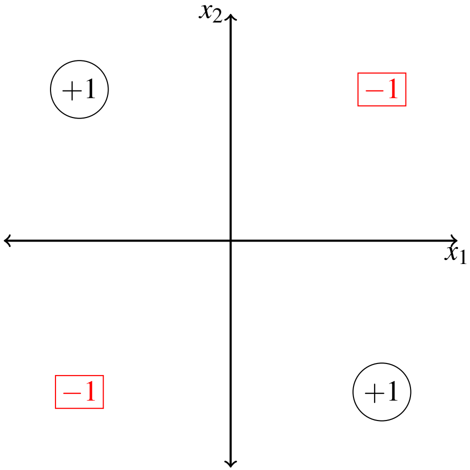
Problema XOR con 3 neuronas

Diego Milone

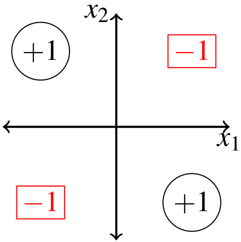
Inteligencia Computacional
Departamento de Informática

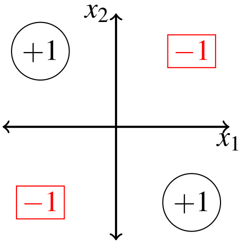
FICH-UNL

¿Cómo podríamos resolver el problema XOR?

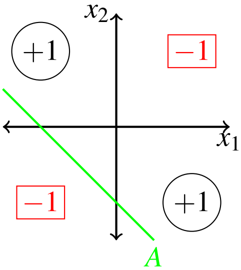


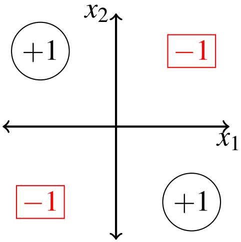
Primera capa: perceptrones A y B



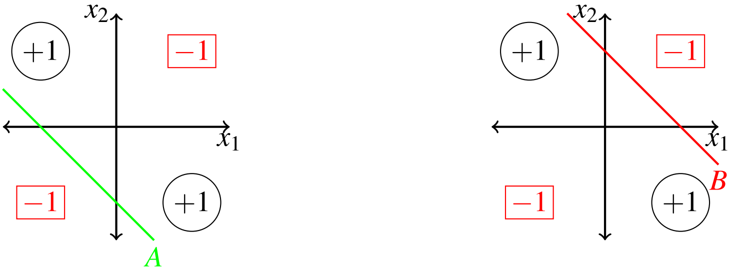


Primera capa: perceptrones A y B

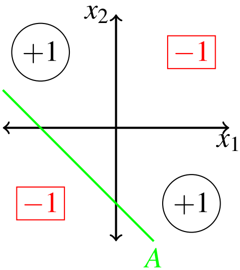


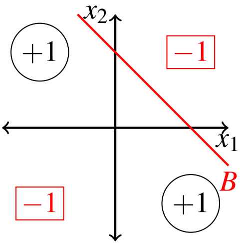


Primera capa: perceptrones A y B



Segunda capa: perceptron C





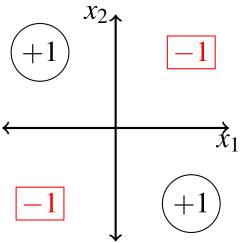
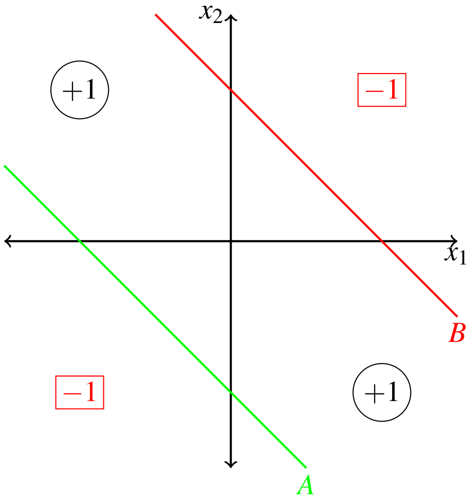


Tabla de verdad para el perceptron C



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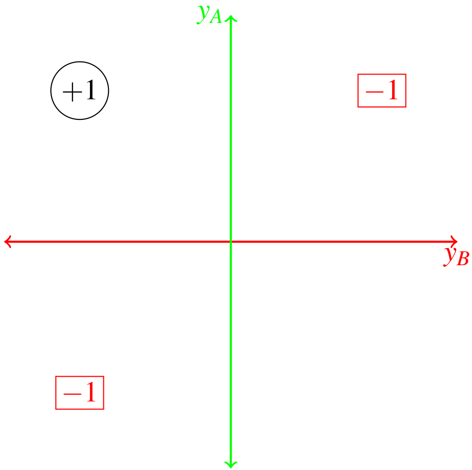

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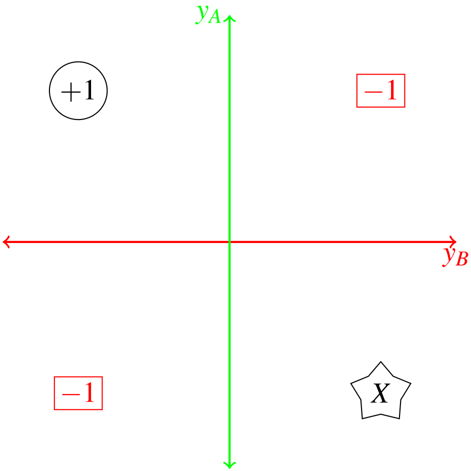

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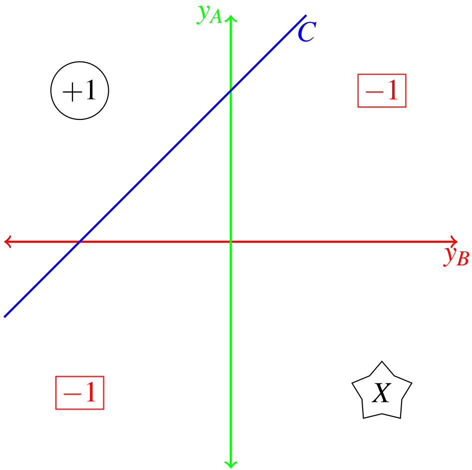

Nuestra primera red neuronal

Un perceptrón multicapa con 3 neuronas

Diego Milone

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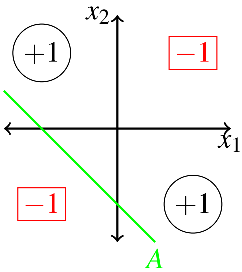
FICH-UNL

Combinación de perceptrones simples: A



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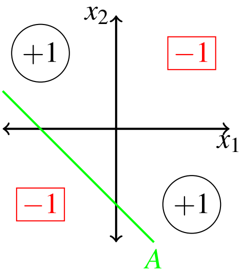
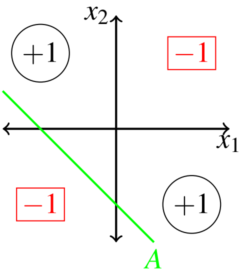


