



Human-Centered Data & AI

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PCP, WFM, Data and AI - Itaú Unibanco

MBA Professor - FIAP

Google Developer Expert – Machine Learning

Co-organizer TFUGSP and AWSUGSP



@vinicius caridá



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“

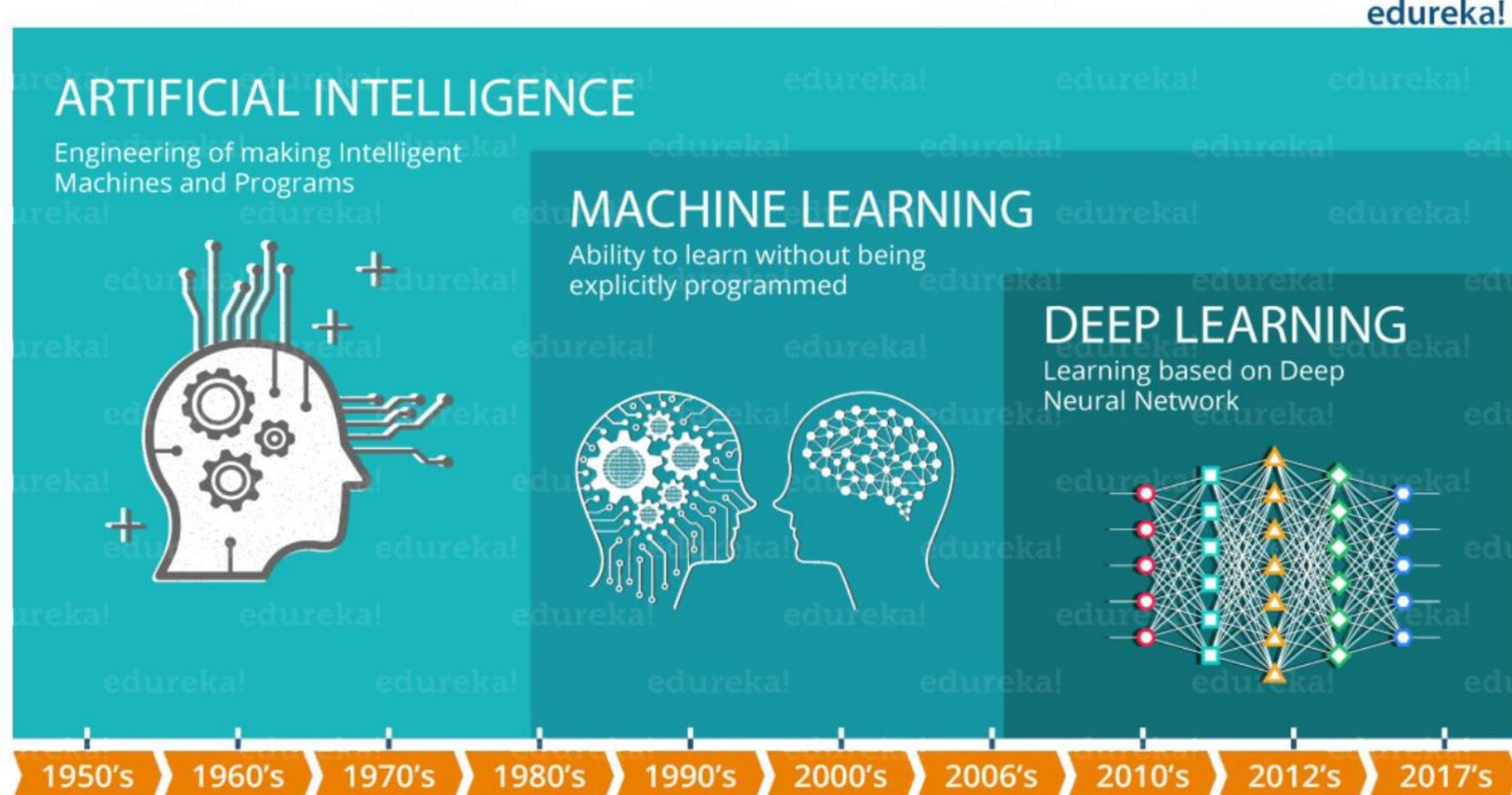
# Zero to Hero Machine Learning na AWS

Parte 4/5

“

# Redes Neurais

# Redes Neurais



# Redes Neurais

Albert Einstein: Insanity Is Doing  
the Same Thing Over and Over Again  
and Expecting Different Results

Machine learning:



# Redes Neurais

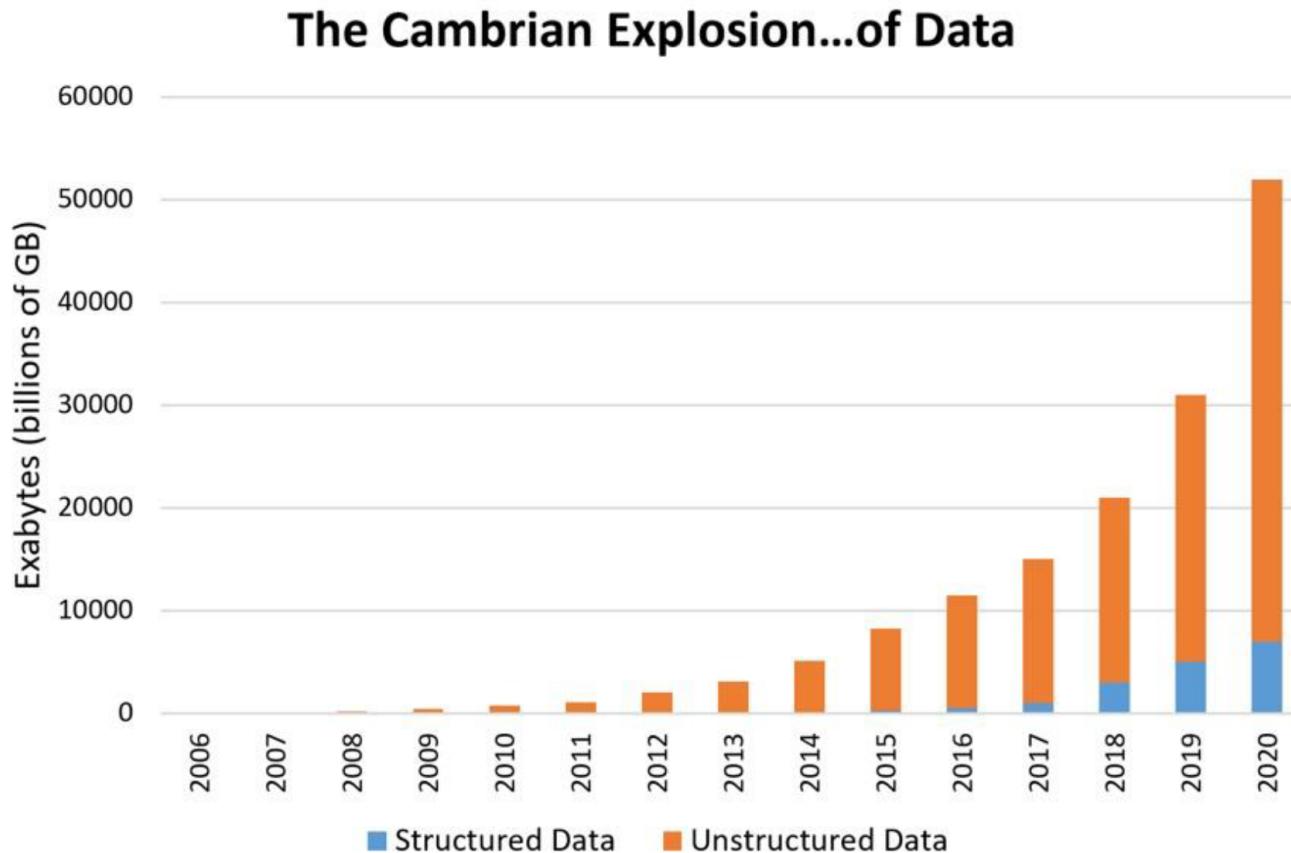


Figura 16 – Taxa de expansão na produção de dados estruturados e não-estruturados

Fonte: [https://www.eetimes.com/author.asp?section\\_id=36&doc\\_id=1330462](https://www.eetimes.com/author.asp?section_id=36&doc_id=1330462)

# Redes Neurais

- O neurônio recebe impulsos (sinais) de outros neurônios por meio dos seus dendritos;
- O neurônio envia impulsos para outros neurônios por meio do seu axônio;
- O axônio termina num tipo de contato chamado sinapse, que conecta-o com o dendrito de outro neurônio.

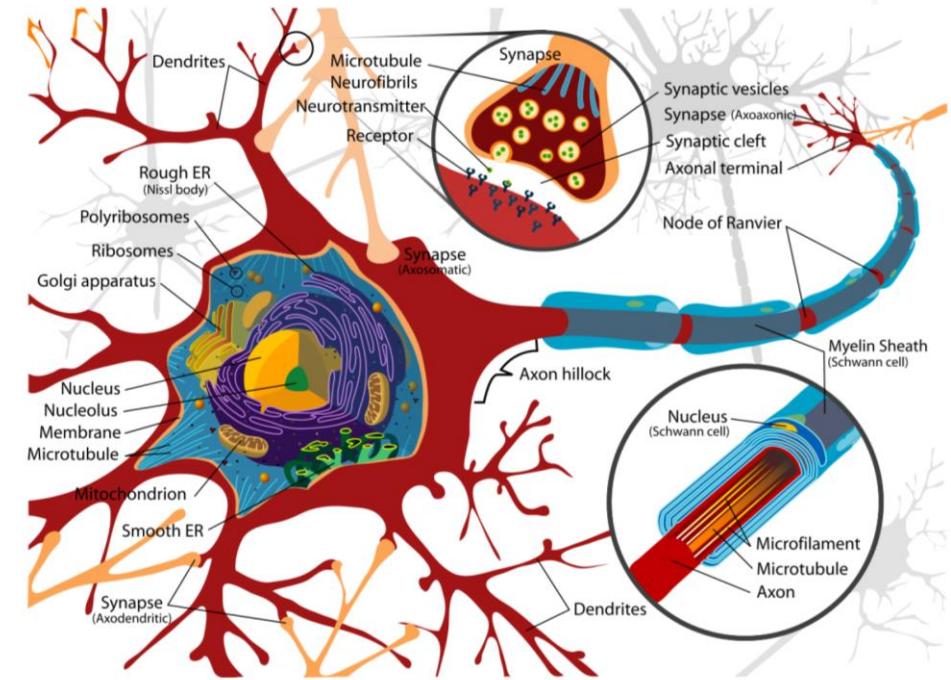


Figura 2 – Elementos constituintes de um neurônio

Extraído de: [[http://upload.wikimedia.org/wikipedia/commons/thumb/a/a9/Complete\\_neuron\\_cell\\_diagram\\_en.svg/1280px-Complete\\_neuron\\_cell\\_diagram\\_en.svg.png](http://upload.wikimedia.org/wikipedia/commons/thumb/a/a9/Complete_neuron_cell_diagram_en.svg/1280px-Complete_neuron_cell_diagram_en.svg.png)]

# Redes Neurais

- Modelo matemático: Simplificações da realidade com o propósito de representar aspectos relevantes de um sistema em estudo, sendo que detalhes de menor significância são descartados para viabilizar a modelagem.

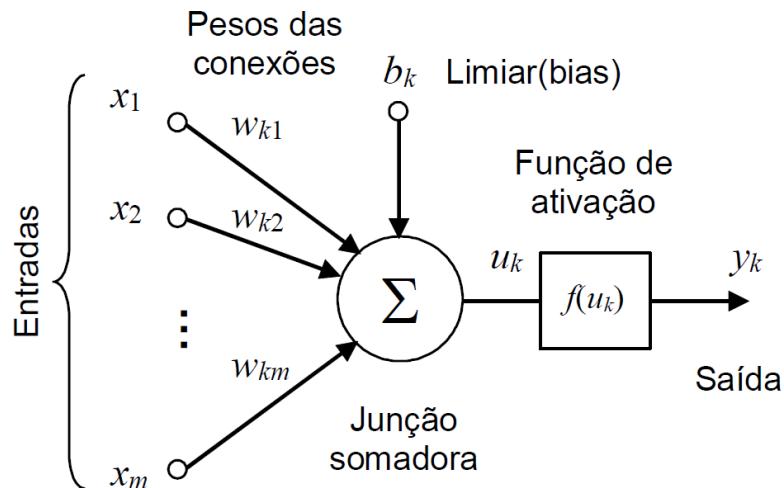


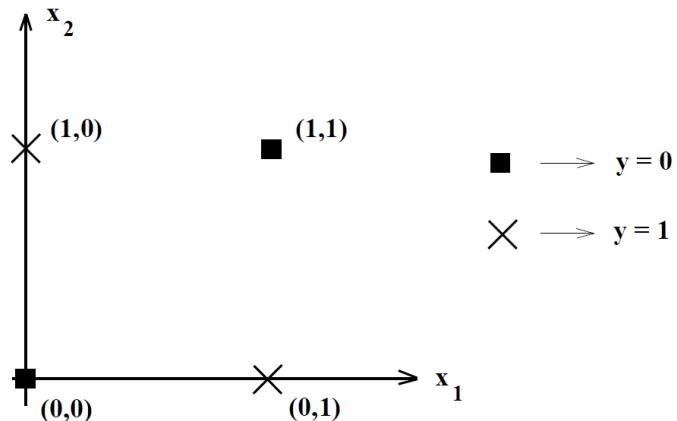
Figura 7 – Modelo matemático de um neurônio artificial

- A saída do neurônio  $k$  pode ser descrita por:  $y_k = f(u_k) = f\left(\sum_{j=1}^m w_{kj}x_j + b_k\right)$

# Redes Neurais

## O problema do OU-exclusivo em MLP

- Considere os pontos  $(0,0), (0,1), (1,0)$  e  $(1,1)$  no plano  $\mathbb{R}^2$ , conforme apresentado na Figura 26. O objetivo é determinar uma rede com duas entradas  $x_i \in \{0,1\}$  ( $i=1,2$ ), e uma saída  $y \in \{0,1\}$  de maneira que:  $\begin{cases} (x_1, x_2) = (0,0) \text{ ou } (1,1) \Rightarrow y = 0 \\ (x_1, x_2) = (1,0) \text{ ou } (0,1) \Rightarrow y = 1 \end{cases}$



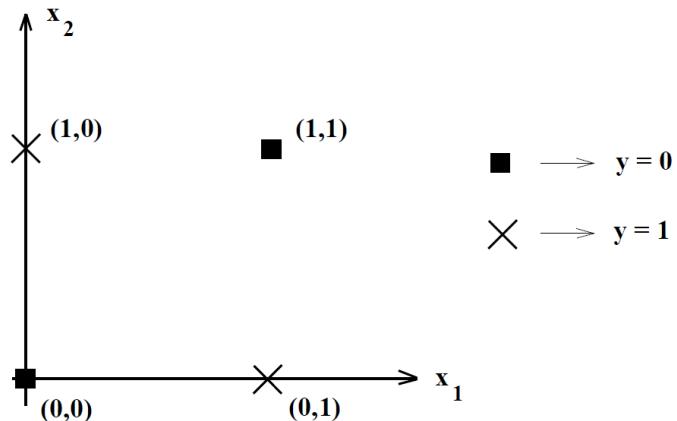
		AND	OR	XOR
0	0	0	0	0
0	1	0	1	1
1	0	0	1	1
1	1	1	1	0

Figura 26 – O problema do OU-exclusivo

# Redes Neurais

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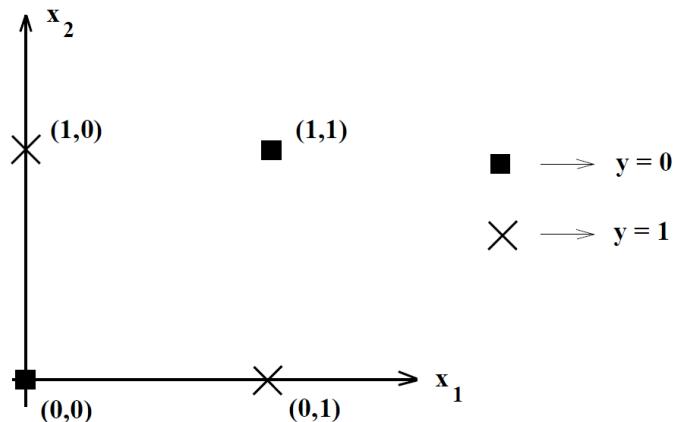
		AND	OR	XOR
0	0	0		
0	1	0		
1	0	0		
1	1	1		

Figura 26 – O problema do OU-exclusivo

# Redes Neurais

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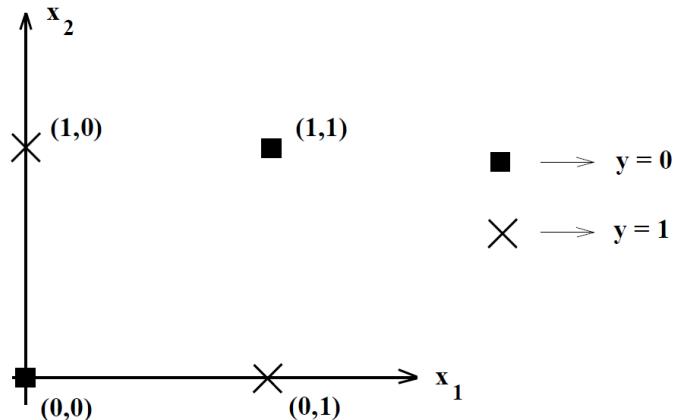
		AND	OR	XOR
0	0	0	0	
0	1	0	1	
1	0	0	1	
1	1	1	1	

Figura 26 – O problema do OU-exclusivo

# Redes Neurais

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		AND	OR	XOR
0	0	0	0	0
0	1	0	1	1
1	0	0	1	1
1	1	1	1	0

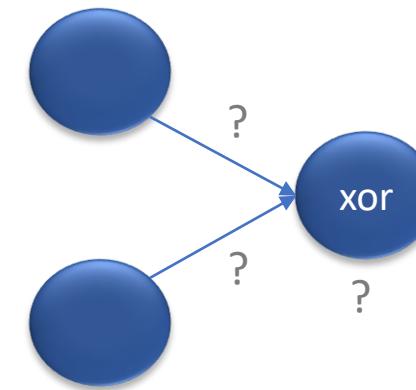
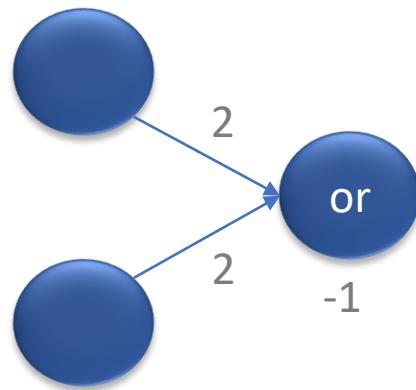
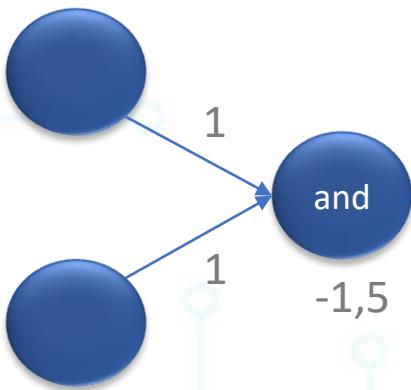
Figura 26 – O problema do OU-exclusivo

# Redes Neurais

0	0	0
0	1	0
1	0	0
1	1	1

0	0	0
0	1	1
1	0	1
1	1	1

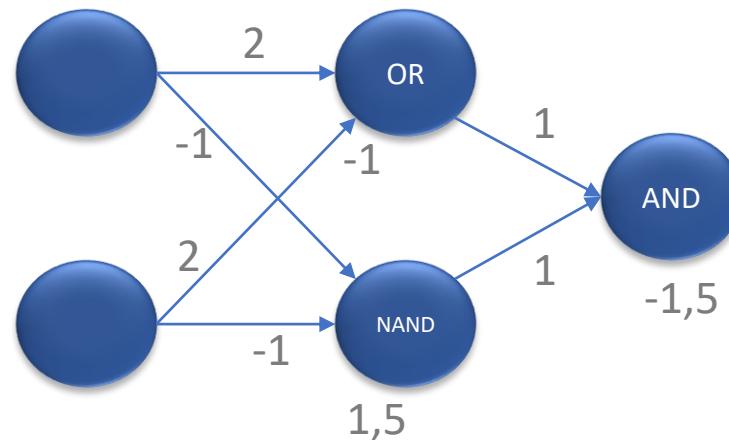
0	0	0
0	1	1
1	0	1
1	1	0



**Função Degrau Padrão**  
 Se  $\geq 0$  então 1  
 Se  $< 0$  então 0

# Redes Neurais

0	0	0
0	1	1
1	0	1
1	1	0



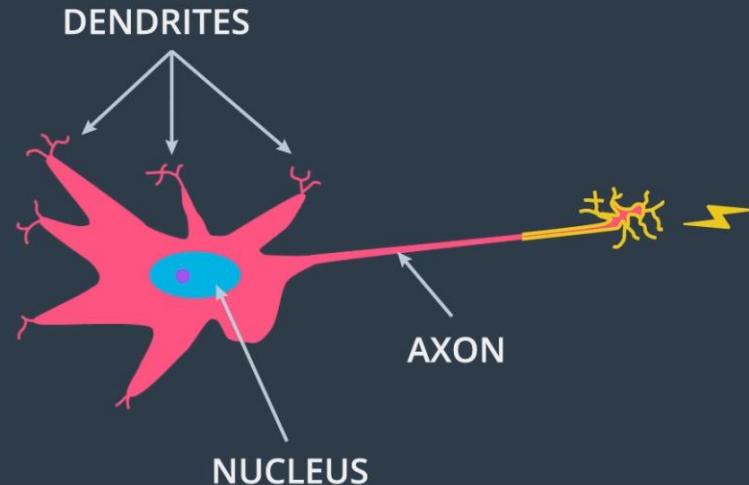
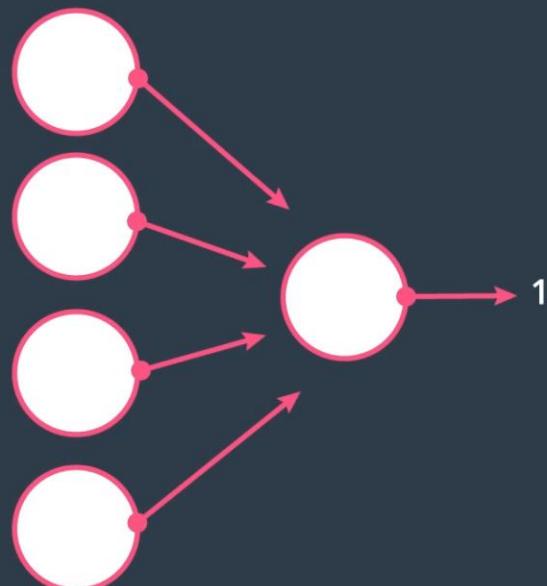
**Função Degrau Padrão**

