

# **A4M33BIA**

# **MLP Implementation**

Jiří Kubalík

kubalik@ciirc.cvut.cz

Jan Drchal

drchajan@fel.cvut.cz

# Back-Propagation Algorithm

random weight initialization

**repeat**

**repeat** // *epoch*

choose an instance from the training set

apply it to the network

evaluate network outputs

compare outputs to desired values

modify the weights

**until** all instances selected from the training set

**until** global error < criterion

# FeedforwardANN.java methods

`sigmoid( $p$ )` // calculates logistic sigmoid of the potential  $p$

`setActivity( $l, n, v$ )` // sets input of neuron  $n$  in layer  $l$  to value  $v$

`getActivity( $l - 1, j + 1$ )`

`getNumLayers()` // the number of layers

`getNumNeurons( $l$ )` // the number of neurons in given layer (including bias neuron)

`getNumOutputs()` // the number of output neurons (there is no bias neuron in the output layer)

`getNumIncomingConnections( $l, n$ )` // the number of connections incoming to neuron  $n$  in layer  $l$  (which is same as the number of neurons in layer  $l-1$ ).

`getWeight( $l, toNeuron, fromNeuron$ )` // returns a weight of connection between  $fromNeuron$  in layer  $l-1$  and  $toNeuron$  in layer  $l$

# FeedforwardANN.java methods

```
propagate(pattern] // Loads input pattern and propagates it through the whole
                    // network. All neurons recalculate their activities.

applyDeltaWeights(double [][][] dw) // The elements of dw array are added to the
                                     // corresponding elements of the weights array.
                                     // Both arrays must have the same shape.

sigmoidDerivative(y) // calculates sigmoid derivative of neurons activity y
```

```
random weight initialization
repeat
  repeat // epoch
    choose an instance from the training set
    apply it to the network
    evaluate network outputs
    compare outputs to desired values
    modify the weights
  until all instances selected from the training set
until global error < criterion
```

$$w_{jk}(t + 1) = w_{jk}(t) + \Delta w_{jk}$$

$$\Delta w_{jk} = \eta \delta_k y_j$$

$$\delta_k = \gamma y_k (1 - y_k) (d_k - y_k)$$

$$\delta_k = \gamma y_k (1 - y_k) \left( \sum_l \delta_l w_{kl} \right)$$