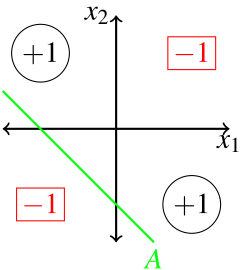
Perceptrón A: $x_2 = -1 - x_1$

Combinación de perceptrones simples: A



Perceptrón A: $x_2 = -1 - x_1 = \frac{w_{A0}}{w_{A2}} - \frac{w_{A1}}{w_{A2}} x_1$

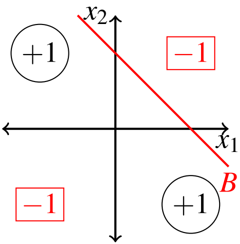
Combinación de perceptrones simples: A



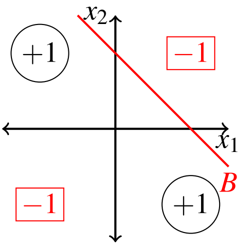
Perceptrón A: $x_2 = -1 - x_1 = \frac{w_{A0}}{w_{A2}} - \frac{w_{A1}}{w_{A2}} x_1$

$$\rightarrow \left\{ \begin{array}{l} w_{A0} = -1 \\ w_{A1} = +1 \\ w_{A2} = +1 \end{array} \right\} \rightarrow y_A = \operatorname{sgn}(x_2 + x_1 + 1)$$

Combinación de perceptrones simples: B

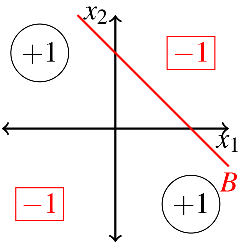


Combinación de perceptrones simples: B



Perceptrón B: $x_2 = +1 - x_1$

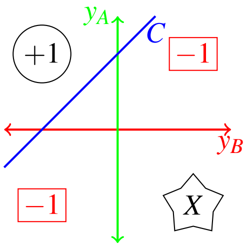
Combinación de perceptrones simples: B



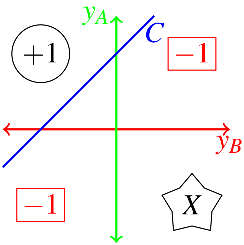
Perceptrón B: $x_2 = +1 - x_1$

$$\rightarrow \left\{ \begin{array}{l} w_{B0} = +1 \\ w_{B1} = +1 \\ w_{B2} = +1 \end{array} \right\} \rightarrow y_B = \mathrm{sgn}(x_2 + x_1 - 1)$$

Combinación de perceptrones simples: C

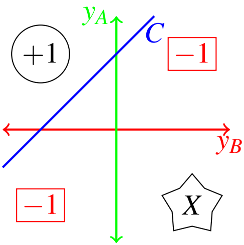


Combinación de perceptrones simples: C



Perceptrón C: $y_A = +1 + y_B$

Combinación de perceptrones simples: C



Perceptrón C: $y_A = +1 + y_B$

$$\rightarrow \left\{ \begin{array}{l} w_{C0} = +1 \\ w_{C1} = -1 \\ w_{C2} = +1 \end{array} \right\} \rightarrow y_C = \mathrm{sgn}(y_A - y_B - 1)$$

¿Cómo es la arquitectura de esta red neuronal?

$$\left\{ \begin{array}{l} w_{C0} = +1 \\ w_{C1} = -1 \\ w_{C2} = +1 \end{array} \right\}$$

$$\left\{ \begin{array}{l} w_{A0} = -1 \\ w_{A1} = +1 \\ w_{A2} = +1 \end{array} \right\} \left\{ \begin{array}{l} w_{B0} = +1 \\ w_{B1} = +1 \\ w_{B2} = +1 \end{array} \right\}$$

$$\left. \begin{array}{l} y_A = \mathrm{sgn}(x_2 + x_1 + 1) \\ y_B = \mathrm{sgn}(x_2 + x_1 - 1) \end{array} \right\} \rightarrow y_C = \mathrm{sgn}(y_A - y_B - 1)$$

Y... ¿resolverá el XOR?

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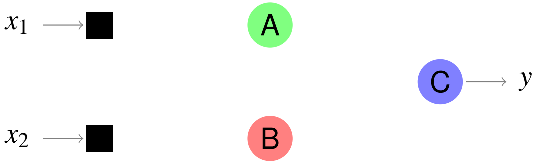

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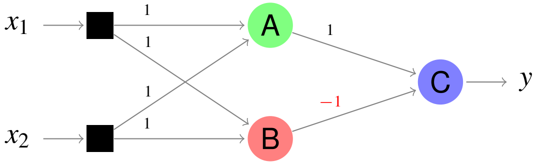
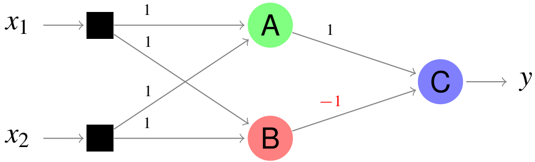


Y... ¿resolverá el XOR?

$x_0 = -1$ ■



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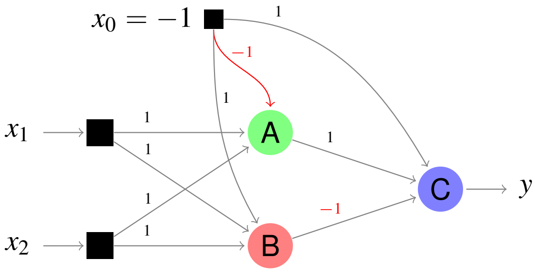

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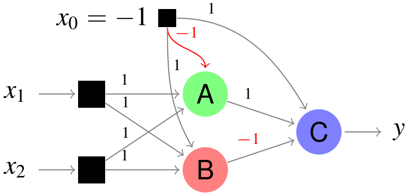

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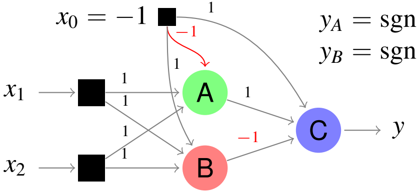

$$\left.\begin{array}{l} y_A = \operatorname{sgn}(x_2 + x_1 + 1) \\ y_B = \operatorname{sgn}(x_2 + x_1 - 1) \end{array}\right\} \rightarrow y_C = \operatorname{sgn}(y_A - y_B - 1)$$

