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DATA PREDICTION FROM A SET OF SAMPLED DATA USING ARTIFICIAL NEURAL NETWORK IN MATLAB SIMULINK

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ABSTRACT

Recent studies have shown the classification and prediction power of the Neural Networks. It has been demonstrated that a NN can approximate any continuous function. Neural networks have been successfully used for forecasting. The classical methods used for time series prediction like Box-Jenkins or ARIMA assumes that there is a linear relationship between inputs and outputs. Neural Networks have the advantage that can approximate nonlinear functions. Classical statistical and econometric models used to predict efficiently handle uncertainty nature of data analysis. Prediction of the data from a set of sampled data is a difficult problem from both theoretical and practical point of view because the collections of data are influenced by many economic and natural factors. During the time, many statistical and econometric models have been developed by researchers for the purpose of prediction of data analysis but this problem remains one of the major challenges in the field of prediction and forecasting methods. In this paper we compared the performances of different feed forward and recurrent neural networks and training algorithms for prediction of the desired data and tried to see the implementation and comparison of the performance for foreign exchange rate prediction and finally to select the best method between this two feed forward of that keep the greater influence than the other in the field of prediction.

KEYWORDS: Artificial Neural Network, MATlab Simulation, Data Prediction.

1. INTRODUCTION

1.1 Background

The classical methods used for prediction like Box-Jenkins, ARMA or ARIMA assume that there is a linear relationship between inputs and outputs. Neural Networks have the advantage that can approximate any nonlinear functions without any apriority information about the properties of the data series. Recent studies have shown the classification and prediction power of the Artificial Neural Networks. It has been demonstrated that a neural network can approximate any continuous function. Neural networks have been successfully used for forecasting of data series. This step involves determining the logical consequences of the hypothesis. One or more predictions are then selected for further testing. The more unlikely that a prediction would be correct simply by coincidence, then the more convincing it would be if the prediction were fulfilled; evidence is also stronger if the answer to the prediction is not already known, due to the effects of hindsight bias. Ideally, the prediction must also distinguish the hypothesis from likely alternatives; if two hypotheses make the same prediction, observing the prediction to be correct is not evidence for either one over the other. These statements about the relative strength of evidence can be mathematically derived using Bayes' Theorem. Markov Chain is also used to predict different type of prediction process. In many applications, such as time series analysis, it is possible to estimate the models that generate the observations. If models can be expressed as transfer functions or in terms of state-space parameters then smoothed, filtered and predicted data estimates can be calculated. If the underlying generating models are linear then a minimum-variance Kalman filter and a minimum-variance smoother may be used to recover data of interest from noisy measurements. These techniques rely on one-step-ahead predictors which minimize the variance of the prediction error. When the generating models are nonlinear then stepwise linearization may be applied within Extended Kalman Filter and smoother recursions. However, in nonlinear cases, optimum minimum-variance performance guarantees no longer apply. [An-Sing Chen, Mark T. Leung, Hazem Daouk, Application of neural networks toforecasting and trading].

1.2 Motivations

This tutorial introduces to the topic of predicting using artificial neural network. In this particular prediction of data using multi-layer feed-forward neural networks will be described. Here the well performed programming machine MATlab is used so that we may train automatically the whole function as we desire. In statistics, prediction is a part of statistical inference. One particular approach to such inference is known as predictive inference, but the prediction can be undertaken within any of the several approaches to statistical inference. Indeed, one possible description of statistics is that it provides a means of transferring knowledge about a sample of a population to the whole population, and to other related populations, which is not necessarily the same as prediction over time. When information is transferred across time, often to specific points in time, the process is known as forecasting. Forecasting usually requires time series methods, while prediction is often performed on cross-sectional data.

2. Literature review

2.1 Introduction

In science, a prediction is a rigorous, often quantitative, statement, forecasting what would happen under specific conditions; for example, if an apple fell from a tree it would be attracted towards the center of the earth by gravity with a specified and constant acceleration. The scientific method is built on testing statements that are logical consequences of scientific theories. This is done through repeatable experiments or observational studies. A scientific theory which is contradicted by observations and evidence will be rejected. New theories that generate many new predictions can more easily be supported or falsified (see predictive power). Notions that make no testable predictions are usually considered not to be part of science (protoscience or nescience) until testable predictions can be made.[S. Haykin, Neural Networks, Chapter-2, Article- 2.2].

2.2 About Matlab

MATLAB is a programming platform designed specifically for engineers and scientists. The heart of MATLAB is the MATLAB language, a matrix-based language allowing the most natural expression of computational mathematics. MATLAB combines a desktop environment tuned for iterative analysis and design processes with a programming language that expresses matrix and array mathematics directly that expresses matrix and array mathematics directly. We can do many things like bellow with MATLAB.

- Analyze data;
- Develop algorithms;
- Create models and applications.

The language, apps, and built-in math functions enable you to quickly explore multiple approaches to arrive at a solution. MATLAB lets you take your ideas from research to production by deploying to enterprise applications and embedded devices, as well as integrating with Simulink and Model-Based Design. A highly efficient language for technical computation is called MATLAB. It combines visual, computations, and programming in an easy-to-use environment where problems and solutions are given in well-known mathematical expressions. It is used for:

- Math and computation;
- Data analysis, exploration, and visualization;
- Algorithm development;
- Scientific and engineering graphics;
- Modeling, simulation, and prototyping;
- Application development, including Graphical User Interface building.

