Agent Based Modelling of Financial Markets and Machine Learning

Anna Mossop

Supervisor: Dimitri Vvedensky
Condensed Matter Theory Group

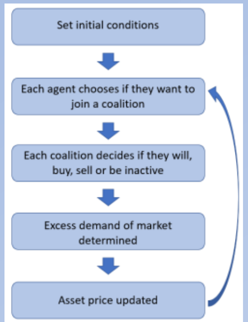
Overview of ABM

There are two methods commonly used to model financial markets, stochastic and agent-based models. Agent based models consist of many microscopic agents with independent decision-making behaviour. The aggregate behaviour of the behaviour produces leads to complex macroscopic phenomena. ABMs can thus be considered as a generalised form of the Ising model and have key benefits of allowing by allowing the input of behavioural characteristics of agents.

For this research project agent based models have been used to simulate the price movement of the USD/CNH currency pair.

Cont-Bouchard Model

The Cont-Bouchard method attempts to model the affects or trading coalitions.



Within the model N independent agents each have a chance of meeting with each other to form coalitions. Once in a coalition traders act unanimously and do not trade amongst themselves. Price changes in the market are subsequently determined by the excess demand of orders submitted by market participants.

Fig 1: Flow chart of Cont-Bouchard Algorithm implemented.

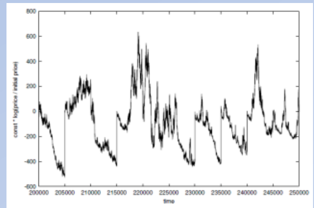


Fig 2: Price trend for Cont-Bouchard model [1].

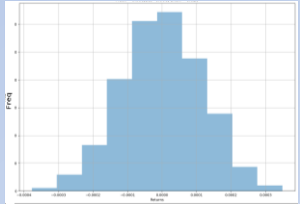


Fig 3: Distribution of returns for a calibrated dataset of the Cont Bouchard model.

Financial Industry Problem

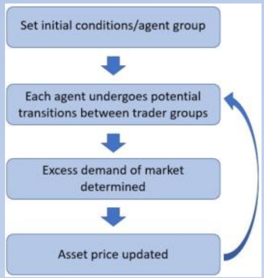
ABMs can be used to investigate a plethora of financial problems by replicating behaviour of individual agents. Different scenarios for example the submission of large orders can be simulated and investigated.

Financial Datasets

Data to calibrate and test the models was provided as part of a collaboration with Standard Chartered Bank. USD/CNH tick data was used for the period January-March 2020

Lux-Marchesi Model

The Lux-Marchesi model encapsulates behaviour heterogeneity and adaption between agents within the market. Within this model agents are split into three trading strategies, fundamentalist, optimistic chartist and pessimistic chartist.



Transitions can occur between the three respective groups based upon majority opinion of the market, price trend and difference between actual and fundamental price. Price changes occur due to these transitions which set the excess demand of the market.

Fig 2: Flow chart of Lux-Marchesi Algorithm implemented.

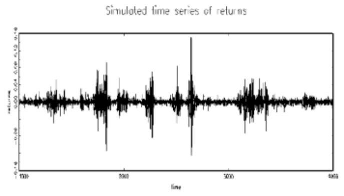


Fig 5: The simulated time series of returns from the original Lux-Marchesi paper. Periods of high volatility clustering can be seen within the plot [2].

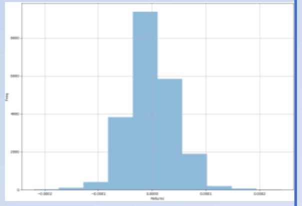


Fig 6: Distribution of returns for a calibrated dataset of the Lux Marchesi model.

Calibration

Both models were calibrated such that their parameters replicated statistical properties of market tick data. Basic statistical metrics of the models were calibrated as close as possible to the real market data.

The main stylised facts of the market were ensured in the models, these facts include the absence of autocorrelations of returns, volatility clustering, fat tails of returns, and unit root properties of prices.

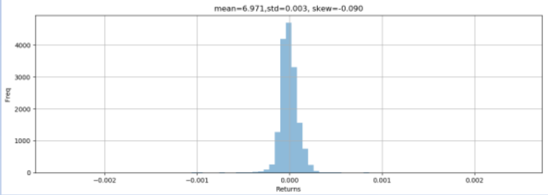
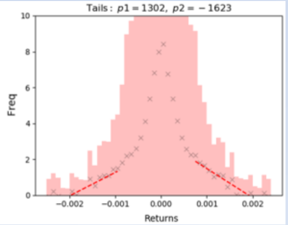


Fig 7: Distribution of returns for 06/01/20. Parameters are tuned to match the statistics of the distribution as closely as possible.

Fig 8: Distribution of returns for USD/CNH currency pair for 06/01/20 with log of returns (points) fitted.



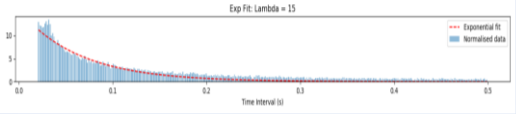


Fig 9: Plot of the distribution of time intervals between trades fitted with an exponential fit, the fit indicates the occurrence of trades follows a Poisson distribution.

Support Vector Machines (SVMs)

SVMs classify data into two categories by separating the input data using a high dimensional hyperplane. SVMs will be used to forecast if a price will move up or down after a certain time period

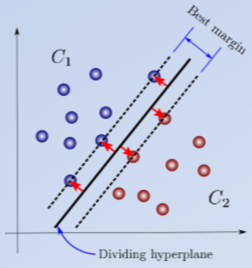


Fig 10: Schematic of SVM. Points are seperated using the mathematical hyperplane, the best margin represents determines where the hyperplane lies with points as close to it as possible [3].

Artificial Neural Networks (ANNs)

A long short term memory recurrent neural network will be used to forecast future time steps of synthetic and real data. Recurrent neural networks specialise in detecting trends throughout temporal data. By adding LSTM within the RNN the neural network retains memory of early time steps.

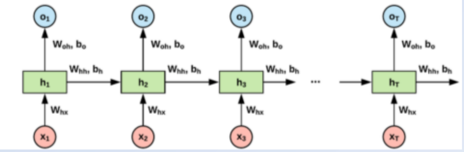


Fig 11: RNN Schematic [4]

Outlook

Once built the machine learning algorithms will be used to evaluate the capabilities of agent based modelling.

It will be tested how well ML algorithms forecast future price movements in the simulations and data when trained on simulation and actual data respectively.

It will then be tested if the ML algorithms can be trained on simulation data to then predict future price movements of real data.

Imperial College London

[1] Agent-based Models of Financial Markets, E. Samanidou et al 2007 *Rep Prog Phys* **70** 409, pp. 435
[2] Volatility Clustering in Financial Markets a Microsimulation of Interacting agents, T. Lux, M. Marchesi 1999 *International Journal of Theoretical and Applied Finance* Vol. 3, No. 4 pp 675-702

[3] Support Vector Machines for Classification, O. Carrasco 2019 *https://towardsdatascience.com/support-vector-machines-for-classification-fc7c1565e3, accessed: 26/02/2020*
[4] Vanilla RNN for Digital Classification, Easy-Tensorflow 2018 https://www.easy-tensorflow.com/tf-tutorials/recurrent-neural-networks/many-to-many accessed: 26/02/2020