



Human-Centered Data & AI

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MBA Professor, FIAP  
GDE – Machine Learning



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“

# Redes Neurais

*Recapitulando...*

# Regressão Linear

	Peso	Altura
	Pessoa 1	80 kg      163
	Pessoa 2	85 kg      168
	Pessoa 3	90 kg      175
	Pessoa 4	95 kg      188
	Pessoa 5	88 kg      175,4

$$\hat{y} = \beta_0 + \beta_1 X_1$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

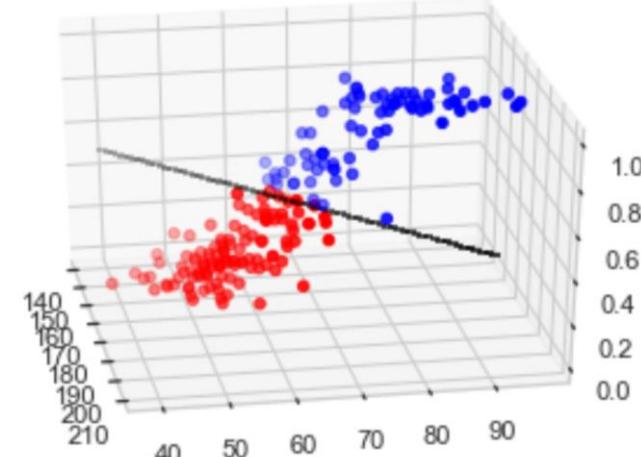
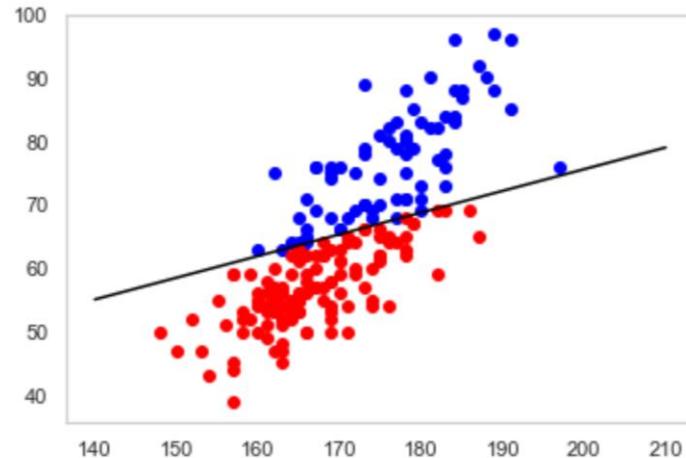
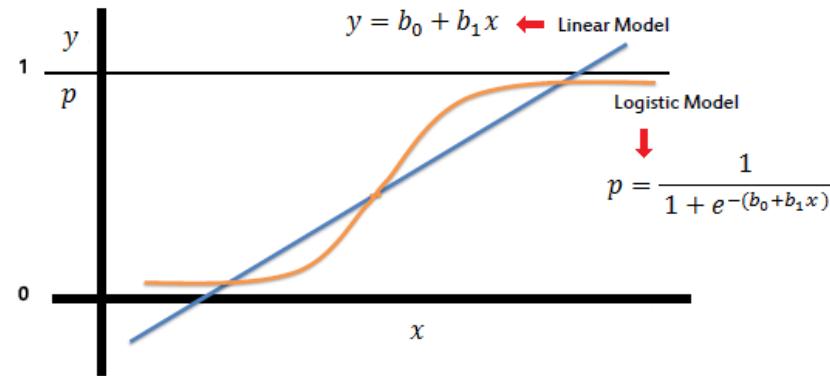
$$\beta_0 = 17$$

$$\beta_1 = 1,8$$

$$MSE = 6$$

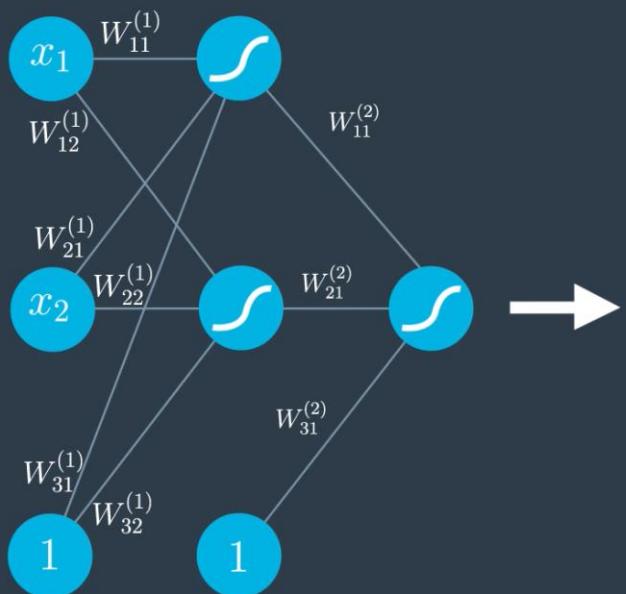
$$\hat{y} = 17 + 1,8 X_1$$

# Redes Neurais – Feedforward



# Redes Neurais – Feedforward

Feedforward



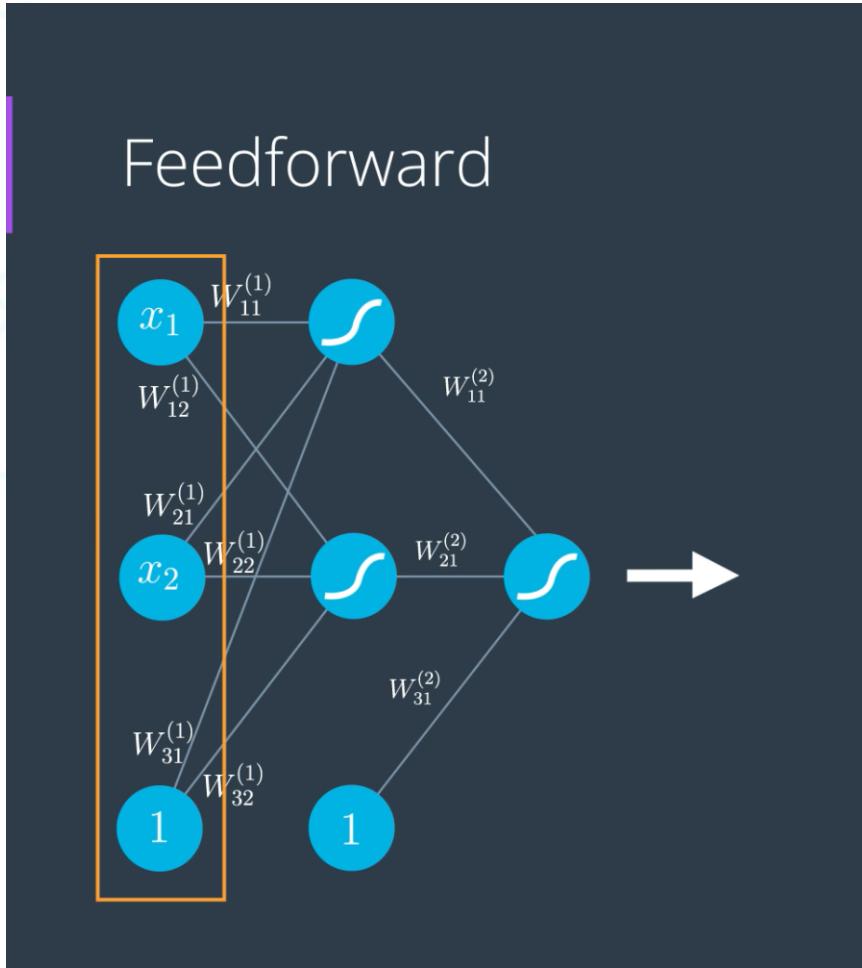
$$\hat{y} = \sigma \begin{pmatrix} W_{11}^{(2)} \\ W_{21}^{(2)} \\ W_{31}^{(2)} \end{pmatrix} \sigma \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$

$$\hat{y} = \sigma \circ W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

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# Redes Neurais

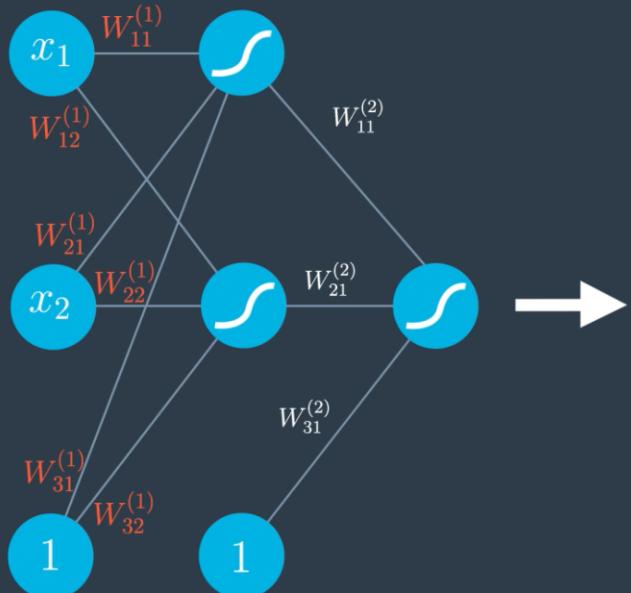
# Redes Neurais – Feedforward



$$\begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$

# Redes Neurais – Feedforward

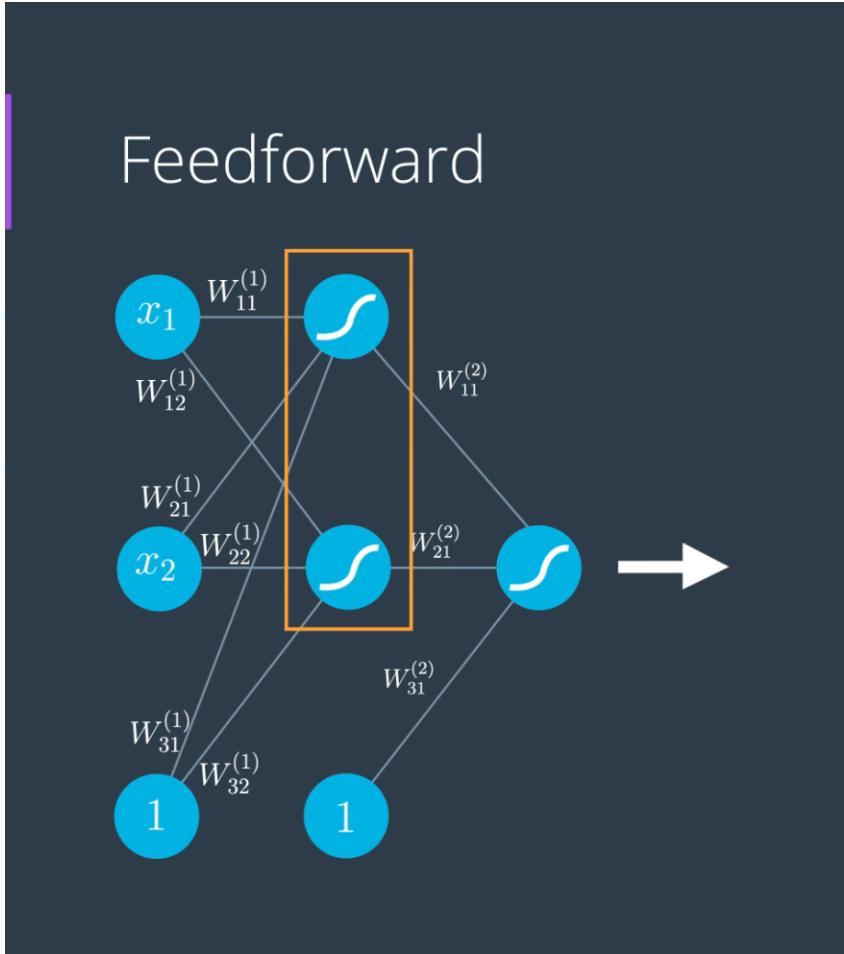
Feedforward



$$\begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$



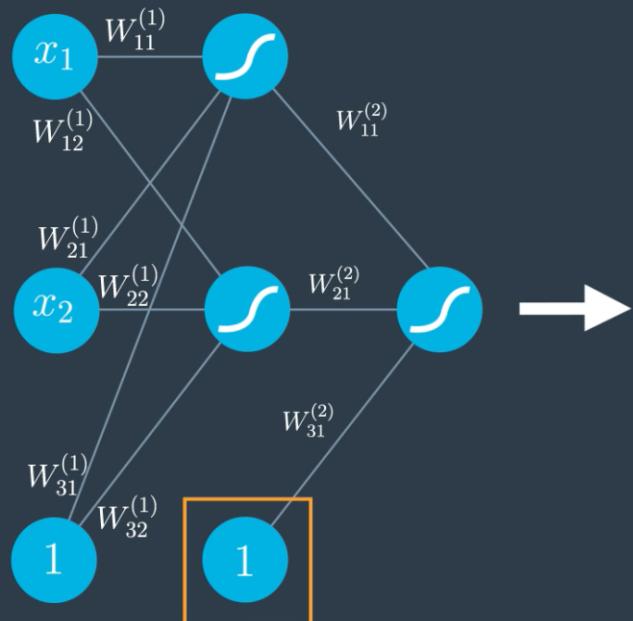
# Redes Neurais – Feedforward



$$\sigma \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$

# Redes Neurais – Feedforward

Feedforward

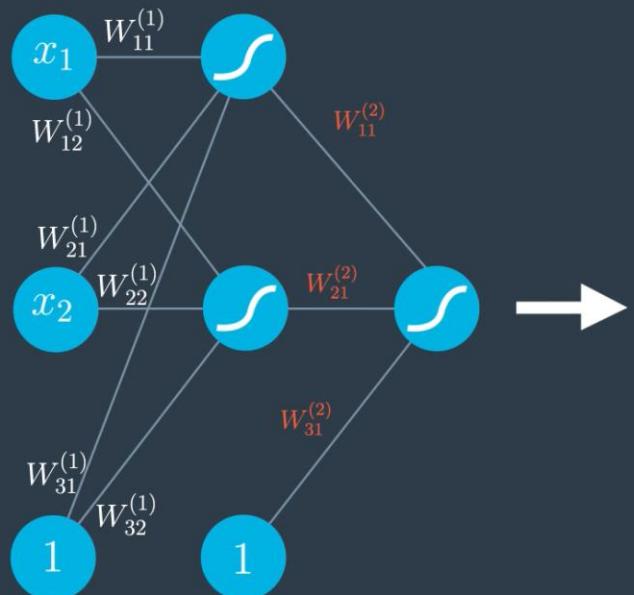


$$\sigma \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$



# Redes Neurais – Feedforward

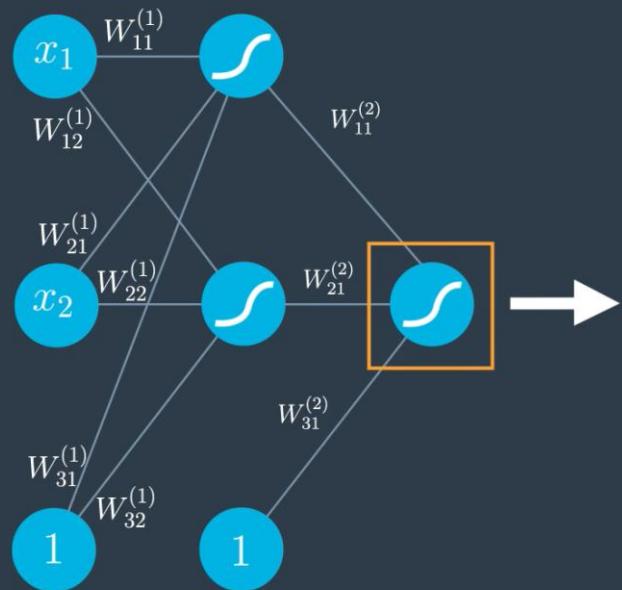
Feedforward



$$\begin{pmatrix} W_{11}^{(2)} \\ W_{21}^{(2)} \\ W_{31}^{(2)} \end{pmatrix} \sigma \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$

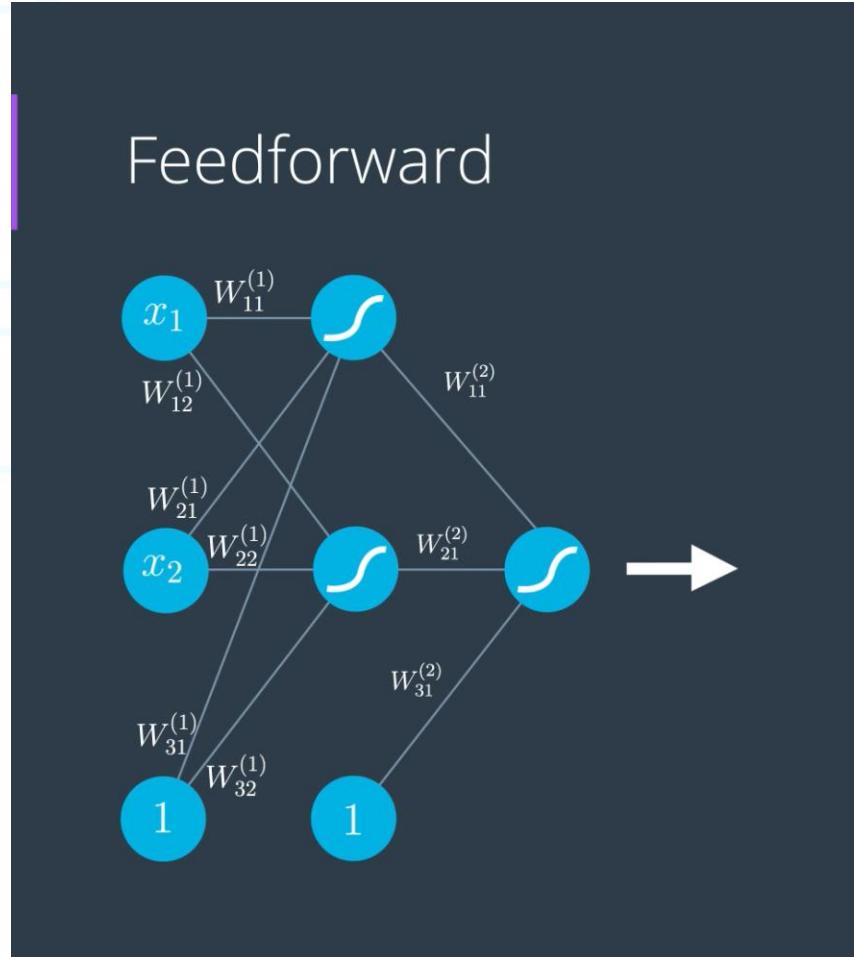
# Redes Neurais – Feedforward

Feedforward



$$\sigma \begin{pmatrix} W_{11}^{(2)} \\ W_{21}^{(2)} \\ W_{31}^{(2)} \end{pmatrix} \sigma \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$

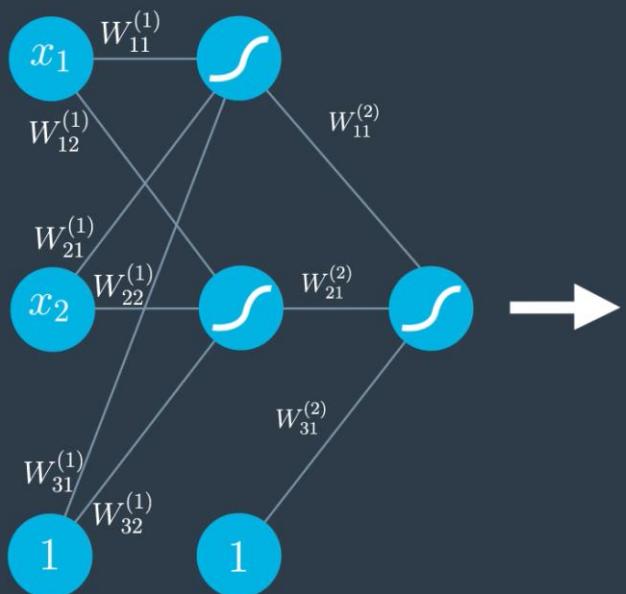
# Redes Neurais – Feedforward



$$\hat{y} = \sigma \begin{pmatrix} W_{11}^{(2)} \\ W_{21}^{(2)} \\ W_{31}^{(2)} \end{pmatrix} \sigma \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$

# Redes Neurais – Feedforward

Feedforward

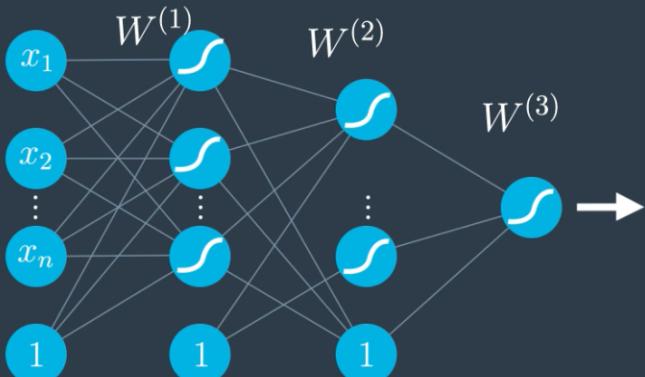


$$\hat{y} = \sigma \begin{pmatrix} W_{11}^{(2)} \\ W_{21}^{(2)} \\ W_{31}^{(2)} \end{pmatrix} \sigma \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$

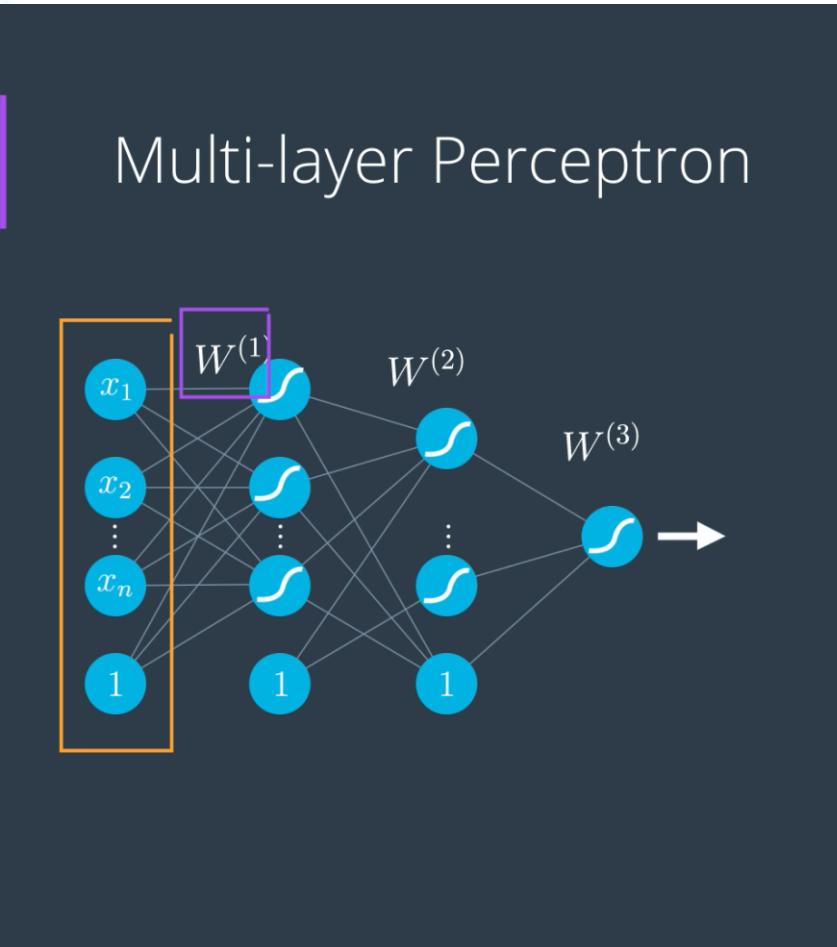
$$\hat{y} = \sigma \circ W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

