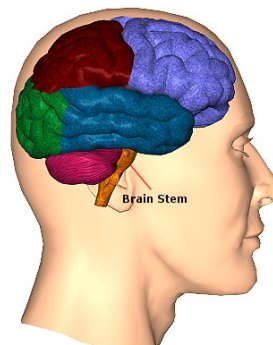
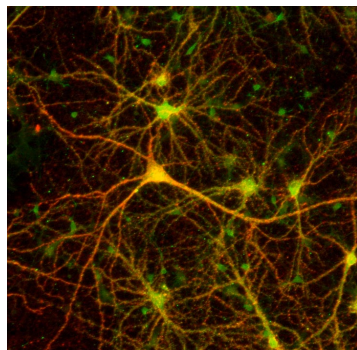
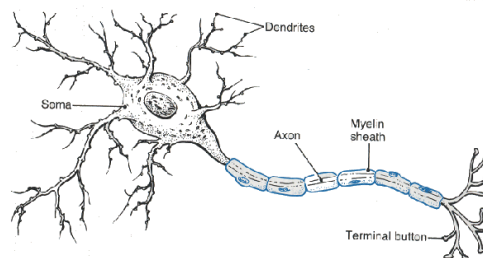
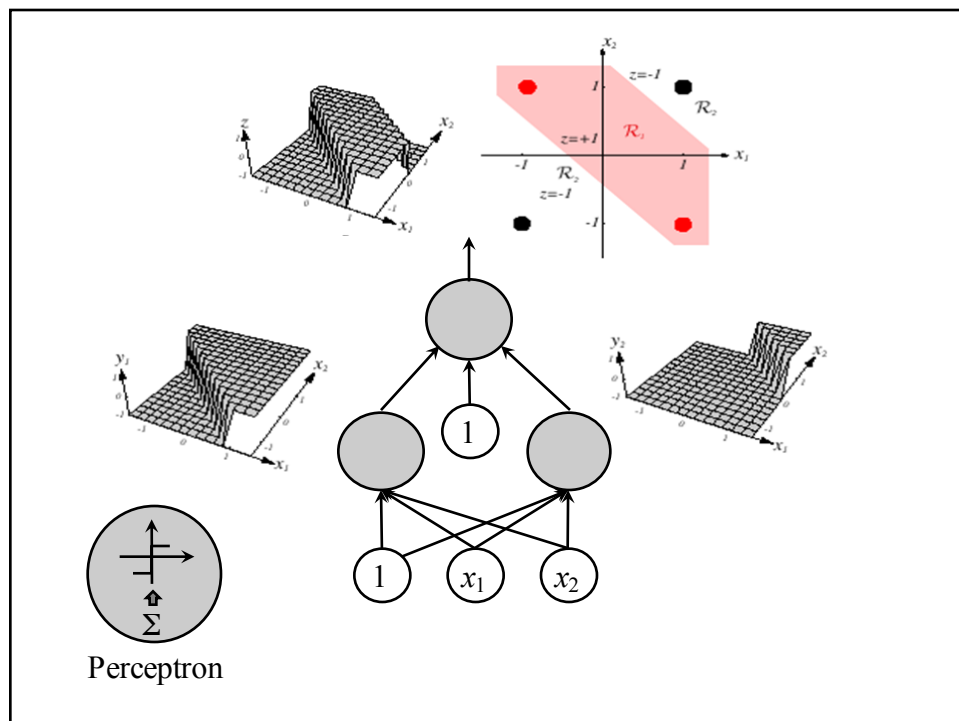
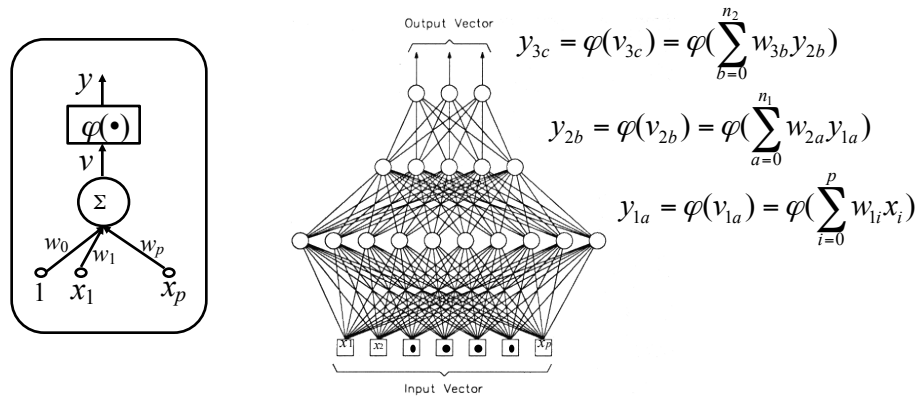