Se  $\geq 0$  então 1

Se  $< 0$  então 0

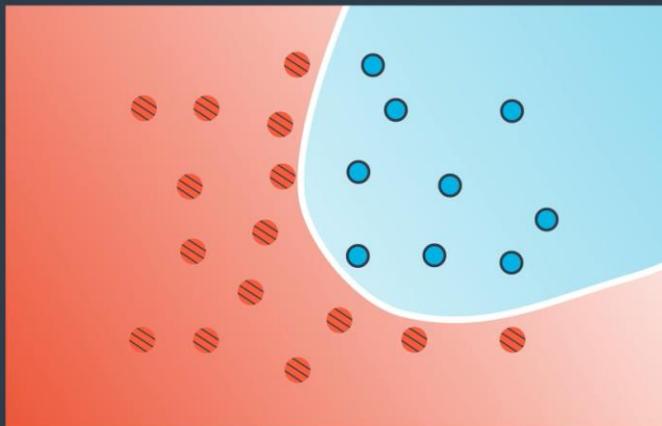
# Redes Neurais

Perceptron



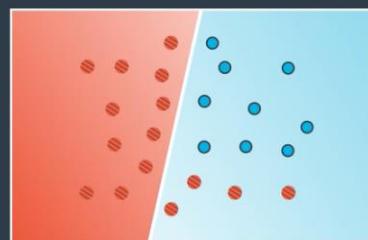
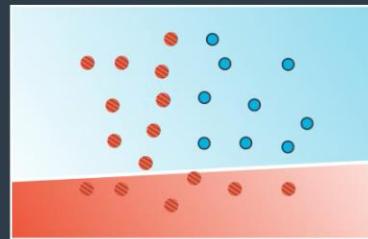
# Redes Neurais - Arquitetura

Non-Linear Regions



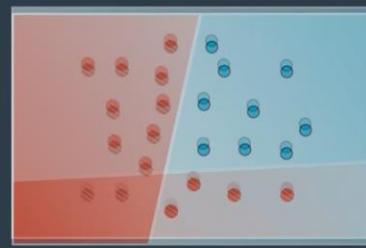
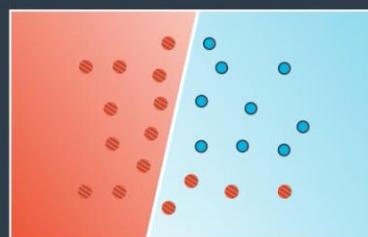
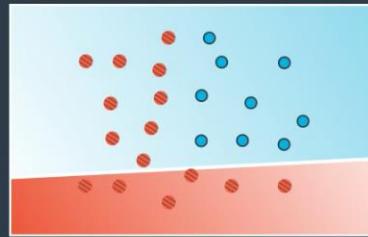
# Redes Neurais - Arquitetura

## Combining Regions



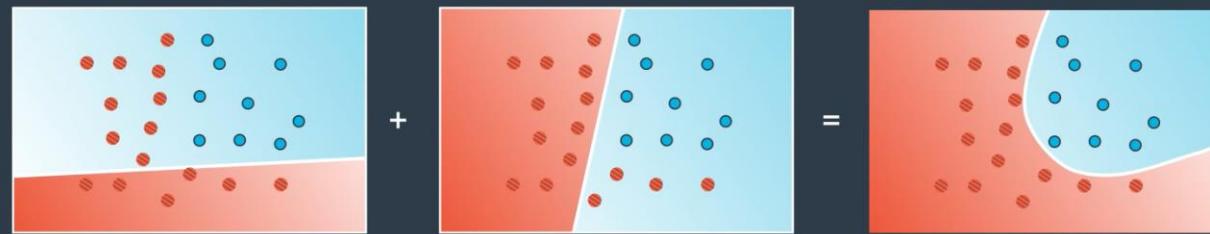
# Redes Neurais - Arquitetura

Combining Regions



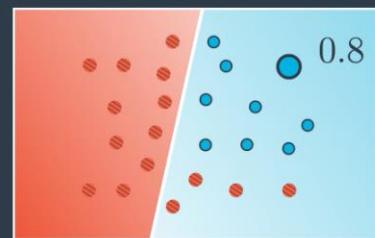
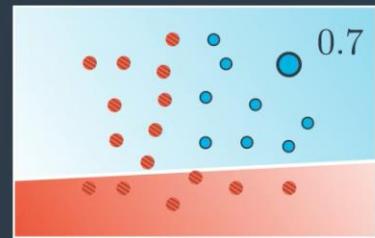
# Redes Neurais - Arquitetura

Combining Regions



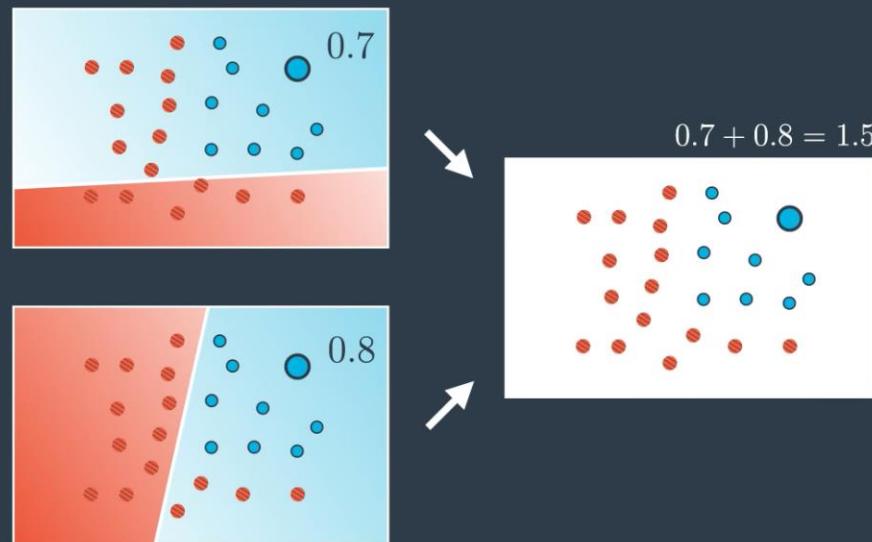
# Redes Neurais - Arquitetura

Neural Network



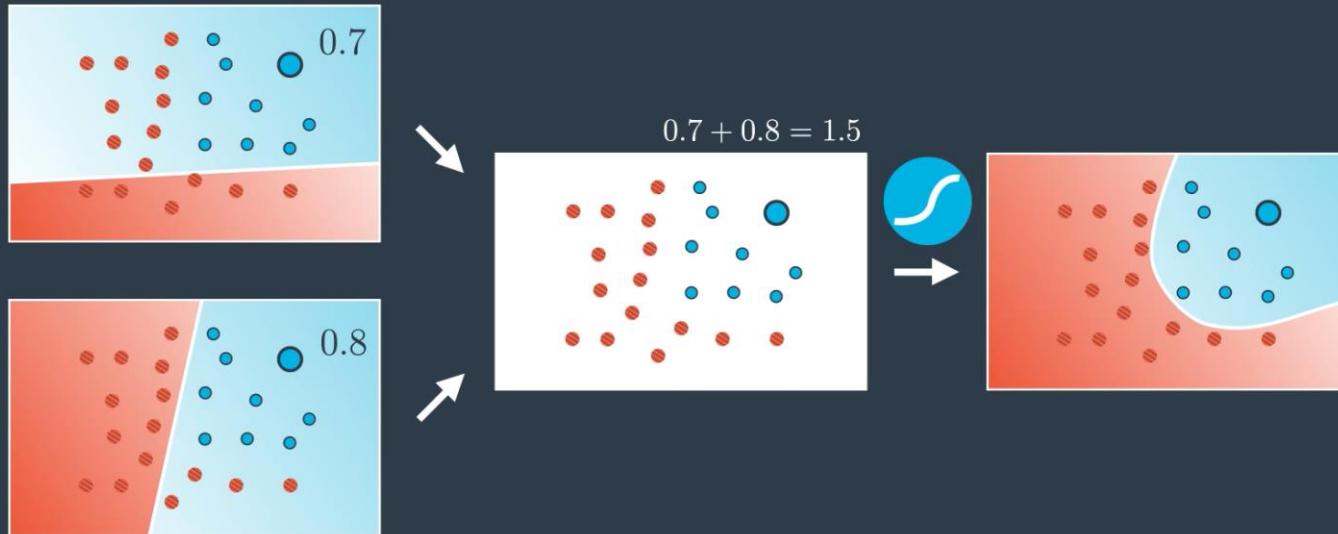
# Redes Neurais - Arquitetura

Neural Network

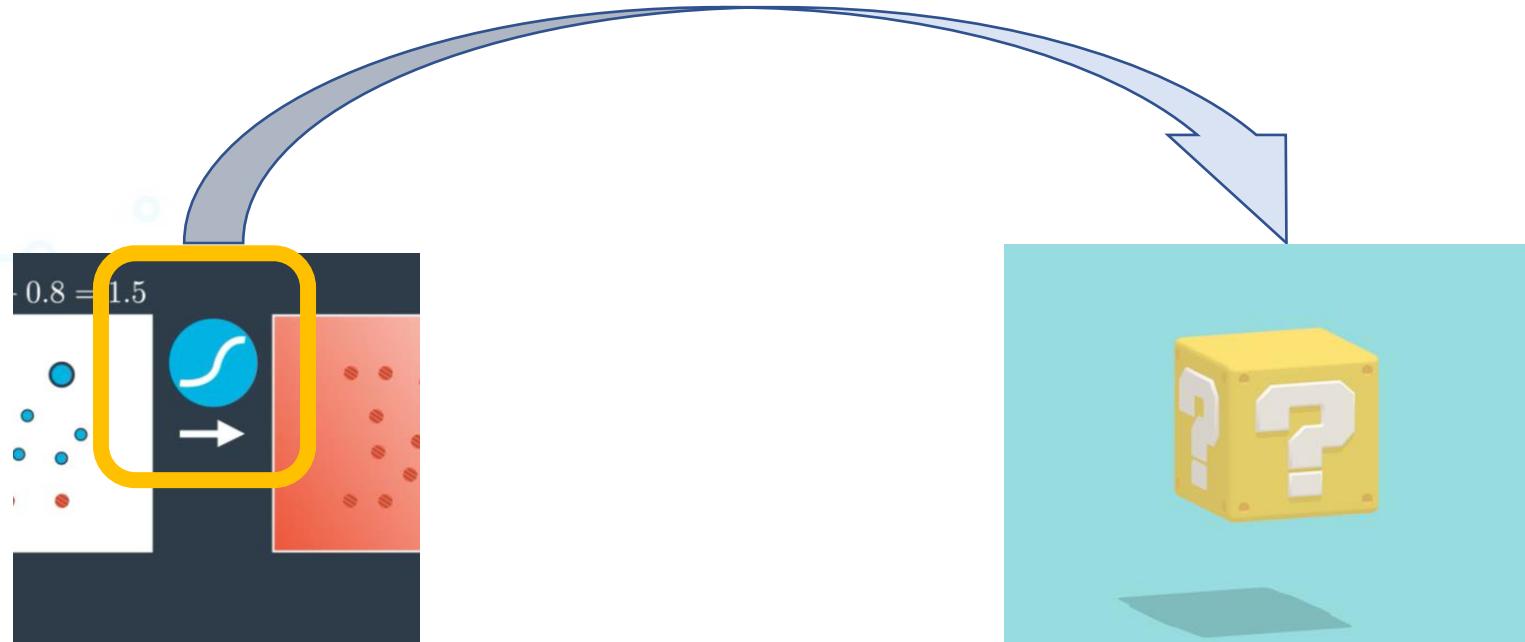


# Redes Neurais - Arquitetura

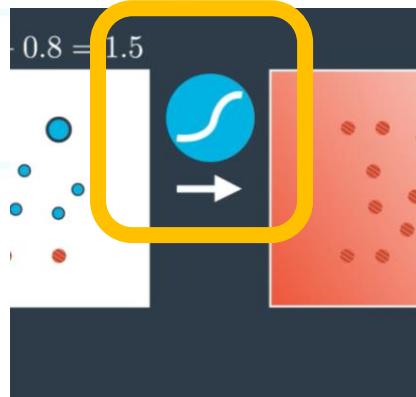
Neural Network



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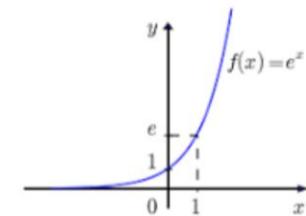


# Redes Neurais - Arquitetura



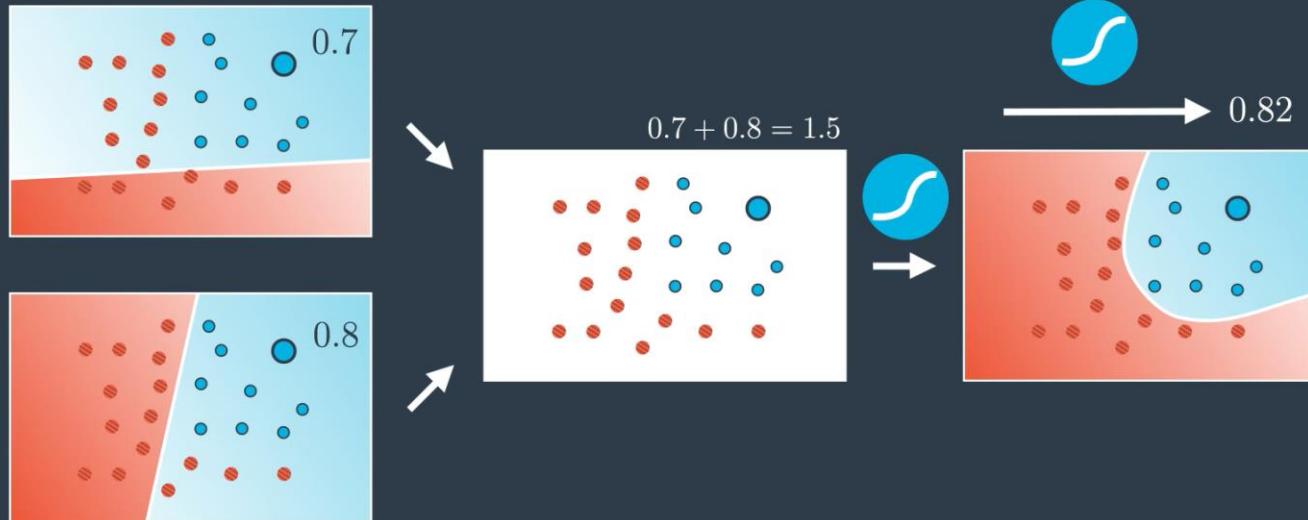
$$f(x) = \frac{1}{1 + e^{-x}} \text{ para todo } x \text{ real.}$$

A função **exponencial** natural, denotada  $e^x$  ou  $\exp(x)$  é a função **exponencial** cuja base é o número de Euler (um número irracional que **vale** aproximadamente 2,718281828).



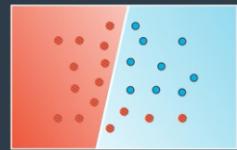
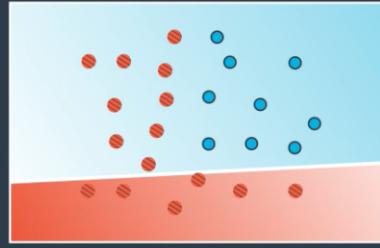
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Neural Network



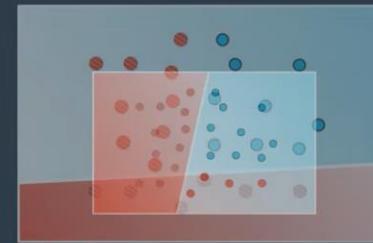
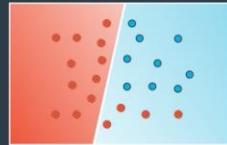
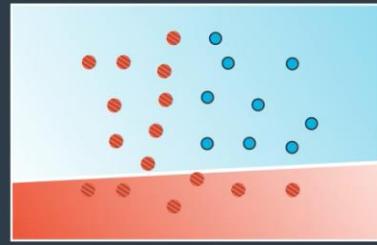
# Redes Neurais - Arquitetura

## Combining Regions



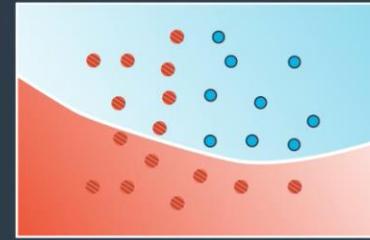
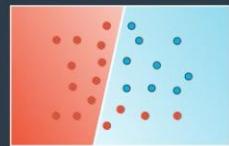
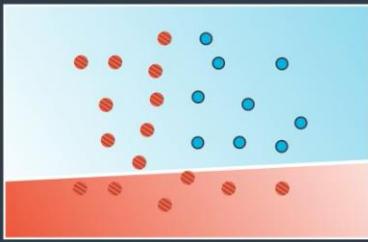
# Redes Neurais - Arquitetura

## Combining Regions



# Redes Neurais - Arquitetura

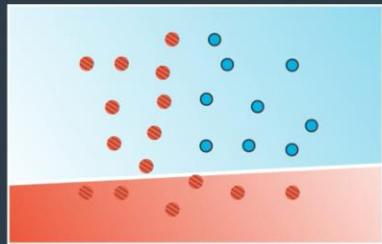
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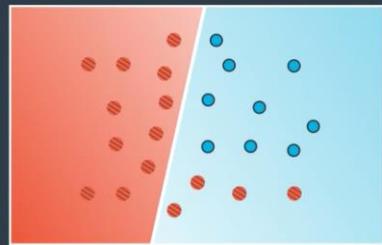
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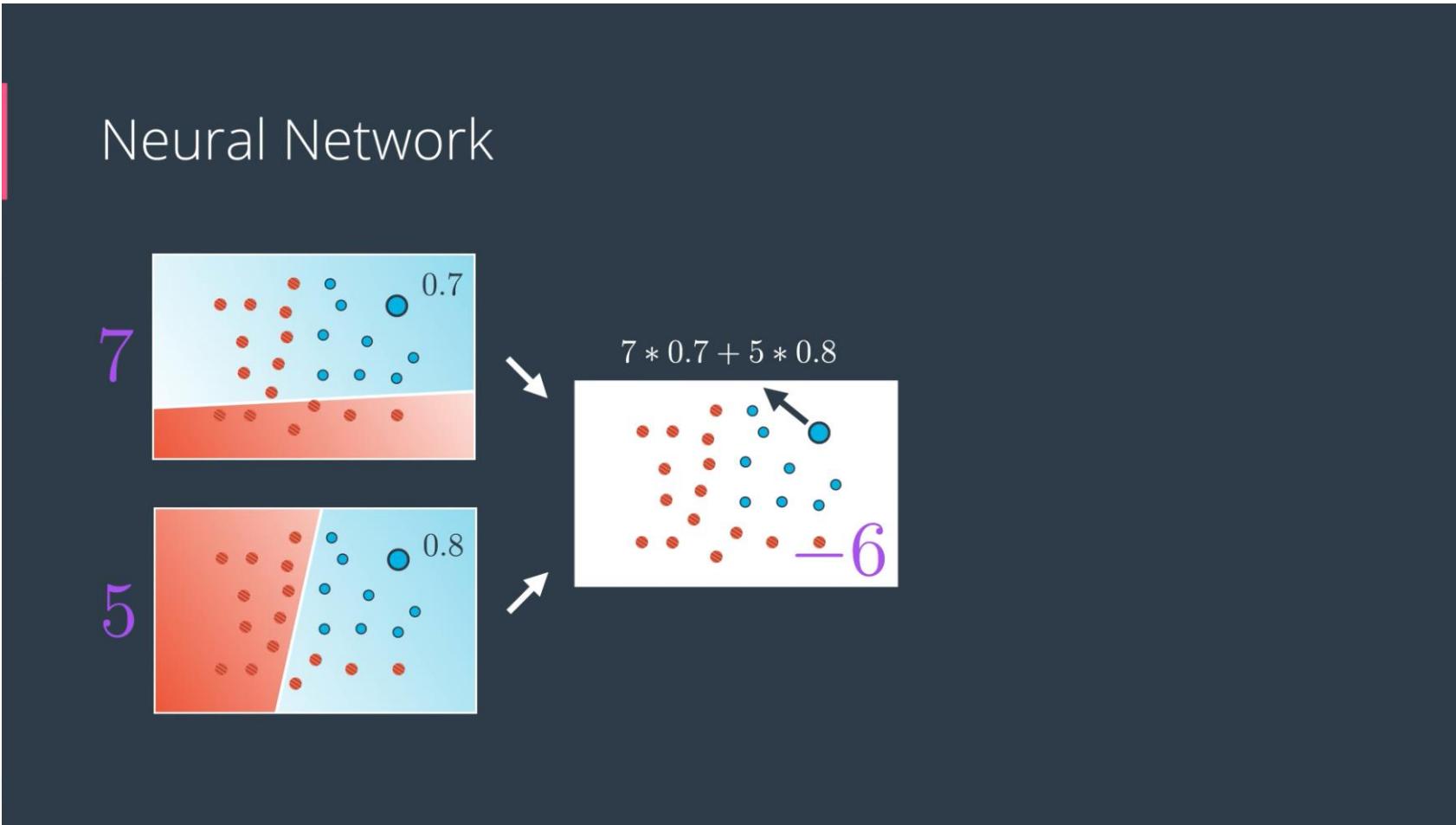
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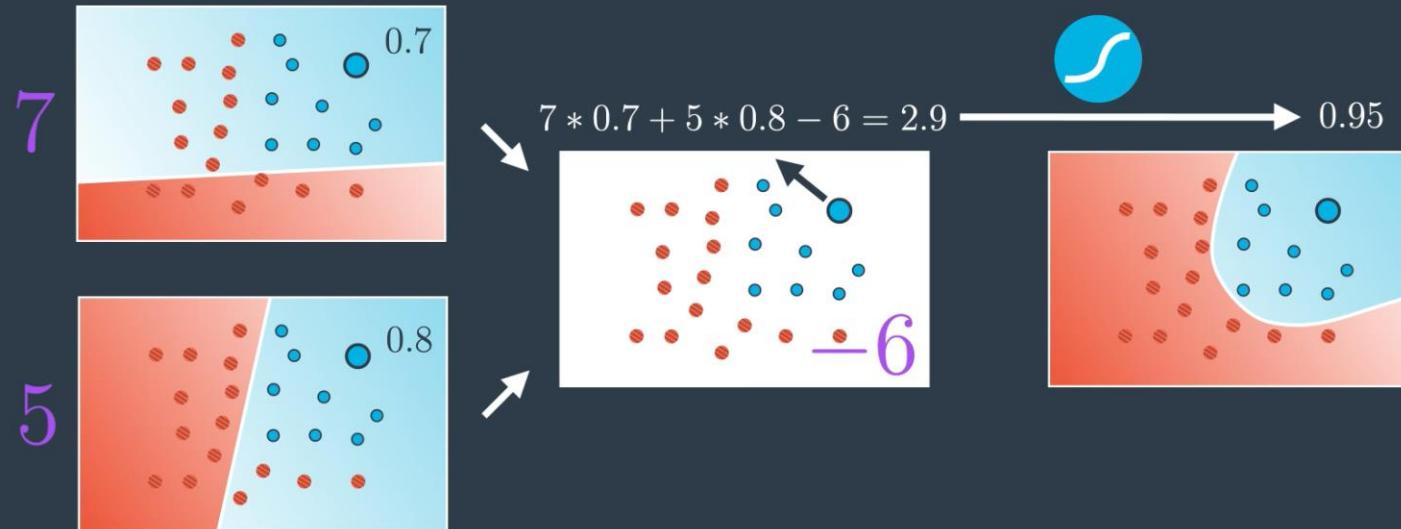


