

# When to consider neural networks

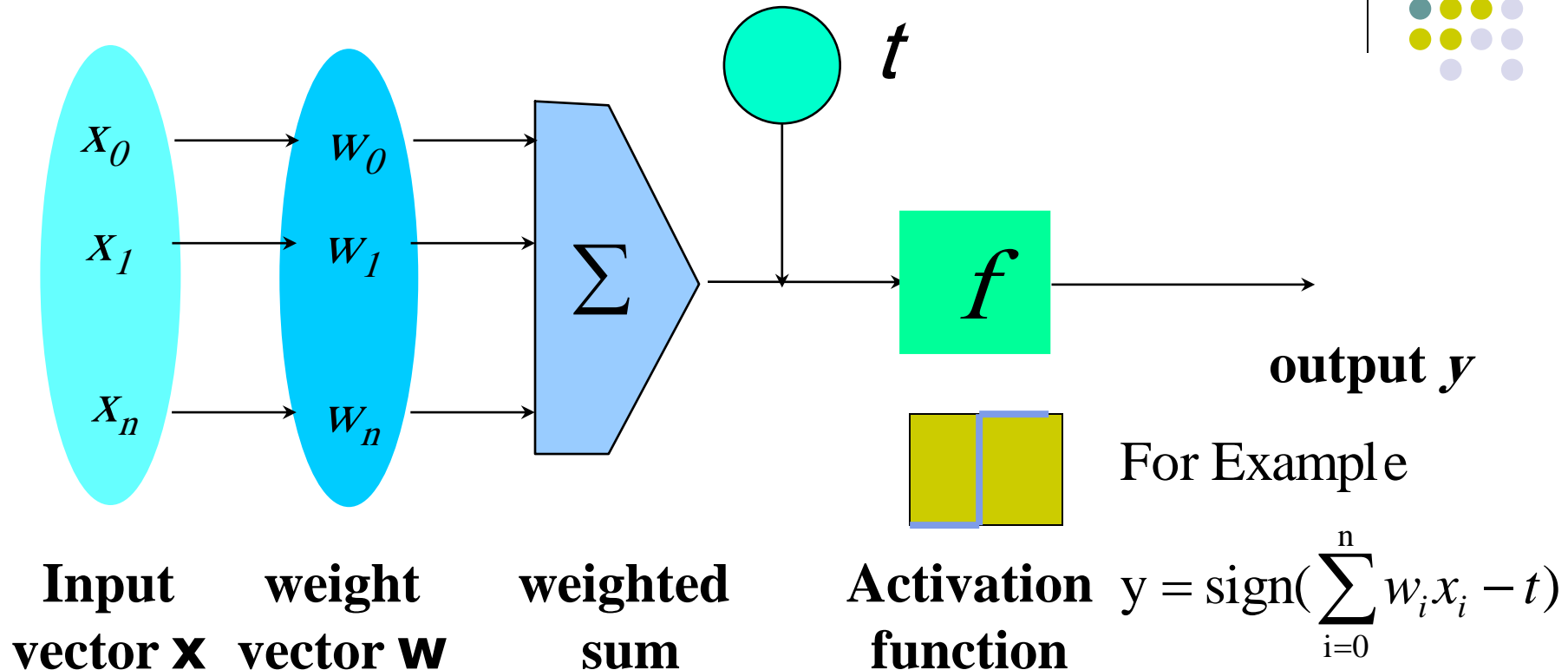


- Input is high-dimensional discrete or raw-valued
- Output is discrete or real-valued
- Output is a vector of values
- Possibly noisy data
- Form of target function is unknown
- Human readability of the result is not important

## **Examples:**

- Speech phoneme recognition
- Image classification
- Financial prediction

# A Neuron (= a perceptron)



- The  $n$ -dimensional input vector  $\mathbf{x}$  is mapped into variable  $y$  by means of the scalar product and a nonlinear function mapping

