

Neural Network Toolbox

A Tutorial for the Course *Computational Intelligence*

<http://www.igi.tugraz.at/lehre/CI>

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Abstract

This tutorial gives an introduction to the Matlab Neural Network Toolbox. The elements of matlab and the neural network toolbox are more easily understood when explained by an example. First a neural network will be used for a classification task. The second example will be a simple logical problem.

Slide presentation and MATLAB script for lecture SS06

[nnt_intro_SS06.zip](#)¹

Usage

To make full use of this tutorial you have

1. to download the file
[nnt_intro.zip](#)² which contains this tutorial and the accompanying Matlab programs.
2. Unzip `nnt_intro.zip` which will generate a subdirectory named `nnt_intro` where you can find all the Matlab programs.
3. Add the path `nnt_intro` to the matlab search path with a command like
`addpath('C:\Work\nnt_intro')`
if you are using a Windows machine or
`addpath('/home/jack/nnt_intro')`
if you are using a Unix/Linux machine.

1 The Neural Network Toolbox

The neural network toolbox makes it easier to use neural networks in matlab. The toolbox consists of a set of functions and structures that handle neural networks, so we do not need to write code for all activation functions, training algorithms, etc. that we want to use!

The Neural Network Toolbox is contained in a directory called `nnet`. Type `help nnet` for a listing of help topics.

A number of demonstrations are included in the toolbox. Each example states a problem, shows

¹http://www.igi.tugraz.at/lehre/EW/tutorials/nnt_intro/nnt_intro_SS06.zip

²http://www.igi.tugraz.at/lehre/CI/tutorials/nnt_intro.zip

the network used to solve the problem, and presents the final results. Lists of the demos and applications scripts that are discussed in this guide can be found with `help nndemos/`.

2 The Structure of the Neural Network Toolbox

The toolbox is based on the network object. This object contains information about everything that concern the neural network, e.g. the number and structure of its layers, the connectivity between the layers, etc. Matlab provides high-level network creation functions, like `newlin` (create a linear layer), `newp` (create a perceptron) or `newff` (create a feed-forward backpropagation network) to allow an easy construction of. As an example we construct a perceptron with two inputs ranging from -2 to 2:

```
>> net = newp([-2 2;-2 2],1)
```

First the architecture parameters and the subobject structures

subobject structures:

```
inputs: {1x1 cell} of inputs
layers: {1x1 cell} of layers
outputs: {1x1 cell} containing 1 output
targets: {1x1 cell} containing 1 target
biases: {1x1 cell} containing 1 bias
inputWeights: {1x1 cell} containing 1 input weight
layerWeights: {1x1 cell} containing no layer weights
```

are shown. The latter contains information about the individual objects of the network. Each layer consists of neurons with the same transfer function `net.transferFcn` and net input function `net.netInputFcn`, which are in the case of perceptrons `hardlim` and `netsum`. If neurons should have different transfer functions then they have to be arranged in different layers. The parameters `net.inputWeights` and `net.layerWeights` specify among other things the applied learning functions and their parameters. The next paragraph contains the training, initialization and performance functions.

functions:

```
adaptFcn: 'trains'
initFcn: 'initlay'
performFcn: 'mae'
trainFcn: 'trainc'
```

The `trainFcn` and `adaptFcn` are used for the two different learning types batch learning and incremental or on-line learning. By setting the `trainFcn` parameter you tell Matlab which training algorithm should be used, which is in our case the cyclical order incremental training/learning function `trainc`. The ANN toolbox include almost 20 training functions. The performance function is the function that determines how well the ANN is doing it's task. For a perceptron it is the mean absolute error performance function `mae`. For linear regression usually the mean squared error performance function `mse` is used. The `initFcn` is the function that initialized the weights and biases of the network. To get a list of the functions that are available type `help nnet`. To change one of these functions to another one in the toolbox or one that you have created, just assign the name of the function to the parameter, e.g.

```
>> net.trainFcn = 'mytrainingfun';
```

The parameters that concerns these functions are listed in the next paragraph.

```

parameters:

    adaptParam: .passes
    initParam: (none)
    performParam: (none)
    trainParam: .epochs, .goal, .show, .time

```

By changing these parameters you can change the default behavior of the functions mentioned above. The parameters you will use the most are probably the components of `trainParam`. The most used of these are `net.trainParam.epochs` which tells the algorithm the maximum number of epochs to train, and `net.trainParam.show` that tells the algorithm how many epochs there should be between each presentation of the performance. Type `help train` for more information.

The weights and biases are also stored in the network structure:

```

weight and bias values:

    IW: {1x1 cell} containing 1 input weight matrix
    LW: {1x1 cell} containing no layer weight matrices
    b: {1x1 cell} containing 1 bias vector

```

The `.IW(i,j)` component is a two dimensional cell matrix that holds the weights of the connection between the input `j` and the network layer `i`. The `.LW(i,j)` component holds the weight matrix for the connection from the network layer `j` to the layer `i`. The cell array `b` contains the bias vector for each layer.

