

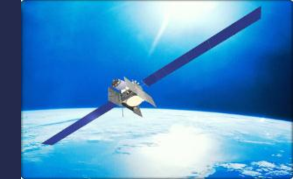

# *Introduction to Neural Networks*

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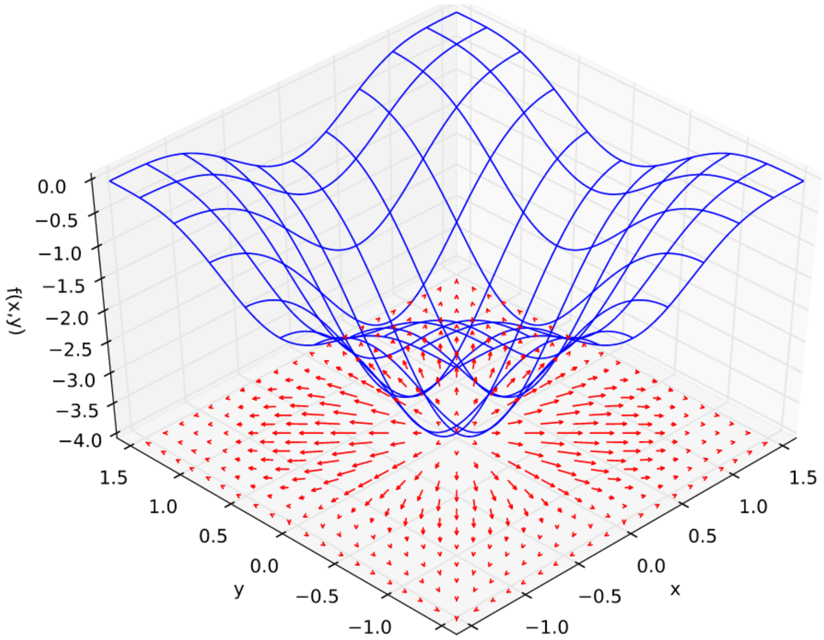
# Basics

- **Gradient**
  - **Generalization of the slope to multidimensional functions**
  - $\nabla f(x) = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \end{bmatrix}$

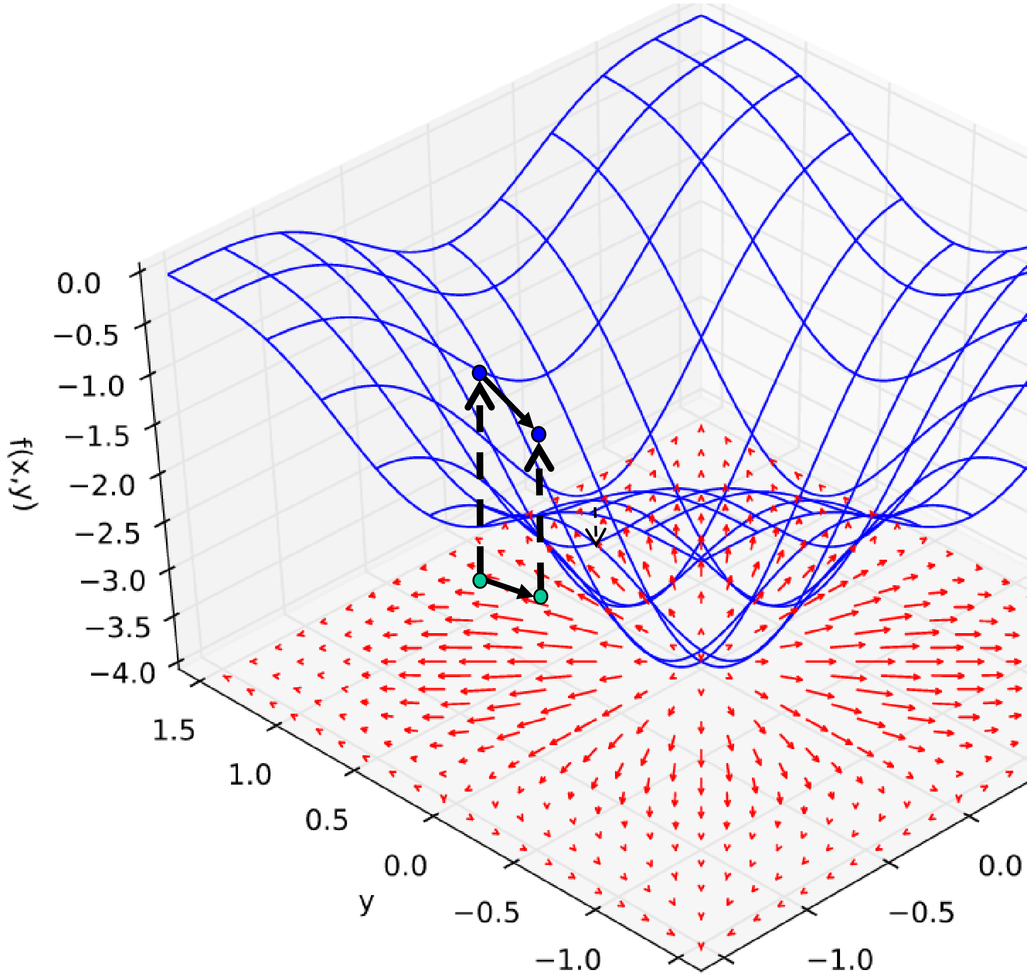


# Basics

- **Gradient Descent**
  - **A method for optimization**
  - **To find the minima of a function, take a step in the direction opposite to the gradient**

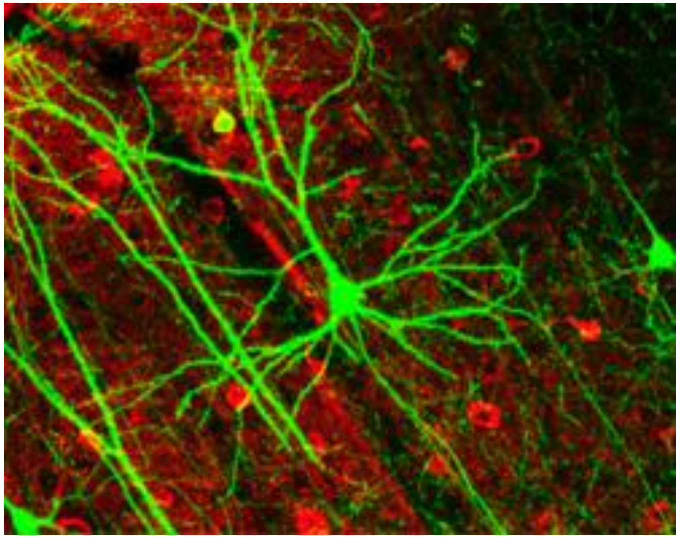
$$\boldsymbol{x_i} = \boldsymbol{x}_{i-1} + \alpha \boldsymbol{\nabla f}(\boldsymbol{x})$$

  - **Local minimas?**



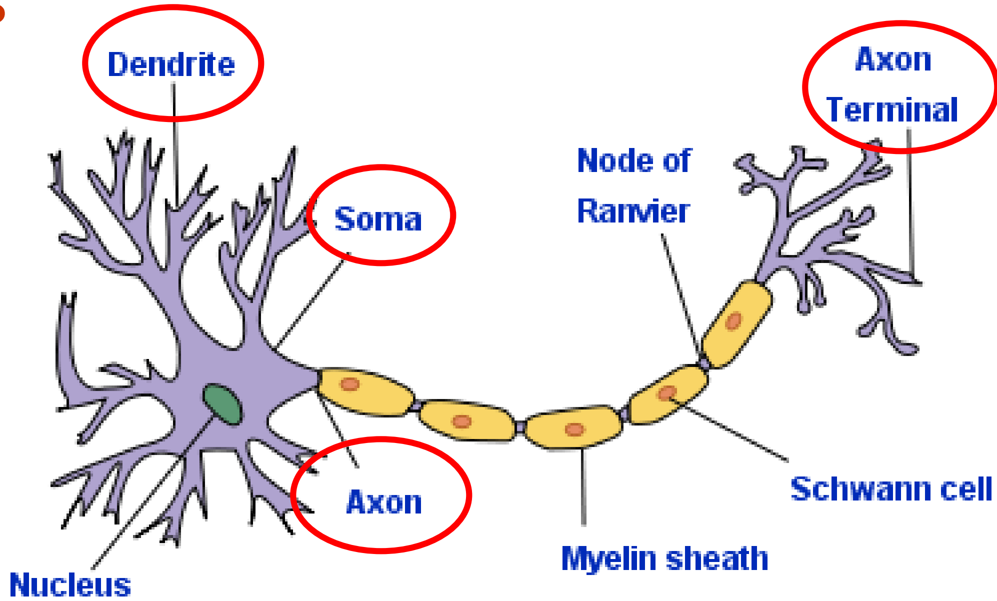
# The Human Brain: Neurons and Nerve Cells

- **Most complex organ in the human body**
- **Contains some $10^{10}$ neurons, which are capable of electrical and chemical communication with tens of thousands of other nerve cells**
- **Nerve cells in turn rely on some quadrillion ($10^{15}$) synaptic connections for their communications.**

