<u>**4YP Interim Report – Sivesh Sukumar**</u>

Introduction

Computerised order flow first emerged in the 1970s. This allowed the development of algorithmic trading strategies and provided a seed for the revolutionary sector of high frequency trading. The aim of this project is to explore how different machine learning techniques can be used to extract signals for algorithmic trading agents and then assess their performance.

Literature Review

Many traders use techniques such as machine learning to look for trading signals. For example, [1] explores the extraction of signals from limit order books using deep learning. When using these signals as an input to a trading bot it can be shown to produce very impressive returns when back tested on equities. [2] explores the use of non-parametric models such as Gaussian Processes to model time series. The formation of covariance kernel functions for a time series is shown to be incredibly powerful. Deep learning can also be used to enhance existing trading strategies, [3] explores the enhancement of a simple moving average crossover strategy using deep learning .

Neural Networks and TensorFlow

When a loss function has been established for a problem, neural networks can be used to map inputs to outputs with minimal loss, often via stochastic gradient descent. They are able to take a data set along with a set of labels and create a model to predict the labels of future data. Recurrent Neural Networks go one step further by retaining past information and are therefore very useful for time series problems.

TensorFlow is an open-source library developed by Google, which simplifies the development of neural networks. It can be used in parallel with Keras, which is a very high level API for building and training models. To begin with I built a simple univariate RNN with two LSTM layers. The data I used is pulled from Yahoo finance and consists of the daily close prices for Vodafone over the last 10 years. The model takes

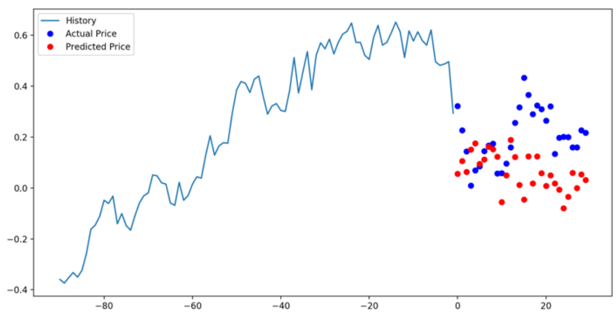

Figure 1 - 30 day prediction of Vodafone share price

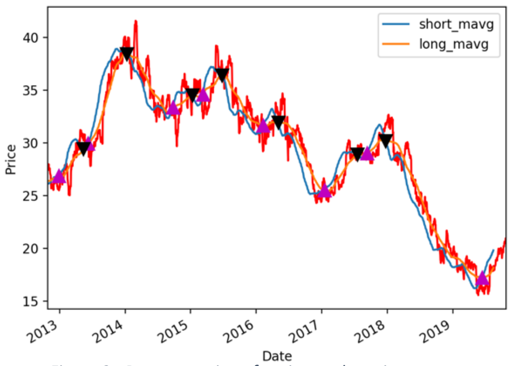

Figure 2 - Demonstration of anti-causal moving average strategy

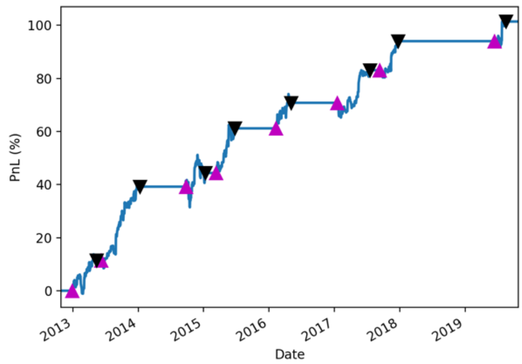

Figure 3 - Returns of the anti-causal moving average strategy

in 90 days and makes a prediction for the next 30 days. To develop this further I created a multivariate model, the extra data set being a set of buy/sell labels. In order to create this data set I used an anti-causal moving average strategy, which can be shown to produce incredible returns when back tested.

Going forward

Going forward I'm going to create a set of tools to help assess the effectiveness of these strategies. This will be done by using a Monte Carlo method on a completely random trading strategy. The data collected from this can be used to create significance levels for the returns produced by a trading strategy. I will then be able to test the effectiveness of the neural network model I created earlier along with several other models. Some ideas are a non-uniform moving average trading strategy, in which the optimal weights of the moving average are determined using deep learning. I also look to explore how information can be extracted from limit order books further, especially in multivariate data streams such as in a triangular arbitrage scenario.

References

[1] Zihao Zhang, Stefan Zohren, and Stephen Roberts, "DeepLOB: Deep Convolutional Neural Networks for Limit Order Books," University of Oxford, Oxford, 2019.

[2] S. Roberts, M. Osborne , M. Ebden , S. Reece, "Gaussian Processes for Timeseries Modelling," University of Oxford, Oxford, 2012.

[3] Bryan Lim, Stefan Zohren, Stephen Roberts, "Enhancing Time Series Momentum Strategies Using Deep Neural Networks," University of Oxford, Oxford, 2019.