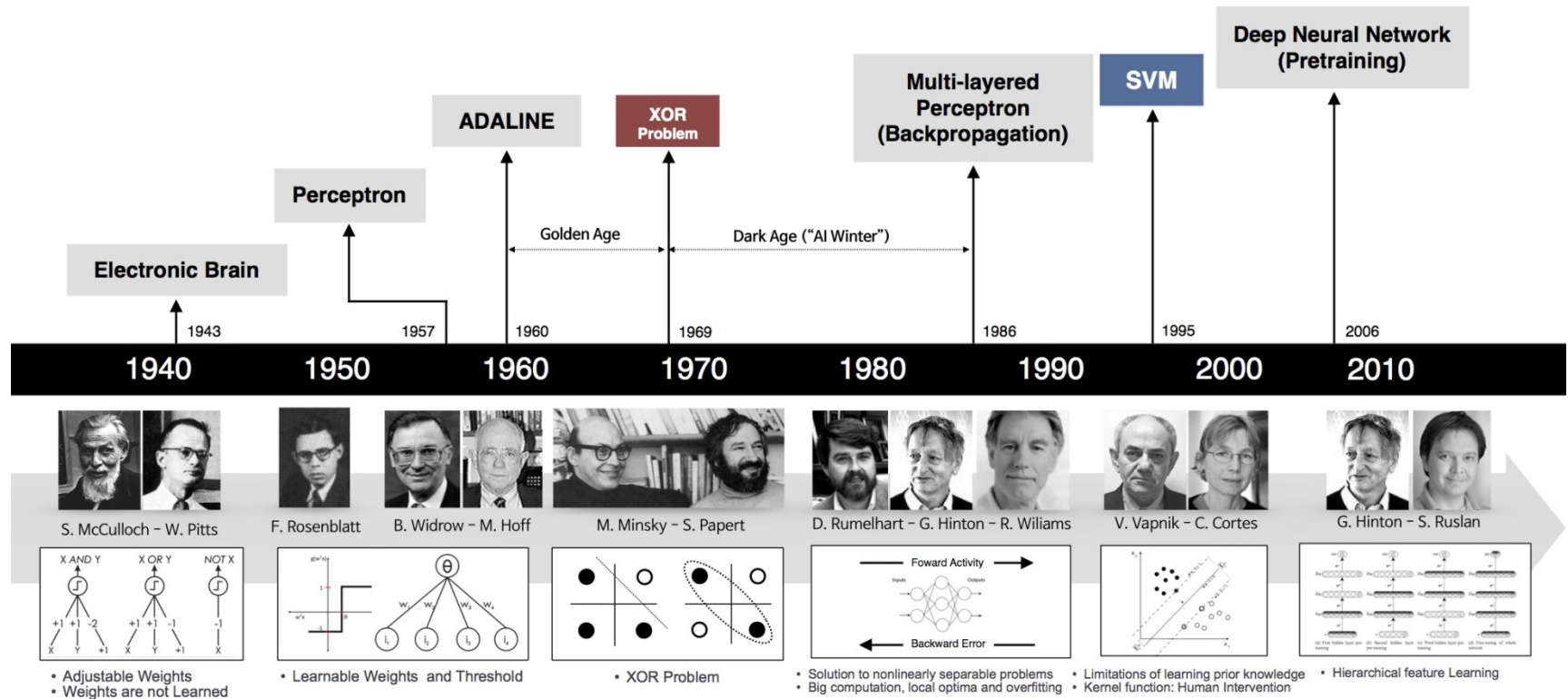
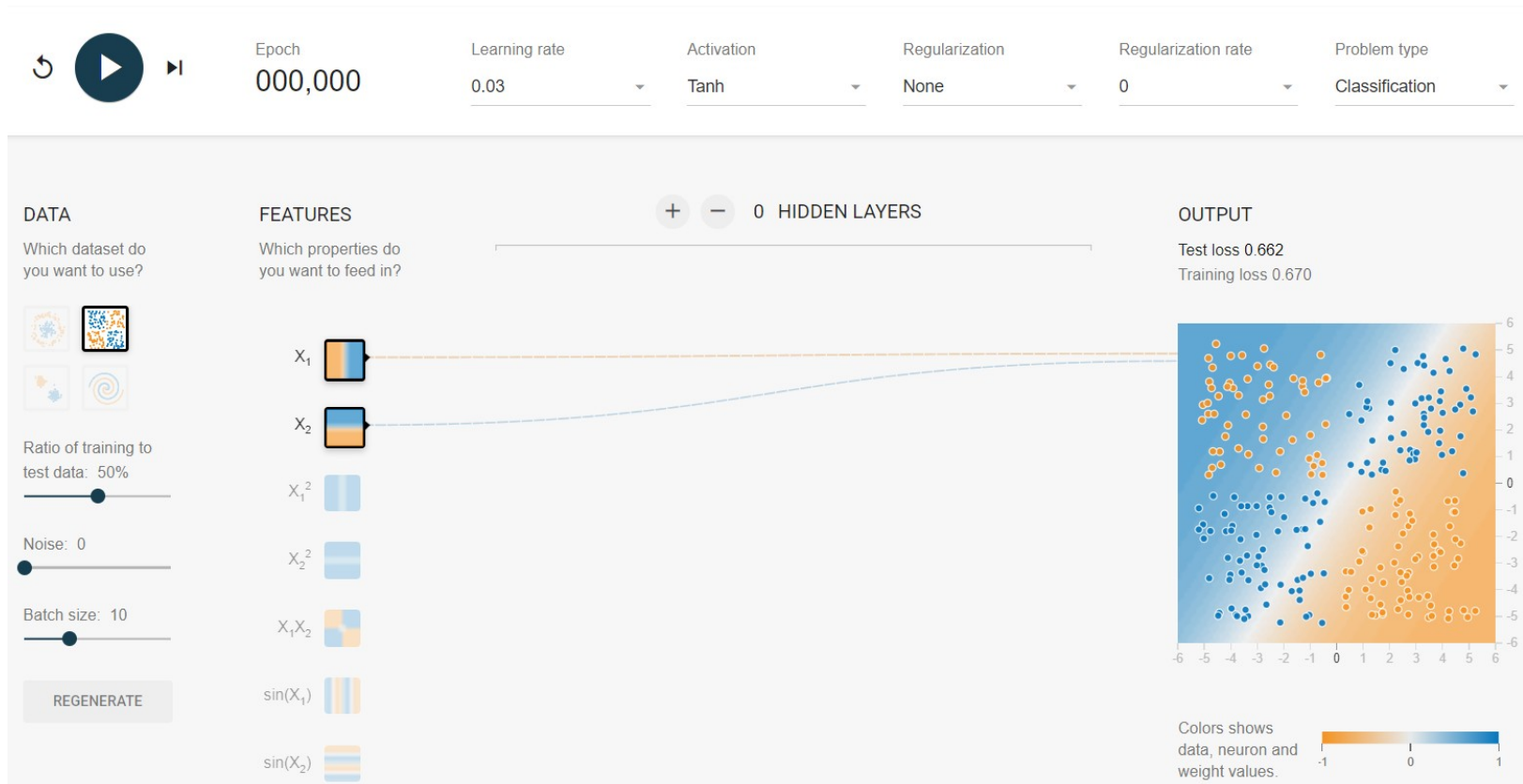


# Marcos Históricos:








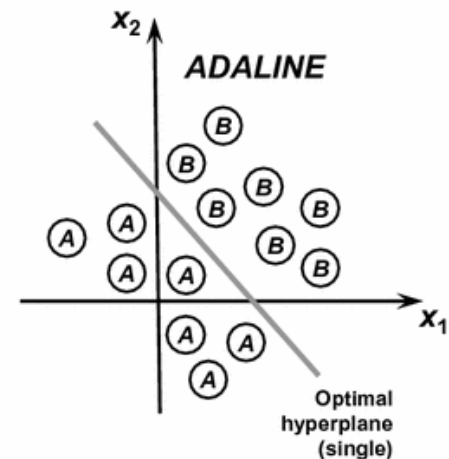
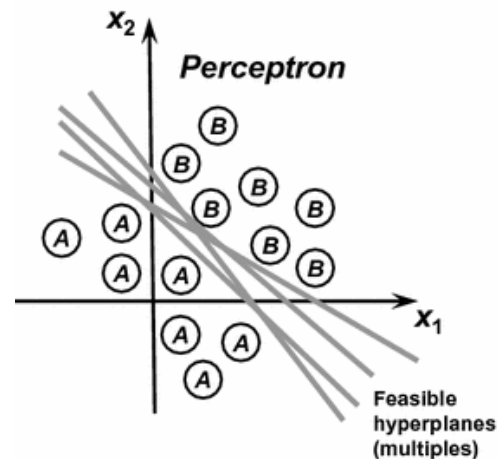
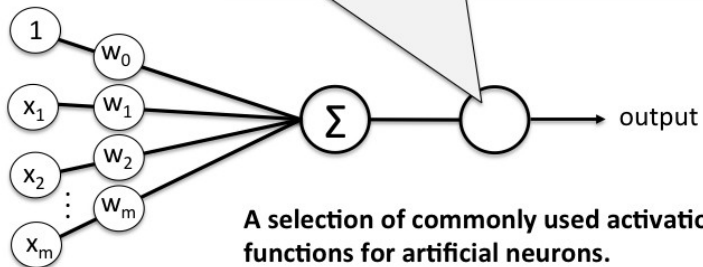
# With 1 layer and 1 neuron



<http://playground.tensorflow.org/>

# Recap

	Unit step	$g(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ -1 & \text{otherwise.} \end{cases}$
		$g(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{otherwise.} \end{cases}$
	Linear	$g(z) = z$
	Logistic (sigmoid)	$g(z) = 1 / (1 + \exp(-z))$
	Hyperbolic tangent (sigmoid)	$g(z) = \frac{\exp(2z) - 1}{\exp(2z) + 1}$
...		