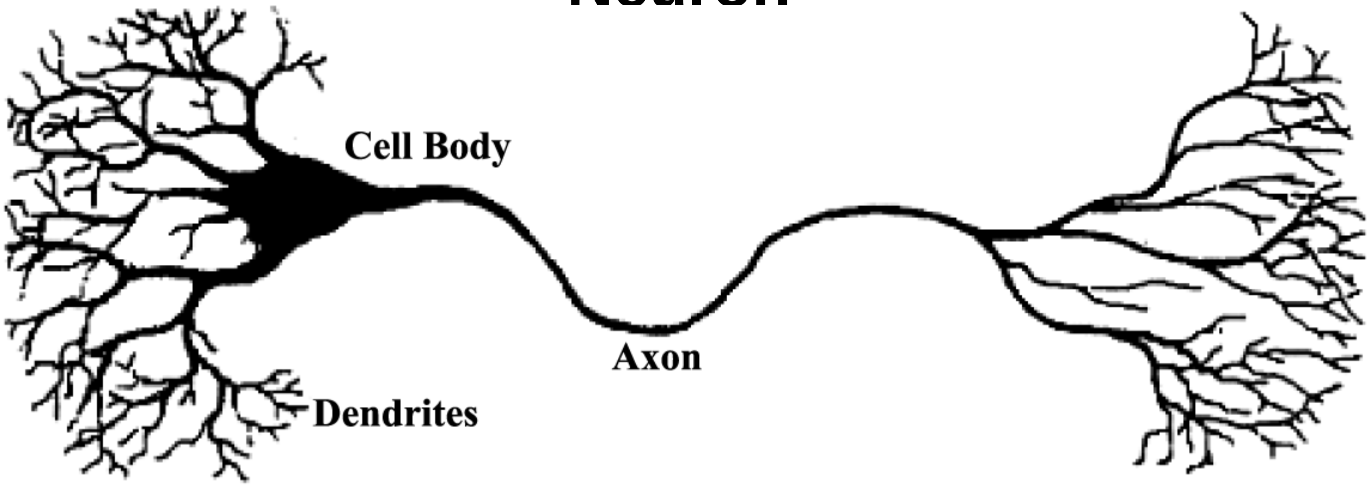


# Functioning of the Biological Neuron

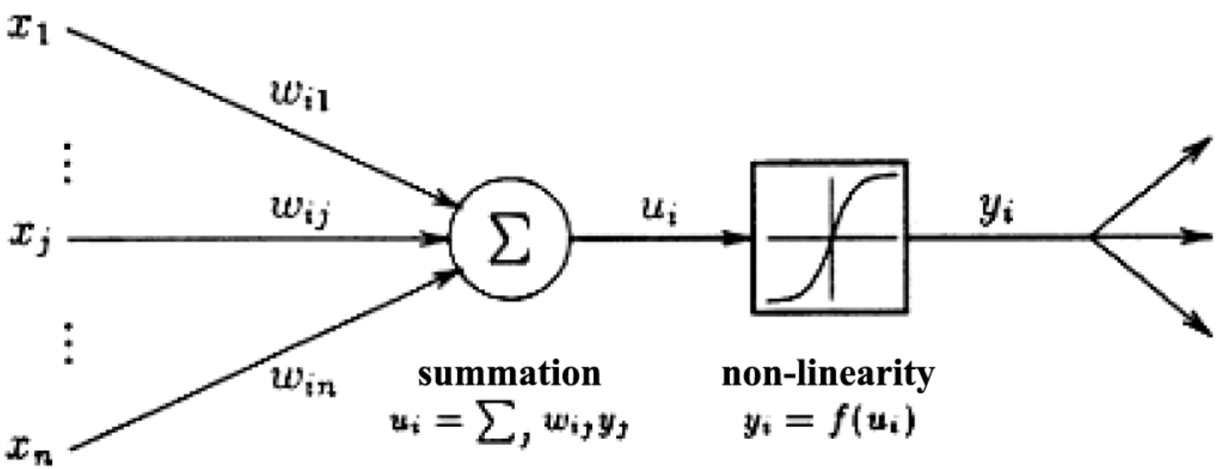
- **Electrically Excitable Cells**
- **Process and Transmit Information**
- **Major Parts**
  - **Soma (3-18um)**
    - **Cell Body**
  - **Dendrites**
    - **Receive Inputs from other Neurons**
  - **Axon**
    - **Transmit Output to other Neurons**



# Structural Mathematical Model for the Biological Neuron




(a)




(b)

# Concepts of Linear Separability

- Find a line that separates
  - (0,0),(0,1),(1,0)
  - (1,1)

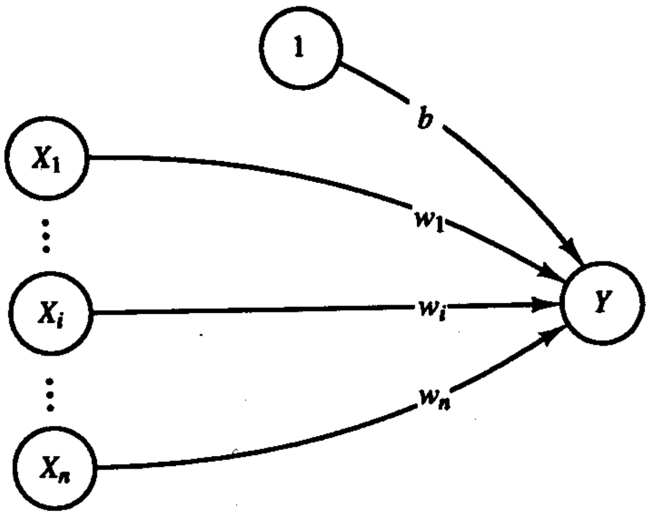
# Perceptron

- **Given:**
  - **Training data and labels**

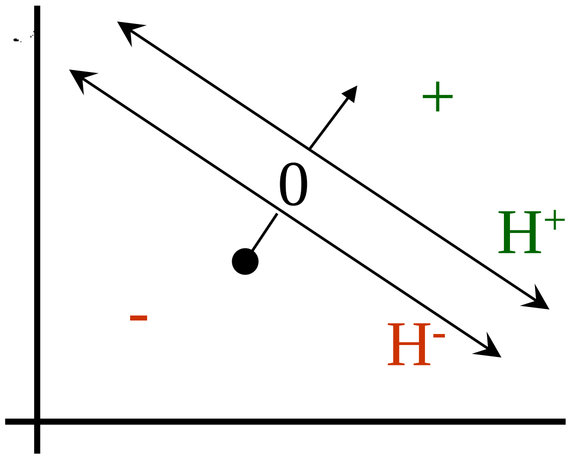
$$y\_in = w_1X_1 + w_2X_2 + \cdots + w_nX_n + b = W^TX + b$$

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}, X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{bmatrix}$$

$$Y = \begin{cases} +1 & W^TX + b > \theta \\ 0 & -\theta \le W^TX + b \le \theta \\ -1 & W^TX + b < -\theta \end{cases}$$




- **Thus there are two hyperplanes)**
  - **$H^+$: $W^TX+b=\theta$**
  - **$H^-$: $W^TX+b=-\theta$**



# Learning Algorithm

*Step 0.* Initialize weights and bias.
(For simplicity, set weights and bias to zero.)
Set learning rate $\alpha$ $(0 < \alpha \leq 1)$.
(For simplicity, $\alpha$ can be set to 1.)

*Step 1.* While stopping condition is false, do Steps 2–6.

*Step 2.* For each training pair s:t, do Steps 3–5.

*Step 3.* Set activations of input units:

$$x_i = s_i.$$

*Step 4.* Compute response of output unit:

$$y\_in = b + \sum_i x_i w_i;$$

$$y = \begin{cases} 1 & \text{if } y\_in > \theta \\ 0 & \text{if } -\theta \leq y\_in \leq \theta \\ -1 & \text{if } y\_in < -\theta \end{cases}$$

*Step 5.* Update weights and bias if an error occurred for this pattern.
If $y \neq t$,

$$w_i(\text{new}) = w_i(\text{old}) + \alpha t x_i,$$

$$b(\text{new}) = b(\text{old}) + \alpha t$$

else

$$w_i(\text{new}) = w_i(\text{old}),$$

$$b(\text{new}) = b(\text{old}).$$

*Step 6.* Test stopping condition:
If no weights changed in Step 2, stop; else, continue.