Perceptrón multicapa:
regiones de decisión y arquitectura

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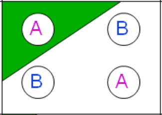
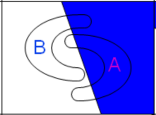
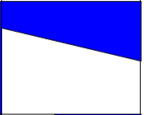
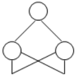
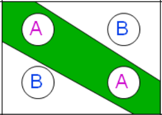
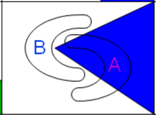
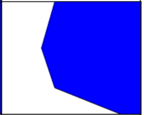
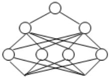
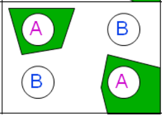
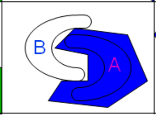
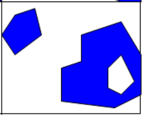
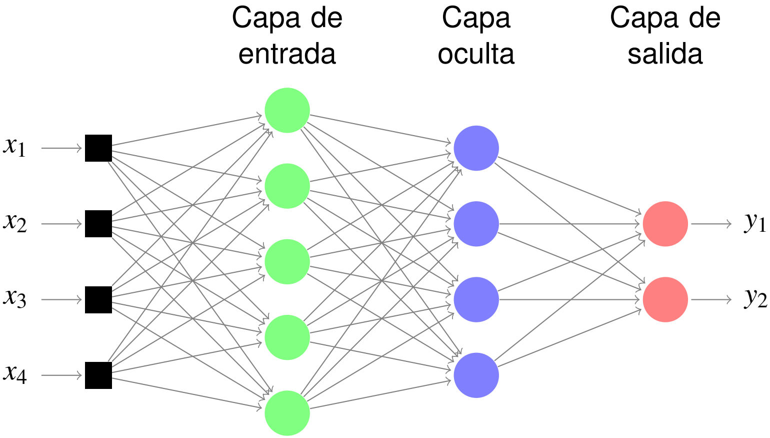
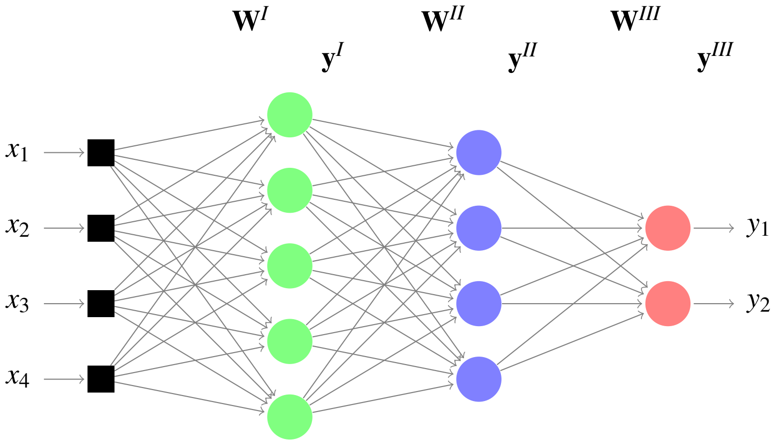
Regiones de decisión

Estructura	Tipos de regiones de decisión	Problema XOR	Separación en clases	Formas regiones más generales
Una capa 	hemiplano limitado por hiperplano			
Dos capas 	Regiones convexas abiertas o cerradas			
Tres capas 	Arbitrarias (Complejidad limitada por N°. de Nodos)			

Arquitectura del perceptrón multicapa



Arquitectura del perceptrón multicapa



Cálculo de las salidas en cada capa

- Capa I:

  $v_j^I = \left\langle \mathbf{w}_j^I, \mathbf{x} \right\rangle = \sum_{i=0}^{N} w_{ji}^I x_i$ (completo $\mathbf{v}^I = \mathbf{W}^I \mathbf{x}$)

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$$y_j^I = \phi(v_j^I) = \frac{2}{1 + e^{-b v_j^I}} - 1 \quad \text{(simétrica} \pm 1\text{)}$$

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$$y_j^I = \phi(v_j^I) = \frac{2}{1 + e^{-b v_j^I}} - 1 \quad \text{(simétrica } \pm 1\text{)}$$

- Capa II:

$$v_j^{II} = \left\langle \mathbf{w}_j^{II}, \mathbf{y}^I \right\rangle \quad \rightarrow \quad y_j^{II} = \phi(v_j^{II})$$

- Capa III:

$$v_j^{III} = \left\langle \mathbf{w}_j^{III}, \mathbf{y}^{II} \right\rangle \quad \rightarrow \quad y_j^{III} = \phi(v_j^{III}) = y_j$$

Propagación hacia atrás: caso general y capa de salida

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Criterio de error

Suma del error cuadrático instantáneo

$$\xi(n) = \frac{1}{2} \sum_{j=1}^{M} e_j^2(n)$$

Aplicación del gradiente (caso general)

$$\boxed{\Delta w_{ji}(n) = -\mu \frac{\partial \xi(n)}{\partial w_{ji}(n)}}$$

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$$\frac{\partial \xi(n)}{\partial w_{ji}(n)} = \frac{\partial \xi(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial v_j(n)} \frac{\partial v_j(n)}{\partial w_{ji}(n)}$$

Aplicación del gradiente (caso general)

$$\boxed{\Delta w_{ji}(n) = -\mu \frac{\partial \xi(n)}{\partial w_{ji}(n)}}$$

$$\frac{\partial \xi(n)}{\partial w_{ji}(n)} = \frac{\partial \xi(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial v_j(n)} \boxed{\frac{\partial v_j(n)}{\partial w_{ji}(n)}}$$

$$\frac{\partial v_j(n)}{\partial w_{ji}(n)} = \frac{\partial \sum_{i=0}^{N} w_{ji}(n) y_i(n)}{\partial w_{ji}(n)} = y_i(n)$$

Aplicación del gradiente (caso general)

$$\boxed{\Delta w_{ji}(n) = -\mu \frac{\partial \xi(n)}{\partial w_{ji}(n)}}$$

$$\frac{\partial \xi(n)}{\partial w_{ji}(n)} = \boxed{\frac{\partial \xi(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial v_j(n)}} y_i(n)$$

Gradiente de error local instantáneo: $\delta_j = \dfrac{\partial \xi(n)}{\partial y_j(n)} \dfrac{\partial y_j(n)}{\partial v_j(n)}$

Aplicación del gradiente (caso general)

$$\boxed{\Delta w_{ji}(n) = \mu \delta_j(n) y_i(n)}$$

Gradiente de error local instantáneo: $\delta_j = \frac{\partial \xi(n)}{\partial y_j(n)} \boxed{\frac{\partial y_j(n)}{\partial v_j(n)}}$

Derivada de la función de activación simétrica (1/2)

$$
\begin{aligned}
\frac{\partial y_j(n)}{\partial v_j(n)} &= \frac{\partial \left\{ \frac{2}{1+e^{-v_j(n)}} - 1 \right\}}{\partial v_j(n)} \\
&= 2 \frac{e^{-v_j(n)}}{\left(1+e^{-v_j(n)}\right)^2} \\
&= 2 \frac{1}{1+e^{-v_j(n)}} \frac{e^{-v_j(n)}}{1+e^{-v_j(n)}} \\
&= 2 \frac{1}{1+e^{-v_j(n)}} \frac{\overbrace{-1+1}^{0} + e^{-v_j(n)}}{1+e^{-v_j(n)}} \\
&= 2 \frac{1}{1+e^{-v_j(n)}} \left(\frac{-1}{1+e^{-v_j(n)}} + \frac{1+e^{-v_j(n)}}{1+e^{-v_j(n)}} \right)
\end{aligned}
$$

