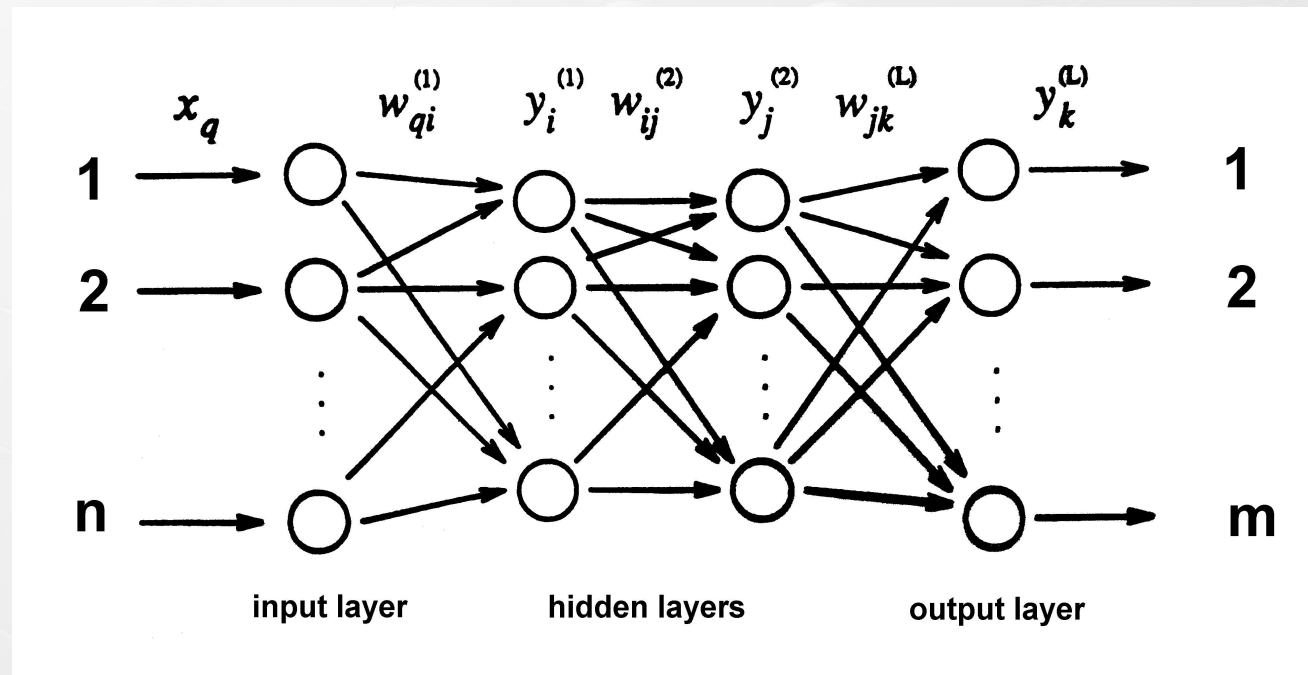


Backpropagation Learning Algorithm

- An algorithm for learning the weights in the network, given a training set of input-output pairs $\{ \mathbf{X}^{\mu}, \mathbf{O}^{\mu} \}$
- The algorithm is based on gradient descent method.
- Architecture



$w_{ij}^{(l)}$: Weight on connection between the i^{th} unit in layer $(l-1)$ to j^{th} unit in layer l

Supervised Learning

Supervised learning algorithms require the presence of a “teacher” who provides the right answers to the input questions.

Technically, this means that we need a *training set* of the form

$$L = \left\{ \left(\bar{x}^1, \bar{y}^1 \right) \dots \left(\bar{x}^p, \bar{y}^p \right) \right\}$$

where :

- \bar{x}^h ($h = 1 \dots p$) is the network input vector
- \bar{y}^h ($h = 1 \dots p$) is the network output vector

Supervised Learning

The learning (or training) phase consists of determining a configuration of weights in such a way that the network output be as close as possible to the desired output, for all examples in the training set.

Formally, this amounts to minimizing the following *error function* :

$$\begin{aligned} E &= \frac{1}{2} \sum_{h=1}^p \left\| \overline{out}_h - \overline{y}_h \right\|_2^2 \\ &= \frac{1}{2} \sum_h \sum_k \left(out_k^h - y_k^h \right)^2 \end{aligned}$$

where \overline{out}_h is the output provided by the network when given x^h as input.

