Prediction of polar vortex intensity signal based on convolution smoothing and long short-term memory

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Abstract. Polar vortex is an important weather system that affects the atmospheric circulation in the Northern Hemisphere and the climate change in the Arctic. The intensity variation of polar vortex is related to El Nino-Southern Oscillation (ENSO), Arctic Oscillation (AO) and many other climate phenomena. However, there are few researches on the prediction of polar vortex intensity change, our study analyzes and predicts the intensity variation of the Northern Hemisphere stratospheric polar vortex, and further uses convolution smoothing and depth learning methods to improve the accuracy of the prediction. The result shows that the long-short time memory network method’s prediction accuracy is not enough high. After the convolution smoothing of the time series of intensity signal, the prediction accuracy of neural network has been significantly improved. The average absolute error of the traditional long short-term memory network method is 18.29, while the average absolute error of the smoothed prediction intensity and the actual intensity is 13.77. In addition, the correlation between the predicted results and the real values is also as high as 0.9981.

1. Introduction

The seasonal variation of the stratospheric polar vortex in winter will have an important impact on the tropospheric weather and climate. Many previous studies have shown that the intensity and position of polar vortex can lead to the anomaly distribution of ozone in the Arctic, the formation of ozone hole and the temperature anomaly in the northern hemisphere [1-2]. Studies have shown that the undisturbed vortex is a strong transport barrier, and the temperature is low enough to form polar stratospheric clouds, which last for more than four months until the end of March. The total amount of columnar ozone in the Northern Hemisphere (NH) polar cap decreased and reached the lowest level from February to April [3-4]. Therefore, accurate prediction of polar vortex intensity variation in the NH can predict the strong or weak polar vortex events in advance, which has a certain role in the prediction of weather and climate.

In the field of signal processing, noise removal is the key research direction, and many denoising methods have been widely used in various scientific research fields [5-7]. We denoise the polar vortex intensity series by using the convolution smoothing process in the traditional mathematical method. The convolution smoothing denoising method has a significant effect on the time series of nonlinear systems.

Deep learning method has played an important role in promoting the development of artificial intelligence. It has a very significant effect on the research of image classification task, clustering analysis and regression prediction [8-10]. Therefore, we use one of the most advanced time series prediction neural networks, long short-term memory network (LSTM) [11], to predict the intensity of
polar vortex. Compared with the traditional deep learning method, the time series prediction combined with signal denoising process achieves higher accuracy. It has important scientific significance for signal prediction and improvement of various numerical prediction models. In view of this research, we can further improve the prediction effect of nonlinear system prediction.

2. Result

In this study, the National Centers for Environmental Prediction (NCEP) geopotential height (GPH) field data from 1948 to 2020 are selected to construct the time series of the intensity variation of the NH stratospheric polar vortex. We adopt the general definition method of polar vortex intensity to calculate the signal time series. The specific calculation formula of polar vortex intensity is as follows:

\[-Z_p = -\frac{\sum (Z' \cos \varphi)}{\sum \cos \varphi}\]  \hspace{1cm} (1)

Where \(Z'\) is the GPH anomaly excluding annual cycle, \(\varphi\) represents the latitude, and the sum sign is the sum of all grid points north of 65°N. \(-Z_p\) indicates that the polar vortex intensity index is opposite to the abnormal sign of the polar GPH, that is, the positive (negative) index corresponds to the strong (weak) polar vortex.

The calculation of moving average filtering method, that is, convolution smoothing method, is very similar to the working principle of one-dimensional convolution. The \(n\) of moving average corresponds to the size of one-dimensional convolution kernel. It can restrain the periodic disturbance and has high smoothness. It is suitable for the system with high frequency oscillation.

Figure 1. The daily averaged distribution of geopotential height of polar vertex at 50 hPa. The arrow indicates the size and direction of the wind speed vector.

Figure 1 shows the daily average distribution of the stratospheric polar vortex in the NH. It illustrates that there is an obvious minimum region of GPH in the center of polar vortex. According to the calculation formula of polar vortex intensity, the smaller the GPH in the central region is, the stronger the corresponding intensity will be.