Derivada de la función de activación simétrica (2/2)

$$
\begin{aligned}
\frac{\partial y_j(n)}{\partial v_j(n)} &= 2\frac{1}{1+e^{-v_j(n)}}\left(1-\frac{1}{1+e^{-v_j(n)}}\right) \\
&= 2\frac{y_j(n)+1}{2}\left(1-\frac{y_j(n)+1}{2}\right) \\
&= (y_j(n)+1)\left(1-\frac{y_j(n)+1}{2}\right) \\
&= (y_j(n)+1)\left(\frac{2-y_j(n)-1}{2}\right) \\
&= \frac{1}{2}(y_j(n)+1)(y_j(n)-1)
\end{aligned}
$$

Aplicación del gradiente (caso general)

$$\boxed{\Delta w_{ji}(n) = \mu \delta_j(n) y_i(n)}$$

Gradiente de error local instantáneo: $\delta_j = -\dfrac{\partial \xi(n)}{\partial y_j(n)} \dfrac{\partial y_j(n)}{\partial v_j(n)}$

$$\delta_j = \frac{\partial \xi(n)}{\partial y_j(n)} \frac{1}{2} (1 + y_j(n))(1 - y_j(n))$$

Retropropagación en la capa III (salida)

$$\Delta w_{ji}^{III}(n) = \mu \delta_j^{III}(n) y_i^{II}(n)$$

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Retropropagación en la capa III (salida)

$$\Delta w_{ji}^{III}(n) = \mu \delta_j^{III}(n) y_i^{II}(n)$$

$$\delta_j^{III}(n) = -\frac{\partial \xi(n)}{\partial y_j^{III}(n)} \frac{1}{2}(1 + y_j^{III}(n))(1 - y_j^{III}(n))$$

$$\delta_j^{III}(n) = -\frac{\partial \xi(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j^{III}(n)} \frac{1}{2}(1 + y_j^{III}(n))(1 - y_j^{III}(n))$$

Retropropagación en la capa III (salida)

$$
\begin{aligned}
\delta_j^{III}(n) \quad = \quad & -\frac{\partial \left\{ \frac{1}{2} \sum_j e_j^2(n) \right\}}{\partial e_j(n)} \cdot \frac{\partial \left\{ d_j^{III}(n) - y_j^{III}(n) \right\}}{\partial y_j^{III}(n)} \cdot \\
& \cdot \frac{1}{2}(1 + y_j^{III}(n))(1 - y_j^{III}(n))
\end{aligned}
$$

Retropropagación en la capa III (salida)

$$\delta_j^{III}(n) = -\frac{\partial\left\{\frac{1}{2}\sum_j e_j^2(n)\right\}}{\partial e_j(n)} \cdot \frac{\partial\left\{d_j^{III}(n) - y_j^{III}(n)\right\}}{\partial y_j^{III}(n)} \cdot \cdot\frac{1}{2}(1 + y_j^{III}(n))(1 - y_j^{III}(n))$$

$$\delta_j^{III}(n) = \tfrac{1}{2} e_j(n)(1 + y_j^{III}(n))(1 - y_j^{III}(n))^{\bigstar}$$

Retropropagación en la capa III (salida)

$$\delta_j^{III}(n) = -\frac{\partial\left\{\frac{1}{2}\sum_j e_j^2(n)\right\}}{\partial e_j(n)} \cdot \frac{\partial\left\{d_j^{III}(n) - y_j^{III}(n)\right\}}{\partial y_j^{III}(n)} \cdot \cdot \frac{1}{2}(1 + y_j^{III}(n))(1 - y_j^{III}(n))$$

$$\delta_j^{III}(n) = \tfrac{1}{2}e_j(n)(1 + y_j^{III}(n))(1 - y_j^{III}(n))^{\star}$$

$$\boxed{\Delta w_{ji}^{III}(n) = \eta e_j(n)(1 + y_j^{III}(n))(1 - y_j^{III}(n))y_i^{II}(n)}$$

Propagación hacia atrás: capas ocultas

Diego Milone

Inteligencia Computacional
Departamento de Informática

FICH-UNL

Retropropagación en la capa II (oculta)

$$\Delta w_{ji}^{II}(n) = \mu \delta_j^{II}(n) y_i^{I}(n)$$

Retropropagación en la capa II (oculta)

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$$\delta_j^{II}(n) = -\frac{\partial \xi(n)}{\partial y_j^{II}(n)} \frac{1}{2} (1 + y_j^{II}(n))(1 - y_j^{II}(n))$$

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Retropropagación en la capa II (oculta)

$$\delta_j^{II}(n) = -\sum_k e_k(n) \frac{\partial e_k(n)}{\partial y_k^{III}(n)} \frac{\partial y_k^{III}(n)}{\partial v_k^{III}(n)} \frac{\partial v_k^{III}(n)}{\partial y_j^{II}(n)} \frac{1}{2}(1+y_j^{II}(n))(1-y_j^{II}(n))$$

Retropropagación en la capa II (oculta)

$$\delta_j^{II}(n) = -\sum_k e_k(n) \frac{\partial e_k(n)}{\partial y_k^{III}(n)} \frac{\partial y_k^{III}(n)}{\partial v_k^{III}(n)} \frac{\partial v_k^{III}(n)}{\partial y_j^{II}(n)} \frac{1}{2}(1+y_j^{II}(n))(1-y_j^{II}(n))$$

$$\delta_j^{II}(n) = -\sum_k e_k(n) \cdot \frac{\partial \left\{ d_k^{III}(n) - y_k^{III}(n) \right\}}{\partial y_k^{III}(n)} \cdot \frac{1}{2}(1+y_k^{III}(n))(1-y_k^{III}(n)) \cdot$$

$$\cdot \frac{\partial \left\{ \sum_j w_{kj}^{III} y_j^{II}(n) \right\}}{\partial y_j^{II}(n)} \cdot \frac{1}{2}(1+y_j^{II}(n))(1-y_j^{II}(n))$$