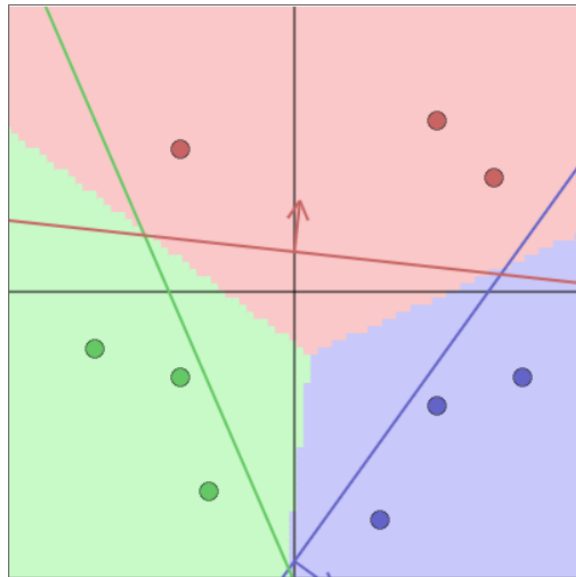


# With 1 layer and N neuron

classifier computes scores as  $\mathbf{w}_{0,0}x_0 + \mathbf{w}_{0,1}x_1 + b_0$  and the triangles to control the parameters.

the blue line shows the set of points  $(x_0, x_1)$  that give score of zero. The blue arrow draws the vector  $(W_{0,0}, W_{0,1})$ , which shows the direction of score increase and its length is proportional to how steep the increase is.

Note: you can drag the datapoints.



$w[0,0]$	$w[0,1]$	$b[0]$
▲	▲	▲
1.48 -0.01	1.07 0.03	-1.01 0.00
▼	▼	▼
$w[1,0]$	$w[1,1]$	$b[1]$
▲	▲	▲
-1.68 -0.04	0.73 -0.02	-0.74 0.11
▼	▼	▼
$w[2,0]$	$w[2,1]$	$b[2]$
▲	▲	▲
0.20 0.05	-1.79 -0.02	-0.25 -0.11
▼	▼	▼

Step size: 0.10000

Single parameter update

Start repeated update

Stop repeated update

Randomize parameters

$x[0]$	$x[1]$	$y$	$s[0]$	$s[1]$	$s[2]$	$L$
0.50	0.40	0	0.16	-1.29	-0.87	0.00
0.80	0.30	0	0.50	-1.87	-0.63	0.00
0.30	0.80	0	0.29	-0.66	-1.63	0.05
-0.40	0.30	1	-1.28	0.15	-0.87	0.00
-0.30	0.70	1	-0.71	0.27	-1.57	0.02
-0.70	0.20	1	-1.83	0.58	-0.75	0.00
0.70	-0.40	2	-0.40	-2.21	0.60	0.00
0.50	-0.60	2	-0.91	-2.02	0.92	0.00
-0.40	-0.50	2	-2.14	-0.43	0.57	0.00

mean:

0.01

Total data loss: 0.01  
Regularization loss: 0.79  
Total loss: 0.80

L2 Regularization strength: 0.07943

Multiclass SVM loss formulation:

- ☐ Weston Watkins 1999
- ☐ One vs. All
- ☒ Structured SVM
- ☐ Softmax

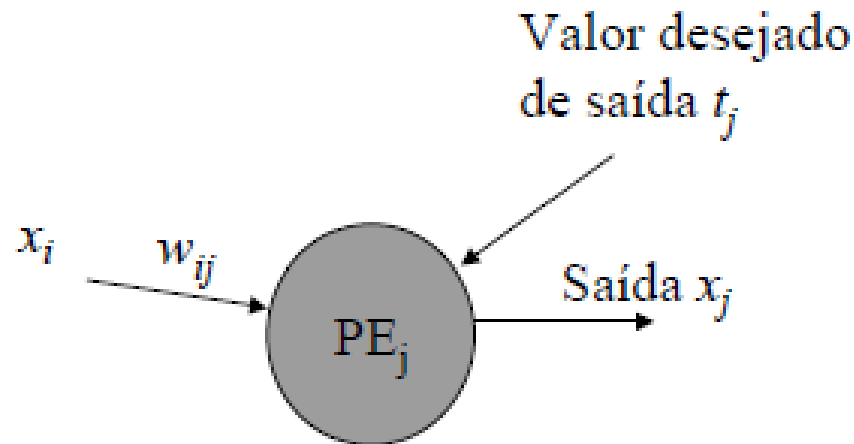
<http://vision.stanford.edu/teaching/cs231n-demos/linear-classify/>

# Multi-Layer Perceptron

- O grande desafio foi achar um algoritmo de aprendizado para atualizar dos pesos das camadas intermediarias
- Idéia Central
  - Os erros dos elementos processadores da camada de saída (conhecidos pelo treinamento supervisionado) são **retro-propagados** para as camadas intermediarias

# Processo de aprendizado

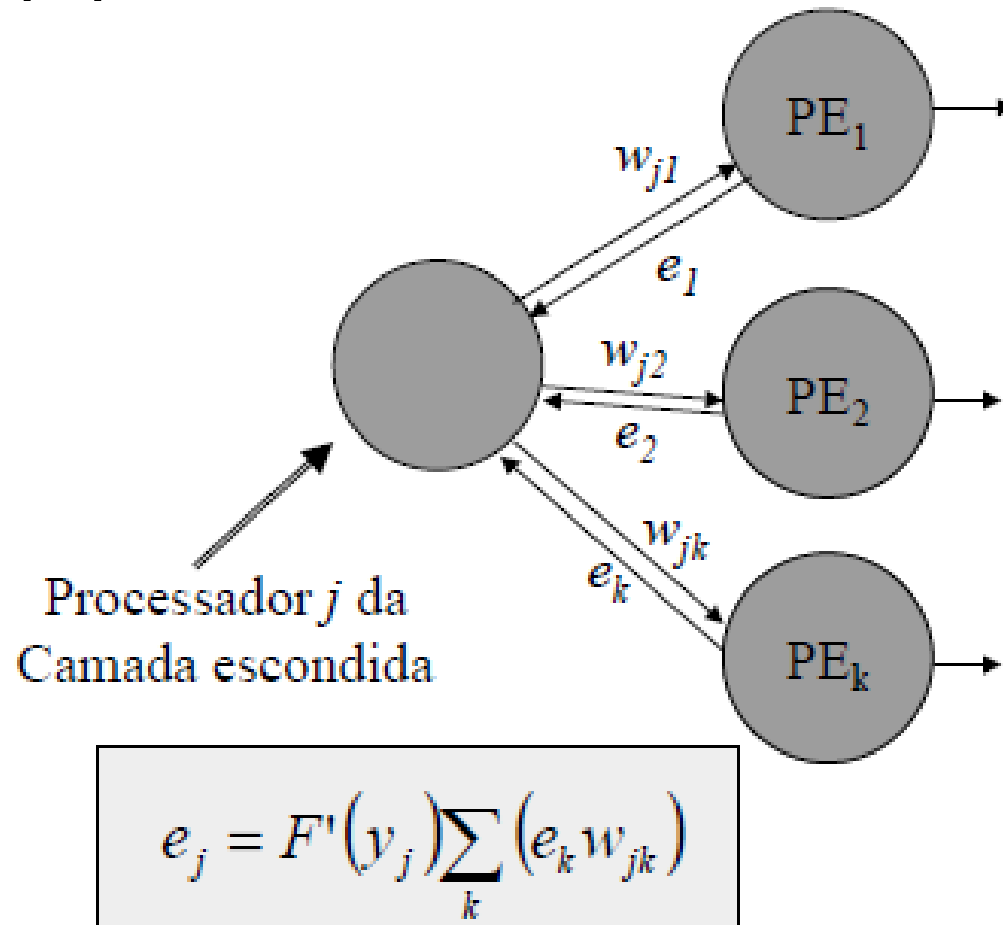
- Processador  $j$  pertence à Camada de Saída:



$$e_j = (t_j - x_j)F'(y_j)$$

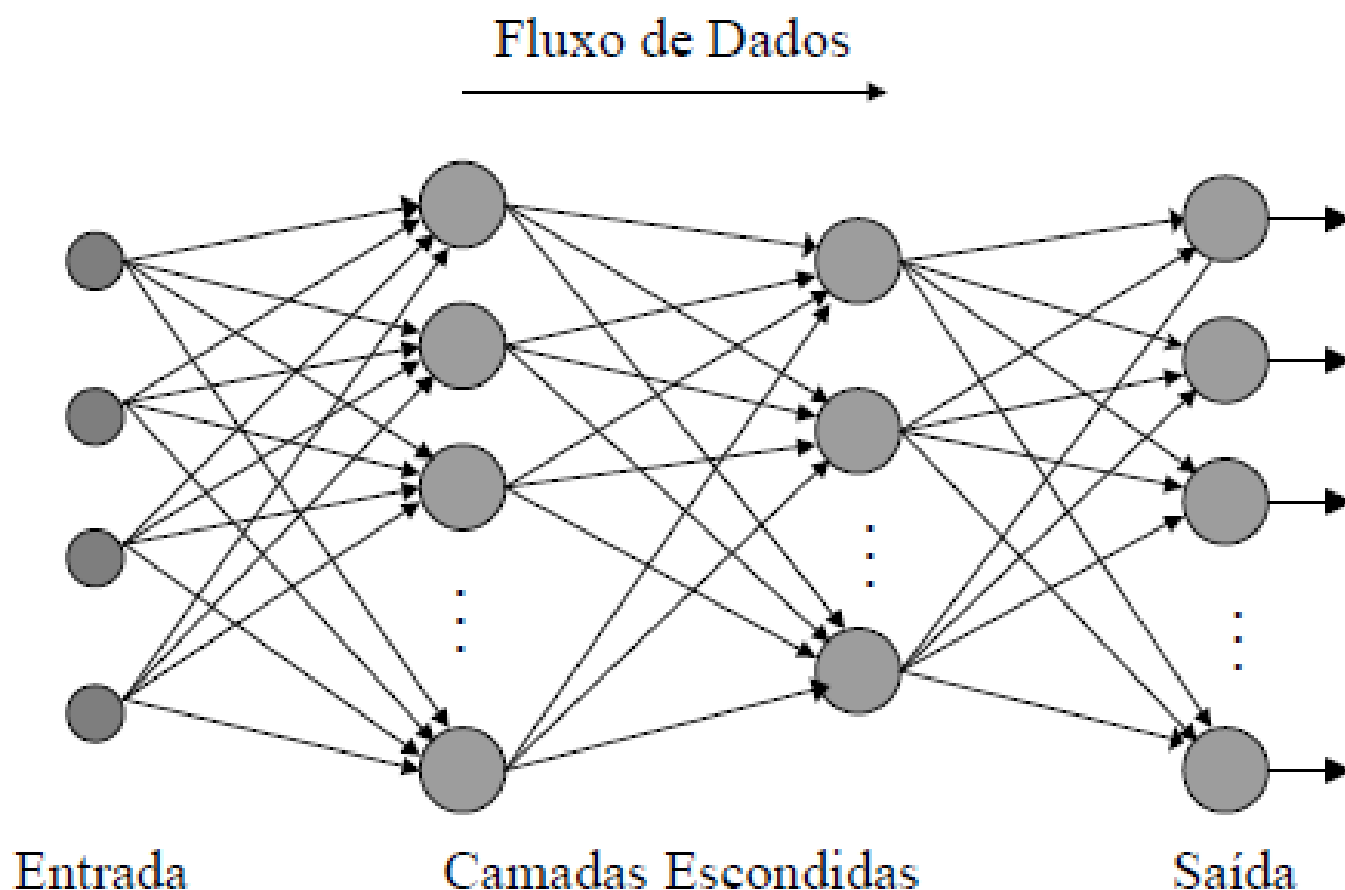
# Processo de aprendizado

- Processador  $j$  pertence à Camada Escon



# Processo de aprendizado

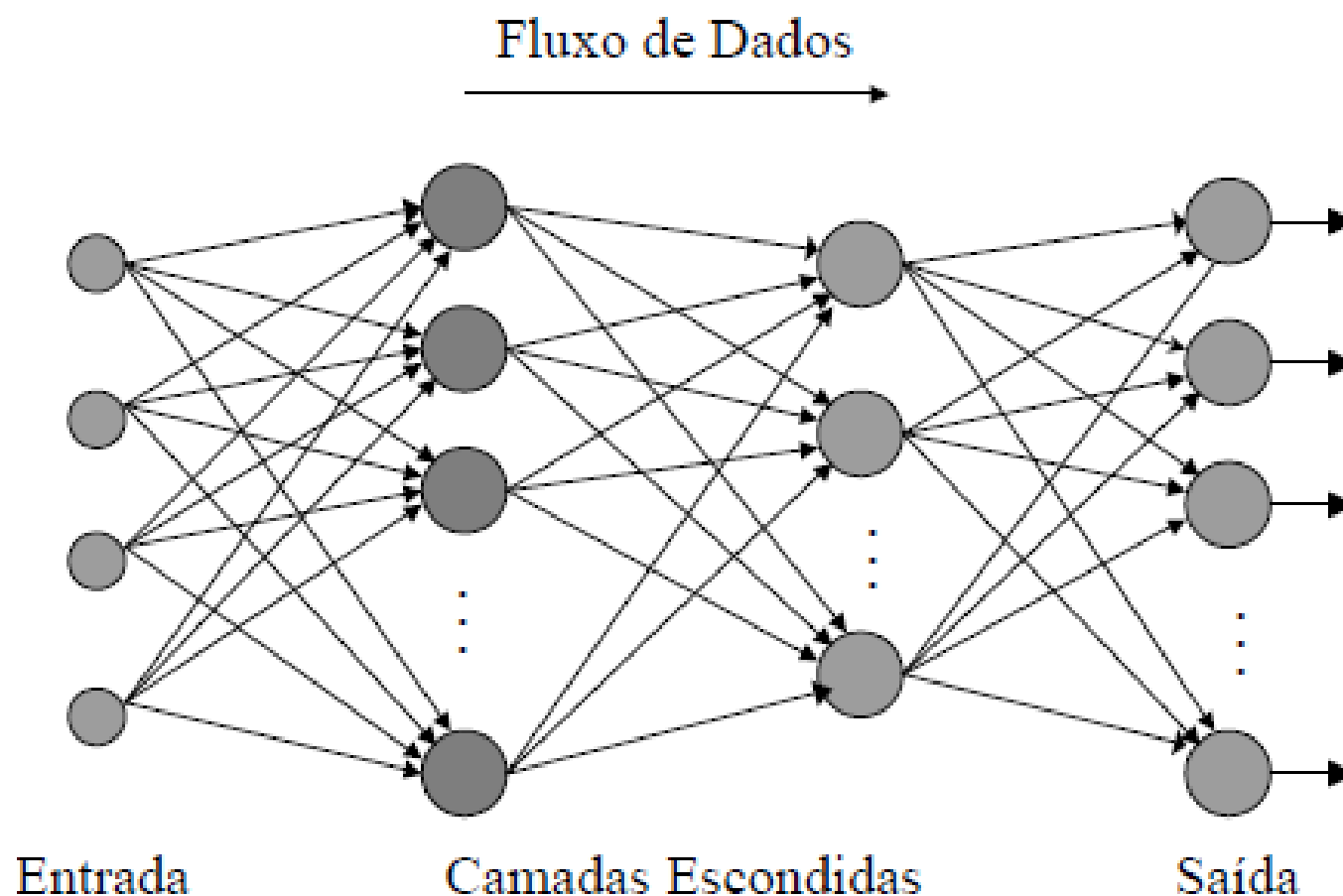
## □ Fase 1: Feed-Forward





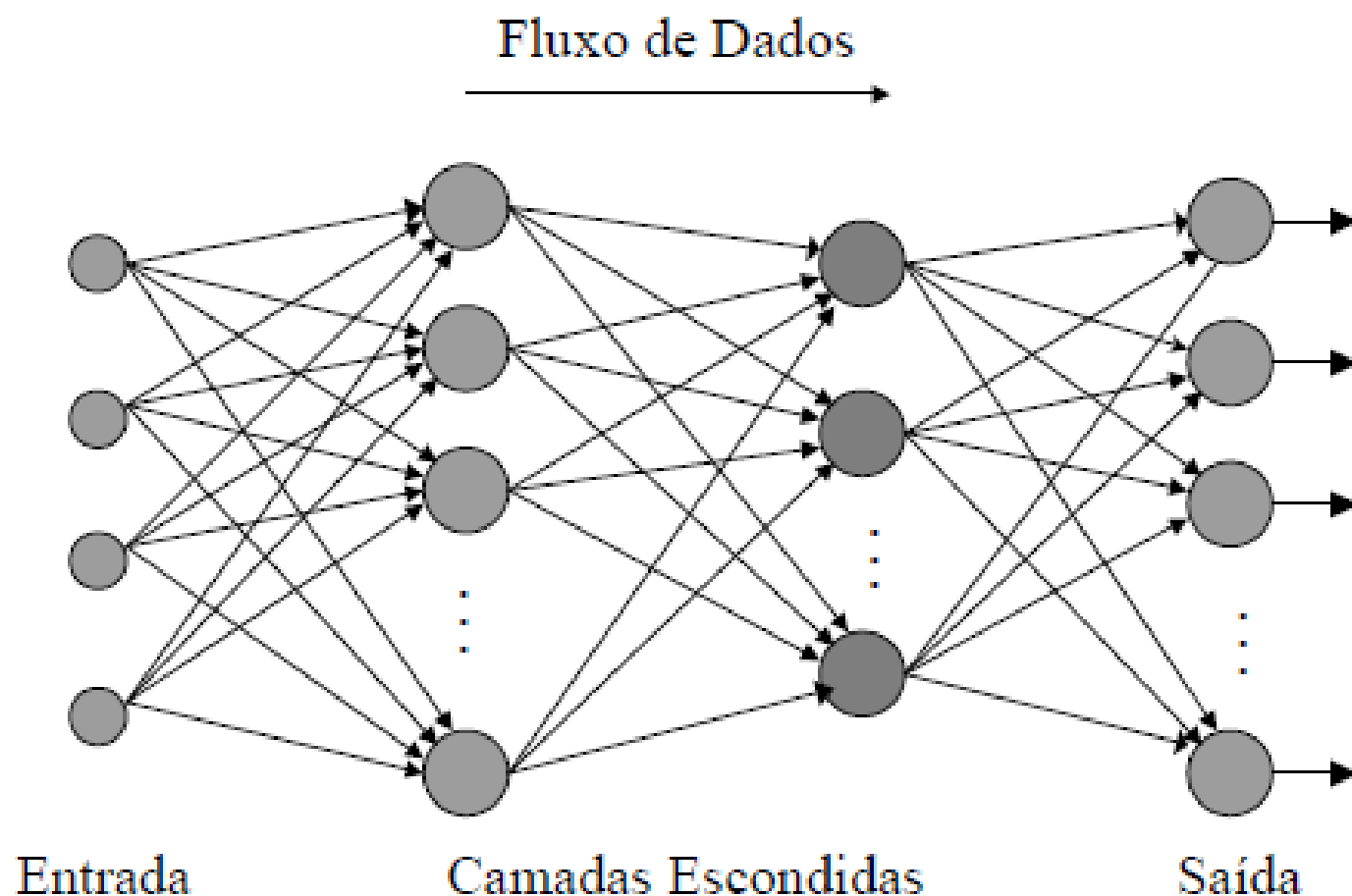
# Processo de aprendizado

## □ Fase 1: Feed-Forward



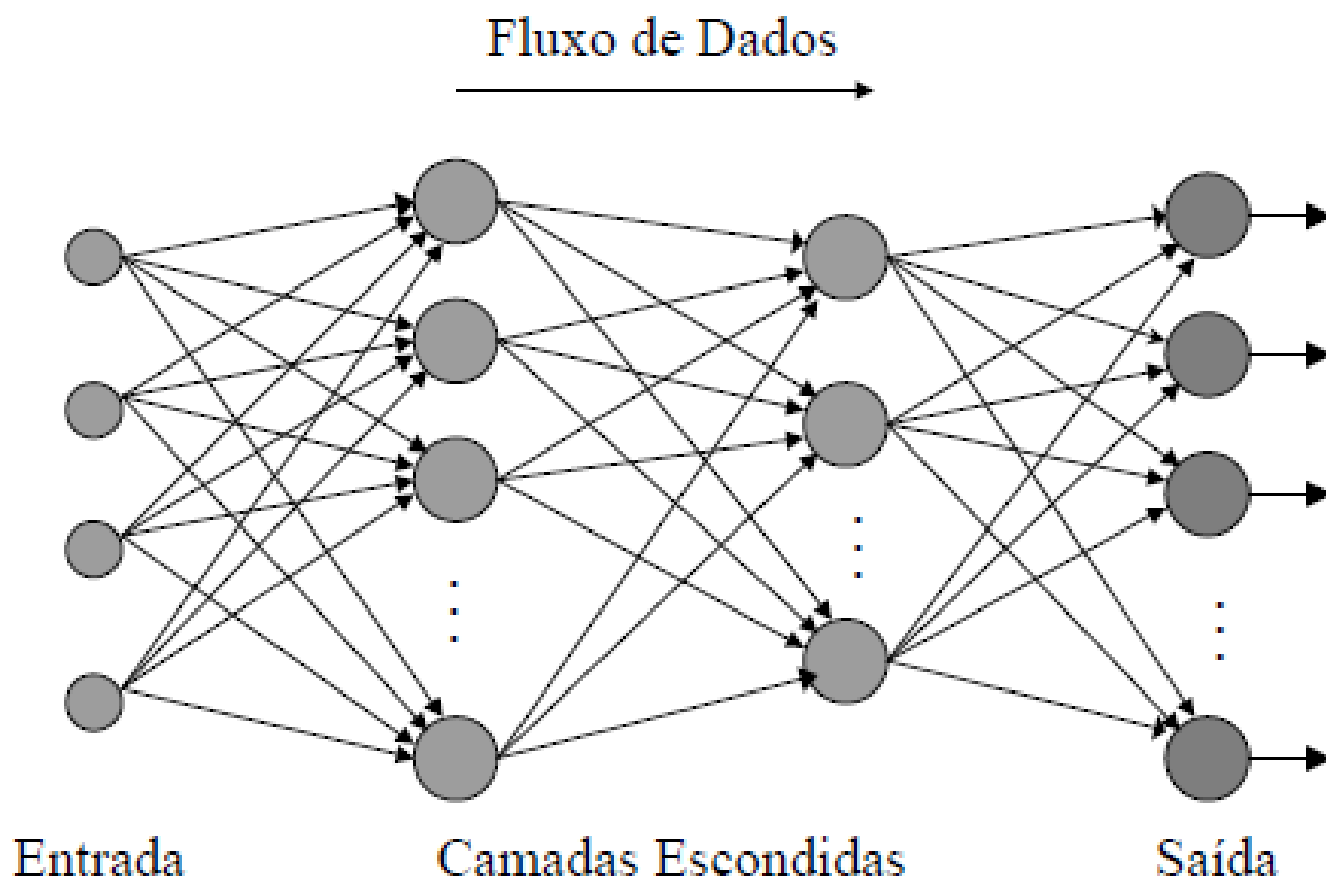
# Processo de aprendizado

## □ Fase 1: Feed-Forward



# Processo de aprendizado

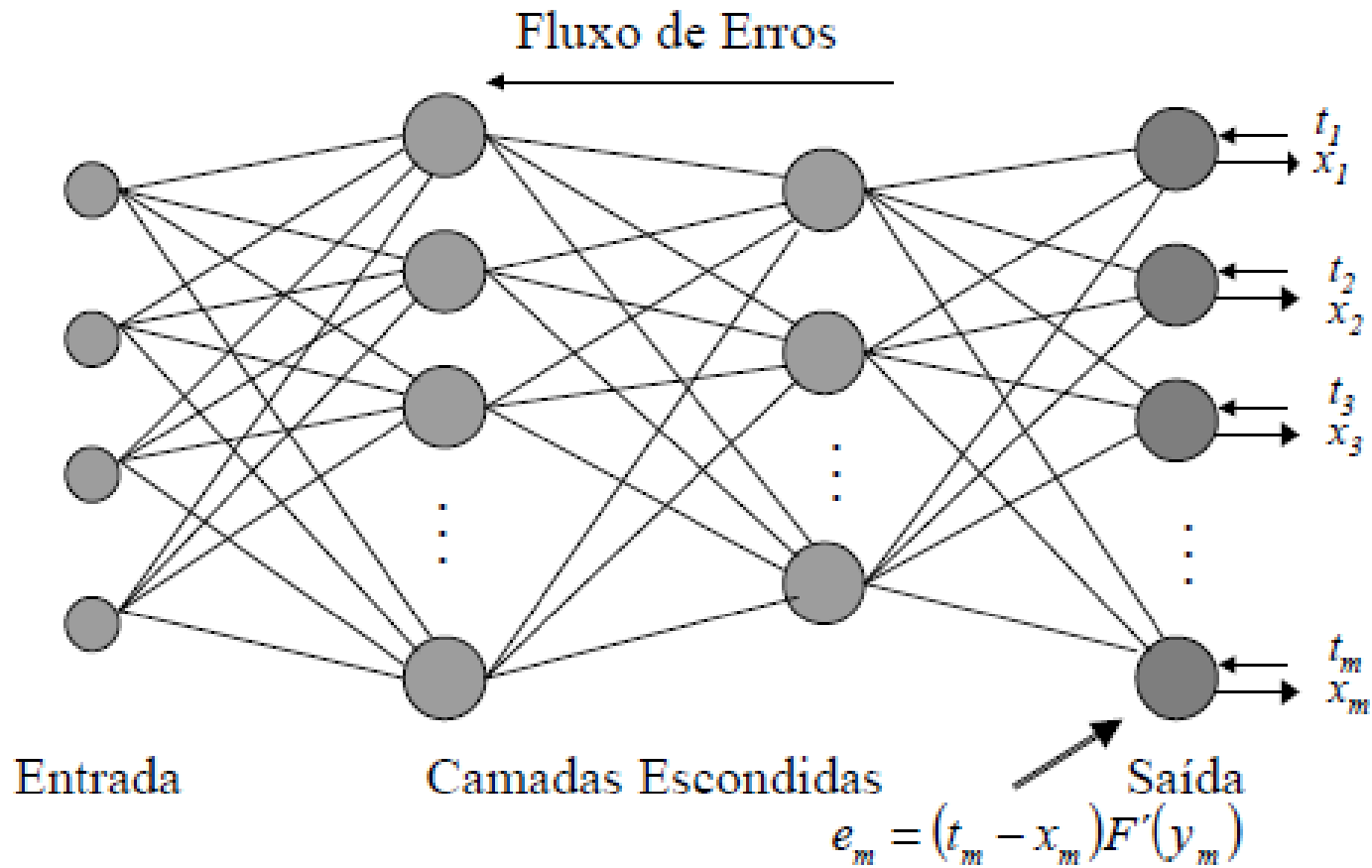