Epoch

Update Occurs only when there is an error

If output is -1 and target is +1, we must increase the net input: Achieves this by increasing weight by alpha when if the input is +1 or decreasing weight if the input is -1 or not changing it when input is 0

# Example: AND Gate, θ=0.2, α=1

| $x_1$ | $x_2$ | 1 | $y_{net}$ | y | T | $dw_1$ | $dw_2$ | db | $w_1 = w_1 + dw_1$ | $w_2 = w_2 + dw_2$ | b=b+db |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 0 | 1 | 2 | 1 | -1 | -1 | 0 | -1 | 0 | 1 | 0 |
| 0 | 1 | 1 | 1 | 1 | -1 | 0 | -1 | -1 | 0 | 0 | -1 |
| 0 | 0 | 1 | -1 | -1 | -1 | 0 | 0 | -1 | 0 | 0 | -1 |
| 1 | 1 | 1 | -1 | -1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| 1 | 0 | 1 | 1 | 1 | -1 | -1 | 0 | -1 | 0 | 1 | -1 |
| 0 | 1 | 1 | 0 | 0 | -1 | 0 | -1 | -1 | 0 | 0 | -2 |
| 0 | 0 | 1 | -2 | -1 | -1 | 0 | 0 | -1 | 0 | 0 | -2 |
| 1 | 1 | 1 | -2 | -1 | 1 | 1 | 1 | 1 | 1 | 1 | -1 |
| 1 | 0 | 1 | 0 | 0 | -1 | -1 | 0 | -1 | 0 | 1 | -2 |
| 0 | 1 | 1 | -1 | -1 | -1 | 0 | -1 | -1 | 0 | 1 | -2 |
| 0 | 0 | 1 | -2 | -1 | -1 | 0 | 0 | -1 | 0 | 1 | -2 |
| 1 | 1 | 1 | -1 | -1 | 1 | 1 | 1 | 1 | 1 | 2 | -1 |
| 1 | 0 | 1 | 0 | 0 | -1 | -1 | 0 | -1 | 0 | 2 | -2 |
| 0 | 1 | 1 | 0 | 0 | -1 | 0 | -1 | -1 | 0 | 1 | -3 |
| 0 | 0 | 1 | -3 | -1 | -1 | 0 | 0 | -1 | 0 | 1 | -3 |
| 1 | 1 | 1 | -2 | -1 | 1 | 1 | 1 | 1 | 1 | 2 | -2 |
| 1 | 0 | 1 | -1 | -1 | -1 | -1 | 0 | -1 | 1 | 2 | -2 |
| 0 | 1 | 1 | 0 | 0 | -1 | 0 | -1 | -1 | 1 | 1 | -3 |
| 0 | 0 | 1 | -3 | -1 | -1 | 0 | 0 | -1 | 1 | 1 | -3 |

| $x_1$ | $x_2$ | 1 | $y_{net}$ | y | T | $dw_1$ | $dw_2$ | db | $w_1 = w_1 + dw_1$ | $w_2 = w_2 + dw_2$ | b=b+db |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 1 | 1 | -3 |
| 1 | 1 | 1 | -1 | -1 | 1 | 1 | 1 | 1 | 2 | 2 | -2 |
| 1 | 0 | 1 | 0 | 0 | -1 | -1 | 0 | -1 | 1 | 2 | -3 |
| 0 | 1 | 1 | -1 | -1 | -1 | 0 | -1 | -1 | 1 | 2 | -3 |
| 0 | 0 | 1 | -3 | -1 | -1 | 0 | 0 | -1 | 1 | 2 | -3 |
| 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 2 | 3 | -2 |
| 1 | 0 | 1 | 0 | 0 | -1 | -1 | 0 | -1 | 1 | 3 | -3 |
| 0 | 1 | 1 | 0 | 0 | -1 | 0 | -1 | -1 | 1 | 2 | -4 |
| 0 | 0 | 1 | -4 | -1 | -1 | 0 | 0 | -1 | 1 | 2 | -4 |
| 1 | 1 | 1 | -1 | -1 | 1 | 1 | 1 | 1 | 2 | 3 | -3 |
| 1 | 0 | 1 | -1 | -1 | -1 | -1 | 0 | -1 | 2 | 3 | -3 |
| 0 | 1 | 1 | 0 | 0 | -1 | 0 | -1 | -1 | 2 | 2 | -4 |
| 0 | 0 | 1 | -4 | -1 | -1 | 0 | 0 | -1 | 2 | 2 | -4 |
| 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 3 | 3 | -3 |
| 1 | 0 | 1 | 0 | 0 | -1 | -1 | 0 | -1 | 2 | 3 | -4 |
| 0 | 1 | 1 | -1 | -1 | -1 | 0 | -1 | -1 | 2 | 3 | -4 |
| 0 | 0 | 1 | -4 | -1 | -1 | 0 | 0 | -1 | 2 | 3 | -4 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 3 | -4 |
| 1 | 0 | 1 | -2 | -1 | -1 | -1 | 0 | -1 | 2 | 3 | -4 |
| 0 | 1 | 1 | -1 | -1 | -1 | 0 | -1 | -1 | 2 | 3 | -4 |
| 0 | 0 | 1 | -4 | -1 | -1 | 0 | 0 | -1 | 2 | 3 | -4 |

# Videos!

# Observations on Perceptron

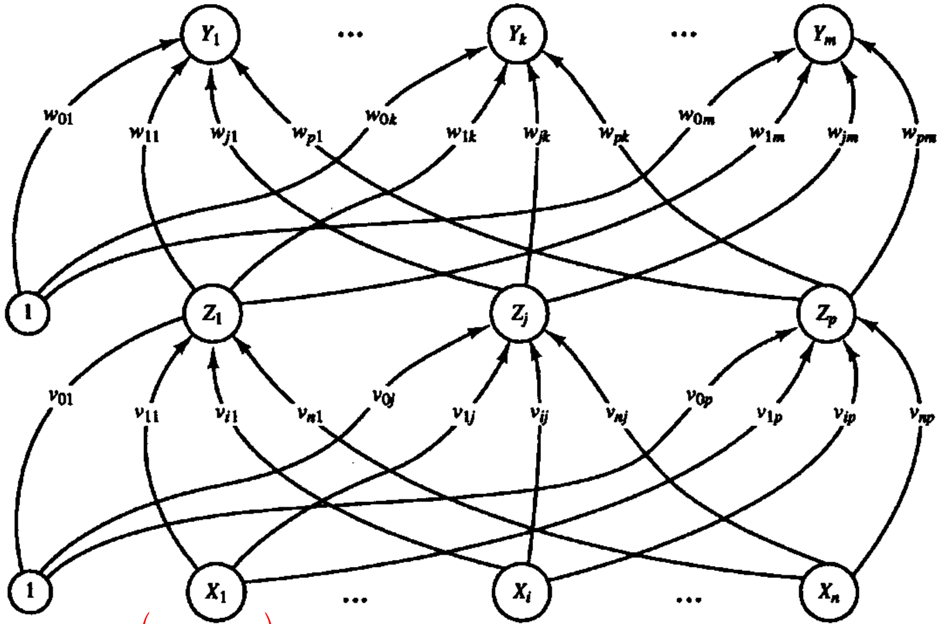
- **Learning rate impacts the speed of learning**
- **Perceptron was unable to learn the XOR problem**
- **Perceptron learning rule convergence theorem**
  - **If the data is linearly separable, you can always use a perceptron algorithm to find a separating hyperplane**

# Feed Forward Backpropagation Neural Networks aka Multi-layer Perceptrons

- **Very General Nature**
  - **Applicable to a variety of practical problems**
    - NETtalk
    - Signature Classification
    - Disease Classification
    - Hand Written Character Recognition
    - Combat Outcome Predication
    - Earthquake Prediction
    - Etc…
- **Objective:**
  - **To achieve a balance between Memorization and Generalization**
    - **Memorization:** Ability to respond correctly to the input patterns used for training
    - **Generalization:** Ability to give reasonable responses to input that is similar but not identical to that used in training

# Architecture

- Consists of multiple layers
- Layers of units other than the input and output are called hidden units
- Unidirectional weight connections and biases
- Activation functions
  - Use of sigmoid functions
    - Nonlinear Operation: Ability to solve practical problems
    - Differentiable: Makes theoretical assessment easier
    - Derivative can be expressed in terms of functions themselves: Computational Efficiency
  - Activation function is the same for all neurons in the same layer
  - Input layer just passes on the signal without processing (linear operation)