The data element is considered as an array in a MATLAB interactive system that does not need dimensioning. It solves many issues regarding technical and computations especially the ones which include vector and matrix expressions, by using languages like C or FORTRAN you can write this program in no time. Matrix laboratory is supported by MATLAB and it was created for giving a user-friendly access to matrix software written by LINPACK and EISPAKC projects, that together gives the state-of-the-art in matrix computation software.

There has been a periodic evolution of MATLAB over the years with many users providing input. For basic and advanced mathematics, science, and engineering it is the general instruction tool used in a university environment. For development, analysis, research, and higher productivity MATLAB is the apt choice used by the industry. A group of application-specific solutions namely tool boxes is the main feature of MATLAB. It permits you for learning and applying specialized technology. There are vast collections of MATLAB functions in Toolboxes that enhances the ambiance of MATLAB to solve problems of a particular class. Signal processing, neural networks, wavelets, simulation, fuzzy logic, control systems and much more are the areas where tool boxes are available.[Introduction to MATLAB, MATHworks, Chapter-2].

2.3 MATLAB System

It comprises of five main parts

1. Matlab Language

It is an array or matrix language at a higher level with control flow statements, functions, input/output, data structures, object-oriented programing features, etc. It permits both small programming for creating fast and junk throw-away programs, and big programming for creating difficult and big application programs.

2. Matlab Ambience

It has a set of tools offering lots of provisions that perform with as the MATLAB user or programmer. It provides help for variable management in your workspace and data transfer. Developing, managing, debugging, and profiling M-files can be done using the tools of MATLAB.

3. Graphics Management

Offering higher level commands for two dimensional and three-dimensional data visualization, animation, image processing, and presentation graphics are included in the Graphics management. Low-level commands for allowing full customization view of graphics for building Graphical User Interfaces on your MATLAB applications.

4. Mathematical Library Functions of Matlab

There are various basic operations like sum, cosine, sine, and complex operations collection of computational algorithms for more sophisticated functions like matrix eigenvalues, inverse, fast Fourier transforms, and Bessel functions.

5. Matlab Application Program Interface (API)

C and FORTRAN programs for interacting with MATLAB are permitted by the library. There are other facilities included for calling routines from MATLAB (dynamic linking), calling MATLAB as a computational engine, MAT-files with reading and writing facility.[S. Haykin, Neural Networks, Chapter-3, Article- 3.2].

2.4 Model & Simulate Dynamic System Behavior with Matlab, Simulink & Simscape

Modeling is a way to create a virtual representation of a real-world system that includes software and hardware. If the software components of this model are driven by mathematical relationships, you can simulate this virtual representation under a wide range of conditions to see how it behaves.

Modeling and simulation are especially valuable for testing conditions that might be difficult to reproduce with hardware prototypes alone, especially in the early phase of the design process when hardware may not be available. Iterating between modeling and simulation can improve the quality of the system design early, thereby reducing the number of errors found later in the design process.

Common representations for system models include block diagrams, schematics, and state charts. Using these representations you can model mechatronic systems, control software, signal processing algorithms, and communications systems. [Introduction to MATLAB, Mathworks, Chapter- 3].

2.5 Artificial Neural Network in Matlab

The work flow for the general neural network design process has seven primary steps:

- Collect data
- Create the network
- Configure the network
- Initialize the weights and biases
- Train the network
- Validate the network (post-training analysis)
- Use the network

2.5.1 Neuron Model (logsig, tansig, purelin)

An elementary neuron with *R* inputs is shown below. Each input is weighted with an appropriate *w*. The sum of the weighted inputs and the bias forms the input to the transfer function *f*. Neurons can use any differentiable transfer function *f* to generate their output.

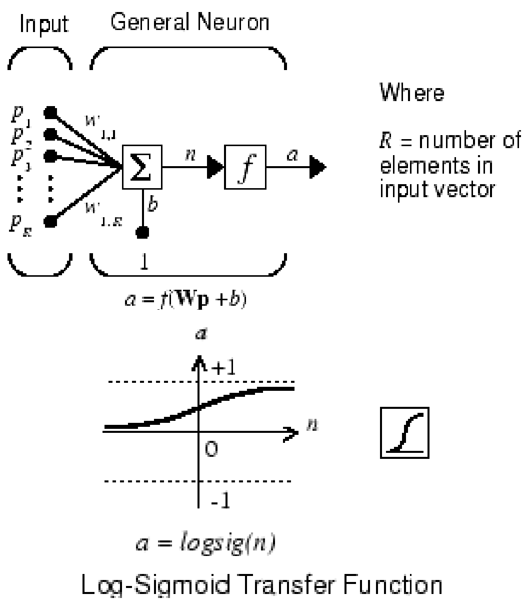


Figure 2.1: Log-Sigmoid Transfer Function.

2.5.2 Feed forward Neural Network

A single-layer network of S log sig neurons having R inputs is shown below in full detail on the left and with a layer diagram on the right.