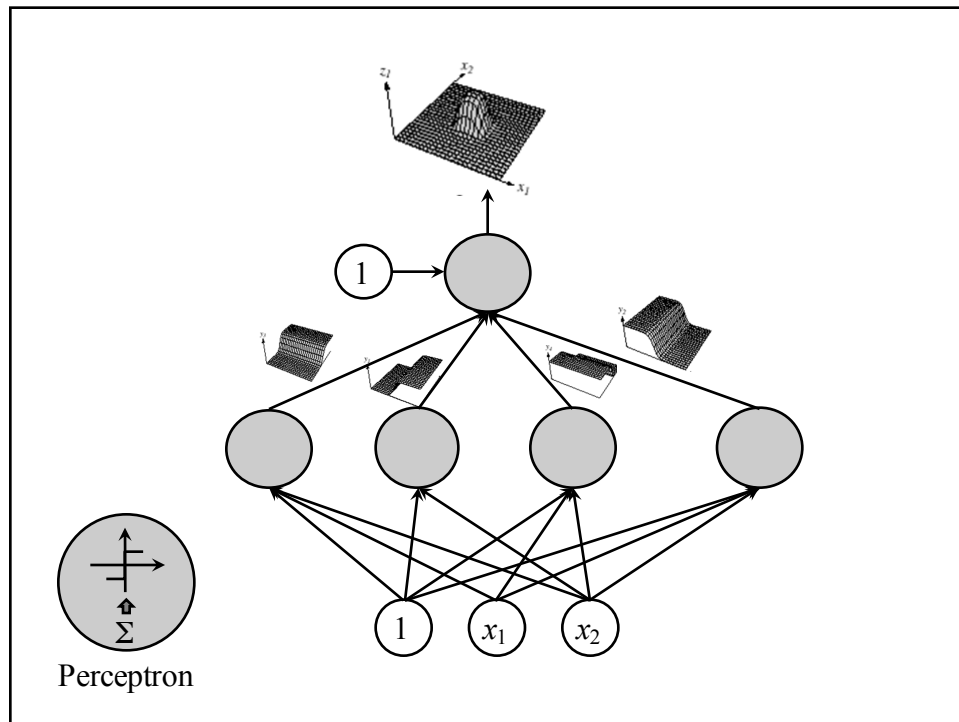
# Multilayer Neural Networks

Pengyu Hong  
CS 101A



# Multilayer Neural Networks



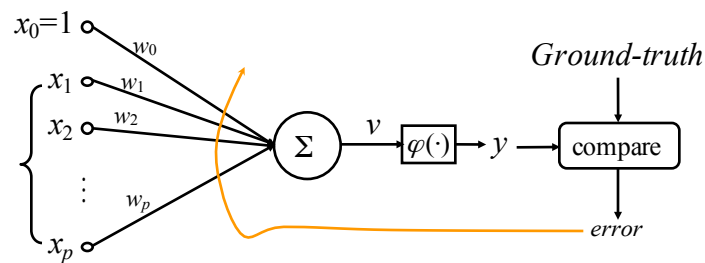


## Universal Approximation Theorem

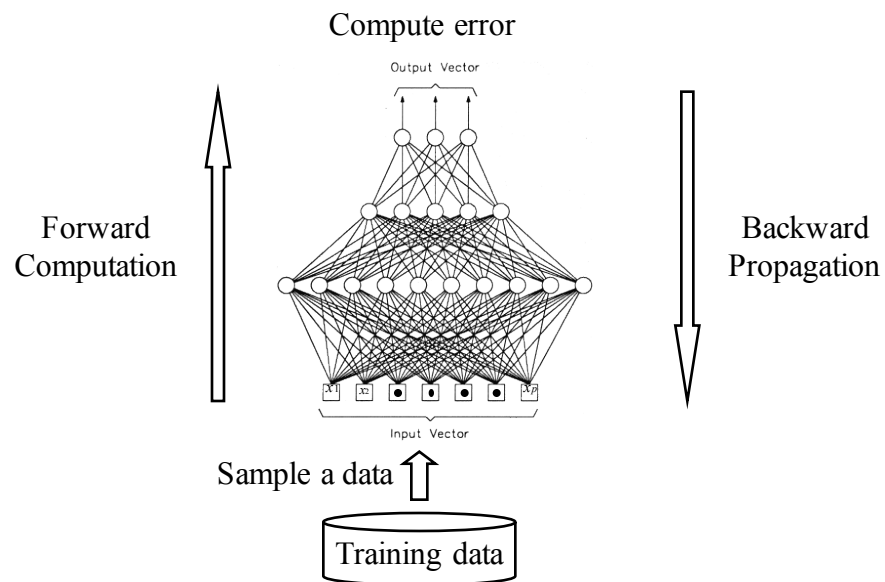
Any mapping function from input to output can be implemented as a three-layer neural network.

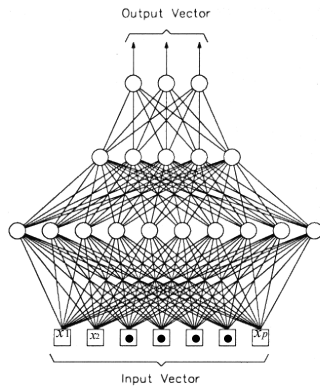
*Neural Networks* (2<sup>nd</sup> ed). Haykin. p. 208-209 and 249

## Error-Correction Learning



## The Back-Propagation Algorithm





Error of a single output neuron  $j$