# Redes Neurais – Feedforward

Multi-layer Perceptron



# Redes Neurais – Feedforward



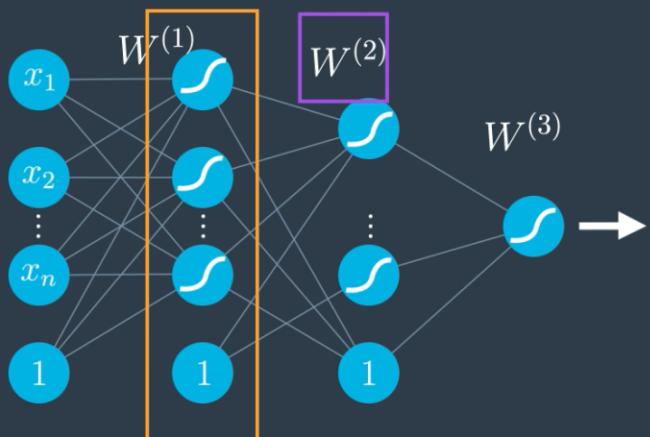
PREDICTION

$$\hat{y} =$$

$$\sigma \circ W^{(1)}(x)$$

# Redes Neurais – Feedforward

Multi-layer Perceptron

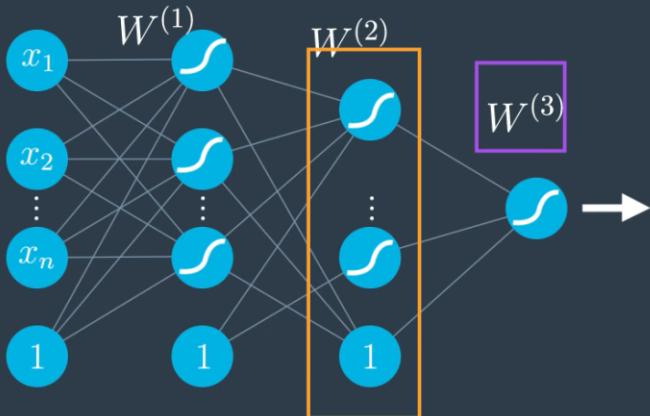


PREDICTION

$$\hat{y} = \sigma \circ W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

# Redes Neurais – Feedforward

Multi-layer Perceptron

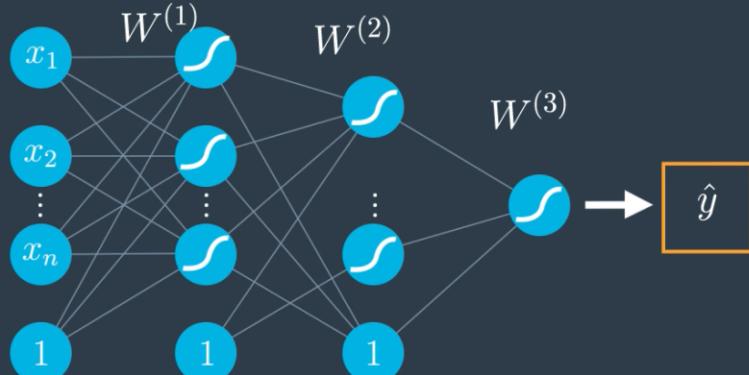


PREDICTION

$$\hat{y} = \sigma \circ W^{(3)} \circ \sigma \circ W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

# Redes Neurais – Feedforward

Multi-layer Perceptron

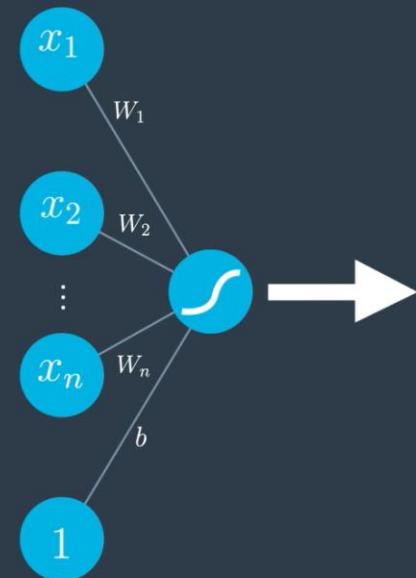


PREDICTION

$$\hat{y} = \sigma \circ W^{(3)} \circ \sigma \circ W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

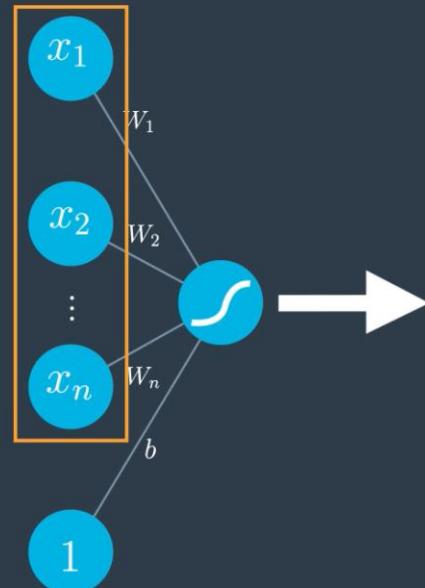
# Redes Neurais – Error Function

## Perceptron



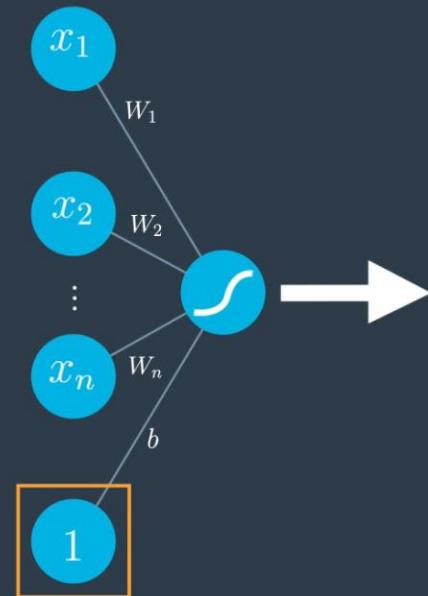
# Redes Neurais – Error Function

## Perceptron



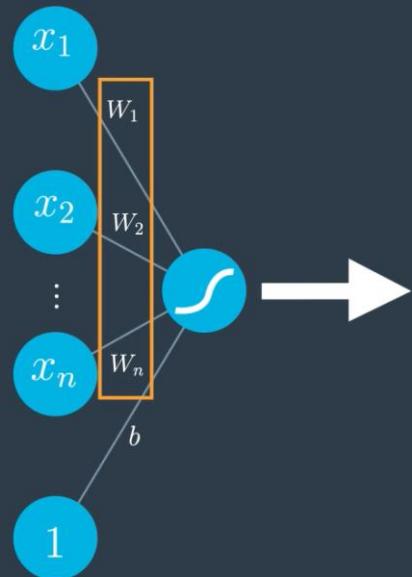
# Redes Neurais – Error Function

Perceptron



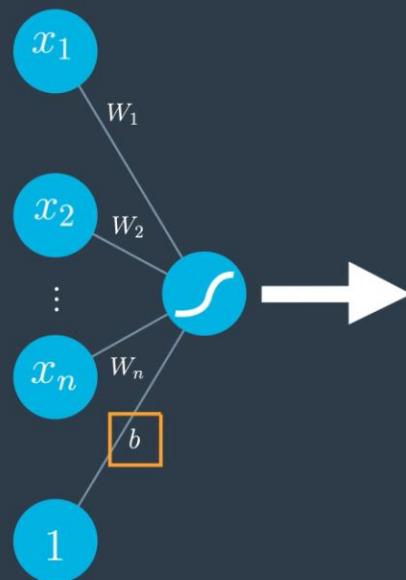
# Redes Neurais – Error Function

## Perceptron



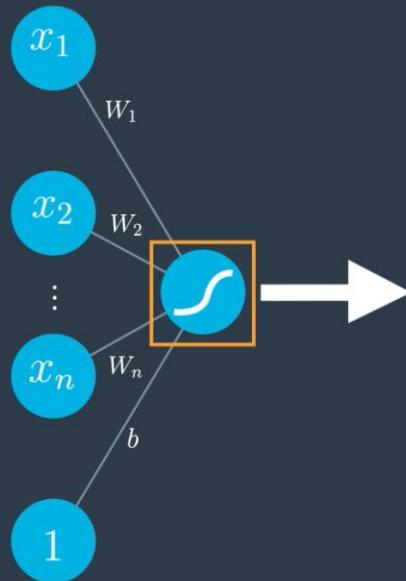
# Redes Neurais – Error Function

## Perceptron



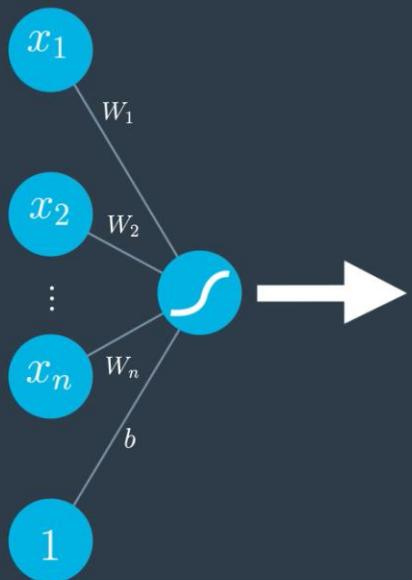
# Redes Neurais – Error Function

Perceptron



# Redes Neurais – Error Function

## Perceptron

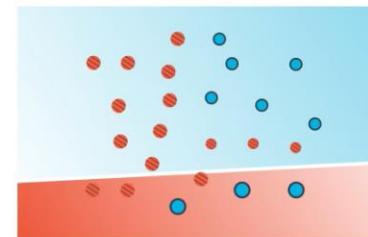


### PREDICTION

$$\hat{y} = \sigma(Wx + b)$$

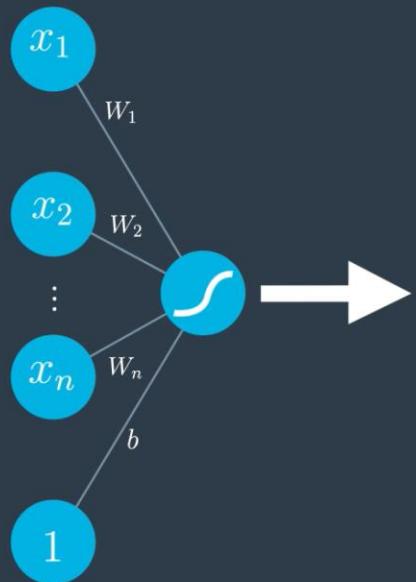
### ERROR FUNCTION

$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$



# Redes Neurais – Error Function

Perceptron

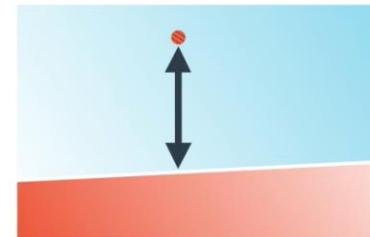


PREDICTION

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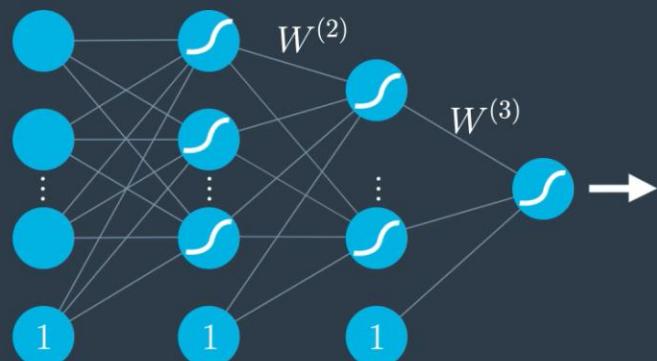
ERROR FUNCTION

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# Redes Neurais – Error Function

Multi-layer Perceptron

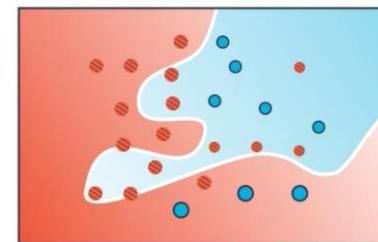


PREDICTION

$$\hat{y} = \sigma \circ W^{(3)} \circ \sigma \circ W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

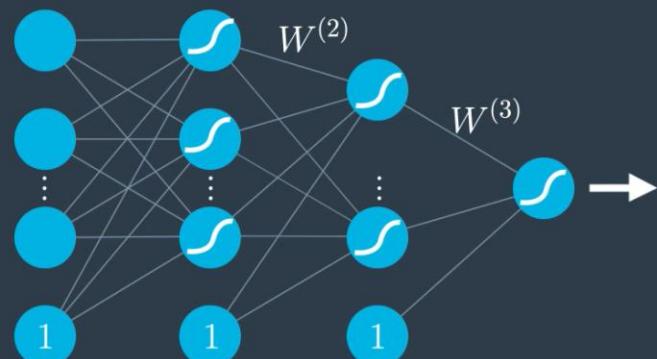
ERROR FUNCTION

$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$



# Redes Neurais – Error Function

Multi-layer Perceptron

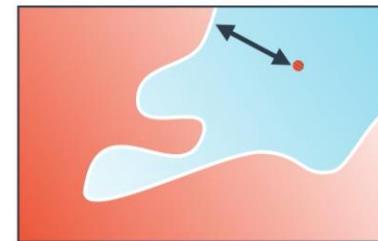


PREDICTION

$$\hat{y} = \sigma \circ W^{(3)} \circ \sigma \circ W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

ERROR FUNCTION

$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

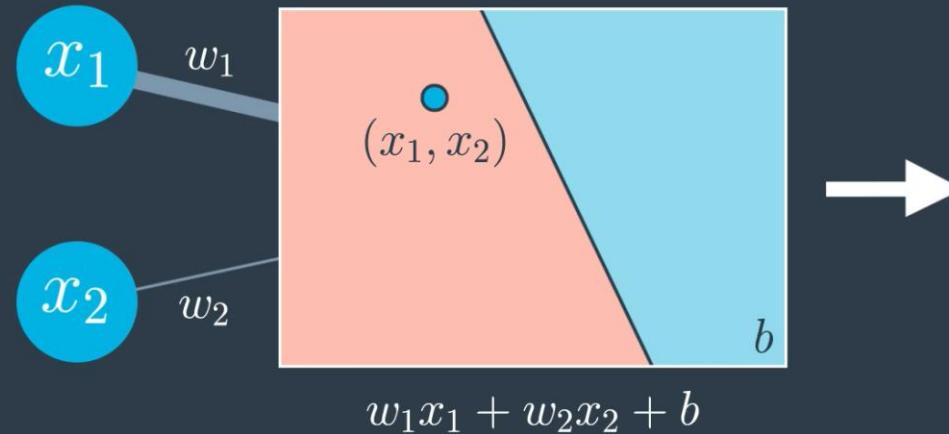


# Redes Neurais – Backpropagation

FeedForward

$$x = (x_1, x_2)$$

$$y = 1$$



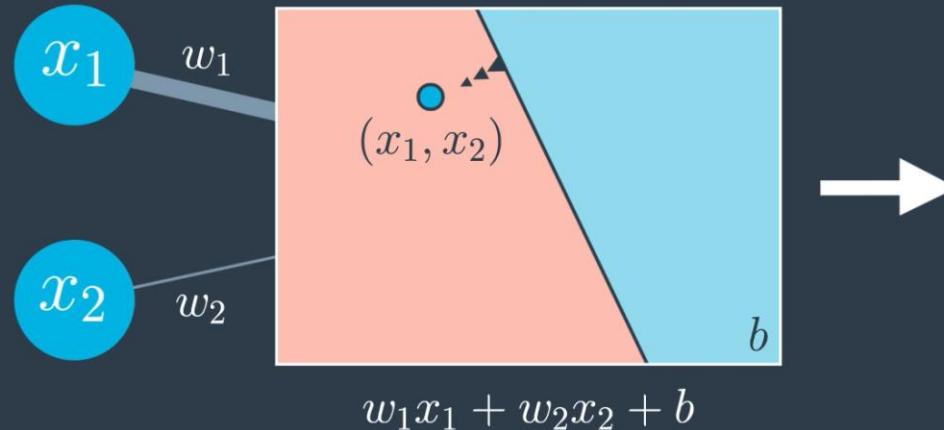
$$w_1x_1 + w_2x_2 + b$$

# Redes Neurais – Backpropagation

Backpropagation

$$x = (x_1, x_2)$$

$$y = 1$$

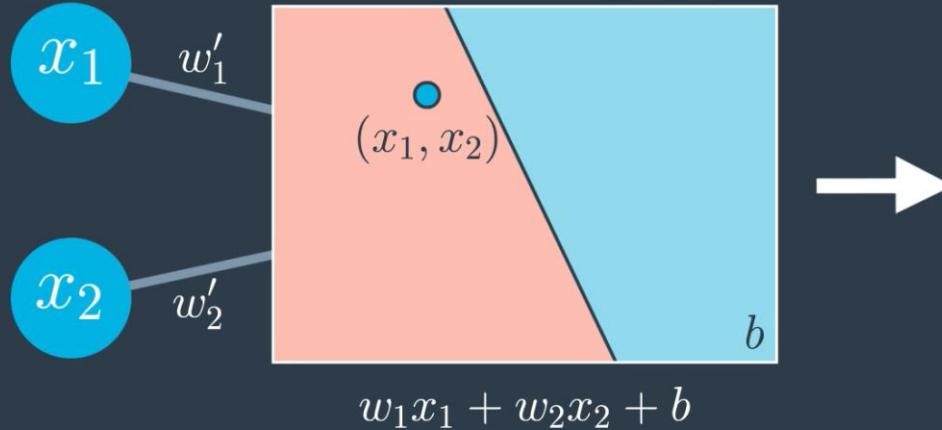


# Redes Neurais – Backpropagation

## Backpropagation

$$x = (x_1, x_2)$$

$$y = 1$$



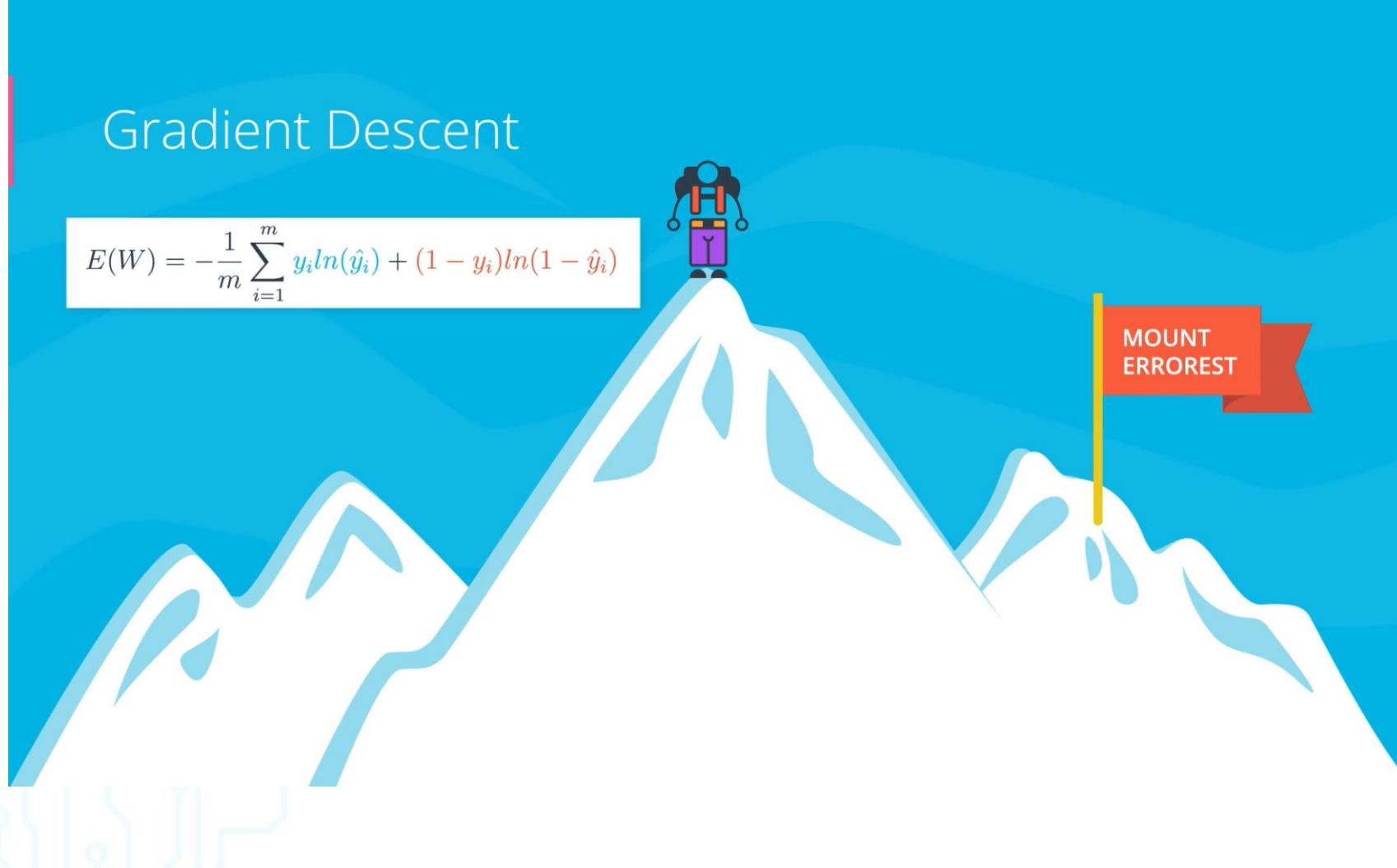
# Redes Neurais – Backpropagation

Gradient Descent

$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$



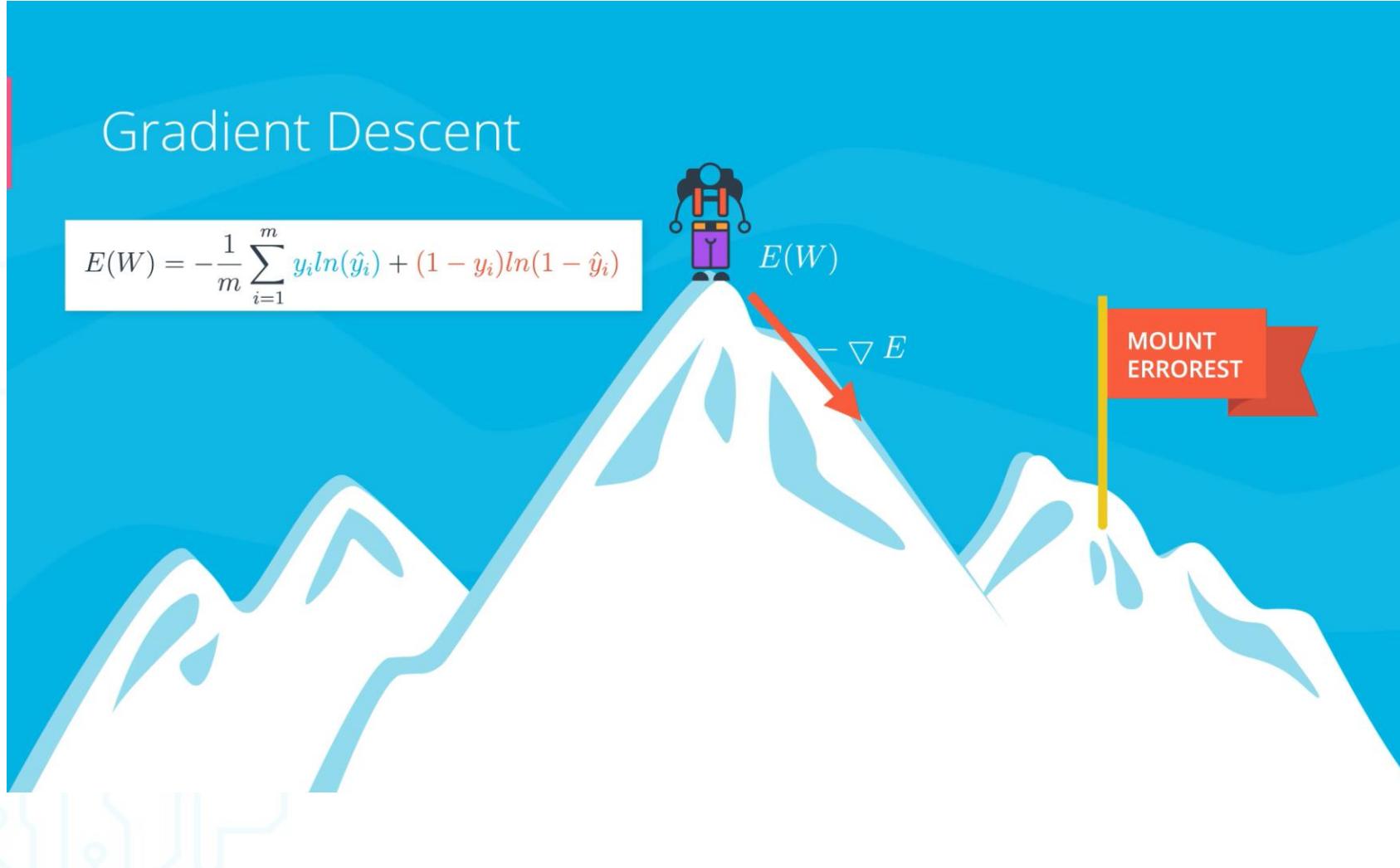
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ERROREST



