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Neural Networks for Prediction of the Sea Surface Temperature (Sst) in the Tropical Pacific Ocean

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Abstract

A brief review of researches on the application of the neural networks in the area of meteorology, oceanography and geographysics is introduced. The method of Neural Networks as one valuable non-linear strategies to reconstruct and predict climatologival signals is also reviewed. Feedforward Neural Networks are implemented in a neural network simulator SNNS for prediction of the Sea Surface Temperature (SST) in the tropical Pacific ocean. The original SST is collected from the NIÑO1-2 (0^0 N-10^0 S, 270^0 E-280^0 E) and NIÑO4 (5^0 N-5^0 S, 160^0 E-150^0 E) regions from January 1950 to now. Using the available data to train the network, the network then provides the next six month prediction. Comparing with the corresponding six month observations, all prediction values are located within the predicted error bars. The error detected have shown that the neural networks method is a uasful tool to perform climatological predictions

Introduction

Neural networks represent non-linear strategies already widely use in pattern recognition, classification and approximation function etc. (Lapedes and Farber, 1987; Rumelhart & Mcclelland, 1986; Welstead, 1994). They have attracted a resurgence of interest from computational researchers in a variety of scientific and engineering disciplines. Recently, in meteorology fields, several interesting applications have been published. Marzban and Stumpf (1996) applied the neural network to tornado prediction based on Doppler radar-derived attributes. They designed a neural network to diagnose important circulations detected by the NSSL MDA (The National Severe Storms Laboratory's mesocyclone detection algorithm). Their results have shown that the neural network outperforms the rule-based algorithm existing in the MDA as well as statistical techniques such as discriminant analysis and logistic regression.

Allen and Marshall (1994) made an evaluation of neural networks and discriminant analysis methods for application in operational rain forecasting. Neural networks and discriminant analysis have been applied to forecasting 24-hour rainfall for the city of Melbourne. Performance comparisons indicated that both neural network and discriminant analysis methods offered improvements over the operational model output statistics (MOS) method and operational forecast.

For prediction of Northeast Brazil rainfall anomalies, Hasteneath and Greischar (1993) used a neural network as an alternative to traditional linear regression analysis. Their experiments with neural networking revealed no advantage over regression. Li et al. (1996) utilized Wavelets and Neural Networks combination method to predict the Northeastern Brazil monthly rainfall anomalies time series too. First, they applied the Neural Networks to the raw signal for prediction. After that, they applied the Neural Networks to the signals obtained by projecting the signal to some special time scales using Wavelet Transform, for example three months or more. Finally, they compared the results obtained from the above cases. In spite of the not satisfatory quality of the analysed data (Nobre et al., 1982), it was possible to perform reasonable climatological predictions and the combination method gave the better results.

As Marzban and Stumpf (1996) mentioned, the utility of Neural Networks is most present in disciplines where intrinsic nonlinearities in the dynamics preclude the development of exactly solvable models. In such case, a trained neural network is synonymous of a solvable model. Although qualitative, physical understanding may be lacking, highly accurate predictions can be made. In a field such as meteorology, all of these criteria are present in that the dynamics is inherently nonlinear, and predictions comprise a central goal.

In the following sections, we show a brief review of the neural network method. The application of the neural network for prediction of the Sea Surface Temperature (SST) in the tropical Pacific ocean will be reported in this work. The original SST is collected from the NIÑO1-2 region (0^0 N-10^0 S, 270^0 E-280^0 E) and NIÑO4 (5^0 N-5^0 S, 160^0 E-150^0 E) of the tropical Pacific ocean. The choice of these regions for data reconstruction and prediction is related with its importancy on general atmospheric circulation above Brazil. The sea surface temperature (SST) for this region is published every month by Climate Prediction Center (CPC, 1996), USA. The original data are from January 1950 upto now.

Methods

Feedforward Neural Network (Rumelhart & McClelland, 1986; Welstead, 1994), one of the well known neural network architectures, was used in this work. Figure 1 shows the classic three-layer feedforward neural network architecture (an input layer, one hidden layer and an output layer). Feedforward Neural Network actually represents a function acting on a vector, or list of numbers. The notation R^d is used to denote the d-dimensional space of all vectors of the form (x_1, x_2, ... x_d), where each x_i is a real number and $d \geq 1$ is an integer. The neural network function sends the vector (x_1, x_2, ... x_N) in R^N to the vector (y_1, y_2, ... y_n) in R^M. Thus, the feedforward network can be represented as:

$$\mathbf{y} = F(\mathbf{x})$$

where $\mathbf{x}$ = (x_1, x_2, ... x_N) and $\mathbf{y}$ = (y_1, y_2, ... y_M). The action of this function is determined in a specific way. For a network with N input nodes, H hidden layer nodes, and M output nodes, the values of y_k are given by:

