UFME7K-15-M Intelligent and Adaptive Systems

Introduction to Artificial Neural Networks

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Intelligent Adaptive Systems Lecture 3

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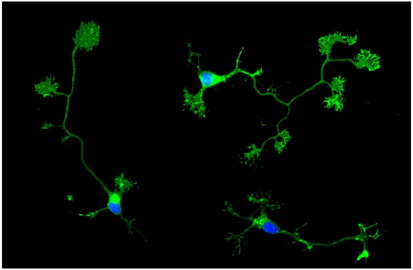
- ANNs can learn or be trained

Some real Neurons



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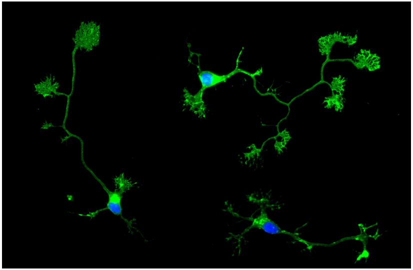

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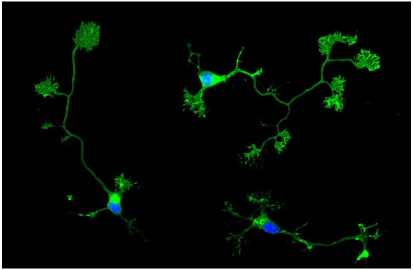

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  - The first step towards this was made by IBM research laboratories.

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    - while the system is as ancient as air traffic control systems, it is still in commercial use.

The Perceptron

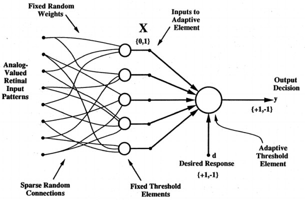

Figure 2: Perceptron

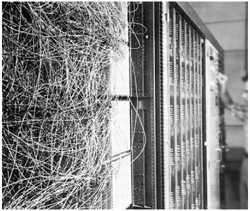

Figure 3: Early prototype

- Rosenblatt's Perceptron (1962)

Feedforward Networks (MLP)

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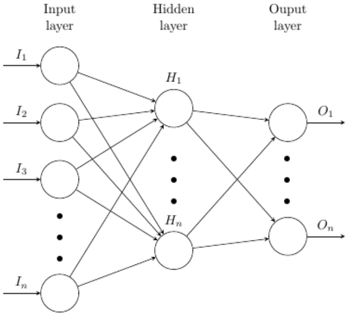

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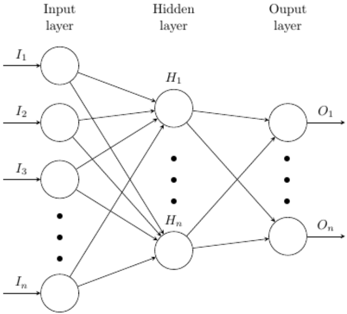

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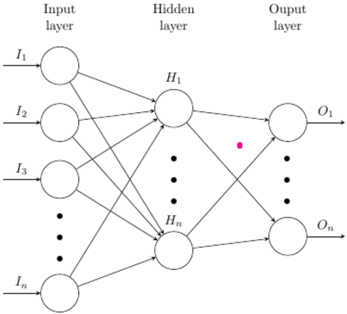

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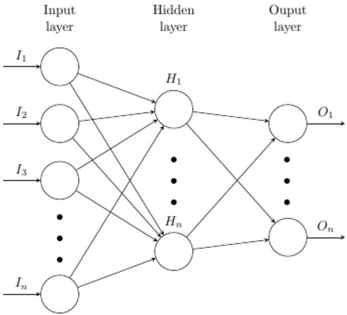

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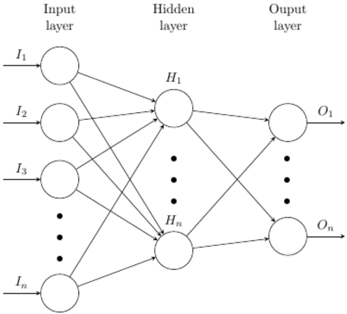

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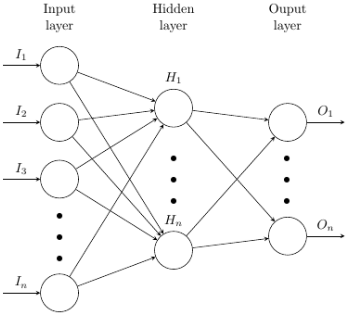
- and one or more **hidden** layers which connect them together.



