

Sunspot Time Series Forecasting using Deep Learning

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Abstract: *In order to forecast solar cycle 25, sunspot numbers(SSN) from 1700 ~ 2018 was used as a time series to predict the next eleven years. deep long short-term memory(LSTM) was exploited to do the forecast, first the dataset was split into training set(80%) and (20%) for the test set, the achieved accuracy led us to forecast the next eleven years. The result shows that the cycle will be from 2019 ~ 2029 with peak at 2024.*

1 Introduction

One interesting aspect of the Sun is its sunspots. Solar flares, coronal mass ejections, high-speed solar wind, and solar energetic particles are all forms of solar activity. All solar activity is driven by the solar magnetic field[14]. Solar activity has important influences on all living beings, and major technologies in the world. As a result of the changes in solar activity at a period of about 11 years, deviations in the near-Earth space in the interplanetary environment and the magnetosphere change the ionospheric plasma density with this period. Furthermore, changes in solar activity affect aero and space navigation,spaceflights, radars, high-frequency radio communications, and ground electrical lines. These changes also may affect climate and living organisms on the earth, including humans([1, 10, 11]). In order to estimate the sunspot cycle, sunspot number(SSN) is one of the main used indices, it is an important parameter in many scientific areas([13, 7]). The sunspot number is an active field of research, because of its importance, difficulty of estimation, and possible applications based on it.

A time series is a set of observations, each one being recorded at a specific time. Time series prediction is a vital research area in which forecasters collect and analyze historical observations to identify a model to capture the underlying data generation process, this model will be used to predict the future values. In the last decades Artificial neural networks(ANN) proved to be a serious contenders to statistical methods in forecasting. In order to use

ANN in forecasting tasks, it must compromise among three issues: solution complexity, forecast accuracy, and data characteristics[16].

Recurrent neural network(RNN) found to be the convenient one to achieve the above mentioned tasks, yet the majority weakness of RNN is vanishing/exploding gradient problem[3]. In [8, 12] this drawback was handled using long short-term memory(LSTM) algorithm as an extension to RNN.

The paper is composed of: LSTM model section(2), Deep-LSTM model section(3), and simulation in section(4).

2 LSTM Model

Recurrent neural networks(RNN)found to be convenient method in forecasting time series, as it compromises among solution complexity, forecast accuracy, and data characteristics[16]. RNN have the ability to store memory since their current output is dependent on the previous computations. However, the major weakness of RNN is the vanishing/explosion gradient problem[5]. Long short-term memory(LSTM) were designed to overcome vanishing/explosion problem by introducing new gates which allow a better control over the gradient flow and enable better presentation of long range dependencies. Figure(1) shows the memory cell of LSTM with three gates: input gate, forget gate, and output gate.

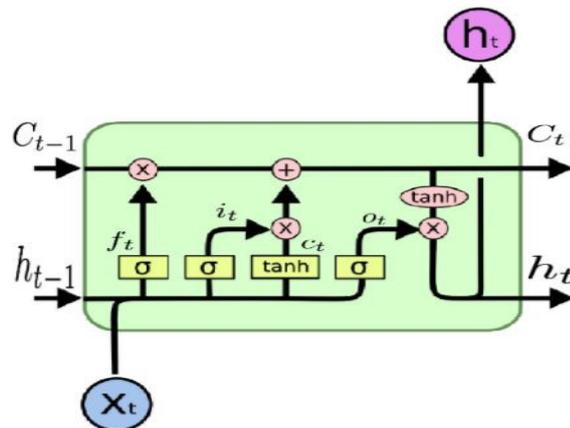


Figure 1: LSTM cell structure.

The input sequence $\{x_1, x_2, \dots, x_n\}$ is input to RNN model using recurrence relation:

$$h_t = f(h_{t-1}, x_t), \quad (1)$$

where $x_t \equiv$ input at time t , $h_t \equiv$ current hidden state.