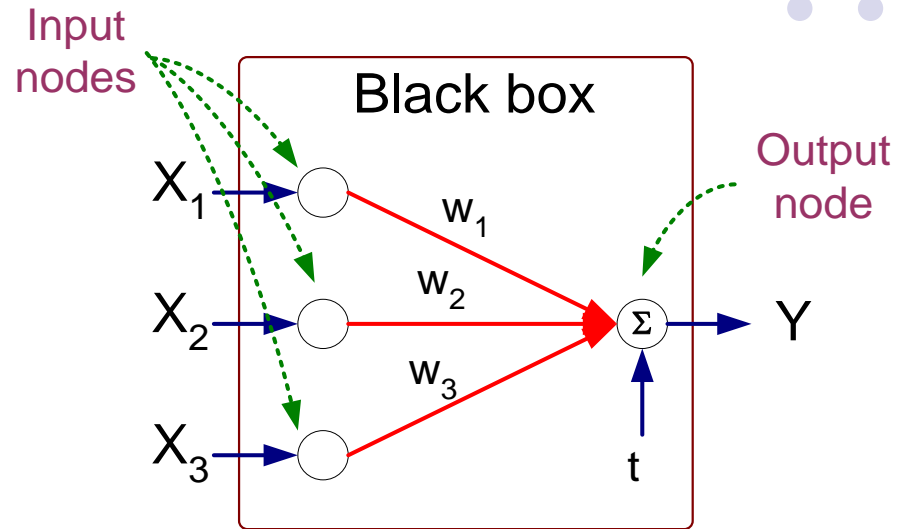
# Perceptron



- Basic unit in a neural network
- Linear separator
- Parts
  - N inputs,  $x_1 \dots x_n$
  - Weights for each input,  $w_1 \dots w_n$
  - A bias input  $x_0$  (constant) and associated weight  $w_0$
  - Weighted sum of inputs,  $y = w_0x_0 + w_1x_1 + \dots + w_nx_n$
  - A threshold function or activation function,
    - i.e 1 if  $y > t$ , -1 if  $y \leq t$

# Artificial Neural Networks (ANN)

- Model is an assembly of inter-connected nodes and weighted links
- Output node sums up each of its input value according to the weights of its links
- Compare output node against some threshold  $t$



## Perceptron Model

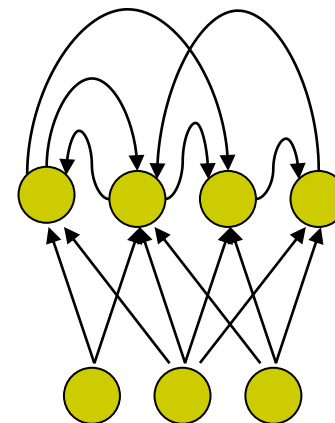
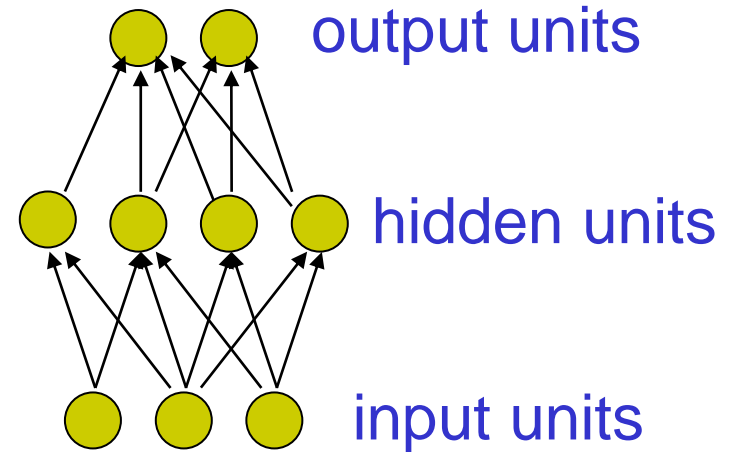
$$Y = I\left(\sum_i w_i x_i - t\right) \quad \text{or}$$