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Using the nftool

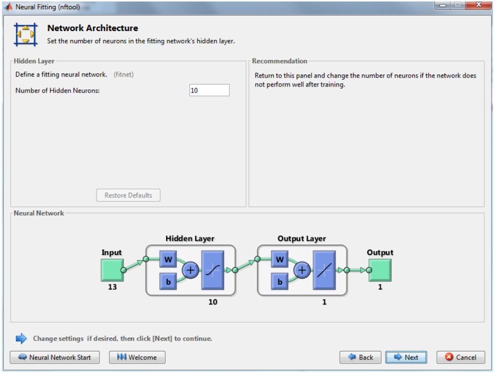

Figure 5: Network architecture

MLP Neuron

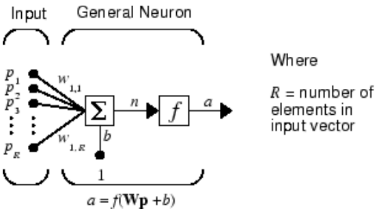

Figure 6: Single MLP Neuron

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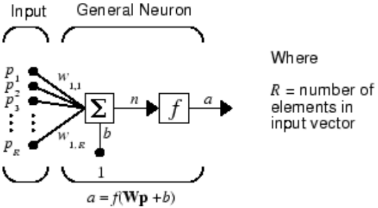

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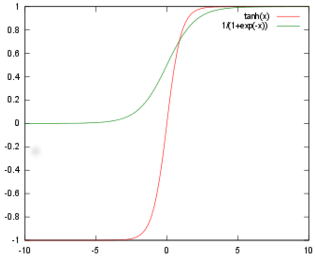
- Each input is multiplied by an appropriate weight $w_{i,j}$
- The sum of the weighted inputs and the bias forms the input to the activation (threshold) function f

Activation Functions



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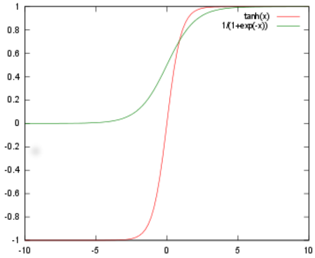

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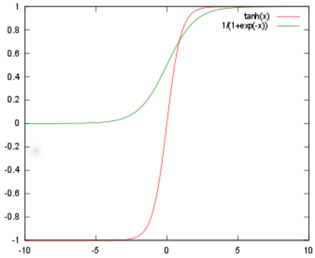

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- generates outputs between 0 and 1 as the neuron's input goes from negative to positive infinity
- Sigmoid output neurons are often used for pattern recognition problems, while linear output neurons are used for function fitting problems

Network design for fitting

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- A feedforward network with one hidden layer and enough neurons in the hidden layers, can fit any finite input-output mapping problem.

Function approximation

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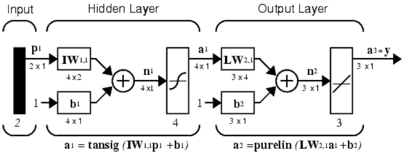

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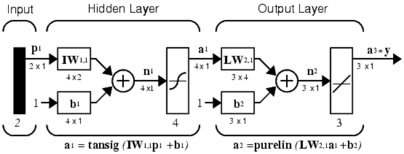

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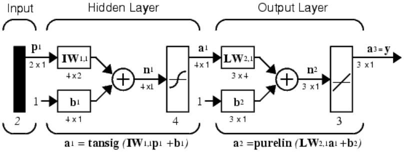

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  - If the error on the test set reaches a minimum at a significantly different iteration number than the validation set error, this might indicate a poor division of the data set.