2.5.3 Multilayer Neural Network Architecture

Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear relationships between input and output vectors. The linear output layer is most often used for function fitting (or nonlinear regression) problems.[R. Schalkoff, Artificial Neural Networks, Chapter-4].

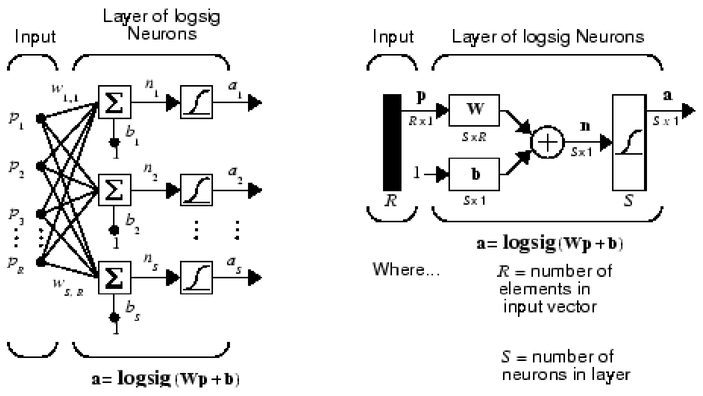

Input
Layer of logsig Neurons
a= logsig (Wp+b)
Where...
R = number of elements in input vector
S = number of neurons in layer

Figure 2.2: Multilayer Neural Network.

2.6 Prepare Data for Multilayer Neural Networks

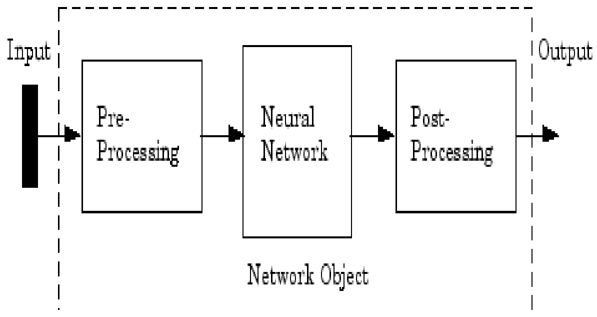
Before beginning the network design process, you first collect and prepare sample data. It is generally difficult to incorporate prior knowledge into a neural network; therefore the network can only be as accurate as the data that are used to train the network. It is important that the data cover the range of inputs for which the network will be used.

Multilayer networks can be trained to generalize well within the range of inputs for which they have been trained. However, they do not have the ability to accurately extrapolate beyond this range, so it is important that the training data span the full range of the input space. After the data have been collected, there are two steps that need to be performed before the data are used to train the network: the data need to be preprocessed, and they need to be divided into subsets.

2.6.1 Choose Neural Network Input-Output Processing Functions

Neural network training can be more efficient if you perform certain preprocessing steps on the network inputs and targets. This section describes several preprocessing routines that you can use. (The most common of these are provided automatically when you create a network, and they become part of the network object, so that whenever the network is used, the data coming into the network is preprocessed in the same way).

For example, in multilayer networks, sigmoid transfer functions are generally used in the hidden layers. These functions become essentially saturated when the net input is greater than three ($\exp(-3) \cong 0.05$). If this happens at the beginning of the training process, the gradients will be very small, and the network training will be very slow. In the first layer of the network, the net input is a product of the input times the weight plus the bias. If the input is very large, then the weight must be very small in order to prevent the transfer function from becoming saturated. It is standard practice to normalize the inputs before applying them to the network.



2.6.2 Create, Configure & Initialize Multilayer Neural Networks

After the data has been collected, the next step in training a network is to create the network object. The function feed forward net creates a multilayer feed forward network. If this function is invoked with no input arguments, then a default network object is created that has not been configured. The resulting network can then be configured with the configure command. The configure command configures the network object and also initializes the weights and biases of the network; therefore the network is ready for training. There are times when you might want to reinitialize the weights, or to perform a custom initialization. “Initializing Weights” on page explains the details of the initialization process. You can also skip the configuration step and go directly to training the network. The train command will automatically configure the network and initialize the weights.

3. METHODOLOGY

3.1 Introduction

Artificial neural networks are relatively crude electronic networks of neurons based on the neural structure of the brain. They process records one at a time, and learn by comparing their prediction of the record (largely arbitrary) with the known actual record. The errors from the initial prediction of the first record is fed back to the network and used to modify the network's algorithm for the second iteration. These steps are repeated multiple times. Neural networks can be used to make predictions on time series data such as weather data. A neural network can be designed to detect pattern in input data and produce an output free of noise. The structure of a neural-network algorithm has three layers:

- The input layer feeds past data values into the next (hidden) layer. The black circles represent *nodes* of the neural network.
- The hidden layer encapsulates several complex functions that create predictors; often those functions are hidden from the user. A set of nodes (black circles) at the hidden layer represents mathematical functions that modify the input data; these functions are called neurons.
- The output layer collects the predictions made in the hidden layer and produces the final result: the model's prediction.

