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A study on a Neural Ecosystems Analyzer

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Abstract- The application of environmental science especially in ecological systems provide many opportunities and challenges for the technologies of modeling, control and analysis .This paper presents an overview of the impact of Artificial Intelligence techniques on the definition and development of ecosystems data.

An artificial neural network (ANN) is a system based on the emulation of biological neural system. In other words artificial neural networks (ANNs) are non-linear.

Mapping structures based on the function of the human brain. They have been shown to be universal and highly flexible function approximates for any data. These make powerful tools for models, especially when the underlying data relationships are unknown. In this paper, we briefly introduce algorithms frequently used; which is the back propagation algorithm. The future development and implementation of ANNs for ecosystems analysis is discussed in the present work. The paper includes selection of successful applications to a wide range of ecosystem problems.

Keywords- *ecosystem;artificial intelligence, ;back-probagation errors problem solving*

I. INTRODUCTION

The Artificial Neural Networks (ANNs) have been applied to an increasing number of real world problems of considerable complexity. Their most important advantage is in solving problems that are too complex for conventional technologies problems that do not have an algorithmic solution or for which an algorithmic Solution is too complex to be found. In general, because of their abstraction from the biological brain, ANNs are well suited to problems that people are good at solving, but for which computers are difficult to be solved.

The main focus of this research is trying to apply ANNs in an ecological system instead of statistical analysis and process. The neural network uses the well-known Back propagation Algorithm with the delta rule for adaptation of the system.

The back propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

II. INITIAL ANALYSIS AND PROBLEM STATEMENT

The general problem of simulating (or creating) intelligence has been broken down into a number of specific sub-problems. These consist of particular traits or capabilities that researchers would like an intelligent system to display. The traits described below have received the most attention. Deduction, reasoning, problem solving.

The research is trying to Study and produce intelligent a neural ecosystems analyzer, publications, and services that are beneficial to the environment especially ecological sciences.

Scope of this particular issue we are trying to apply Artificial Neural net works (ANNs) for Application of Neural computation to classification of ecology systems area which deal with Deduction, reasoning, problem solving like marine field , soil analysis and air pollutions.(Variations of ozone (O3) in specific industrial area).

An expert artificial neural ecosystem analyzer is designed; at the first which traces ingested food sources of marine species on inter tidal flats in Okinawa Island-Japan by analyzing their fatty acid profiles.

- Development An expert ecosystem analyzer for classifications data problems in environmental science especially ecology field.
- Speeding up weight adjustment Process Using Artificial Intelligence one of very important techniques in computer science.
- Improving the convergence of the back-propagation Algorithm (effective algorithm in Artificial intelligence science).
- Doing Graphics User Interface (GUI) Interface using the Java language for an Expert ecosystem Analyzer and implement the system analyzer to many applications in ecological science.

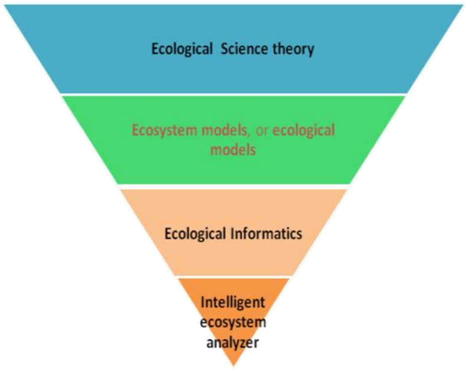


Fig. 1. Represents the current scope of ecological informatics indicating that ecological data is consecutively refined to ecological information, ecosystem theory and ecosystem decision support by two basic computational operations: data archival, retrieval and visualization, and ecosystem analysis, synthesis and forecasting.