3 A Classification Task

As example our task is to create and train a perceptron that correctly classifies points sets belonging to three different classes. First we load the data from the file `winedata.mat`

```
>> load winedata X C
```

Each row of `X` represents a sample point whose class is specified by the corresponding element (row) in `C`. Further the data is transformed into the input/output format used by the Neural Network Toolbox

```
>> P=X';
```

where `P(:,i)` is the `i`th point. Since we want to classify three different classes we use 3 perceptrons, each for the classification of one class. The corresponding target function is generated by

```
>> T=ind2vec(C);
```

To create the perceptron layer with correct input range type

```
>> net=newp(minmax(P),size(T,1));
```

The difference between train and adapt

Both functions, `train` and `adapt`, are used for training a neural network, and most of the time both can be used for the same network. The most important difference has to do with incremental training (updating the weights after the presentation of each single training sample) versus batch training (updating the weights after each presenting the complete data set).

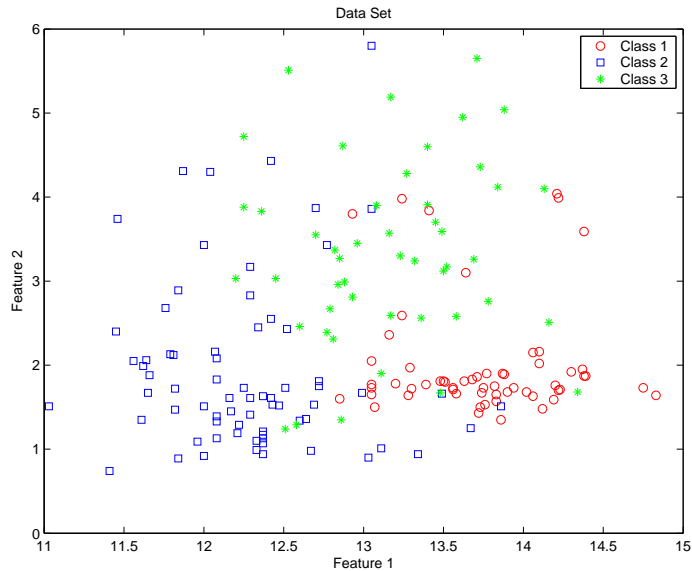


Figure 1: Data set X projected to two dimensions.

Adapt

First, set `net.adaptFcn` to the desired adaptation function. We'll use `adaptwb` (from 'adapt weights and biases'), which allows for a separate update algorithm for each layer. Again, check the Matlab documentation for a complete overview of possible update algorithms.

```
>> net.adaptFcn = 'trains';
```

Next, since we're using `trains`, we'll have to set the learning function for all weights and biases:

```
>> net.inputWeights{1,1}.learnFcn = 'learnp';
>> net.biases{1}.learnFcn = 'learnp';
```

where `learnp` is the Perceptron learning rule. Finally, a useful parameter is `net.adaptParam.passes`, which is the maximum number of times the complete training set may be used for updating the network:

```
>> net.adaptParam.passes = 1;
```

When using `adapt`, both incremental and batch training can be used. Which one is actually used depends on the format of your training set. If it consists of two matrices of input and target vectors, like

```
>> [net,y,e] = adapt(net,P,T);
```

the network will be updated using batch training. Note that all elements of the matrix `y` are one, because the weights are not updated until all of the trainings set had been presented.

If the training set is given in the form of a cell array

```
>> for i = 1:length(P), P2{i} = P(:,i); T2{i}= T(:,i); end
>> net = init(net);
>> [net,y2,e2] = adapt(net,P2,T2);
```

then incremental training will be used. Notice that the weights had to be initialized before the network adaption was started. Since `adapt` takes a lot more time then `train` we continue our analysis with second algorithm.

Train

When using `train` on the other hand, only batch training will be used, regardless of the format of the data (you can use both). The advantage of `train` is that it provides a lot more choice in training functions (gradient descent, gradient descent w/ momentum, Levenberg-Marquardt, etc.) which are implemented very efficiently. So for static networks (no tapped delay lines) usually `train` is the better choice.