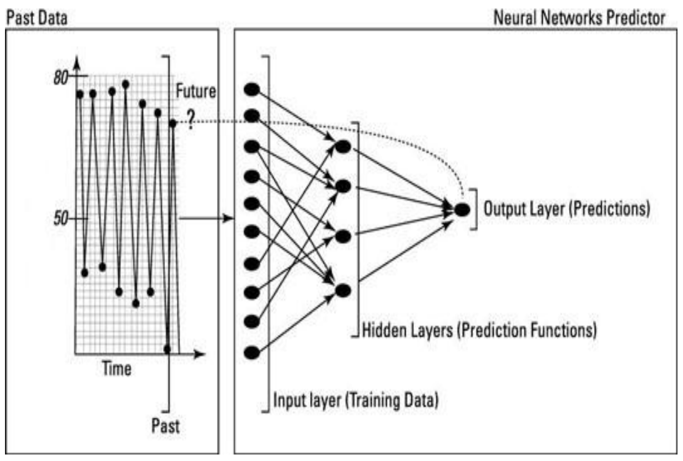

Past Data
Neural Networks Predictor
80
50
Future
?
Time
Past
Output Layer (Predictions)
Hidden Layers (Prediction Functions)
Input layer (Training Data)

Figure 3.1: Layers of a function.

A neuron in an artificial neural network is:

1. A set of input values (xi) with associated weights (wi)
2. An input function (g) that sums the weights and maps the results to an output function(y).

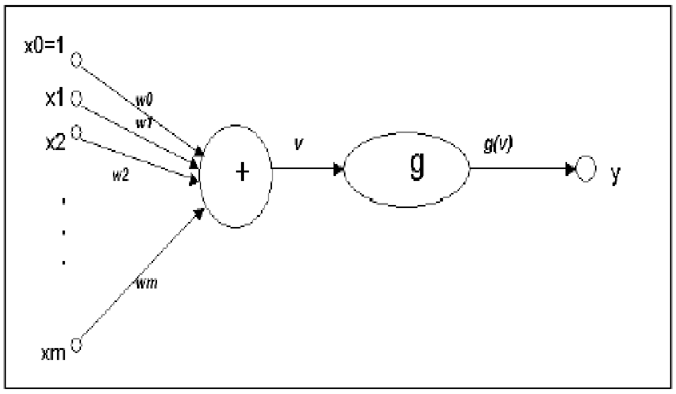


Figure 3.2: Structure of a function.

Neurons are organized into the following layers: input, hidden, and output. The input layer is composed not of full neurons, but simply of the values in a record that are inputs to the next layer of neurons. The next layer is the hidden layer of which there could be several. The final layer is the output layer, where there is one node for each class. A single sweep forward through the network results in the assignment of a value to each output node. The record is assigned to the class node with the highest value.[T. Masters, Practical Neural Network Recipes, Chapter- 4, Article- 4.4].

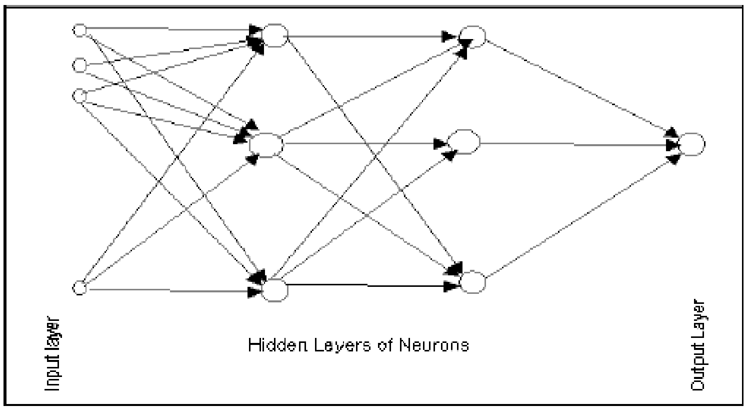


Figure 3.3: Working process of a neuron.

3.2 Neural Network Models

Neural networks have been achieving great success in natural language processing. Work in this field with neural networks is mostly based on learning continuous vector representations of words By representing words in a low dimensional continuous embedding space, continuous word vectors can encode semantic and syntactic features of words and are supposed to be superior to conventional methods that treat words as discrete symbols or use discrete word representations such as one-hot vectors.

Our neural network based approaches to sequence prediction are developed on top of the continuous word vectors that are trained using Continuous Bag-of-Words Model (CBOW) proposed and implemented by. With pre trained word vectors, we transform the original discrete symbol sequences as follows. Given a sequence of length L, we first right pad it with the symbol END, which indicates the end of the sequence. Assume that we predict the next symbol from the previous k symbols; we also need to left pad the sequence with k DUMMY symbols, so that we can construct the inputs to the classifier when predicting the first k symbols of the sequence. We then construct the training set for the neural network classifier: for each symbol s in the sequence (other than the DUMMY symbols), we sequentially concatenate the word vectors of its previous k symbols as the input and regard s as the label. Figure in below gives an example of this procedure.