Retropropagación en la capa II (oculta)

$$\delta_j^{II}(n) = -\sum_k e_k(n) \frac{\partial e_k(n)}{\partial y_k^{III}(n)} \frac{\partial y_k^{III}(n)}{\partial v_k^{III}(n)} \frac{\partial v_k^{III}(n)}{\partial y_j^{II}(n)} \frac{1}{2}(1+y_j^{II}(n))(1-y_j^{II}(n))$$

$$\delta_j^{II}(n) = -\sum_k e_k(n) \cdot \frac{\partial \left\{ d_k^{III}(n) - y_k^{III}(n) \right\}}{\partial y_k^{III}(n)} \cdot \frac{1}{2}(1 + y_k^{III}(n))(1 - y_k^{III}(n)) \cdot$$

$$\cdot \frac{\partial \left\{ \sum_j w_{kj}^{III} y_j^{II}(n) \right\}}{\partial y_j^{II}(n)} \cdot \frac{1}{2}(1 + y_j^{II}(n))(1 - y_j^{II}(n))$$

$$\delta_j^{II}(n) = -\sum_k e_k(n) \cdot (-1) \cdot \frac{1}{2}(1 + y_k^{III}(n))(1 - y_k^{III}(n)) \cdot$$

$$\cdot w_{kj}^{III} \cdot \frac{1}{2}(1 + y_j^{II}(n))(1 - y_j^{II}(n))$$

Retropropagación en la capa II (oculta)

$$
\begin{aligned}
\delta_j^{II}(n) &= \sum_k e_k(n) \cdot \frac{1}{2}(1 + y_k^{III}(n))(1 - y_k^{III}(n)) \cdot w_{kj}^{III} \cdot \\
&\cdot \frac{1}{2}(1 + y_j^{II}(n))(1 - y_j^{II}(n))
\end{aligned}
$$

Retropropagación en la capa II (oculta)

$$\begin{aligned}\delta_j^{II}(n) &= \sum_k e_k(n) \cdot \frac{1}{2}(1 + y_k^{III}(n))(1 - y_k^{III}(n)) \cdot w_{kj}^{III} \cdot \\ &\quad \cdot \frac{1}{2}(1 + y_j^{II}(n))(1 - y_j^{II}(n))\end{aligned}$$

Pero de la capa III* sabemos que:

$$\delta_k^{III}(n) = \tfrac{1}{2} e_k(n)(1 + y_k^{III}(n))(1 - y_k^{III}(n))$$

Retropropagación en la capa II (oculta)

$$\begin{aligned}\delta_j^{II}(n) &= \sum_k e_k(n) \cdot \frac{1}{2}(1 + y_k^{III}(n))(1 - y_k^{III}(n)) \cdot w_{kj}^{III} \cdot \\ &\cdot \frac{1}{2}(1 + y_j^{II}(n))(1 - y_j^{II}(n))\end{aligned}$$

Pero de la capa III★ sabemos que:

$$\delta_k^{III}(n) = \tfrac{1}{2} e_k(n)(1 + y_k^{III}(n))(1 - y_k^{III}(n))$$

Reemplzando:

$$\delta_j^{II}(n) = \sum_k \delta_k^{III}(n) w_{kj}^{III} \cdot \frac{1}{2}(1 + y_j^{II}(n))(1 - y_j^{II}(n))$$

Retropropagación en la capa II (oculta)

Volviendo a:

$$\Delta w_{ji}^{II}(n) = \mu \delta_j^{II}(n) y_i^{I}(n)$$

Retropropagación en la capa II (oculta)

Volviendo a:

$$\Delta w_{ji}^{II}(n) = \mu \delta_j^{II}(n) y_i^{I}(n)$$

Por lo tanto:

$$\boxed{\Delta w_{ji}^{II}(n) = \eta \left[\sum_k \delta_k^{III} w_{kj}^{III}(n) \right] (1 + y_j^{II}(n))(1 - y_j^{II}(n)) y_i^{I}(n)}$$

Generalizando para la capa "p"

$$\Delta w_{ji}^{II}(n) = \eta \left[\sum_k \delta_k^{III} w_{kj}^{III}(n) \right] (1 + y_j^{II}(n))(1 - y_j^{II}(n)) y_i^{I}(n)$$

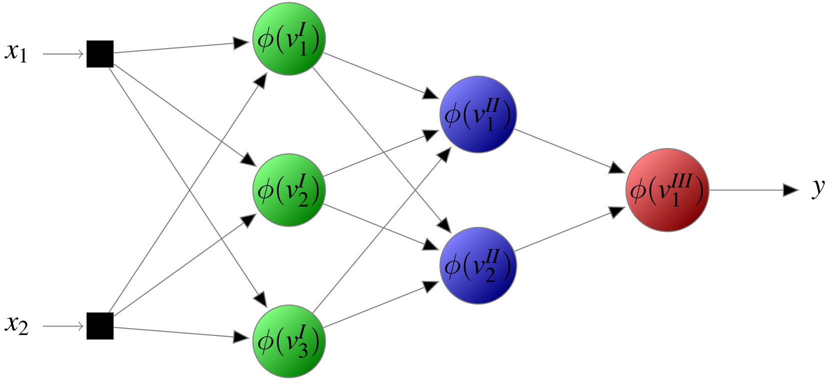
$$\Downarrow$$

$$\boxed{\Delta w_{ji}^{(p)}(n) = \eta \left\langle \delta^{(p+1)}, \mathbf{w}_j^{(p+1)} \right\rangle (1 + y_j^{(p)}(n))(1 - y_j^{(p)}(n)) y_i^{(p-1)}(n)}$$

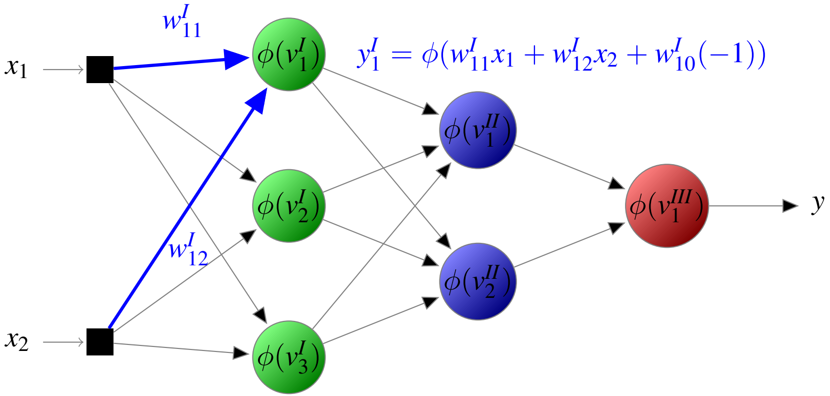
Resumen del algoritmo de retropropagación (BP)

1. Inicialización aleatoria
2. Propagación hacia adelante
3. Propagación hacia atras
4. Adaptación de los pesos
5. Iteración: vuelve a 2 hasta convergencia o finalización