Firstly, we use convolution smoothing method to denoise the intensity signal. Figure 2 shows the time series distribution of the original signal and the denoised signal. It can be seen that after convolution smoothing, the reconstructed signal becomes smoother, and the noise part of the signal has been significantly eliminated. And on the basis of the original signal, the value does not change greatly. The difference between the original signal and smoothed signal is ±20.
Figure 2. Time series diagram of polar vortex intensity. The upper panel represents the original intensity and the lower panel represents the intensity signal after the process of convolution smoothing.

Figure 3. The time series of training set and test set of polar vortex intensity is given. Purple solid segment represents the divided training intensity data set, and green represents the test set data. The red dotted line splits these two datasets.

After smoothing the signal and removing the noise, we divide the data into training set and test set. As shown in Figure 3, the purple line segment represents the training set data, and the green line represents the test set. Because there exist 73 years of data. We input the data of the first 60 years as the training set into the LSTM model, and test and predict the data of the remaining 13 years. Since we are studying the intensity prediction of polar vortex in winter, we choose November to December and January to March of each year. There are 8852 data in total.
Figure 4. The time series and scatter plots between the predicted polar vortex intensity time series and the real value are obtained by using the traditional LSTM depth learning method and convolution smoothing + LSTM method. The left bottom panel represents the correlation between polar vortex intensity predicted by the LSTM and the real intensity of polar vortex. The right bottom panel represents the correlation between polar vortex intensity predicted by the convolutional smoothing + LSTM and the real intensity of polar vortex. The correlation coefficient is shown in the upper left corner.

Before training the input intensity signal data, we need to divide the data into time steps. Here we take the intensity data of the first ten days as the input and predict the intensity of the next day. Since only a few months are selected each year, we have to divide the annual data. Finally, the input and output shapes of the training set are (6675, 10, 1) and (6675, 1) respectively, while the input and output shapes of the test set are (1447, 10, 1) and (1447, 1) respectively. Figure 4 shows the time series distribution of intensity signal value and true value and their correlation after using LSTM and smooth + LSTM models for prediction. We can see that the correlation between the predicted signal and the real value is higher after convolution smoothing. Figure 5 shows the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Square Error (MSE) between the predicted results of the two models and the real values. The RMSE, Mae and MSE of intensity predicted by LSTM model and true intensity are 38.34, 18.29 and 1470.38 respectively, while the RMSE, Mae and MSE of smooth + LSTM model are 20.61, 13.77 and 424.97 respectively. The results show that the training effect of the smooth LSTM deep learning neural network is better and has higher accuracy.
Figure 5. The histogram of Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Square Error (MSE) generated by traditional LSTM neural network and convolution smoothing LSTM neural network. The orange square represents the RMSE, the green square represents the MAE, and the red square represents the MSE.

3. Conclusion

There are many nonlinear and complex weather systems and phenomena in the atmosphere. Polar vortex is a typical nonlinear system. The change of polar vortex intensity is closely related to many phenomena in weather and climate. It is worthy of further study to accurately predict the change of polar vortex intensity. In this study, a new LSTM method based on convolution smoothing is proposed. Firstly, convolution smoothing is used to remove the noise from the intensity signal. Then the traditional deep learning method LSTM is used to predict the polar vortex intensity. Compared with the traditional LSTM time series prediction neural network, it has better effect and higher accuracy. The improved deep learning method can better capture the variation of polar vortex intensity. The correlation between the predicted polar vortex strength and the real value is as high as 0.998. The MAE, RMSE and MSE of this method are greatly improved on the basis of traditional LSTM method. Therefore, the results show that the time series prediction method of convolution smoothing combined with LSTM has a positive effect on the variation of polar vortex intensity. This method can be further applied to the prediction of other nonlinear systems in the atmosphere, such as the prediction of El Nino index and AO Index. In the future works, we will contribute to the teleconnection relationship between polar vortex intensity and other nonlinear systems, and make more accurate prediction for this kind of noisy signal with higher complexity.

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