Evaluating the Performance of a Stacked Long Short-Term Memory Model on AEX Stock Price Prediction

Attain new insights into Deep Learning

CS4180 Deep Learning
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Repository: `https://github.com/benjamindebosscher/DL-LSTM-Stock-Prediction`

Introduction

Recent trends have shown a successful application of deep learning architectures on stock prices. Recurrent neural network models are best suited for this form of time series data. For this project, an existing long short-term memory (LSTM) model will be further developed. The goal is to predict future trends of a company's stock value as doing this successfully could yield a significant profit or a reduction in losses. The data set on which the algorithm is applied are all the underlying stocks of the Amsterdam Exchange Index (AEX) companies.

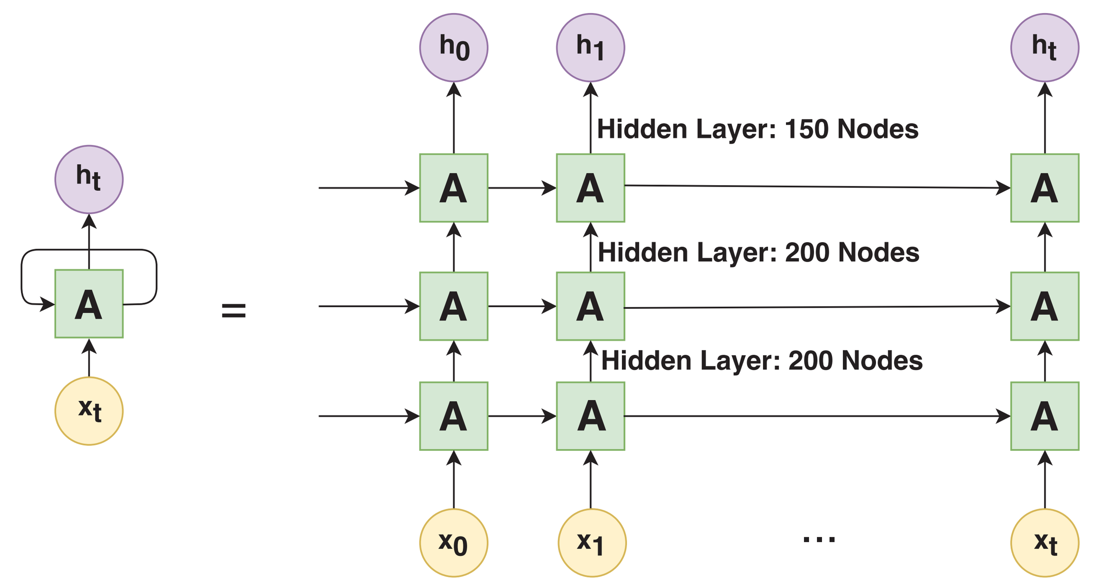
Research Question

How can the prediction performance of an LSTM model on the stock prices of companies in the Amsterdam Exchange Index (AEX) be improved?

Method

Stacked Long Short-Term Memory Model

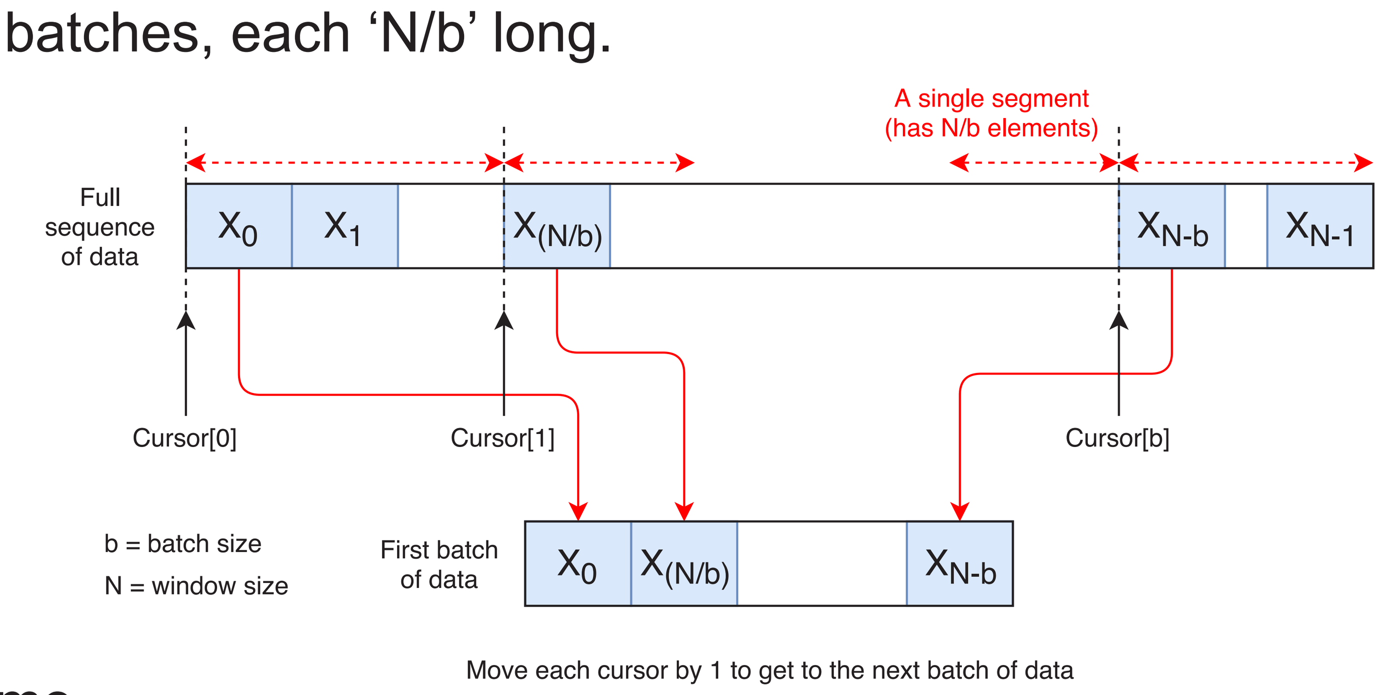
An LSTM model is very powerful in modelling a sequence dependent input. They are classified under the bigger group of Recurrent Neural Networks (RNNs). RNNs are able to persist information as they consist of networks with loops within them.