$$Y = \text{sign}\left(\sum_i w_i x_i - t\right)$$

# Types of connectivity



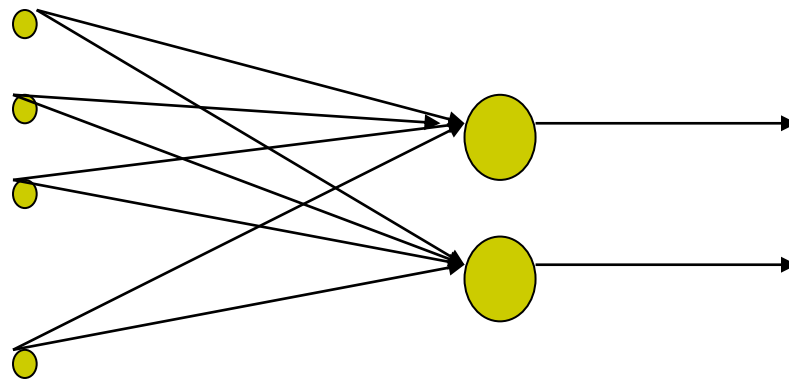
- Feedforward networks
  - These compute a series of transformations
  - Typically, the first layer is the input and the last layer is the output.
- Recurrent networks
  - These have directed cycles in their connection graph. They can have complicated dynamics.
  - More biologically realistic.



# Different Network Topologies



- Single layer feed-forward networks
  - Input layer projecting into the output layer