# Redes Neurais – Backpropagation

## Gradient Descent

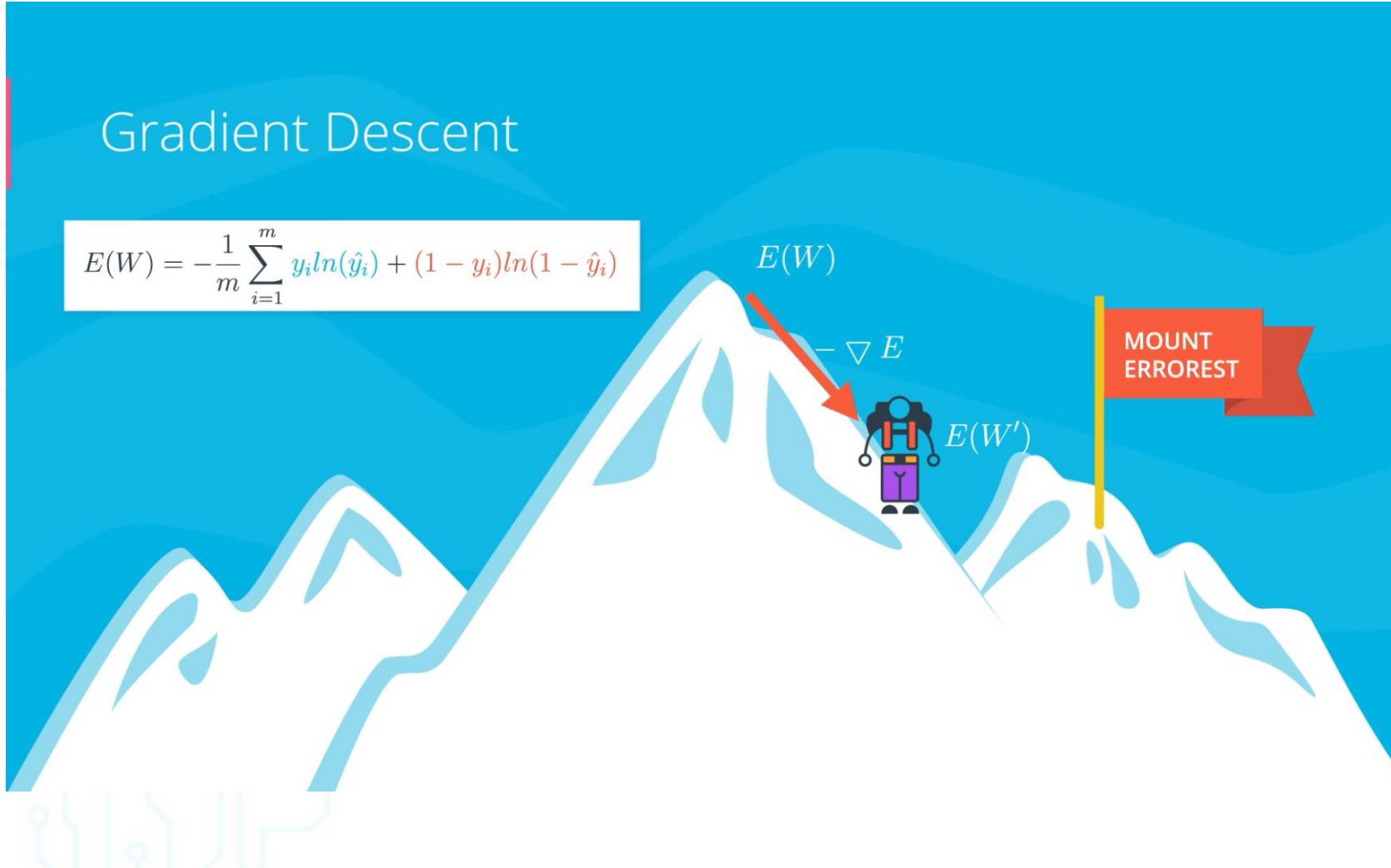
$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$



# Redes Neurais – Backpropagation

## Gradient Descent

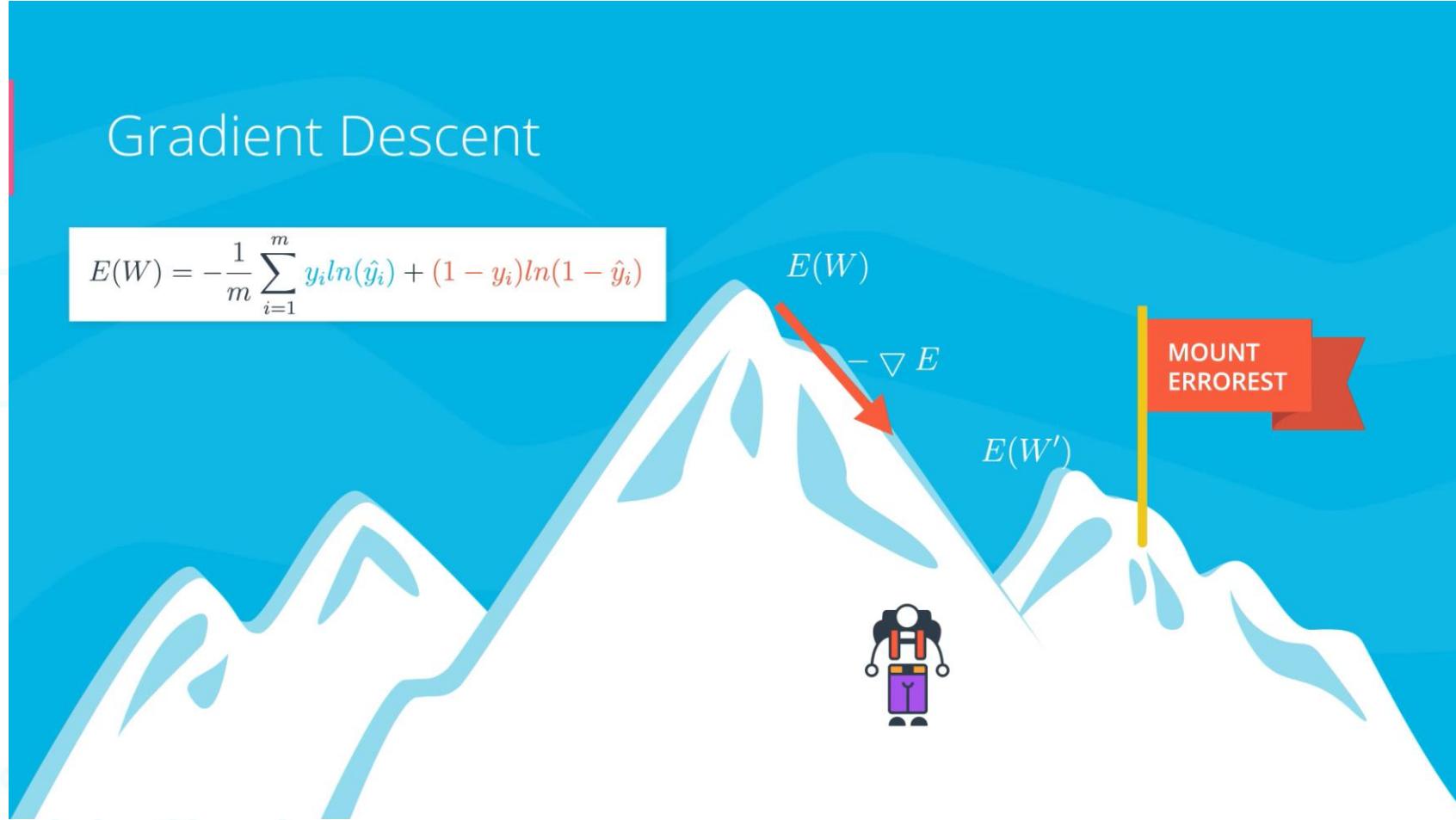
$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$



# Redes Neurais – Backpropagation

## Gradient Descent

$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$



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What about  
Multi-Layer Perceptrons?

# Redes Neurais – Backpropagation

## Gradient Descent

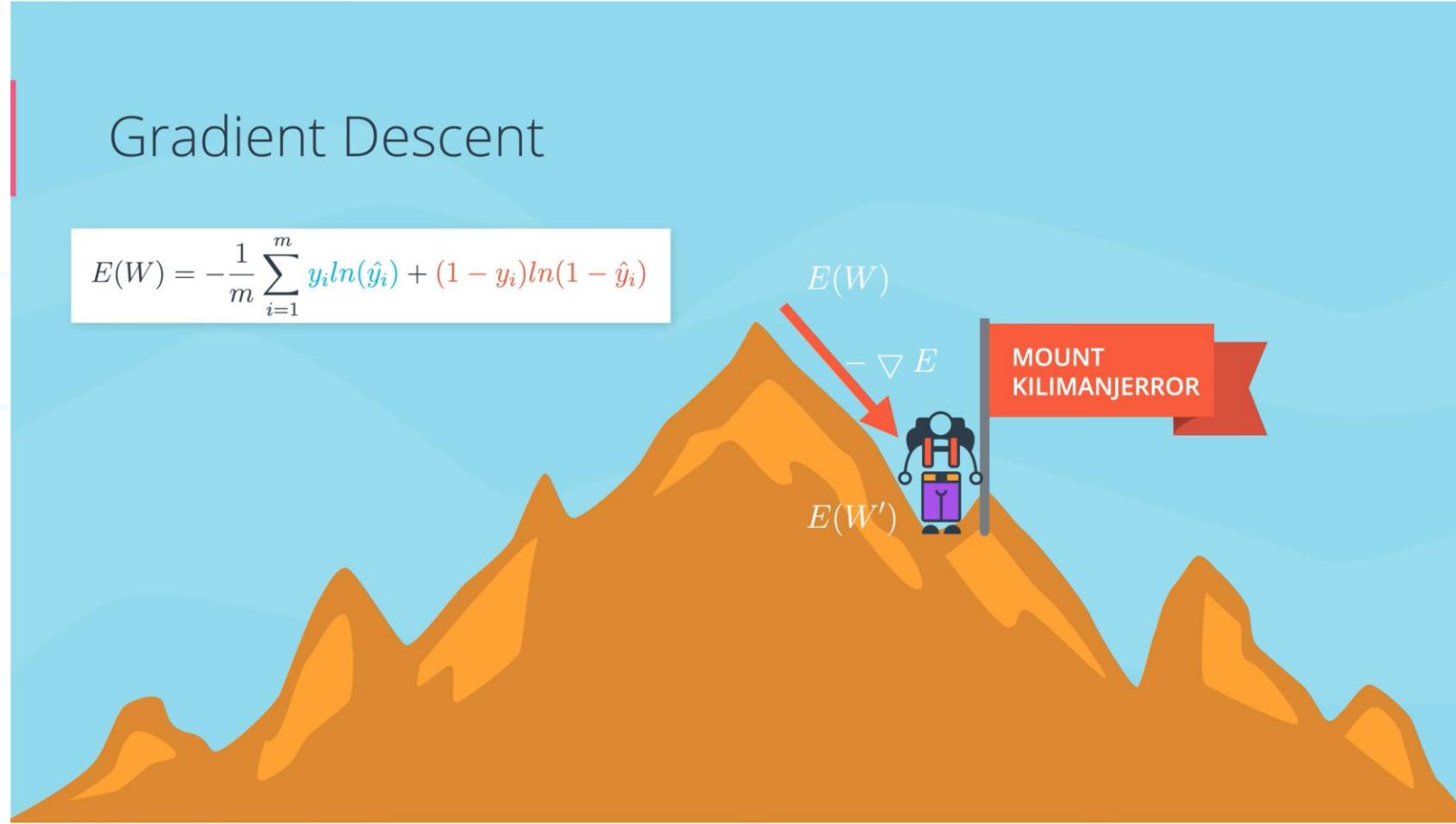
$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$



# Redes Neurais – Backpropagation

## Gradient Descent

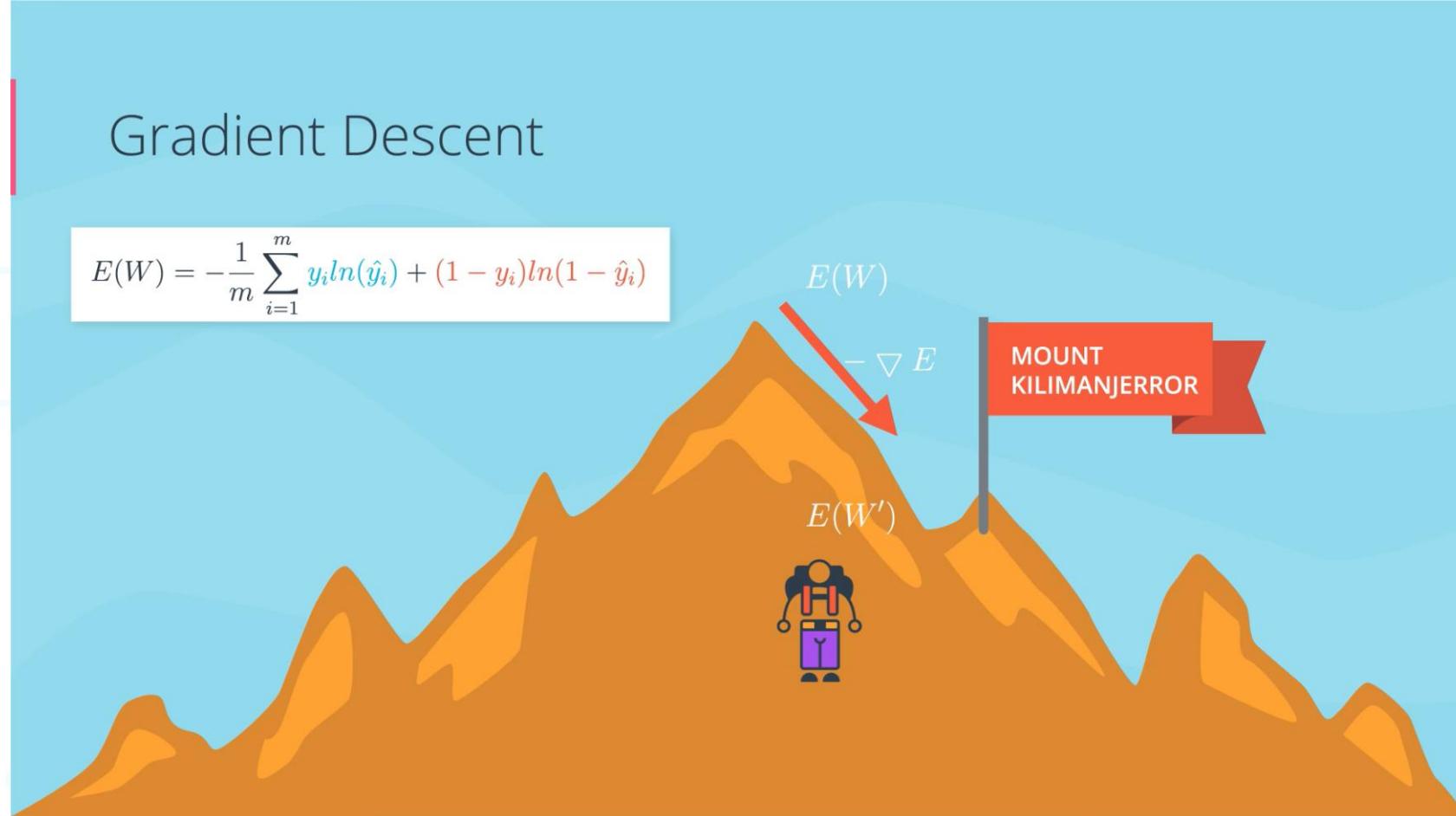
$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$



# Redes Neurais – Backpropagation

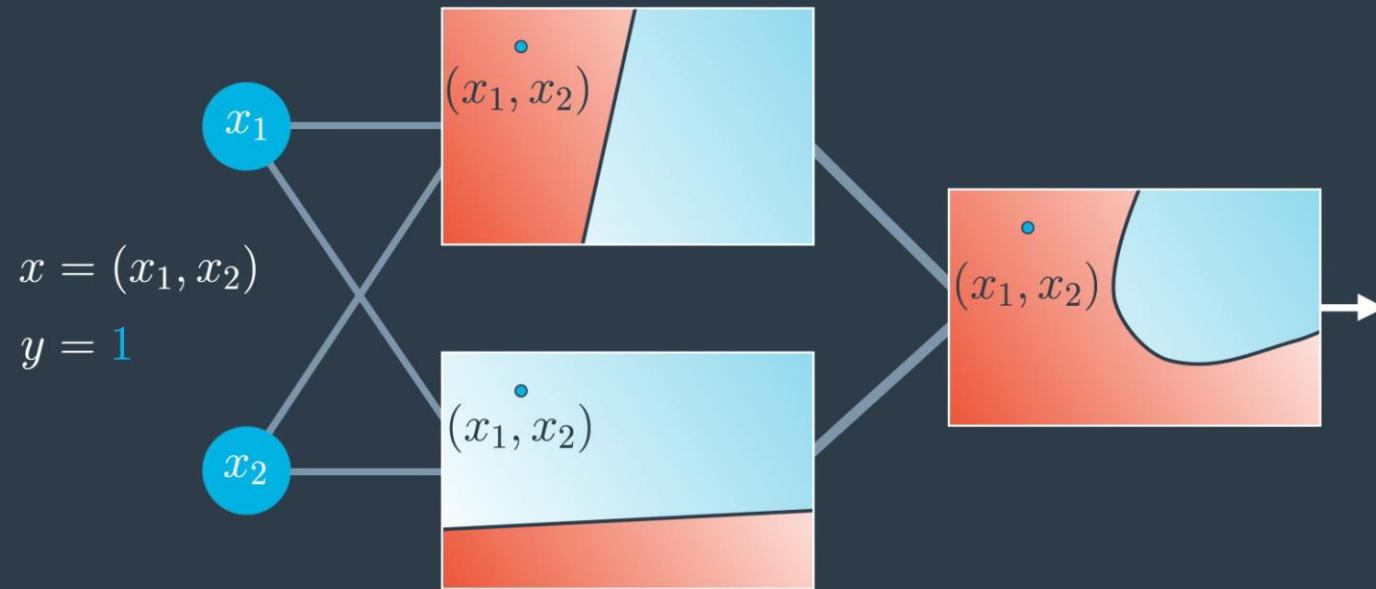
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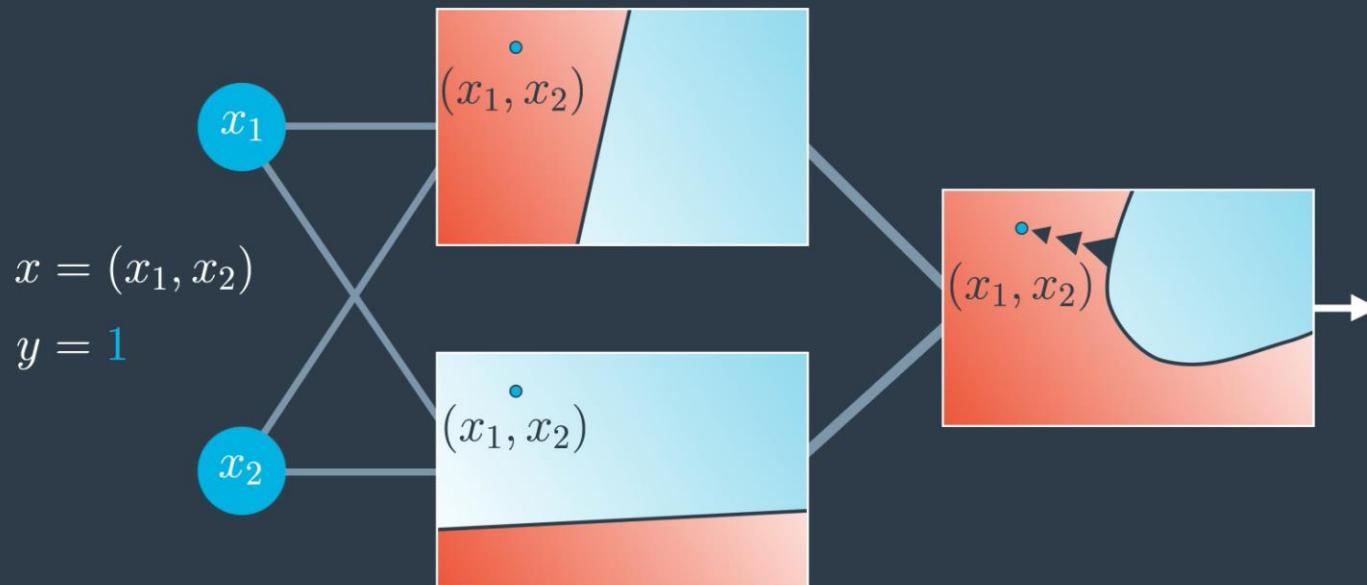
# Redes Neurais – Backpropagation

