Using Machine Learning to develop Short term Trend Trading Strategies

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Abstract

This paper presents a research on a profitable trading strategy on some selected best performing FOREX currency pairs after considering realistic trading scenarios and analyzing the performance on out of sample data. Machine Learning models like Random Forest, eXtreme Gradient Boosting (XGBoost), Support Vector Classifier (SVC), Logistic Regression, and Deep learning methods were tested. Technical indicators derived from the traditional ones like moving averages, Average True Range (ATR) and Bollinger bands are used to generate features for training. The Triple Barrier method for labelling is applied to the generated signals to enhance the results. The best performing algorithm is then deployed as a webapp using streamlit.

Keywords: Machine Learning, Deep Learning, Traditional Indicators, algorithm, webapp, FOREX, XGBoost, SVC, Logistic Regression, Triple Barrier method, features, labelling

1. Introduction - Problem Definition

Python has become the de factor programming language for algorithmic trading and different platforms (quantopian, numerai, quantconnect) have risen to cater for traders who want to create their own signal generating algorithms. Unfortunately, some traders do not seem to have the skills nor the aptitude to learn how to code in Python so they can use some of these platforms.

This project aims at leveraging on the power of Python for algorithmic trading to create a standalone signal generating web app traders can access to use for their trading purposes without knowing how to write a single line of Python code.

2. Literature Review

2.1. Introduction

A market is said to be trending if you can look at the chart and see which direction it seems to be headed (up or down). Experienced traders have long observed that markets do not trend all the time - sometimes a market seems to be stuck in a range with no clear direction.

Charles Dow co-founded The Wall Street Journal in 1889 primarily to cover business and financial news[1]. He began to publish a series of periodicals on his views of the markets using two market averages he had earlier developed called the Dow Jones Industrial Average (DJIA) and the Dow Jones Transportation Average (DJTA)

The Dow theory can be summarized thus: when the market is trending upwards and if one of the averages (DJIA or DJTA) breaches a previous important high then it is expected that the other will follow suit within a reasonable period of time. Dow theory also explains the movement of the market as consisting of a top, a bottom, an uptrend, and a downtrend. His principles are the basis of what we now call Technical Analysis.

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After his death, a lot of people tried to organize and collectively represent the Dow theory based on Dow's published editorials. Many other theorists and speculators later also proposed theories to explain their observations of the behaviour of the markets. Notable of which are the Wyckoff Methodology[2] and Elliot Waves[3] just to name a few.

In the early 1980's, commodity traders Richard Dennis and William Eckhard decided to test to see if traders were born or they were made. They recruited and trained 23 individuals (calling them "Turtles") by teaching them for two weeks and then tested with real money. The trading strategy they used was a trend following technique that used new four-week highs as an entry signal for longs.

Since the complete rules that made up the Turtle strategy have been made public, it has and still is possible to backtest them and see the performance on recent market activity. From some of the backtests it has been reported that the CAGR which was about 216% between 1970 to 1986 when Dennis and Eckhardt were developing the system, and eventually when his Turtle Traders learnt and traded the system to 10.5% between 1986 and 2009[4].

The market is constantly changing from a period of movement to a period of rest and back to a period of movement. This interchange between the phases of motion and rest is constantly taking place[5]. Understanding this simple explanation can aid us in developing trading strategies that can be used to exploit the forex markets. Machine learning techniques can be mobilized to identify movements in the market for profits that are sustainable.

2.2. Technical Analysis

The use of past price data to guide a trader's decision today on how to engage the market (either to go long, short, exit a position or to stand aside) is known as Technical Analysis[6]. In this work, I will use technical analysis to generate my signals. I will start by generating buy and sell signals from some technical indicators out some indicators.

2.2.1. Technical Indicators

We will list some traditional indicators that have been used in stock and commodities trading for some time. The list is endless and some of them have seen a fair use in trading the forex market.