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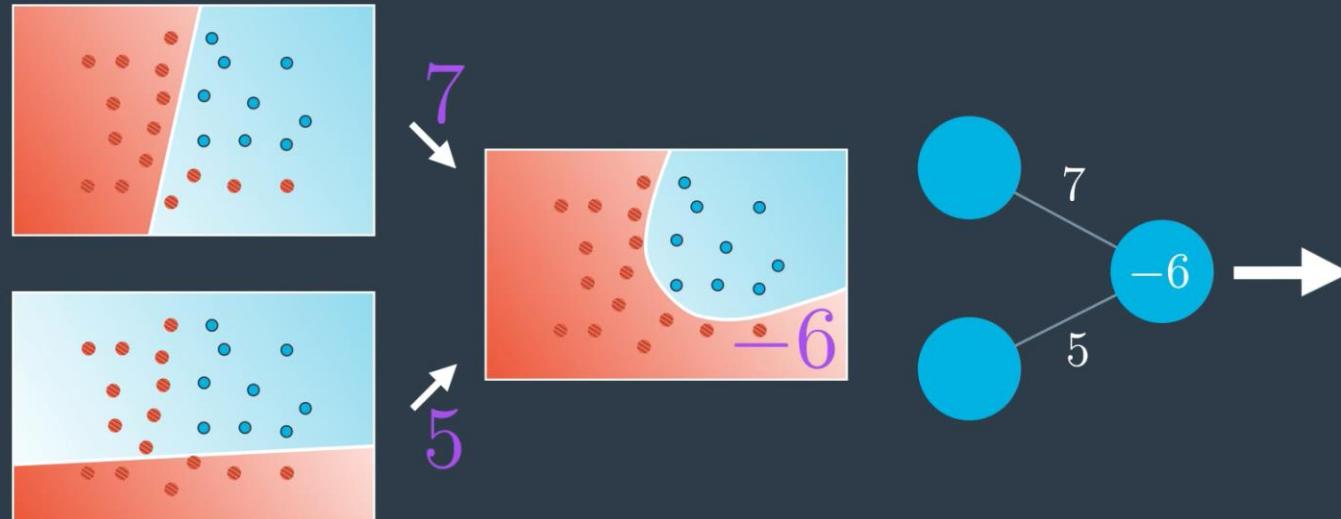
# Redes Neurais - Arquitetura

Neural Network



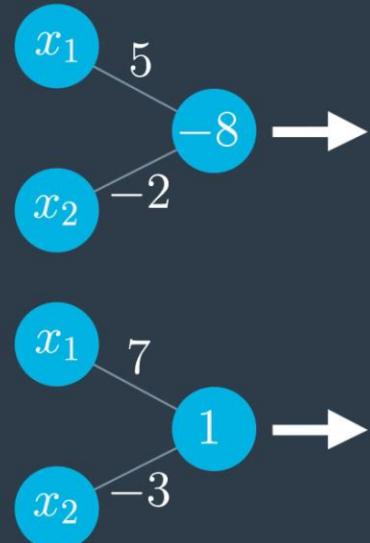
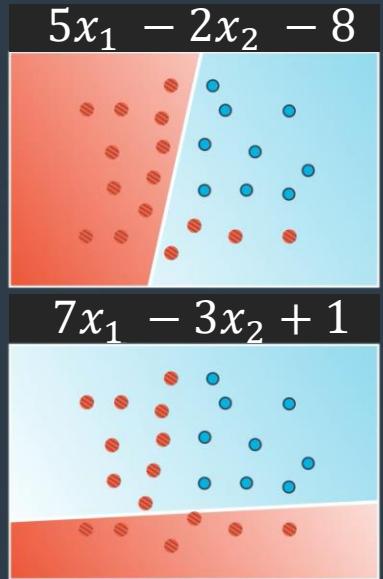
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Neural Network

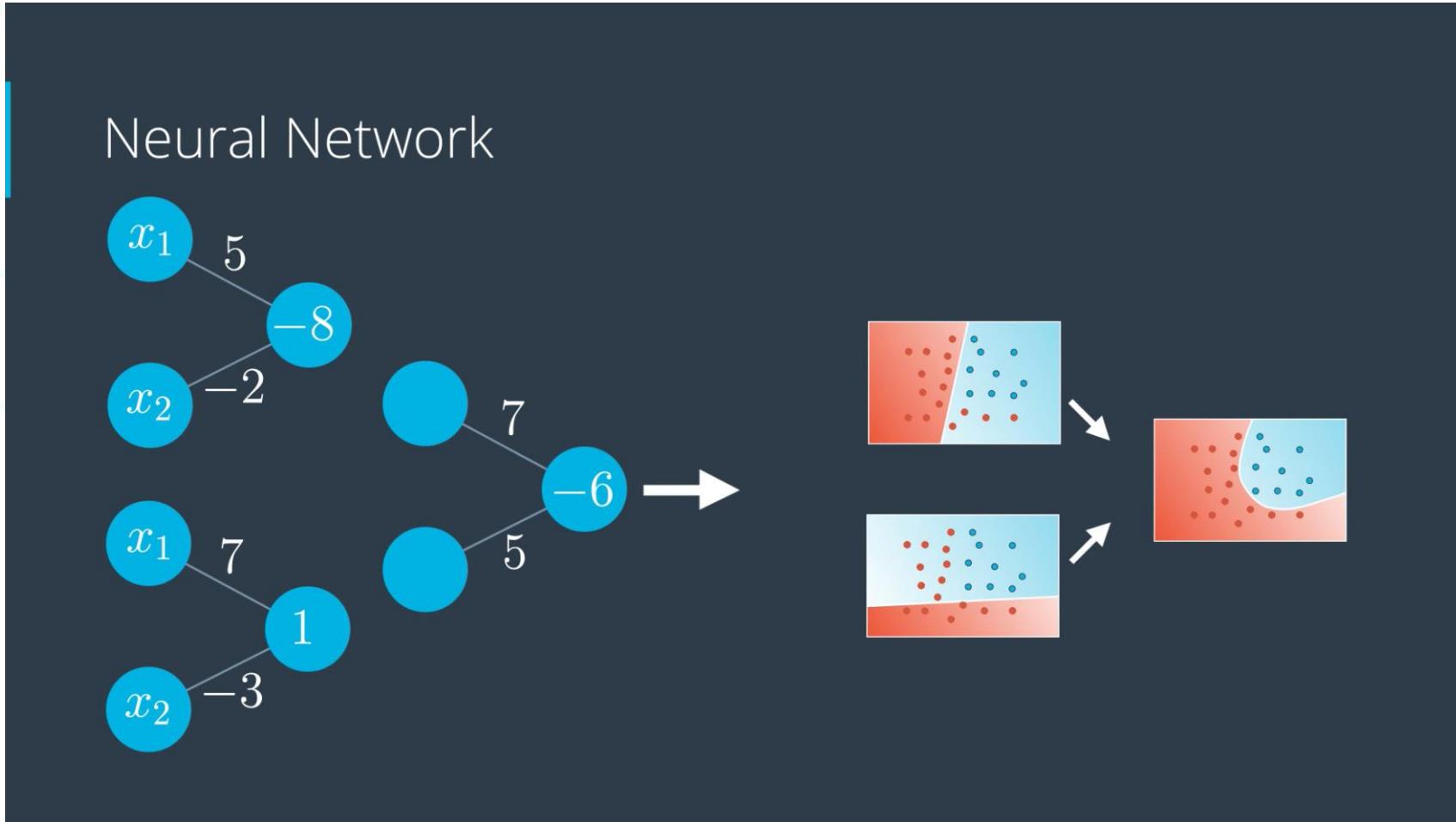


# Redes Neurais - Arquitetura

## Neural Network

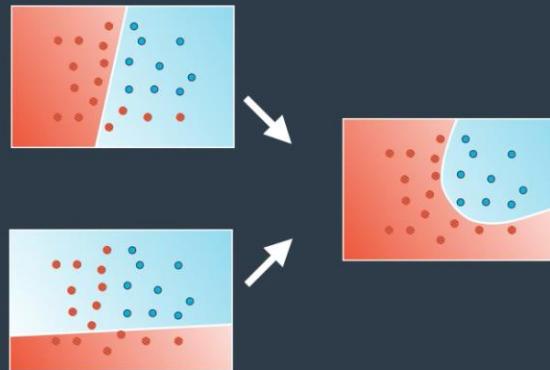
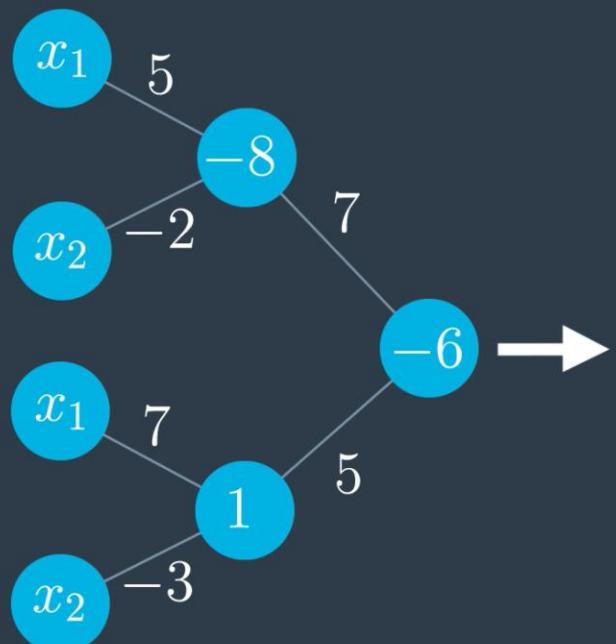


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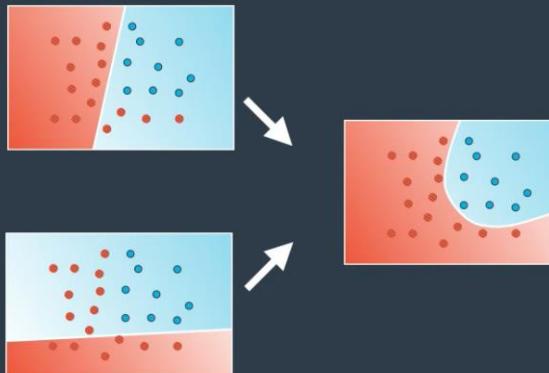
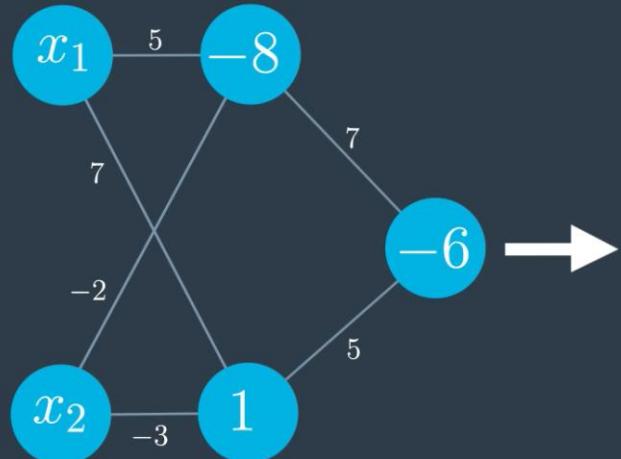
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Neural Network



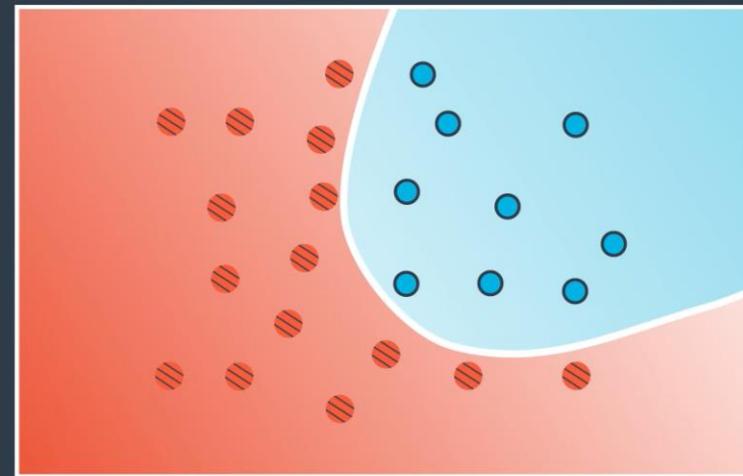
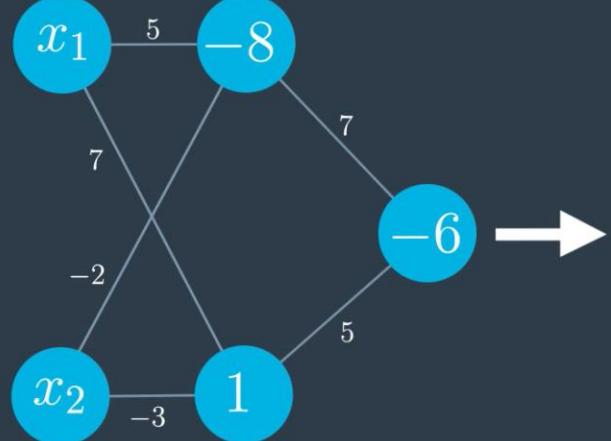
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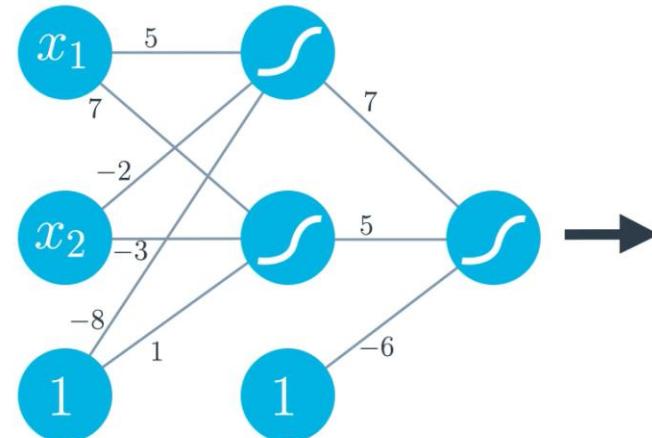
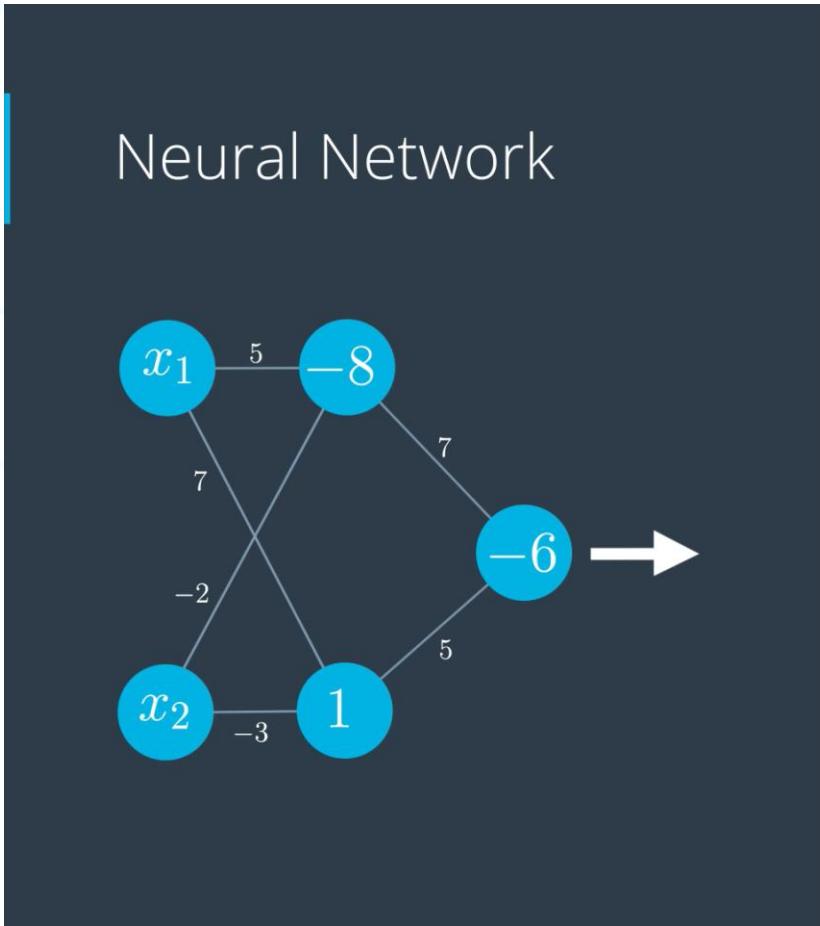


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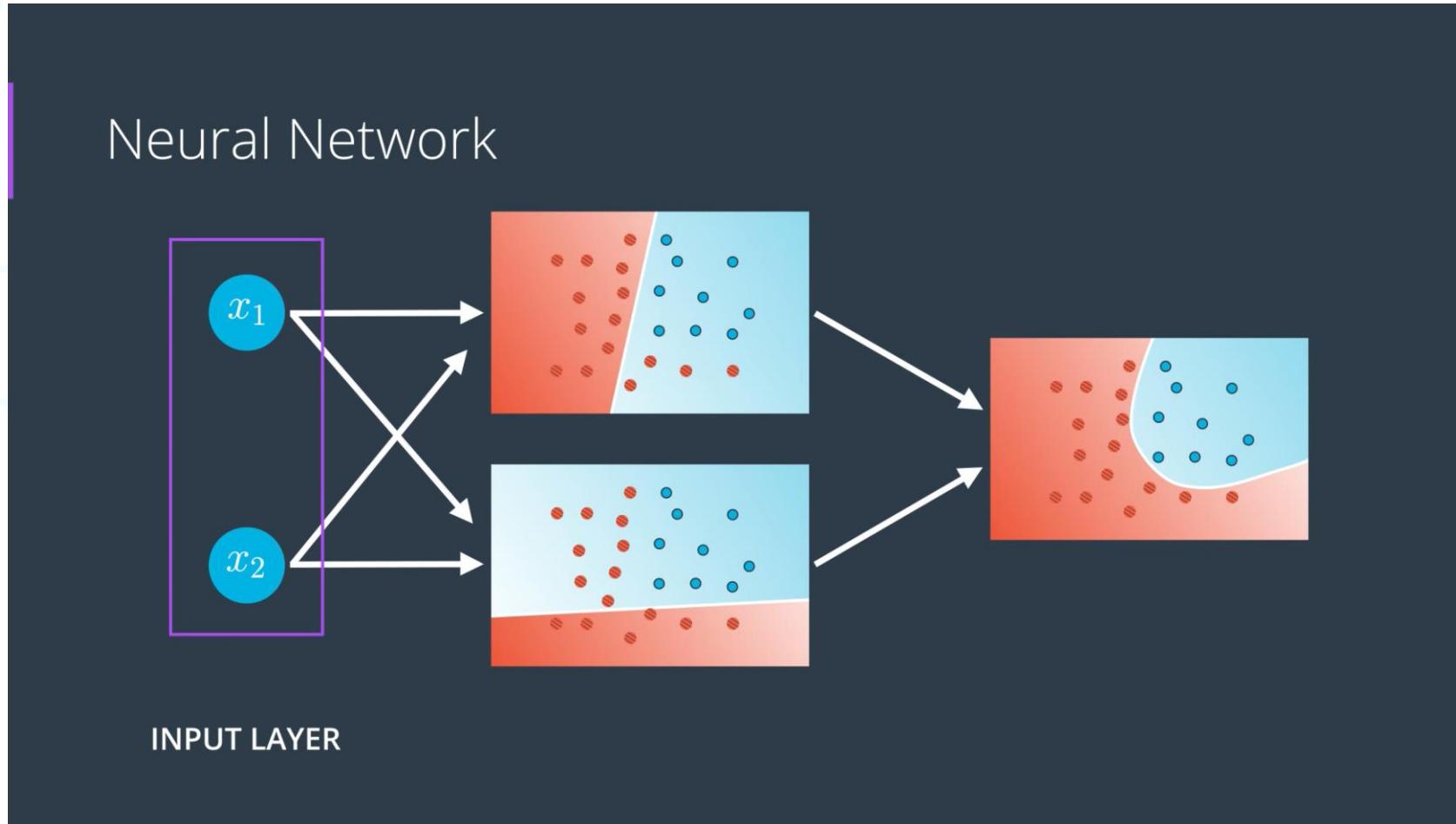
Neural Network