## □ Fase 1: Feed-Forward



# Processo de aprendizado

## □ Fase 1: Feed-Backward

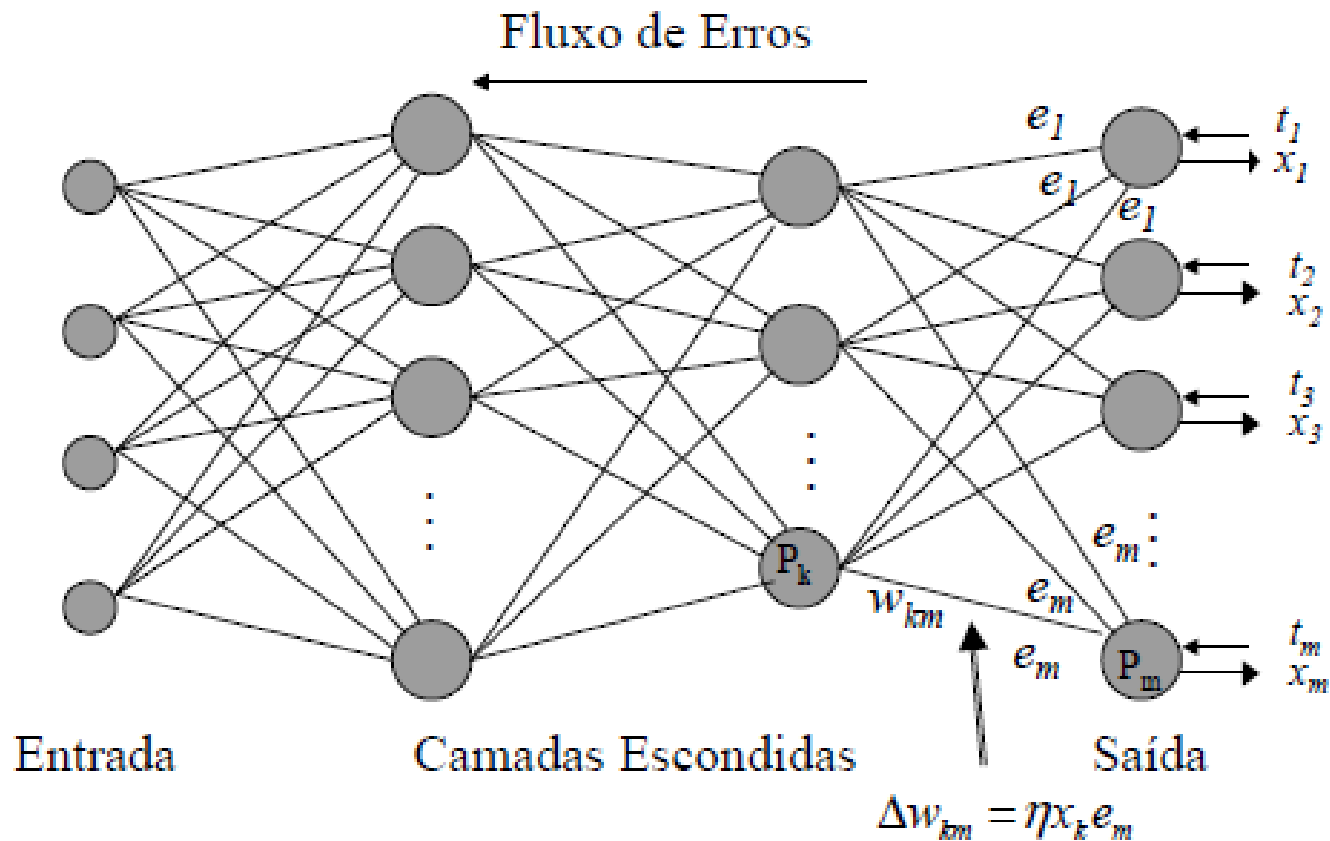
- Cálculo do erro da camada de saída



# Processo de aprendizado

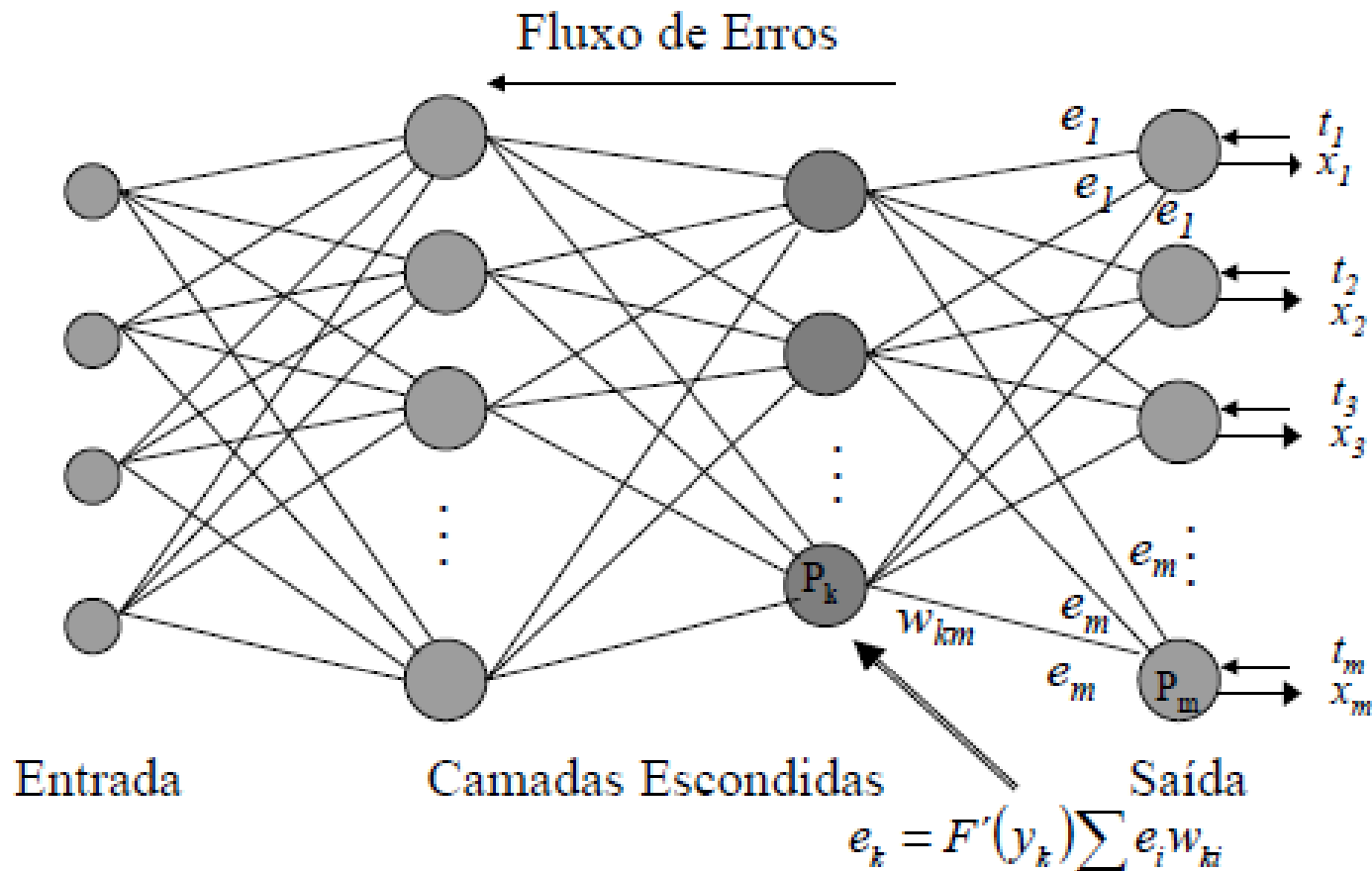
## □ Fase 1: Feed-Backward

- Atualização dos pesos da camada de saída



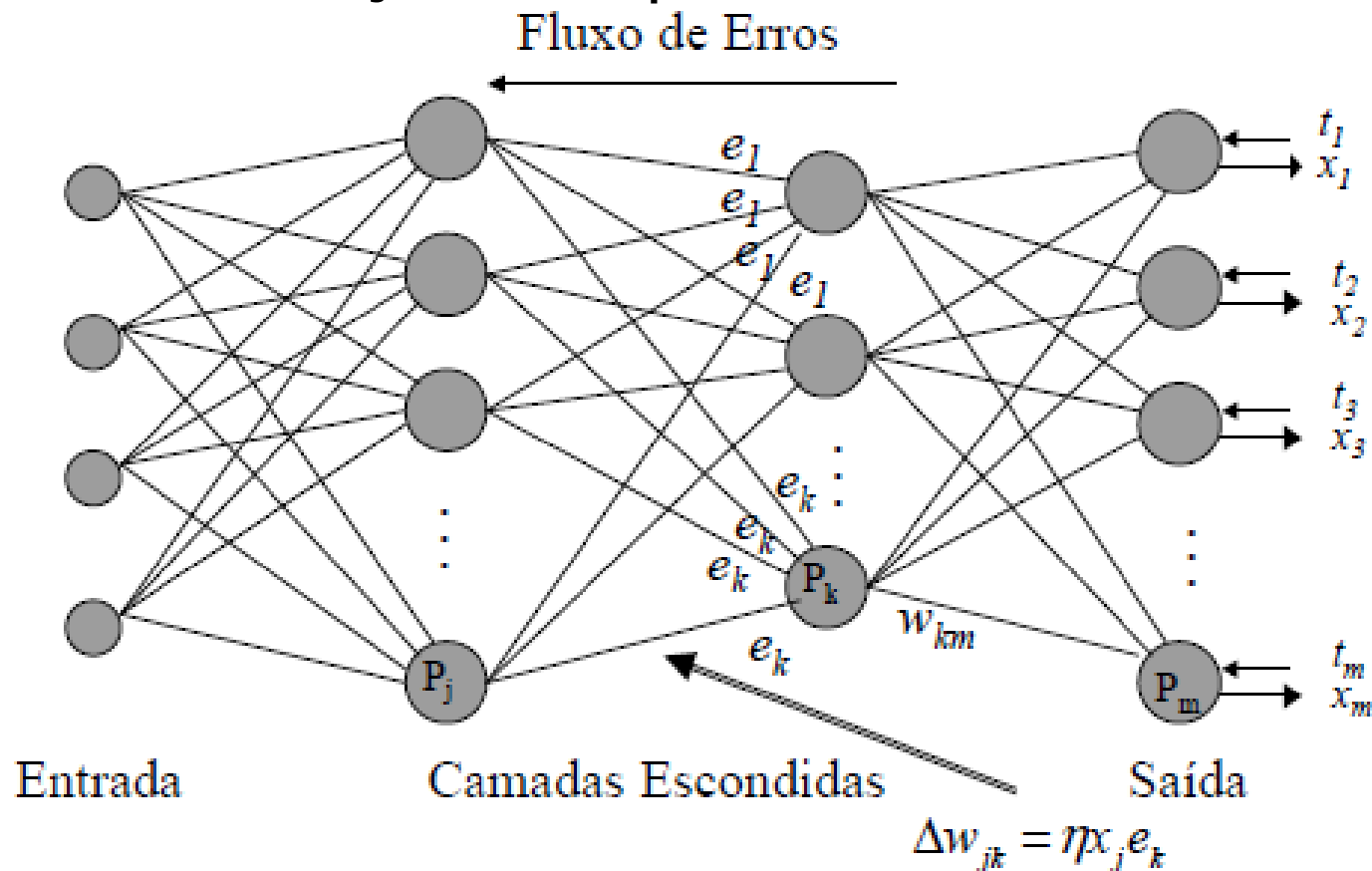
# Processo de aprendizado

- Fase 1: Feed-Backward
  - Cálculo do erro da 2ª camada escondida



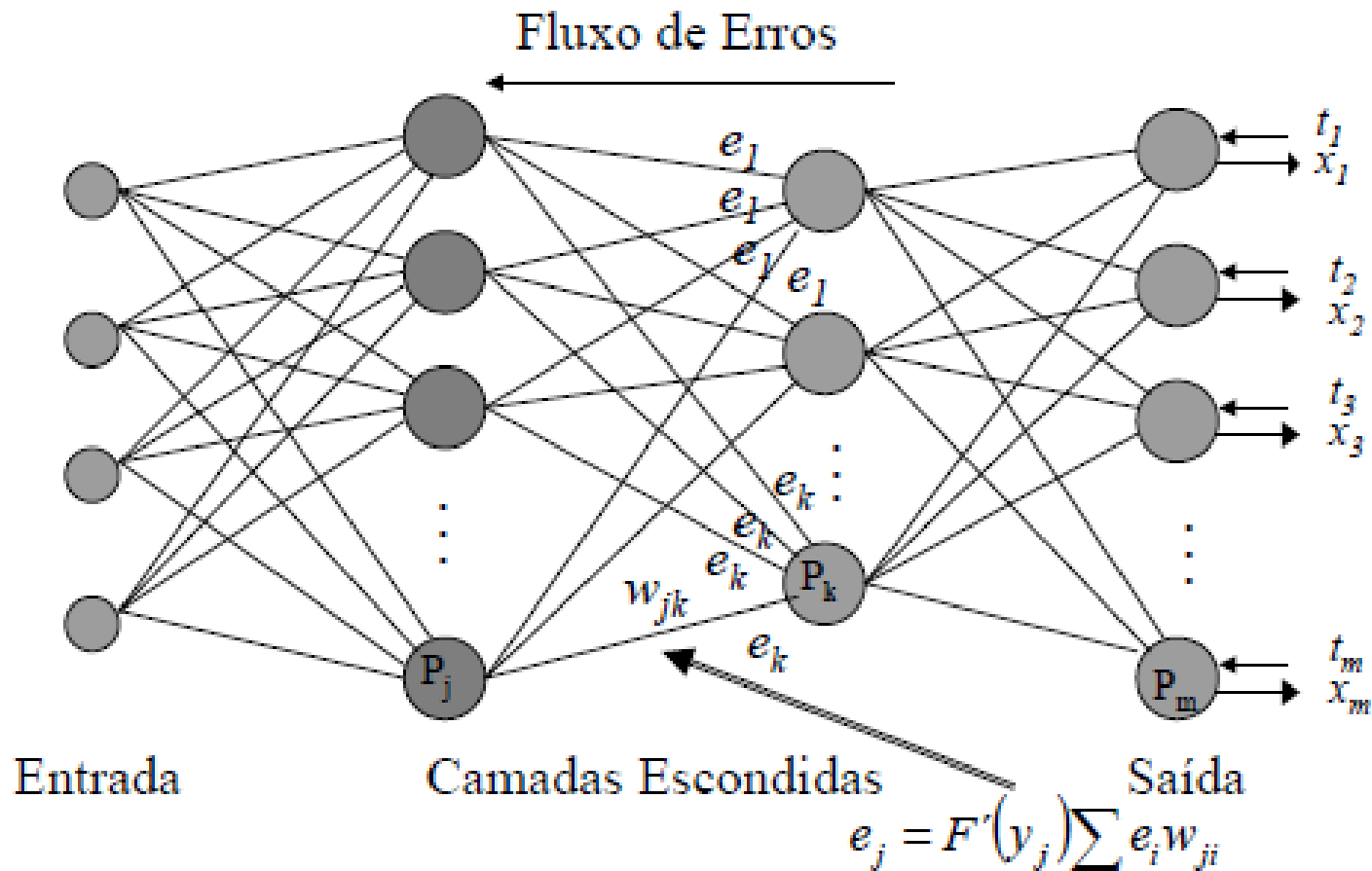