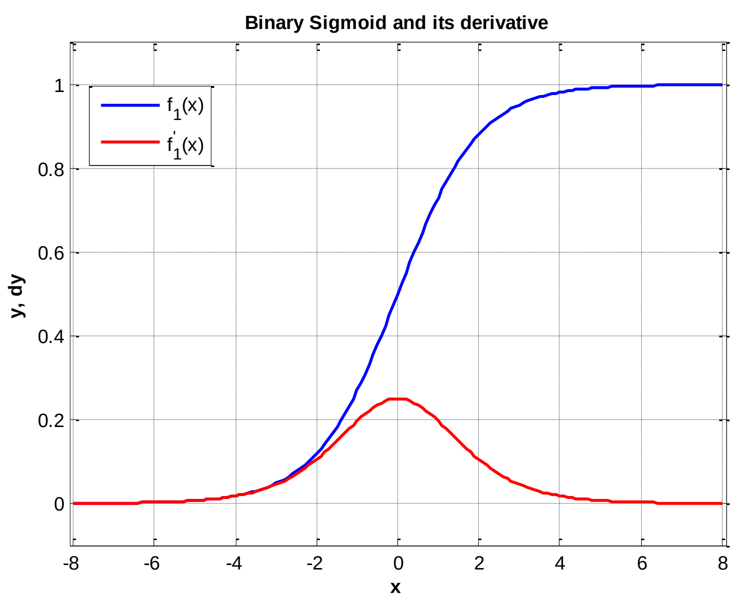

$$z_j = f\left(z\_in_j\right)$$

$$z\_in_j = \sum_{i=0}^{n} x_i v_{ij}, \qquad x_0 = 1, \qquad j = 1 \ldots p$$

$$y_k = f\left(y\_in_k\right)$$

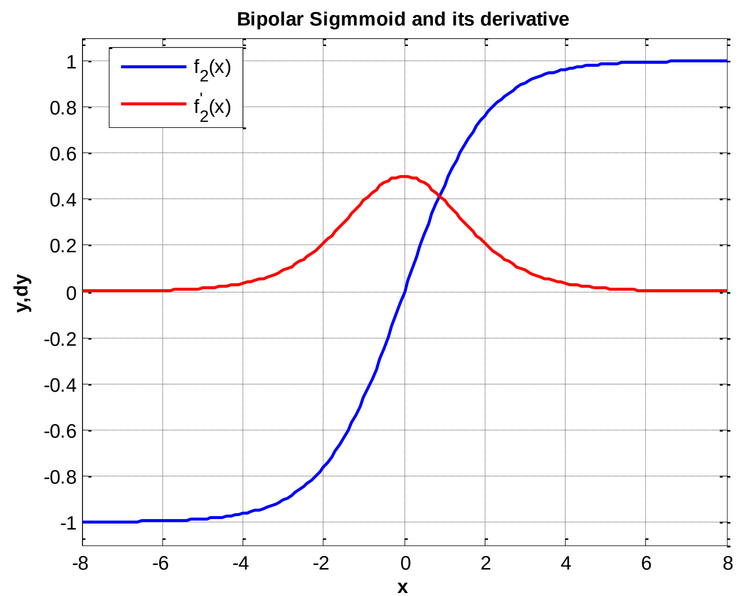
$$y\_in_k = \sum_{j=0}^{p} z_j w_{jk}, \qquad z_0 = 1, \qquad k = 1 \ldots m$$

# Architecture: Activation functions




$$f_1(x) = \frac{1}{1 + \exp(-x)}$$

$$f_1'(x) = f_1(x)[1 - f_1(x)]$$

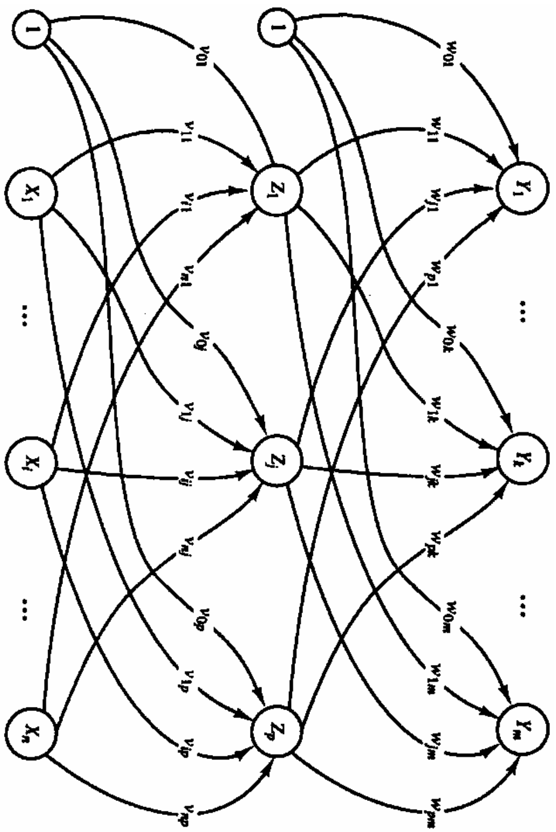



$$f_2(x) = \frac{2}{1 + \exp(-x)} - 1,$$

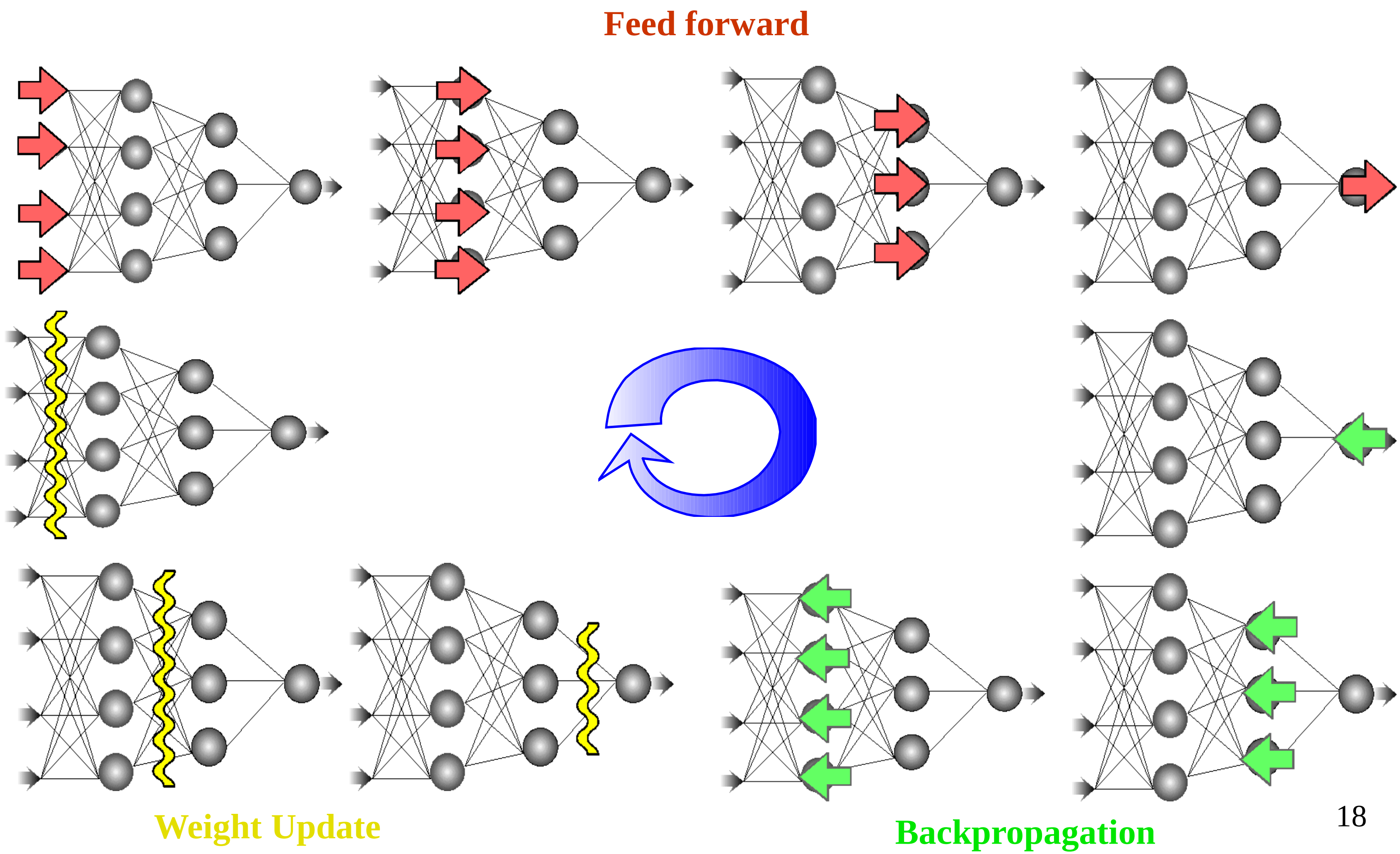
$$f_2'(x) = \frac{1}{2}[1 + f_2(x)][1 - f_2(x)].$$

# Training

- During training we are presented with input patterns and their targets
- At the output layer we can compute the error between the targets and actual output and use it to compute weight updates through the Delta Rule
- But the Error cannot be calculated at the hidden input as their targets are not known
- Therefore we propagate the error at the output units to the hidden units to find the required weight changes (Backpropagation)
- 3 Stages
  - Feed-forward of the input training pattern
  - Calculation and Backpropagation of the associated error
  - Weight Adjustment
- Based on minimization of SSE (Sum of Square Errors)