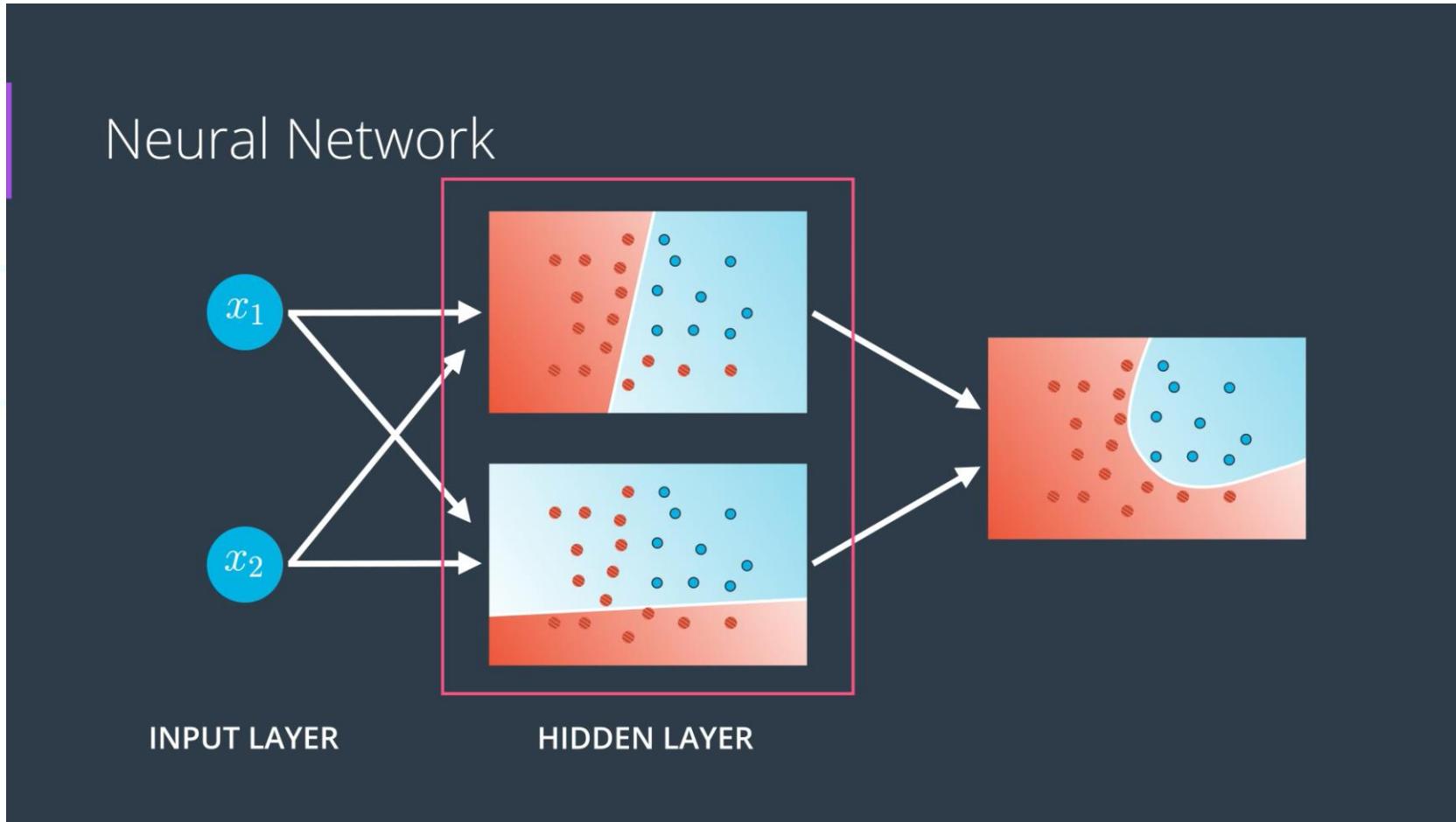
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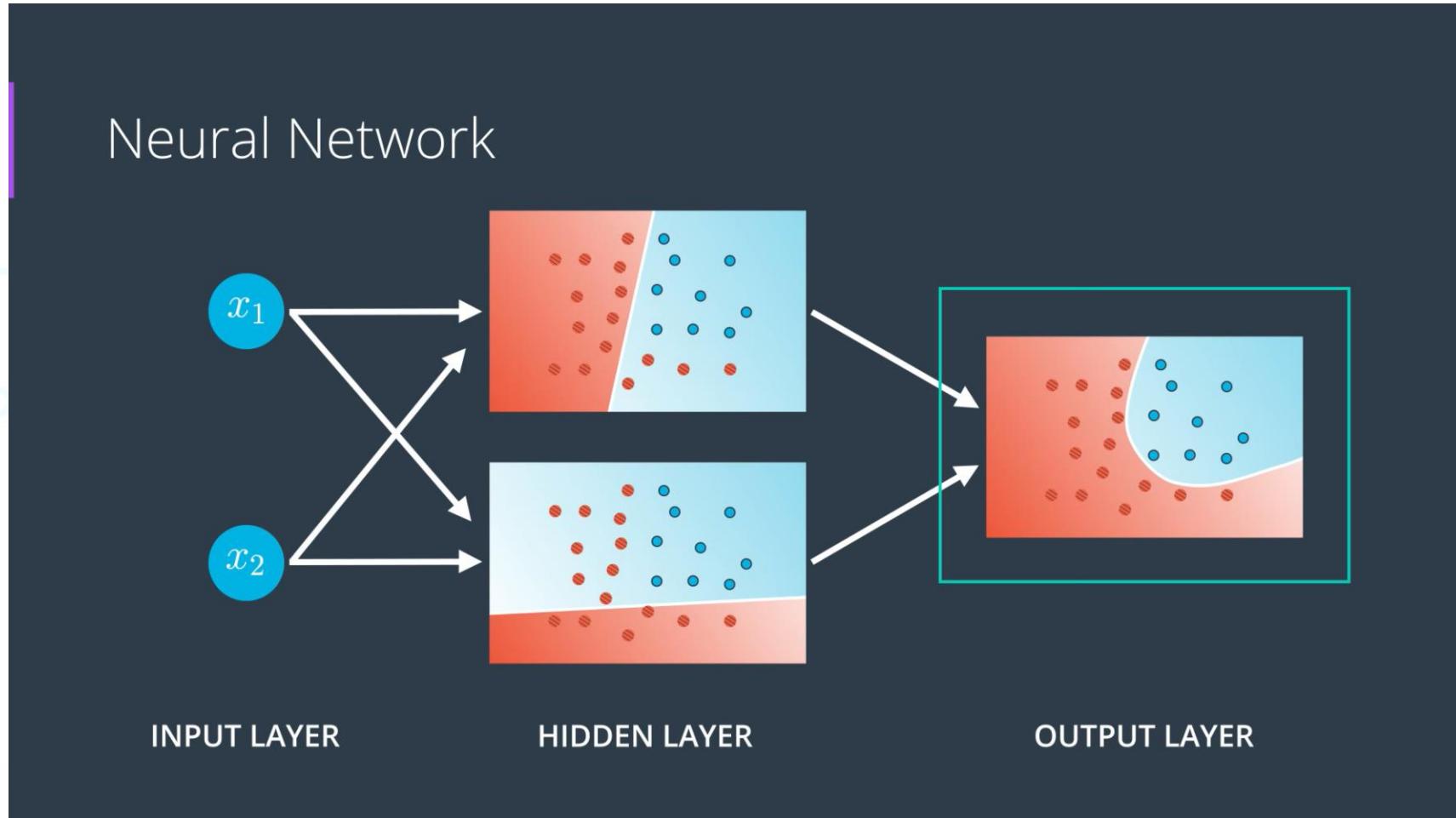
# Redes Neurais – Multiple Layers



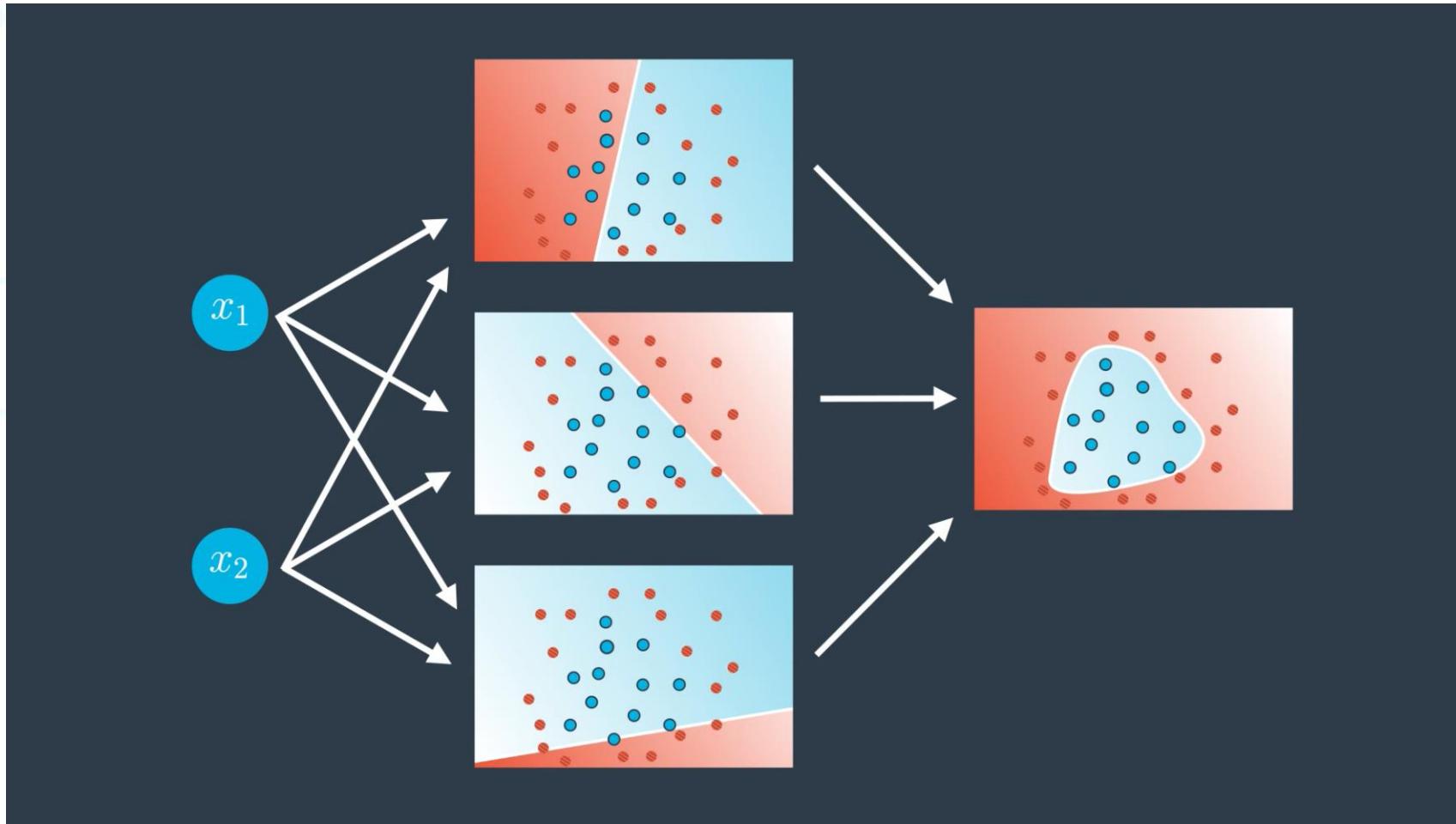
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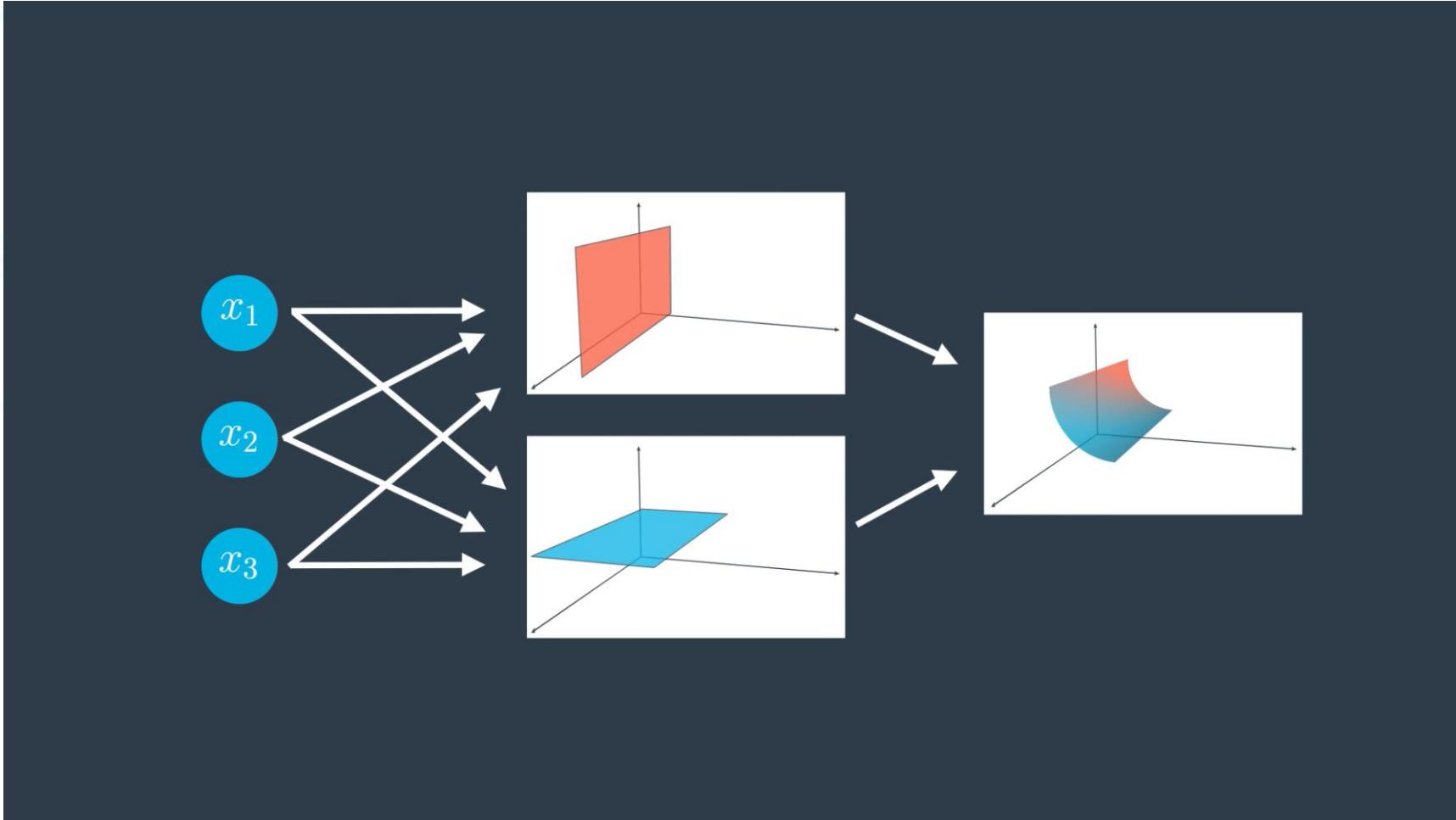
# Redes Neurais – Multiple Layers



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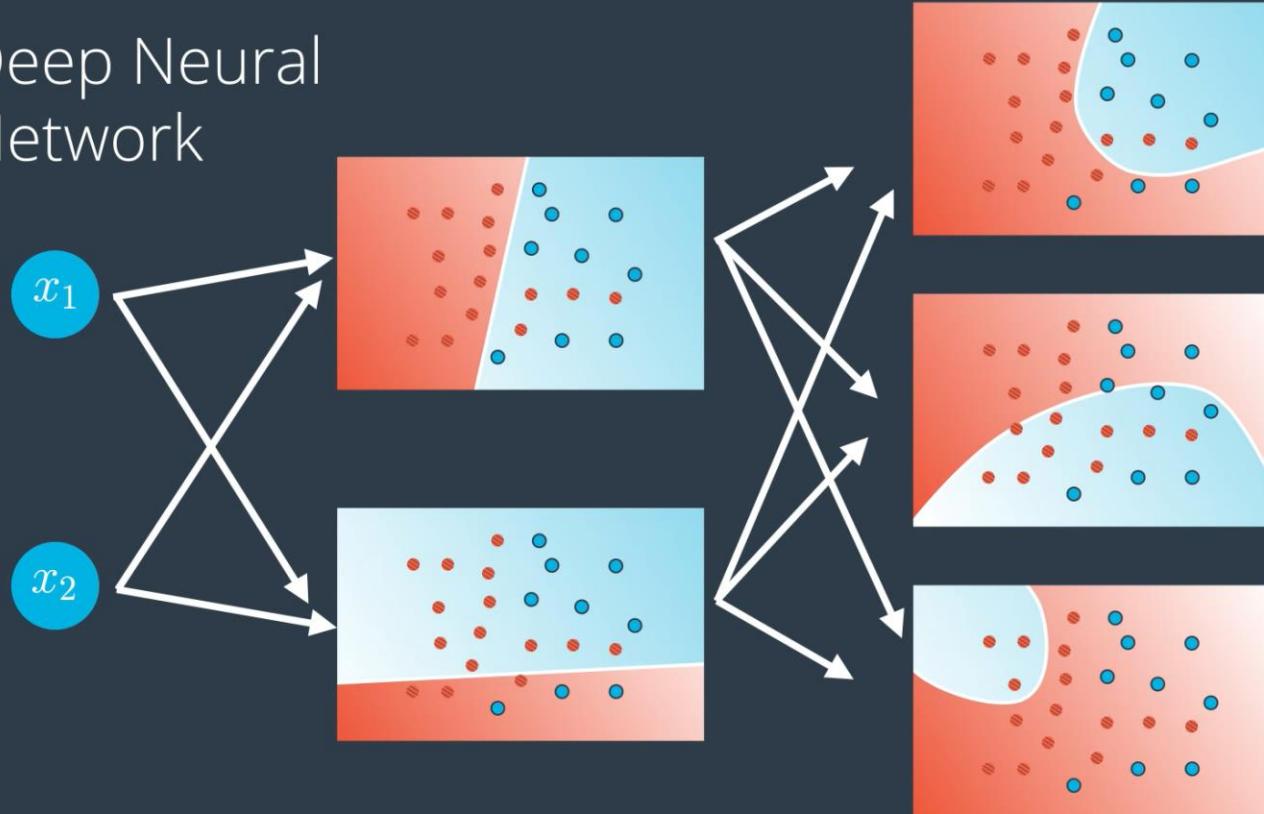


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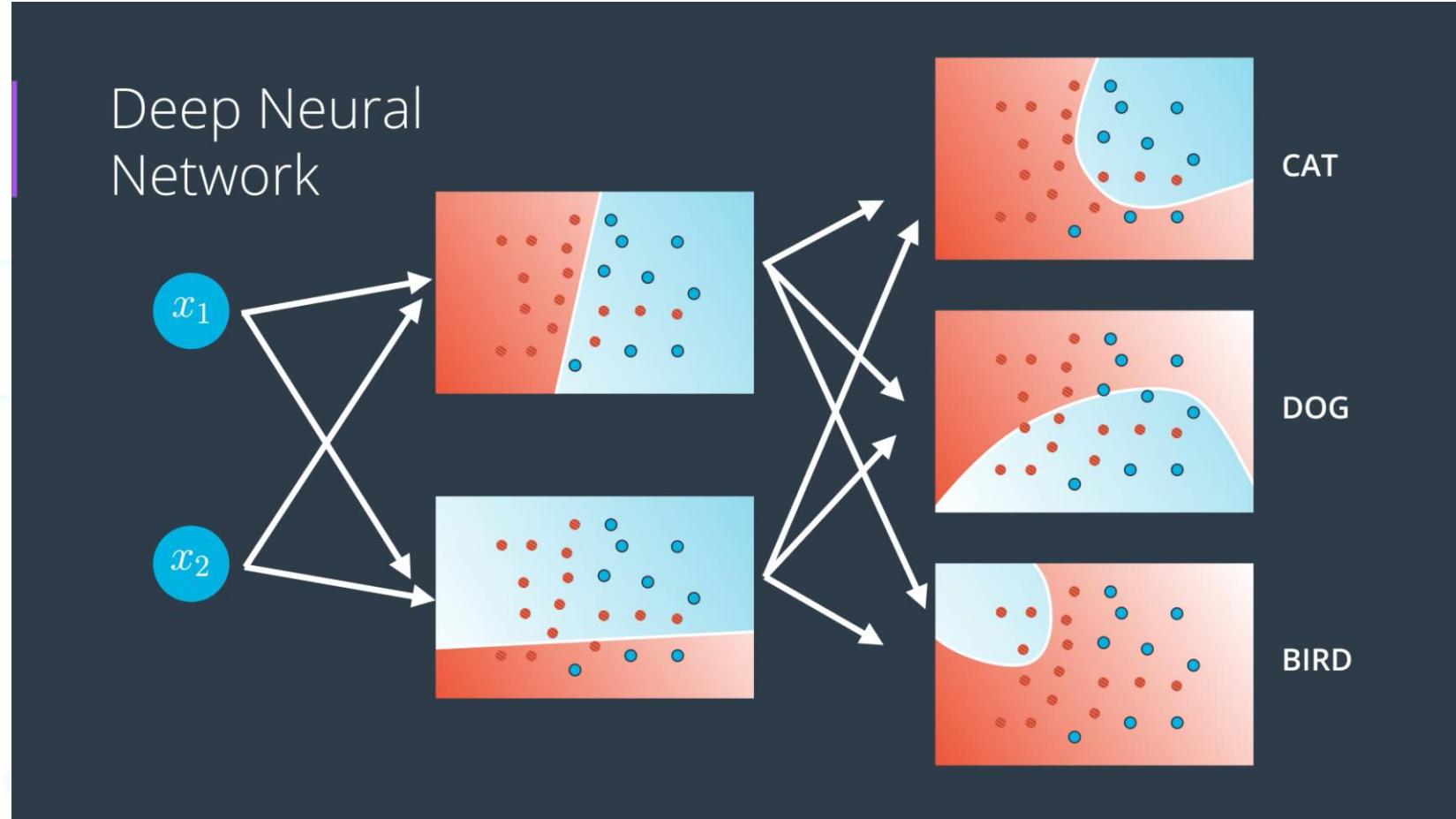


