MANCHESTER 1824

The University of Manchester

Deep Learning Algorithms Applied to Blockchain-Based Financial Time Series

Background and Motivation

This project aims to exploit recent advances in deep learning to investigate the predictability challenges posed by cryptocurrencies. These emerging blockchain-based financial time series have been shown to behave somewhat differently from traditional currencies, especially in their volatility. As cryptocurrencies are now maturing beyond their stigma of underground criminality from the dark web era, only a handful of academic studies have tried to build deep learning models for accurate forecasting of cryptocurrency prices and this subject is still in its infancy.

Aims and Objectives

The aim of this thesis is to develop a **Deep Neural Network (DNN)** capable of modelling cryptocurrencies to offer accurate real-time trading predictions. More specifically, the objectives are as follows:

- Learn how to implement and apply competitive trading algorithms (ARIMA, GARCH, SOM, NN) to cryptocurrency data, using the R language and the TensorFlow library
- Use Granger Causality analysis to identify the best trading pair
- Engineer a DNN-based trading algorithm which achieves a forecast performance of at least 55% (current level of competitors)
- Investigate various DNN architectures and demonstrate that DNNs are a strong alternative for cryptocurrency trading algorithms via live trading with real money on the Poloniex Exchange

Traditional FTS Analysis

Auto-Regressive Integrated Moving Average (ARIMA) models non-stationary FTS. Exploits regression, moving averages and differencing

$$r = x_t - x_{t-1} \quad (1)$$

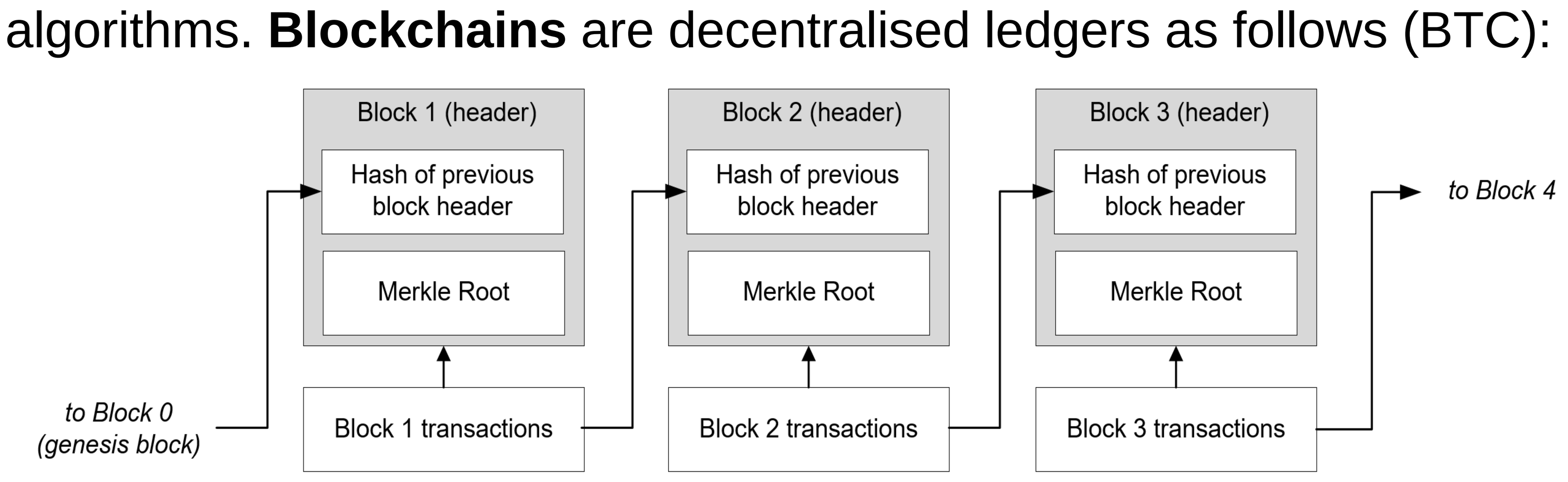
$$\therefore\ \hat{x}[t] = \mu + \sum_{i=0}^{p}(\alpha_p x_{t-p}) - \sum_{i=0}^{q}(\beta_q \epsilon_{t-q}) \quad (2)$$

Generalised Auto-Regressive Conditional Heteroscedasticity (GARCH) models the variance of FTS. Exploits prior squared errors.