$$\begin{aligned} e_j(t) &= d_j(t) - y_j(t) \\ &= d_j(t) - \varphi_j(v_j(t)) \\ &= d_j(t) - \varphi_j\left(\sum_{i=0}^m w_{ji}(t)y_i(t)\right) \end{aligned}$$

Error of the output layer

$$Err(t) = \frac{1}{2} \sum_{j \in \{\text{output Neurons}\}} e_j^2(t)$$

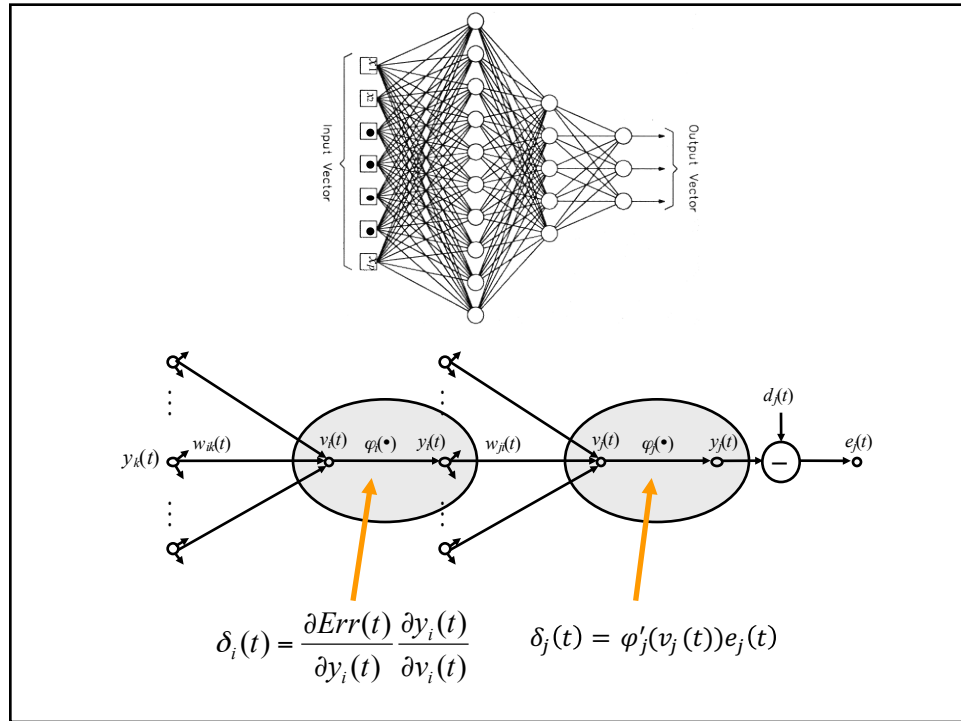
$$\frac{\partial Err(t)}{\partial w_{ji}(t)} = \frac{\partial Err(t)}{\partial e_j(t)} \frac{\partial e_j(t)}{\partial y_j(t)} \frac{\partial y_j(t)}{\partial v_j(t)} \frac{\partial v_j(t)}{\partial w_{ji}(t)}$$