III. RELATED WORK

The modern notion of ecosystem services can be traced back to at least the early 1970s. Since the late 1990s, however, several well-known studies have codified ecosystem services into generally accepted lists or typologies (Daily 1997; DeGroot, Wilson et al. 2002) The Millennium Ecosystem Assessment (Millennium Ecosystem Assessment 2002; Mooney, Cropper et al. 2004; Pereira, Queiroz et al. 2005) classified ecosystem services into “supporting services,” the ecological processes and functions that generate other ecosystem services, “regulating services” that maintain global and local conditions at levels appropriate for human survival, “provisioning services” that offer physical resources directly contributing to human well-being, and “cultural services” that satisfy psychological, emotional, and Abbreviations and Acronyms cultural needs. This classification has been extremely useful for communicating nature’s importance in satisfying different domains of human well-being. Yet recent authors have noted that the MA ecosystem services classification does not lend itself well to economic decision-making (Hein and van Ierland 2006; Boyd and Banzhaf 2007; Wallace 2007). This is because the MA categories do not explicitly link specific benefits to specific human beneficiaries of ecosystem services. Improved definition of these benefits and beneficiaries, combined with their spatial mapping, could aid in ecosystem service valuation, environmental accounting (Boyd and Banzhaf 2007), identification of winners and losers in conservation and development choices, and in supporting payments for ecosystem services programs.

From a spatial perspective, the supply side of ecosystem services has been relatively well-explored. A number of recent studies have used GIS analysis to measure the ecological factors contributing to the provision of certain services (Naidoo and Ricketts 2006; Beier, Patterson et al. 2008; Nelson, Mendoza et al. 2009). These studies explore how the provision of ecosystem services varies across the landscape. However, far fewer studies have explicitly identified the demand side, or human beneficiaries (Hein et al. 2006) or mapped these beneficiaries (Beier et al. 2008). Yet the need for such mapping is becoming increasingly recognized (Naidoo, Balmford et al. 2008). Supply and demand side mapping are complex, since ecosystem services provision and use often occur across different spatial and temporal scales (Hein et al. 2006). Others (Tallis and Polasky 2009) clearly describe the “spatial flow problem” in ecosystem services. The ecosystem services research community has as yet been unable to move beyond “static maps” to consider the cross-scale flows of ecosystem service to different groups of human beneficiaries. Existing attempts to categorization (Costanza 2008) break ecosystem services into coarse categories based on how their benefits spatially flow to beneficiaries but stop short of providing a quantitative conceptualization. In order to promote a breakthrough in ecosystem services assessment, we must start from the concepts of the MA framework.

Incorporate several key elements proposed by others, and move towards a science of ecosystem services that quantitatively assesses spatio-temporal flows of clearly identified benefits towards clearly identified beneficiaries.

IV. ABOUT TECHNIQUES AND METHODECOLOGICAL INFORMATICS BY COMPUTATIONAL ANALYSIS OF ECOLOGICAL DATA

Artificial intelligence methods include a wide variety of computational and algorithmic approaches to problem solving. Their common theme, however, is that they attempt to provide computers with a capability to solve problems in ways that have traditionally been the purview of humans. This means that AI methods incorporate such human cognitive abilities as: reasoning with anecdotal information and best-guess judgment (knowledge-based systems), using vague and commonplace descriptions of objects and events (fuzzy logic), making decisions based on learned patterns with little explicit knowledge or rationale (artificial neural networks), and dealing with large amounts of uncertain, yet interrelated, data and information (Bayesian belief networks).

V. ARTIFICIAL NEURAL NETWORKS (ANNS) BACKGROUND AND ECOLOGICAL APPLICATIONS

An artificial neural network (ANN), or, more generally, a multilayer perception, is modeling approach inspired by the way biological nervous systems process complex information.

The key element of the ANN is the novel structure of the information processing system, which is composed of a large number of highly interconnected elements called neurons, working in unity to solve specific problems. The concept of ANNs was first introduced in the 1940s (McCulloch and Pitts 1943); however, it was not popularized until the development of the back propagation training algorithm by Rumelhart et al. (1986). The flexibility of this modeling technique has led to its widespread use in many disciplines such as physics, economics, and biomedicine.