# Processo de aprendizado

- Fase 1: Feed-Backward
  - Atualização dos pesos da 2ª camada



# Processo de aprendizado

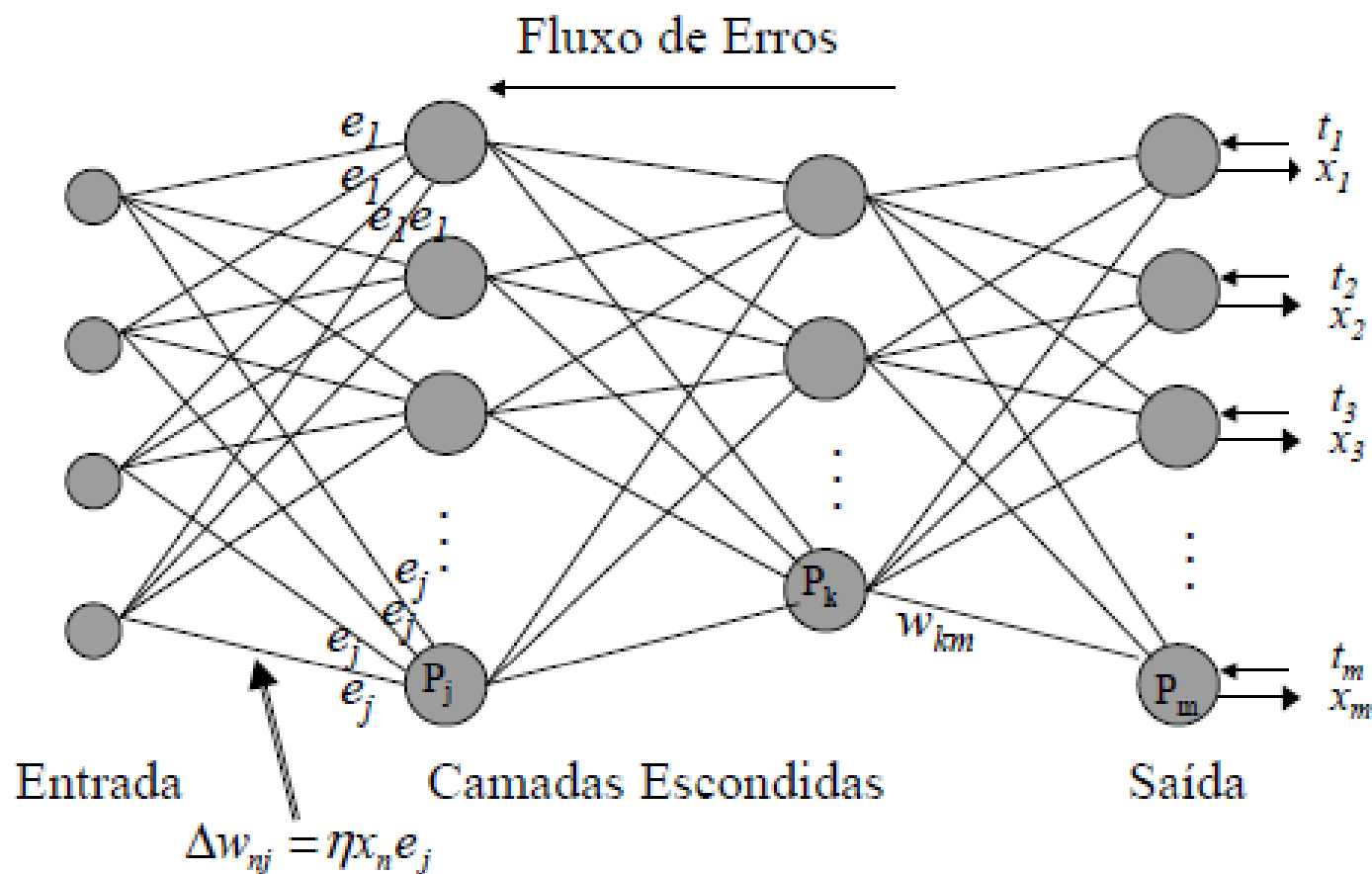
- Fase 1: Feed-Backward
  - Cálculo do erro da 1ª camada escondida



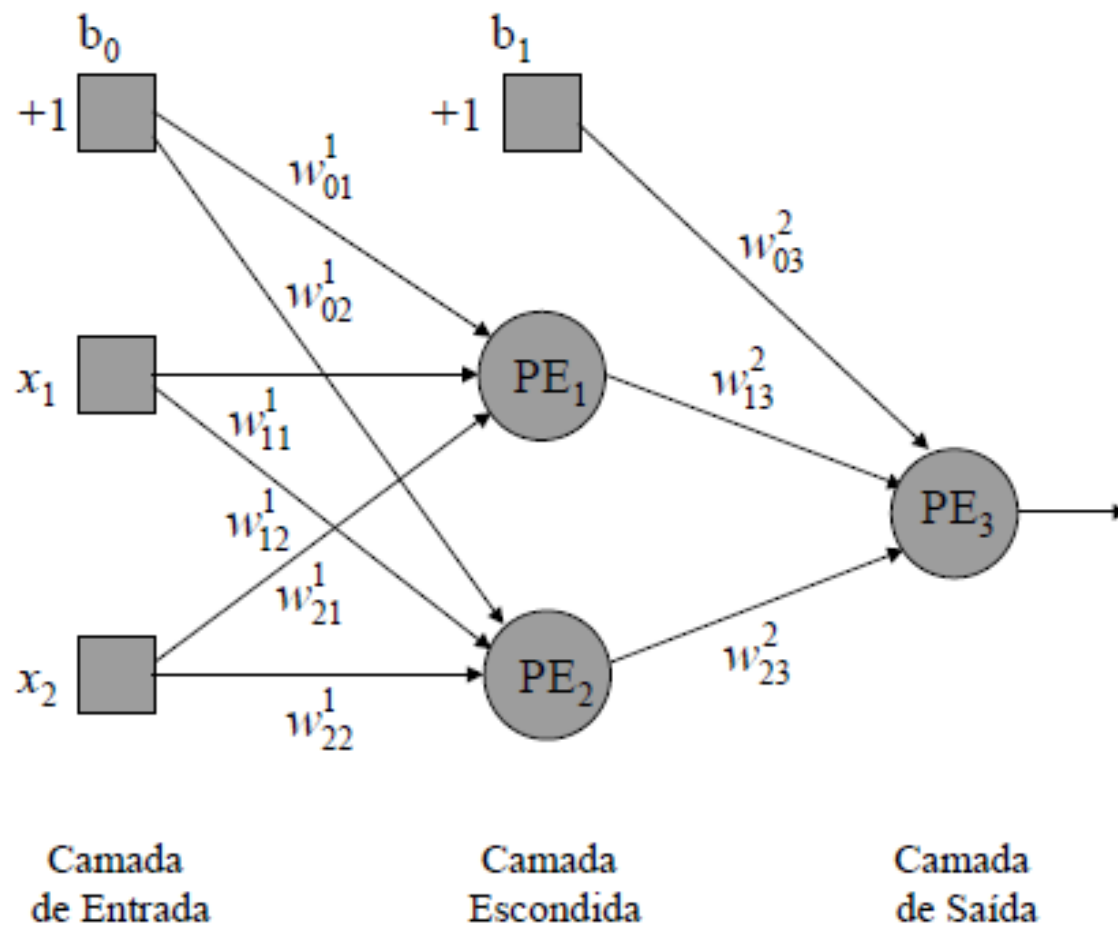


# Processo de aprendizado

- Fase 1: Feed-Backward
  - Atualização dos pesos da 1ª camada



# Exemplo MLP



# Exemplo MLP

- Entrada:

- $x_1=1, x_2=0$

- Saída Desejada:

- $t_3 = 1$

- Pesos iniciais:

- $w_{ij}(0) = 0$

- Taxa de Aprendizagem:

- $\eta = 0.5$

- Função de Ativação:

$$F(y_i) = \frac{1}{1 + \exp(-y_i)}$$

- Derivada da Função de Ativação:

$$F'(y_i) = \frac{\exp(-y_i)}{[1 + \exp(-y_i)]^2}$$

# Exemplo MLP

- Algoritmo de Aprendizado:

$$w_{ij} = w_{ij} + \eta x_i e_j$$

- Camada de Saída

$$e_j = (t_j - x_j) F'(y_j)$$

- Camada Escondida

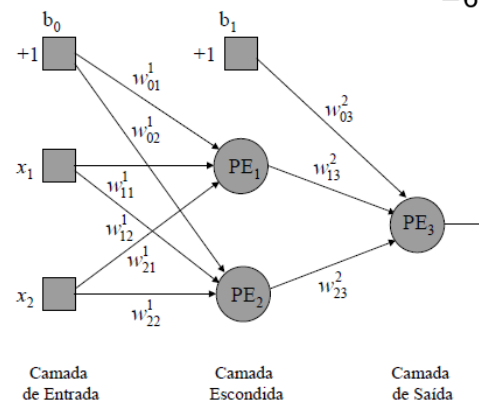
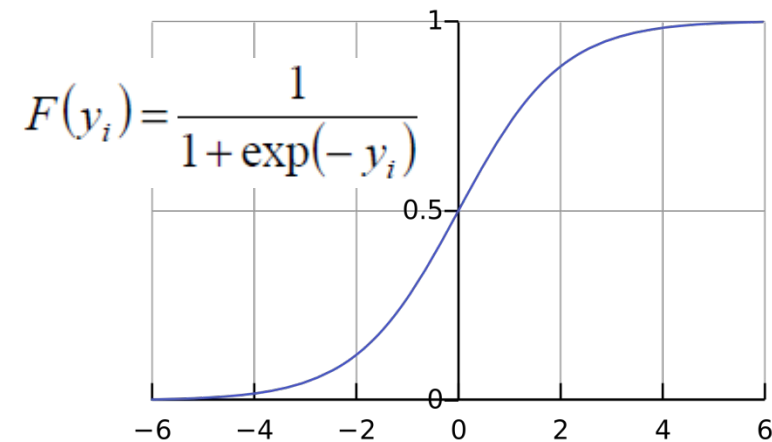
$$e_j = F'(y_j) \sum_k e_k w_{jk}$$