$$\frac{\partial Err(t)}{\partial w_{ji}(t)} = \frac{\partial Err(t)}{\partial e_j(t)} \frac{\partial e_j(t)}{\partial y_j(t)} \frac{\partial y_j(t)}{\partial v_j(t)} \frac{\partial v_j(t)}{\partial w_{ji}(t)}$$

$$\begin{aligned} \frac{\partial Err(t)}{\partial e_j(t)} &= \frac{\partial \left( \frac{1}{2} \sum_{j=1}^{n_o} e_j^2(t) \right)}{\partial e_j(t)} = e_j(t) & \frac{\partial e_j(t)}{\partial y_j(t)} &= \frac{\partial (d_j(t) - y_j(t))}{\partial y_j(t)} = -1 \\ \frac{\partial y_j(t)}{\partial v_j(t)} &= \frac{\partial \varphi_j(v_j(t))}{\partial v_j(t)} = \varphi_j'(v_j(t)) & \frac{\partial v_j(t)}{\partial w_{ji}(t)} &= \frac{\partial \left( \sum_{i=0}^m w_{ji} y_i(t) \right)}{\partial w_{ji}(t)} = y_i(t) \\ \frac{\partial Err(t)}{\partial w_{ji}(t)} &= -e_j(t) \varphi_j'(v_j(t)) y_i(t) & \Delta w_{ji} &= -\eta \frac{\partial Err(t)}{\partial w_{ji}(t)} = \eta \delta_j(t) y_i(t) \end{aligned}$$

$$\delta_j(t) = \frac{\partial Err(t)}{\partial v_j(t)} = \frac{\partial Err(t)}{\partial y_j(t)} \frac{\partial y_j(t)}{\partial v_j(t)} = e_j(t) \varphi_j'(v_j(t))$$

Local gradient



$$\delta_i(t) = \frac{\partial Err(t)}{\partial y_i(t)} \frac{\partial y_i(t)}{\partial v_i(t)} \quad Err(t) = \frac{1}{2} \sum_{j=1}^{n_o} e_j^2(t)$$