Using Data Subsets in nftool

- A simple example of partitioning data

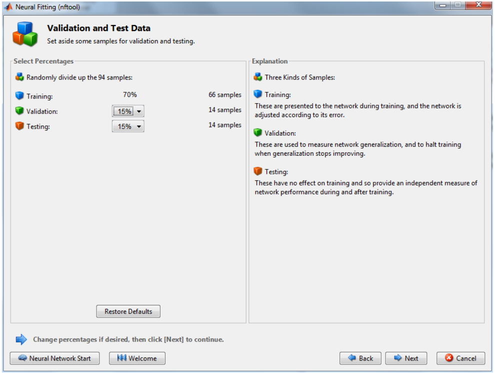

Figure 9: Simplefit Example

Training algorithms in the Matlab Toolbox

Function	Algorithm
trainlm	Levenberg-Marquardt (default)
trainbr	Bayesian Regularization
trainbfg	BFGS Quasi-Newton
trainrp	Resilient Backpropagation
trainscg	Scaled Conjugate Gradient
traincgb	Conjugate Gradient with Powell/Beale Restarts
traincgf	Fletcher-Powell Conjugate Gradient
traincgp	Polak-Ribiére Conjugate Gradient
trainoss	One Step Secant
traingdx	Variable Learning Rate Gradient Descent
traingdm	Gradient Descent with Momentum
traingd	Gradient Descent (backpropagation)

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- All of these methods are gradient-based and can be prone to converging on local minima.

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- During this iterative process, an input pattern is presented to the network and propagated forward to determine the resulting signal at the output units.
- differences between the resulting output signal and the predetermined desired output signal in each output unit represent an error that is back-propagated through the network in order to adjust the weights.
- The process continues until the the sum of root-mean-square errors from the desired output signals is less than a preset value.

Generalisation

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- This is known as generalisation and it can be quantified using the test set.
- The key to achieving this is in the design of the network, particularly in the number of hidden layer neurons
- A good practice is to start with a small number (the default in the feedforwardnet is 10) and try increasing to see if the fit improves or gets worse.

Over-fitting

- If the number of hidden neurons is increased too much, the error at the training points can go to zero but large errors can occur between the training points

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- This is known as over-fitting and is one of the biggest problems in ANN design

Failure to converge

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- Sometimes, gradient-based learning algorithms converge on local minima or simply diverge if the function is complicated and there are too few training points
- There are alternative training methods such as using Evolutionary Algorithms but that is beyond the scope of this introduction

Fitnet (Matlab Function)

- `fitnet` is a very easy to use method for creating feedforward neural networks (feedforwardnet) which are used to fit an input-output relationship.

```
fitnet(hiddenSizes,trainFcn)
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- takes these arguments:
  - `hiddenSizes`
    - Row vector of one or more hidden layer sizes (default = 10)
  - `trainFcn`
    - Training function (default = 'trainlm')
- and returns a fitting neural network.

Example MATLAB code

- Here a fitting neural network is used to solve a simple regression problem.

```
[x,t] = simplefit_dataset;
% Create and display the network
net = fitnet(10);
% Train the network using the data in x and t
net = train(net,x,t);
view(net)
% Predict the response using the trained network
y = net(x);
% Measure the performance
perf = perform(net,y,t)
```

Plot of trained network

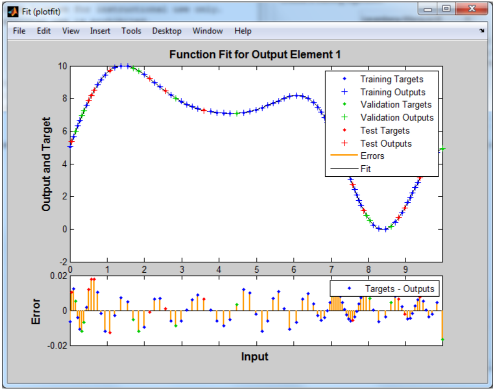

Figure 10: Plot of results of fitnet example

References and Further Reading

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- Beale and Jackson, Neural Computing: An Introduction, Adam Hilger, 1991
    - good introductory textbook which covers all of the ANN types which we will look at