Researchers in ecology have also recognized the potential mathematical utility of neural network algorithms for addressing an array of problems. Previous applications include the modeling of species distributions(Mastrorillo et al. 1997; O¨ zesmi and O¨ zesmi 1999), species diversity (Gue´gan et al. 1998; Brosse et al. 2001; Olden et al. 2006b), community composition (Olden et al. 2006a), and aquatic primary and secondary production (Scardi and Harding).

VI. METHODOLOGY

There are many types of supervised and unsupervised learning methods for ANNs (Bishop 1995). Here we describe the most frequently used method in ecology: the one hidden-layer, supervised, feed forward neural network trained by the back propagation algorithm. These neural networks are popular in the ecological literature because they are considered to be universal approximators of any continuous function (Hornik et al. 1989). In this section, we will discuss neural network architecture and the back-propagation algorithm used to parameterize the network, and we will describe the various methods available to quantify variable importance. Network architecture refers to the number and organization of the neurons in the network (see Figure 2 for the general anatomy of a neural network). In the feed forward network, neurons are organized in an input layer, a hidden layer, and an output layer, with each layer containing one or more neurons. Each neuron is connected to all neurons in adjacent layers with an axon; however, neurons within each layer and in nonadjacent layers are not connected. The input layer typically contains p neurons, one neuron representing each of the independent variables x1 through xp. The number of neurons in the hidden layer can be selected arbitrarily or determined empirically by the investigator to minimize the trade-off between bias and variance (Geman et al. 1992). The addition of hidden neurons increases the ability of a network to approximate any underlying relationship among the variables, i.e., resulting in reduced bias, but also increases the variance of predictions due to overfitting the data. Although mathematical derivations exist for selecting an optimal design (see Bishop 1995), in practice it is common to train networks with different numbers of hidden neurons and to use the performance on a test data set to choose the network that performs the best. For continuous and binary response variables, the output layer commonly contains one neuron, but the number of output neurons can be greater than one if there is more than one response variable or if the response variable is categorical (i.e., a separate neuron for classifying observations into each category). Additional bias neurons with a constant output are also added to the hidden and output layers, although this is not mandatory, as these neurons play a similar role to the intercept term in general linear regression. Each neuron in the network has an "activity level" that is defined by the value of the incoming signals received from the other neurons connected to it. In turn, each axon in a network is assigned a "connection weight" that reflects the overall intensity of the signal it transmits (i.e., input to hidden or hidden to output). The activity levels of the input neurons are defined by the values of the predictor variables (Figure 2).

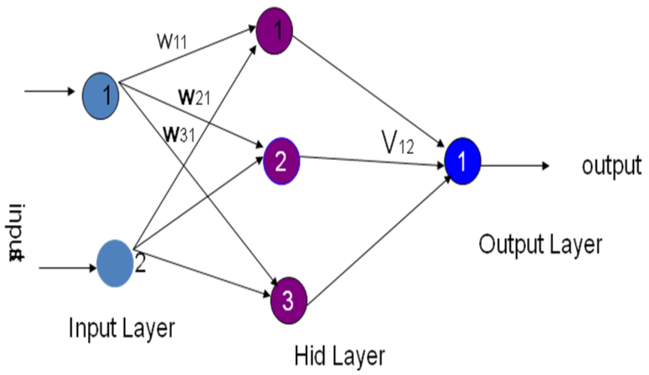
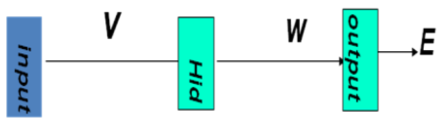