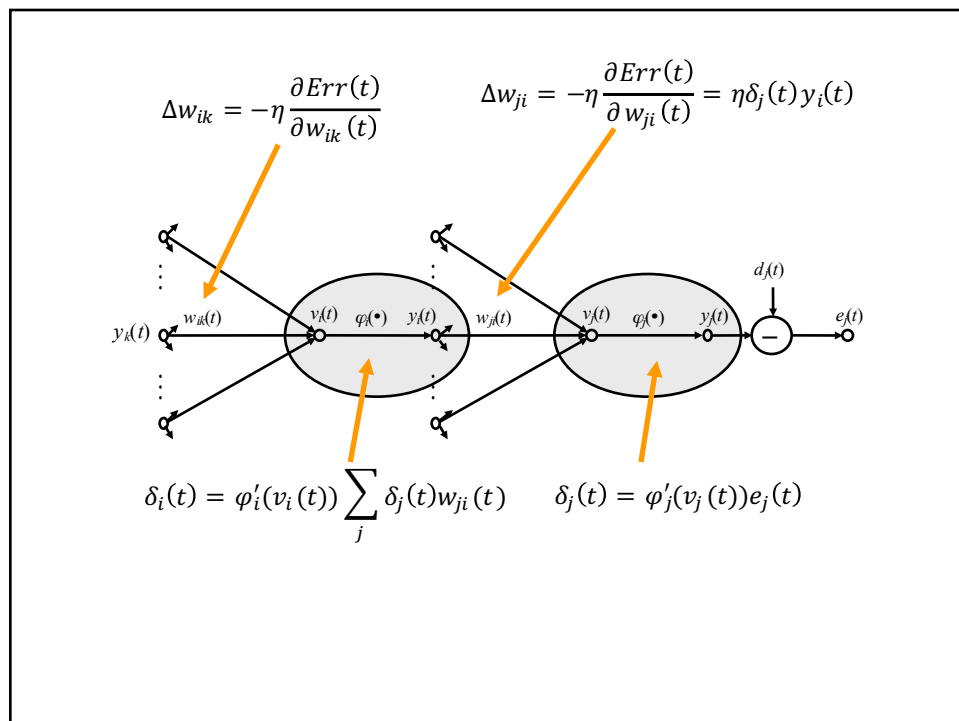
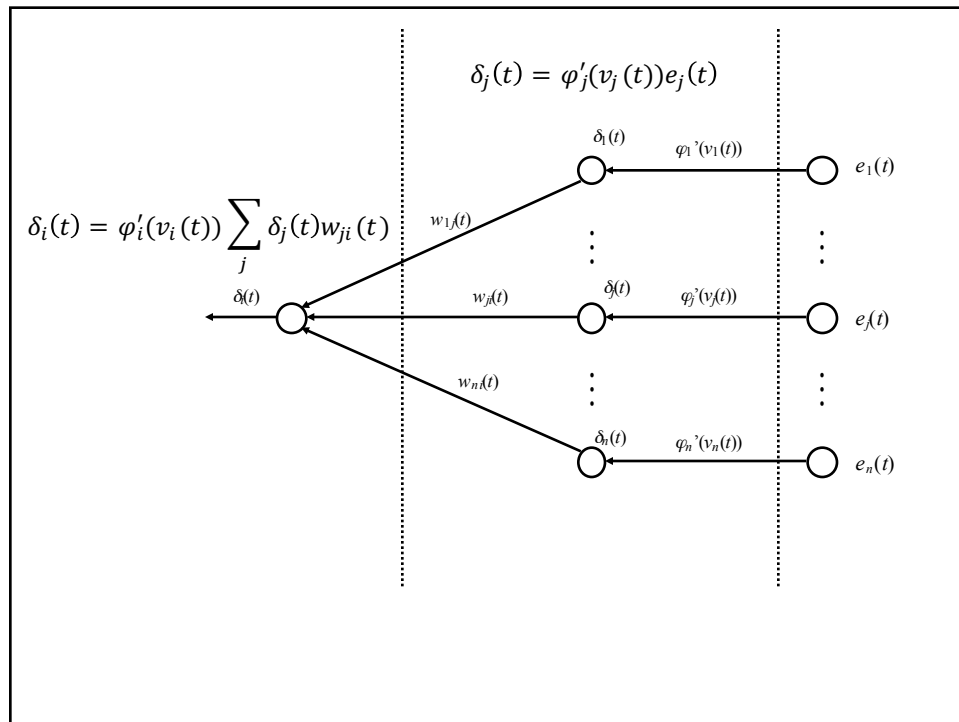
$$\frac{\partial Err(t)}{\partial y_i(t)} = \sum_j \frac{\partial Err(t)}{\partial e_j(t)} \frac{\partial e_j(t)}{\partial y_i(t)} = \sum_j e_j(t) \frac{\partial e_j(t)}{\partial y_i(t)} = \sum_j e_j(t) \frac{\partial e_j(t)}{\partial v_j(t)} \frac{\partial v_j(t)}{\partial y_i(t)}$$