LSTM overcomes vanishing/explosion problem by introducing the gates and states of LSTM are computed as follows:

input gate:

$$i_t = \sigma(W_1^i \cdot x_t + W_h^i \cdot h_{t-1} + b_i), \quad (2)$$

forget gate:

$$f_t = \sigma(W_1^f \cdot x_t + W_h^f \cdot h_{t-1} + b_f), \quad (3)$$

output gate:

$$o_t = \sigma(W_1^o \cdot x_t + W_h^o \cdot h_{t-1} + b_o), \quad (4)$$

cell input:

$$\bar{C}_t = \tanh(W_1^C \cdot x_t + W_h^C \cdot h_{t-1} + b_C), \quad (5)$$

where $W_1^i, W_1^f, W_1^o, W_1^C$ are the weight matrices connecting x_t to the three gates and the cell input, $W_h^i, W_h^f, W_h^o, W_h^C$ are the weight matrices connecting h_{t-1} to the three gates and the cell input, b_i, b_f, b_o, b_C are the bias terms of the three gates and the cell input, σ represents the Sigmoid function and \tanh represents the hyperbolic tangent function. Secondly, calculate the cell output state:

$$C_t = i_t * \bar{C}_t + f_t * C_{t-1}, \quad (6)$$

where $i_t, f_t, \bar{C}_t, C_{t-1}$ and C_t have the same dimension. Thirdly, calculate the hidden layer output:

$$h_t = o_t * \tanh(C_t). \quad (7)$$

To predict the future value y_t , we use the observed historical data x_t as the network input(see figure(2)). From the above LSTM calculations, h_t is obtained and hence the network output is

$$y_t = W_2 \cdot h_t + b \quad (8)$$

where W_2 is the weight matrix between the output layer and the hidden layer, b is the bias term of the output layer.

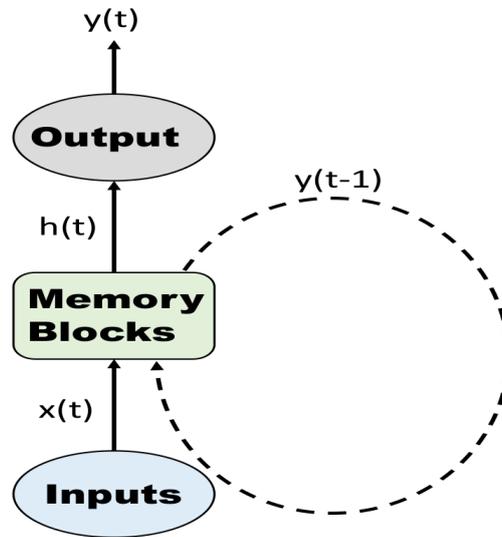


Figure 2: LSTM structure for time series prediction.

3 Deep LSTMs

Stacked LSTMs or Deep LSTMs were introduced by Graves[4], et al. in their application of LSTMs to speech recognition, beating a benchmark on a challenging standard problem. They found that the depth of the network was more important than the number of memory cells in a given layer to model skill. Stacked LSTMs are now a stable technique for challenging sequence prediction problems. A Stacked LSTM architecture (figure(3)) can be defined as an LSTM model comprised of multiple LSTM layers. An LSTM layer above provides a sequence output rather than a single value output to the LSTM layer below. Specifically, one output per input time step, rather than one output time step for all input time steps.

To increase efficiency of the LSTM networks, several stacked blocks of LSTM were used in a similar way to deep recurrent network[2].

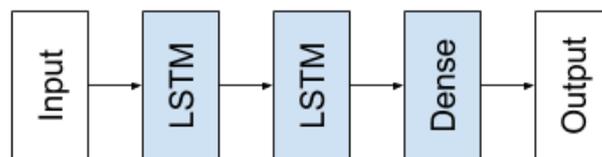


Figure 3: Stacked Long Short-Term Memory Architecture.

4 Experiments

The dataset of the sunspot number are freely available from world data center SILSO[15] for daily, monthly, and yearly in csv-format. The simulation run on yearly dataset from year 1700 till 2108, i.e., 318 years.

