Artificial Neural Networks and Forecasting Disasters

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Abstract

Since artificial neural networks (ANNs) can approximate any function, they have been applied in many fields including hydrology. In hydrology, there are important issues such as flood estimation and predicting rainfall-runoff in a certain area. In this presentation, we briefly introduce a popular feed-forward neural network model, so called "multi-layer perceptron (MLP)", and review its application to hydrology.

Keywords: multilayer perceptron, flood estimation, rainfall-runoff prediction.

1. Introduction

Among disasters, flooding has been focused because of its drastic impact on lives and properties in wide area. It is estimated that of the total economic loss caused by all kinds of disasters, 40% are due to flooding. The relationship between rainfall and flood discharge is very complex[1]. So, modelling the relationships between rainfall and flooding or runoff are still unsolved problems[2-7].

There have been increasing of interest in artificial neural networks (ANNs) because of their information processing capability through learning from exemplars[8]. When modelling a phenomena using ANN, it is not necessary to elucidate complex mechanisms involving the phenomena[6]. Because of this property, ANN has been widely applied in hydrology. In this presentation, we firstly introduce ANNs, especially multilayer perceptron (MLP) model. And, we review the modelling of rainfall-runoff and rainfall-flooding.

2. Artificial Neural Networks (ANNs)

ANNs are models imitating neural networks in human brain which are capable of high level information processing[8]. They can be categorized into unsupervised and supervised models. Supervised models learn from exemplars with their targets, which are desired output values when the exemplars are presented to the supervised neural network model. On the contrary, unsupervised models learn from exemplars without any target. SOM (self-organizing feature map) and ICA(independent component analysis) network belong to the unsupervised model. GPFN(Gaussian potential function network) and MLP(multi-layer perceptron) are representative supervised models. Especially, it had been proved that MLP can approximate any function with enough hidden nodes. Based on the mathematical proof, MLP has been applied to many fields such as pattern recognition, time series prediction, fraud detection etc.

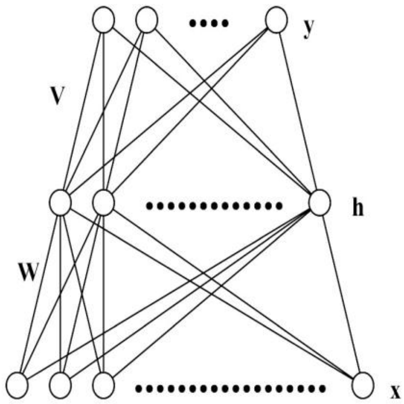

Figure 1. The architecture of MLP.

In this presentation, we briefly review MLP and its application to hydrology. Fig. 1 shows the architecture of MLP, which consists of input node vector **x**, hidden node vector **h**, output node vector **y**, and their connection weights. When an input vector $\mathbf{x} = [x_1, x_2, \cdots, x_N]^T$ is presented to the MLP, a weighted sum to the *j*-th hidden node is given by $a_j = \sum_{i=1}^{N} w_{ji} x_i + w_{j0}$ and its hidden node value is $h_j = \tanh(a_j)$. Here, w_{j0} is a bias and w_{ji} is a weight between h_j and x_i. The k-th output node y_k is calculated through the same procedure of weighted sum and nonlinear transform $\tanh(.)$ using the weight v_{kj} and the hidden node value h_j. When $y_k^{(p)}$ is given with its target value $t_k^{(p)}$ for a specific training exemplar $\mathbf{x}^{(p)}$, we usually updates weights w_{ji} and v_{kj} to minimize the error function $E^{out} = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{M}\left(t_k^{(p)} - y_k^{(p)}\right)^2$. Here, P is the number of training exemplars and M is the number of output nodes. The error back-propagation (EBP) algorithm provides updating procedure of w_{ji} and v_{kj} [8] as follows:

$$\Delta v_{kj} = -\eta \frac{\partial E^{out}}{\partial v_{kj}} = \eta \delta_k^{(p)} h_j^{(p)} \text{ where} \delta_k^{(p)} = -\frac{\partial E^{out}}{\partial \hat{y}_k^{(p)}} = (t_k^{(p)} - y_k^{(p)}) f'(\hat{y}_k^{(p)})$$

$$\Delta w_{ji} = -\eta \frac{\partial E^{out}}{\partial w_{ji}} = \eta f'(\hat{h}_j^{(p)}) x_i^{(p)} \sum_{k=1}^{M} v_{kj} \delta_k^{(p)}.$$

3. Hydrological Modelling Using MLPs

As examples of applying MLPs to hydrological modeling, firstly, we review the predicting catchment flow in a semi-grid region by Riad et al[7]. In the study, the flow and rainfall time-series observed in Ourika basin at Aghbalou station in Morocco is analyzed. The rainfall and runoff data at the Aghbalou station for a period of 28 years (1969 to 1996) were used for model development. It represents 10220 daily values of rainfall and runoff pairs. The input vector of MLP consists of rainfall and runoff values for previous 7 days (*t-1, t-2, ..., t-7*) as well as the rainfall value expected for day *t*. And, the output node is the expected runoff value for day *t*.

Among 28 years of daily sets of rainfall-runoff values for the Ourika basin, the data for last 3 years are used for testing and the others are used for training. According to the test result of figure 3 in [7], predicted/actual flow points are near the equality line[7]. So, we can argue that the MLP successfully models the rainfall-runoff in Ourika basin.

There are many similar applications. Feng and Lu predicted the lower peak stage based on the upper peak stage at Dadu river in China[2]. Dawson et al. estimated flood in UK based on 16 inputs such as catchment drainage area, longest drainage path, mean distance between each node and catchment outlet, average annual rainfall, etc[3]. Wei et al. proposed a neural network based predictive method for flood disaster area in China[5]. In hydrology, ANNs are applied in wide problems through the learning capability from exemplars. Here, gathering data and preprocessing them for training and test are important issue[7].

4. Discussion and Conclusion

In this presentation, we briefly introduce ANNs and review the application of MLPs to hydrological problems. Since MLP can approximate any function with enough hidden nodes, we can apply MLP to many problems with proper data. So, gathering, preprocessing, and analyzing data are very important for application of ANNs to hydrology. Also, deep architecture of MLP will improve the performance.

5. References

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