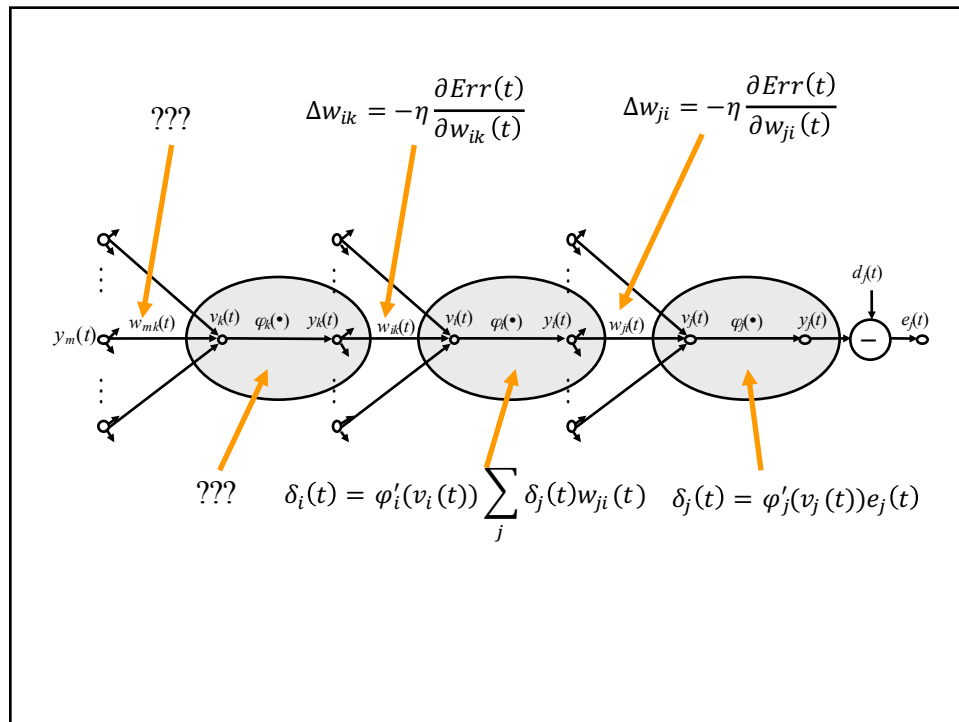
$$\frac{\partial e_j(t)}{\partial v_j(t)} = -\frac{\partial \varphi_j(v_j(t))}{\partial v_j(t)} = -\varphi'_j(v_j(t))$$

$$v_j(t) = \sum_{i=0}^m w_{ji}(t)y_i(t) \quad \frac{\partial v_j(t)}{\partial y_i(t)} = w_{ji}(t)$$

$$\frac{\partial Err(t)}{\partial y_i(t)} = -\sum_j e_j(t) \varphi'_j(v_j(t)) w_{ji}(t) = -\sum_j \delta_j(t) w_{ji}(t)$$

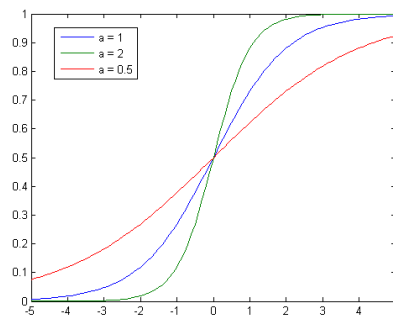
$$\delta_i(t) = \varphi'_i(v_i(t)) \sum_j \delta_j(t) w_{ji}(t)$$





## Activation Functions

- Logistic Function  $\varphi(v) = \frac{1}{1 + \exp(-av)}$   $a > 0, -\infty < v < \infty$



$$\varphi'(v_j) = \frac{a \cdot \exp(-av_j)}{[1 + \exp(-av_j)]^2}$$

$$= ay_j(1 - y_j)$$

Output neuron

$$\delta(v_j) = a \times e_j \times y_j(1 - y_j)$$

Hidden neuron

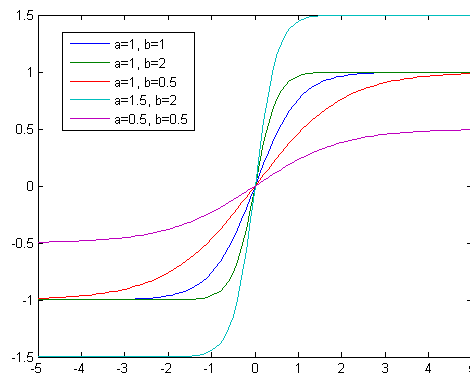
$$\delta(v_i) = a \times y_i(1 - y_i) \times \sum_j \delta_j w_{ji}$$