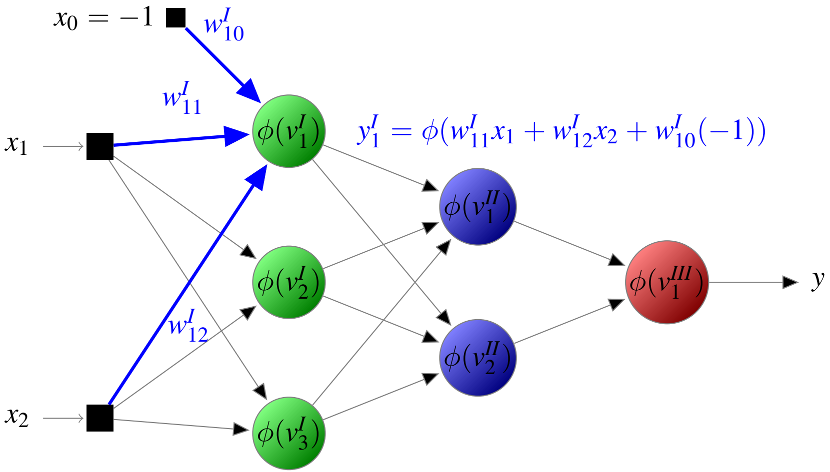
Resumen: propagación hacia adelante



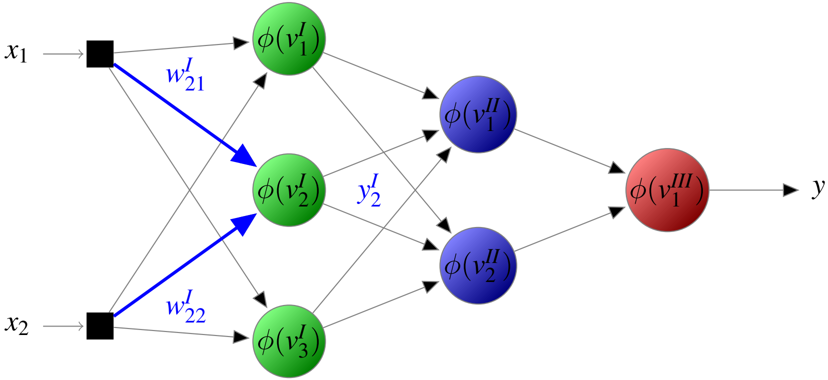
Resumen: propagación hacia adelante



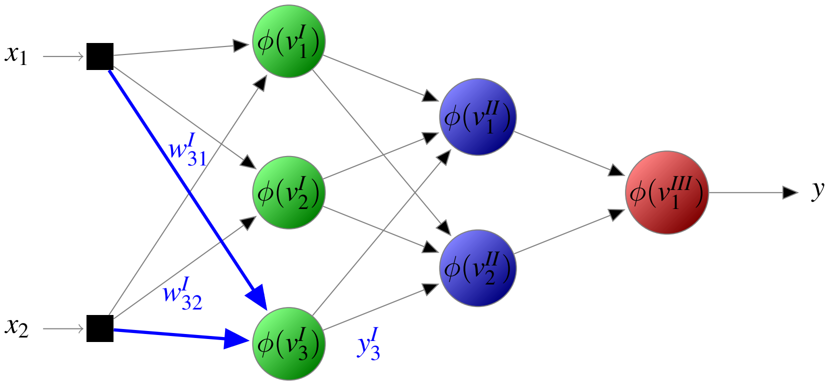
Resumen: propagación hacia adelante



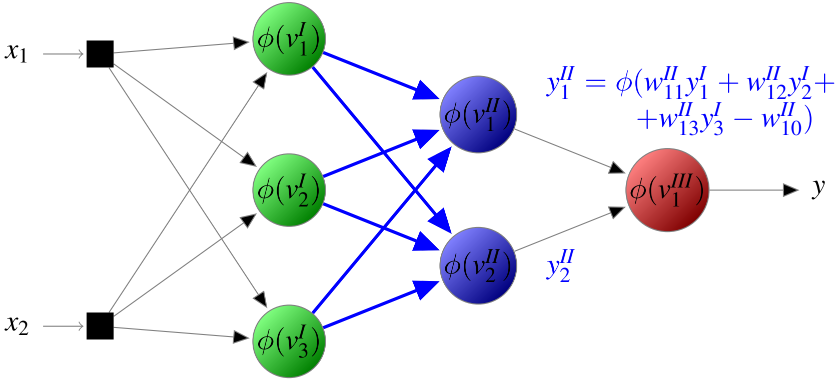
Resumen: propagación hacia adelante



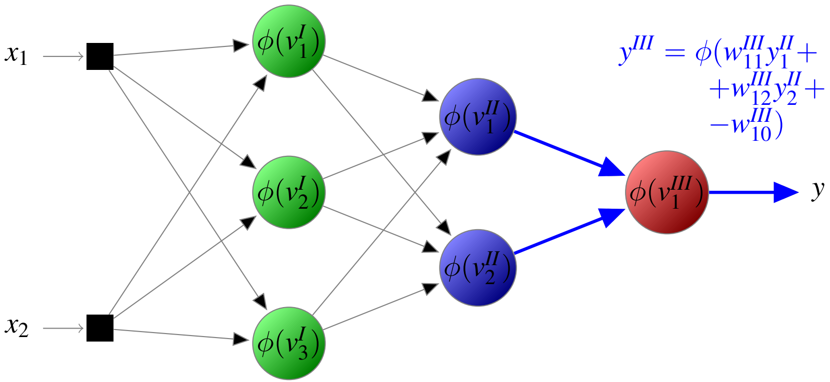
Resumen: propagación hacia adelante



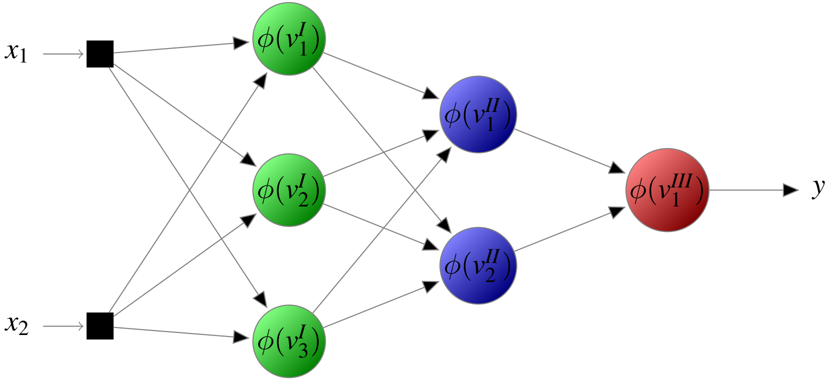
Resumen: propagación hacia adelante



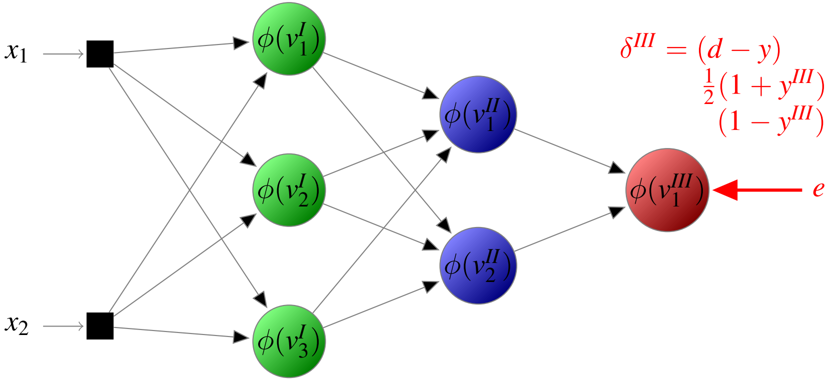