Fig. 2. The General Anatomy of an Artificial Neural Network

The state of each hidden neuron is evaluated locally by calculating the weighted sum of the incoming signals from the neurons of the input layer, which is then subjected to an activation function, i.e., a differentiable function of the neuron's total incoming signal from all input neurons. The same procedure described above is repeated for the axon signals from the hidden layer to the output layer. Training the neural network typically involves an error back-propagation algorithm that searches for an optimal set of connection weights that produces an output signal with a small error relative to the observed output (i.e., minimizing the fitting criterion). For continuous output variables, the most commonly used criterion is the least-squares error function, whereas for dichotomous output variables, the most commonly used criterion is the cross entropy error function, which is similar to log likelihood (Bishop 1995). The algorithm adjusts the connection weights in a backwards fashion, layer by layer, in the direction of steepest descent, thus minimizing the error function (this is also called gradient descent). The training of the network is a recursive process where observations from the training data are entered into the network in turn, each time modifying the input-hidden and hidden output connection weights. This procedure is repeated with the entire training dataset (i.e., each of the n observations) for a number of iterations or epochs until a stopping rule (e.g., error rate) is achieved. Prior to training the network, the independent variables should be converted to z scores (0 to 1) in order to standardize the measurement scales of the inputs into the network.



Adapt the weights (W,V) So that E 0

$$W_{ji} = W_{ji} - \eta \frac{\partial E}{\partial W_{ji}}$$

$$V_{ik} = V_{ik} - \mu \frac{\partial E}{\partial V_{ik}}$$

Fig. 3. Adaptations of connections weights. The Bp algorithm uses the gradient descendent to adapt the weights (delta rule)

Recent efforts have focused on the development of methods for understanding the explanatory contributions of the independent variables in ANNs (Olden and Jackson 2002b). This was, in part, prompted by the fact that neural networks were considered a "black box" approach to modeling ecological data because of the perceived difficulty in understanding their inner workings. Recent studies in the biological sciences have provided a variety of methods for quantifying and interpreting the contributions of the independent variables in neural networks (see Olden and Jackson 2002b; Gevrey et al. 2003; Olden et al. 2004). These approaches utilize the fact that the connection weights between neurons are the linkages between the inputs and the output of the neural network, and, therefore, the relative contribution of each independent variable depends on the magnitude and direction of these connection weights. Input variables with larger connection weights represent greater intensities of signal transfer; they are more important in predicting the output compared to variables with smaller weights. Negative connection weights reduce the intensity or contribution of the incoming signal and negatively affect the output, whereas positive connection weights increase the intensity of the incoming signal and positively affect the output.

One method, the connection weight approach, uses the product of the input-hidden and hidden-output connection weights to determine variable importance (Olden et al. 2004). Other approaches include Garson's algorithm (Garson 1991), partial derivatives (Dimopoulos et al. 1995), a sensitivity analysis to determine the spectrum of input variable contributions in the neural network (Lek et al. 1996), and a number of pruning algorithms (Bishop 1995), including a randomization test to remove small connection weights (Olden and Jackson 2002b). Although these approaches can determine the overall influence of each independent variable, the interpretation of interactions among the variables requires the direct examination of the network connection weights (e.g., O¨ zesmi and O¨ zesmi 1999; Olden and Jackson 2001)

Artificial Intelligence for Ecosystem Services (ARIES)

Using Artificial Intelligence for ecosystems services is and methodology and web application meant to assess ecosystem services (ES) and illuminate their values to humans in order to make environmental decisions easier and more effective. By creating ad-hoc, probabilistic models of both provision and usage of ES in a region of interest, and mapping the actual physical flows of those benefits to their beneficiaries, ARIES helps discover, understand, and quantify environmental assets, and what factors influence their value according to explicit needs and priorities. In this contribution, we present the basic elements of the ARIES methodology and illustrate perspectives for integration of new ES thinking into science, decision- and policy-making.

VII. CONCLUSIONS AND FUTURE WORK

Jobs being under investigation are to improve further the success rate, enhancement of both the underlying neural network structure and the adopted back-propagation learning algorithm.

And more tasks are speeding up the weight adjustment process, improving the convergence of Back-Propagation learning Algorithm. And doing Graphics user Interface (GUI) Interface Framework using Java Language for the Neural Ecosystem Analyzer.

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