We set

```
>> net.trainFcn = 'trainb';
```

for batch learning and

```
>> net.trainFcn = 'trainc';
```

for on-line learning. Which training parameters are present depends in general on your choice for the training function. In our case two useful parameters are `net.trainParam.epochs`, which is the maximum number of times the complete data set may be used for training, and `net.trainParam.show`, which is the time between status reports of the training function. For example,

```
>> net.trainParam.epochs = 1000;
>> net.trainParam.show = 100;
```

We initialize and simulate the network with

```
>> net = init(net);
>> [net,tr] = train(net,P,T);
```

The trainings error is calculated with

```
>> Y=sim(net,P);
>> train_error=mae(Y-T)
```

```
train_error =
    0.3801
```

So we see that the three classes of the data set were not linear seperable. The best time to stop learning would have been

```
>> [min_perf,min_epoch]=min(tr.perf)

min_perf =
    0.1948

min_epoch =
    703
```

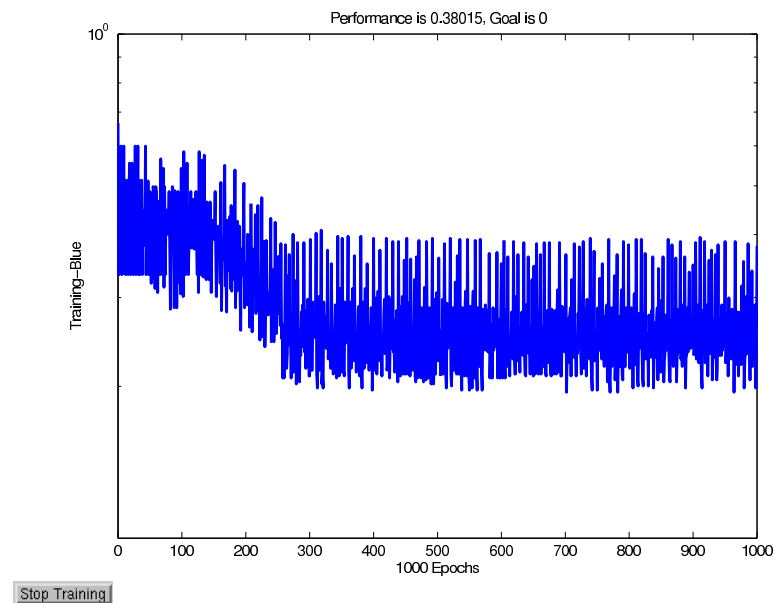


Figure 2: Performance of the learning algorithm `train` over 1000 epochs.

4 A Simple logical problem

The task is to create and train a neural network that solves the XOR problem. XOR is a function that returns 1 when the two inputs are not equal,

Construct a Feed-Forward Network

To solve this we will need a feedforward neural network with two input neurons, and one output neuron. Because that the problem is not linearly separable it will also need a hidden layer with two neurons. To create a new feed forward neural network use the command `newff`. You have to enter the max and min of the input values, the number of neurons in each layer and optionally the activation functions.

```
>> net = newff([0 1; 0 1],[2 1],{'logsig','logsig'});
```

The variable `net` will now contain an untrained feedforward neural network with two neurons in the input layer, two neurons in the hidden layer and one output neuron, exactly as we want it. The `[0 1; 0 1]` tells matlab that the input values ranges between 0 and 1. The `'logsig','logsig'` tells matlab that we want to use the `logsig` function as activation function in all layers. The first parameter tells the network how many nodes there should be in the input layer, hence you do not have to specify this in the second parameter. You have to specify at least as many transfer functions as there are layers, not counting the input layer. If you do not specify any transfer function Matlab will use the default settings.

First we construct a matrix of the inputs. The input to the network is always in the columns of the matrix. To create a matrix with the inputs "1 1", "1 0", "0 1" and "0 0" we enter:

```
>> input = [1 1 0 0; 1 0 1 0]
```

```
input =  
      1      1      0      0  
      1      0      1      0
```

Further we construct the target vector:

```
>> target = [0 1 1 0]
```

```
target =  
      0      1      1      0
```

Train the Network via Backpropagation

In this example we do not need all the information that the training algorithms shows, so we turn it of by entering:

```
>> net.trainParam.show=NaN;
```

Let us apply the default training algorithm Levenberg-Marquardt backpropagation `trainlm` to our network. An additional training parameters is `.min_grad`. If the gradient of the performance is less than `.min_grad` the training is ended. To train the network enter:

```
>> net = train(net,input,target);
```

Because of the small size of the network, the training is done in only a second or two. Now we simulate the network, to see how it reacts to the inputs:

```
>> output = sim(net,input)
```

```
output =  
  
      0.0000      1.0000      1.0000      0.0000
```

That was exactly what we wanted the network to output! Now examine the weights that the training algorithm has set

```
>> net.IW{1,1}

ans =
    11.0358    -9.5595
    16.8909   -17.5570

>> net.LW{2,1}

ans =
    25.9797   -25.7624
```

5 Graphical User Interface

A graphical user interface has been added to the toolbox. This interface allows you to:

- Create networks
- Enter data into the GUI
- Initialize, train, and simulate networks
- Export the training results from the GUI to the command line workspace
- Import data from the command line workspace to the GUI

To open the Network/Data Manager window type `nnTool`.