Prediction of the Dst-index using a Long Short-Term Memory network

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We use Artificial Neural Networks (ANN) to forecast the Dst index several hours in advance, using as input solar wind observations at 1AU. Inspired by state-of-the-art models used in automatic translation and image captioning, we use Long-Short Term Memory (LSTM) ANNs to treat the prediction of the Dst as a sequence-to-sequence analysis. Using as input values during the window of time of the previous hours, the goal of the LSTM model is to "translate" this time series into the Dst series of the upcoming 6 hours. In our work, we also focus on the problem of the persistence model being learned by the neural network.

Introduction

Geomagnetic storms pose a threat to our technological infrastructure. Intense storms can cause power surges in electric distribution systems, errors in geolocation, electric arcs in satellites and radiation of humans at high altitudes. The occurence of geomagnetic storms are measured through the so-called Disturbance Storm-Time index, or Dst-index for short. This index represents the strength of the magnetic field of the Earth, and is measured by four equatorial stations located around the globe. When a storm occurs, a significant decrease in the Dst-index is measured by these stations. An example can be seen in figure 1.

The prediction of the Dst multiple hours in advance has been a recurring topic [1, 2], and with the upcoming of Artificial Intelligence, new techniques are being used to predict the Dst [3, 4].

Predicting the Dst

Since the solar wind heavily interacts with the magnetic field of the Earth, which in turn determines the Dst, we will use some properties of the solar wind as an input for our neural network. This data is freely available data at OMNIWeb[1]. The neural network we use is the so-called Long Short-Term Memory network (or LSTM), as this has proven to be very effective when working with time-series. The inputs of the LSTM are the solar wind speed, density, scalar and southward magnetic field component together with the Dst itself for 6 hours in advance of the time we start to predict. The result of predicting two hours in advance can be seen in figure 2.

Notice the result, where we see that the LSTM prediction of time $t+2$ is almost nothing more then a shift of the result at time t. The model has learned to behave as the so-called persistence model, which simply assumes that $y(t-1) = y(t)$. While this result obviously does not learn us anything, there is a pitfall with this results that we have observed in

[1] `http://omniweb.gsfc.nasa.gov/`

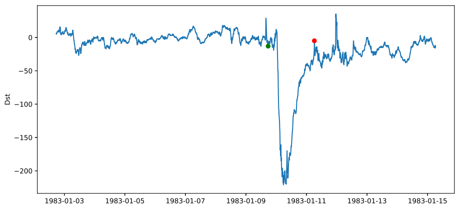

Figure 1: A snapshot of the Dst. Green and red dots denote the respective start and end of the storm

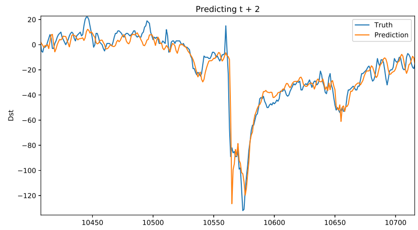

Figure 2: Prediction two hours in advance versus the truth-value. Notice the clear shift in the predicted values

some papers. Although this result is useless, its Root Mean Square error (RMSE) and linear correlation coefficient (CC) still seem very good, giving the illusion that the neural network is in fact able to predict the Dst, as can be seen at the result in table 1.

T+2	Persistence	LSTM	Gruet et. al. [4]	Wu & Lundtstedt
RMSE	6.61	5.64	6.55	16.3
CC	0.935	0.952	0.946	0.98

Table 1: Persistence model compared to our results and results in the literature

Predicting ΔDst

This problem of learning the persistence model occurs most of the time when one is trying to predict a random walk. A common solution is, instead of predicting the Dst, to predict $\Delta\text{Dst}(t+1) = \text{Dst}(t)$ - $\text{Dst}(t+1)$. This gives a time series that is not heavily auto-correlated with its previous timestep, allowing a neural network to learn something other than the persistence model, as seen in figure 3. This is what our current research is focusing on.

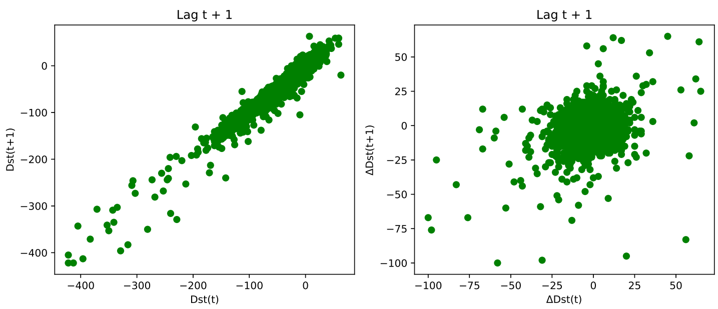

Figure 3: A lag-plot of the Dst and ΔDst. Notice the strong auto-correlation of the Dst, while this completely disappears in the lag-plot of ΔDst.

References

[1] M. Temerin and Xinlin Li. A new model for the prediction of Dst on the basis of the solar wind. *Journal of Geophysical Research: Space Physics*, 107(A12), 2002.

[2] Eun Young Ji, Y. J. Moon, N. Gopalswamy, and D. H. Lee. Comparison of Dst forecast models for intense geomagnetic storms. *Journal of Geophysical Research: Space Physics*, 117(3):1–9, 2012.

[3] J. A. Lazzús, P. Vega, P. Rojas, and I. Salfate. Forecasting the Dst index using a swarm-optimized neural network. *Space Weather*, 15(8):1068–1089, 2017.

[4] M. A. Gruet, M. Chandorkar, A. Sicard, and E. Camporeale. Multiple-Hour-Ahead Forecast of the Dst Index Using a Combination of Long Short-Term Memory Neural Network and Gaussian Process. *Space Weather*, 16(11):1882–1896, 2018.