Input  
layer

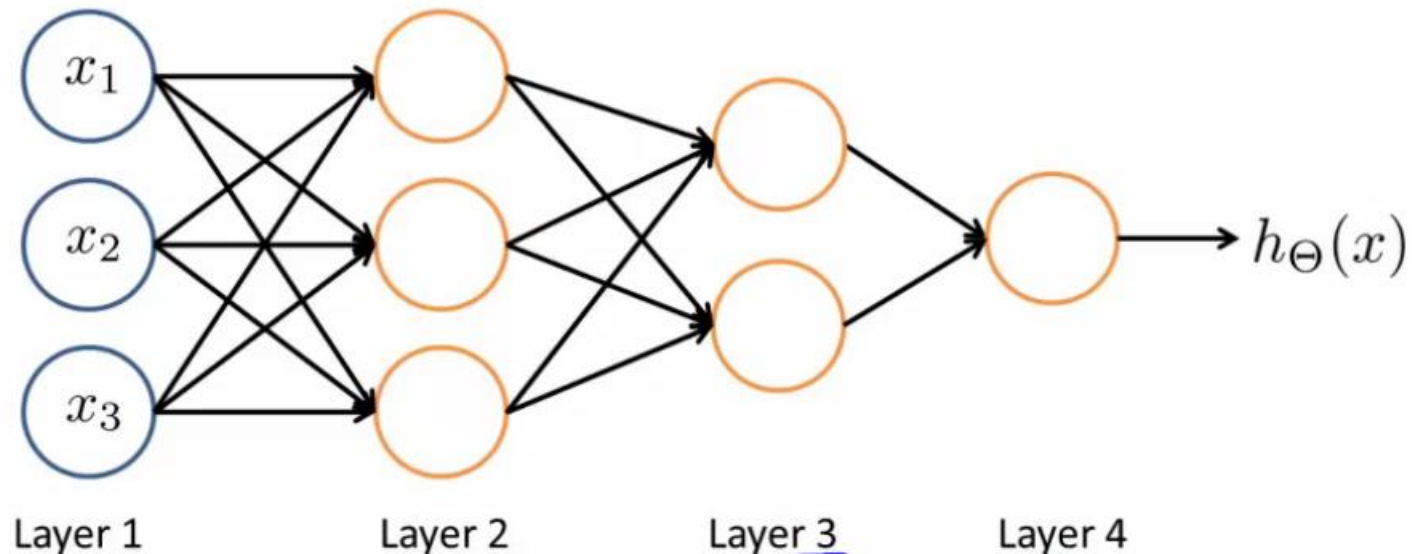
Output  
layer

Single layer  
network

# Different Network Topologies



- Multi-layer feed-forward networks



Input  
layer

Hidden  
layers

Output  
layer

# Algorithm for learning ANN



- Initialize the weights ( $w_0, w_1, \dots, w_k$ )
- Adjust the weights in such a way that the output of ANN is consistent with class labels of training examples

- Error function: 
$$\text{Loss} = -\frac{1}{\text{output size}} \sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i + (1 - y_i) \cdot \log (1 - \hat{y}_i)$$

- Find the weights  $w_i$ 's that minimize the above error function
  - e.g., gradient descent, backpropagation algorithm

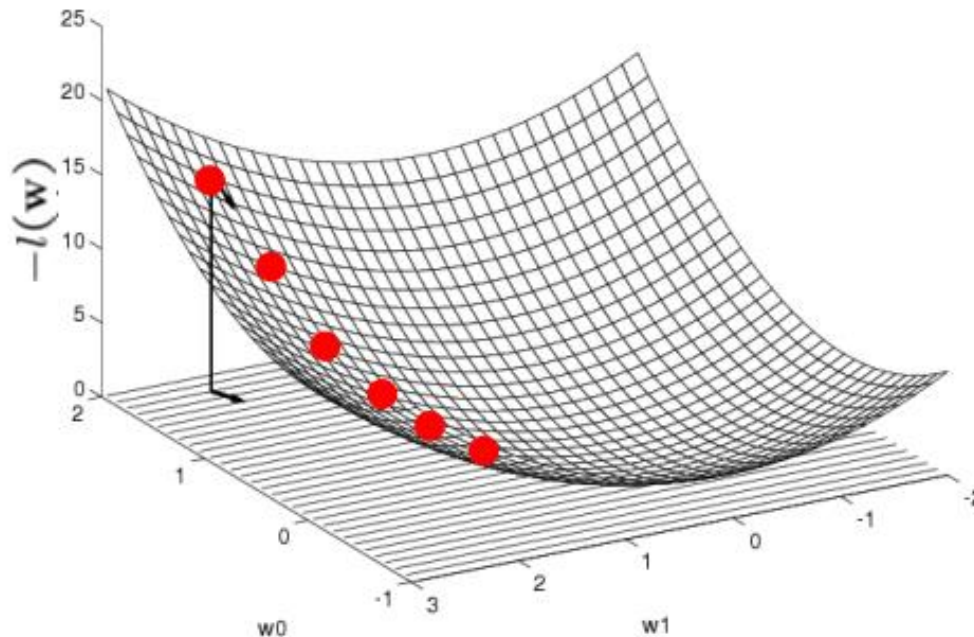


# Optimizing concave/convex function



- Maximum of a concave function = minimum of a convex function

**Gradient ascent (concave) / Gradient descent (convex)**



**Gradient:**

$$\nabla_{\mathbf{w}} l(\mathbf{w}) = \left[ \frac{\partial l(\mathbf{w})}{\partial w_0}, \dots, \frac{\partial l(\mathbf{w})}{\partial w_d} \right]'$$