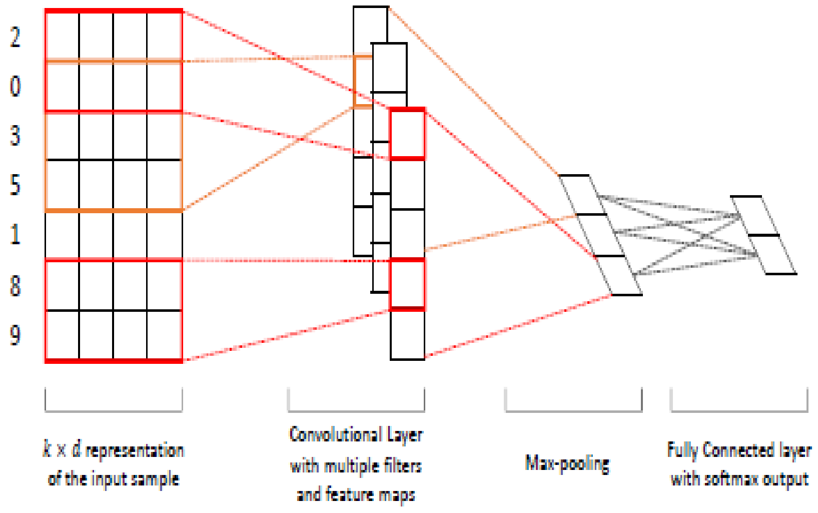

2
0
3
5
1
8
9
k x d representation of the input sample
Convolutional Layer with multiple filters and feature maps
Max-pooling
Fully Connected layer with softmax output

Figure 3.4: Sequence layers of Neural Network.

We use three different neural network classifiers as described below.

- MLP is a feed forward artificial neural network model that consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Each node in intermediate layers (hidden layers) is a neuron with a nonlinear activation function (tanh, ReLU, or sigmoid). The output layer is a soft max layer that implements soft max function for classification and cross-entropy cost function is used while training the MLP model.

- CNN is a feed forward neural network that contains convolution layers with a nonlinear activation function such as ReLU. Besides, CNN could also contain pooling layers that are usually used immediately after each convolution layer. In SPiCe we employ the CNN model. For simplicity, the input layer only contains a static channel, and we do not enforce the L2-norm constraint on the weight vectors that parameterize the soft max function, which Zhang and Wallace (2015) found generally did not improve performance much. Figure 2 shows our CNN model architecture for sequence prediction.

- LSTM is a special kind of recurrent neural network (RNN) architecture that was proposed by Hoch Reiter and Schmidhuber (1997) to combat the vanishing gradient problem. Featured with the gating mechanism, LSTM is well-suited to model long term dependencies and has been successfully applied to language modeling. In P Spice we use the standard LSTM architecture, and the hidden state of the LSTM model is fed to the logistic regression classifier.

3.3 Feed Forward

The feed forward, back-propagation architecture was developed in the early 1970s by several independent sources (Werbor, Parker, Rumelhart, Hinton, and Williams). This independent co-development was the result of a proliferation of articles and talks at various conferences that stimulated the entire industry. Currently, this synergistically developed back-propagation architecture is the most popular and effective model for complex, multi-layered networks. Its greatest strength is in non-linear solutions to ill-defined problems. The typical back-propagation network has an input layer, an output layer, and at least one hidden layer. Theoretically, there is no limit on the number of hidden layers, but typically there are just one or two. Some studies have shown that the total number of layers needed to solve problems of any complexity is five (one input layer, three hidden layers, and an output layer). Each layer is fully connected to the succeeding layer.

The training process normally uses some variant of the Delta Rule, which starts with the calculated difference between the actual outputs and the desired outputs. Using this error, connection weights are increased in proportion to the error times, which are a scaling factor for global accuracy. This means that the inputs, the output, and the desired output all must be present at the same processing element. The most complex part of this algorithm is determining which input contributed the most to an incorrect output and how to modify the input to correct the error. (An inactive node would not contribute to the error and would have no need to change its weights.) To solve this problem, training inputs are applied to the input layer of the network, and desired outputs are compared at the output layer. During the learning process, a forward sweep is made through the network, and the output of each element is computed layer by layer. The difference between the output of the final layer and the desired output is back-propagated to the previous layer(s), usually modified by the derivative of the transfer function. The connection weights are normally adjusted using the Delta Rule. This process proceeds for the previous layer(s) until the input layer is reached.

3.4 Structuring the Network

The number of layers and the number of processing elements per layer are important decisions. To a feed forward, these parameters back-propagation topology, are also the most ethereal - they are the art of the network designer. There is no quantifiable, best answer to the layout of the network for any particular application. There are only three general rules picked up over time and followed by most researchers and engineers applying this architecture to their problems.

Rule One: As the complexity in the relationship between the input data and the desired output increases, the number of the processing elements in the hidden layer should also increase.

Rule Two: If the process being modeled is separable into multiple stages, then additional hidden layer(s) may be required. If the process is not separable into stages, then additional layers may simply enable memorization of the Training Set, and not a true general solution.

Rule Three: The amount of training data available sets an upper bound for the number of processing elements in the hidden layer(s). To calculate this upper bound, use the number of cases in the Training Set and divide that number by the sum of the number of nodes in the input and output layers in the network. Then divide that result again by a scaling factor between five and ten. Larger scaling factors are used for relatively less noisy data. If too many artificial neurons are used, the Training Set will be memorized, not generalized, and the network will be useless on new data sets.