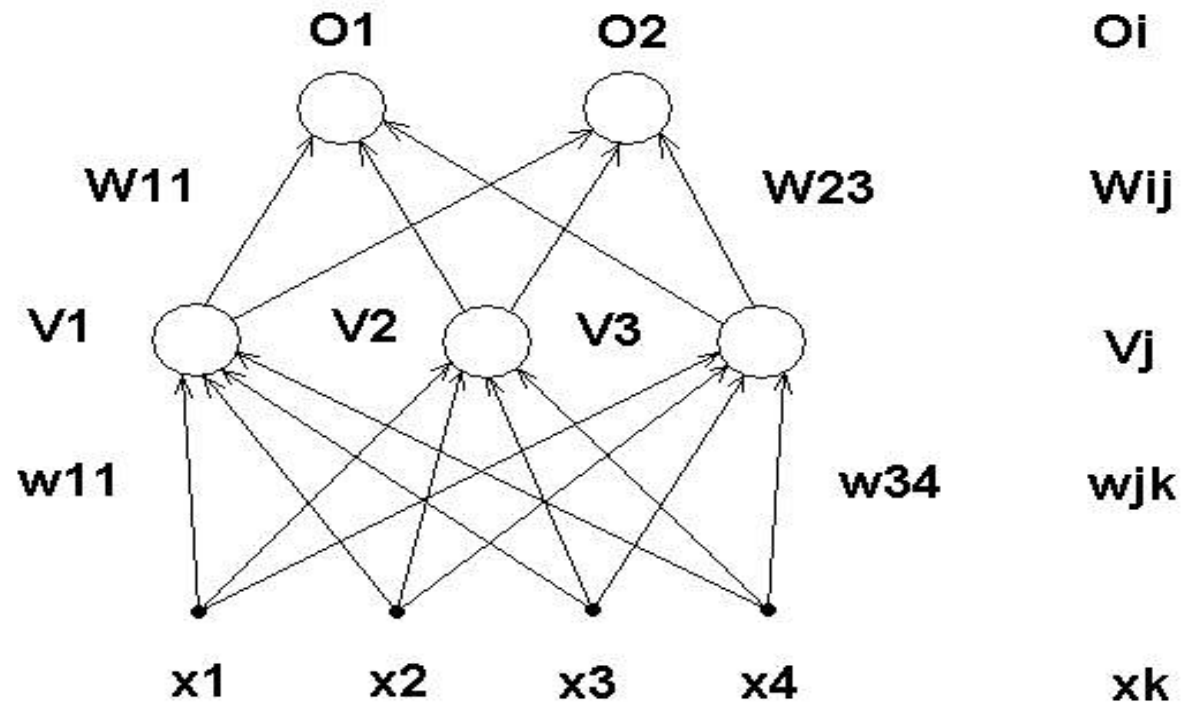
Back-Propagation

To minimize the error function E we can use the classic gradient – descent algorithm.

To compute the partial derivatives $\partial E / \partial w_{ij}$, we use the *error back propagation* algorithm.

It consists of two stages:

- *Forward pass* : the input to the network is propagated layer after layer in forward direction
- *Backward pass* : the “ error ” made by the network is propagated backward, and weights are updated properly



Dato il pattern μ , l'unità nascosta j riceve un input netto dato da

$$h_j^\mu = \sum_k w_{jk} x_k^\mu$$

e produce come output :

$$V_j^\mu = g(h_j^\mu) = g\left(\sum_k w_{jk} x_k^\mu\right)$$

Back-Prop : Updating Hidden-to-Output Weights

$$\begin{aligned}\Delta W_{ij} &= -\eta \frac{\partial E}{\partial W_{ij}} \\ &= -\eta \frac{\partial}{\partial W_{ij}} \left[\frac{1}{2} \sum_{\mu} \sum_k (y_k^{\mu} - o_k^{\mu})^2 \right] \\ &= \eta \sum_{\mu} \sum_k (y_k^{\mu} - o_k^{\mu}) \frac{\partial o_k^{\mu}}{\partial W_{ij}} \\ &= \eta \sum_{\mu} (y_i^{\mu} - o_i^{\mu}) \frac{\partial o_i^{\mu}}{\partial W_{ij}} \\ &= \eta \sum_{\mu} (y_i^{\mu} - o_i^{\mu}) g'(h_i^{\mu}) V_j^{\mu} \\ &= \eta \sum_{\mu} \delta_i^{\mu} V_j^{\mu}\end{aligned}$$

where: $\delta_i^{\mu} = (y_i^{\mu} - o_i^{\mu}) g'(h_i^{\mu})$

Back-Prop : Updating Input-to-Hidden Weights (I)

$$\begin{aligned}\Delta w_{jk} &= -\eta \frac{\partial E}{\partial w_{jk}} \\ &= \eta \sum_{\mu} \sum_i (y_i^{\mu} - O_i^{\mu}) \frac{\partial O_i^{\mu}}{\partial w_{jk}} \\ &= \eta \sum_{\mu} \sum_i (y_i^{\mu} - O_i^{\mu}) g'(h_i^{\mu}) \frac{\partial h_i^{\mu}}{\partial w_{jk}}\end{aligned}$$

$$\begin{aligned}\frac{\partial h_i^{\mu}}{\partial w_{jk}} &= \sum_l W_{il} \frac{\partial V_l^{\mu}}{\partial w_{jk}} \\ &= W_{ij} \frac{\partial V_j^{\mu}}{\partial w_{jk}} \\ &= W_{ij} \frac{\partial g(h_j^{\mu})}{\partial w_{jk}} \\ &= W_{ij} g'(h_j^{\mu}) \frac{\partial h_j^{\mu}}{\partial w_{jk}}\end{aligned}$$