# Backpropagation training cycle



# Proof for the Learning Rule

$$E = .5 \sum_k [t_k - y_k]^2.$$

By use of the chain rule, we have

$$\frac{\partial E}{\partial w_{JK}} = \frac{\partial}{\partial w_{JK}} .5 \sum_k [t_k - y_k]^2$$

$$= \frac{\partial}{\partial w_{JK}} .5[t_K - f(y\_in_K)]^2$$

$$= -[t_K - y_K] \frac{\partial}{\partial w_{JK}} f(y\_in_K)$$

$$= -[t_K - y_K] f'(y\_in_K) \frac{\partial}{\partial w_{JK}} (y\_in_K)$$

$$= -[t_K - y_K] f'(y\_in_K) z_J.$$

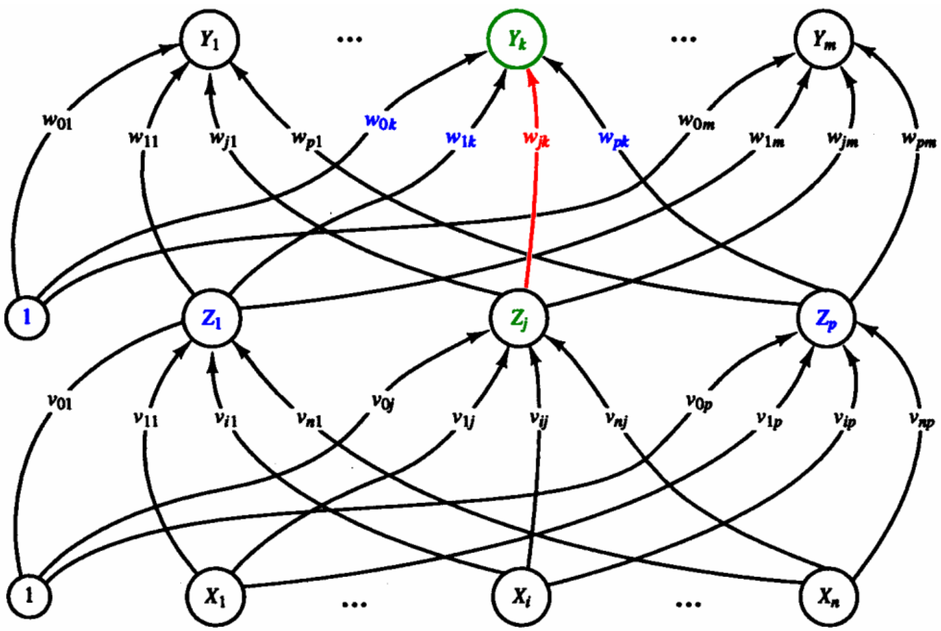
It is convenient to define $\delta_K$:

$$\delta_K = [t_K - y_K] f'(y\_in_K).$$

$$\Delta w_{jk} = -\alpha \frac{\partial E}{\partial w_{jk}}$$

$$= \alpha [t_k - y_k] f'(y\_in_k) z_j$$

$$= \alpha \delta_k z_j;$$




Change in $w_{jk}$ affects only $Y_k$

Use of Gradient Descent Minimization

# Proof for the Learning Rule…

For weights on connections to the hidden unit $Z_J$:

$$\frac{\partial E}{\partial v_{IJ}} = -\sum_k [t_k - y_k] \frac{\partial}{\partial v_{IJ}} y_k$$

$$= -\sum_k [t_k - y_k] f'(y\_in_k) \frac{\partial}{\partial v_{IJ}} y\_in_k$$

$$= -\sum_k \delta_k \frac{\partial}{\partial v_{IJ}} y\_in_k$$

$$= -\sum_k \delta_k w_{Jk} \frac{\partial}{\partial v_{IJ}} z_J$$

$$= -\sum_k \delta_k w_{Jk} f'(z\_in_J)[x_I].$$

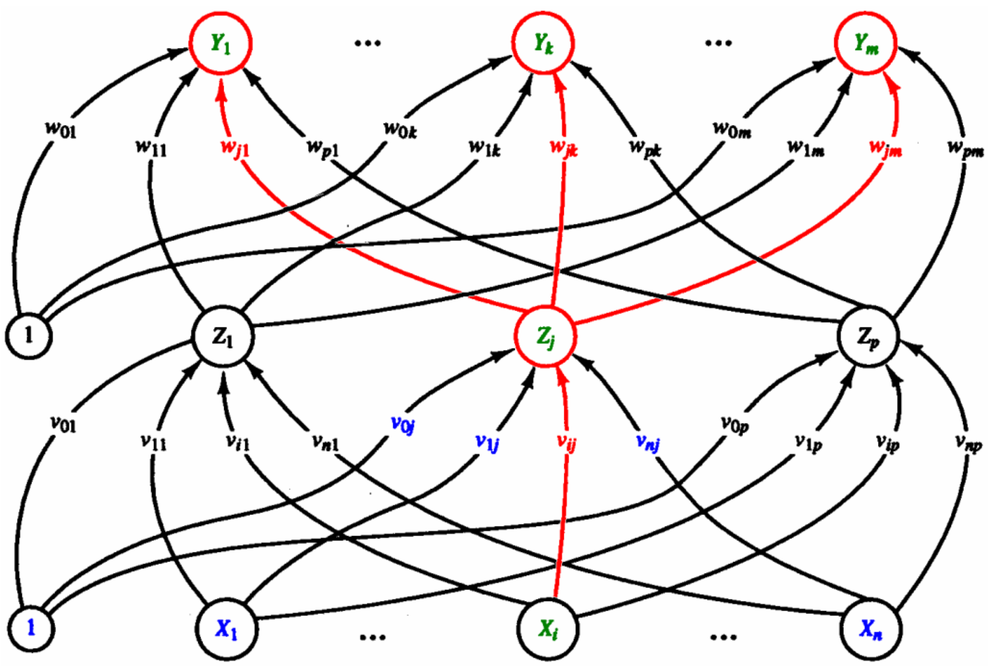
Define:

$$\delta_J = \sum_k \delta_k w_{Jk} f'(z\_in_J)$$

$$\Delta v_{ij} = -\alpha \frac{\partial E}{\partial v_{ij}}$$

$$= \alpha f'(z\_in_j) x_i \sum_k \delta_k w_{jk},$$

$$= \alpha \delta_j x_i.$$




Change in $v_{ij}$ affects all $Y_{1..m}$

Change in $v_{ij}$ affects only $z_j$

Use of Gradient Descent Minimization

# Training Algorithm

*Step 0.* Initialize weights.
(Set to small random values).

*Step 1.* While stopping condition is false, do Steps 2–9.

*Step 2.* For each training pair, do Steps 3–8.

*Feedforward:*

*Step 3.* Each input unit ($X_i$, $i = 1, \ldots, n$) receives input signal $x_i$ and broadcasts this signal to all units in the layer above (the hidden units).

*Step 4.* Each hidden unit ($Z_j$, $j = 1, \ldots, p$) sums its weighted input signals,

$$z\_in_j = v_{0j} + \sum_{i=1}^{n} x_i v_{ij},$$

applies its activation function to compute its output signal,

$$z_j = f(z\_in_j),$$

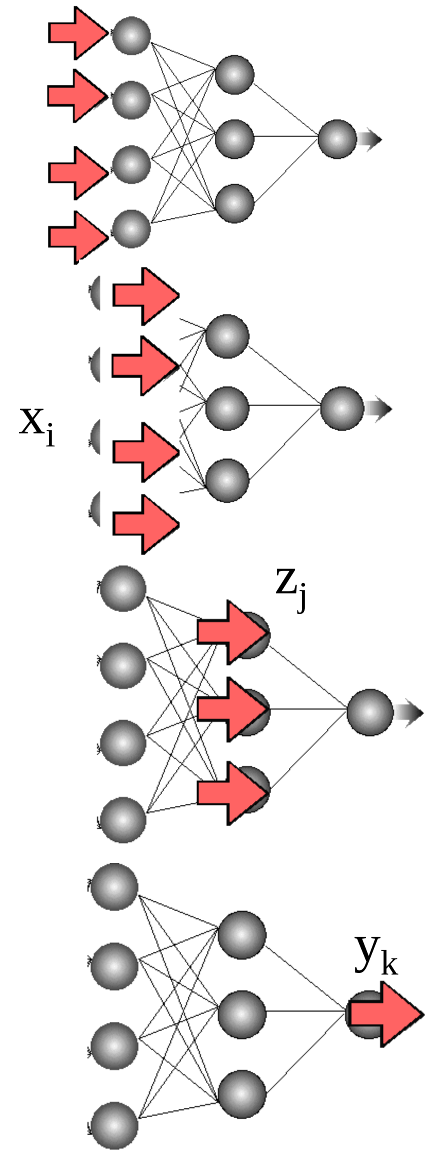
and sends this signal to all units in the layer above (output units).

*Step 5.* Each output unit ($Y_k$, $k = 1, \ldots, m$) sums its weighted input signals,

$$y\_in_k = w_{0k} + \sum_{j=1}^{p} z_j w_{jk}$$

and applies its activation function to compute its output signal,

$$y_k = f(y\_in_k).$$



# Training Algorithm…

*Backpropagation of error:*

*Step 6.* Each output unit ($Y_k, k = 1, \ldots, m$) receives a target pattern corresponding to the input training pattern, computes its error information term,

$$\delta_k = (t_k - y_k)f'(y\_in_k),$$

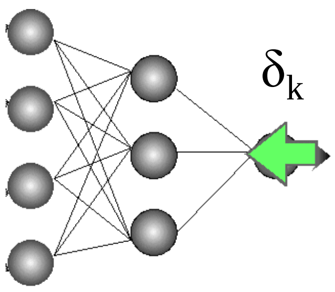
calculates its weight correction term (used to update $w_{jk}$ later),

$$\Delta w_{jk} = \alpha\delta_k z_j,$$

calculates its bias correction term (used to update $w_{0k}$ later),

$$\Delta w_{0k} = \alpha\delta_k,$$

and sends $\delta_k$ to units in the layer below.