4.1 Forecasting Accuracy Errors

To measure forecast accuracy and performance evaluation, the commonly used measures are[6]:

- Root Mean Squared Error(RMSE) easy to interpret your model accuracy written as:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

- Another commonly used one is Root Mean Square Percentage Error(RMSPE)

$$\text{RMSPE} = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{y_i - \hat{y}_i}{y_i}\right)^2} \times 100$$

- MAPE refers to Mean Absolute Percentage Error, which is

$$\text{MAPE} = \frac{100}{n} \sum_i \frac{y_i - \hat{y}_i}{y_i}$$

where y_i is the true value(observation) and \hat{y}_i is the predicted value.

4.2 Results

The SSN dataset from 1700 ~ 2018 was split into 80% for training set and (20% \approx 64 years) for test set. Then we run the deep LSTM program with configurations in table(1) to get the result shown in figure(4)

Table 1: Deep LSTM configurations.

No. of layer	No. of hidden units in each layer	No. of Epochs	RMSE	RMSPE	MAPE
2	[5,5]	1000	23.478	58.383	32.042

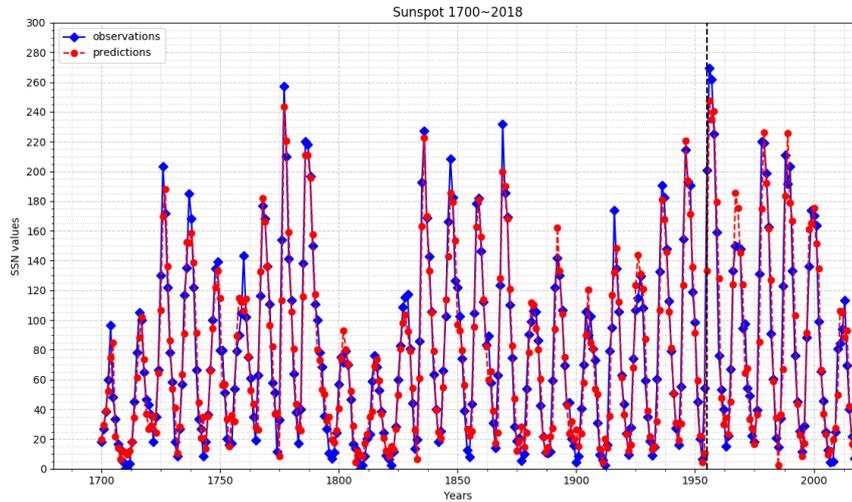


Figure 4: SSN and their forecasts.

It is important to predict the next solar cycle, so the deep LSTM model run to predict the future eleven years and the results shown in figure(5) and table(2). It is clear that solar cycle 25 will have a peak SSN of 120 at year 2024.

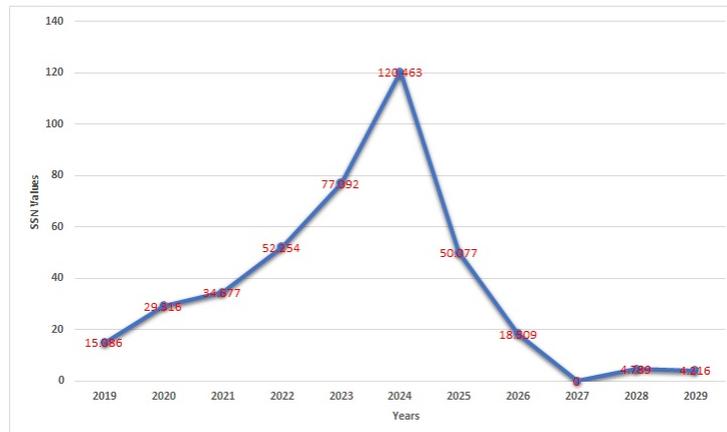


Figure 5: SSN and their forecasts for the next 11 years.

Table 2: SSN numbers and their predicted values.

Year	SSN value
2019	15.086
2020	29.316
2021	34.677
2022	52.254
2023	77.092
2024	120.463
2025	50.077
2026	18.509
2027	0
2028	4.789
2029	4.216

5 Conclusion

In this paper, solar cycle 25 was studied using deep LSTM, first data split into training/test sets with 80%/20% and after choosing the right parameters it was run to predict the next solar cycle.

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