**Update rule:** Learning rate,  $\eta > 0$

$$\Delta \mathbf{w} = \eta \nabla_{\mathbf{w}} l(\mathbf{w})$$

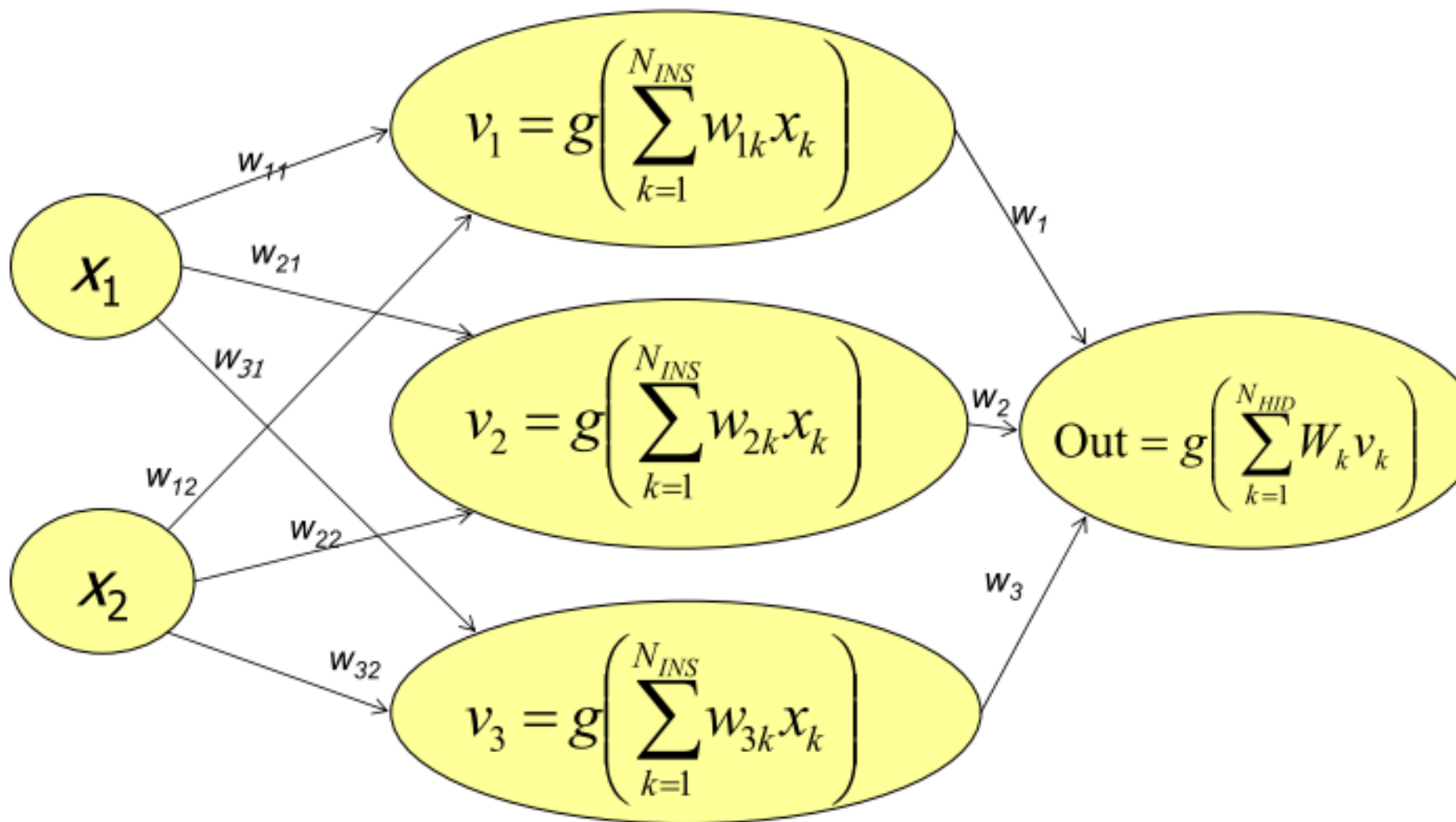
$$w_i^{(t+1)} \leftarrow w_i^{(t)} + \eta \left. \frac{\partial l(\mathbf{w})}{\partial w_i} \right|_t$$