# Training Algorithm…

*Step 7.* Each hidden unit ($Z_j, j = 1, \ldots, p$) sums its delta inputs (from units in the layer above),

$$\delta\_in_j = \sum_{k=1}^{m} \delta_k w_{jk},$$

multiplies by the derivative of its activation function to calculate its error information term,

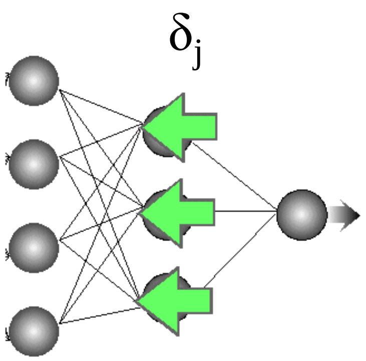
$$\delta_j = \delta\_in_j \, f'(z\_in_j),$$

calculates its weight correction term (used to update $v_{ij}$ later),

$$\Delta v_{ij} = \alpha \delta_j x_i,$$

and calculates its bias correction term (used to update $v_{0j}$ later),

$$\Delta v_{0j} = \alpha \delta_j.$$



# Training Algorithm…

*Update weights and biases:*

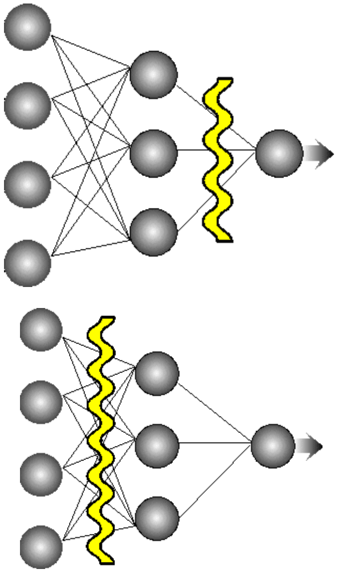
*Step 8.* Each output unit ($Y_k$, $k = 1, \ldots, m$) updates its bias and weights ($j = 0, \ldots, p$):

$$w_{jk}(\text{new}) = w_{jk}(\text{old}) + \Delta w_{jk}.$$

Each hidden unit ($Z_j$, $j = 1, \ldots, p$) updates its bias and weights ($i = 0, \ldots, n$):

$$v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij}.$$

*Step 9.* Test stopping condition.



# Effect of Learning Rate

- Controls the change in synaptic weights
- The smaller the learning rate the smoother the trajectory in the weight space
  - Slower rate of learning
- If learning rate is made too large (for speedy convergence) the network may become unstable (oscillatory)

# Stopping Criterion

- The Backpropagation (BP) algorithm cannot be shown to converge
  - No well defined criterion for stopping its operation
- Criterion Used
  - BP is considered to have converged when the Euclidean norm of the gradient vector reaches a sufficiently small threshold
    - Ideally Gradient is zero at the minima
    - Drawbacks
      - For successful trials, learning times may be large
      - Calculation of the gradient is required
  - BP is considered to have converged when the absolute rate of change in the average squared error per epoch is sufficiently small
    - May result in premature termination of the learning process

# Application Procedure

- Involves only the feed-forward phase (fast!)

*Step 0.* Initialize weights (from training algorithm).

*Step 1.* For each input vector, do Steps 2–4.

*Step 2.* For $i = 1, \ldots, n$: set activation of input unit $x_i$;

*Step 3.* For $j = 1, \ldots, p$:

$$z\_in_j = v_{0j} + \sum_{i=1}^{n} x_i v_{ij};$$

$$z_j = f(z\_in_j).$$

*Step 4.* For $k = 1, \ldots, m$:

$$y\_in_k = w_{0k} + \sum_{j=1}^{p} z_j w_{jk};$$

$$y_k = f(y\_in_k).$$

# Solution of the XOR Problem

- **Initial weights**

$v_{01} = -0.8$

$v_{11} = 0.5$

$v_{12} = 0.9$

$v_{02} = +0.1$

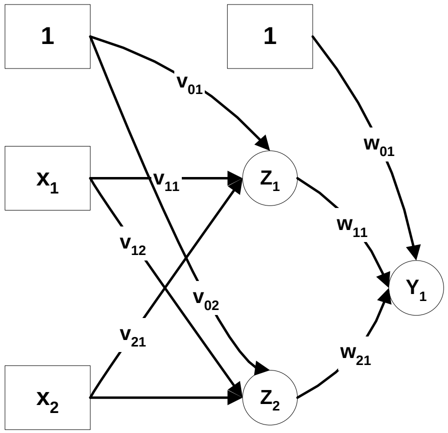
$v_{21} = 0.4$

$v_{22} = 1$

$w_{01} = -0.3$

$w_{11} = -1.2$

$w_{21} = 1.1$




$$z_j = f\left(z\_in_j\right)$$

$$z\_in_j = \sum_{i=0}^{2} x_i v_{ij}, \qquad x_0 = 1, \qquad j = 1 \ldots 2$$

$$y_k = f\left(y\_in_k\right)$$

$$y\_in_k = \sum_{j=0}^{2} z_j w_{jk}, \qquad z_0 = 1, \qquad k = 1$$

# Solution of the XOR Problem…

- We consider the input pattern as (1,1) with target = 0 and α=0.1
- Feed Forward

$$z_1 = sigmoid\,(V_1^T X) = 1/\left[1 + e^{-(1\cdot 0.5 + 1\cdot 0.4 - 1\cdot 0.8)}\right] = 0.5250$$

$$z_2 = sigmoid\,(V_2^T X) = 1/\left[1 + e^{-(1\cdot 0.9 + 1\cdot 1.0 + 1\cdot 0.1)}\right] = 0.8808$$

$$y_1 = sigmoid\,(W^T Z) = 1/\left[1 + e^{-(-0.5250\cdot 1.2 + 0.8808\cdot 1.1 - 1\cdot 0.3)}\right] = 0.5097$$

- Backpropagation

$$e = t - y_1 = 0 - 0.5097 = -0.5097$$

$$\delta_{k=1} = y_1\,(1 - y_1)\,e = 0.5097\cdot(1 - 0.5097)\cdot(-0.5097) = -0.1274$$

$$\Delta w_{21} = \alpha\cdot z_2\cdot\delta_{k=1} = 0.1\cdot 0.8808\cdot(-0.1274) = -0.0112$$

$$\Delta w_{11} = \alpha\cdot z_1\cdot\delta_{k=1} = 0.1\cdot 0.5250\cdot(-0.1274) = -0.0067$$

$$\Delta w_{01} = \alpha\cdot(1)\cdot\delta_{k=1} = 0.1\cdot(+1)\cdot(-0.1274) = -0.0127$$

# Solution of the XOR Problem…

- **Backpropagation…**

$$\delta_{j=1} = z_1(1-z_1)\cdot\delta_1\cdot w_{11} = 0.5250\cdot(1-0.5250)\cdot(-0.1274)\cdot(-1.2) = 0.0381$$

$$\delta_{j=2} = z_2(1-z_2)\cdot\delta_1\cdot w_{21} = 0.8808\cdot(1-0.8808)\cdot(-0.1274)\cdot 1.1 = -0.0147$$

$$\Delta v_{11} = \alpha\cdot x_1\cdot\delta_{j=1} = 0.1\cdot 1\cdot 0.0381 = 0.0038$$

$$\Delta v_{21} = \alpha\cdot x_2\cdot\delta_{j=1} = 0.1\cdot 1\cdot 0.0381 = 0.0038$$

$$\Delta v_{01} = \alpha\cdot(+1)\cdot\delta_{j=1} = 0.1\cdot(+1)\cdot 0.0381 = +0.0038$$

$$\Delta v_{12} = \alpha\cdot x_1\cdot\delta_{j=2} = 0.1\cdot 1\cdot(-0.0147) = -0.0015$$

$$\Delta v_{22} = \alpha\cdot x_2\cdot\delta_{j=2} = 0.1\cdot 1\cdot(-0.0147) = -0.0015$$

$$\Delta v_{02} = \alpha\cdot(+1)\cdot\delta_{j=2} = 0.1\cdot(+1)\cdot(-0.0147) = -0.0015$$

