Master's Thesis
Progress Report - Results

Deep Learning for Term Structure Forecasting

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1 Progress discussion

Since the last consultations, I have been programming the preprocessing of the data, and some basic neural network (NN) model architectures. The preprocessing source code can be viewed here on my thesis GitHub repository, and the neural network fitting here. The preprocessing consists of loading up the data from the downloaded CSV (11GB for one maturity and one country), cleaning the data so they are in a more convenient format, and trimming the one dataset into a smaller timeframe for testing purposes. Only loading up the one maturity CSV takes 15 minutes, and we have several maturities for the US and EU bonds available. So for now I am working just with an excerpt of one maturity of US 30Y bond futures, namely I cut the data into just May 2019 so it is manageable. This one month of data already contains 780 thousand tick observations. The tick observations will later be aggregated into most likely 5 minute frequency. For now this data excerpt serves as a testing dataset for making sure our models work.

Before feeding the data into the models, I split them into 60% training, 20% validation, 20% testing datasets. Later on, I plan to implement k-fold cross-validation as well, in order to make the results more robust. I might also code up some kind of a gradual loading and generation of the input data for our models due to the sheer size of our datasets. Learning big data packages should help with this part.

I designed a basic layout for a few hyperparameters to tune the neural networks, but it needs more work to make it robust for GPU and big data training. This will be an essential part of my thesis contribution. So far I got a few basic neural network architectures to work on my structure of the data input. In the following weeks, I plan to also include the factor models into this empirical work, and then focus on the hyperparameter tuning.

2 Graphs

What follows are a few preliminary outputs, none of these shall be used in the final thesis, but eventually I will polish these graphs into a nicer form and generate more

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final results once all my models are coded up and evaluated.

In Figure 1 we can see one day excerpt of our dataset (from the 30 year maturity of US bond futures), where the tick frequency is apparent. One day has about 24 thousand tick observations. In Figure 2 we can see a whole month of May 2019, and Figure 3 shows the time series after differencing. I will also explore various differencing approaches later on.

Figure 4 shows the training results of one neural network model fitted on our time series of one month of the tick data. This is not a final result as I will eventually use different frequency, timespan, and most importantly factor models before neural network models. All these results are without any factor models. The Dynamic Nelson-Siegel model will be implemented before the data is fed into the neural network models, only then the NNs shall be trained and evaluated.

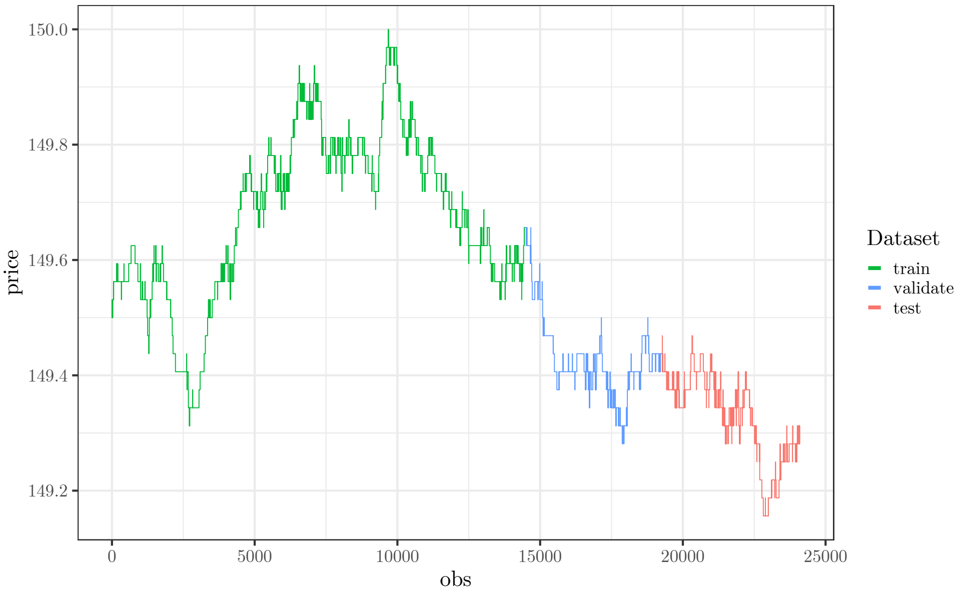

Figure 1: US 30Y bond futures tick frequency, spans one day of 20 May 2019.