# Activation Functions

- Hyperbolic Tangent Function

$$\varphi(v) = a \tanh(bv) = a \frac{e^{bv} - e^{-bv}}{e^{bv} + e^{-bv}} \quad a > 0, b > 0$$



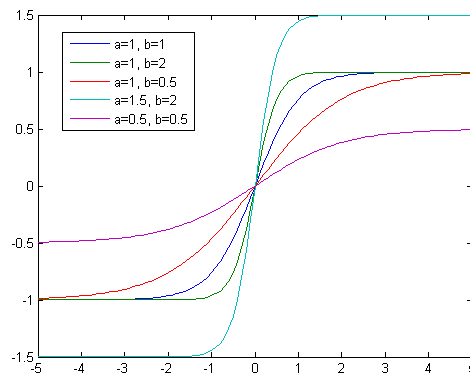
$$y = \varphi(v) = a \tanh(bv) = a \frac{e^{bv} - e^{-bv}}{e^{bv} + e^{-bv}}$$

$$\begin{aligned} \frac{\partial \varphi(v)}{\partial v} &= a \frac{b(e^{bv} + e^{-bv})(e^{bv} + e^{-bv}) - (e^{bv} - e^{-bv})b(e^{bv} - e^{-bv})}{(e^{bv} + e^{-bv})^2} \\ &= ab \frac{(e^{bv} + e^{-bv})^2 - (e^{bv} - e^{-bv})^2}{(e^{bv} + e^{-bv})^2} \\ &= \frac{4ab}{(e^{bv} + e^{-bv})^2} = \frac{b}{a} \frac{2ae^{bv} \times 2ae^{-bv}}{(e^{bv} + e^{-bv})^2} \\ &= \frac{b}{a} \frac{2ae^{bv}}{(e^{bv} + e^{-bv})} \frac{2ae^{-bv}}{(e^{bv} + e^{-bv})} \\ &= \frac{b}{a} \left( a + a \frac{e^{bv} - e^{-bv}}{e^{bv} + e^{-bv}} \right) \left( a - a \frac{e^{bv} - e^{-bv}}{e^{bv} + e^{-bv}} \right) \\ &= \frac{b}{a} (a - y)(a + y) \end{aligned}$$

## Activation Functions

- Hyperbolic Tangent Function

$$\varphi(v) = a \tanh(bv) = a \frac{e^{bv} - e^{-bv}}{e^{bv} + e^{-bv}} \quad a > 0, b > 0$$



$$\varphi'(v_j) = \frac{b}{a} (a - y_j)(a + y_j)$$

Output neuron

$$\delta(v_j) = \frac{b}{a} e_j (a - y_j)(a + y_j)$$

Hidden neuron

$$\delta(v_i) = \frac{b}{a} (a - y_i)(a + y_i) \times \sum_j \delta_j w_{ji}$$

## Sequential vs Batch

- Sequential mode  $\Delta w_{ji} = -\eta \frac{\partial \text{Err}}{\partial w_{ji}} = -\frac{\eta}{N} \sum_{n=1}^N e_j(n) \frac{\partial e_j(n)}{\partial w_{ji}}$
- Batch mode

$$\text{Err} = \frac{1}{2N} \sum_{n \in \text{samples}} \sum_{j \in \text{output neurons}} e_{nj}^2$$

$$\Delta w_{ji} = -\eta \frac{\partial \text{Err}(t)}{\partial w_{ji}(t)} = \eta \sum_n e_{nj} \frac{\partial e_{nj}}{\partial w_{ji}}$$

Online, memory, implementation, stochastic

- Number of hidden neurons?