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha_i\, \epsilon_{t-i}^2) + \sum_{i=1}^{p}(\beta_i\, \sigma_{t-i}^2) \quad (3)$$

Blockchain-Based Finance

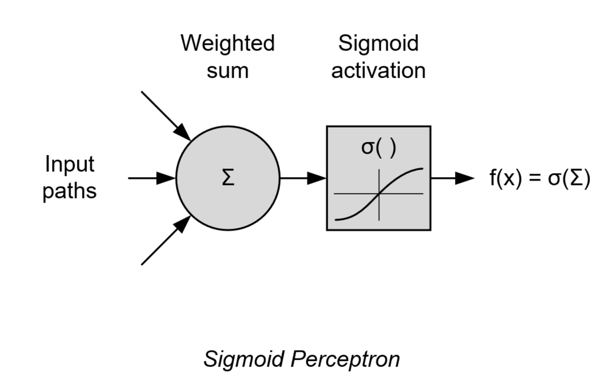
A major advantage of cryptocurrencies is that blockchains contain a huge amount of publicly downloadable data for use in trading algorithms. **Blockchains** are decentralised ledgers as follows (BTC):



Neural Networks

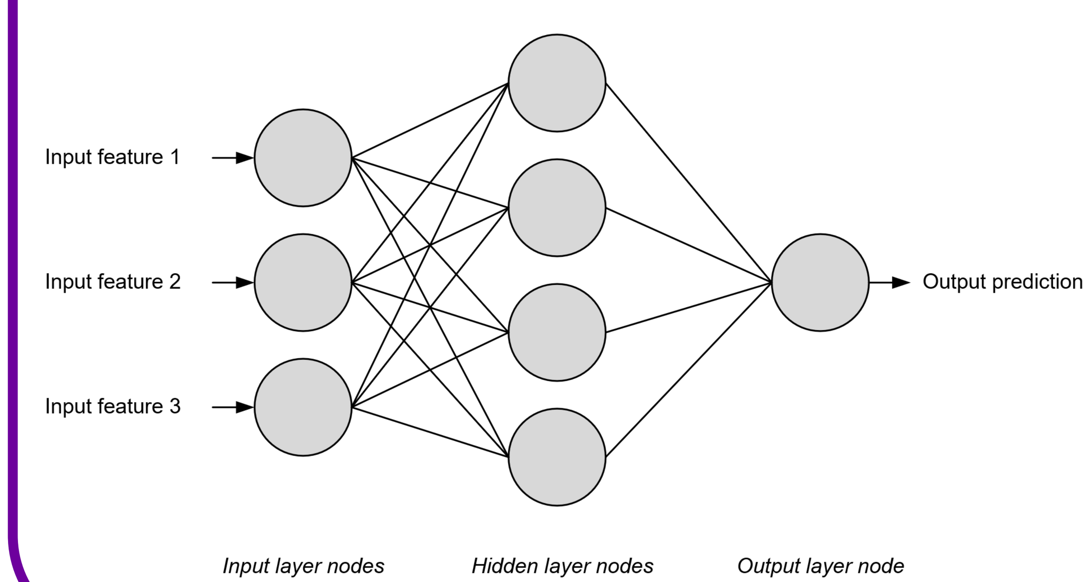
The fundamental building block of **Neural Networks (NN)** is the perceptron, aside:

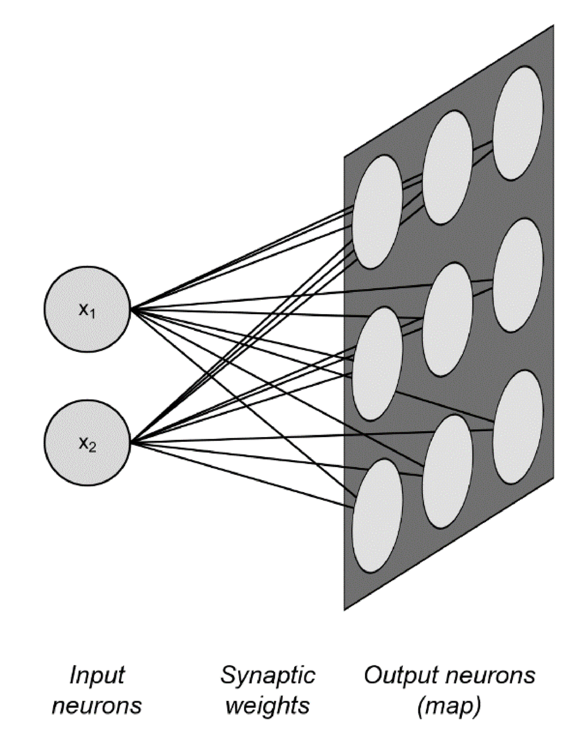
$$f(x) = \begin{cases} 1 & \text{if } \sigma(\sum_{i=1}^{m} w_i x_i + b) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$



Sigmoid Perceptron

Combing multiple perceptrons together forms a **Multi-Layer Perceptron (MLP)**, as shown below. Another NN model is the **Self-Organising Map (SOM)**, aside.