# Exemplo MLP

## □ Feed-Forward:

- $y_1 = 1*0 + 1*0 + 0*0 = 0$ 
  - $x_1 = F(y_1) = 0.5$
- $y_2 = 1*0 + 1*0 + 0*0 = 0$ 
  - $x_2 = F(y_2) = 0.5$
- $y_3 = 1*0 + 0.5*0 + 0.5*0 = 0$ 
  - $x_3 = F(y_3) = 0.5$

$$y_j = \sum x_i w_{ij} + \theta_j$$



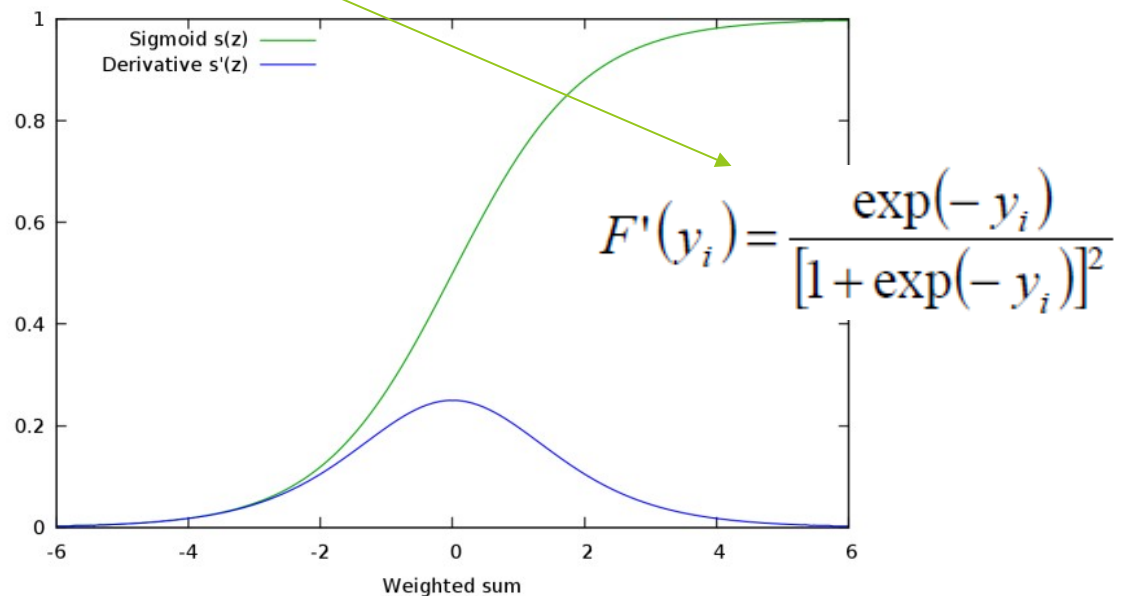
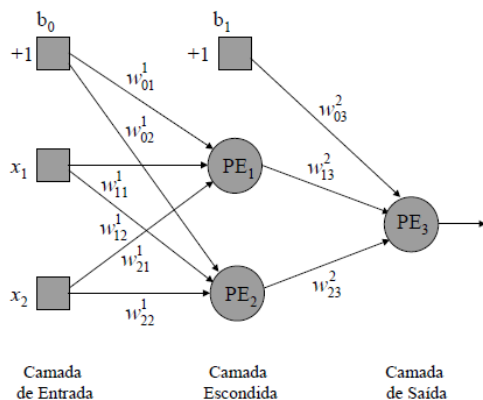
# Exemplo MLP

## □ Feed-Backward:

- $t_3 - x_3 = 1 - 0.5 = 0.5$

- $e_3 = 0.5 * 0.25 = 0.125$

$$e_j = (t_j - x_j) F'(y_j)$$

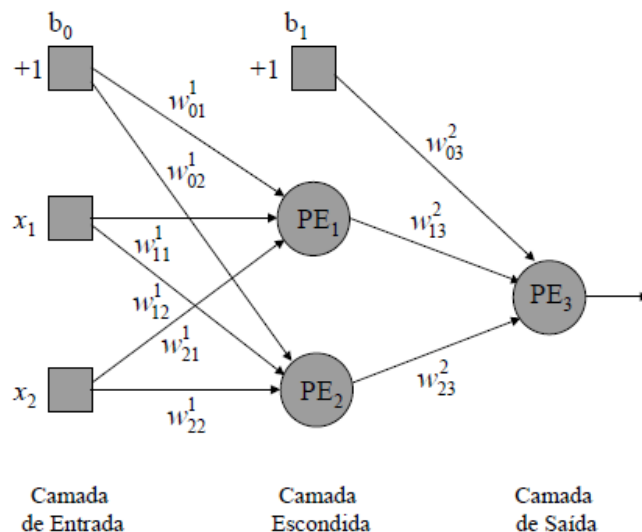


# Exemplo MLP

## □ Feed-Backward:

$$w_{ij} = w_{ij} + \eta x_i e_j$$

- $w_{03}^2 = 0 + 0.5 * 1 * 0.125 = 0.0625$
- $w_{13}^2 = 0 + 0.5 * 0.5 * 0.125 = 0.0313$
- $w_{23}^2 = 0 + 0.5 * 0.5 * 0.125 = 0.0313$

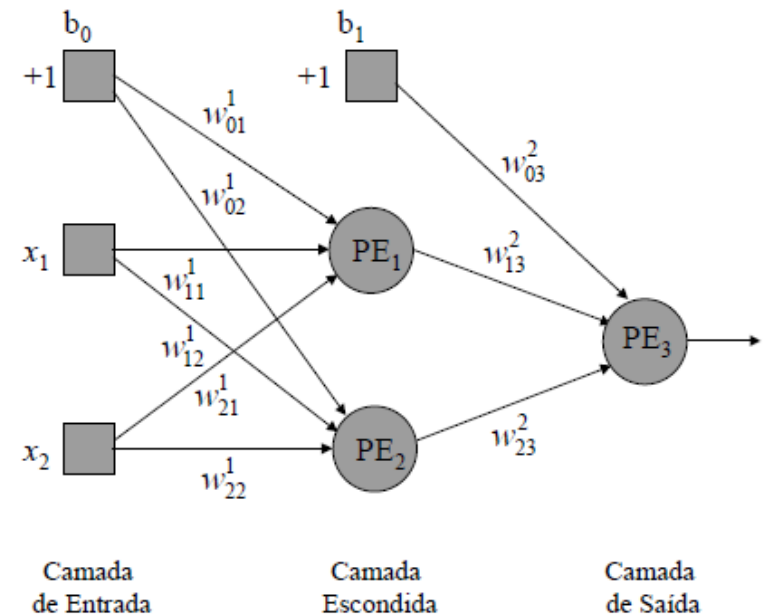


# Exemplo MLP

## □ Feed-Backward:

- $e_1 = 0.25 * (0.125 * 0.0313) = 0.00097813$
- $e_2 = 0.25 * (0.125 * 0.0313) = 0.00097813$

$$e_j = F'(y_j) \sum_k e_k w_{jk}$$



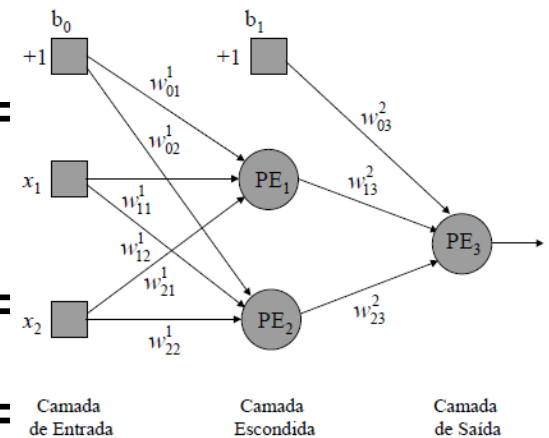


# Exemplo MLP

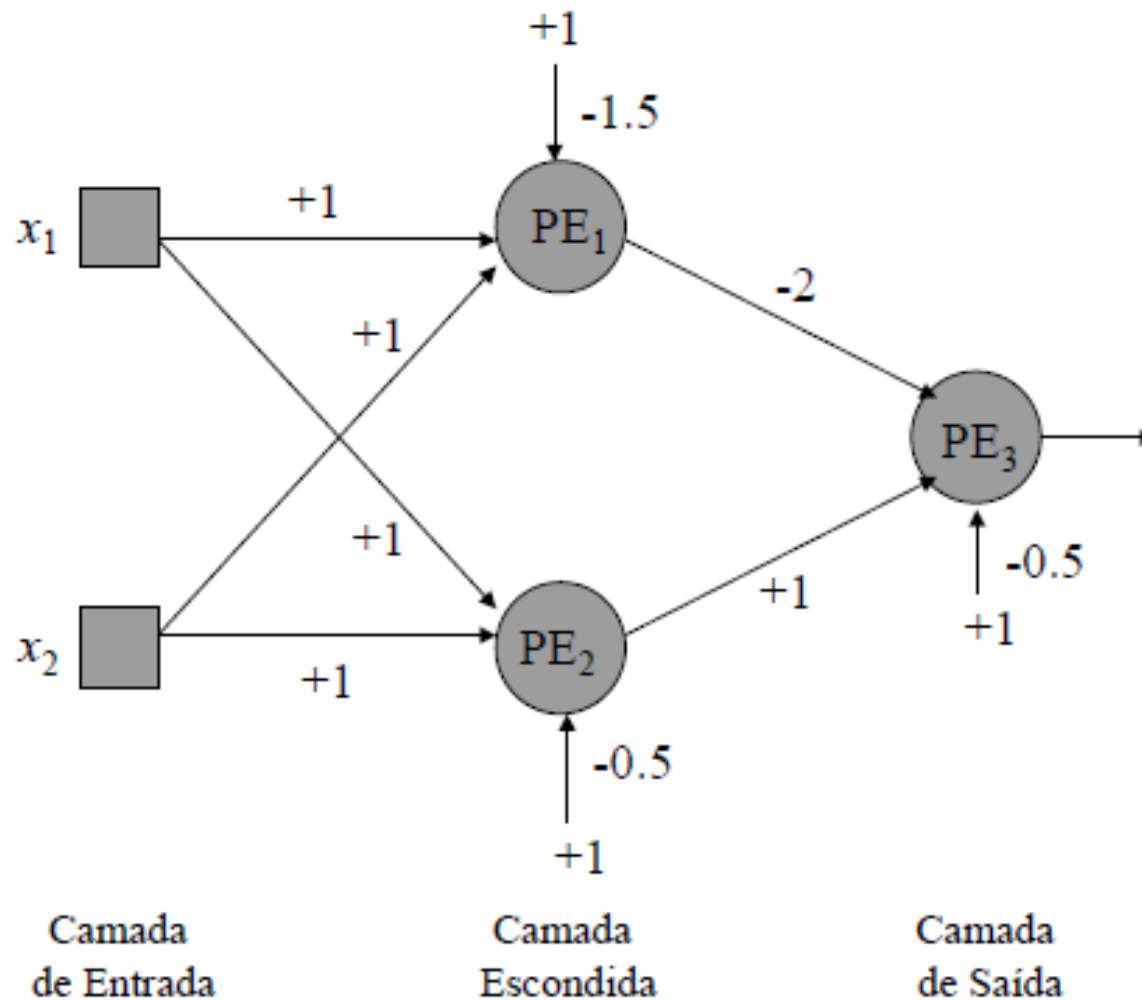
## □ Feed-Backward:

$$w_{ij} = w_{ij} + \eta x_i e_j$$

- $w_{01}^1 = 0 + 0.5 * 1 * 0.00097813 = 0.00048907$
- $w_{02}^1 = 0 + 0.5 * 1 * 0.00097813 = 0.00048907$
- $w_{11}^1 = 0 + 0.5 * 1 * 0.00097813 = 0.00048907$
- $w_{12}^1 = 0 + 0.5 * 1 * 0.00097813 = 0.00048907$
- $w_{21}^1 = 0 + 0.5 * 0 * 0.00097813 = 0$
- $w_{22}^1 = 0 + 0.5 * 0 * 0.00097813 = 0$

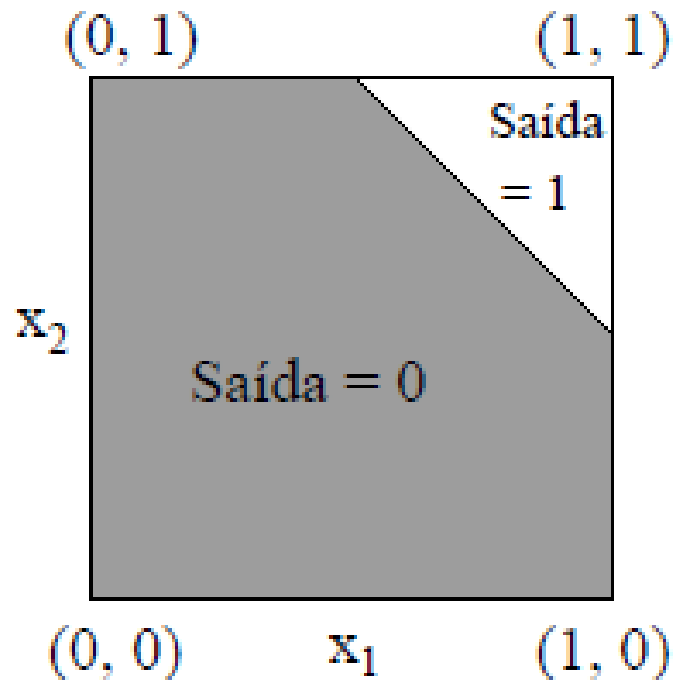


# Problema XOR

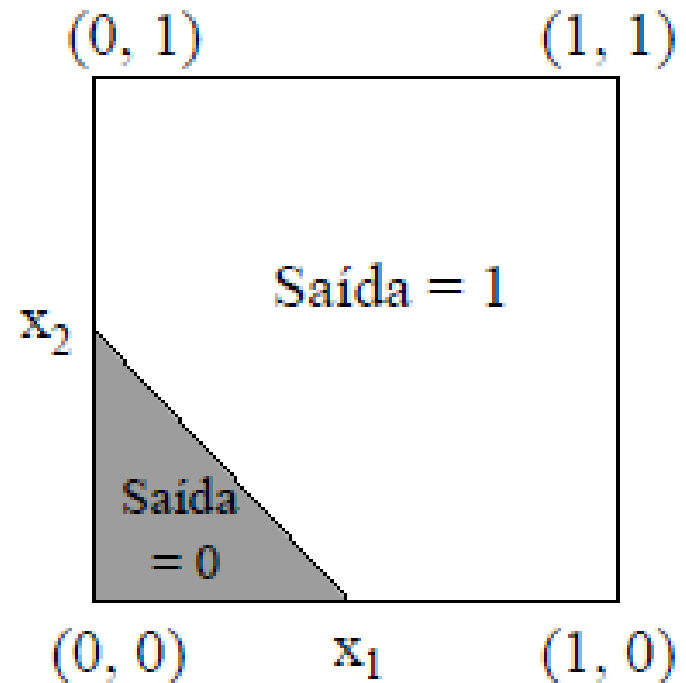


# Problema XOR

- Borda de decisão construída pelo 1º neurônio escondido

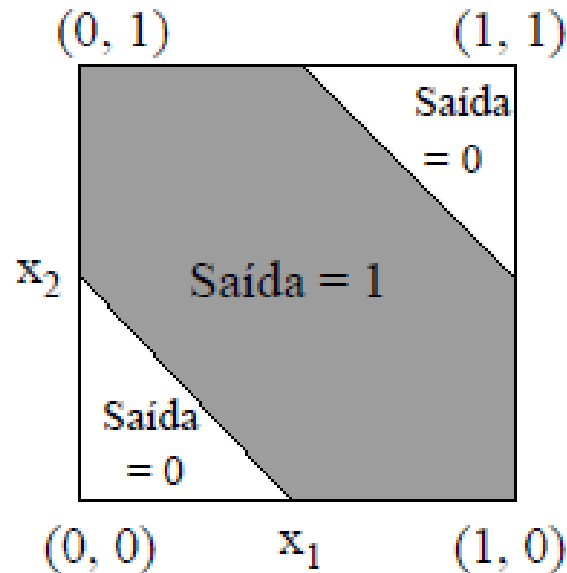


- Borda de decisão construída pelo 2º neurônio escondido

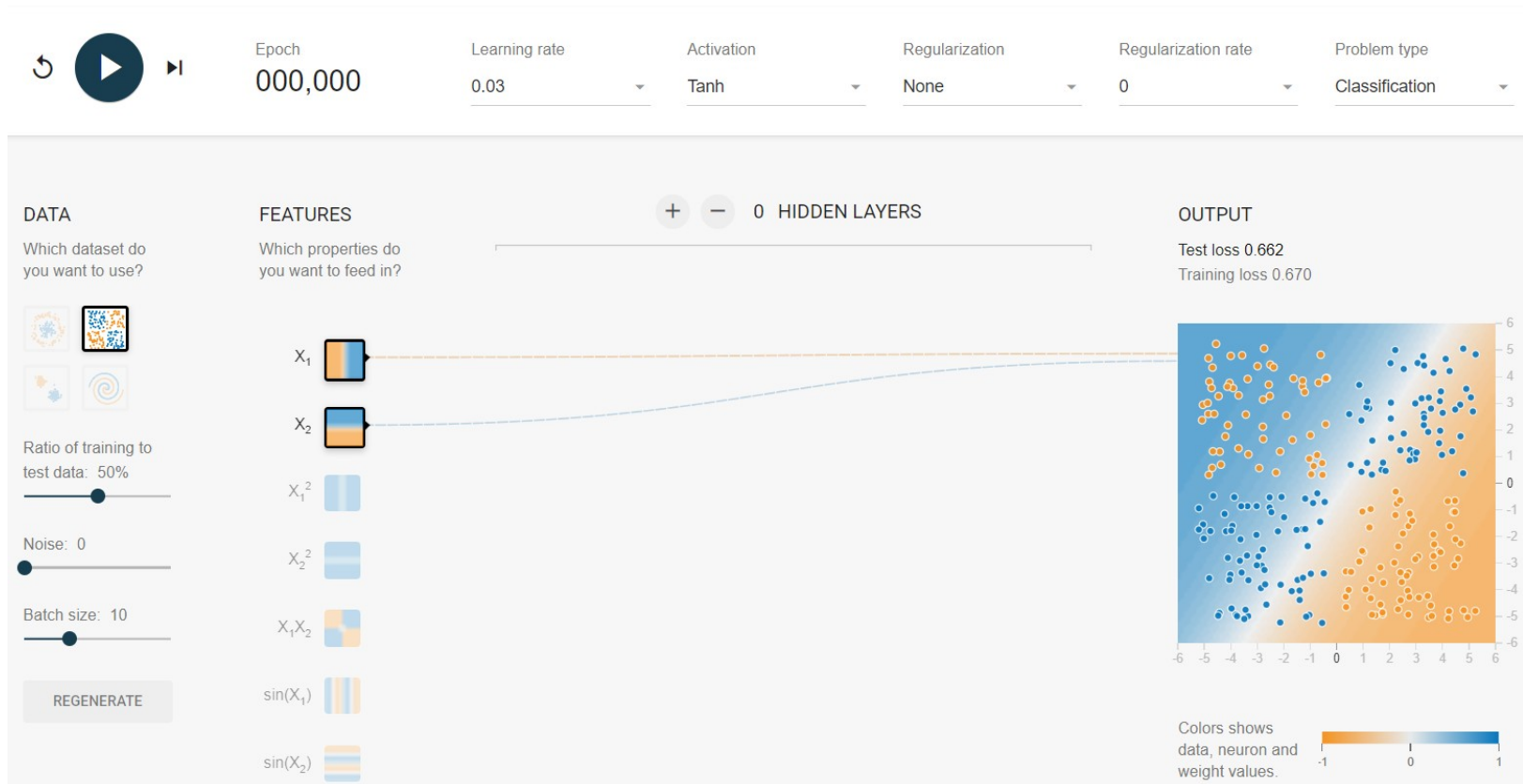


# Problema XOR

- Borda de decisão construída pela rede completa



# With N layer and 1 neuron



<http://playground.tensorflow.org/>