Time Series Prediction with Multilayer Perceptron (MLP): A New Generalized Error Based Approach

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Abstract. The paper aims at training multilayer perceptron with different new error measures. Traditionally in MLP, Least Mean Square error (LMSE) based on Euclidean distance measure is used. However Euclidean distance measure is optimal distance metric for Gaussian distribution. Often in real life situations, data does not follow the Gaussian distribution. In such a case, one has to resort to error measures other than LMSE which are based on different distance metrics [7,8]. It has been illustrated in this paper on wide variety of well known time series prediction problems that generalized geometric and harmonic error measures perform better than LMSE for wide class of problems.

1 Introduction

Time series prediction and forecasting are key problems of function approximation. In the existing literature, various neural network learning algorithms have been used for these problems [1,2,3]. In this paper, we have used multilayer perceptron (MLP) neural network for time series prediction. MLP is composed of a hierarchy of processing units, organized in series of two or more mutually exclusive sets of neurons or layers. The input layer serves as the holding site for the input applied to the network. The output layer is the point at which the overall mapping of the network input is available [4,5]. Most widely used algorithm for learning MLP is the back-propagation algorithm [6]. In Back-propagation algorithm, error between target value and observed value is minimized. Typically Euclidean distance is used to for the error measure. It has been proven based on Maximum Likelihood criterion that Euclidean distance is optimal distance metric for Gaussian distribution [7,8].Since the distribution of data is unknown, using LMSE for training of MLP may not give the actual approximation of the functions.In this paper, Back-propagation algorithm with some new error measures based on distance metrics (for similarity measures) given by Jie Yu et al

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[7,8] has been used for training MLP for time series prediction. Comparative performance for each of the error measures has been done on a wide variety of well known time series prediction problems. The performance measures used are chi-square goodness of fit test, AIC and training and testing error.

Rest of the paper is organized as follows, Section 2, gives the overview of distance metrics used as various error measures. The network architecture of feed-forward (MLP) neural network is presented in section 3. In section 4, learning rule of MLP using Back-propagation (BP) algorithm with different error measures has been discussed. In section 5, results have been tested on several widely known time series prediction and forecasting data sets. In section 6, we have concluded our work.

2 New Error Measures

Traditionally Back-propagation (BP) algorithm is used in training Artificial Neural Network (ANN). The performance of Neural Network depends on the method of error computation. It has been proven that when the underlying distribution of data is Gaussian, Least mean square error (LMSE) [7,8] is best for training the network. %begincenter Since the distribution of data is unknown, it may be possible that error computed based on Euclidean distance may not be suitable for training of neural network. It will be reasonable to assume that there may be some distance metric which will give new error measure to fit the unknown data better. Some new error measures based on distance metric for similarity measures [7,8] is given in Table 1. In Table 1, y_i denotes the desired value of neuron, t_i denotes the target value and N denotes number of pattern.In error estimation, if the target value is far away from the desired value, error measure

Table 1.

	Error Measure
LMS	$E = \frac{1}{2}\sum_{i=1}^{N}(t_i - y_i)^2$
Geometric	$E = \frac{1}{2}\sum_{i=1}^{N}[log(t_i/y_i)]^2$
Harmonic	$E = \frac{1}{2}\sum_{i=1}^{N}[t_i(y_i/t_i) - 1]^2$
Generalized Geometric	$E = \frac{1}{2}\sum_{i=1}^{N}[{t_i}^r \log(t_i/y_i)]^2$
Generalized Harmonic Type-1	$E = \frac{1}{2}\sum_{i=1}^{N}[{t_i}^p(y_i/t_i) - 1]^2$
Generalized Harmonic Type-2	$E = \frac{1}{2}\sum_{i=1}^{N}({t_i}^q - {y_i}^q)^2$