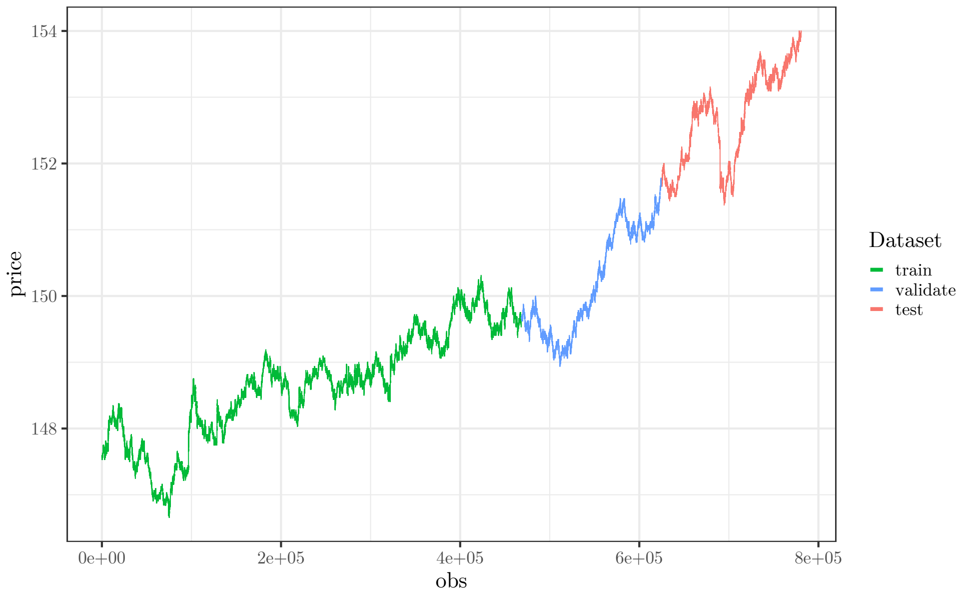

Figure 2: US 30Y bond futures tick frequency, spans one month of May 2019.

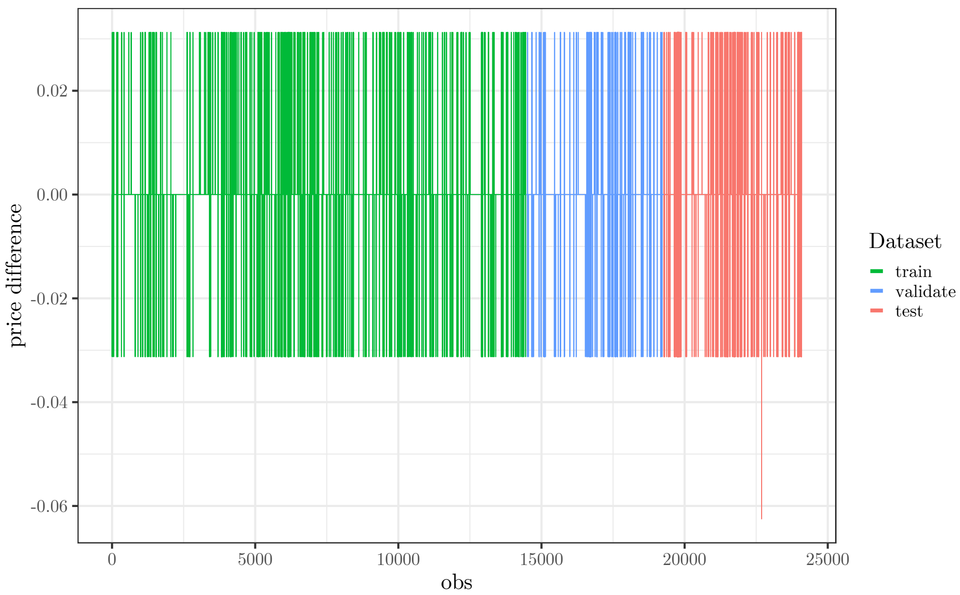

Figure 3: US 30Y bond futures tick frequency, spans one month of May 2019, differenced.