- Trend Indicators: Moving Averages are the most deployed trend indicators on a technical analysts chart. They are usually used to smooth out the price of an asset over a specified length of time by calculating and displaying a constantly updated mean value of the closing price. Simple Moving Averages use Arithmetic means while the Exponential moving (EMA) is a weighted average that is meant to give greater importance to recent price data which tends to it more responsive to new information.
- Momentum Indicators: These help the technical analyst to get a better understanding of the rate of change of price. Some commonly used momentum indicators include: Moving Average Convergence Divergence (or the MACD which is really derived from the difference between two moving averages), the Relative Strength Index (RSI) and the Average Directional Index (ADX) which is derived from the smoothed averages of the -DI and +DI, which are themselves derived from the comparison of two consecutive lows and their respective highs.

2.2.2. Trend Trading

Trend trading is a style of trading where technical analyst attempts to make profit on the price movement of a particular asset in the market in a particular direction. When the price of the asset is moving up indicated by the price bars on the chart making consistent higher-highs and higher-lows, the trend is said to be up. Conversely, if the price bars on the chart are making consistent lower-lows and lower highs then the trend is said to be down.

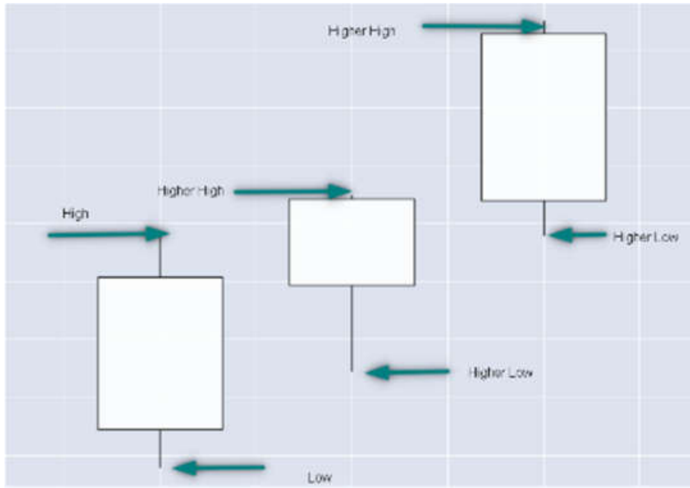

Figure 1. Candles making higher highs and higher lows.

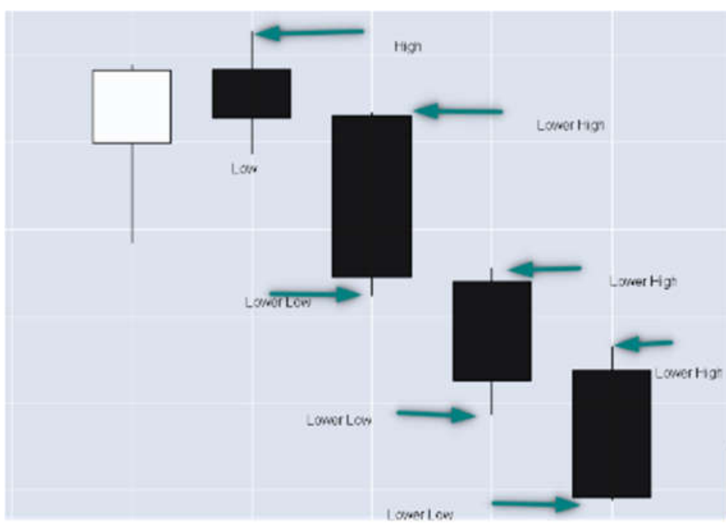

Figure 2. Candles making lower lows and lower highs

One common way of generating signals for trend trading using the moving average is to consider a long trade when a fast moving average crosses above a slow one and for shorts we wait for the fast moving average to cross down. Another signal generating technique is for the closing price of the asset be above or below the moving average in question. The choice of technique is at the discretion of the trader. We will use a similar technique as the latter, however using less traditional indicators most of which have seen some great success in the forex market.

Figure 3. Simple moving average cross over system

2.2.3. Machine Learning

Since Arthur Samuel popularized the term Machine Learning in the late 1950's the field has seen tremendous progress in recent years. The financial industry especially algorithmic traders around the world also try to benefit from these technological advances[7]. Arthur Samuel's idea was instead of programming a computer step by step on how to solve a particular problem, it is shown examples of problems and their solutions thus allowing it to figure it out by itself using statistical and Machine Learning techniques[8]. Like Statistical techniques, Machine Learning techniques also seeks to map the elements of a particular domain (in our case features we have selected from our dataset) with those of another domain (the direction of the market up or down).

