jcis@epacis.org

Neural networks in the study of climate patterns seasonal

Juliana A. Anochi[a c1], Haroldo F. de Campos Velho[b c], José Demisio S. da Silva†

[a]Applied Computing Graduate Program (CAP)
[b]Associated Laboratory for Computing and Applied Mathematics (LAC)
[c]National Institute for Space Research (INPE) São José dos Campos, SP, Brazil

Abstract

This work describes an Artificial Intelligence based technique to prepare data for constructing a climate prediction empirical model from reanalysis data in the South region of Brazil using Artificial Neural Network (ANN). The method uses Rough Sets Theory (RST) to reduce the amount of variables. The input of ANN there is two kinds of data: the variables chosen by the RST and full variables data to learn the seasonal behavior of the variable precipitation.

Keywords: Climate Prediction, Neural Networks, Rough Sets Theory.

1. CLIMATE PRECIPITATION PREDICTION BY ANN

The development of regional climate models from data considers the hypothesis that it is possible to extract information from historical data on the behavior of climatic conditions. Accordingly, development methodology needs to have a large number of data to ensure that the model considers a wide range of situations. However, despite able to ensure, in principle, greater robustness to the derived models, the handling of large volumes of data may require much computational. In this paper considered the use of Rough Sets Theory principles in extracting relevant information from the available data to achieve the reduction among the variables used for forecasting purposes.

Artificial Neural Networks (ANN) have emerged as excellent tools for deriving data oriented models because of their inherent characteristic of plasticity that permits the adaptation of the learning task when data is provided. In this regards, the use of an ANN is adequate to derive the forecasting

[1]E-mail Corresponding Author: juliana.anochi@lac.inpe.br

model proposed in this paper. For the problem of building prediction models, as proposed in this paper, are used Multilayer Perceptron and models of recurrent Elman and Jordan [2].

1.1 Rough Sets Theory

Rough Sets Theory was proposed in 1982 by Zdzislaw Pawlak as a mathematical theory to treat uncertain and imprecise information, by deriving approximations of a data set [4]. Roguh Sets are based on the similarities among objects measured by an indiscernibility relation, which establish that a set of objects are similar (indiscernible) if they hold the same values for all of their attributes.

Rough Sets Theory uses the concept of Information Systems in which the available data are represented in a table in which the objects are displayed in the rows and the attributes in the columns [3]. Formally, an information system is composed of a finite non-empty set U (Universe) of objects and a finite non-empty set A of attributes, $IS = (U, A)$, so that, for each $a \in A$, $a : U \rightarrow V_a$. The set V_a is the set of values of a, that is, the domain of a.

A Decision System is an IS augmented with a decision attribute $d \notin A$. Formally, $DS = (U, A\{d\})$, where $d \notin A$ is the decision attribute [3].

The indiscernibility relation is used as a measure of similarity among objects. Thus, a set of objects with the same attributes are indiscernible if only if their attributes hold the same values from their corresponding domains. This is a equivalence relation that may be used to treat problems as redundancy of attributes or the existence of irrelevant attributes in the data assigned to only one representative of a class.

The attribute reduction procedure is performed by the discernibility function $f_A(B)$ derived from the discernibility matrix which is a symmetric matrix constructed by comparing the attribute values that discern the objects. The attribute representing discernible values are inserted into the matrix. Each entry in the matrix consists of a set of attributes that distinguish a pair of objects x_i and x_j expressed by [3]:

$$M_{i,j} = \{a \in B | a\left(x_i\right) \neq a\left(x_j\right)\} \tag{1}$$

where $1 \leq i, j \leq n$ and $n = |U/IND_A(B)|$

2. EXPERIMENTS AND RESULTS

In the dimensionality reduction process the relevant attributes are those that mostly occur in the data, in terms of the indiscernibility relation. The data was downloaded from the reanalysis data repository from NCEP/NCAR. The data consists of monthly means from January 2000 to December 2009. The geographic coordinates (Lat 35S, 22.5S) to (Lon 60W, 45W) with a spatial resolution of $2.5^o \times 2.5^o$.

The available variables are: air temperature (airt), Zonal Wind Components at vertical levels: 300hPa (v300), 500hPa (v500) and 850hPa (v850), Meridional Wind Components at vertical levels: 300hPa (u300), 500hPa (u500) and 850hPa (u850), Surface pressure (spres), Specific humidity (shum) and Precipitation (prec).

The variables that were reduced by the use of RST are: airt (77%), u300 (79%), u850 (80%), v300 (77%), v500 (79%), v850 (70%) and spres (78%). It is to be noticed that the variables that form the reducts have a presence greater than 70% in the dicernibility function.

It is observed that of 7 variables out of 10, were considered relevant for South. Figure 1 shows the results for season winter of 2007 in the South region of Brazil.

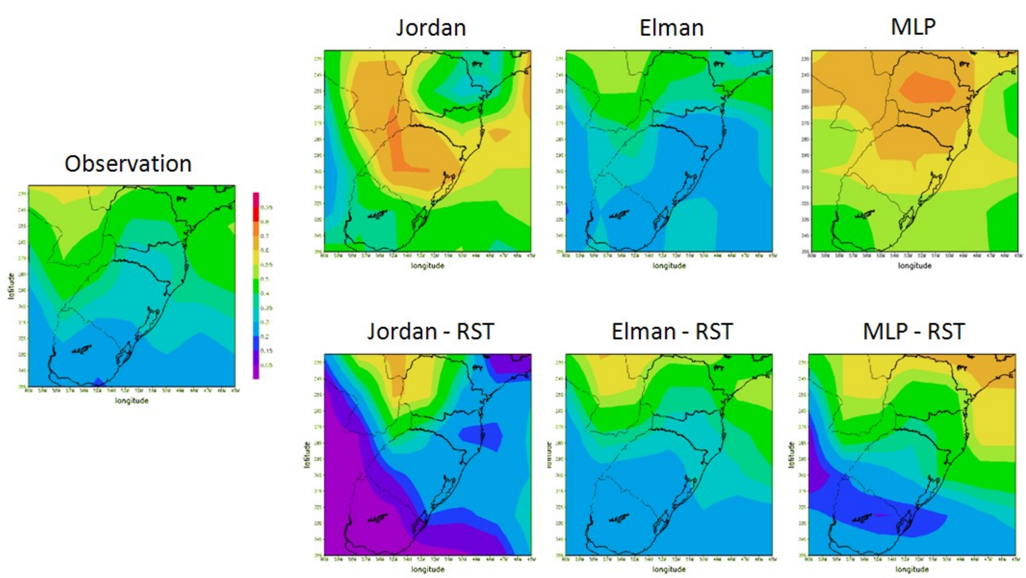

Figure 1 - Estimation of precipitation in the winter of 2007 in the South.

3. FINAL REMARKS

The proposed methodology works weel with Elman-ANN using RST. The data reduction approach allows the derivation of smaller data sets derived from the resulting reducts for the training phase of the neural network without losing data expressiveness for forecasting purposes. Thus, the rough sets technique used in the data reduction process allows the identification of relevant information of the data for climate prediction. In addition, it is a technique that approaches the problem of dealing with huge amounts of data which is a characteristic of the processes in meteorology.

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