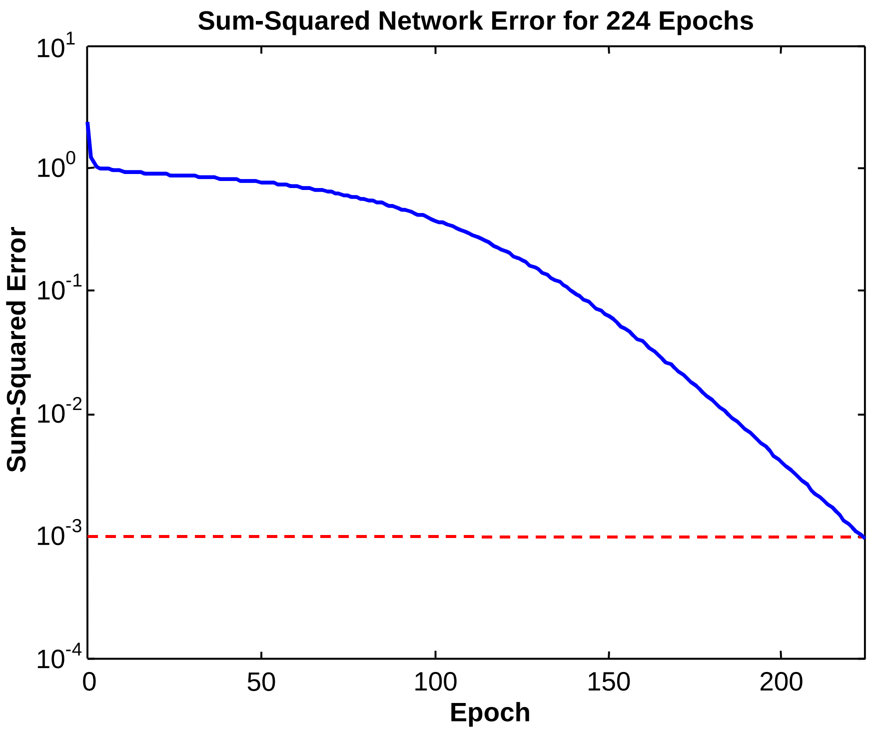
# Solution of the XOR Problem…

- **Weight Update**

$$v_{01} = -0.7962$$
$$v_{11} = 0.5038$$
$$v_{12} = 0.8985$$
$$v_{02} = +0.0985$$
$$v_{21} = 0.4038$$
$$v_{22} = 0.9985$$
$$w_{01} = -0.3127$$
$$w_{11} = -1.2067$$
$$w_{21} = 1.0888$$

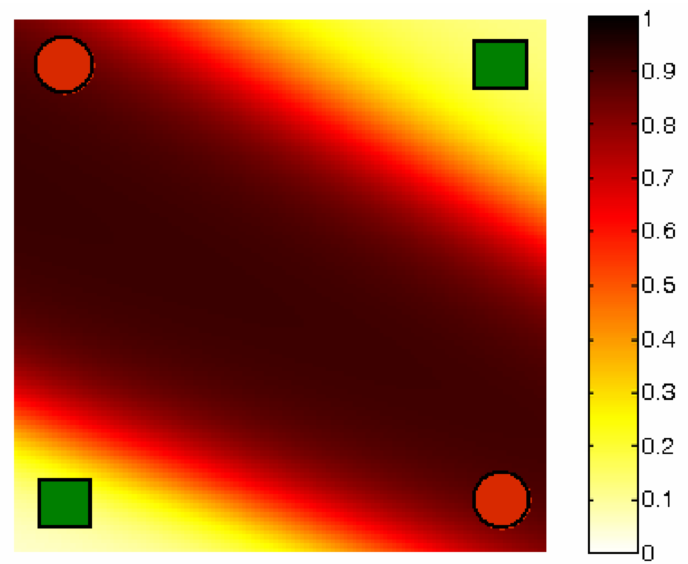
- **The training process is repeated until the sum of squared errors is less than 0.001.**

# Solution of the XOR Problem…




See Video!

| Inputs $x_1$ | Inputs $x_2$ | Desired output | Actual output | Error $e$ | Sum of squared errors |
|---|---|---|---|---|---|
| 1 | 1 | 0 | 0.0155 | −0.0155 | 0.0010 |
| 0 | 1 | 1 | 0.9849 | 0.0151 | |
| 1 | 0 | 1 | 0.9849 | 0.0151 | |
| 0 | 0 | 0 | 0.0175 | −0.0175 | |



# Number of hidden layers…

- Theoretically, One hidden layer is sufficient for a Backpropagation net to approximate any continuous mapping from the input patterns to the output pattern to an arbitrary degree of accuracy
- However two hidden layers may make training easier in some situations

# Selecting parameters

- Architecture
  - Number of layers
  - Number of neurons in each layer
- Activation Function
- Learning rate
- Stopping criterion

# Implementation

```python
from keras.models import Sequential
from keras.layers import Dense
import numpy
seed = 7
numpy.random.seed(seed)
# Load the dataset
dataset = numpy.loadtxt("pima-indians-diabetes.csv", delimiter=",")
X = dataset[:,0:8]
Y = dataset[:,8]
# Define and Compile
model = Sequential()  # The network is not recurrent and has a sequence of layers
model.add(Dense(12, input_dim=8, init='uniform', activation='relu'))
model.add(Dense(8, init='uniform', activation='relu'))
model.add(Dense(1, init='uniform', activation='sigmoid'))
model.compile(loss='binary_crossentropy' , optimizer='adam', metrics=['accuracy'])
# Fit the model
model.fit(X, Y, nb_epoch=150, batch_size=10)
# Evaluate the model
scores = model.evaluate(X, Y)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

# Number of layers, neurons, activations & weight init.

# Loss function and optimization

# Doing all this in Keras

- Layers

```
model = Sequential()
model.add(Dense(32, input_shape=(500,)))
model.add(Dense(10, activation='softmax'))
model.compile(optimizer='rmsprop',
loss='categorical_crossentropy', metrics=['accuracy'])
```

**Useful attributes of Model**

`model.layers`: is a flattened list of the layers comprising the model graph.
`model.inputs`: is the list of input tensors
`model.outputs`: is the list of output tensors.

# Doing all this in Keras

- Activations

```
from keras.layers import Activation, Dense
model.add(Dense(64))
model.add(Activation('tanh'))

model.add(Dense(64, activation='tanh'))
```

- Available Activation
  - Softmax
  - Elu
  - Softplus
  - Softsign
  - Relu
  - Tanh
  - Sigmoid
  - Hard Sigmoid
  - Linear

# Doing all this in Keras

- Losses

```
model.compile(loss='mean_squared_error', optimizer='sgd')

from keras import losses model.compile(loss=losses.mean_squared_error, optimizer='sgd')
```

- Available
  - Mean Squared Error
  - Mean Absolute Error
  - Mean Absolute Percentage Error
  - Mean Squared Logarithmic Error
  - Squared Hinge
  - Hinge
  - Categorical Cross Entropy
  - Sparse categorical crossentropy
  - Binary Crossentropy
  - Kullback Leibler Divergence
  - Posison
  - Cosine Proximity

# Doing all this in Keras

- Metrics
  - Used to evaluate model performance

```
from keras import metrics
model.compile(loss='mean_squared_error',
              optimizer='sgd',
              metrics=[metrics.mae, metrics.categorical_accuracy])
```

- Available
  - Binary Accuracy
  - Categorical Accuracy
  - Sparse Categorical Accuracy
  - Top K Categorical Accuracy
  - Custom

# Doing all this in Keras

- Optimizers

```
from keras import optimizers
model = Sequential()
model.add(Dense(64, init='uniform', input_shape=(10,)) model.add(Activation('tanh'))
model.add(Activation('softmax'))
sgd = optimizers.SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)
model.compile(loss='mean_squared_error', optimizer=sgd)
```

- Available
  - SGD
  - RMSprop
  - Adagrad
  - AdaDelta
  - Adam
  - Adamax
  - Nadam

# Doing all this in Keras

- Initializers

