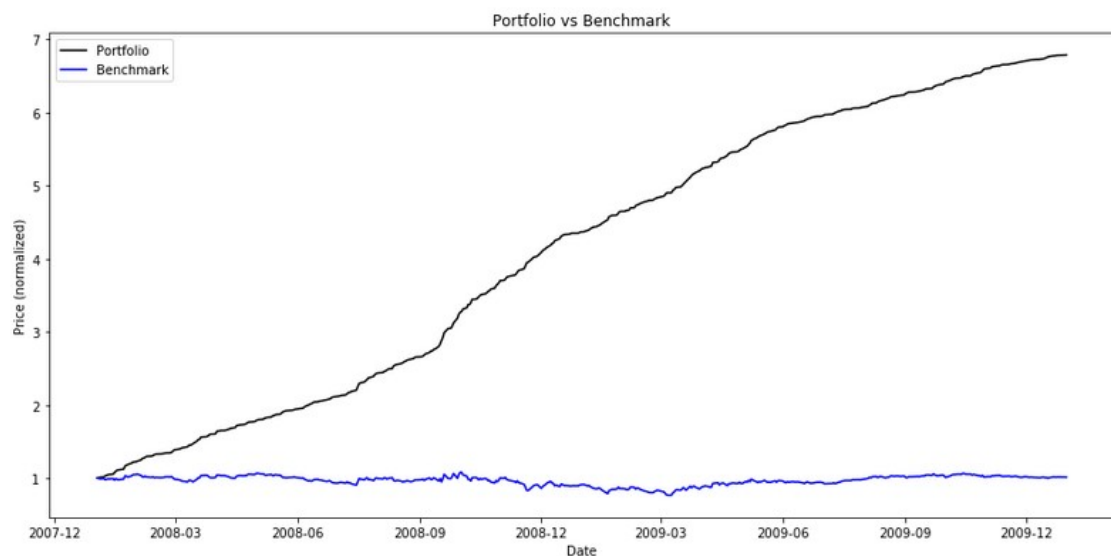
B] Benchmark

Benchmark is defined as the performance of a portfolio starting with \$100,000 cash, investing in 1000 shares of JPM and holding that position. It is normalized to 1.0 at the start. The purpose of the benchmark, as the name suggests, is to set a checkpoint which should be attained at the least by the trading strategy.

To implement this, I create a dataframe for benchmark with just 2 rows, 1 each for the starting and ending dates of transactions. On the first day, decision is stated as BUY 1000 shares of JPM. And since we hold it forever, the decision for the last day is to BUY 0 shares of JPM.

2.2 Chart (Dates and equity curve)

A comparison of the benchmark normalized to 1.0 at the start (in blue line) with the value of the best possible portfolio normalized to 1.0 at the start (in black line) is shown in the graph below:



2.3 Reported performance criteria

A] Fund = Best possible Portfolio

Cumulative Return of Fund: 5.7861

Standard Deviation of Fund: 0.00454782319791

Average Daily Return of Fund: 0.00381678615086

B] Fund = Benchmark

Cumulative Return of Fund: 0.0123

Standard Deviation of Fund: 0.0170043662712

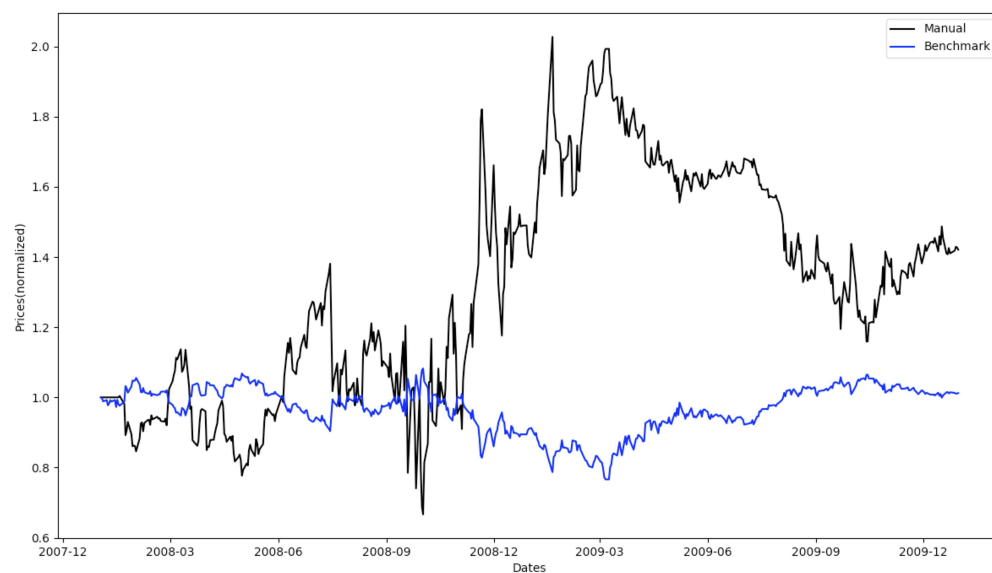
Average Daily Return of Fund: 0.000168086978191

3. Manual Rule-Based Trader

3.1 Trading Strategy

The rule-based trading strategy assigns thresholds to different indicators and accordingly decides the holdings of the shares to create a new orders dataframe. The trick here is to tweak the threshold parameters for every set of indicators in order to find the one that best suits the requirements such that the manual rule-based trader performs better than the benchmark value in most cases.

3.2 Charts (Dates and equity curve)



4. Comparative Analysis

In this step, we use the trained trader for in sample data on out sample data to test its performance. It is observed that the trader performs significantly well on insample data but fails to beat even the benchmark with out of sample data.