PYTHON PROJECT

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Trading Strategy

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In accordance with the assignment no. 3, we decided to build an algorithm trading program.

Introduction

Financial markets often move along hidden patterns that cannot be always detected by human intuition and insight: such basic consideration was at the foundation of a data-driven/quantitative approach in trading, which nowadays is largely adopted by investment banks and hedge funds. At the same time, big players rely on automated pre-programmed trading instructions for executing their buy and sell orders.

Main advantages of algorithm trading can be briefly summarized as follows:

a) speed and high frequency (faster than any human in execution);

b) accuracy (no human errors while trading);

c) rational decisions (removal of human emotions, like greed and fear, from trading);

d) back-testing before live trading (thanks to the huge amount of available past data).

Nonetheless, this implies some disadvantages, such as:

a) possible bugs (programming errors)

b) no recourse to sometimes brilliant human intuition and insight, which are not programmable.

Feasible trading strategies for algo-trading

We decide to focus on trading strategies that can be implemented in an algorithm trading program, namely:

a) Mean reversion: this strategy is built on the assumption that the "regression toward the mean" phenomenon can be applied also to securities'/assets' prices (i.e. eventually, they will revert to the long-run mean or average level of the entire historical dataset).

Therefore, such strategy is based on:

1) identifying trading ranges and computing the average price
2) selling the overbought (i.e. when the price is higher than the average) and buying the oversold (i.e. when the price is lower than the average).

Therefore, the trading approach is contrarian to the current price pattern, which is expected to correct soon.

b) Trend following: this strategy does not aim to anticipate the future price pattern but tries to exploit the current price pattern. Therefore, trades are executed in the direction of the strength and momentum: when a signal is crossed, the securities'/assets' price is expected to keep on rising/falling (depending on the signal).

Wrong trades are inevitable due to the high number of false signals and fake breakouts: it is therefore paramount to never miss a trade, since it could be the trade that makes profitable the overall strategy.

Fundamental elements of an algo-trading strategy

To build a proper algo-trading strategy, it is essential to identify the following elements:

a) **Trading timeframe**: decide if the trading horizon should be very low (swing trading), low (intraday trading) or long-term (position trading)

b) **Entry conditions**: set the rules for the algorithm to buy (open the position)

c) **Position management**: set the rules for the algorithm to manage the position opened at the occurrence of certain market conditions

d) **Exit conditions**: set the rules for the algorithm to sell (close the position).

Fundamental vs technical analysis

Two major schools of thought exist in the world of investing in capital markets:

a) **Fundamental analysis**: its goal is to measure the intrinsic value of a security/asset. This is done through an analysis of a wide range of information: economic data (GDP, financial statements, etc.), news, various macro scenarios, etc. Therefore, such analysis usually requires a complete and comprehensive understanding of the political and economic scenario influencing the securities'/assets' price.

b) **Technical analysis**: its goal is to forecast the future price movements of a security/asset through the analysis of various historical statistical trends, identifying possible patterns. One of the assumptions of such analysis is the so called "efficient market hypothesis", which states that when new information comes into capital markets, it is immediately reflected in securities'/assets' (current) prices.

Algorithmic trading strategies are based on technical analysis.

Analysis and improvement of the algo-trading strategy

In order to develop a scientific, hypothesis-driven algorithmic trading strategy, it is fundamental to first know and analyze important performance indicators, and second to optimize the strategy:

a) **Performance indicators:** the first important indicator is the strategy's accuracy, so how many profits or losses were generated. On top of this for both, profits and losses, the average and maximum must be conducted. Furthermore, the return on investment in included. Lastly, the maximum drawdown is computed. A drawdown is an asymmetric risk measure, which represents a loss between a high and the following low within a certain period. The maximum drawdown is therefore the cumulative loss that could have occurred during a period if it would have been invested at the time of a peak.

b) **Optimizing the strategy:** due to the use of historical data, it is important to not overfit the model. An overfitted model is so closely attached to the past data, that its efficiency decreases for future applications. Consequently, back testing is necessary. During back testing the prior trained algorithm is ran against unseen historical data and the performance is then analyzed. Demo trading would be another option to test the algorithm against a different data sample. After ensuring that the model is not overfit and the back testing is successfully done, real trading is possible.