**Gradient ascent rule**

# A 1-HIDDEN LAYER NET

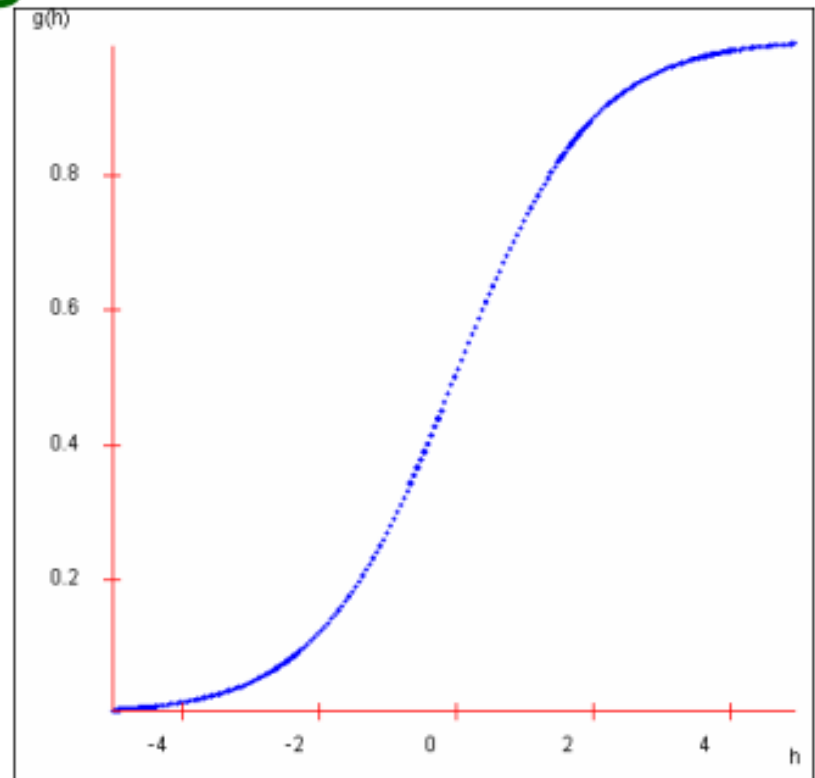
$N_{\text{INPUTS}} = 2$

$N_{\text{HIDDEN}} = 3$



# The Sigmoid

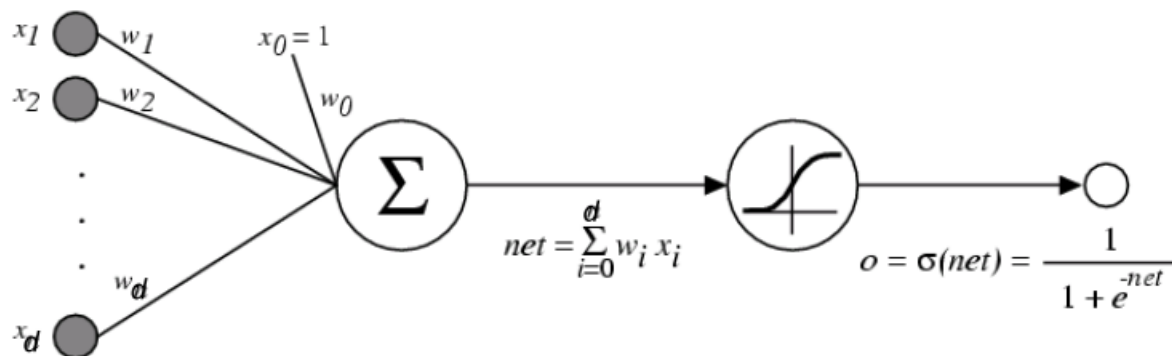
$$g(h) = \frac{1}{1 + \exp(-h)}$$



Now we choose  $\mathbf{w}$  to minimize

$$\sum_{i=1}^R [y_i - \text{Out}(\mathbf{x}_i)]^2 = \sum_{i=1}^R [y_i - g(\mathbf{w}^T \mathbf{x}_i)]^2$$