$$y_k = g(\sum_{j=1}^{H} w^{o}_{jk} h_j), k = 1, \ldots, M \tag{1}$$

Here w^o_{jk} is the output "weight" from hidden node j to output node k, and g is an output function. The values of the hidden layer nodes h_j, $j = 1, \ldots, H$ are given by:

$$h_j = \sigma(\sum_{i=1}^{N} w^I_{ij} x_i + w^T_j), j = 1, \ldots, H \tag{2}$$

Here, w^I_{ij} is the input "weight" from input node I to hidden node j, w^T_j is a threshold "weight" from an input node which ha the constant value 1 to hidden node j, x_i is the value at input node I, and σ is the sigmoid function given by

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

The function σ in Equation (2) is called the *activation function* of the neural network. The function in equation (1) may b the same as the activation function or may be a different function. In our implementation, we will allow g to be either σ c a linear output function.

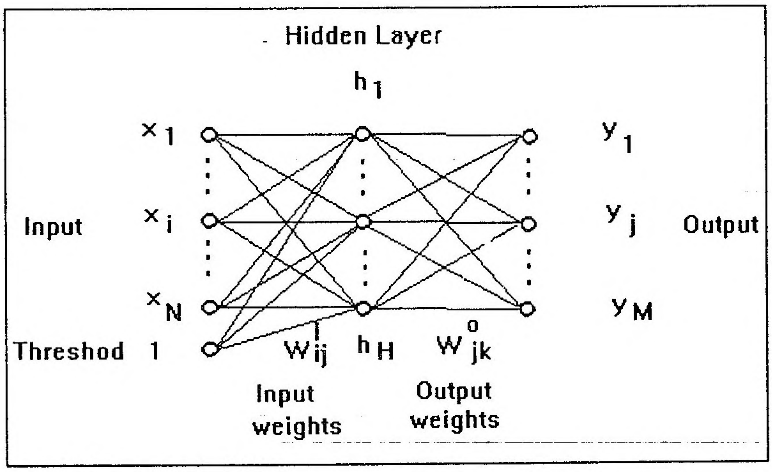

Fig. 1 Three-layer feedforward neural network architecture

The action of the feedforward network is determined by two things: the architecture of the network and the values of th weights of the network. The architecture, that is, how many input, hidden, and output nodes it has. The widespread applicability of feedforward networks comes from the fact that: three-layer feedforward networks are universal approximators (Hornik, et al., 1989). With the architecture set, it is then the weight values which determine how the network performs. The process of adjusting these weight values in order to obtain a desired network performance is known as training the network. The network is said to learn as the weight values are being modified to achieve the training goal. The difference between the network outputs and the actual desired outputs is the "error" produced by the network. In training the network, we want to reduce this error to as small a value as possible.

Suppose, for simplicity, that we have just a single data point ($\boldsymbol{x}$, $\boldsymbol{d}$) consisting of an input vector $\boldsymbol{x}$ = (x_1, x_2, ... x_N) and a desired output vector $\boldsymbol{d}$ = (d_1, d_2, ... d_M). For a given set $\boldsymbol{W}$ of weight values, the feedforward network produces the output vector $\boldsymbol{y}(\boldsymbol{W})$ = ($y_1(\boldsymbol{W})$, $y_2(\boldsymbol{W})$, ... $y_M(\boldsymbol{W})$). One way to express the error $e(\boldsymbol{W})$ is the following:

$$e(\boldsymbol{W}) = 1/2 \; || \; \boldsymbol{d} - \boldsymbol{y}(\boldsymbol{W}) \; ||^2 = 1/2 \sum (d_k - y_k(\boldsymbol{W}))^2 \tag{4}$$

In calculus, we shall settle for finding the value of $\boldsymbol{W}$ that minimizes this expression to within some tolerance. Pick som random starting point and at each step of the iteration, move some amount in the negative derivative direction. For a vector function, the derivative is called a *gradient*, and the above procedure is a *gradient descent* algorithm. We have:

does not discriminate the variability influences of both sides of the air-sea interface. In the future, we shall try to analyze physical factors involved in SST in order to improve the Neural network prediction process and to obtain better results.

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Experimento Integrado do Sigtec - Eis

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Abstract

This work presents a field experiment called EIS (Experimento Integrado do SIGTEC) which took place in the Northeast Region of Brazil from 24th March to 6th April 1995. SIGTEC stands for "Sistema de Informações Gerenciais em Tempo, Clima e Recursos Hídricos"(management system of informations concerning weather, climate and water resources) which serves as a technical and scientific tool to help the hidro-environmental monitoring and to have an efficient utilization of water resources capabilities in the Northeast Region.