FeedForward



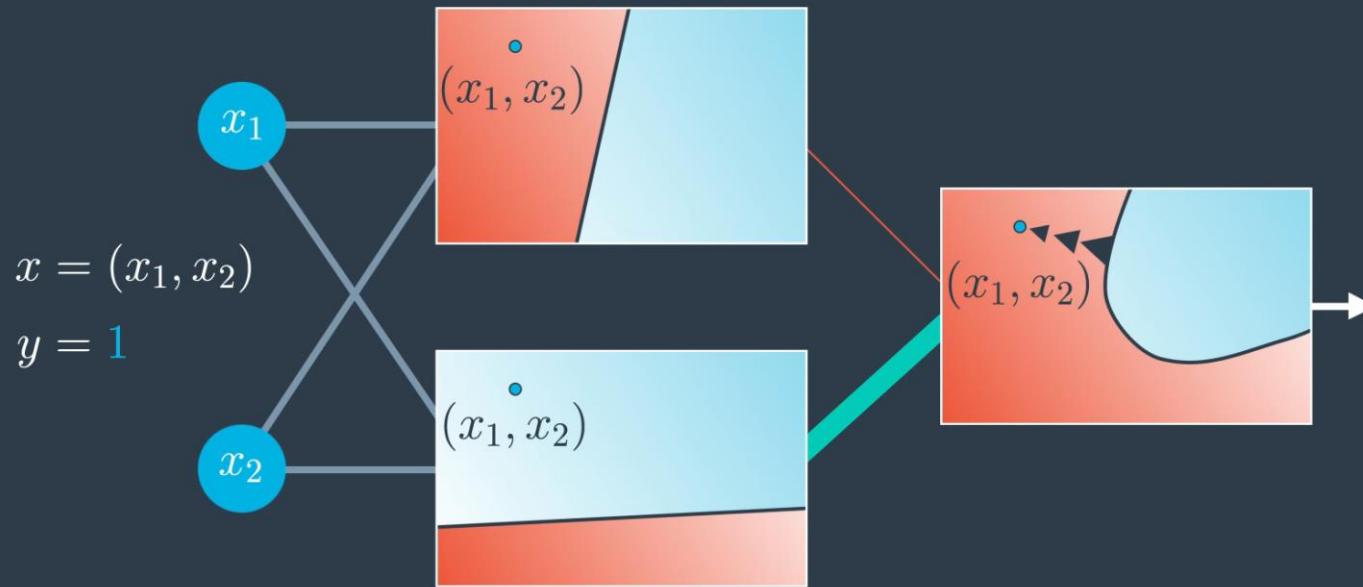
# Redes Neurais – Backpropagation

Backpropagation



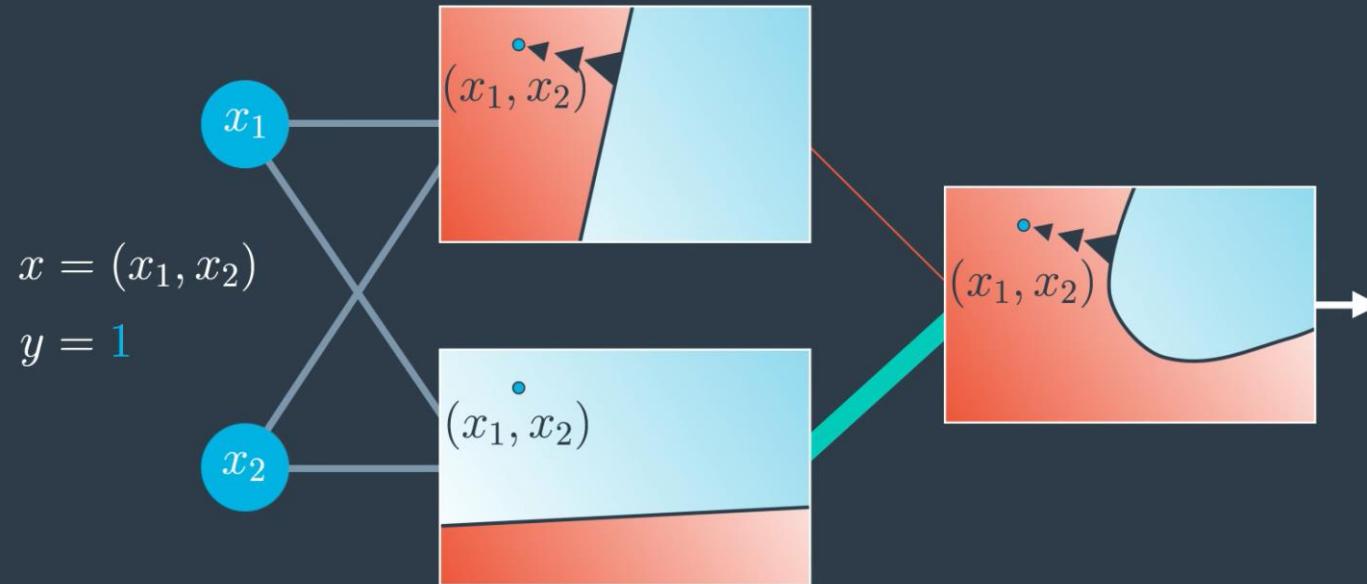
# Redes Neurais – Backpropagation

Backpropagation



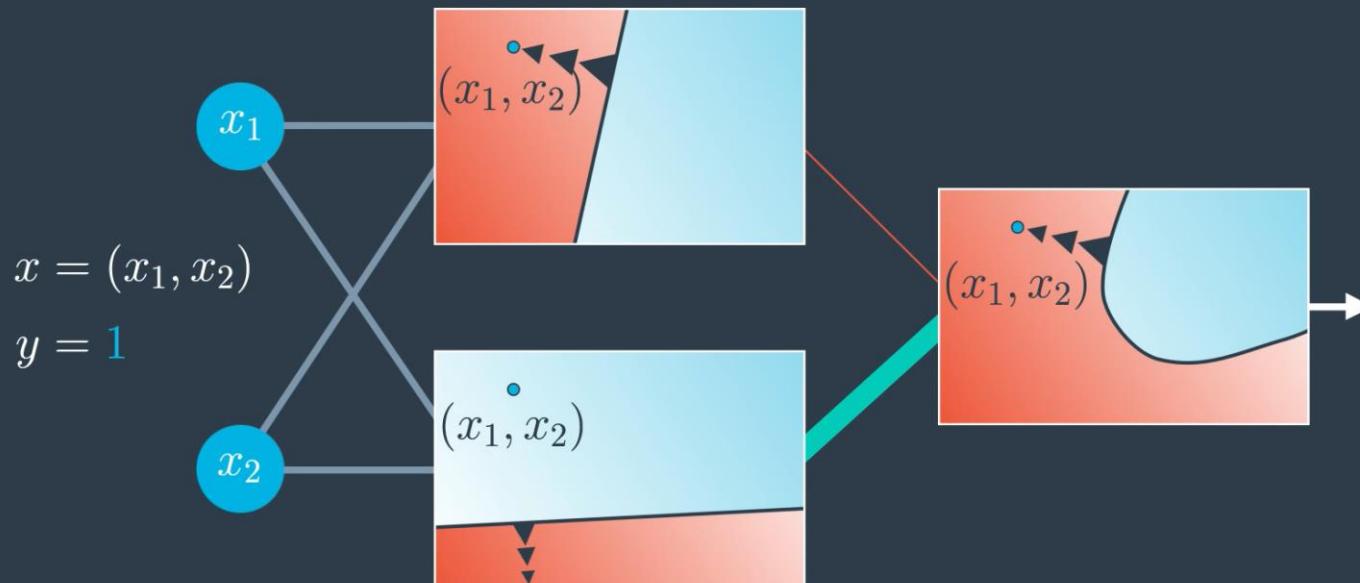
# Redes Neurais – Backpropagation

Backpropagation



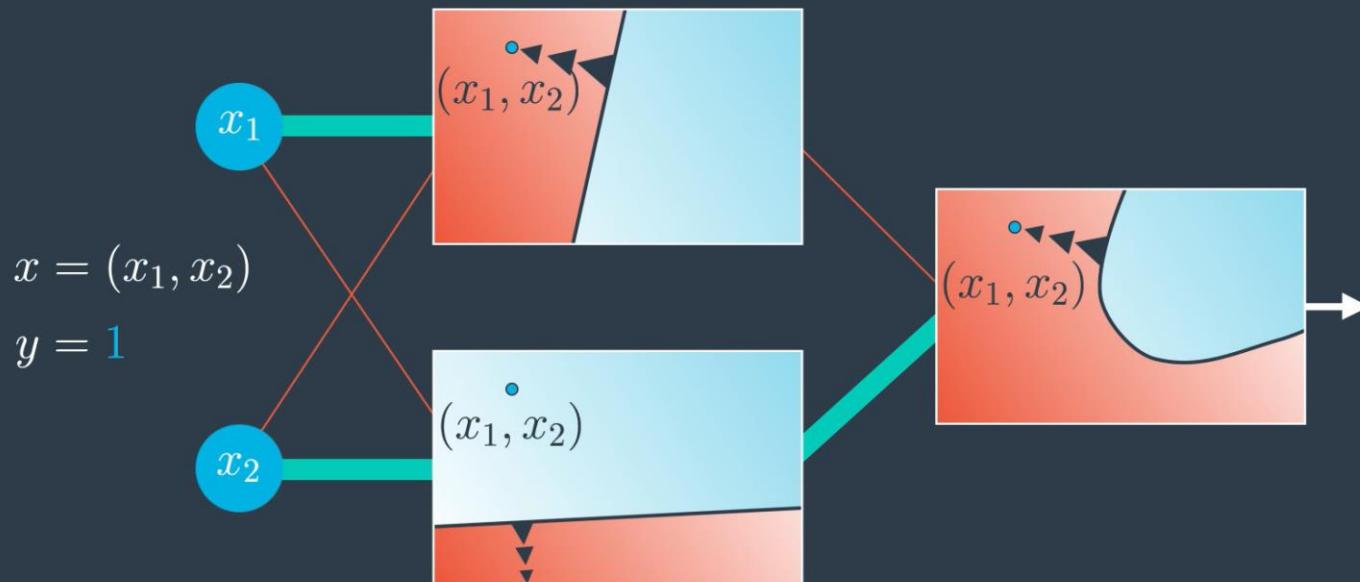
# Redes Neurais – Backpropagation

## Backpropagation



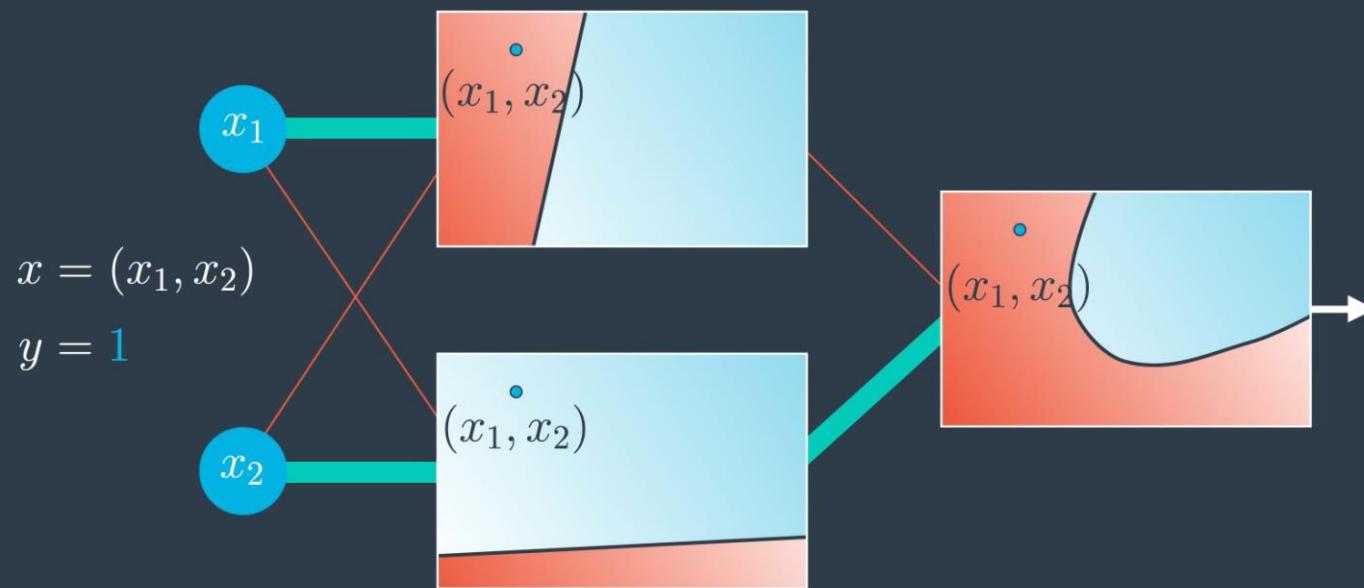
# Redes Neurais – Backpropagation

## Backpropagation

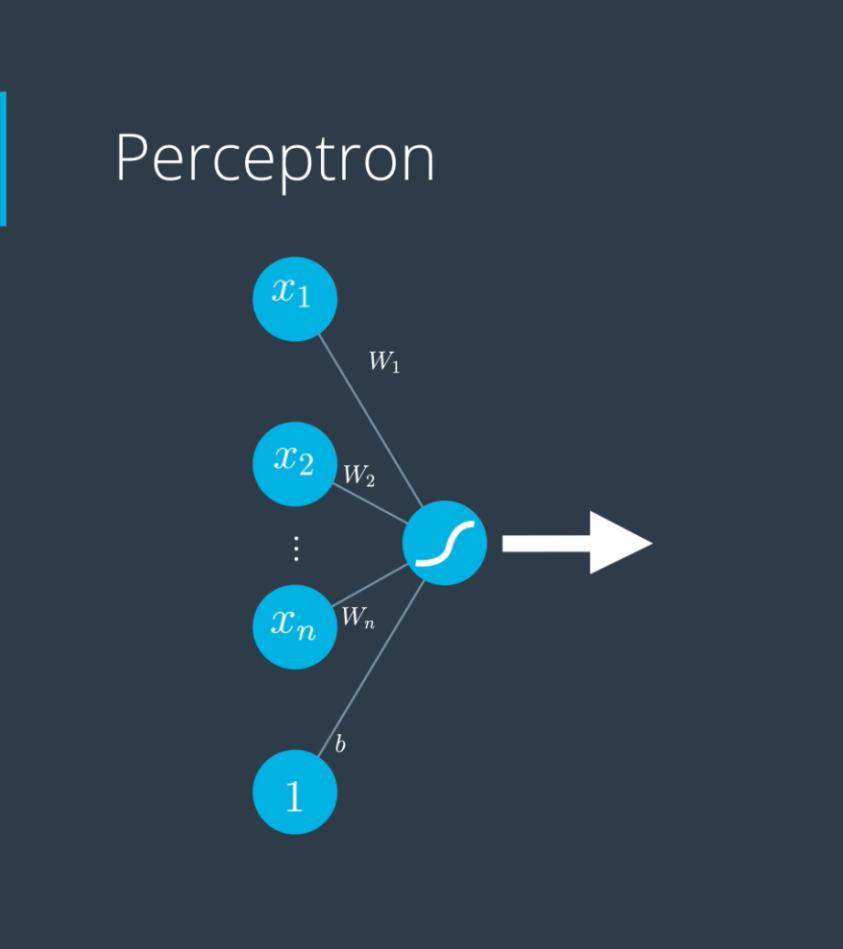


# Redes Neurais – Backpropagation

## Backpropagation



# Redes Neurais – Backpropagation



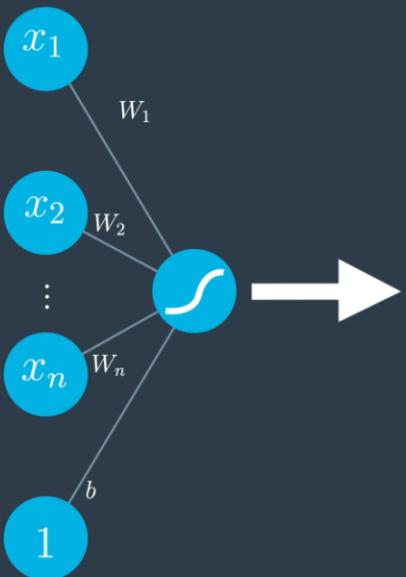
PREDICTION

ERROR FUNCTION

GRADIENT OF THE ERROR FUNCTION

# Redes Neurais – Backpropagation

Perceptron



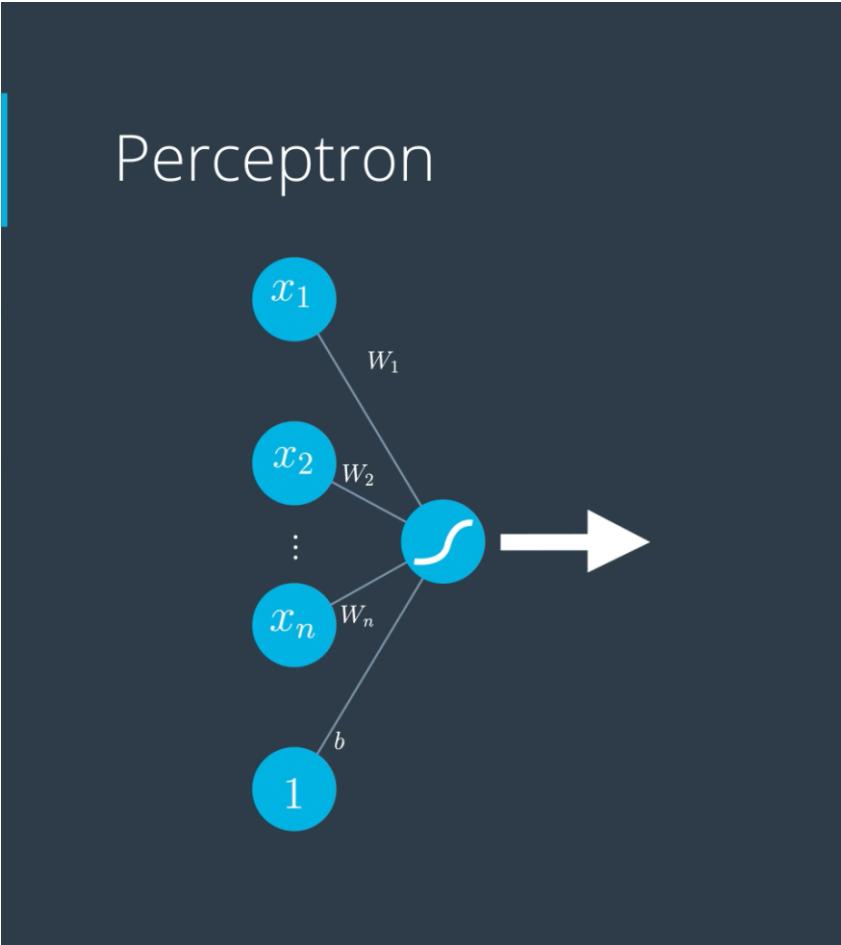
PREDICTION

$$\hat{y} = \sigma(Wx + b)$$

ERROR FUNCTION

GRADIENT OF THE ERROR FUNCTION

# Redes Neurais – Backpropagation



PREDICTION

$$\hat{y} = \sigma(Wx + b)$$

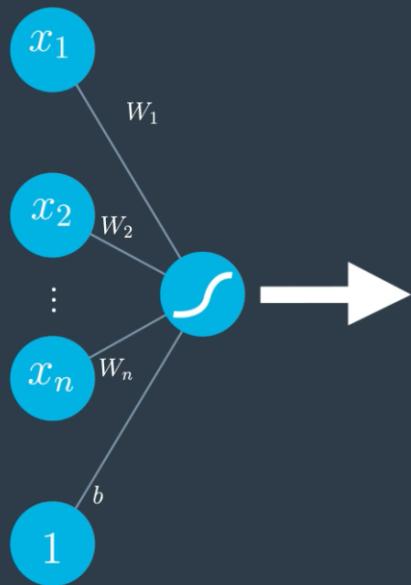
ERROR FUNCTION

$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

GRADIENT OF THE ERROR FUNCTION

# Redes Neurais – Backpropagation

## Perceptron



### PREDICTION

$$\hat{y} = \sigma(Wx + b)$$

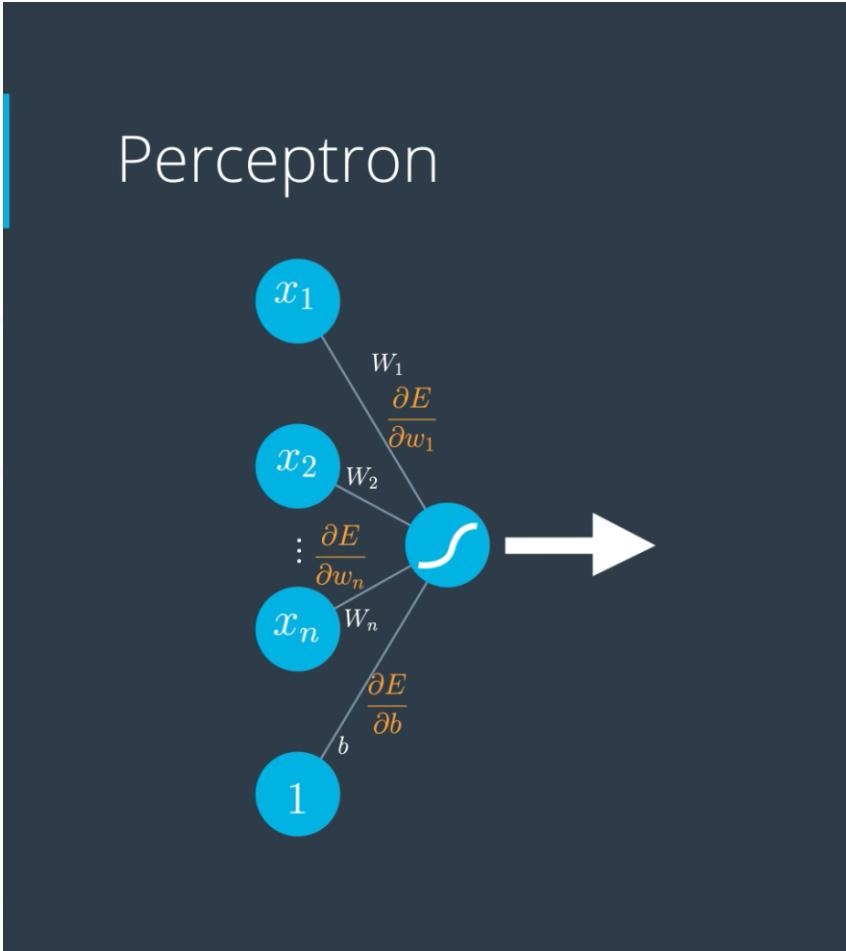
### ERROR FUNCTION

$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

### GRADIENT OF THE ERROR FUNCTION

$$\nabla E = \left( \frac{\partial E}{\partial w_1}, \dots, \frac{\partial E}{\partial w_n}, \frac{\partial E}{\partial b} \right)$$

# Redes Neurais – Backpropagation



PREDICTION

$$\hat{y} = \sigma(Wx + b)$$

ERROR FUNCTION

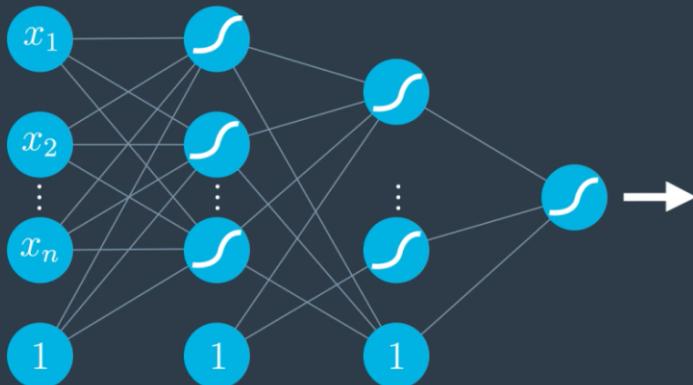
$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

GRADIENT OF THE ERROR FUNCTION

$$\nabla E = \left( \frac{\partial E}{\partial w_1}, \dots, \frac{\partial E}{\partial w_n}, \frac{\partial E}{\partial b} \right)$$