Resumen: propagación hacia adelante



Resumen: propagación hacia atras

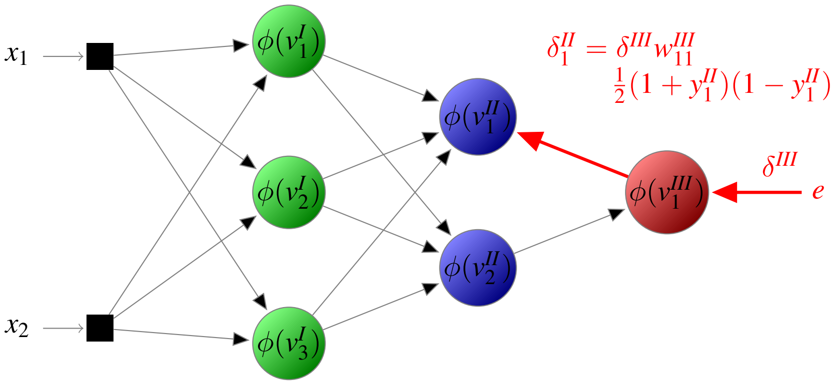


Resumen: propagación hacia atras

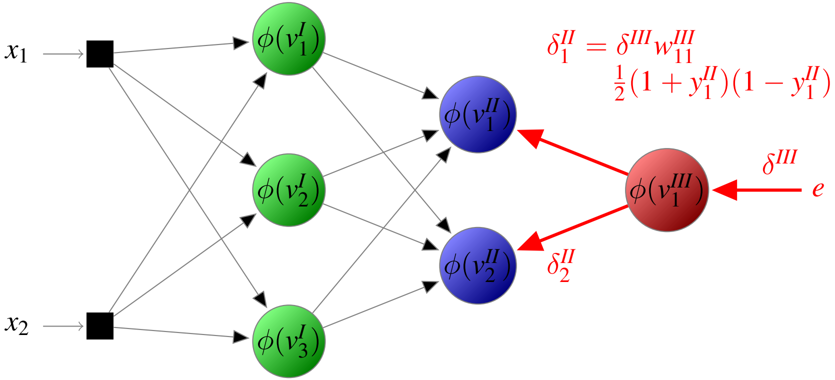


$$\delta^{III} = (d-y)\,\frac{1}{2}(1+y^{III})\,(1-y^{III})$$

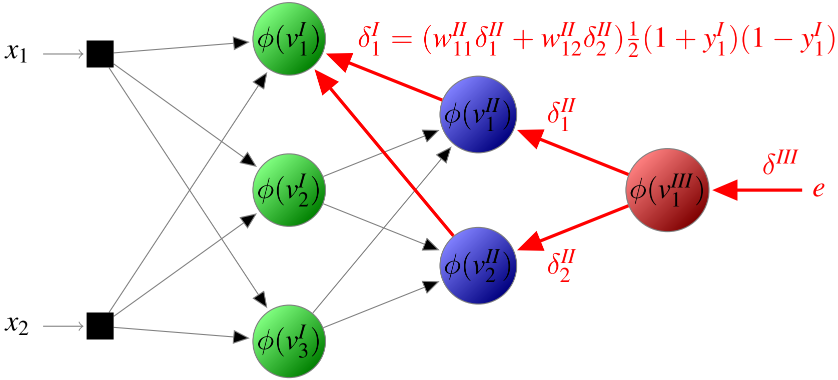
Resumen: propagación hacia atras



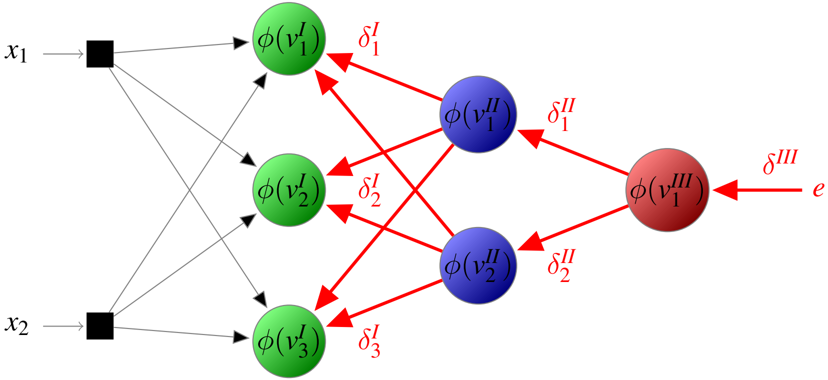
Resumen: propagación hacia atras



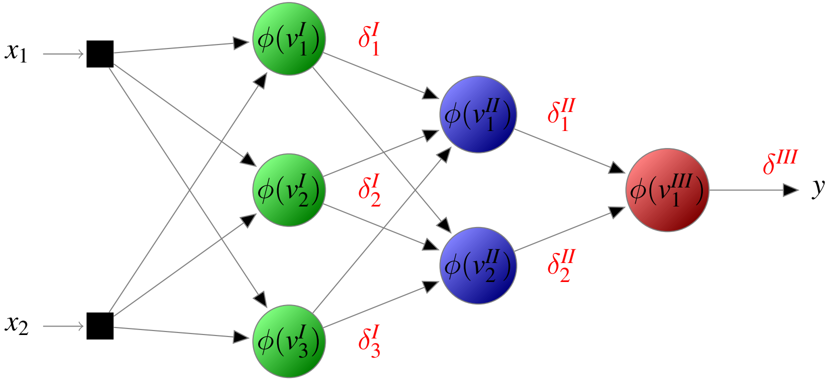
Resumen: propagación hacia atras



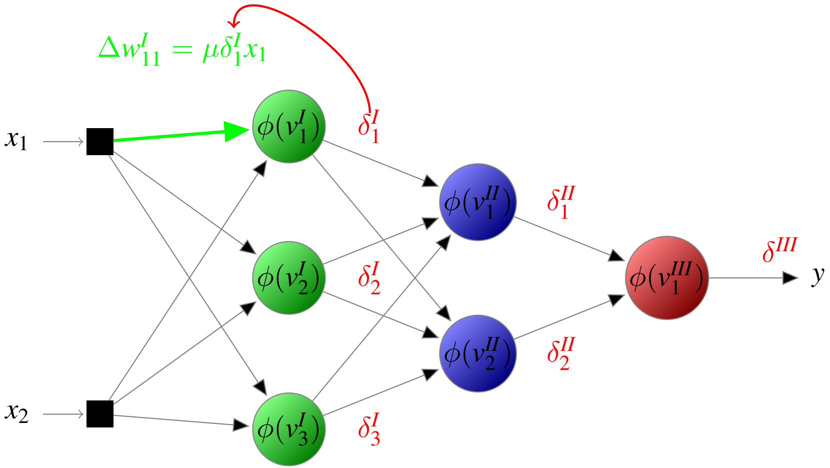
Resumen: propagación hacia atras