Trading trends and trading ranges

In developing our algorithm trading program, we assumed the following:

a) Even in an efficient market, securities'/assets' prices are **still predictable to some degree** since prices movements are not totally random.

b) It is possible to identify trading trends and trading ranges: a **trading trend** is said to occur when the price moves constantly in one direction (i.e. up or down). Trading trends are interspersed with **trading ranges**: they are represented by sideways chart pattern, i.e. when prices are generally consolidating and not making any noticeable moves upward or downward for an extended period.

c) Price movements within the trading ranges are random and unpredictable, whereas trend movements can be identified thanks to the **breach** (above or below) **of trading ranges**: once the breach has taken place, it is assumed that the trend has completed its cycle and will start to reverse. In other words, a downtrend begins when the price breaks below the low of the previous trading range; an uptrend begins when the price breaks above the trading range.

Technical analysis: steps to follow

1) **Identify long -term short-term trends**: because technical analysis can be applied to many different timeframes, it is possible to spot both short-term and long-term trends.

2) **Understand the current overall trend and its status**: it is paramount to answer to the following questions:

   a) "are prices on the upswing or on the downswing?".
   b) "is the trend at its start or at its end?".

3) **Identify support and resistance levels**: these levels/areas are crucial for predicting the trend reversal and, therefore, the price movement. A **support** level is an area of price congestion, where demand is thought to be strong enough to overcome supply and, therefore, prevent the price from declining further: a break below this level would be considered as "bearish". A **resistance** level is an area of is an area of price congestion, where supply is thought to be overcome demand and, therefore, prevent the price from rising further: a break above this level would be considered as "bullish".

4) **Identifying the proper indicators**, to define the rules for the algorithm to buy/sell (*see below*).

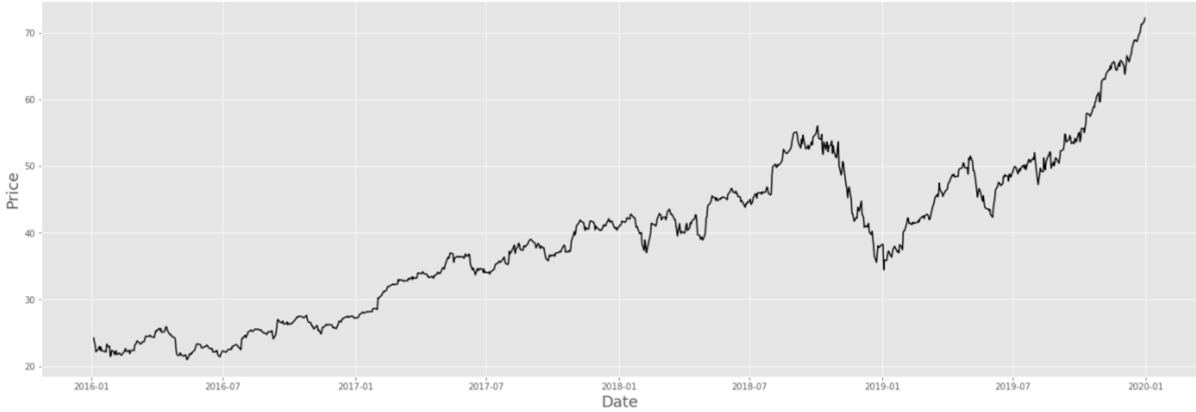
5) **Use the scientific method**: as Richard Feynman taught, science is the process of first making a guess, then computing the consequences of that guess (building a model) and finally confirming or rejecting the guess with experiment (in our case, back-testing).

Identifying the proper indicators:

a) **Moving Averages:** Simple Moving Average (SMA) and Exponential Moving Average (EMA)
b) **Volume Weighted Average Price (VWAP):** is the average price weighted according to volume. It distributes the order volumes evenly over a certain period at the price of the best demands or offers, but it does not exceed the weighted average price for the given period.
c) **Average True Range (ATR):** is a key indicator which is used to measure volatility. The ATR breaks down the complete price range for a certain period.

Example of the Moving Average Strategy

First, we would like to start by making a introduce the Moving Averages using data for Apple from Yahoo for the period 01.01.2016 to 01.01.2020.



The 50 and 200-day SMA using the adjusted returns.

The 50 and 200-day EMA using the adjusted returns.

The intersection between the 50 and 200-say SMA.

