Thesis design

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Research domain and problem statement

The research topic for this project will be financial time-series forecasting. More specifically on a dataset containing prices for commodities such as raw milk and whey. Price forecasting is becoming increasingly relevant to producers within various markets. Such forecasts can be of great benefit for developing strategies and negotiation skills ahead of time. Commodity market information is sequential and partially observable, so historical prices are important for predicting those in the future and can potentially be combined with more static data obtained from market snapshots, such as the data about changes in certain regulations or laws, which affects the prices.

Literature review

The existing time series forecasting methods include a variety of both linear and non-linear algorithms. The autoregressive integrated moving average (ARIMA) models and their variations such as AR, MA, ARMA, which fall in the linear model class, have been extensively researched for this purpose[3]. Since these models only consider univariate time series, the interdependencies between different but correlated time series are not captured[4]. There exist multi-variate generalizations for these models, however, they suffer from overfitting with too many free insignificant parameters[3]. Nonetheless, there have been many successful applications of the univariate counterpart for financial time series such as for electricity prices in Sweden[6], tomato prices in Serbia[**?**] and household food retail prices[5].
A non-linear approach for time series forecasting has been to look at the effectiveness of Neural Networks. Earlier methods include comparisons between the use of feed-forward ANN models and linear models. However, these comparisons were inconclusive given contradictory results, some claiming linear models produce more accurate predictions, while others favor ANN's for this task[3].
More recent studies explore the use of Recurrent Neural Networks(RNN's), more specifically the Long Short-Term Memory(LSTM) variants. In contrast to traditional neural networks which are based on the assumption that the input data are independent of each other, RNN's are able to capture sequential information, by carrying results from previous computations or states into the next states, which are often referred to as memory units. These networks can be trained on variable sized input and are able to produce variable sized output, this makes them suitable for capturing temporal data and thus for the task of forecasting. LSTM networks are variations of the vanilla RNN that employ a gating system for solving the vanishing and exploding gradient problems which are present in the vanilla versions. Within the domain of forecasting have been utilized for house price predictions[2] and various studies on stock price predictions[4][1]. In this study, these LSTM models will be explored for the use of Dutch commodity price forecasting.

Research questions

Main research question:
Can a Long Short-Term Memory(LSTM) based model outperforms a baseline autoregressive integrated moving average (ARIMA) model in the task of predicting commodity price time series.
Subquestions:
Does this approach require additional features over the baseline model, and what would those features be.
Are there specific time frames in which this approach would be more effective, and is the model thus more accurate in short-term predictions, for periods shorter than a month or longer-term predictions, as for several months ahead.
Furthermore, are there any disadvantages of utilizing this model over the baseline model for this particular task.
If there is an increase in performance does this improvement generalize to different types of commodity markets?

Planning

- Inquiring about the baseline ARIMA model that is already employed by the company
- Feature engineering and preprocessing the available data
- Exploring possibilities regarding other relevant data sets
- Programming the LSTM model locally
- Transferring this pipeline to the AWS environment and training the model
- Writing the introduction for the thesis paper and expanding the relevant work section
- Running the baseline model and comparing the results
- Fine tuning the parameters, and expanding the number features and documenting the results
- Incorporating the results in the paper, and writing the discussion and conclusion sections.

References

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