Wang *et al.* [9] used volume as a feature to help in forecasting the direction of S&P 500 and DJI of which they found no strong correlation. Using a Machine Learning technique called support vector machine (SVM) model on stock prediction,[10] made a comparison between multi-layer perceptron (MLP) and SVM. They showed that in many cases, SVM seemed to have outperformed MLP on the datasets they used. [11] combined machine learning and deep learning techniques that have been utilised by prior research approaches, to get new training features for prediction.

2.3. Competitor Analysis

With the rise of machine learning and the interest that trading equities, CFDs, Stocks and the foreign exchange markets, so many researchers and retail traders are interested in merging the two to find out how they could beat the market. Platforms like Quantopian, QuantConnect and NumerAI (to mention a few) have risen to fill that gap. Despite the success of these platforms in bringing great traders and technicians together, a large niche of non-techie traders are not involved as learning Python, C# or R stands as a barrier for many of them.

This project aims on concentrating on such traders. When fully launched, the traders would be heavily assisted from receiving signals while they spend time on trading using whatever money management approach they prefer. Waiting by a computer screen for a trade setup can cause traders to start imagining chart patterns or to be affected by paralysis of analysis.

2.3.1. Strengths

- This project aims to be designed to provide signals generated from machine learning algorithms that have been found to better than chance (>50%) to non-tech traders via a simple webapp.
- It will encourage traders to concentrate more on entries and exit making them less prone to paralysis of analysis.

2.3.2. Weakness

- This project will not include money management techniques as that would be left to the discretion of the trader interacting with it.

2.3.3. Opportunities

- This will bring in more players from the trading community into the machine learning by lowering the barriers to entry.
- Since it will be an open source project, it would also bring in other machine learning enthusiast to contribute there by increasing the popularity.

2.3.4. Threats

- There are big corporations with deep pockets who are interested in this domain.
- Some trading platforms already have signal generation via dashboards.

3. Methodology

This project uses python (and libraries like Pandas, Numpy, Matplotlib, Scikit Learn, FastAI and Pytorch) to import the data, visualize it, generate features, and create a Machine Learning algorithm for our webapp. Streamlit will be used to host the webapp for the public to access.

3.1. Data Collection

We will use the Foreign Exchange (FOREX) data collected from the Oanda API[12]. The best instruments to trade are the ones that are trending (moving in the same direction) most strongly over a given period. In sideways environments, it is usually best to watch out for those which have shown the highest volatility over recent days. Since we will be working on short term trending strategies, we would use our system to select those that show great performances during our test period to display on out webapp.

We intend to use the daily timeframe when accessing the data from the broker. This will not be a day trading webapp. The signals would be generated once a day so the trader can spend the rest of his time on something else.

We will choose to use for our algorithm currency pairs selected from the collection of currencies shown in the bale below.

Table 1. Table of currencies and % of Daily Trades April 2019

Rank	Currency	ISO 4217 code(symbol)	% of daily trades(bought or sold)(April 2019)
1	United States dollar	USD (US$)	88.3%
2	Euro	EUR (€)	32.3%
3	Japanese yen	JPY (¥)	16.8%
4	Pound sterling	GBP (£)	12.8%
5	Australian dollar	AUD (A$)	6.8%
6	Canadian dollar	CAD (C$)	5.0%
7	Swiss franc	CHF (CHF)	5.0%
8	Renminbi	CNY (元 / ¥)	4.3%
9	Hong Kong dollar	HKD (HK$)	3.5%
10	New Zealand dollar	NZD (NZ$)	2.1%

Figure 4. The 10 most traded currencies in 2019 [13], [14]

We will not use the Chinese Renminbi and the Hong Kong dollar because of the wide spreads and the fact that the brokers that offer any currency pair involving them are rare. The pairing of the remaining 8 will form a basket of 28 currency pairs that we can choose from based on performance.

3.2. Feature Generation

Once we have set the API from the broker, we use the pandas package to load up the data. We now begin to use some traditional technical analysis indicators to generate features that tell us to go long, short or to stand aside. We will explain some of them following.