# Redes Neurais – Backpropagation

Multi-layer Perceptron



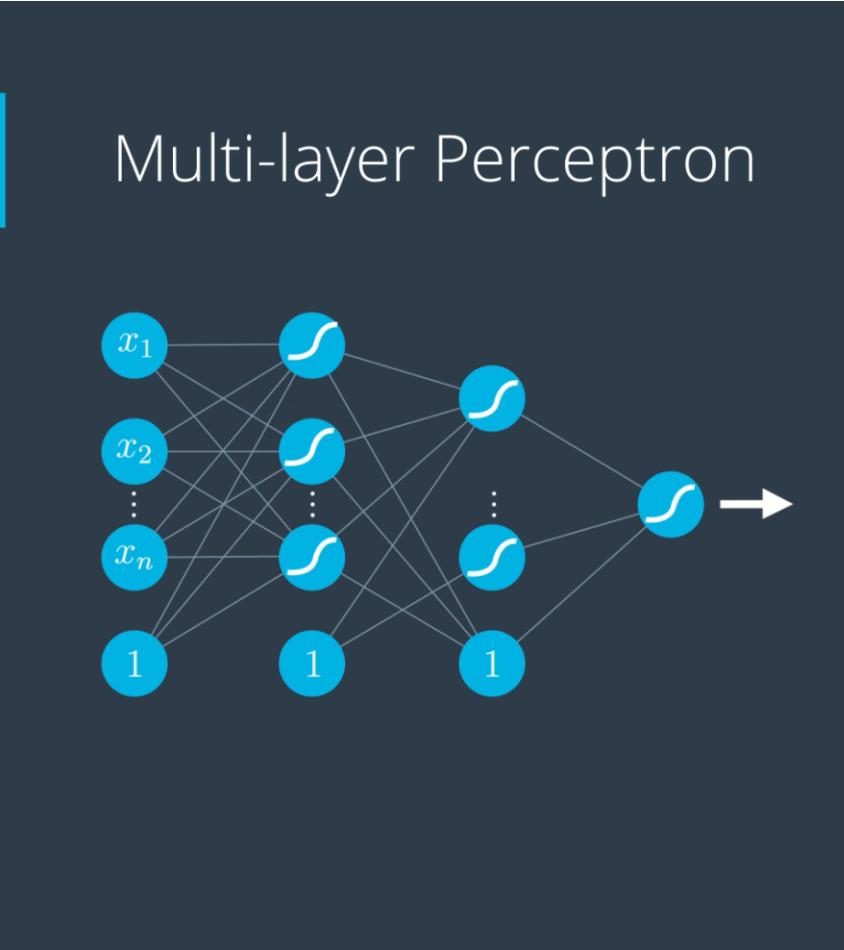
PREDICTION

ERROR FUNCTION

$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

GRADIENT OF THE ERROR FUNCTION

# Redes Neurais – Backpropagation



### PREDICTION

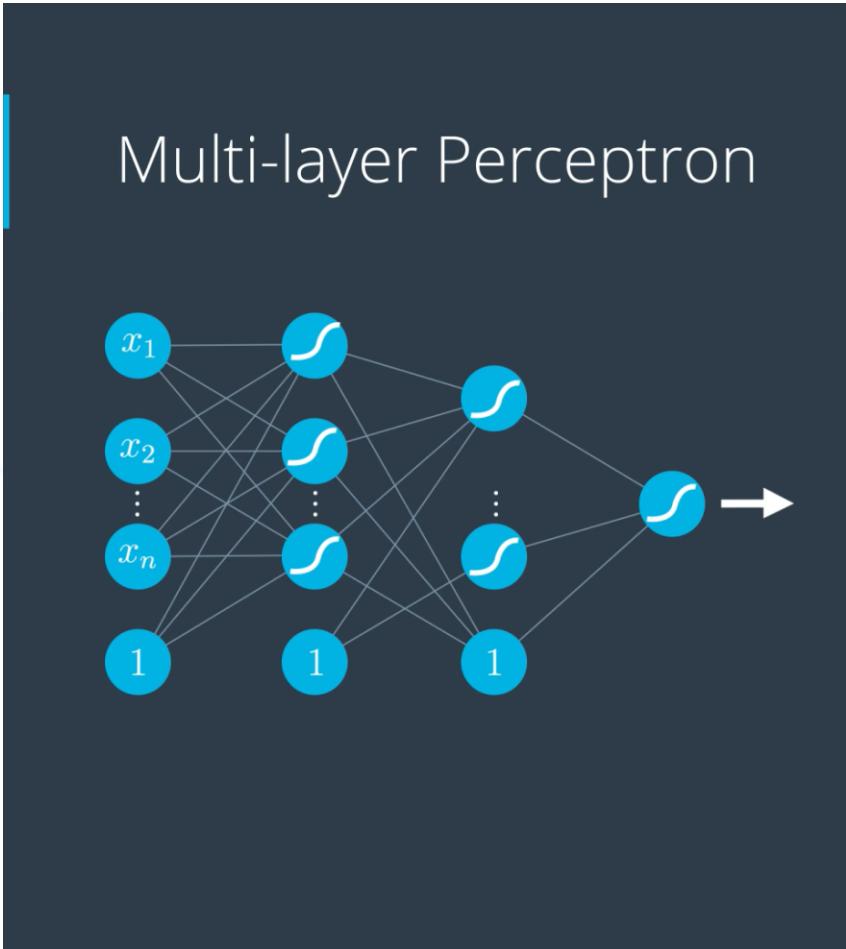
$$\hat{y} = \sigma W^{(3)} \circ \sigma W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

### ERROR FUNCTION

$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

### GRADIENT OF THE ERROR FUNCTION

# Redes Neurais – Backpropagation



### PREDICTION

$$\hat{y} = \sigma W^{(3)} \circ \sigma W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

### ERROR FUNCTION

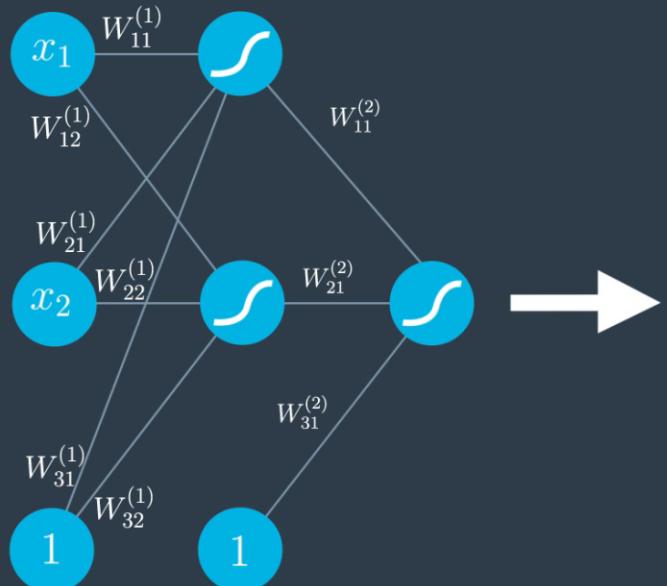
$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

### GRADIENT OF THE ERROR FUNCTION

$$\nabla E = \left( \dots, \frac{\partial E}{\partial w_j^{(i)}}, \dots \right)$$

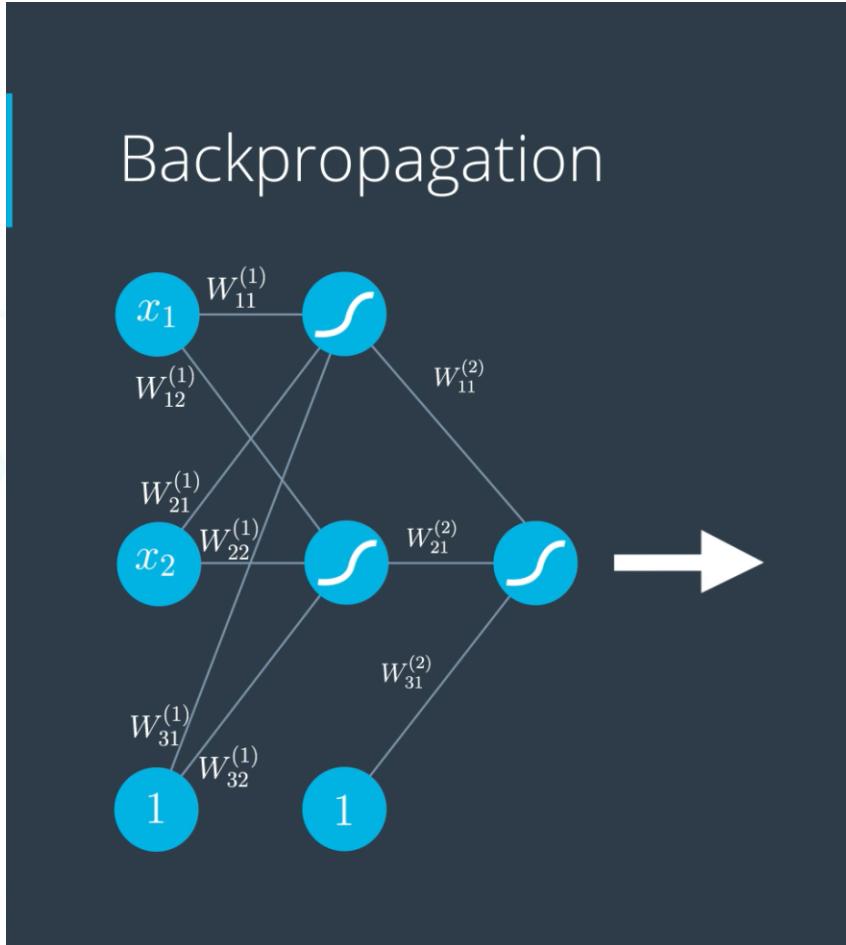
# Redes Neurais – Backpropagation

Backpropagation



$$\hat{y} = \sigma W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

# Redes Neurais – Backpropagation



$$\hat{y} = \sigma W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

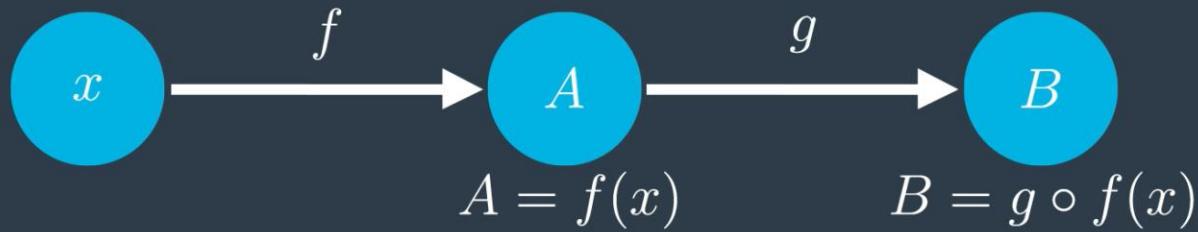
$$W^{(1)} = \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \quad W^{(2)} = \begin{pmatrix} W_{11}^{(2)} \\ W_{21}^{(2)} \\ W_{31}^{(2)} \end{pmatrix}$$

$$\nabla E = \begin{pmatrix} \frac{\partial E}{\partial W_{11}^{(1)}} & \frac{\partial E}{\partial W_{12}^{(1)}} & \frac{\partial E}{\partial W_{11}^{(2)}} \\ \frac{\partial E}{\partial W_{21}^{(1)}} & \frac{\partial E}{\partial W_{22}^{(1)}} & \frac{\partial E}{\partial W_{21}^{(2)}} \\ \frac{\partial E}{\partial W_{31}^{(1)}} & \frac{\partial E}{\partial W_{32}^{(1)}} & \frac{\partial E}{\partial W_{31}^{(2)}} \end{pmatrix}$$

$$W'_{ij}^{(k)} \leftarrow W_{ij}^{(k)} - \alpha \frac{\partial E}{\partial W_{ij}^{(k)}}$$

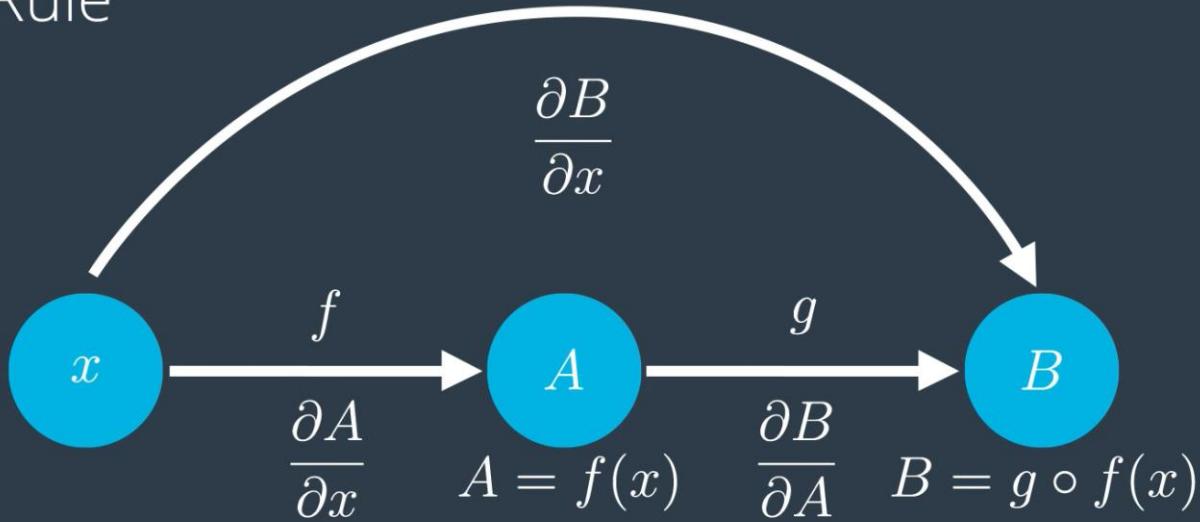
# Redes Neurais – Backpropagation

Chain Rule



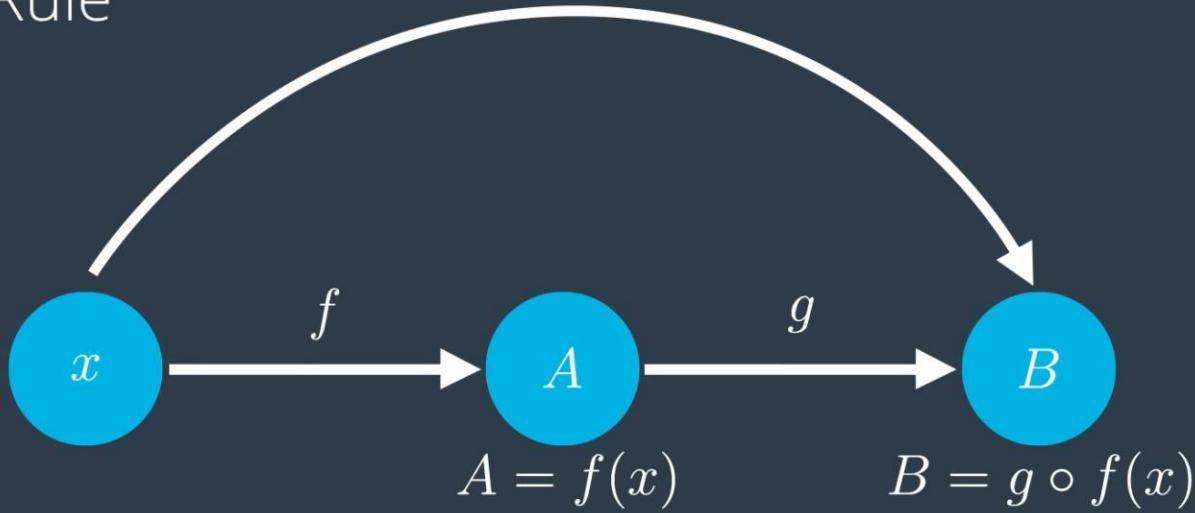
# Redes Neurais – Backpropagation

Chain Rule



# Redes Neurais – Backpropagation

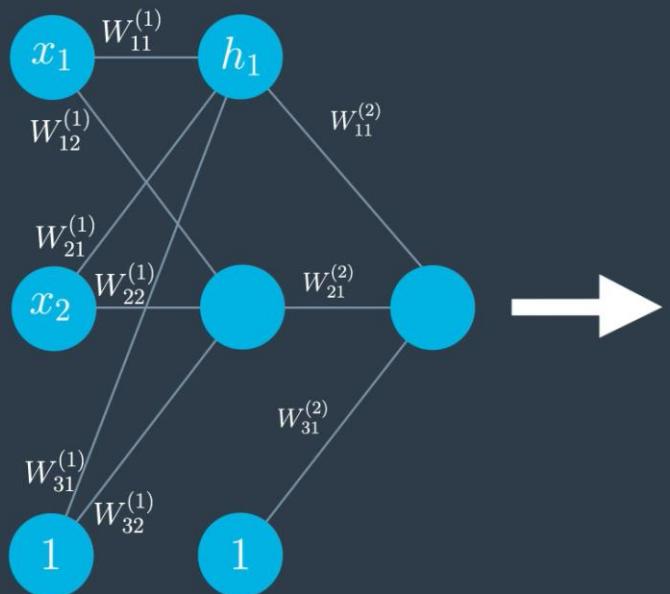
Chain Rule



$$\frac{\partial B}{\partial x} = \frac{\partial B}{\partial A} \frac{\partial A}{\partial x}$$

# Redes Neurais – Backpropagation

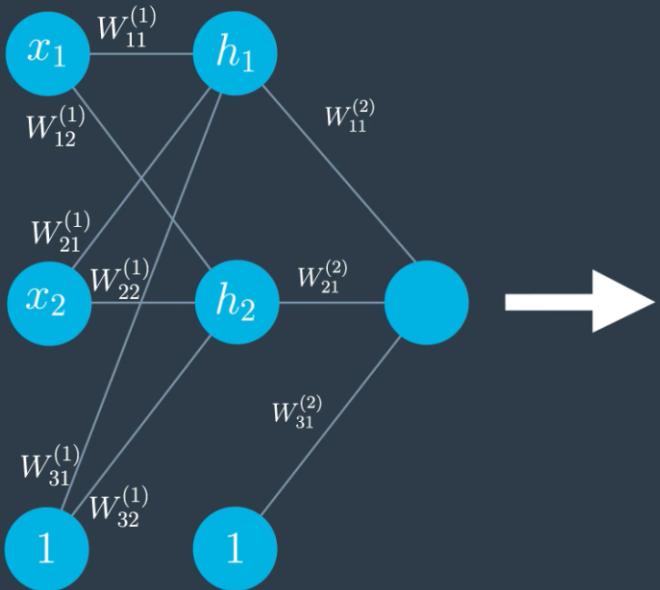
Feedforward



$$h_1 = W_{11}^{(1)}x_1 + W_{21}^{(1)}x_2 + W_{31}^{(1)}$$

# Redes Neurais – Backpropagation

Feedforward

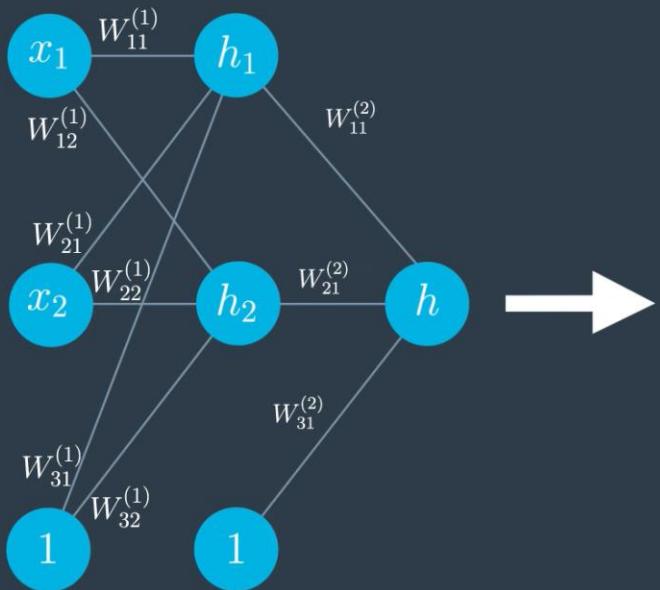


$$h_1 = W_{11}^{(1)}x_1 + W_{21}^{(1)}x_2 + W_{31}^{(1)}$$

$$h_2 = W_{12}^{(1)}x_1 + W_{22}^{(1)}x_2 + W_{32}^{(1)}$$

# Redes Neurais – Backpropagation

Feedforward



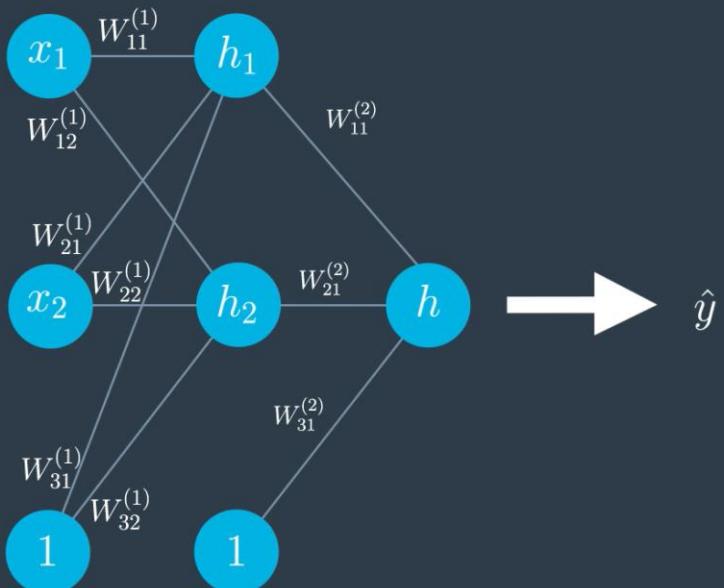
$$h_1 = W_{11}^{(1)}x_1 + W_{21}^{(1)}x_2 + W_{31}^{(1)}$$

$$h_2 = W_{12}^{(1)}x_1 + W_{22}^{(1)}x_2 + W_{32}^{(1)}$$

$$h = W_{11}^{(2)}\sigma(h_1) + W_{21}^{(2)}\sigma(h_2) + W_{31}^{(2)}$$

# Redes Neurais – Backpropagation

Feedforward



$$h_1 = W_{11}^{(1)}x_1 + W_{21}^{(1)}x_2 + W_{31}^{(1)}$$

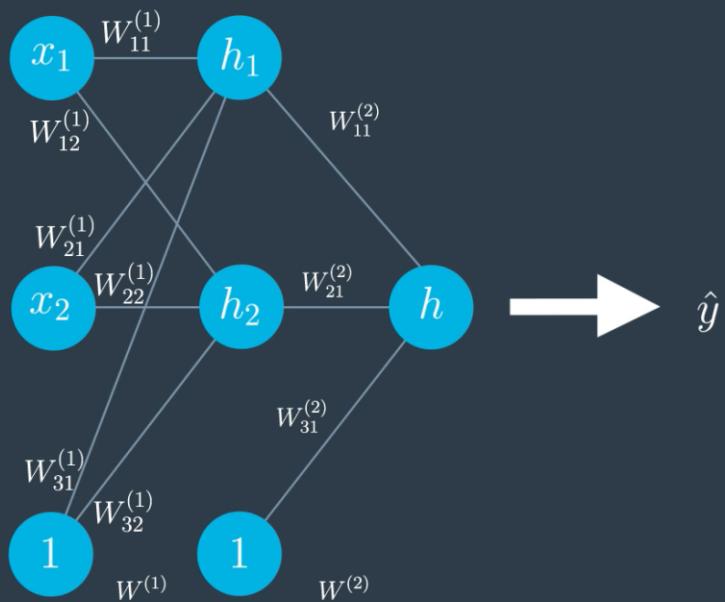
$$h_2 = W_{12}^{(1)}x_1 + W_{22}^{(1)}x_2 + W_{32}^{(1)}$$