The general principle of an LSTM is visualised on the left side of the picture. The 'x' stands for the input of the LSTM-cell state 'A' which outputs 'h'. The right side of the picture displays the structure of the stacked LSTM model that is taken as the basis which has three LSTM-cells per time step and is able to predict multiple time steps in the future.

Data Preprocessing and Augmentation

First of all, the stock data is split up into a training and test set according a respective 80% - 20% ratio. Both sets are then normalised within predefined windows with respect to the training set. Subsequently, the training data is smoothed using the exponential moving average in order to erase its sharpness. Thereafter, the data is augmented as visually explained in the picture underneath. In the end, this results in 'b' batches, each 'N/b' long.



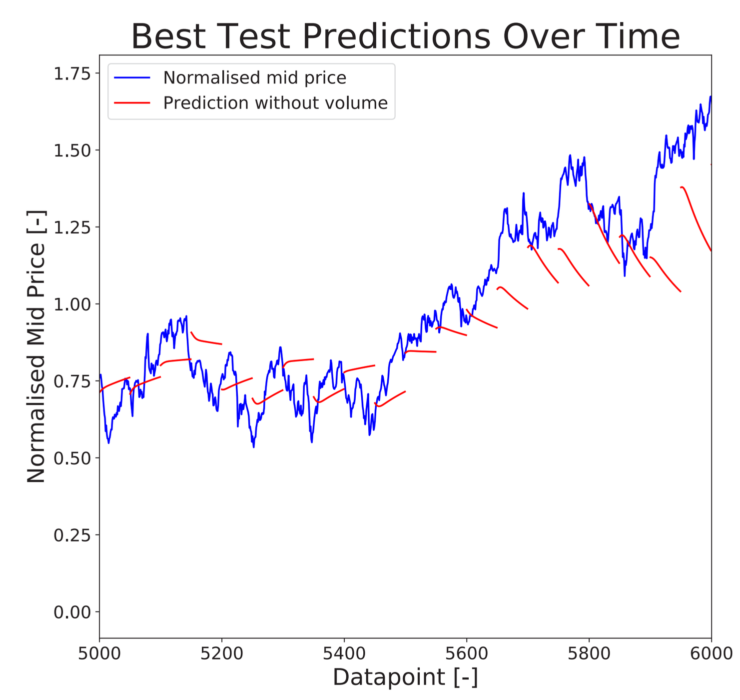
Volume

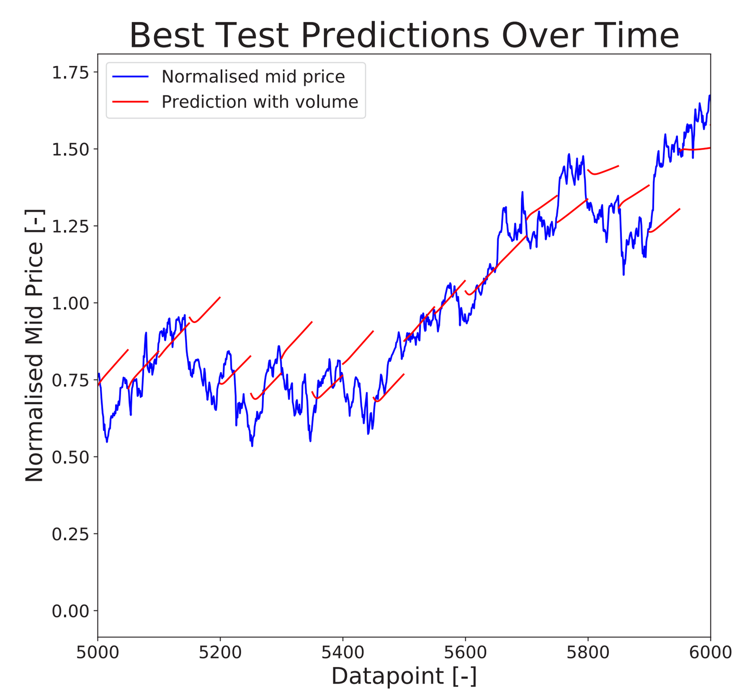
The original stacked SISO (single input single output) LSTM model only takes the mid-price as input and output. The mid-price is defined as the average between the opening and closing price of a trading day. Hereby, the volume is added as an additional input parameter.

This means that the output also has to be altered such that it predicts both mid price and volume because the model predicts multiple time steps in the future. Therefore, both input and output become two-dimensional.

Results

The evolution of the normalised mid-price predictions for the electronics company Philips (AMS: PHIA) are visualised in the plots. On the left side, the results for the model without consideration of the volume are shown. On the right side, the volume is included.





A prediction correctness key performance indicator is used in order to evaluate the the model quantitatively. This KPI tells us how much of the up or down predictions are correct. For the model without volume, this was found to be 56%. For the model with volume, this performance indicator equals 60%.

Discussion and Conclusion

According the prediction correctness KPI, the model which includes the volume gives slightly better results. These results are also visible in the plots. The predictions of the model on the right are more correct than the ones on the left. This concludes that for the Philips stock, including the volume increases the performance of the LSTM model, albeit not significantly.

References

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