```
model.add(Dense(64,
          kernel_initializer='random_uniform',
          bias_initializer='zeros'))
```

# Doing all this in Keras

- Regularization
  - L1 and L2
- Drop-Out
- Batch Normalization

# Doing all this in Keras

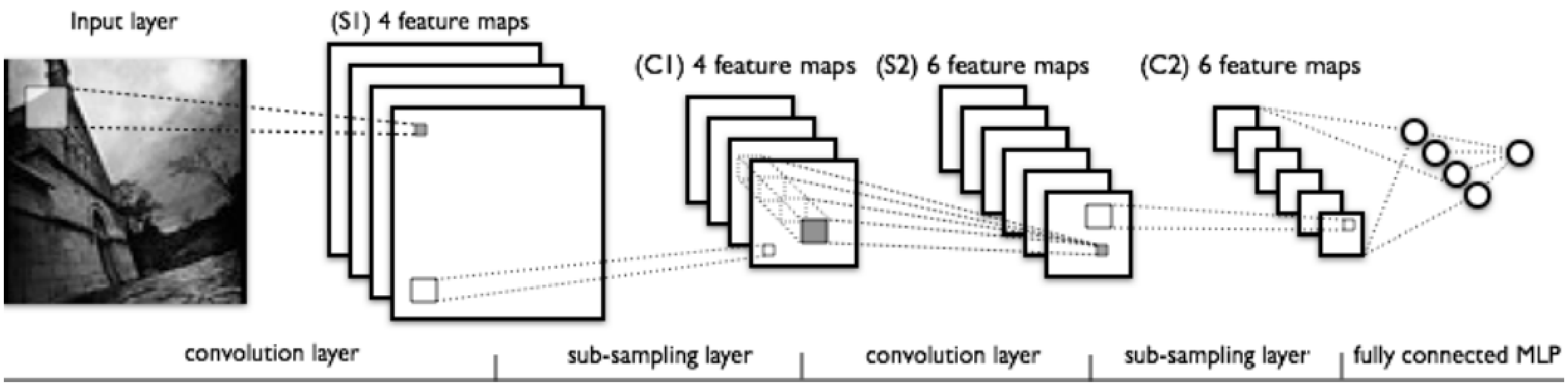
- Data Augmentation
  - Noise Layer
  - ImageDataGenerator

# Class Exercise!

- Requires Keras based computers
- Solve the XOR using a single hidden layer BPNN with sigmoid activations
  - See what is the effect of different parameters on the convergence characteristics of the neural network

# Applications

The LeNet-5 network:




Important ideas:

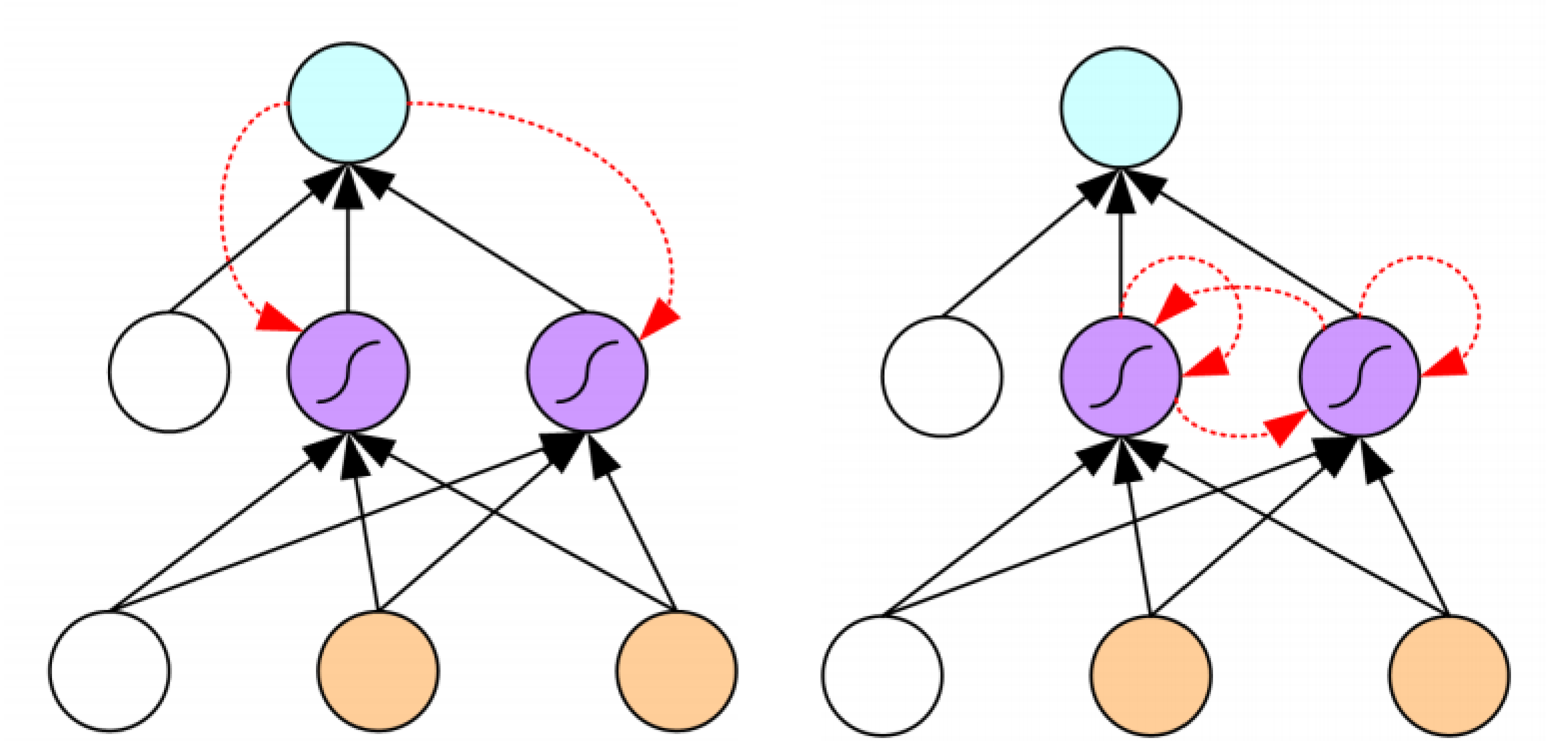
Extract local features (local receptive fields) and merge them later to create global features

Local features that are useful in one region are likely to be useful elsewhere - weight sharing

http://yann.lecun.com/exdb/lenet/

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, november 1998.

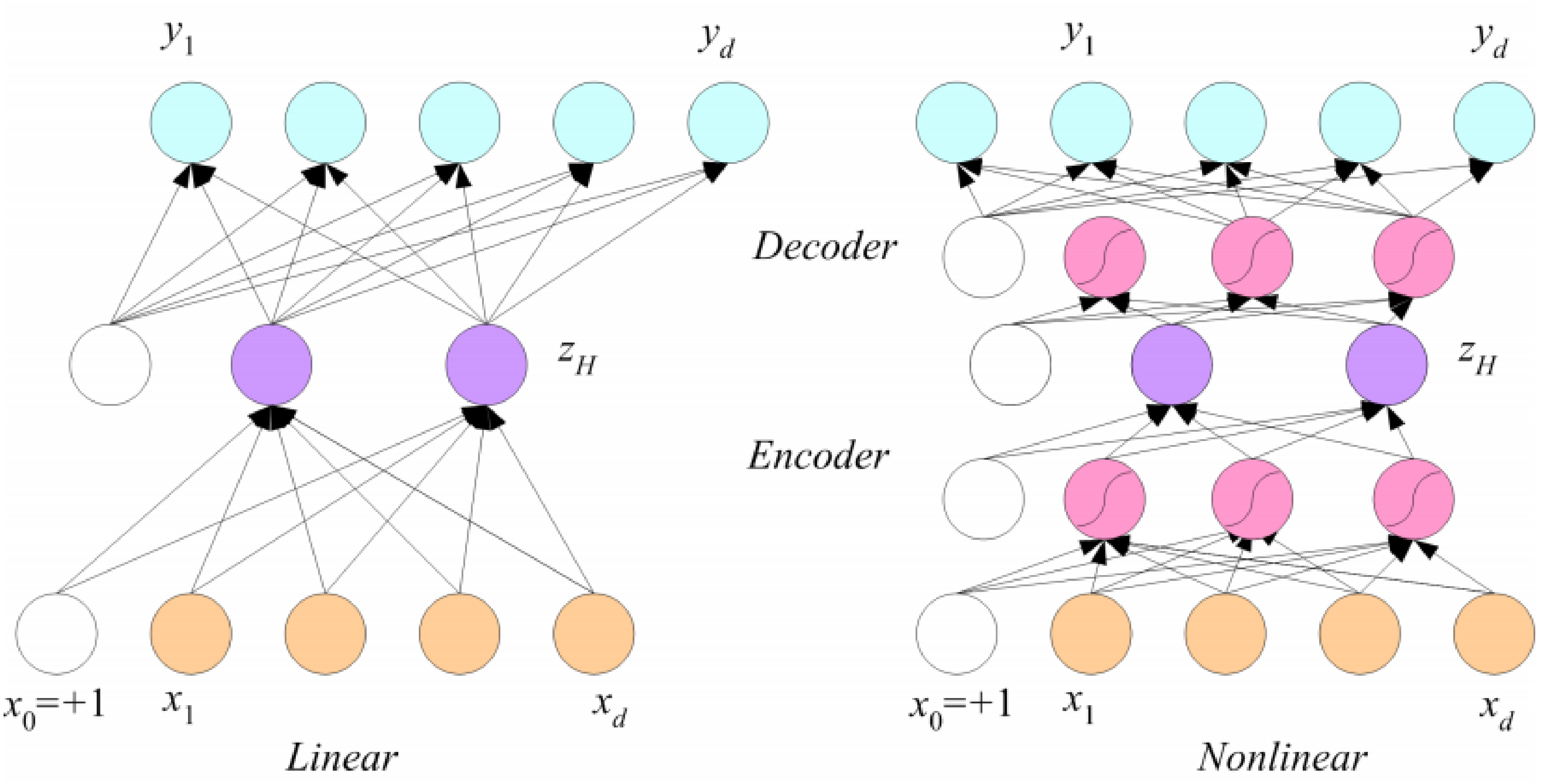
# Recurrent Networks



The cycles allow the network to exhibit dynamic temporal behavior

RNNs can use their internal memory to process arbitrary sequences of inputs.

# Dimensionality Reduction



# Deep learning

- NNs can be used for feature learning

# Reading

- Fundamentals of Neural Networks (Laurene Faucett)
  - Perceptron: Chapter 2
  - MLP: Chapter 6
- Neural Networks a comprehensive foundation (1999)