# Sigmoid Unit



$\sigma(x)$  is the sigmoid function/activation function (also linear, threshold)

$$\frac{1}{1 + e^{-x}}$$

Nice property:  $\frac{d\sigma(x)}{dx} = \sigma(x)(1 - \sigma(x))$     Differentiable

We can derive gradient decent rules to train

- One sigmoid unit
- *Multilayer networks* of sigmoid units → Backpropagation

# Backpropagation

$$\text{Out}(\mathbf{x}) = g\left(\sum_j W_j g\left(\sum_k w_{jk} x_k\right)\right)$$

Find a set of weights  $\{W_j\}, \{w_{jk}\}$   
to minimize

$$\sum_i (y_i - \text{Out}(\mathbf{x}_i))^2$$

by gradient descent.

**That's it!**

**That's the backpropagation  
algorithm.**

# Backpropagation

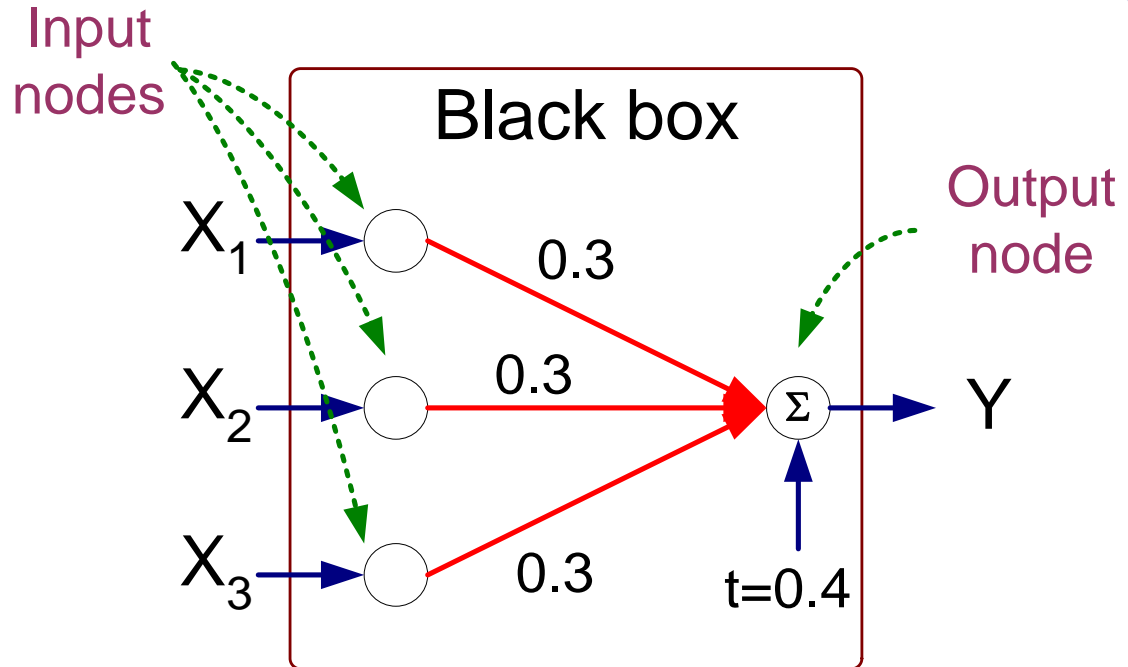


- Iteratively process a set of training tuples & compare the network's prediction with the actual known target value
- For each training tuple, the weights are modified to **minimize the mean squared error** between the network's prediction and the actual target value
- Modifications are made in the “**backwards**” direction: from the output layer, through each hidden layer down to the first hidden layer, hence “**backpropagation**”
- Steps
  - Initialize weights (to small random #s) and biases in the network
  - Propagate the inputs forward (by applying activation function)
  - Backpropagate the error (by updating weights and biases)
  - Terminating condition (when error is very small, etc.)