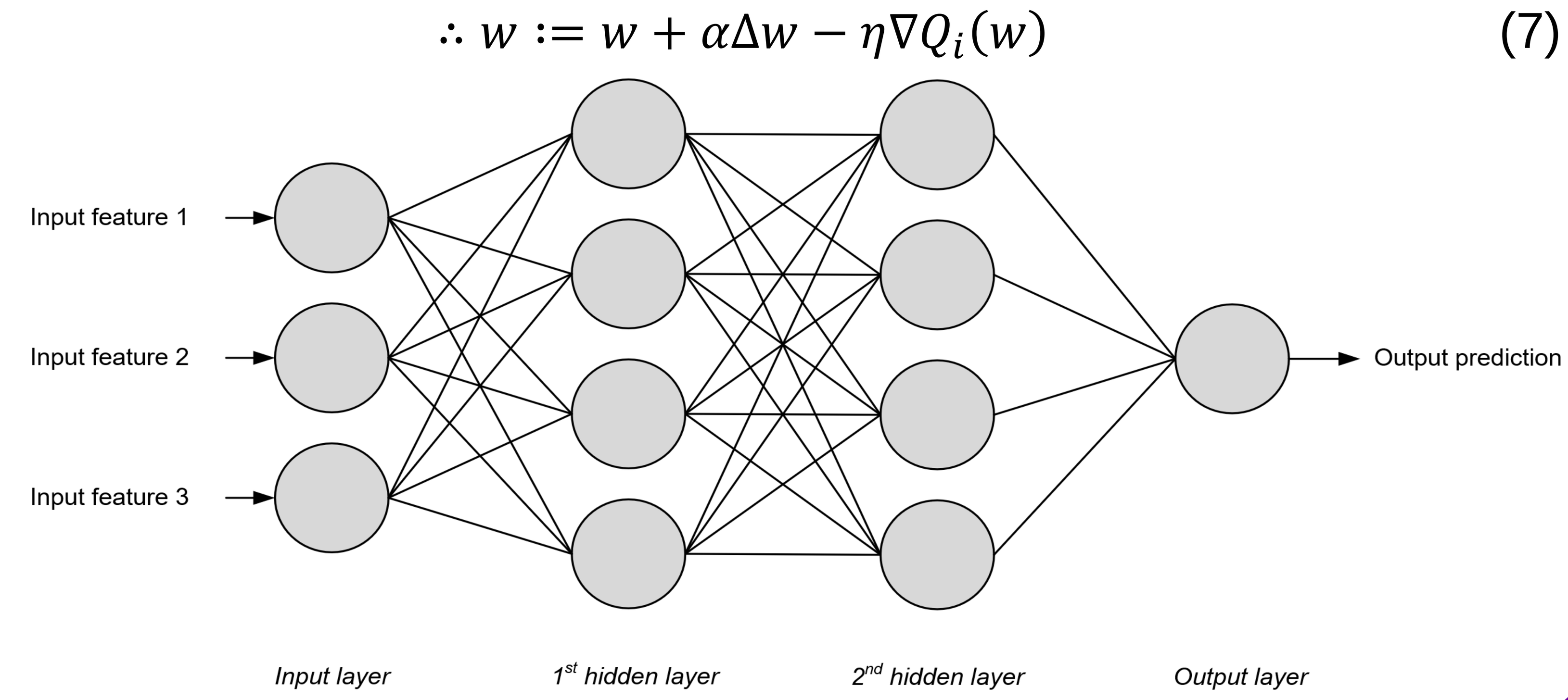




Deep Neural Networks

From the DNN below, the 12 – 4 DNN was selected as the final model for live testing with an expected performance of around 58%. This DNN's performance can be further improved via confidence intervals. Training is done through the **Adaptive Moment Estimation (ADAM)** algorithm: $\Delta w := \alpha\Delta w - \eta\nabla Q_i(w)$ (5), $w := w + \Delta w$ (6)

$$\therefore\ w := w + \alpha\Delta w - \eta\nabla Q_i(w) \quad (7)$$



Achievements and Conclusion

Model	Predictability
AR	0.495
ARMA	0.515
ARIMA	0.529
ARIMA-GARCH	0.530
SOM	0.544

Model	Predictability
NN (exogenous BTC input)	0.564
DNN (exogenous BTC input)	0.576

This investigation succeeded in its aim of highlighting the opportunities offered by deep neural networks. The implication of this key result is the encouragement of further examinations into deep learning algorithms which may one day help stabilise the fierce cryptocurrency market.

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