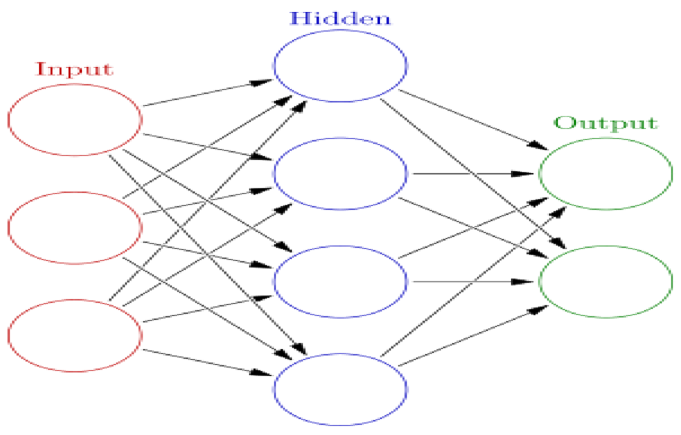


Figure 3.5: Structure of ANN.

4. RESULT AND ANALYSIS

4.1 Introduction

Predicting is making claims about something that will happen, often based on information from past and from current state. Everyone solves the problem of prediction every day with various degrees of success. For example weather, harvest, energy consumption, movements of foreign exchange currency pairs or of shares of stocks, earthquakes, and a lot of other stuff needs to be predicted. In technical domain predictable parameters of a system can be often expressed and evaluated using equations - prediction is then simply evaluation or solution of such equations. However, practically we face problems where such a description would be too complicated or not possible at all. In addition, the solution by this method could be very complicated computationally, and sometimes we would get the solution after the event to be predicted happened.

For the computation of this study first the topic of prediction will be described together with classification of prediction into types. After that, the prediction using neural networks (NNs) will be described. The focus will be on the creation of a training set from collected data. For the illustration of this topic MATlab from MATH works are available that illustrate the creation of a training set and that show the result of a prediction using a neural network of both on primary and secondary data.

4.2 Prediction

Neural networks can be used for prediction with various levels of success. The advantage of then includes automatic learning of dependencies only from measured data without any need to add further information (such as type of dependency like with the regression). The neural network is trained from the historical data with the hope that it will discover hidden dependencies and that it will be able to use them for predicting into future. In other words, neural network is not represented by an explicitly given model. It is more a black box that is able to learn something.

It is possible to predict various types of data, however in the rest of this text we will focus on predicting of time series. Time series shows the development of a value in time. Of course, the value can be influenced by also other factors than just time. Time series represents discrete history of a value and from a continuous function it can be obtained using sampling. The prediction type can be classified according to various criteria. Basic criteria are,

- Data that we have for teaching prediction and for prediction.
- What we want to predict - value or trend.

4.3 Predicting Value or Trend

When we want to get exact value (or more values) of a variable in future, then we are predicting value. Other possibility is to predict trend of a variable, i.e., whether the value will go up or down without considering size of the change - then we are predicting trend. When predicting trend we are in fact classifying into two (or three) classes - up and down (or no significant change). Prediction of a close value is generally easier than predicting a trend. Besides trend we may also want to predict other parts of the trend, such as moving average change etc.

4.4 Data for Prediction

For time series predicting we usually have values of a variable in equidistant intervals - then we can try to predict the development of the value based on historical values and time only. In this case the historical time series should be long enough and dense enough.

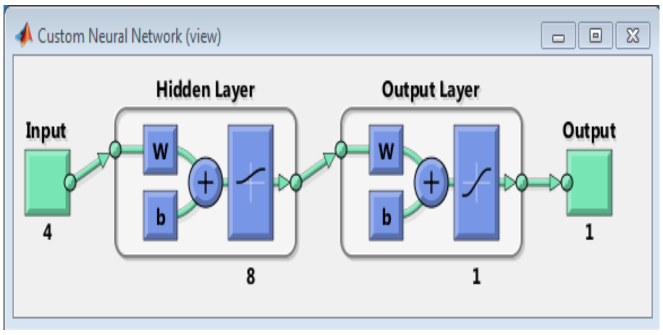
We can have additional information to time series, such as derivation. This information can be then used for more exact prediction. Important information can be added using so called interventional variables (intervention indicators), which represent information about time series or information about the period into which we predict. For example when predicting energy consumption then knowing whether we predict for Monday or Saturday can improve the prediction dramatically - this information does not follow from time series explicitly and must be added. It is usually very helpful to use the values of intervention indicator when creating a model that will be used for prediction.

We can also have information about other related variables, preferably also in time series. From the history of related variables we can reason about other variables. The relation can be expressed in various ways. An example is a static (or slowly changing) sum of two variables. It does not have to be expressed explicitly - for example changes of prices of stocks of shares in one sector are dependent, but can be hard to express in a computational way. This kind of information is selected in a hope that it will cohere with the predicted value, but we do not have to be sure about it. The field of data mining can help with selecting appropriate information and its interpretation.