In the charts above we can see that the 50-day averages for both models is much more sensitive than the 200-day averages. Overall, the models are similar and the most significant difference that can be noticed is that the EMA averages are closer together than the SMA averages leading us to conclude that the 200-day EMA average is more sensitive than its SMA counterpart. We can observe an intersection between the 50 and 200-day averages in both SMA and EMA models around the December 2018 and May 2019. To explain the moving average trading strategy please look at the fourth graph. When the 50-day moving average dips lower than the 200-day moving average, we buy the asset and sell when the 50-day moving average crosses above the 200 day moving average, meaning that we can sell the asset. A1

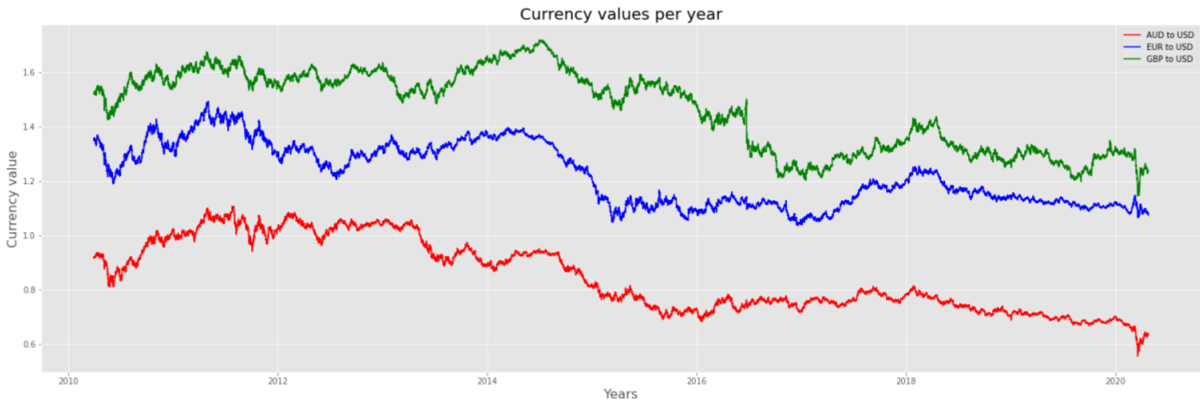
Step-by-step guide to run the code

Prior information: Since we used Jupyter to code, we did not use the function library with the PyCharm module as discussed in class.

1. Save the dataset of csv files in the same folder as the code file. Make sure that there are no other csv files in this folder because the code will not run otherwise.
2. Change the path in the code according to your personal path the data is stored in.
3. Run the code.

Asset Overview

We will start our trading strategies by looking at the forex closing values for the three assets that are included in our trading strategy, i.e., Austrian Dollars (AUD), Euros (EUR) and Great British Pounds (GBP), all of which are valued against United States Dollars (USD).



All three of the assets have significantly depreciated against the value of the USD since the second quarter of 2010. However, they never intersected with one another and the relative distance between the currencies in 2020 is relatively similar to what it was in the second quarter of 2010.

Moving Average Crossover Strategy Using Average True Range

Formula behind ATR

$$ATR_t = \frac{ATR_{t-1} \times (n - 1) + TR_t}{n}$$

with:

$First\ ATR = \frac{1}{n} \sum_{i=1}^{n} TR_i$

$TR("True\ Range) = max(high, close_{prev}) - min(low, close_{prev})$

t = Point of time

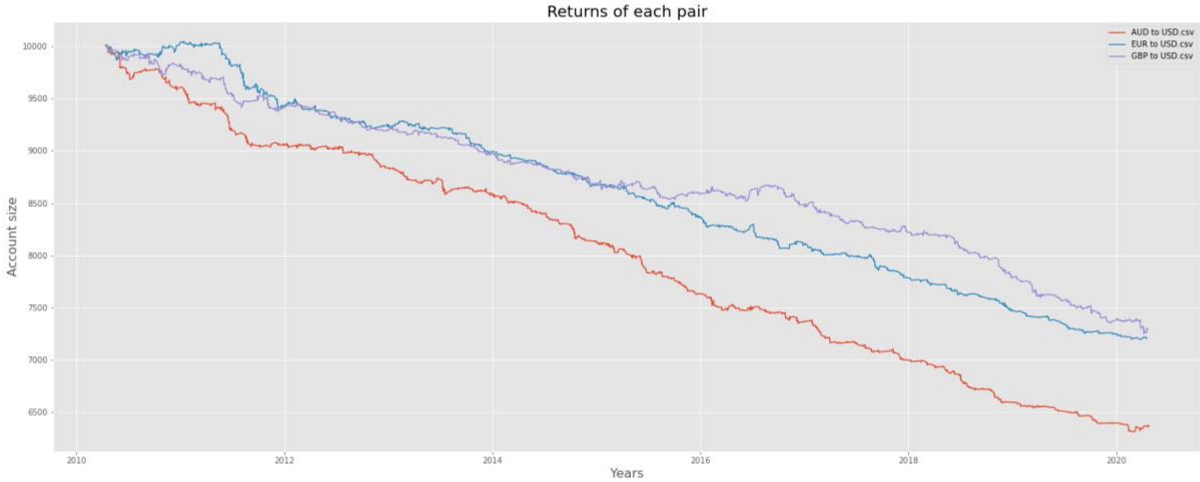
n = Amount of total periods

Overview

Below, we will be looking into the table detailing the performance of the strategy as well as a graph showing the returns of the investments when using the Moving Average Crossover Strategy Using Average True Range.