# Redes Neurais – Multiple Layers

Deep Neural Network

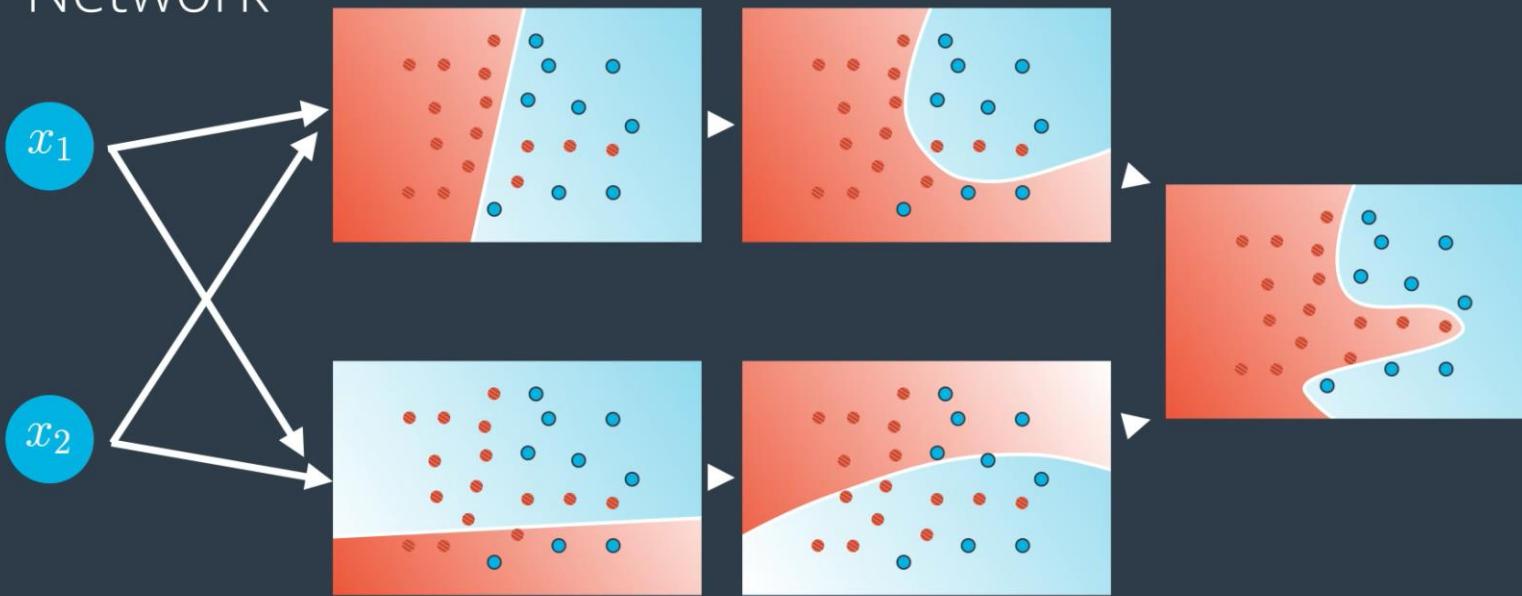


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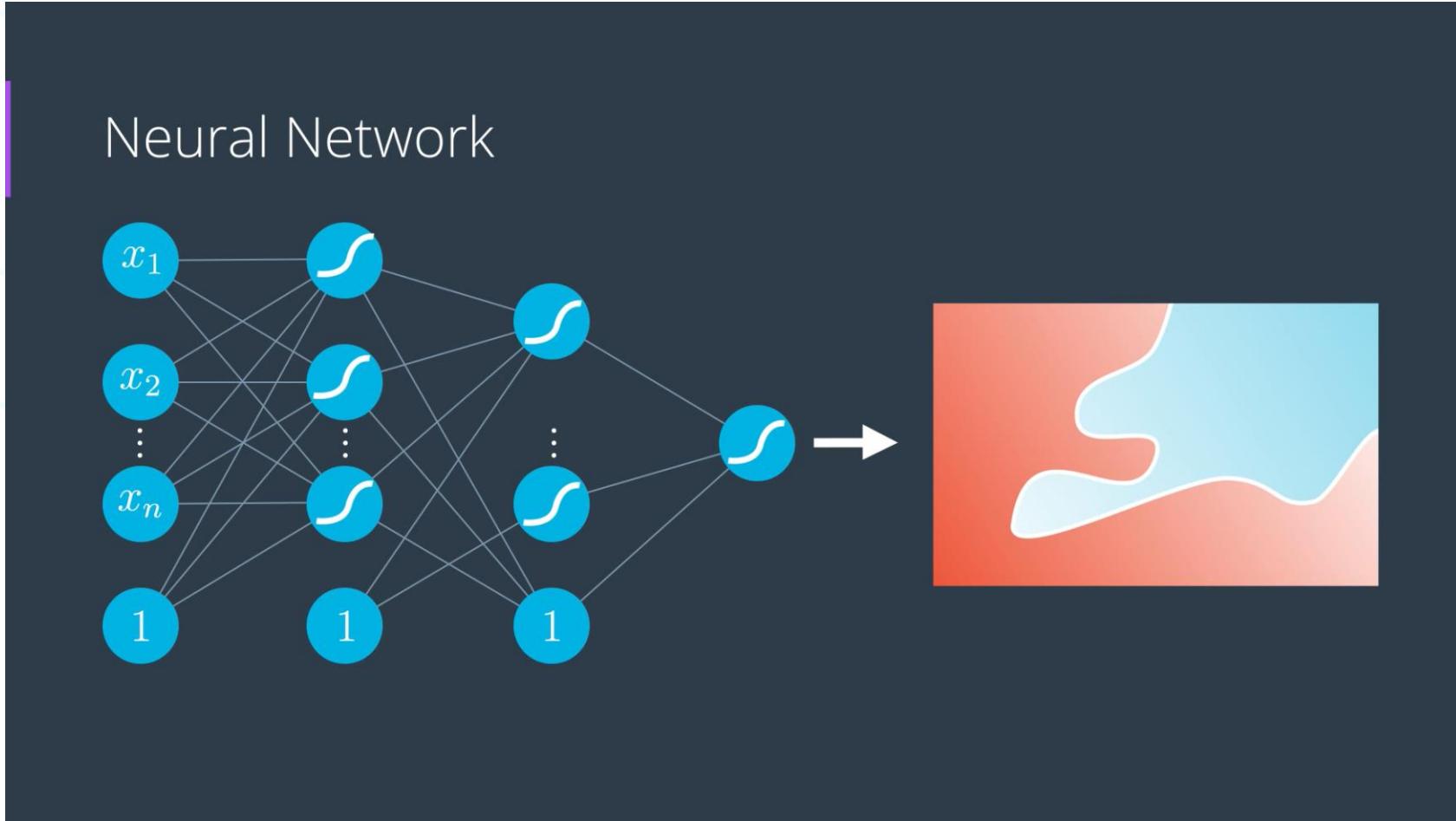


# Redes Neurais – Multiple Layers

Deep Neural Network

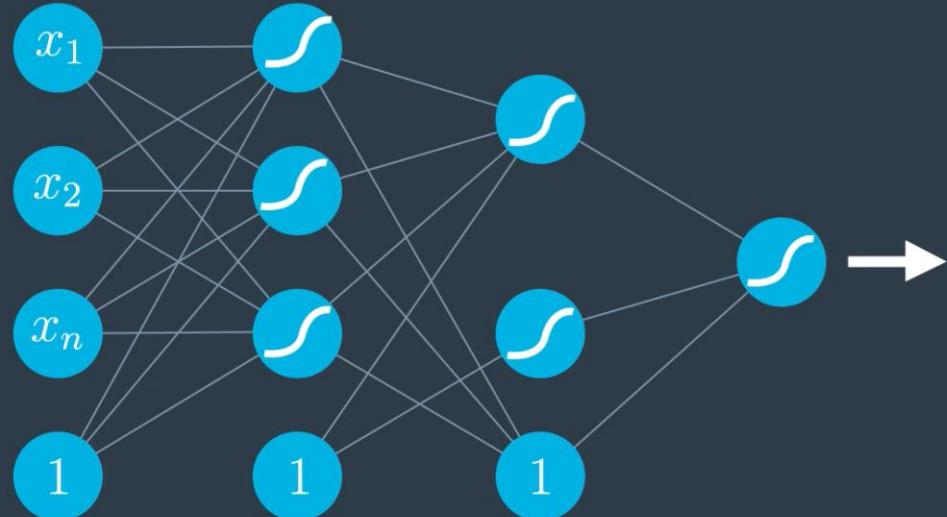


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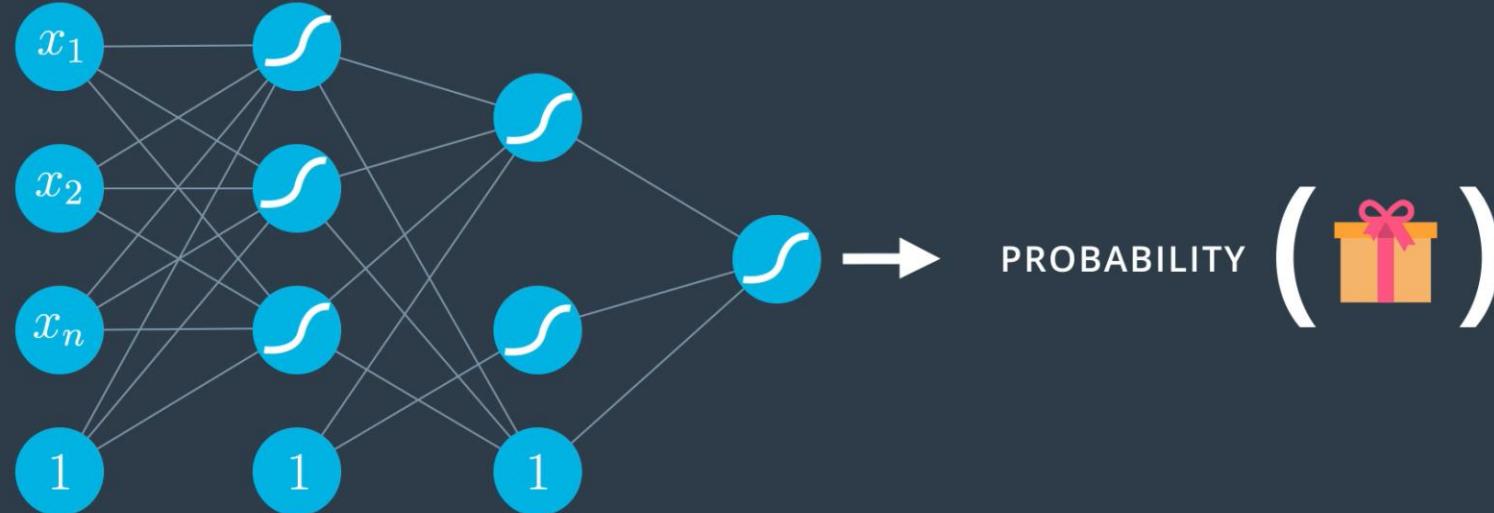
# Redes Neurais – Multi-Class classification

Binary Classification



# Redes Neurais – Multi-Class classification

Binary Classification



# Redes Neurais – Multi-Class classification

Multi-Class  
Classification

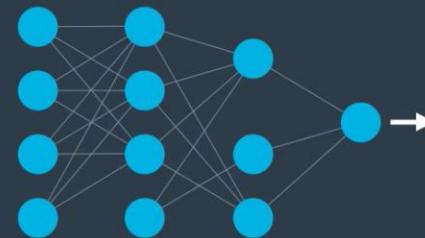
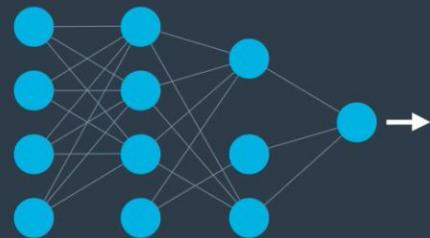
PROBABILITY 