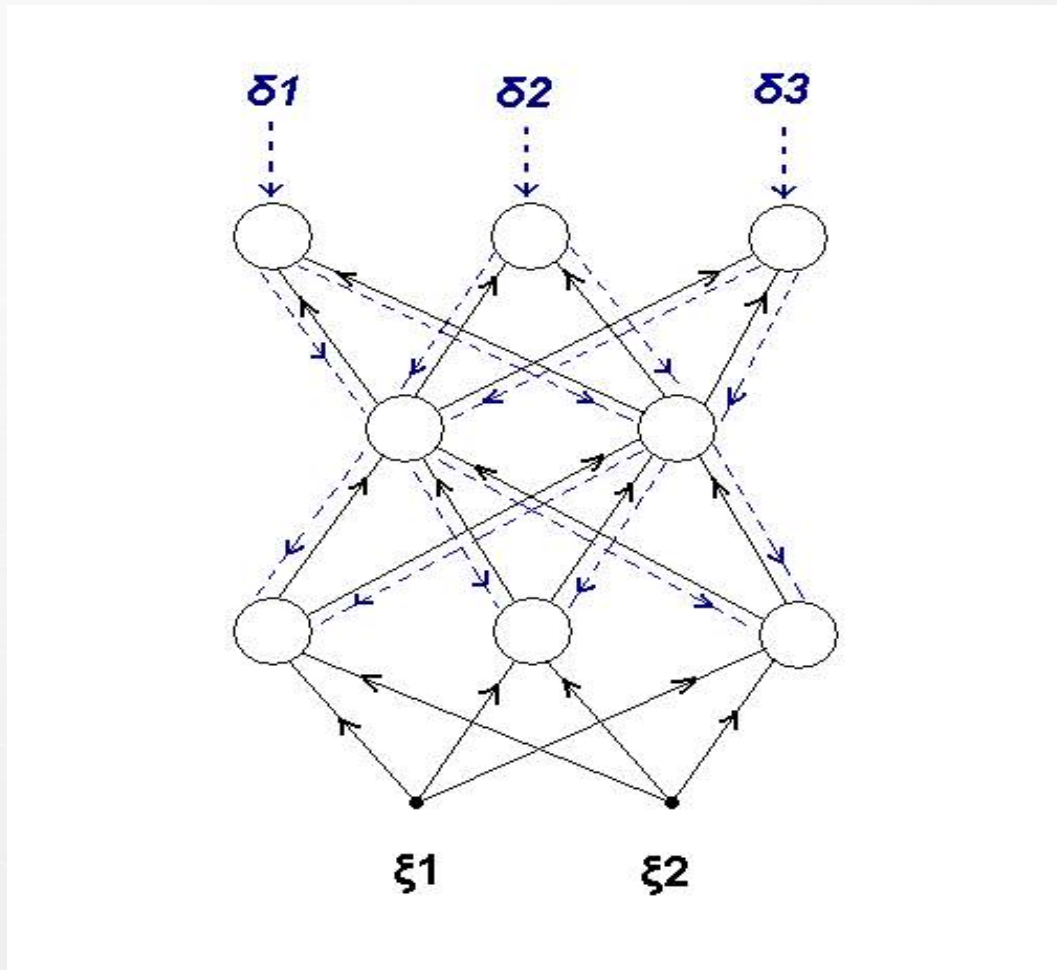
Back-Prop : Updating Input-to-Hidden Weights (II)

$$\begin{aligned}\frac{\partial h_j^\mu}{\partial w_{jk}} &= \frac{\partial}{\partial w_{jk}} \sum_m w_{jm} x_m^\mu \\ &= x_k^\mu\end{aligned}$$

Hence, we get :

$$\begin{aligned}\Delta w_{jk} &= \eta \sum_{\mu,i} (y_i^\mu - O_i^\mu) g'(h_i^\mu) W_{ij} g'(h_j^\mu) x_k^\mu \\ &= \eta \sum_{\mu,i} \delta_i^\mu W_{ij} g'(h_j^\mu) x_k^\mu \\ &= \eta \sum_{\mu} \hat{\delta}_j^\mu x_k^\mu\end{aligned}$$

where: $\hat{\delta}_j^\mu = g'(h_j^\mu) \sum_i \delta_i^\mu W_{ij}$



Retropropagazione dell'errore :

- le linee nere indicano il segnale propagato in avanti
- Le linee blu indicano l'errore (i δ) propagato all'indietro