MOVING AVERAGE CROSSOVER PERFORMANCE TABLE	
Number of trades	4293
Number of profits	1998
Number of losses	2290
Number of break evens	5
Winning percentage	46.6%
Return on investment	-9139
Average profitable trade	6.95
Average losing trade	-10.06
Maximum profitable trade	86.71
Maximum losing trade	-36.43

The number of trades executed with this strategy for the 10 observed years was 4,293, of which 1,998 resulted in a profitable outcome (46.6%). Although the maximum value of a profitable trade (85.71) is more than twice the absolute value of the maximum loss (36.43), the average profitable trade (6.95) was significantly lower than the average absolute value of a losing trade (10.06). The return on the 30,000 USD invested on the three assets equally has experienced a loss of 9,139 USD with this strategy.



This graph shows the returns of a 10,000 USD investment in each of the three assets. The aforementioned loss is clearly visualized and divided amongst the three assets. The only asset that was momentarily in the money was EUR, briefly, in 2011. The worst performing assets was AUD followed by EUR and GBP.

Bollinger Bands Strategy

Formula behind Bollinger Bands

$$BB_t^{mid} = \overline{C}_t = \frac{\sum_{i=0}^{n-1} C_{t-i}}{n}$$

$$BB_t^{up} = \overline{C}_t + k\sigma_t$$

$$BB_t^{down} = \overline{C}_t - k\sigma_t$$

with:

C = Closing

t = Point of time

n = Past days of closing

k = Specific factor, usually 2 or 3

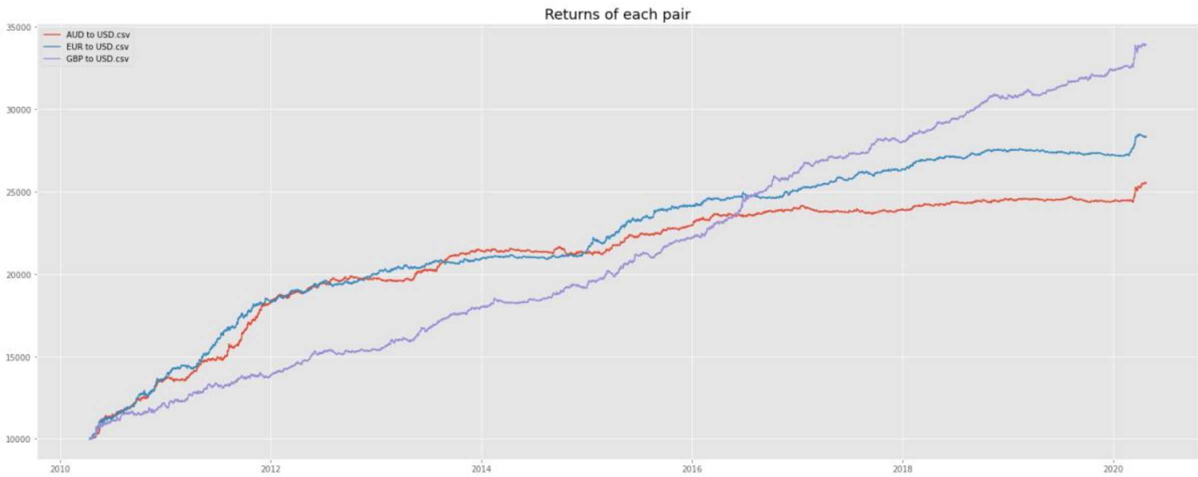
σ_t = Standard deviation

Overview

The Bollinger Bands is a popular trading strategy. To explain how it works we have to look at the XX-day moving average of an asset and the Bollinger bands are two lines, one above and one below the moving average with a distance of 1.96 times the standard deviation. These two lines contract around the average when there is low volatility and expand when there is high volatility, giving a more precise reading on the position of the asset. The Bollinger Bands strategy works by showing you when to buy and sell an asset. If an asset price is nearing the lower Bollinger Band than it is a in a good position to buy and if it is nearing the upper Bollinger Band than it is in a good position to sell.