$$h = W_{11}^{(2)}\sigma(h_1) + W_{21}^{(2)}\sigma(h_2) + W_{31}^{(2)}$$

$$\hat{y} = \sigma(h)$$

# Redes Neurais – Backpropagation

Feedforward



$$h_1 = W_{11}^{(1)}x_1 + W_{21}^{(1)}x_2 + W_{31}^{(1)}$$

$$h_2 = W_{12}^{(1)}x_1 + W_{22}^{(1)}x_2 + W_{32}^{(1)}$$

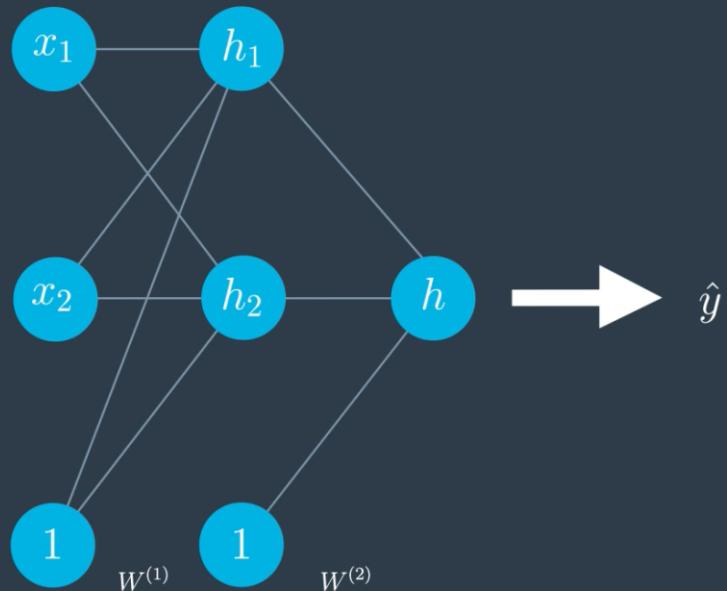
$$h = W_{11}^{(2)}\sigma(h_1) + W_{21}^{(2)}\sigma(h_2) + W_{31}^{(2)}$$

$$\hat{y} = \sigma(h)$$

$$\hat{y} = \sigma \circ W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

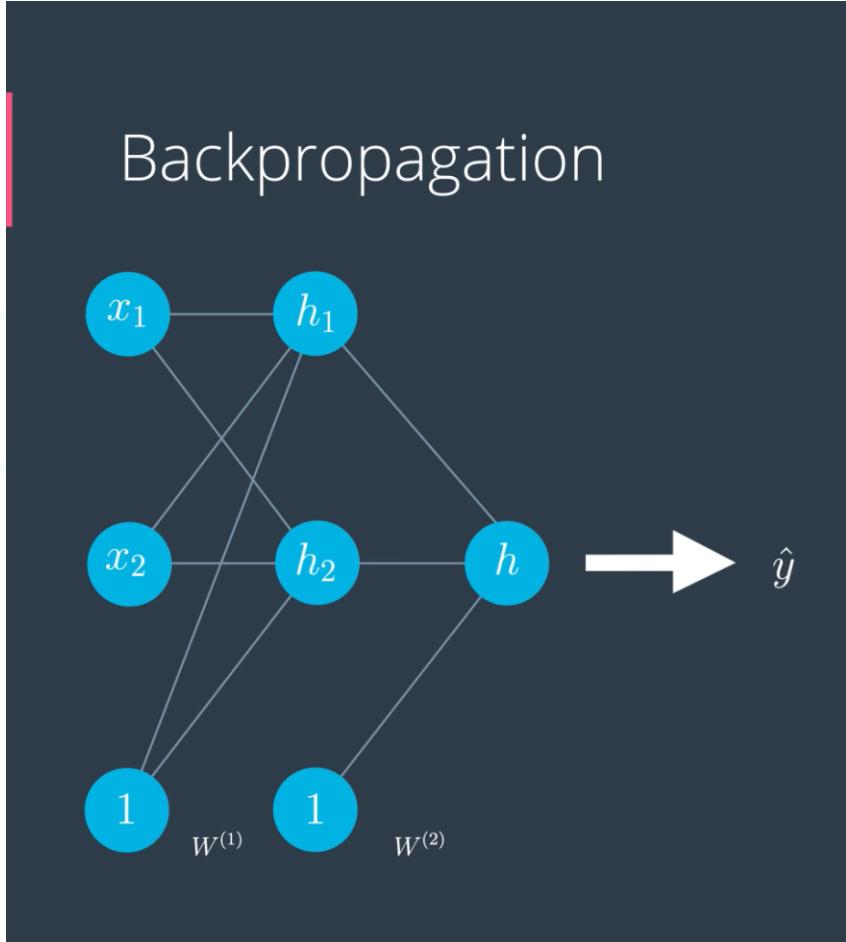
# Redes Neurais – Backpropagation

## Backpropagation



$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

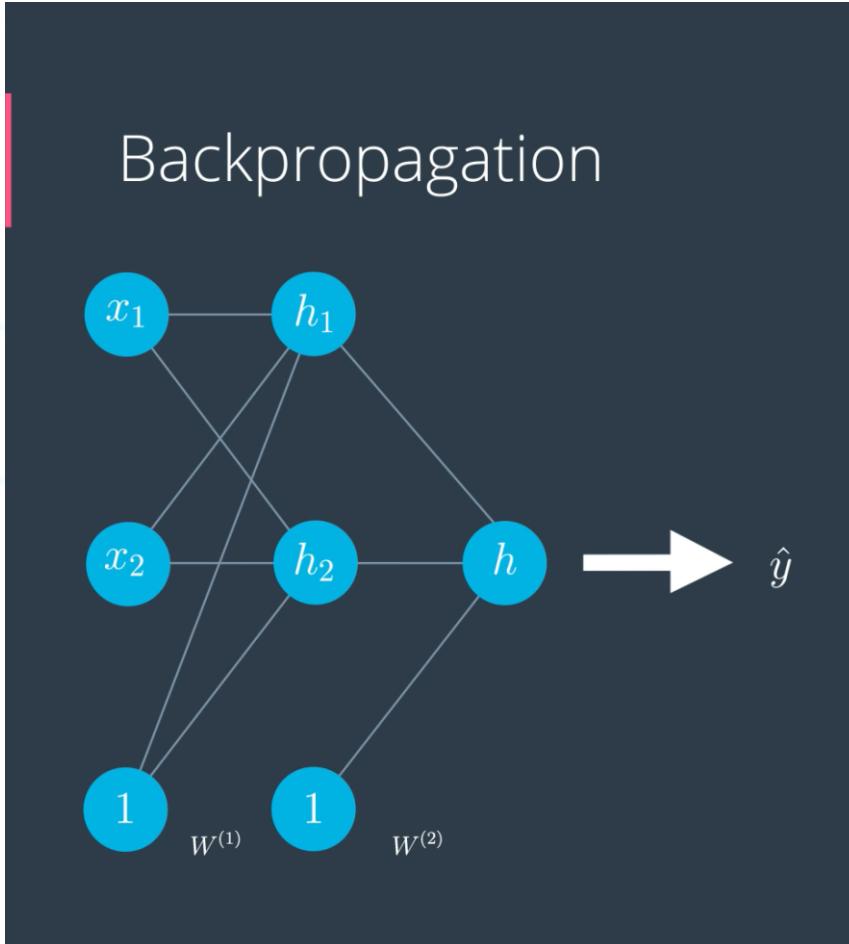
# Redes Neurais – Backpropagation



$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

$$E(W) = E(W_{11}^{(1)}, W_{12}^{(1)}, \dots, W_{31}^{(2)})$$

# Redes Neurais – Backpropagation



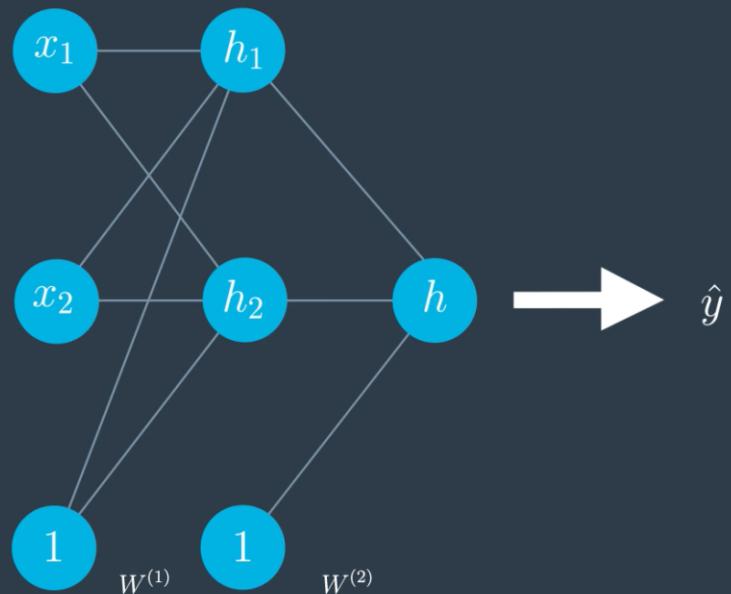
$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

$$E(W) = E(W_{11}^{(1)}, W_{12}^{(1)}, \dots, W_{31}^{(2)})$$

$$\nabla E = \left( \frac{\partial E}{\partial W_{11}^{(1)}}, \dots, \frac{\partial E}{\partial W_{31}^{(2)}} \right)$$

# Redes Neurais – Backpropagation

## Backpropagation



$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$

$$E(W) = E(W_{11}^{(1)}, W_{12}^{(1)}, \dots, W_{31}^{(2)})$$

$$\nabla E = \left( \frac{\partial E}{\partial W_{11}^{(1)}}, \dots, \frac{\partial E}{\partial W_{31}^{(2)}} \right)$$

$$\frac{\partial E}{\partial W_{11}^{(1)}} = \frac{\partial E}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial h} \frac{\partial h}{\partial h_1} \frac{\partial h_1}{\partial W_{11}^{(1)}}$$

# Redes Neurais

	Peso	Altura
Pessoa 1	80 kg	163
Pessoa 2	85 kg	168
Pessoa 3	90 kg	175
Pessoa 4	95 kg	188

$$\hat{y} = \beta_0 + \beta_1 X_1$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$\hat{y} = 3 + 0,7 \times 80$$

$$MSE = \sum (163 - 60)^2$$

$$\hat{y} = 60$$

$$MSE = 10.609$$

$$\hat{y} = 5 + 1.3 \times 85$$

$$MSE = \sum (168 - 115,5)^2$$

$$\hat{y} = 115,5$$

$$MSE = 2.756,25$$

$$\hat{y} = 10 + 1.6 \times 90$$

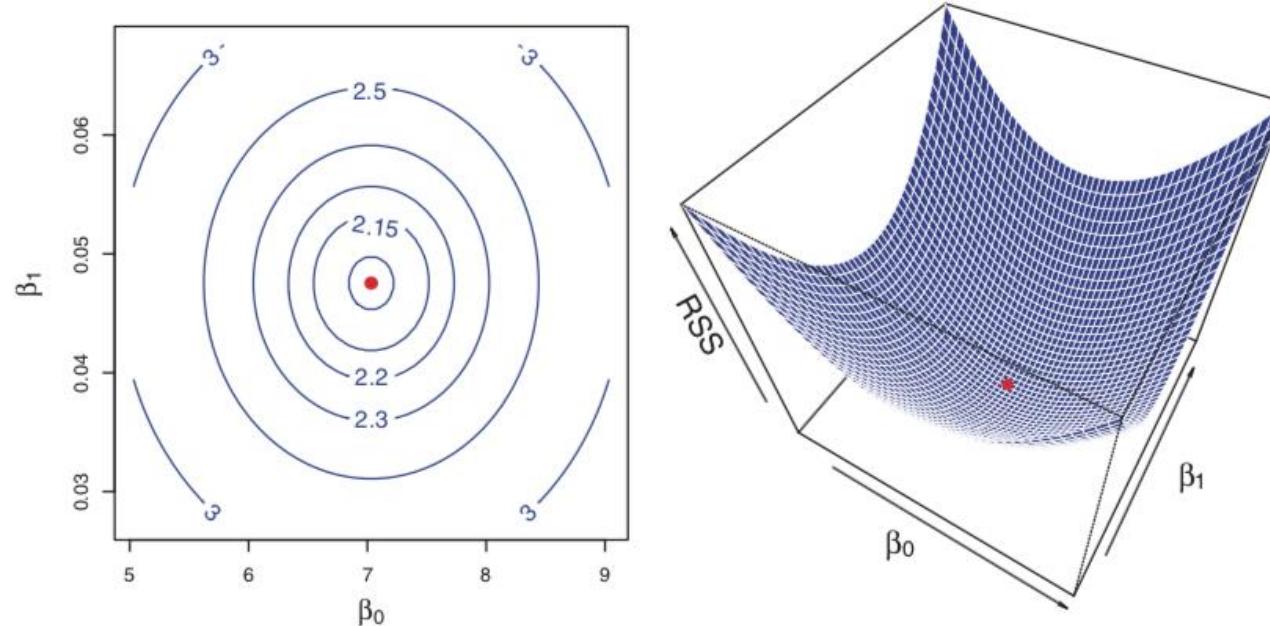
$$MSE = \sum (175 - 154)^2$$

$$\hat{y} = 154$$

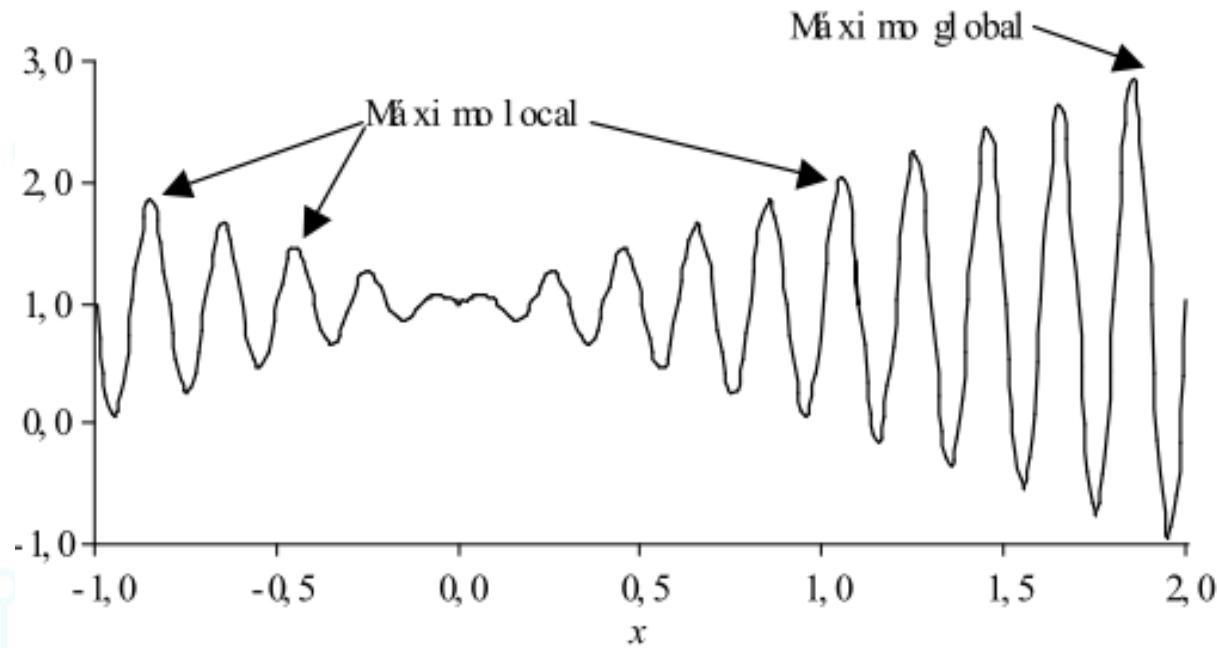
$$MSE = 441$$

# Regressão Linear

- Como a função RMSE é convexa, é possível encontrar o valor mínimo por meio de algoritmos de otimização

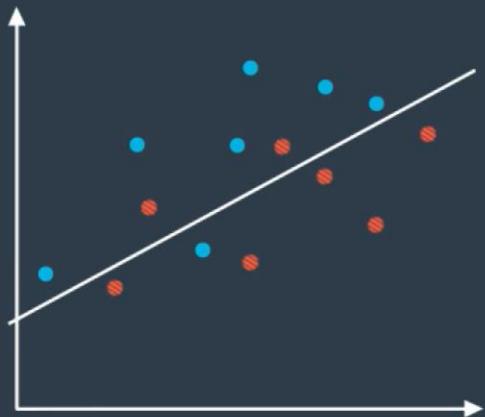


# Redes Neurais



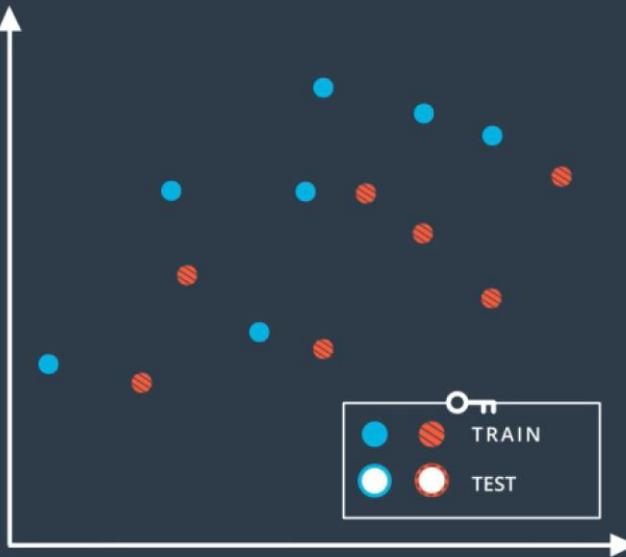
# Redes Neurais – Testing

WHICH MODEL IS BETTER?

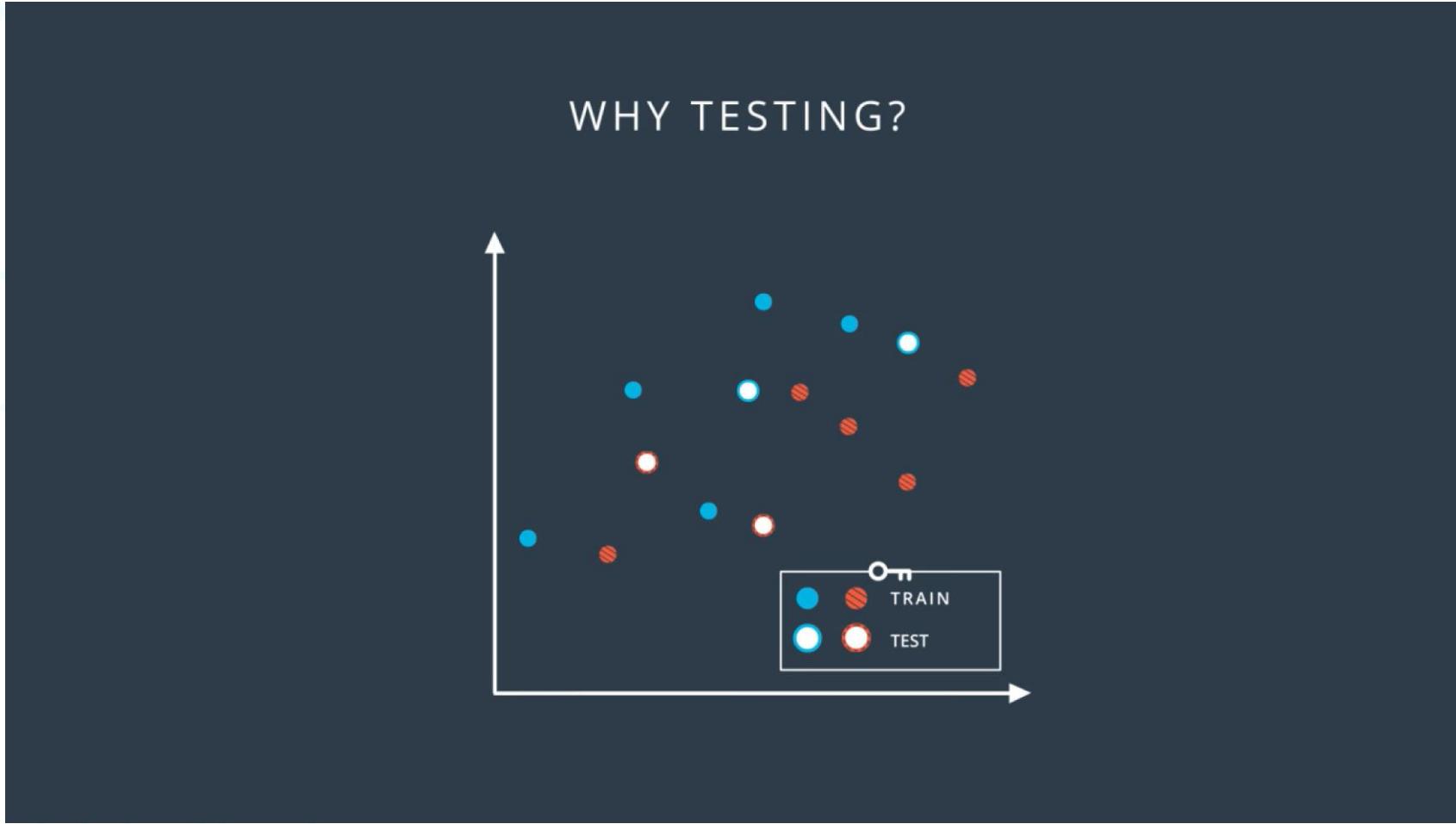


# Redes Neurais – Testing

WHY TESTING?

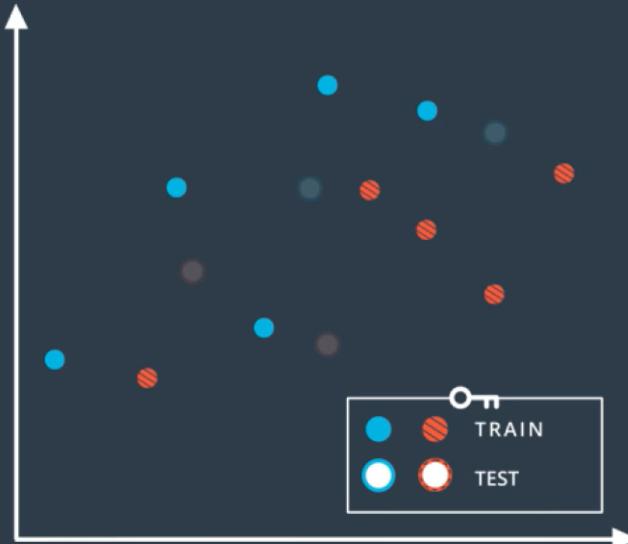


# Redes Neurais – Testing



# Redes Neurais – Testing

WHY TESTING?



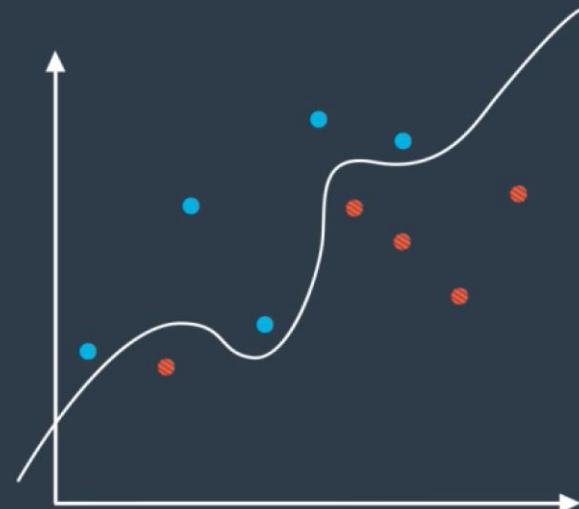
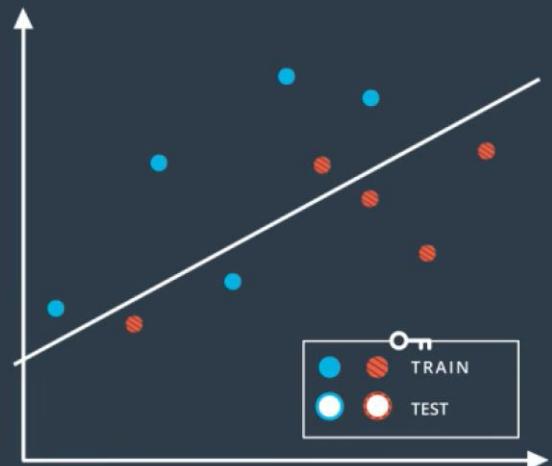
# Redes Neurais – Testing

WHY TESTING?