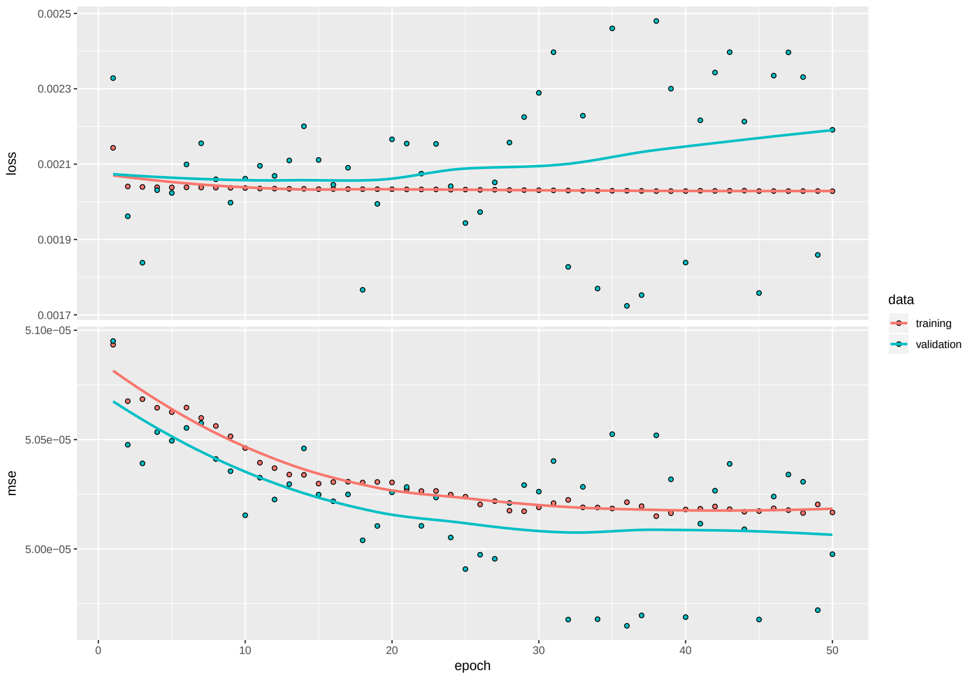

Figure 4: US 30Y bonds differenced data from May 2019, fitted using a neural network (2 hidden layers, 8+16 neurons), trained for 50 epochs.

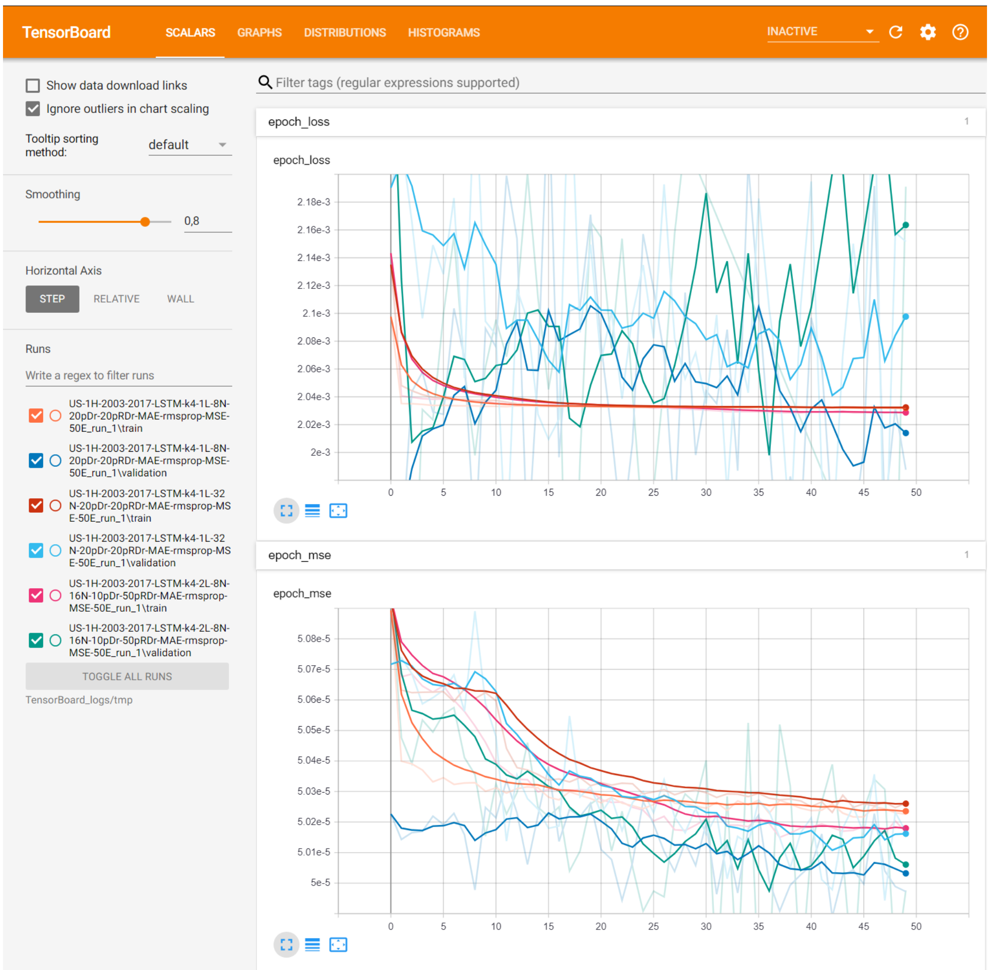

Figure 5: US 30Y bonds differenced data from May 2019, fitted using three different architectures of neural networks, from more shallow ones to a deeper one.

3 Appendix

3.1 R Code

If needed by the reader, the author provides R source codes on his GitHub repository (mrkoubek/deep-learning-for-term-structure-forecasting).