PROBABILITY 

PROBABILITY 

# Redes Neurais – Multi-Class classification

## Multi-Class Classification

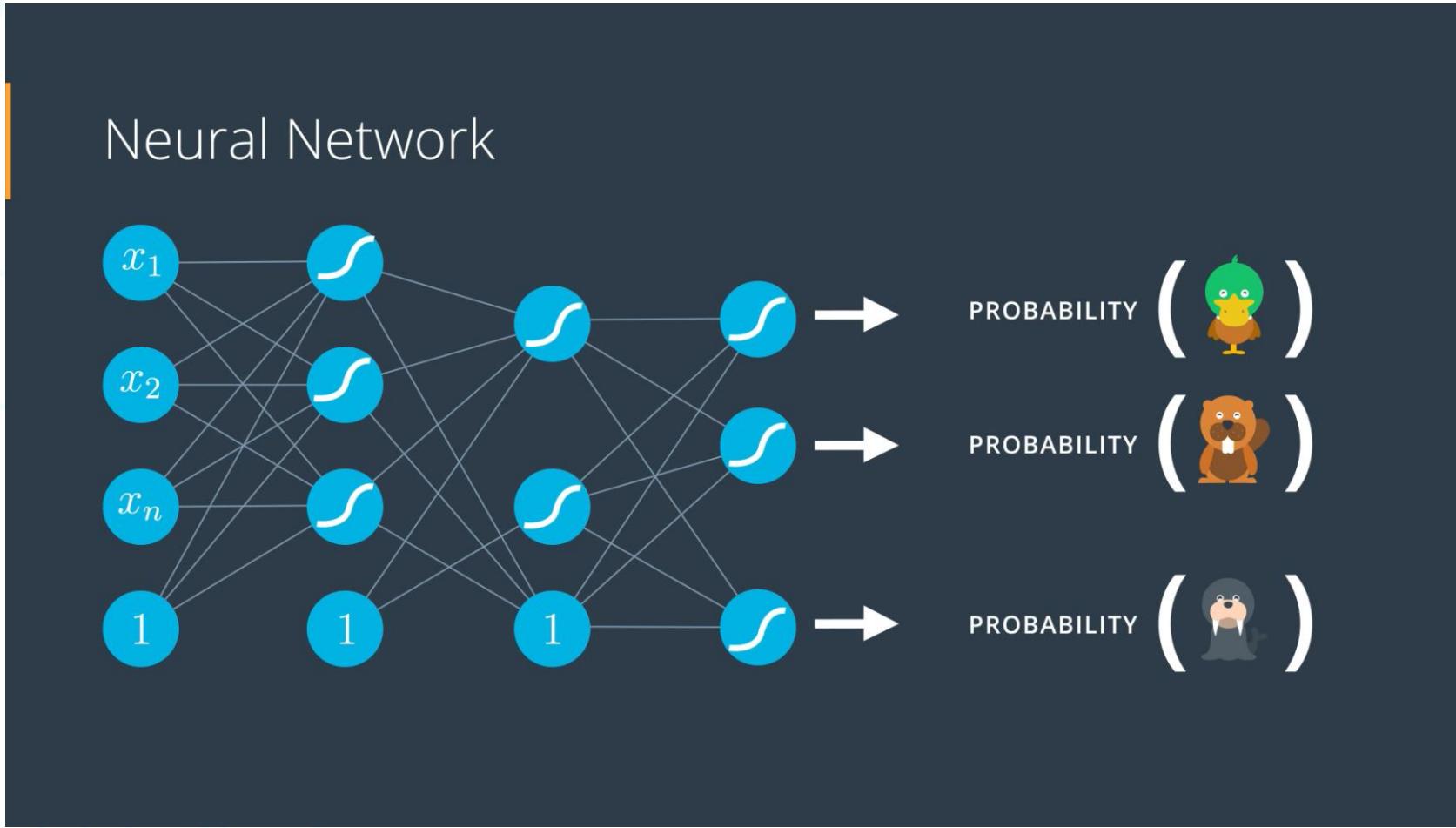


PROBABILITY 

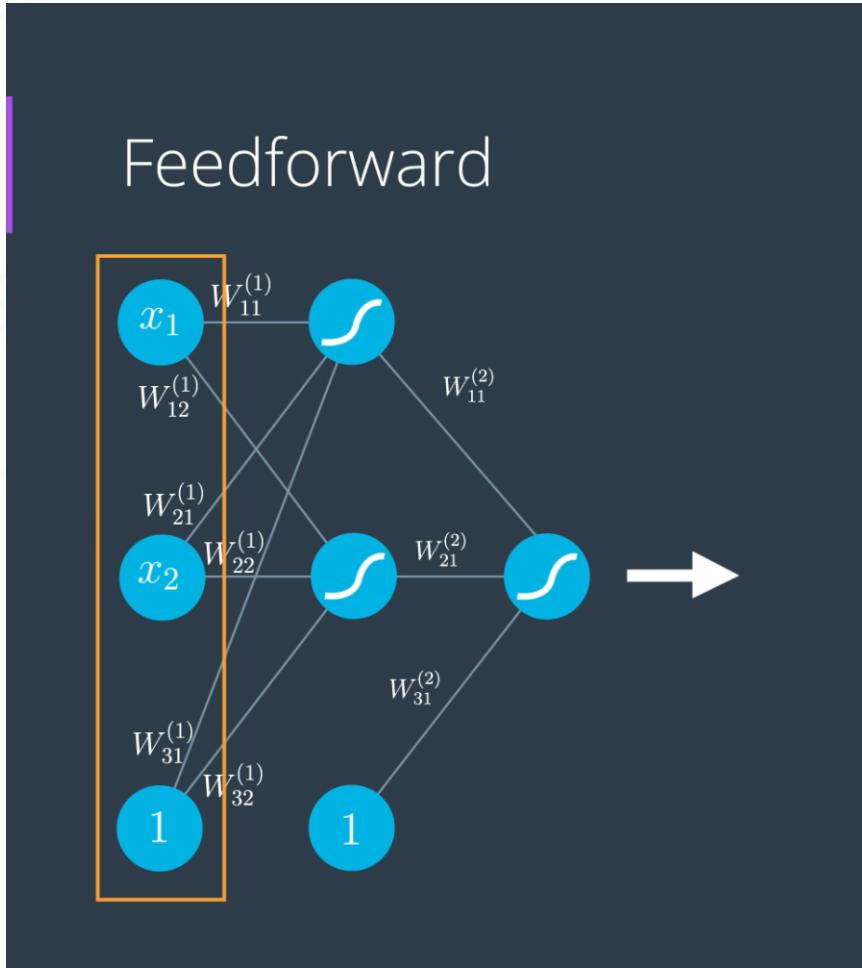
PROBABILITY 

PROBABILITY 

# Redes Neurais – Multi-Class classification



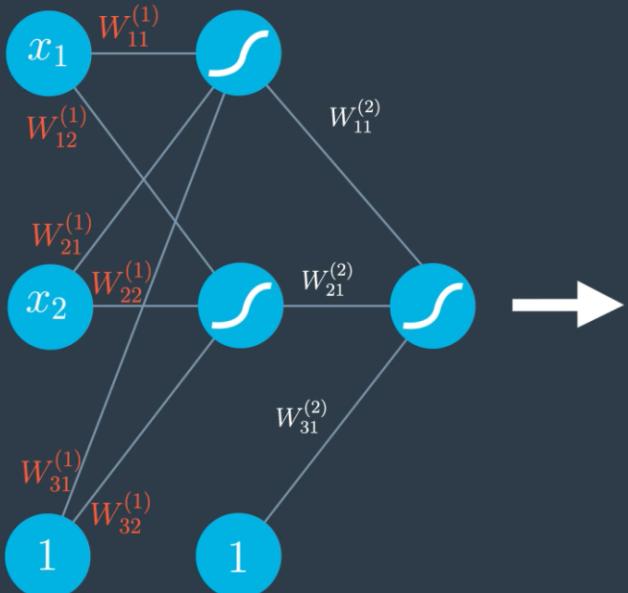
# Redes Neurais – Feedforward



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

# Redes Neurais – Feedforward

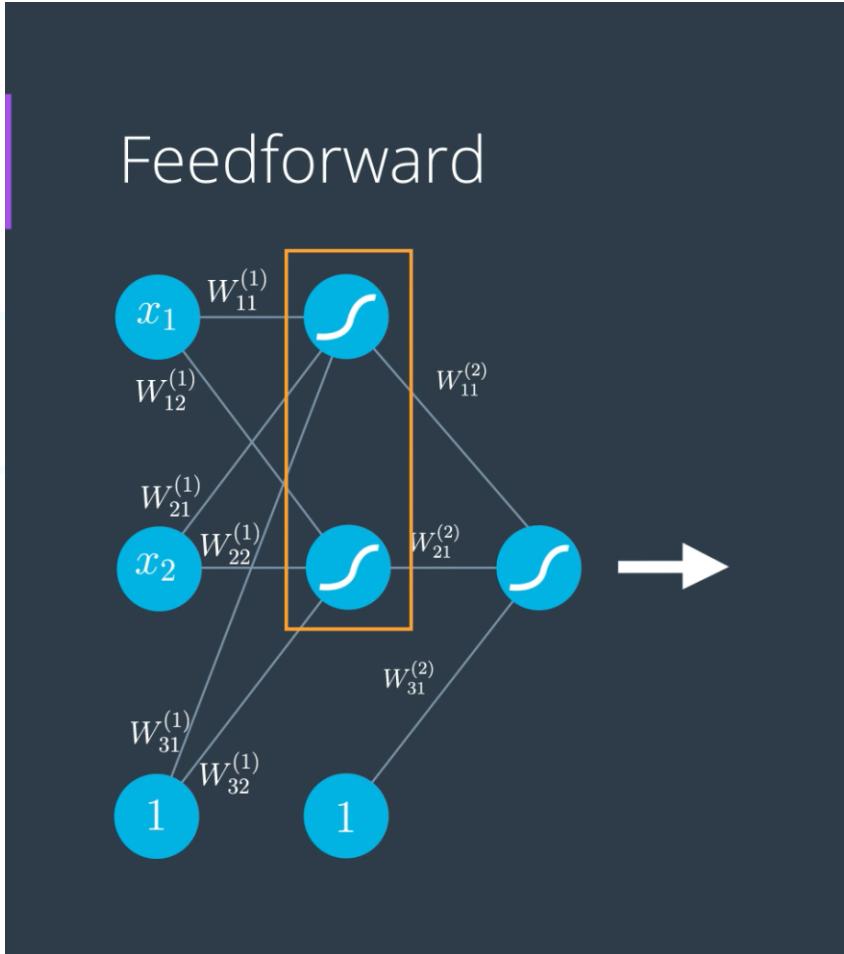
Feedforward



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



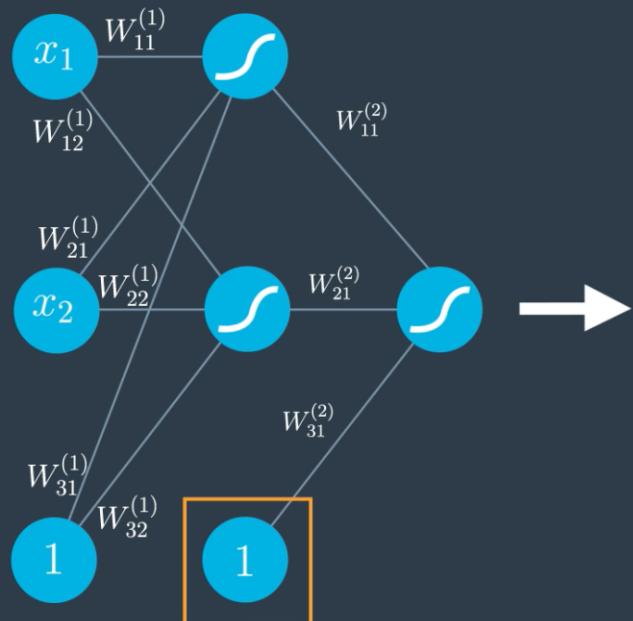
# Redes Neurais – Feedforward



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

# Redes Neurais – Feedforward

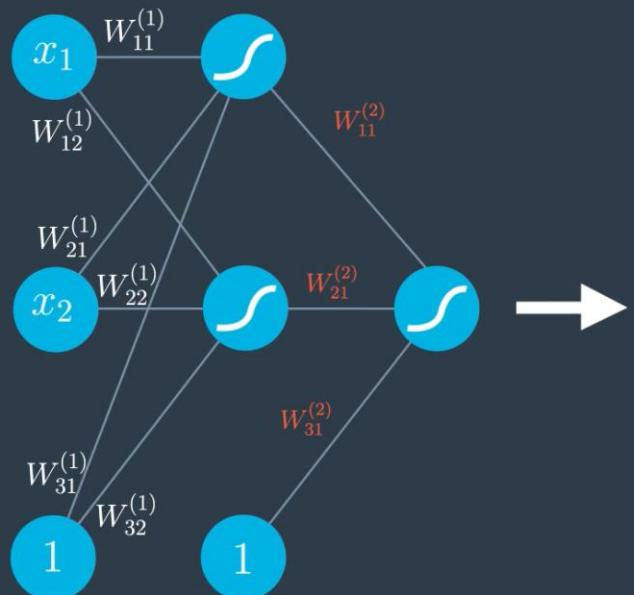
Feedforward



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

# Redes Neurais – Feedforward

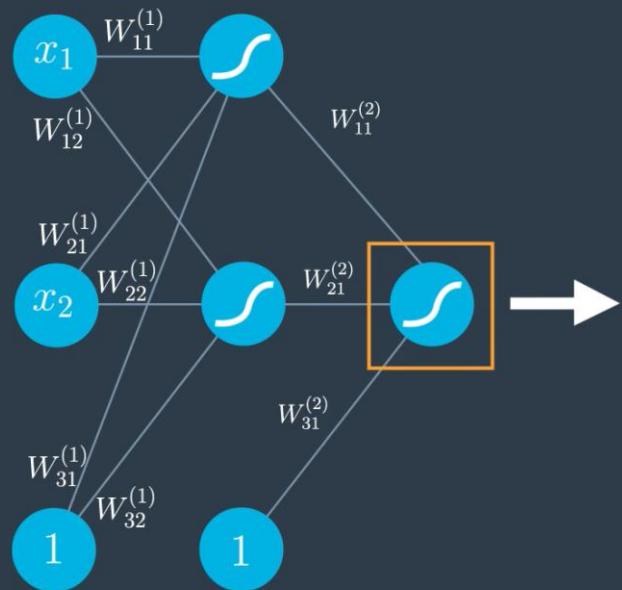
Feedforward



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

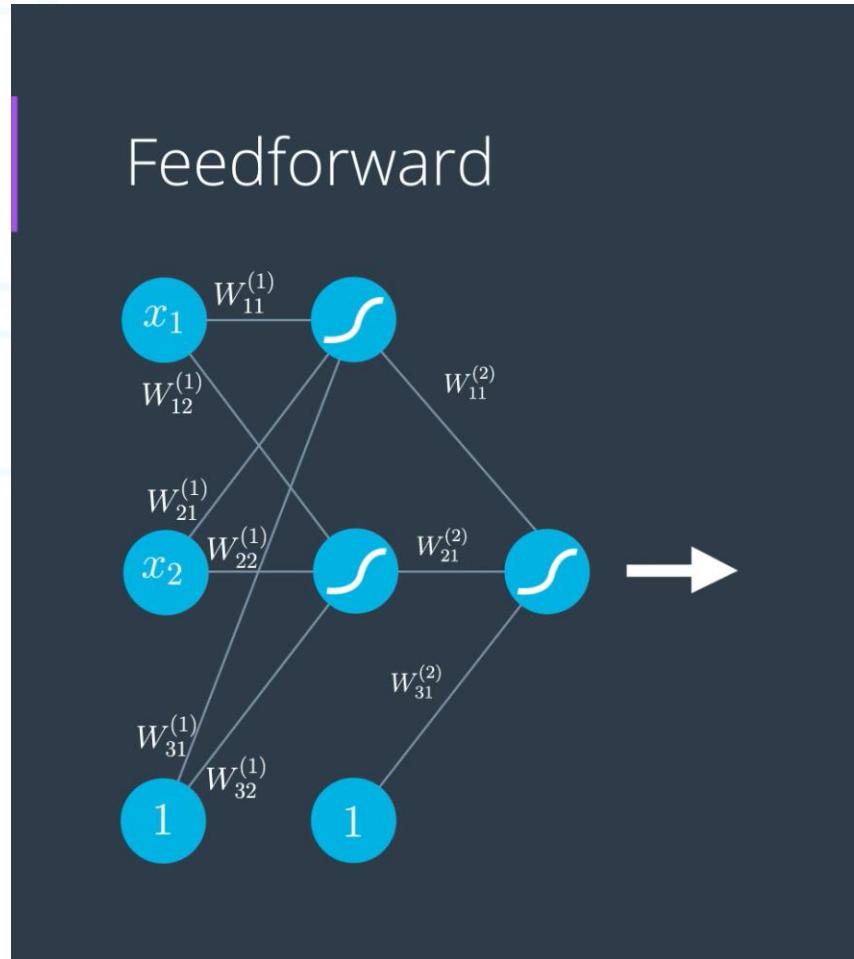
# Redes Neurais – Feedforward

Feedforward



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

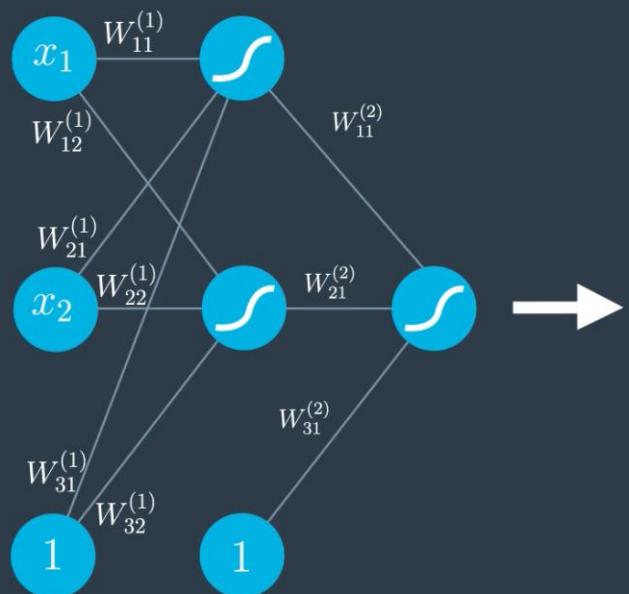
# Redes Neurais – Feedforward



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

# Redes Neurais – Feedforward

Feedforward

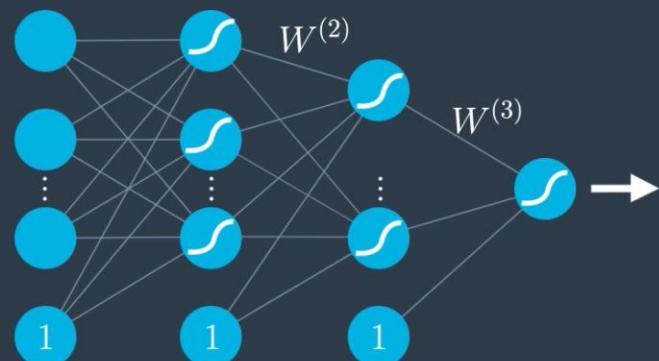


$$\hat{y} = \sigma \begin{pmatrix} W_{11}^{(2)} \\ W_{21}^{(2)} \\ W_{31}^{(2)} \end{pmatrix} \sigma \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$

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

# Redes Neurais – Error Function

Multi-layer Perceptron

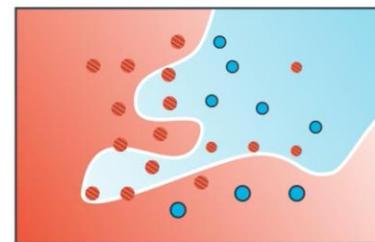


PREDICTION

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

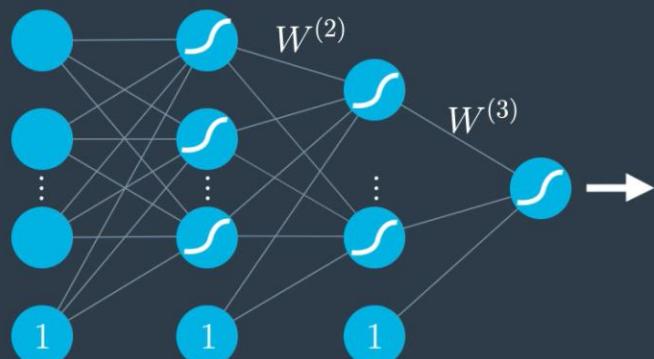
ERROR FUNCTION

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



# Redes Neurais – Error Function

Multi-layer Perceptron

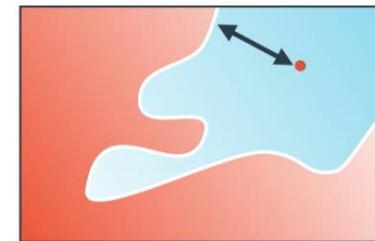


PREDICTION

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

ERROR FUNCTION

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



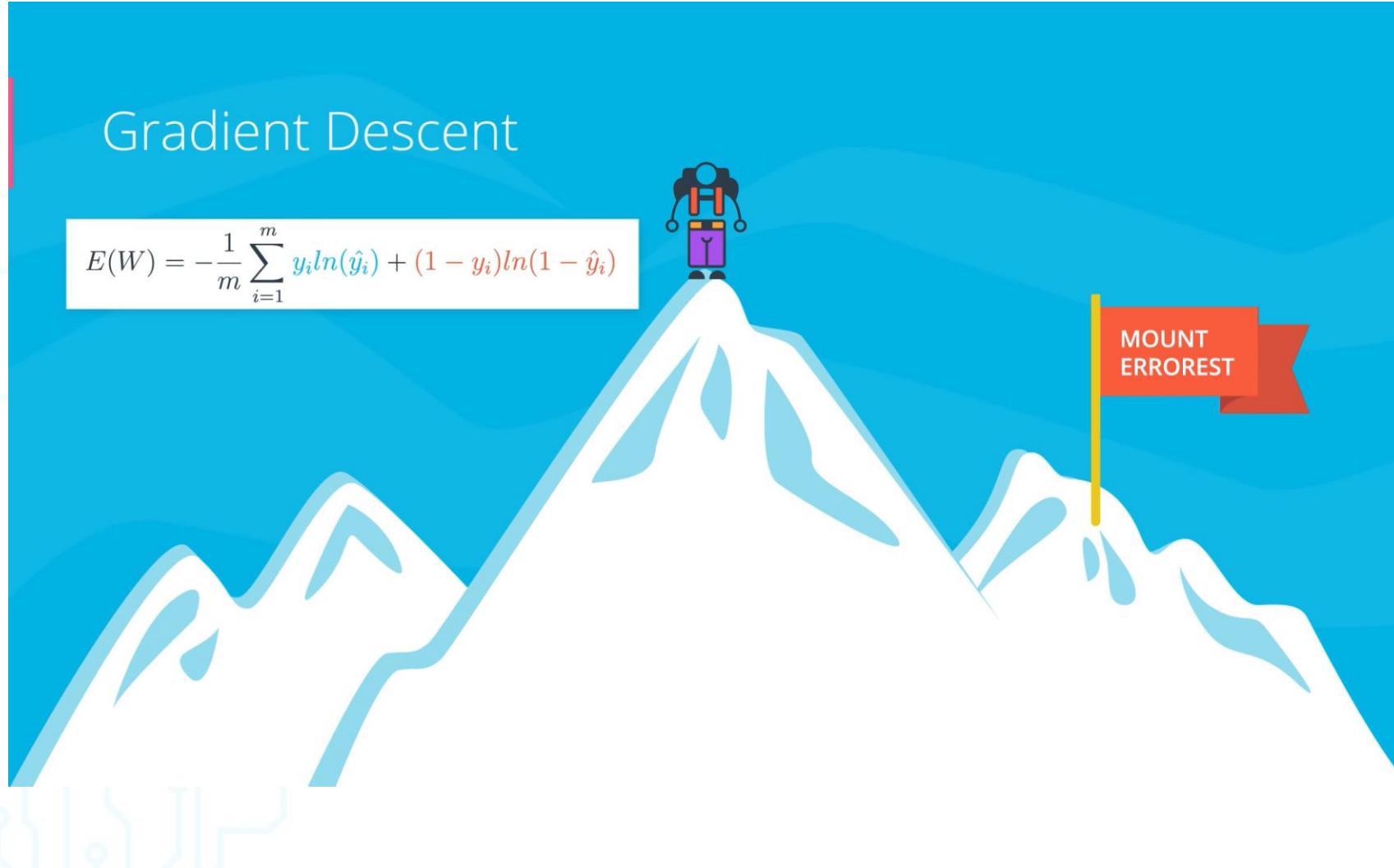
# Redes Neurais – Backpropagation

## Gradient Descent

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



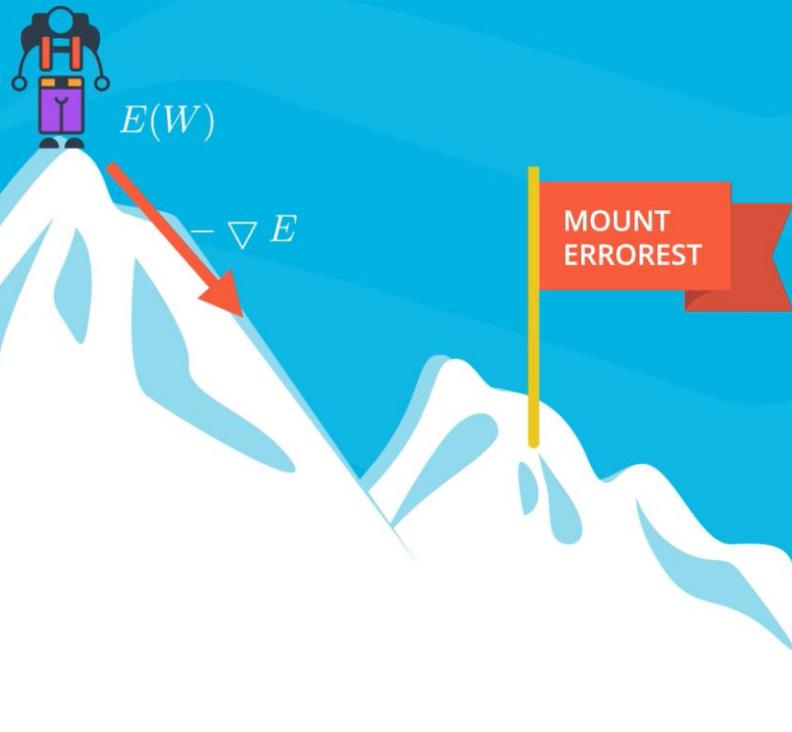
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# Redes Neurais – Backpropagation

## Gradient Descent

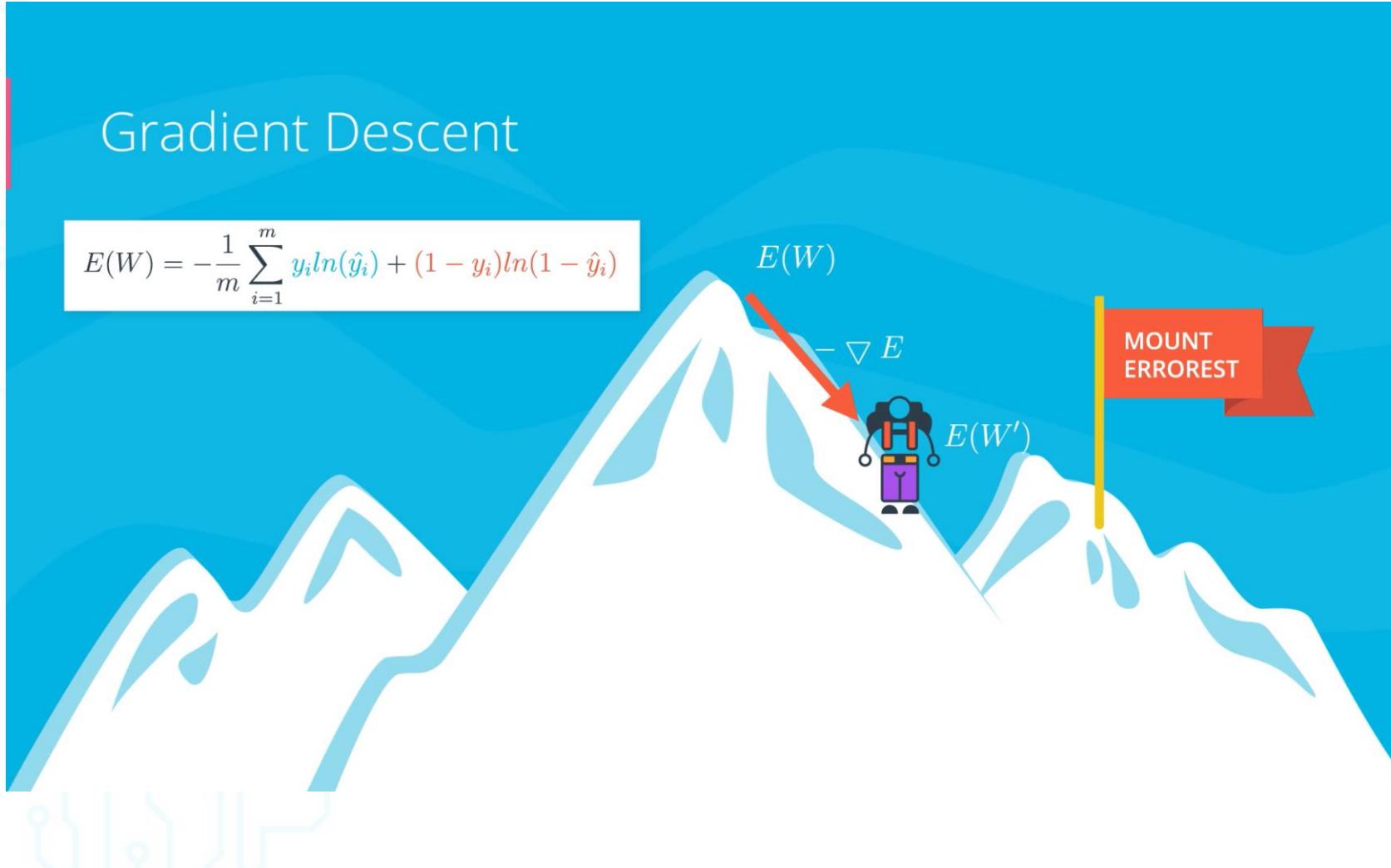
$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$