4.5 Prediction using ANN

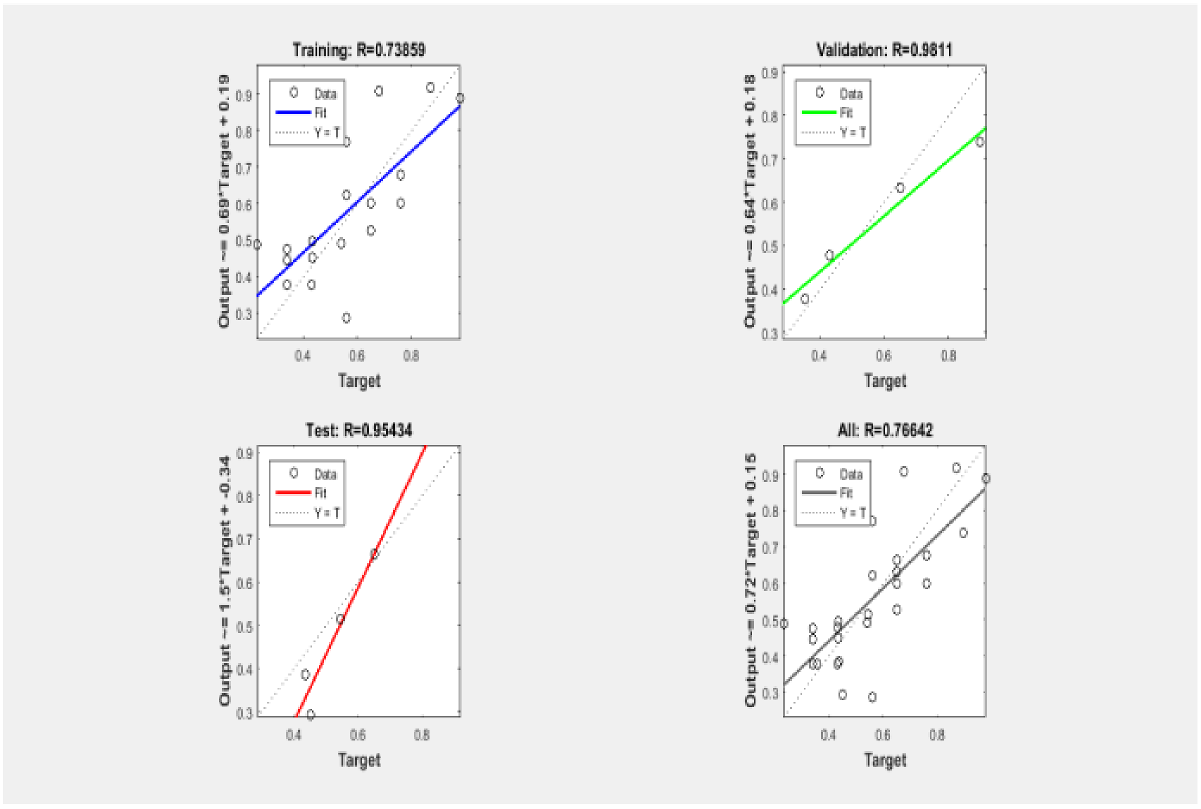
The advantage of the usage of neural networks for prediction is that they are able to learn from examples only and that after their learning is finished, they are able to catch hidden and strongly non-linear dependencies, even when there is a significant noise in the training set. The disadvantage is that NNs can learn the dependency valid in a certain period only. The error of prediction cannot be generally estimated.

4.6 Graphical Output Analysis

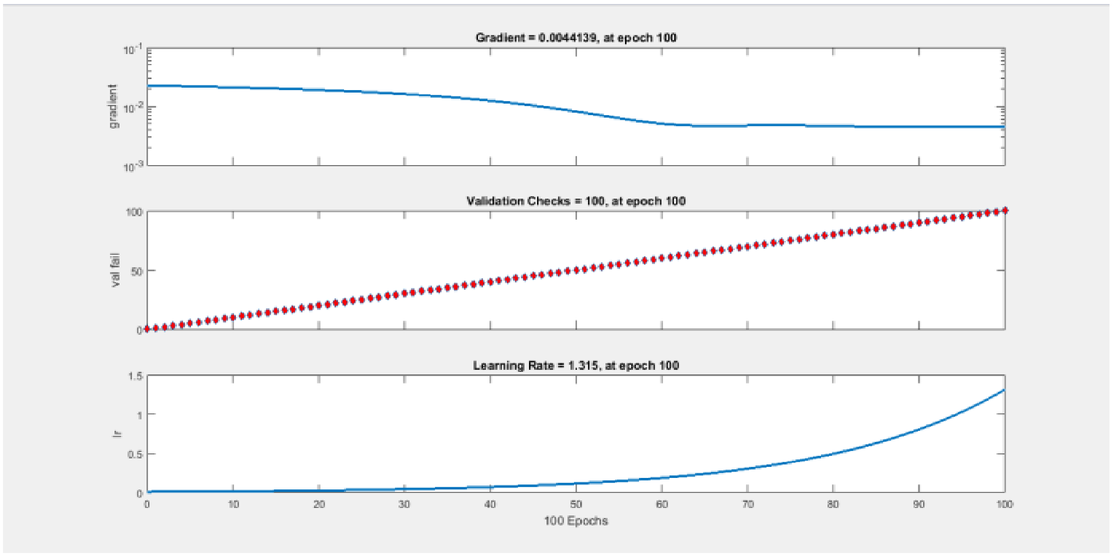


The above figure shows the structure of Artificial Neural Network in Matlab where the four types of layers are displayed- Input Layer, Hidden Layer, Output Layer and final the Output.

