Modelling volatility in US equity market with RNN-LSTM

Problem Statement

The number one topic in investment, which literally is the base of all kinds of financial decisions, is risk. In terms of asset value, risk is defined as volatility. Risk is regarded as high when volatility is high, and low otherwise. Understanding volatility and modelling them mathematically have long been a very hot topic in finance, even until today. But mathematical models can only do so much as most of them are hardly accurate and in the form of linearized models. By being able to create and predict volatility, more sophisticated investment decisions can be made and implemented. A good model of volatility will give investors/traders an immense edge in gaining profits.

Criteria for Success

Market naturally goes up, but volatility goes up and down sporadically. The goal of this project is to be able to predict whether volatility will go up, or down in every next time point, at an accuracy that is better than a random chance.

Dataset:

- SP500 (market) and AAPL (stock)
- SP500/AAPL rolling volatility (long-med-short window (5,20,60 trading days))
- VIX (volatility ETF)
- TNX (10-yr treasury bond rate)

Data will be acquired through Simfin API, Finnhub API, and Yahoo finance API

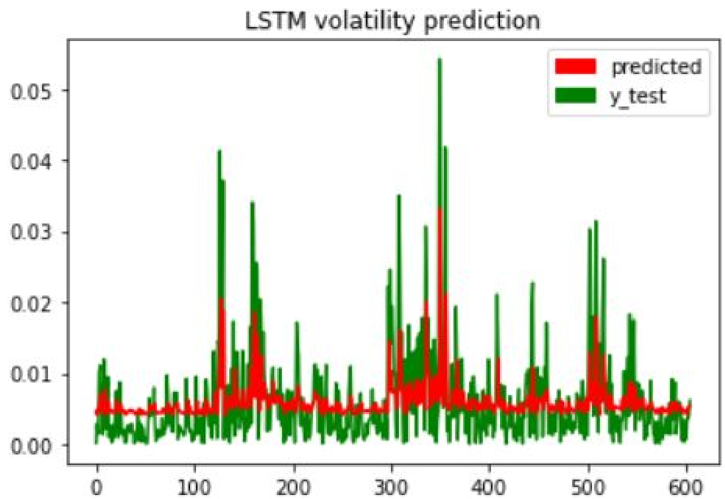
Methodology

For this project, I am implementing a deep learning model to try to model volatility stochastically, using a few features that closely reflects and affects volatility in different ways. The problem is first transformed into a binary classification problem, with ‘1’/’0’ being ‘up’/’down’ for the next trading day. Volatility is calculated by taking the rolling 2 day volatility of the asset. Multiple different hyperparameters will be attempted and a value-prediction neural network model will also be explored.

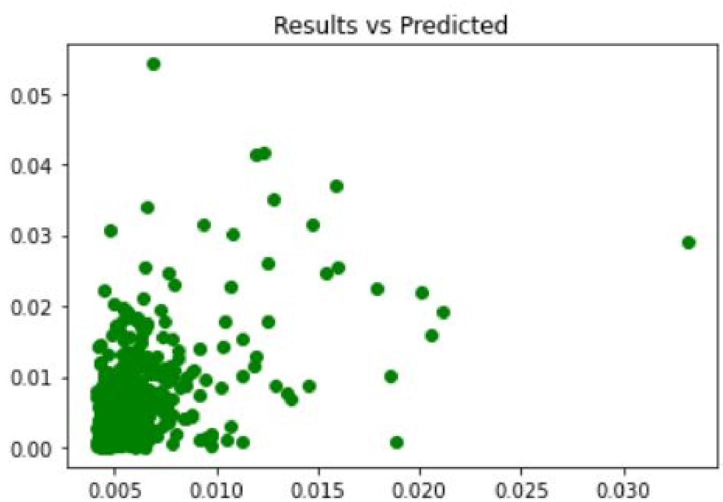
The models and results are as follows:

- MLP with 2 hidden layers. 1028 neurons in each layer with relu as activation function. (74.54% accuracy for binary classification)

- LSTM with .0001 learning rate, sigmoid as activation function (MSE = 4.135e-05 for value prediction)



Although resulting in a relatively low MSE, the model prediction seems to ‘converge’ to a certain value when volatility is channeled. My assumption is that this is the level where the mean error of the prediction is the lowest, while it fails to capture the volatility’s volatility stable time. On the other hand, the model can capture sudden large movements in volatility pretty well.



Looking at the distribution of y_test vs predicted, it is clear that there are a lot of unexplained variance in the results. This suggests there are other factors needed that are not in the model, and more relevant data are needed.

Conclusion

The MLP binary classification model is good enough to be used in financial applications, but not the LSTM model, as explained above. For potential clients, there is certainly an enormous potential for the MLP model to be applied, one example being to profit on derivatives by playing volatility arbitrage. Since derivatives prices are highly dependent on volatility, a good volatility prediction model can certainly be applied to do a long-short position and profit consistently and continuously.