# Redes Neurais – Backpropagation

## Gradient Descent

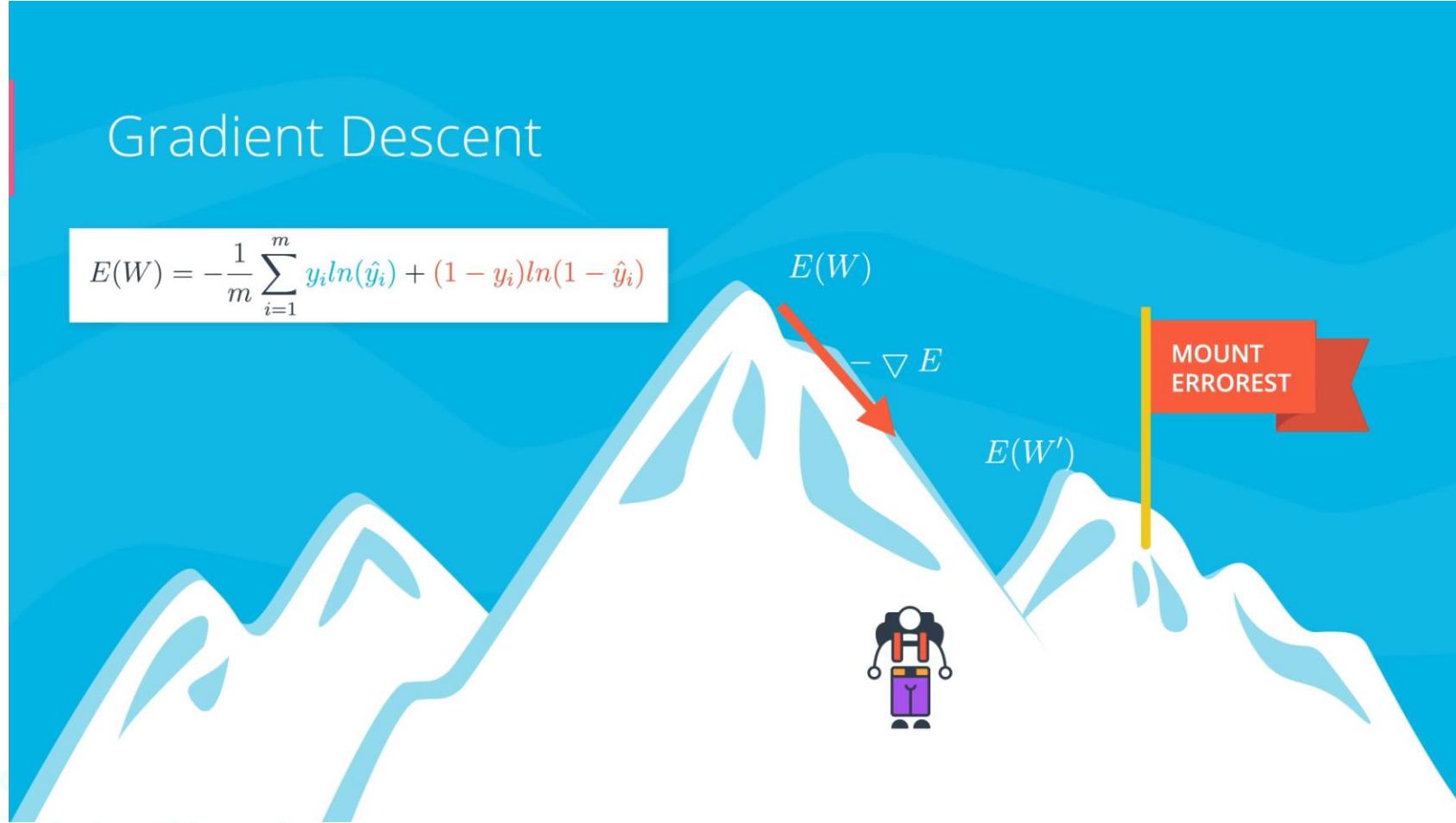
$$E(W) = -\frac{1}{m} \sum_{i=1}^m y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)$$