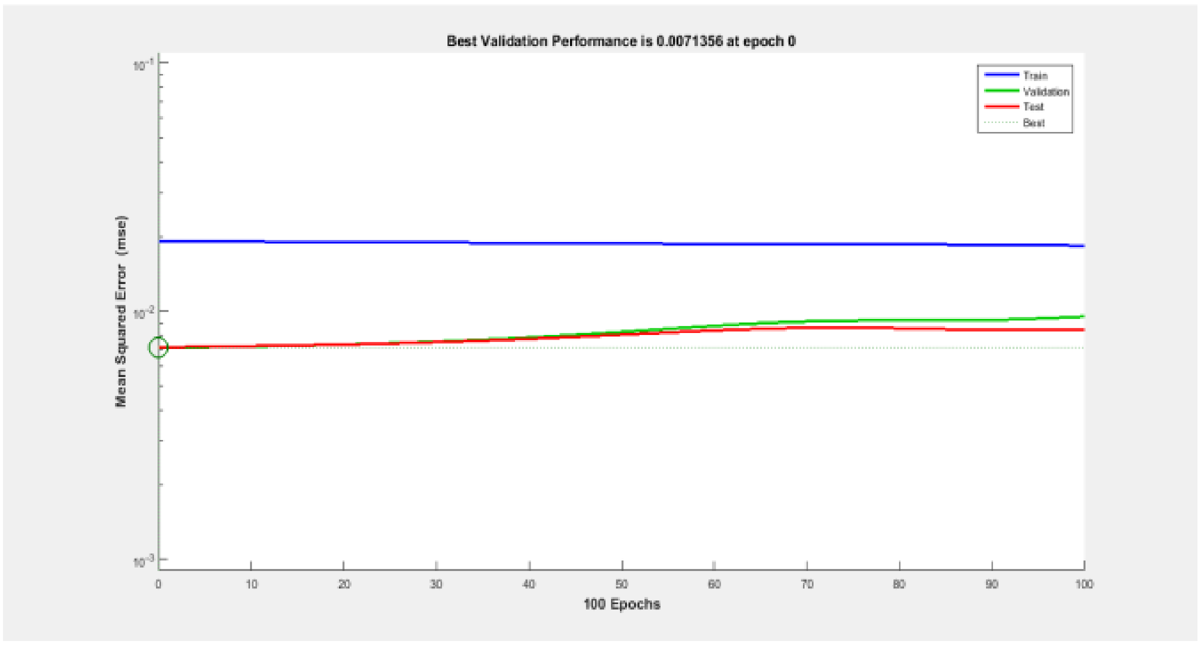
The working process of a neural network happens in the hidden layer. In this layer there are different types of probabilities results but the most probable out is displayed in the output layer. The input layer and the output layer are as usual input and output of the function.



This figure shows the graphical representation of the most probable output of the following project. Here the main line shows the standard data and the round shapes circles shows the probable outputs.



This graphical presentation shows the different states of the training. The gradient, the validation and the learning rate graphs are shown here.



This graph shows the comparison between the main standard expected outputs with the given input. Here a little bit of fluctuation is occurred due to training period. The blue line shows the train state and the green and the red line shows the validation and test state. The white line notifies the most expected output state.

4.7 Predicted Data

0.32976	0.38914	0.93677	0.44013

Accurate prediction and forecasting are very difficult in some areas, such as natural disasters, pandemics, demography, dynamics and meteorology. For example, it is possible to predict the occurrence of solar cycles, but their exact timing and magnitude is much more difficult. Established science makes useful predictions which are often extremely reliable and accurate; for example, eclipses are routinely predicted.

New theories make predictions which allow them to be disproved by reality. For example, predicting the structure of crystals at the atomic level is a current research challenge. In the early 20th century the scientific consensus was that there existed an absolute frame of reference, which was given the name aluminiferous ether. The existence of this absolute frame was deemed necessary for consistency with the established idea that the speed of light is constant. The famous Michelson-Morley experiment demonstrated that predictions deduced from this concept were not borne out in reality, thus disproving the theory of an absolute frame of reference. The special theory of relativity was proposed by Einstein as an explanation for the seeming inconsistency between the constancy of the speed of light and the non-existence of a special, preferred or absolute frame of reference.

5. SUMMARY AND CONCLUSION

Neural networks are suitable for predicting because of learning only from examples, without any need to add additional information that can bring more confusion than prediction effect. Neural networks are able to generalize and are resistant to noise. On the other hand, it is generally not possible to determine exactly what a neural network learned and it is also hard to estimate possible prediction error. However, neural networks were often successfully used for predicting data. They are ideal especially when we do not have any other description of the observed series.

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