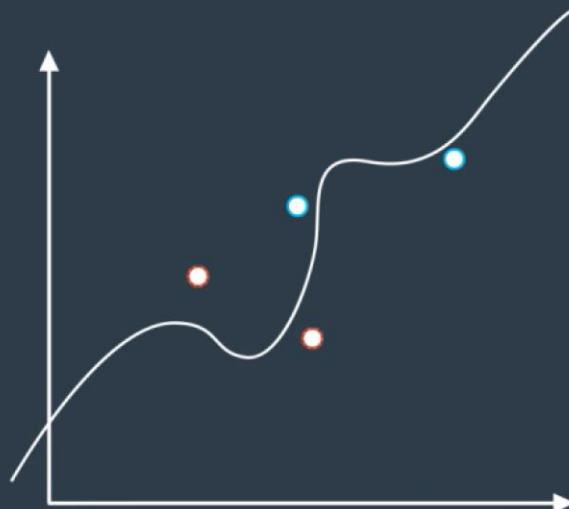
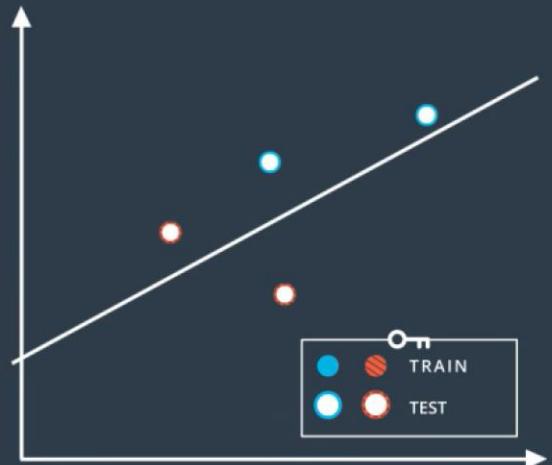
# Redes Neurais – Testing

## WHY TESTING?



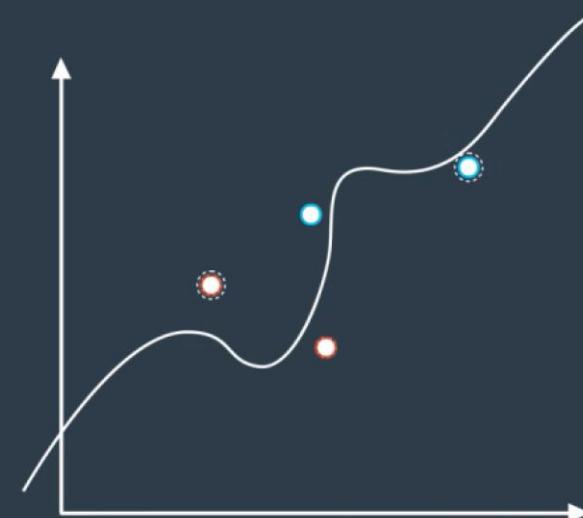
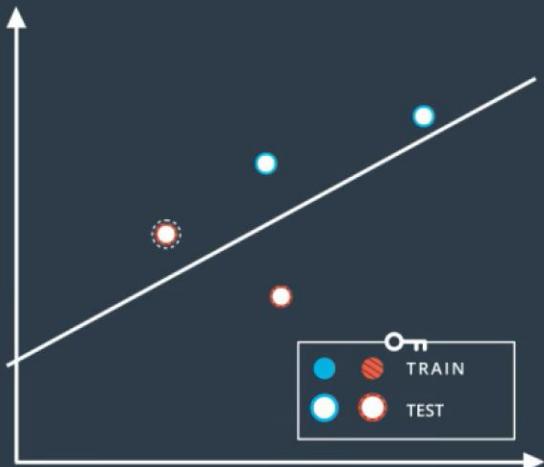
# Redes Neurais – Testing

WHY TESTING?



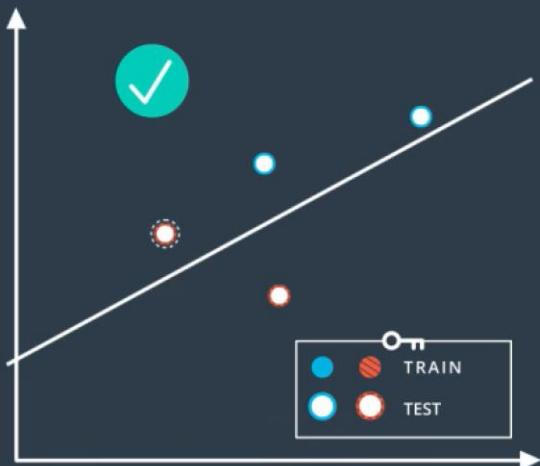
# Redes Neurais – Testing

WHY TESTING?

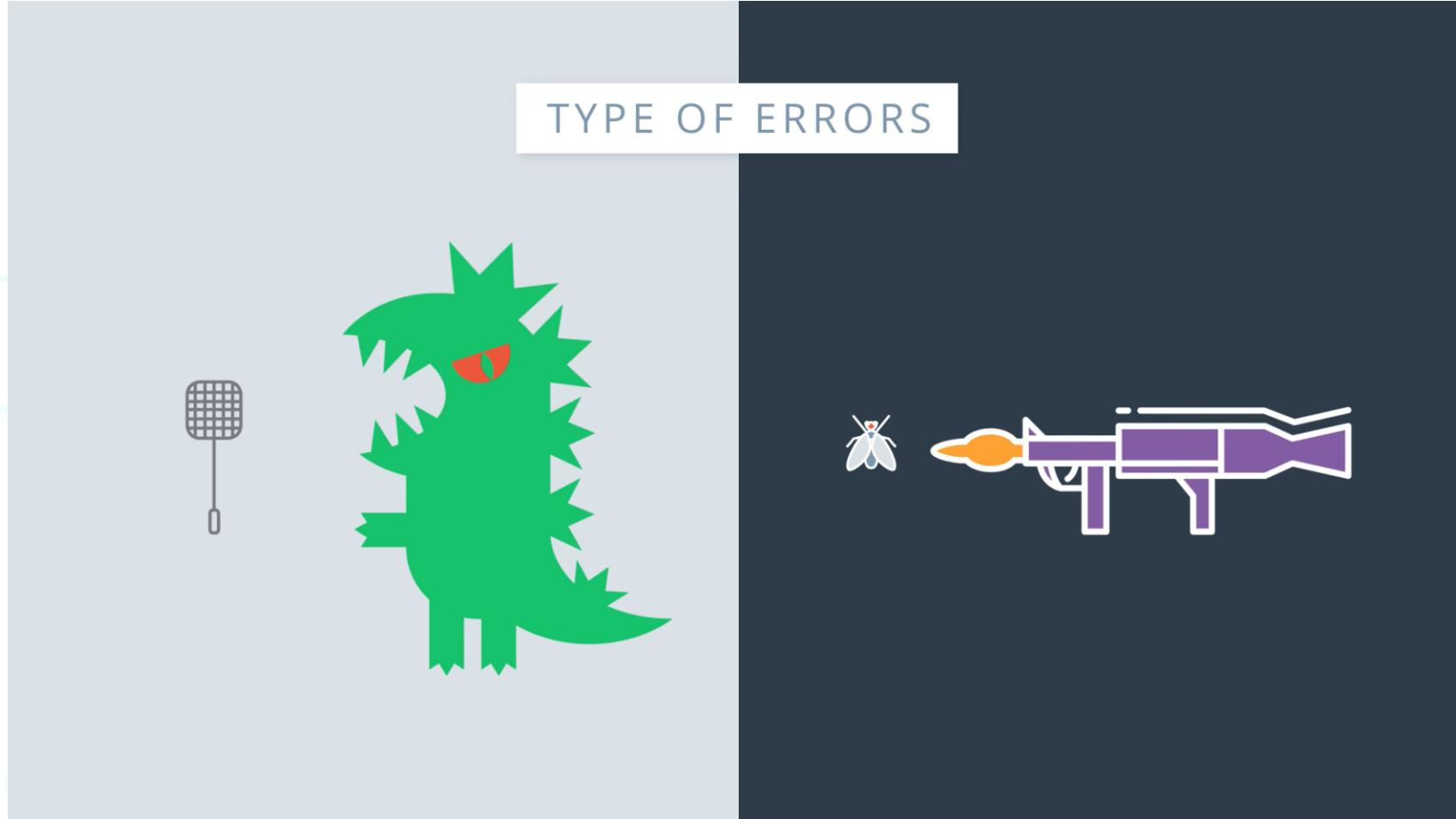


# Redes Neurais – Testing

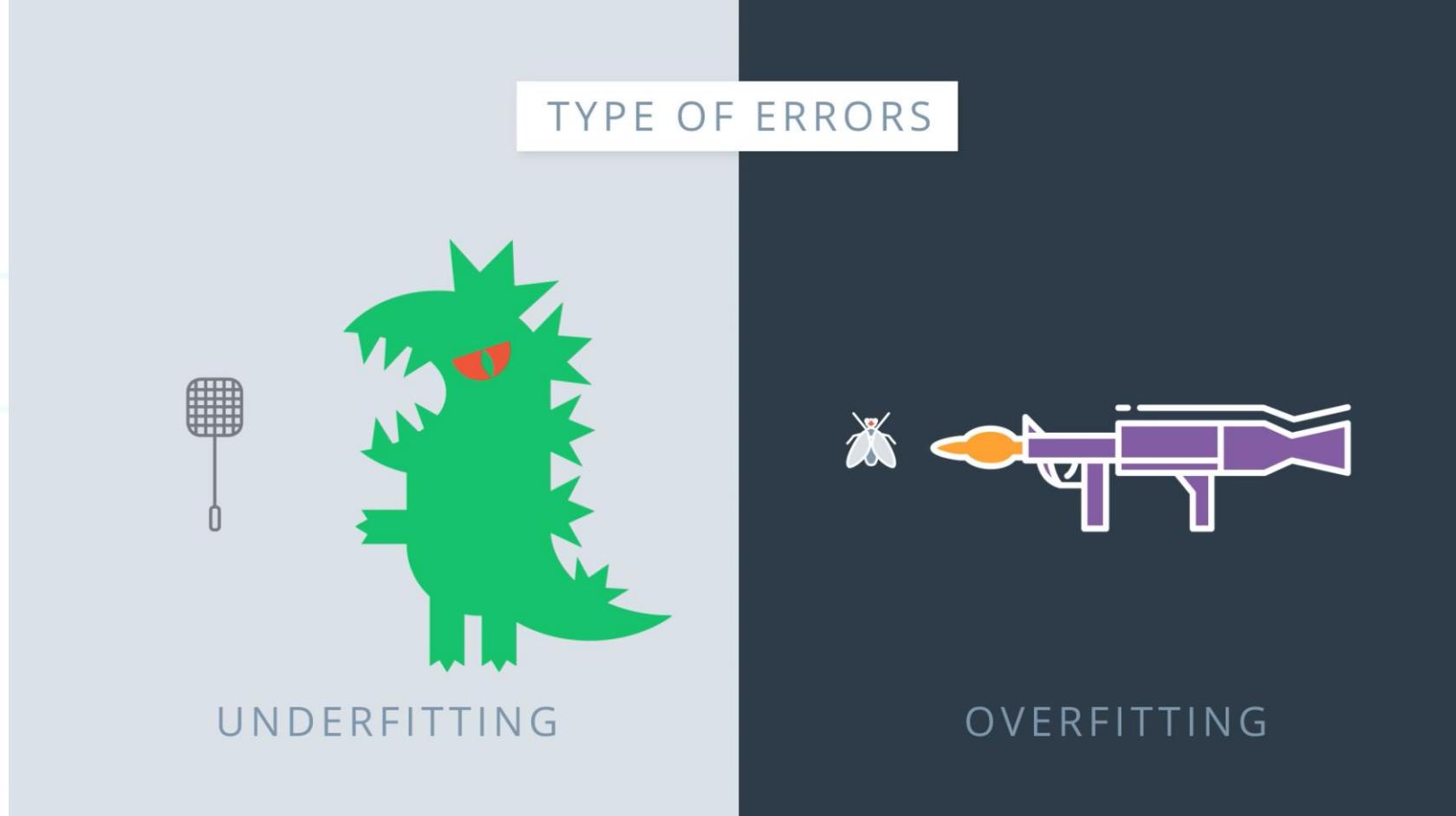
WHY TESTING?



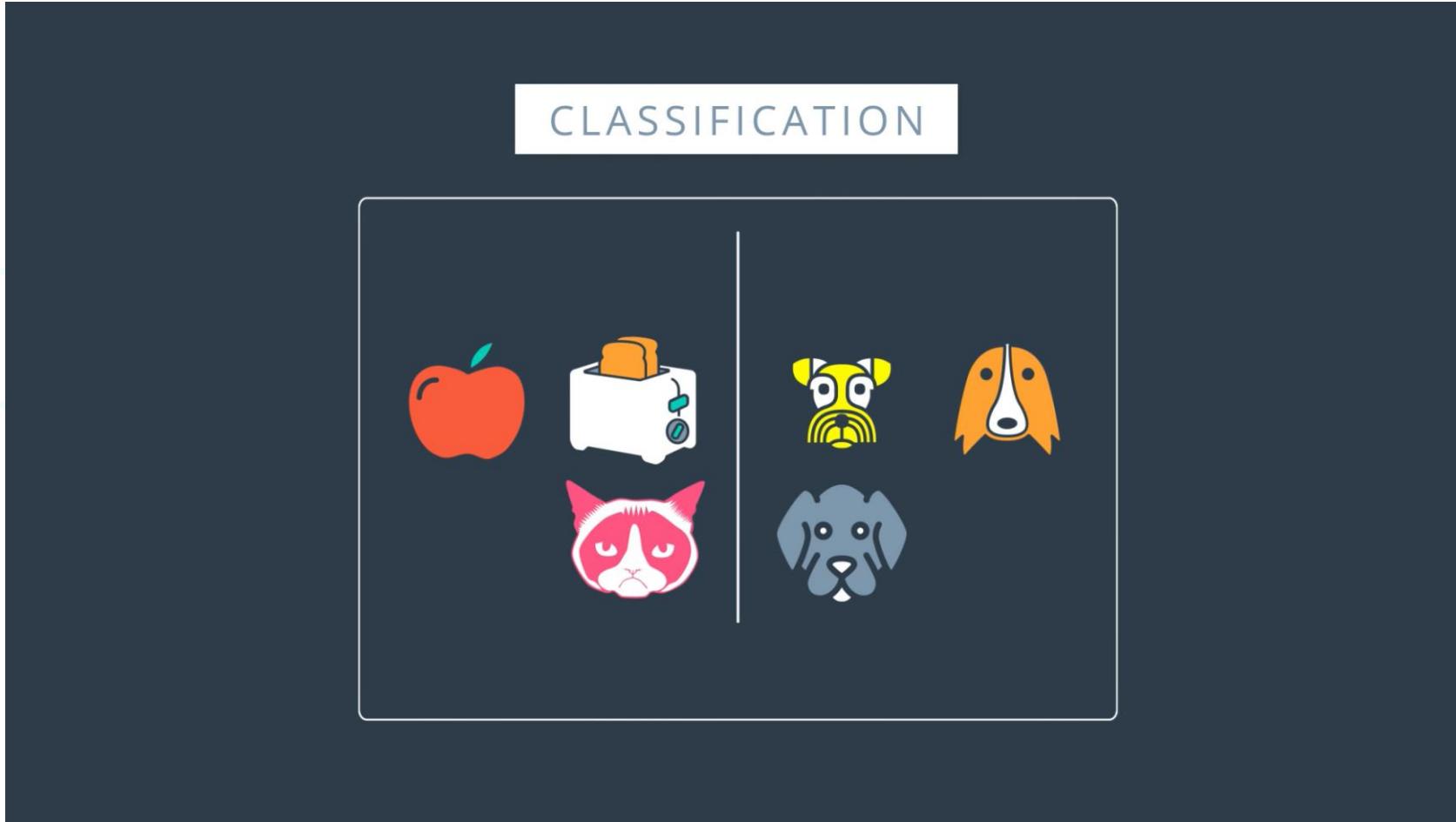
# Redes Neurais – Overfitting and Underfitting



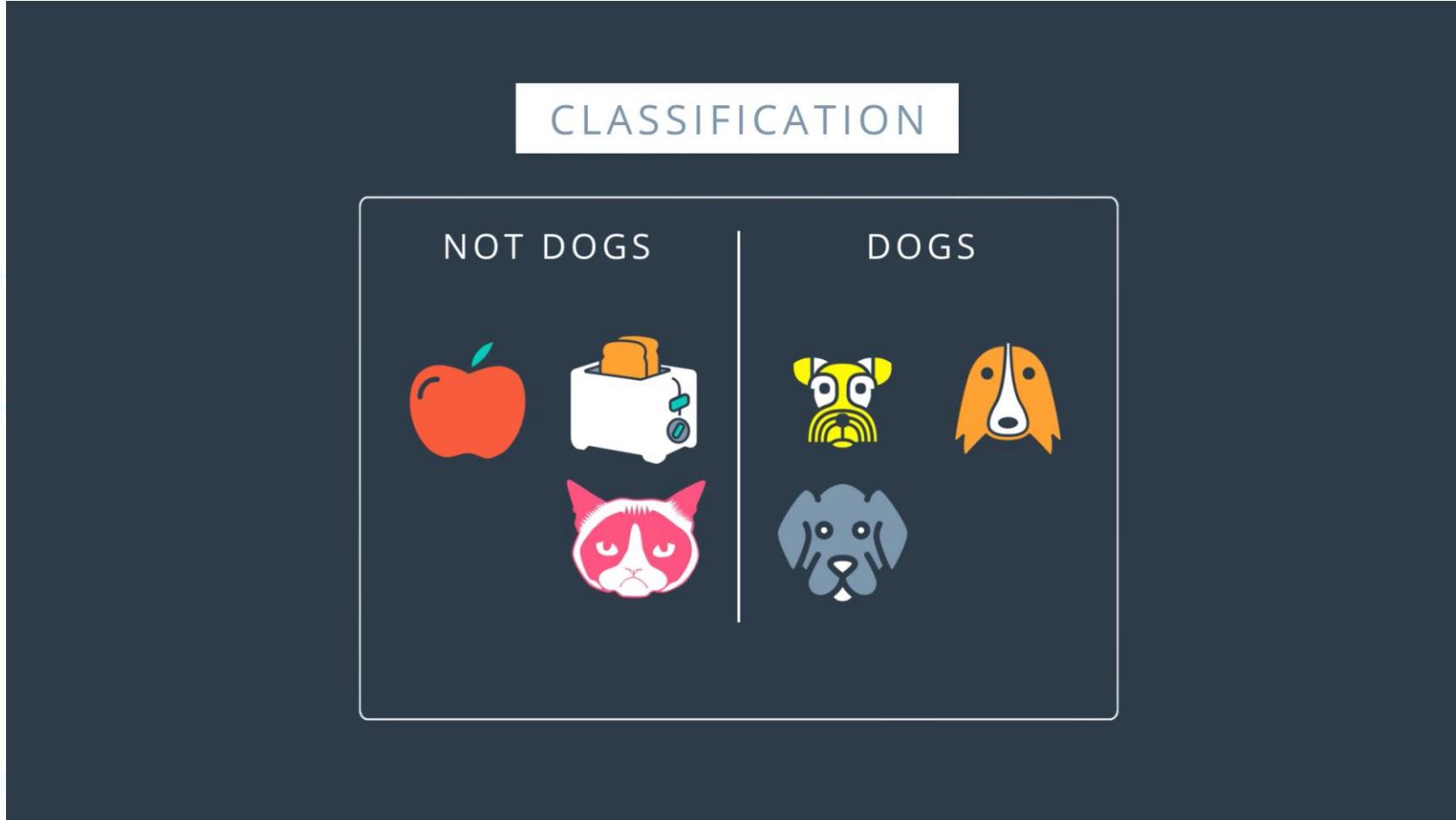
# Redes Neurais – Overfitting and Underfitting



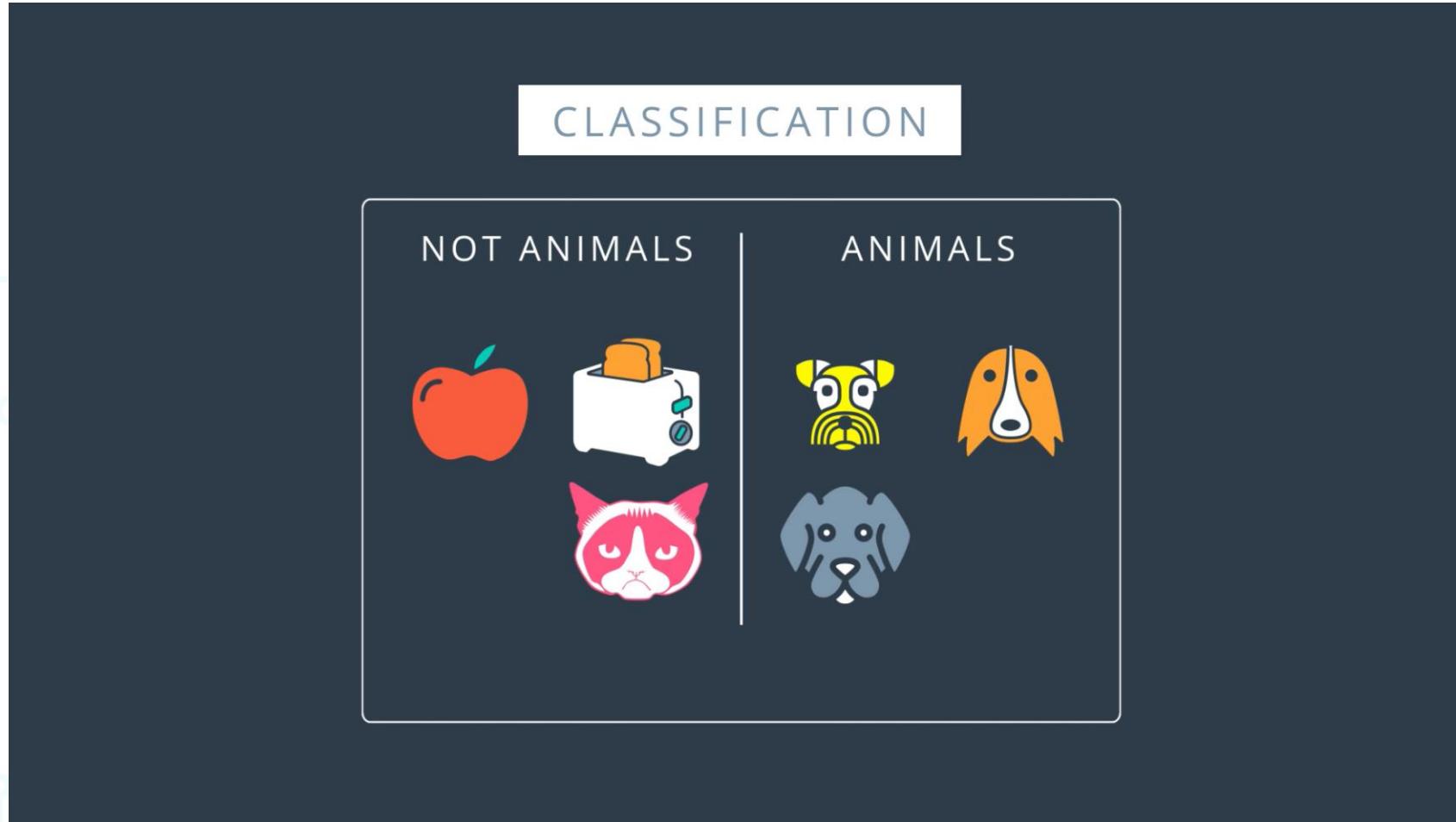
# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting



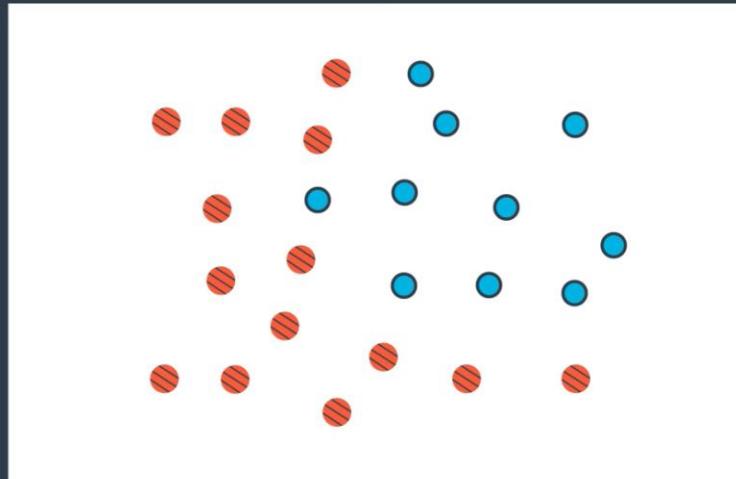
# Redes Neurais – Overfitting and Underfitting



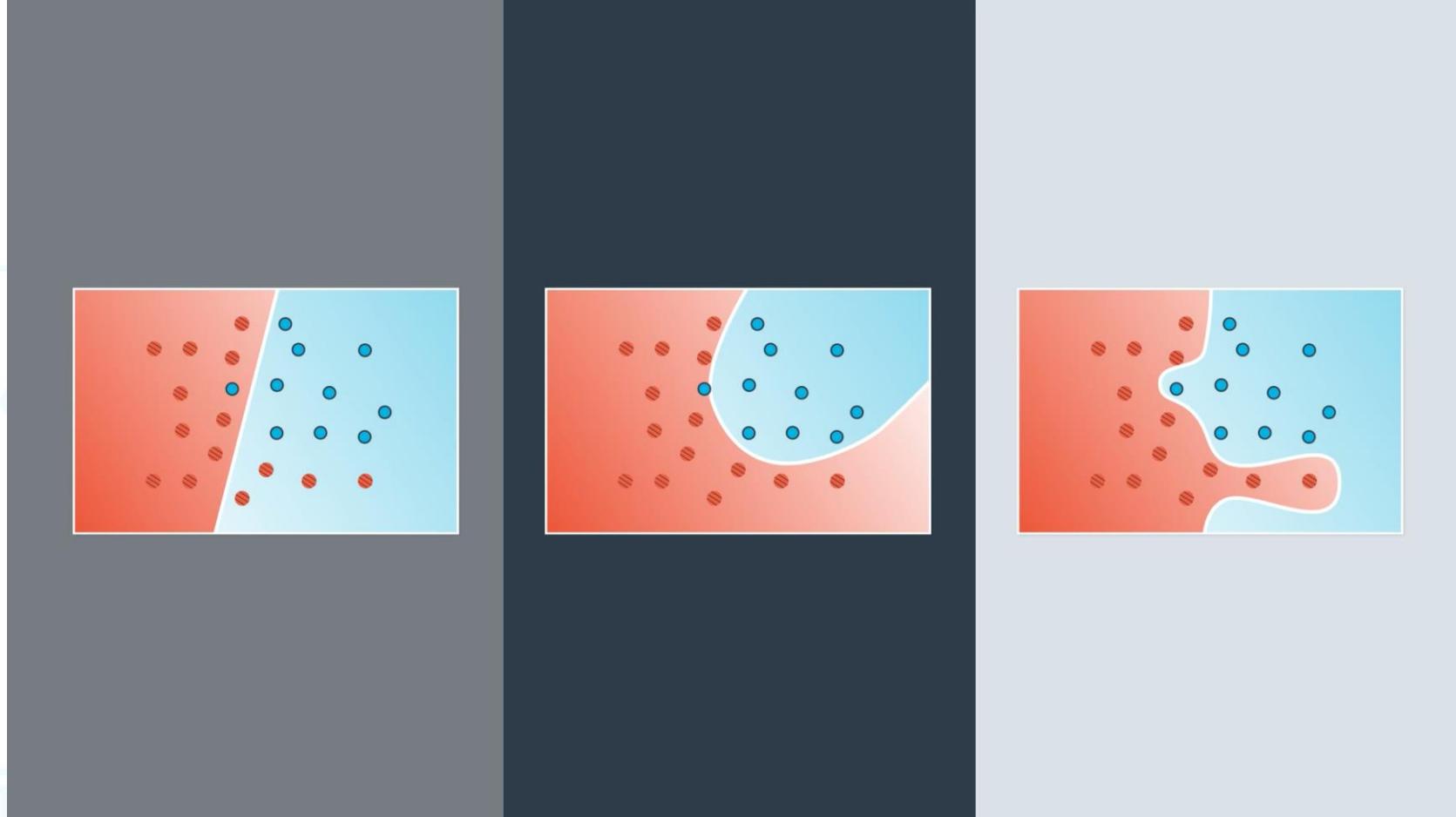
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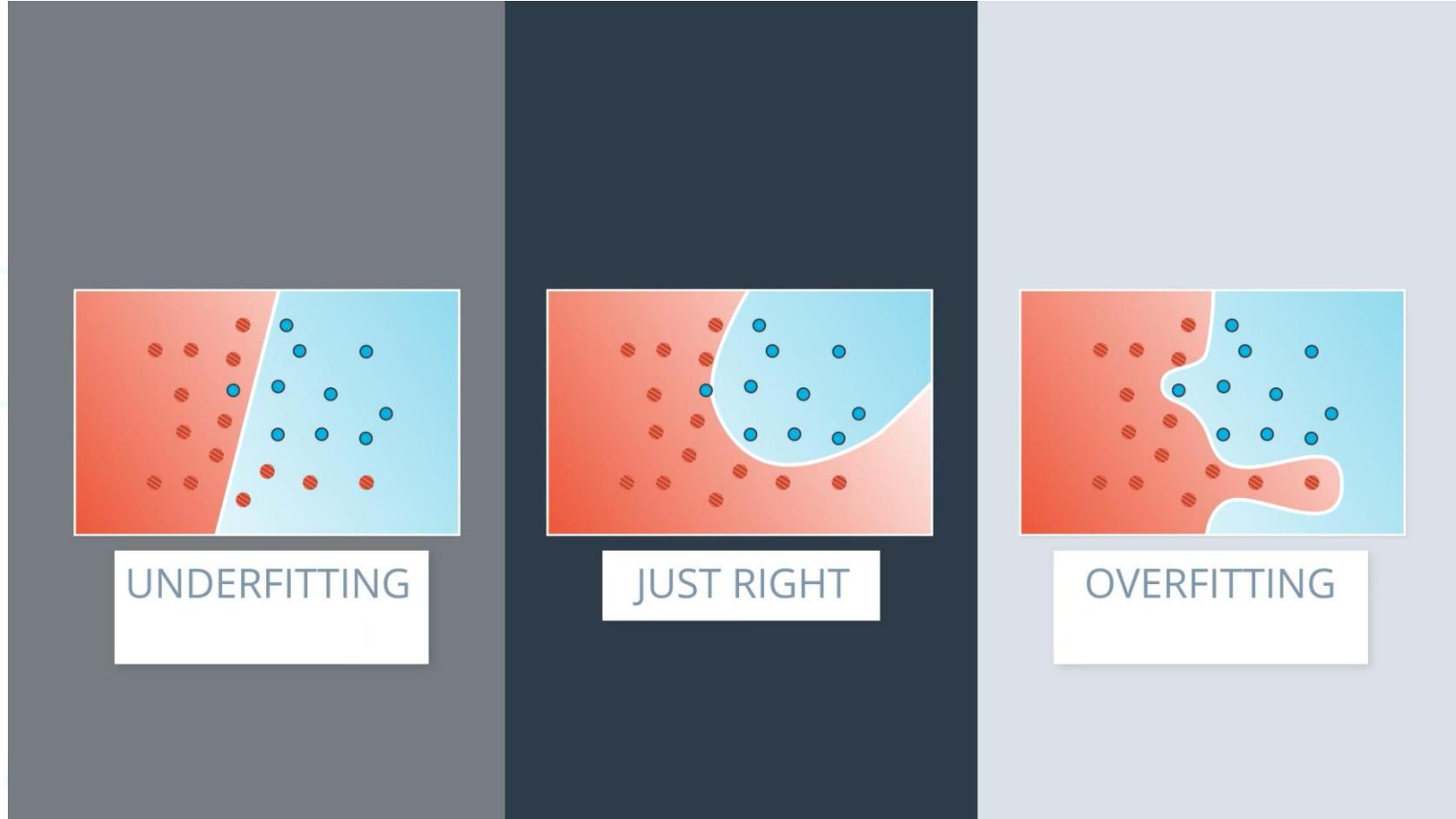
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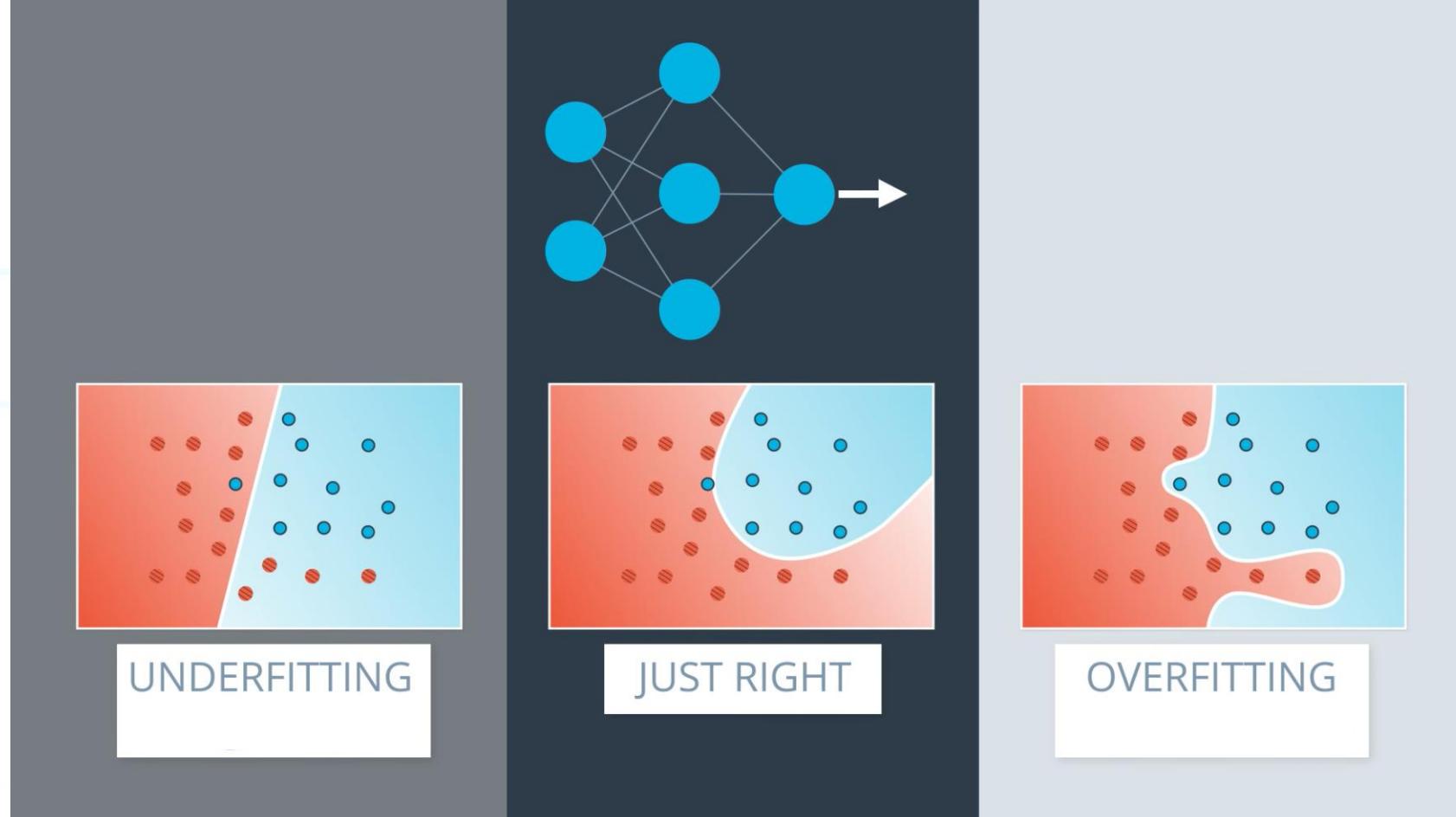
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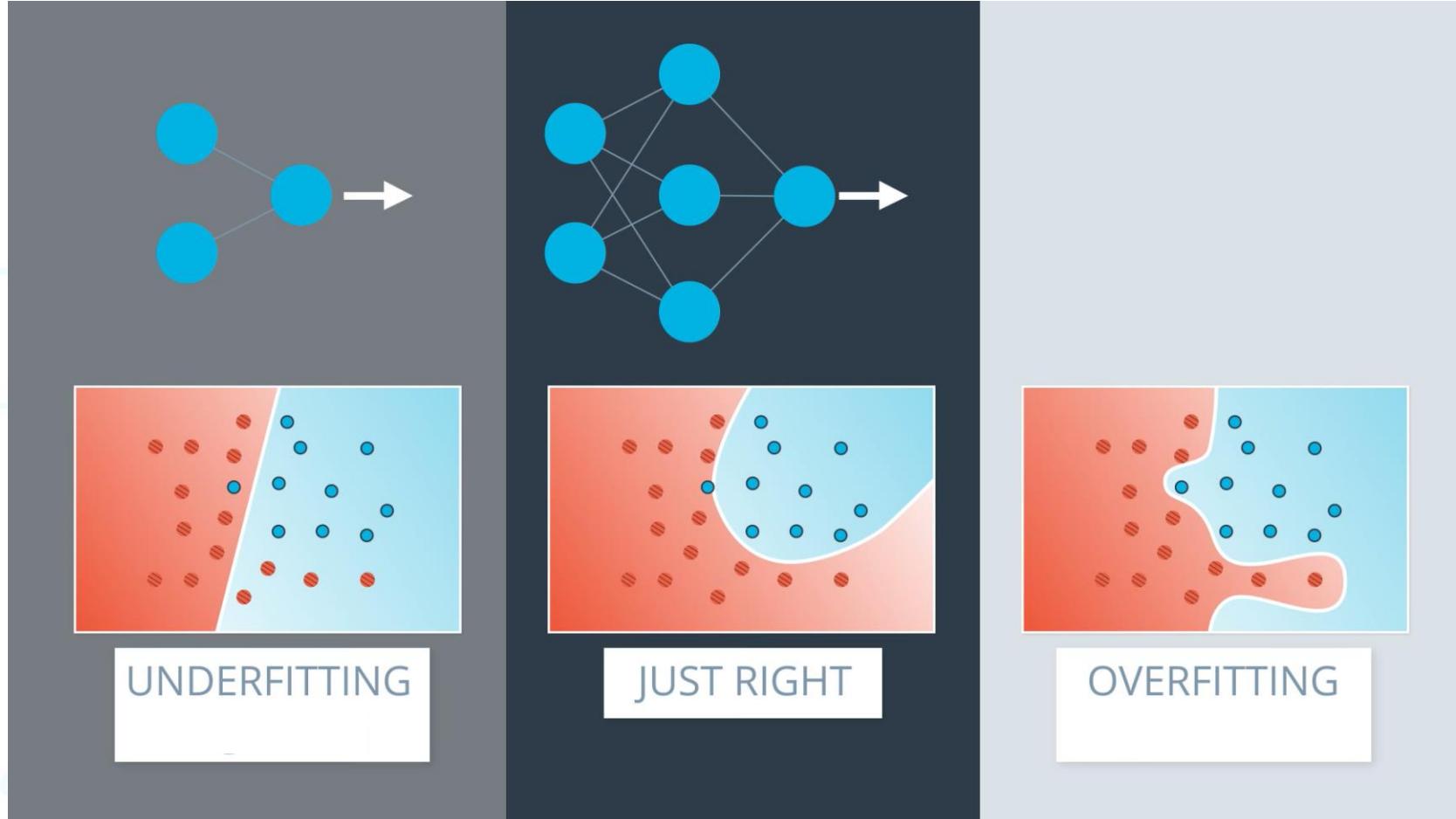
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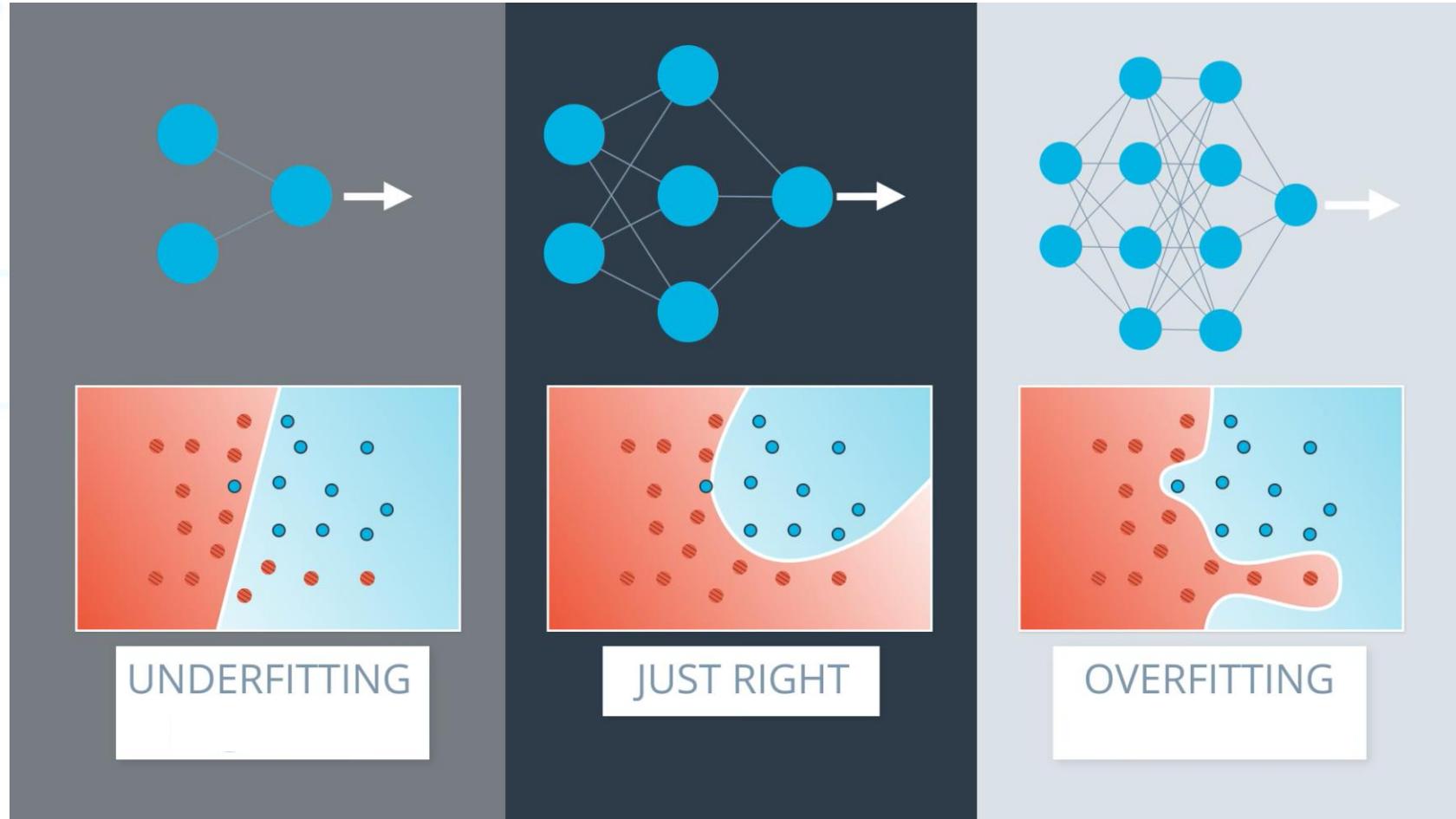
# Redes Neurais – Overfitting and Underfitting



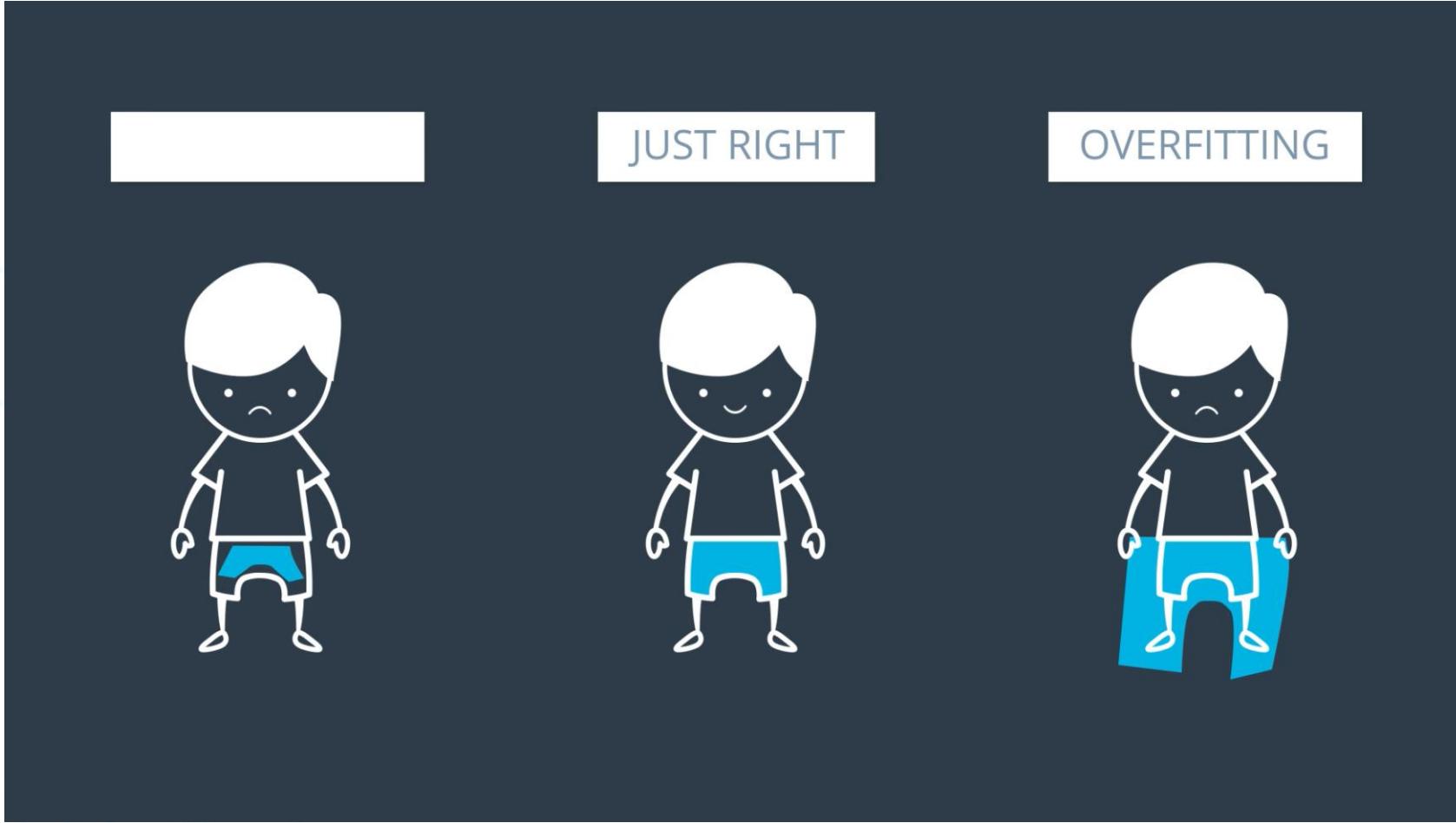
# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting



# Thanks !



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