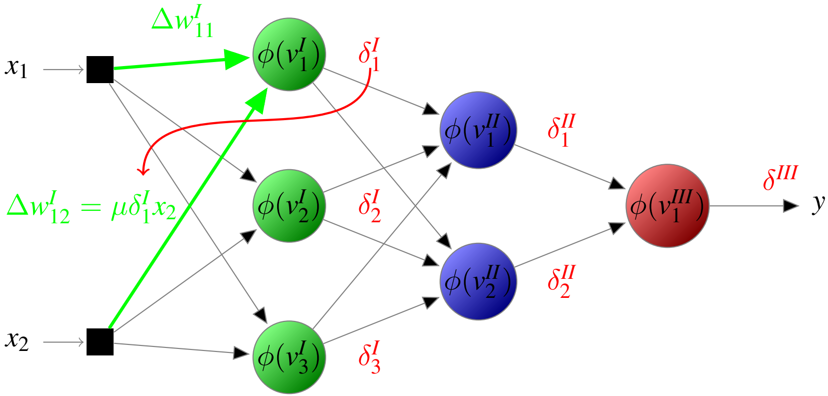
Resumen: ajuste de pesos



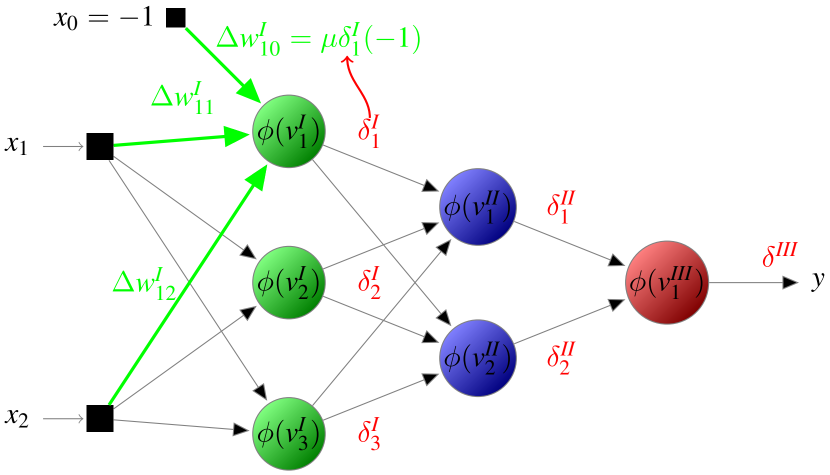
Resumen: ajuste de pesos



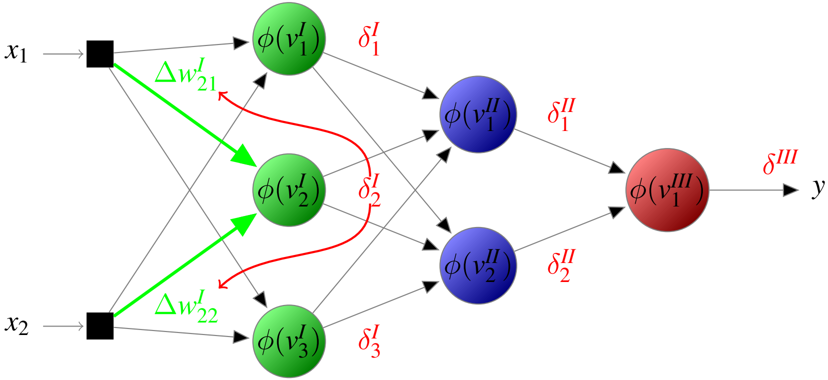
Resumen: ajuste de pesos



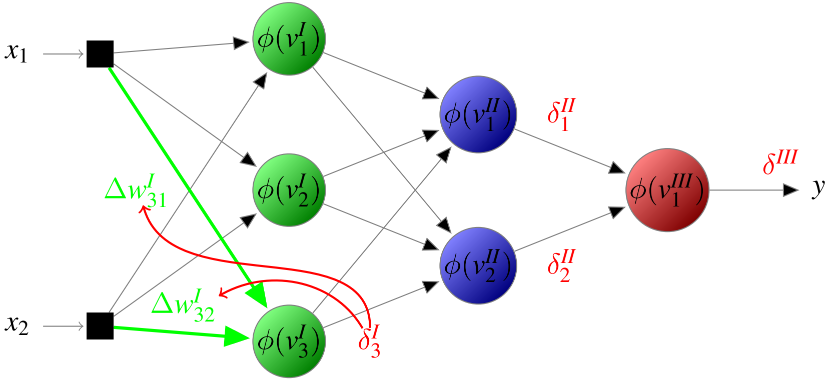
Resumen: ajuste de pesos



Resumen: ajuste de pesos



Resumen: ajuste de pesos



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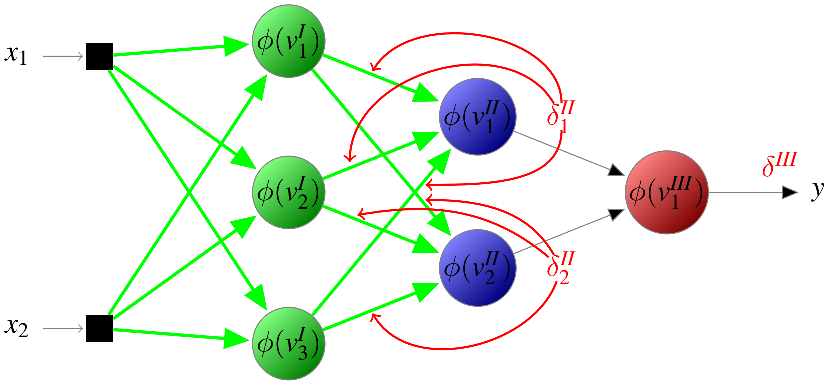
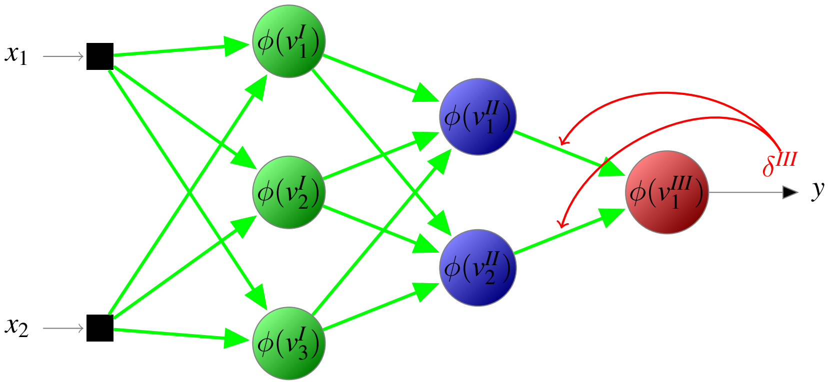


Resumen: ajuste de pesos



Resumen: ajuste de pesos