BOLLINGER BANDS PERFORMANCE TABLE	
Number of trades	35287
Number of profits	13544
Number of losses	21649
Number of break evens	94
Winning percentage	38.48%
Return on investment	57731
Average profitable trade	19.52
Average losing trade	-9.54
Maximum profitable trade	231.5
Maximum losing trade	-113.87

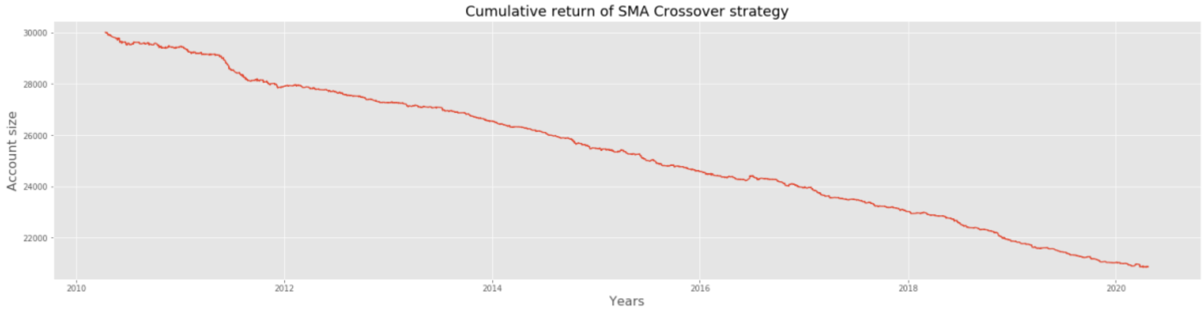
Of the 35,287 trades that were performed using the Bollinger Bands strategy, 13,544 resulted in a profitable trade (38.48%). The maximum profit from a single trade (231.5) is twice as high as the absolute value of the highest loss (113.87). Moreover, the average profitable trade (19.52) is also more than twice as high the average absolute loss value (9.54). The 30,000 USD invested equally amongst the three assets have a cumulative value of 87,731 USD, meaning that there was a return on investment of 57,731 USD.

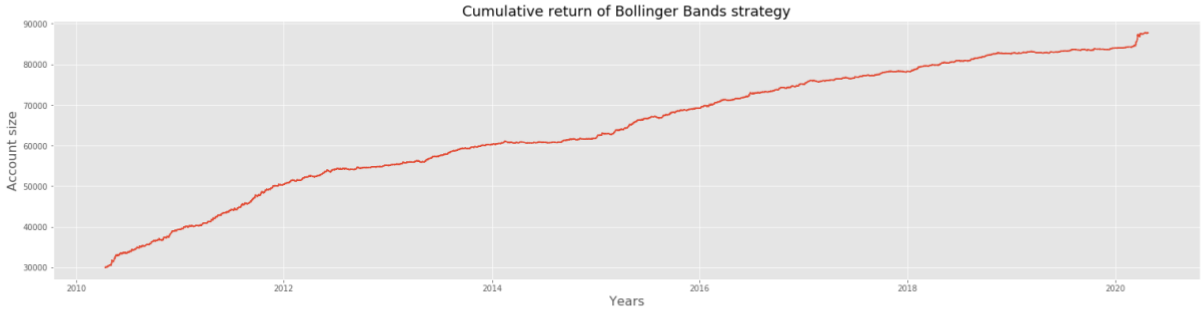


All three of the assets performed exceptionally with the Bollinger Bands strategy. The GBP performed best, followed by EUR then AUD. The performance of the GBP was more linear, meaning that it was more stable through the 10 years measures. Whereas the performance of EUR and AUD peaked between 2010 and 2013, then increased more gradually after 2013.

Conclusions

Now, we will be looking over the cumulative return graphs of both strategies so we can compare the results.





The value of the 30,000 USD invested in the Moving Average strategy resulted in significant losses, leading to a value 20,861 USD at the end of our period. The 30,000 USD invested using the Bollinger Bands strategy resulted in significant winnings, leading to a value of 87,731 USD. Looking back at the forex closing prices for each of the assets we invested in (AUD, EUR and GBP) we can notice that their values were depreciating against the USD in the observed timeframe, making this a bear market for each of the assets. This could be the reason why the Moving Average strategy did not work. If we assume that this was the only issue, then we can conclude that we should buy in bear when we would sell in a bull and vice versa. If we did that from the beginning than it would have led the investment to a value of 39,139 USD. The Bollinger Bands strategy on the other hand performed admirably, making it the best of the two since the value of the investment nearly tripled in the timeframe.