3.2.1. Daily Log Returns.

We will use the daily log returns to generate features and shift that by one day. The log returns were chosen over the simple returns for the reason that they are non-desicrete, continuous and time additive. We want to see if the previous N day's price could help us to predict the price of the following day in question.

$$r_t = \ln \frac{y_t}{y_{t-1}} \tag{1}$$

Where,

r_t = returns

y_t = todays close price

y_{t-1} = yesterday's close price

3.2.2. Technical Indicators

We will select a few non-traditional technical indicators for some the features we would generate. These technical indicators have found favor in the eyes of many forex traders who claim they perform better than the traditional ones even though many of them were derived from the so-called old school traditional indicators.

- TTM Squeeze: John F. Carter introduced the TTM Squeeze indicator in his book Mastering the Trade [15]. It is really a combination of several traditional Indicators. In this work we will not use it as it was presented in the original work.

Our indicator will be a combination of the Bollinger Bands, the Keltner Channel and the ADX. We will want the Bollinger Bands to be found within the Keltner Channel and the ADX to be below the value of 20. The moment that the Bollinger bands leave the Keltner Channel then we have a signal.

- Supertrend: This is a trend following indicator that was developed by Olivier Seban and has been moving around the FOREX trading forums for a while. The indicator is based off the Average True Range and it is usually overlaid on the price chart; it has been used as a trailing stop indicator as well as used to determine the direction of the trend. When the close price of the instrument is above the indicator we say the market is in an uptrend and when close price is below we say that it is in a downtrend.
- SSL Channel Indicator: The Semaphore Signal Level channel Indicator is a price chart overlay indicator that is made from a pair of moving averages that have equal periods: one of the highs of the price and the other of the lows. When the close price of the instrument is above the indicator we say the market is in an uptrend and when close price is below we say that it is in a downtrend.

3.2.3. Handling Dates

Sometimes dates handle market participation which can affect how the prices move for a particular instrument. Training our model by letting it know what month or day of the weeks or if it's a holiday or the end of the quarter could greatly help. Part of the features would be to add these as features for the model to train with. This concept is part of the fastai methodology and is part of the course offered online [16].

3.3. Classification using Machine Learning

Since our intention is to predict if the market is going up or down, it will seem appropriate to tackle this as a binary classification problem. A simple classifier is some rule, or preferably a function, that maps to a domain x a class label $\tilde{y}$:

$$\tilde{y} = f(x) \tag{2}$$

The predicted class is expected to be the one with the highest probability of occurrence, mathematically represented as:

$$\tilde{y} = arg\, max_y Pr(Y = y|X) \tag{3}$$

We will choose from a few supervised learning models provided by the library scikit-learn which runs on Python. After the initial training we will apply meta-labelling as introduced by Marcos de Prado in [17].

3.3.1. Random Forest

A common supervised learning approach for tackling regression and classification in known a Decision Tree. In this approach, the goal is predicting a target by using decision rules shaped from the features available in the dataset in question. A large number of Decision trees makes a Random forest which generally averages the predictions of the trees.

3.3.2. XGBoost

eXtreme Gradient Boosting (or XGBoost) also uses Decision Trees just like the Random Forest model, however the difference here is the fact that weaker learners from the decision trees are boosted. This is believed to help to reduce bias and it is based on the a question posed by Kearns and Valiant in [18]: "Can a set of weak learners create s single strong learner…?"

3.3.3. SVC

Support Vector Machines (SVM) are generally used for regression and classification problems. The Support Vector Classifier (SVC) being the one used for classifications. The logic is to draw a so-called decision boundary between two classes of vectors, in our case the vectors would be up and down.

4. Project Work Plan and Deliverables

The table below displays the work plan this entire capstone project will follow:

Table 2. Work Plan

Using Machine Learning to develop Short term Trend Trading Strategies											
Task	Deliverable	Duration									
		Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10
Project	Project Proposal										
Analysis	Literature Review and Competitor Analysis										
Project Design	Project proposal and Methodology										
Peer Review	Refined Project Proposal based on Feedback										
Project	Draft Project Report										
Implementation and Presentation	Final Project Report and Presentation of Findings										

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