# Artificial Neural Networks (ANN)



$X_1$	$X_2$	$X_3$	$Y$
1	0	0	0
1	0	1	1
1	1	0	1
1	1	1	1
0	0	1	0
0	1	0	0
0	1	1	1
0	0	0	0



$$Y = I(0.3X_1 + 0.3X_2 + 0.3X_3 - 0.4 > 0)$$

$$\text{where } I(z) = \begin{cases} 1 & \text{if } z \text{ is true} \\ 0 & \text{otherwise} \end{cases}$$



# A Multi-Layer Feed-Forward Neural Network

**Output vector**

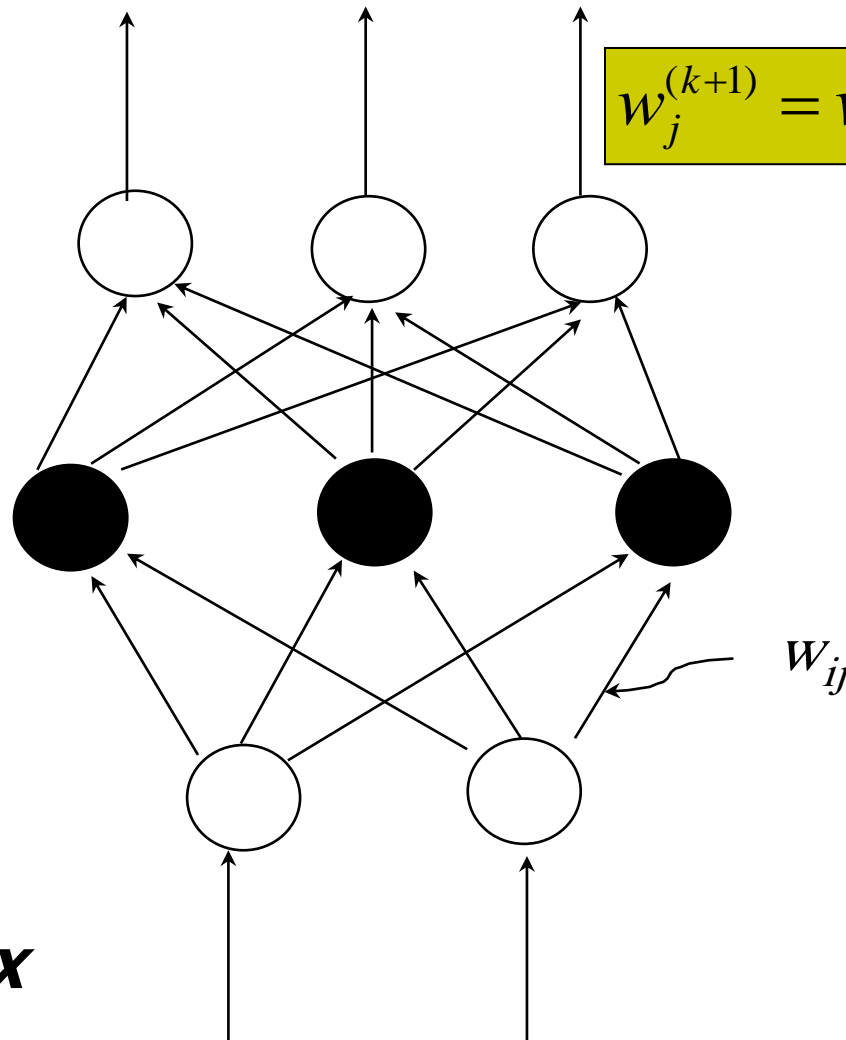
**Output layer**

$$w_j^{(k+1)} = w_j^{(k)} + \lambda(y_i - \hat{y}_i^{(k)})x_{ij}$$

**Hidden layer**

**Input layer**

**Input vector:  $X$**





# General Structure of ANN