# Redes Neurais – Backpropagation

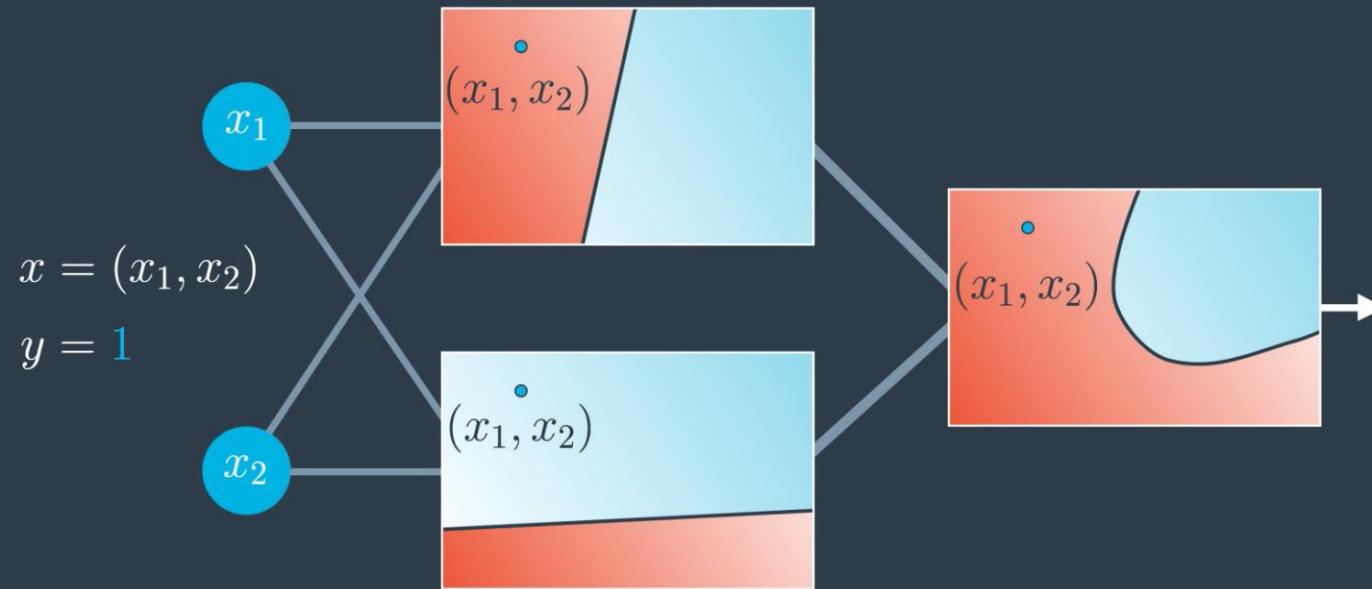
## Gradient Descent

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



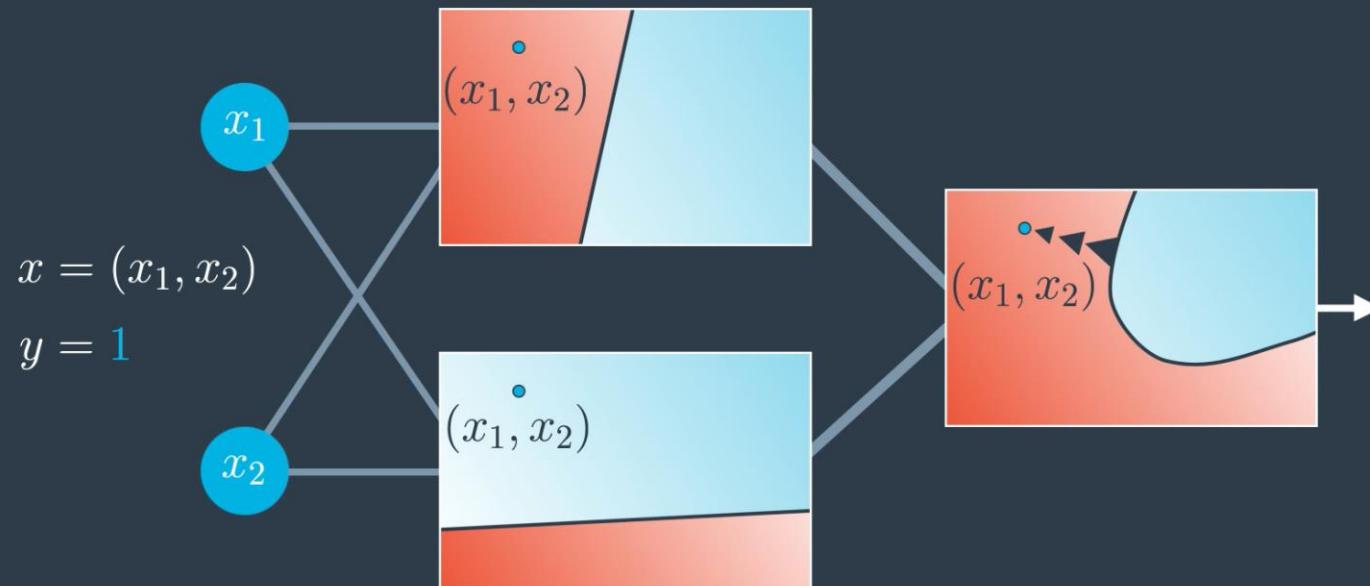
# Redes Neurais – Backpropagation

FeedForward



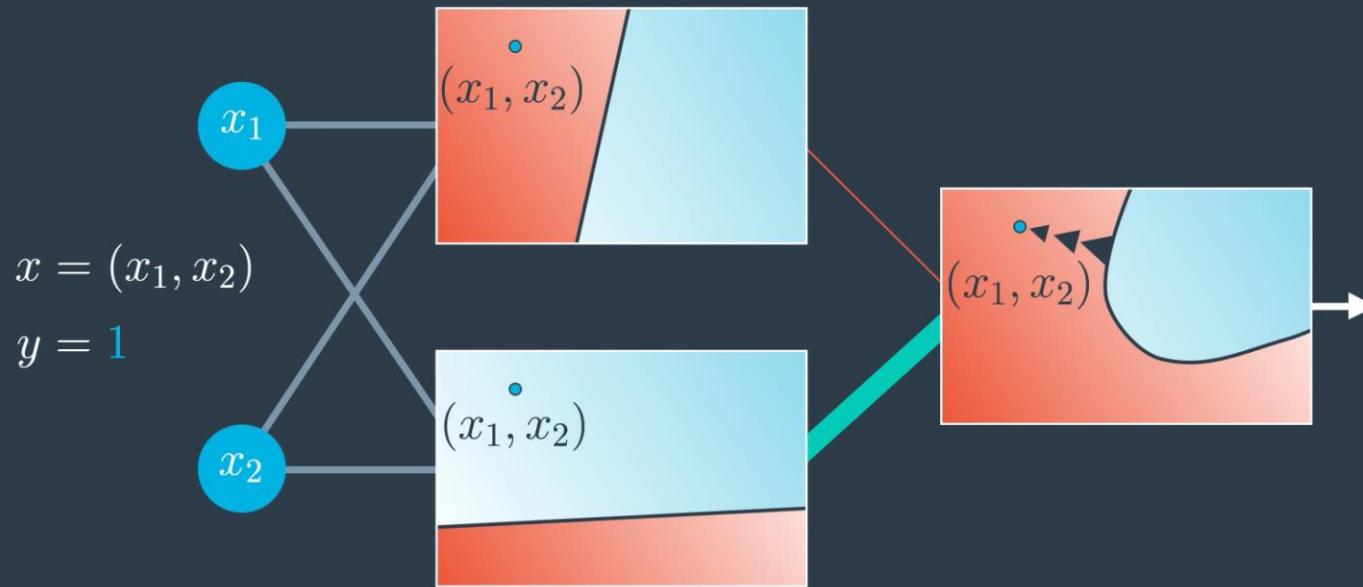
# Redes Neurais – Backpropagation

Backpropagation



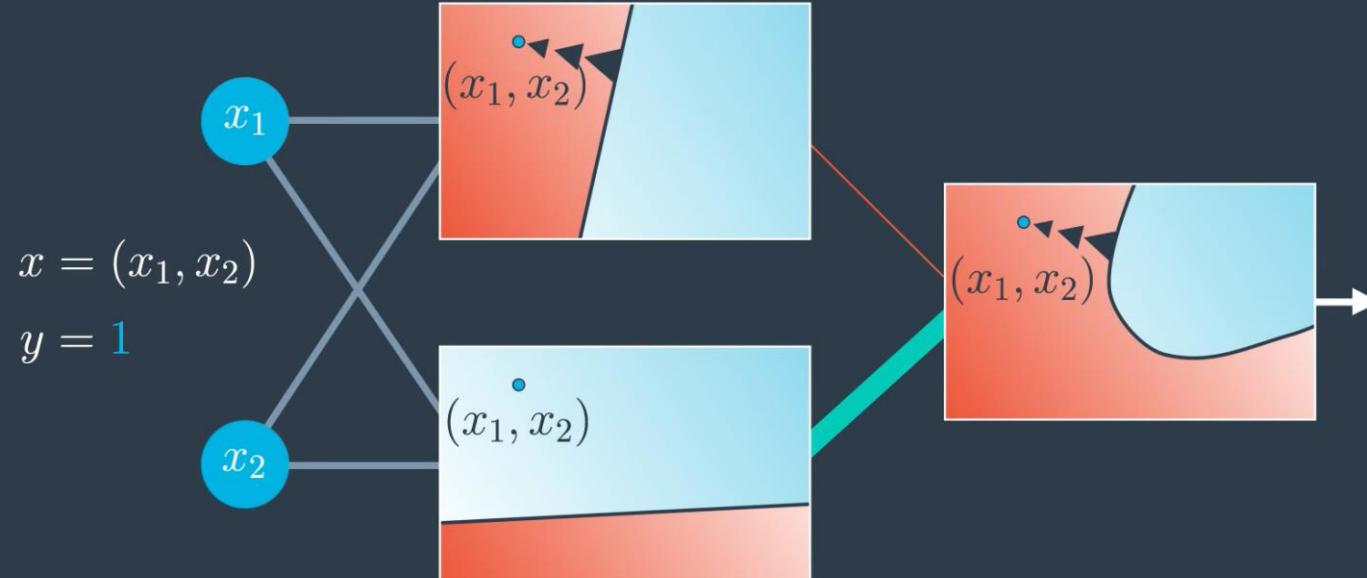
# Redes Neurais – Backpropagation

Backpropagation



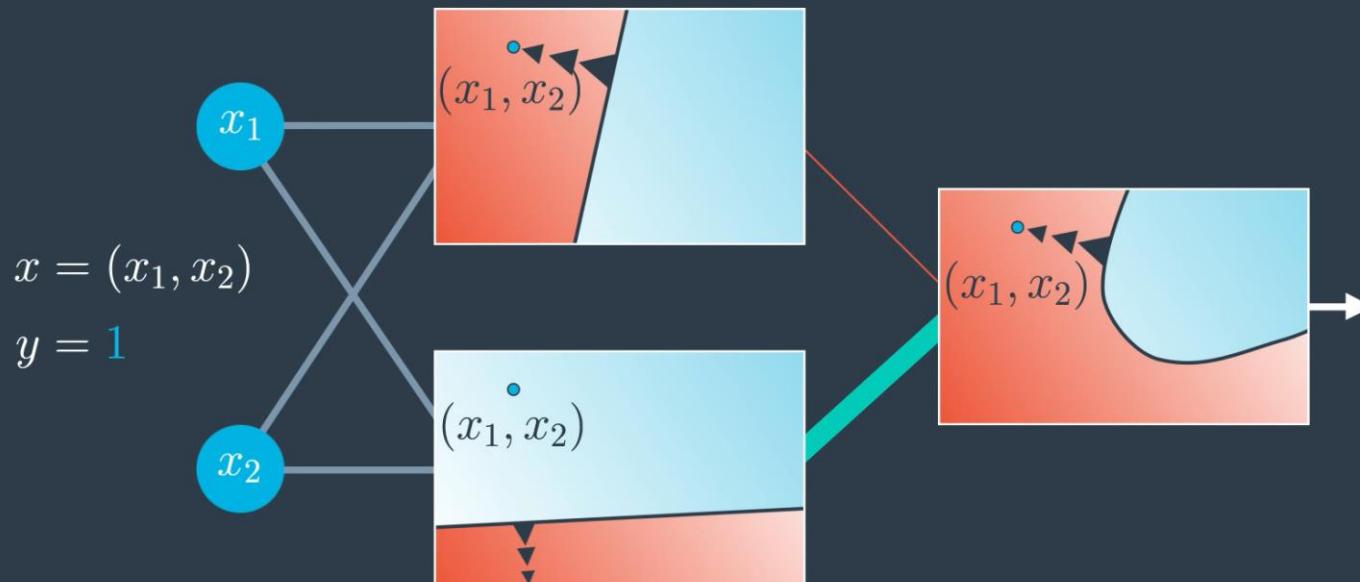
# Redes Neurais – Backpropagation

Backpropagation



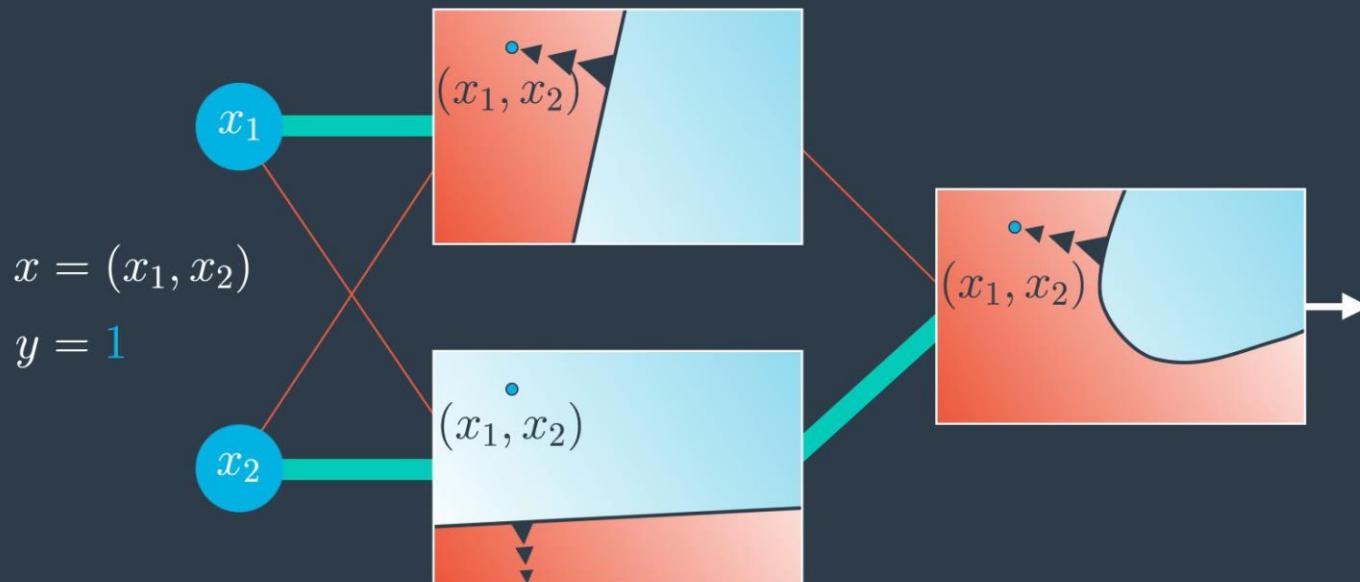
# Redes Neurais – Backpropagation

## Backpropagation



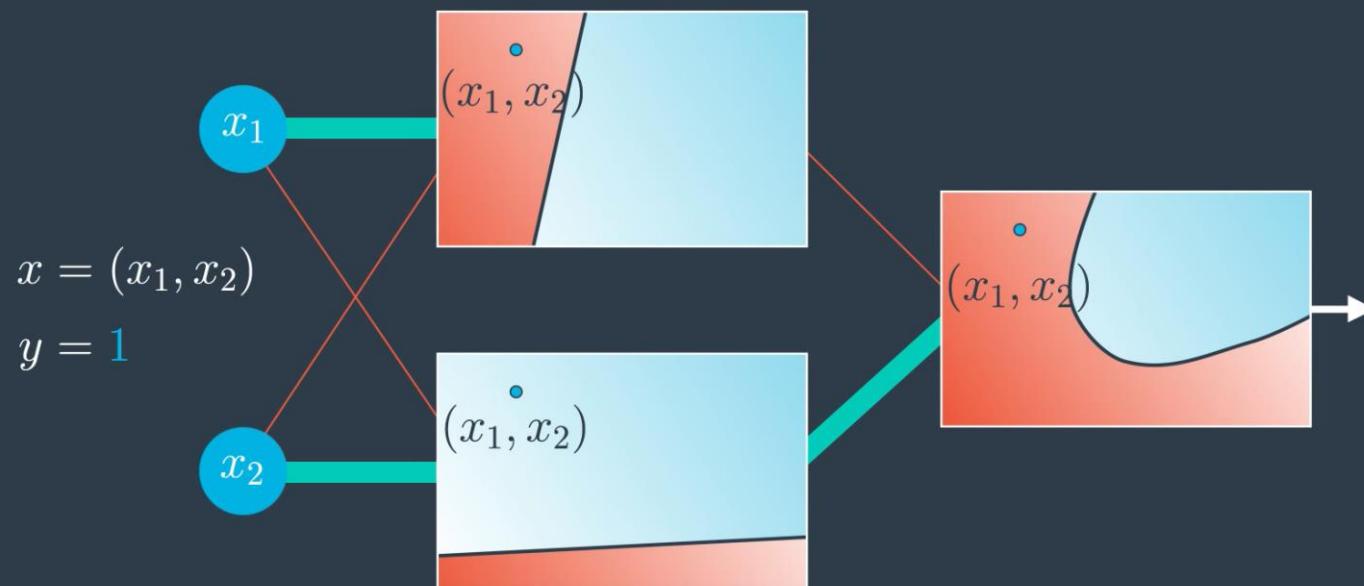
# Redes Neurais – Backpropagation

## Backpropagation

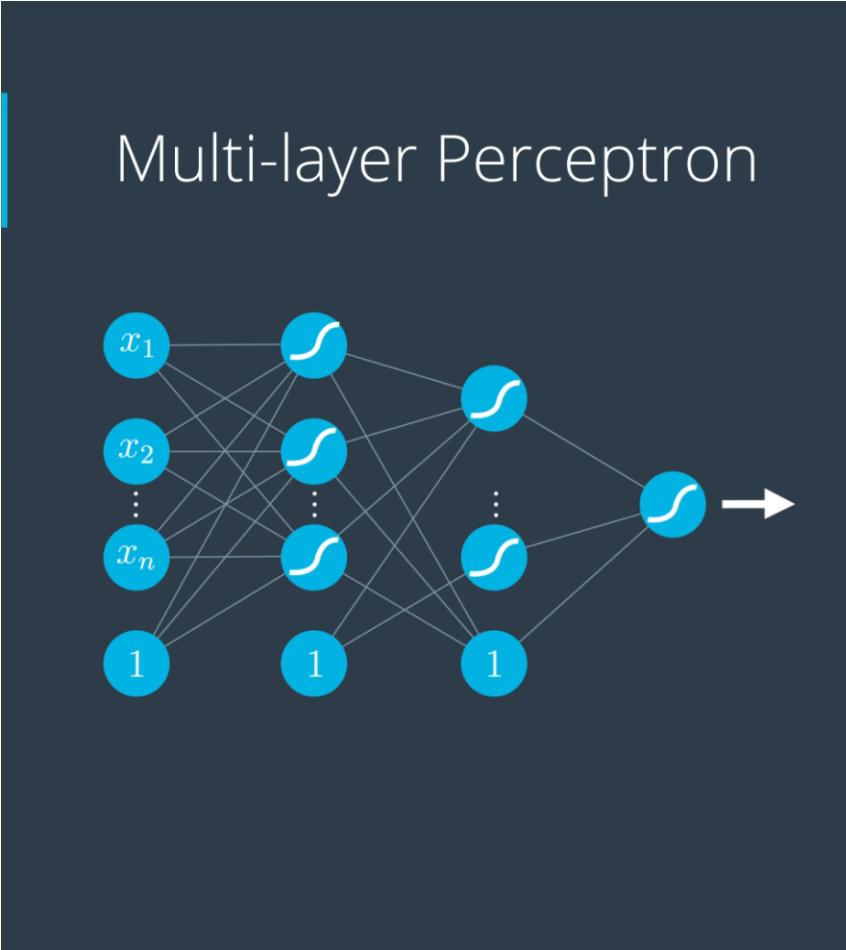


# Redes Neurais – Backpropagation

## Backpropagation



# Redes Neurais – Backpropagation



### PREDICTION

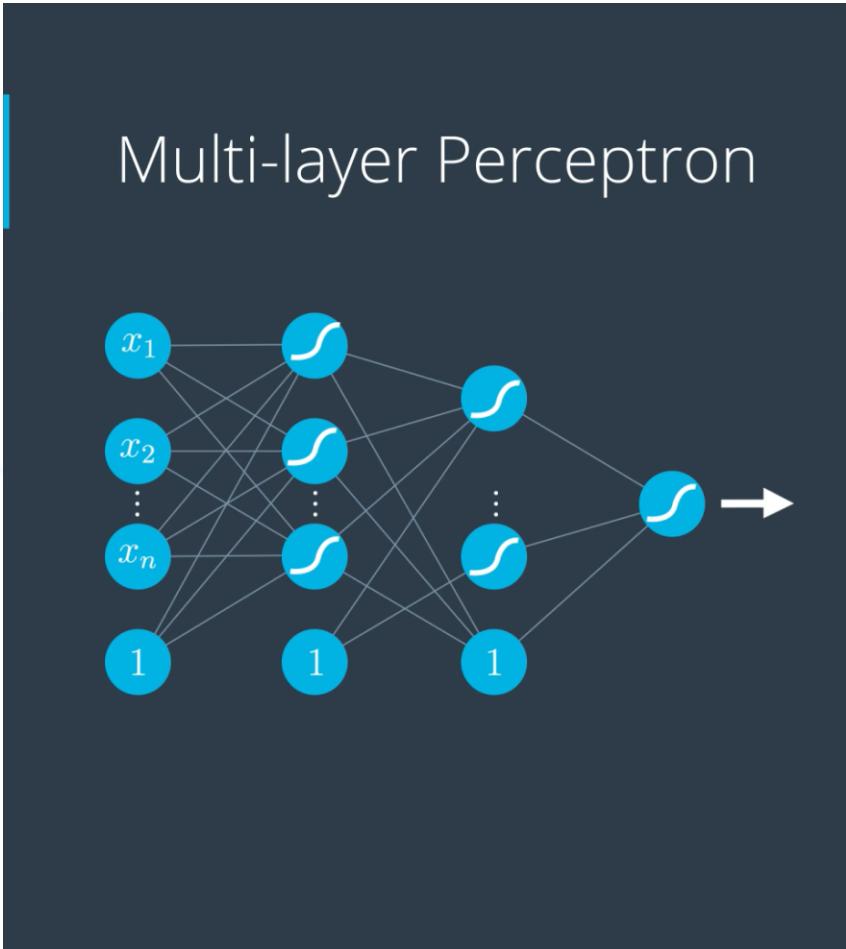
$$\hat{y} = \sigma W^{(3)} \circ \sigma W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

### 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

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

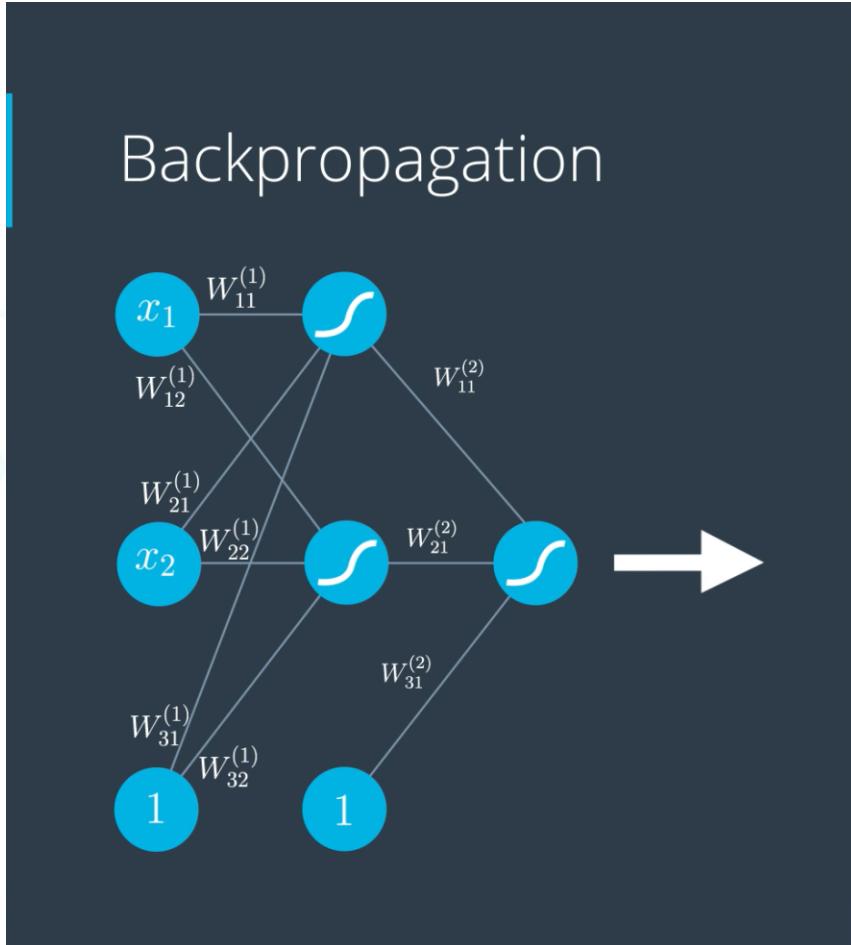
### ERROR FUNCTION

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

### GRADIENT OF THE ERROR FUNCTION

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

# Redes Neurais – Backpropagation



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

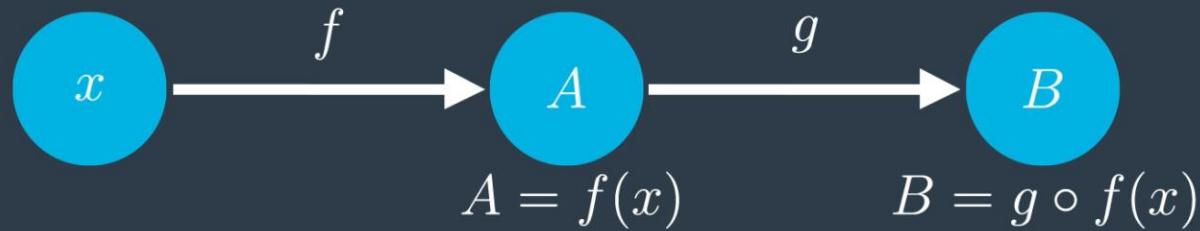
$$W^{(1)} = \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \quad W^{(2)} = \begin{pmatrix} W_{11}^{(2)} \\ W_{21}^{(2)} \\ W_{31}^{(2)} \end{pmatrix}$$

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

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

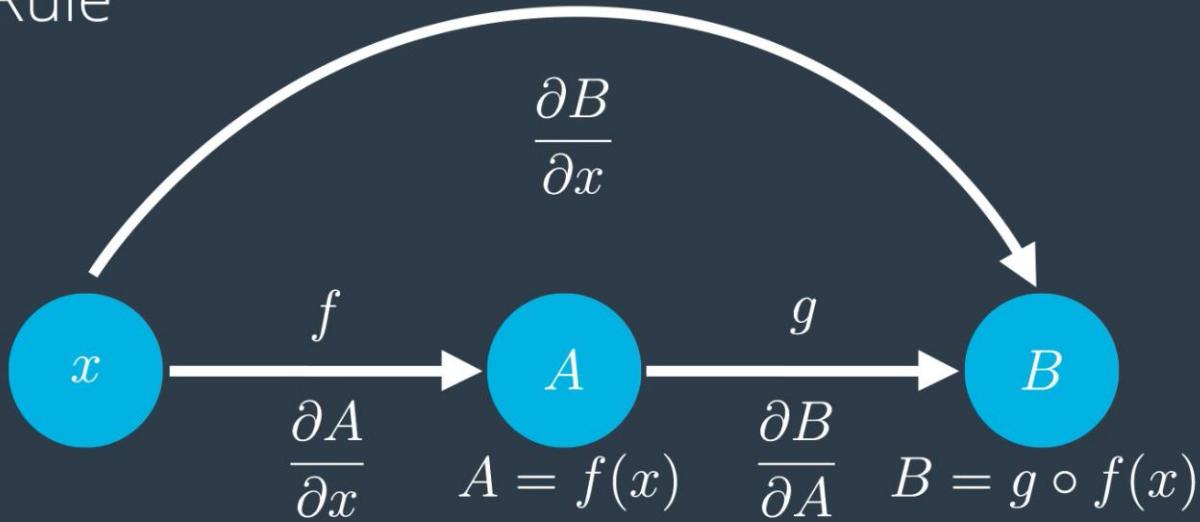
# Redes Neurais – Backpropagation

Chain Rule



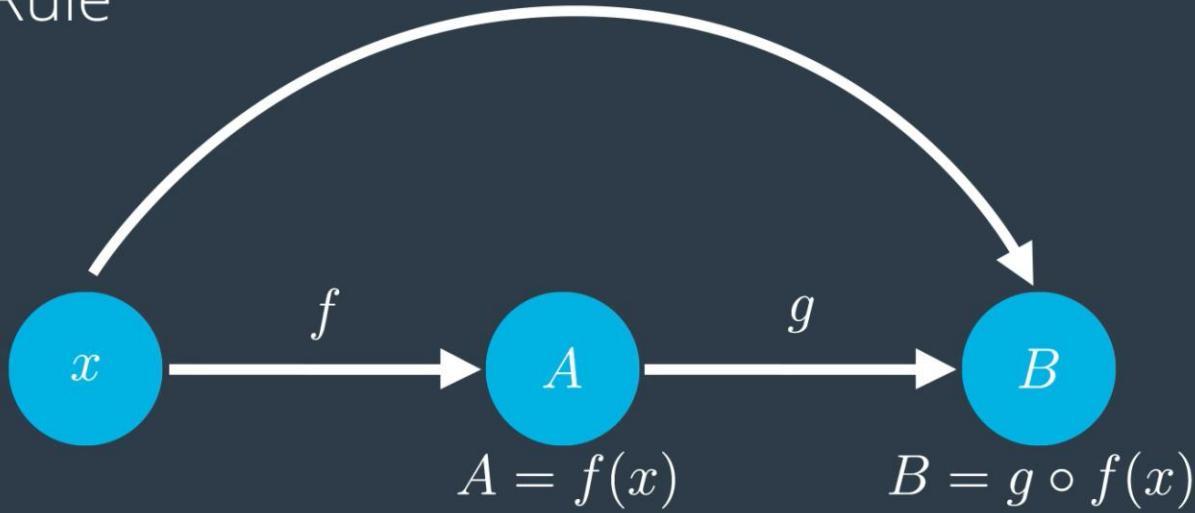
# Redes Neurais – Backpropagation

Chain Rule



# Redes Neurais – Backpropagation

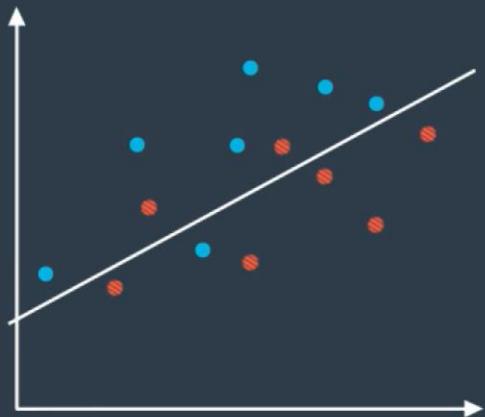
Chain Rule



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

# Redes Neurais – Testing

WHICH MODEL IS BETTER?

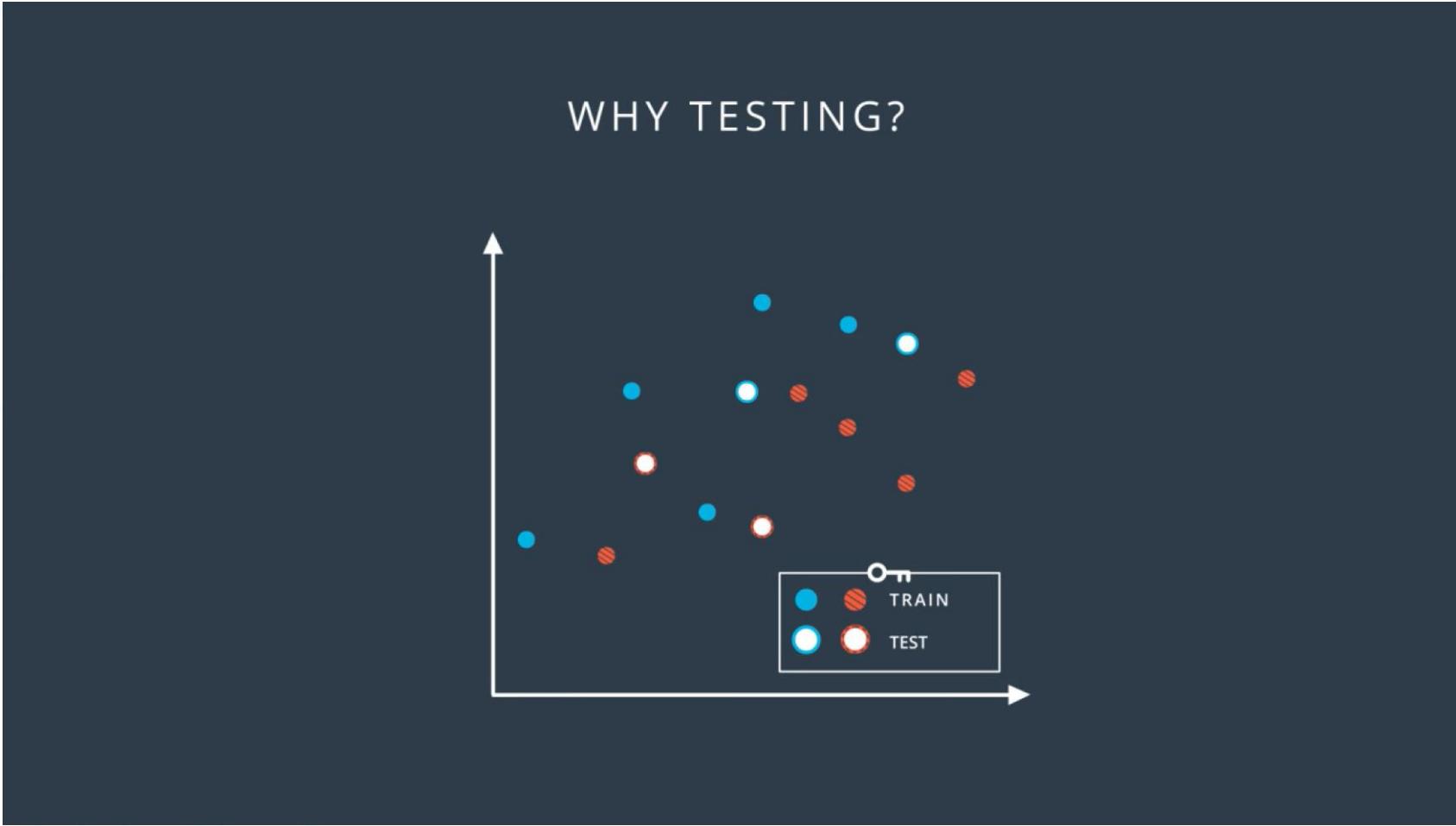


# Redes Neurais – Testing

WHY TESTING?

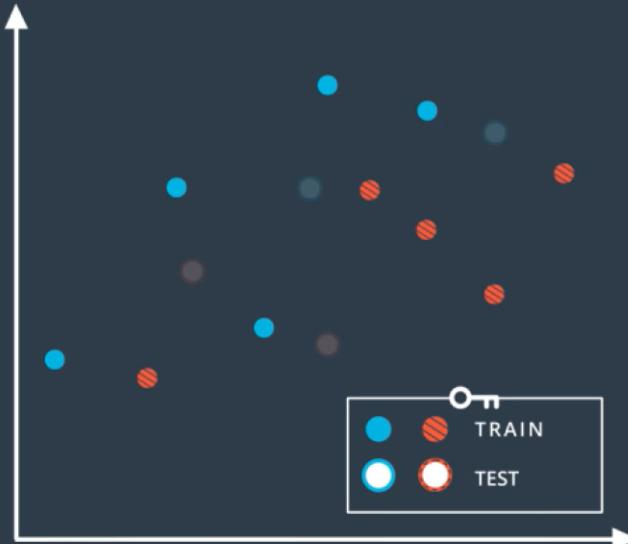


# Redes Neurais – Testing



# Redes Neurais – Testing

WHY TESTING?



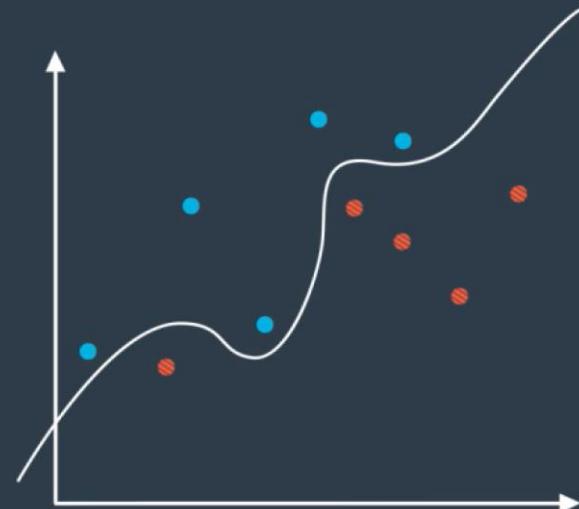
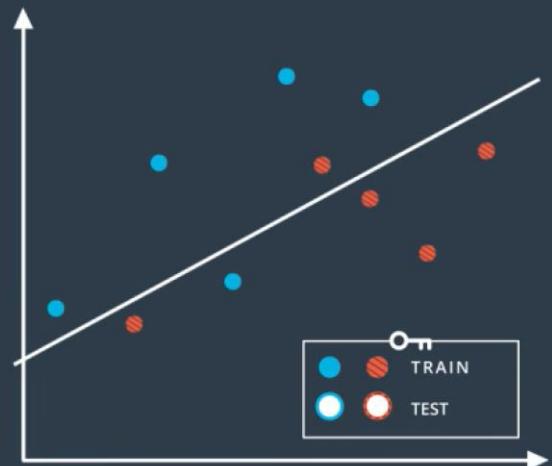
# Redes Neurais – Testing

WHY TESTING?



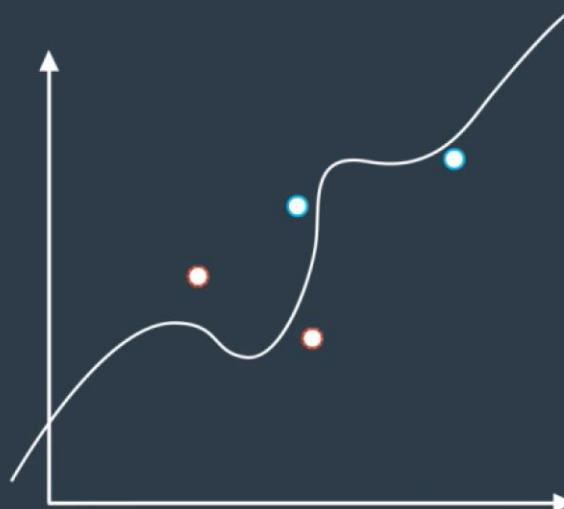
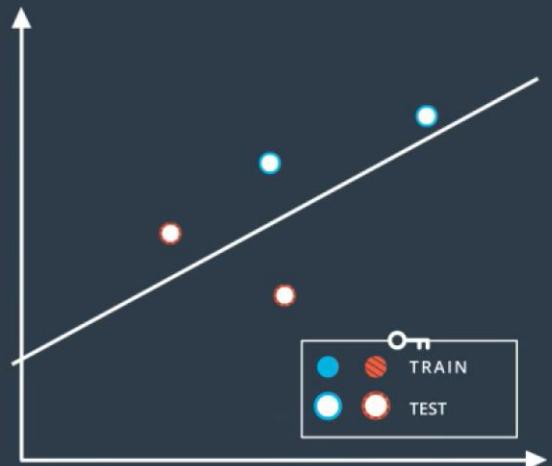
# Redes Neurais – Testing

## WHY TESTING?



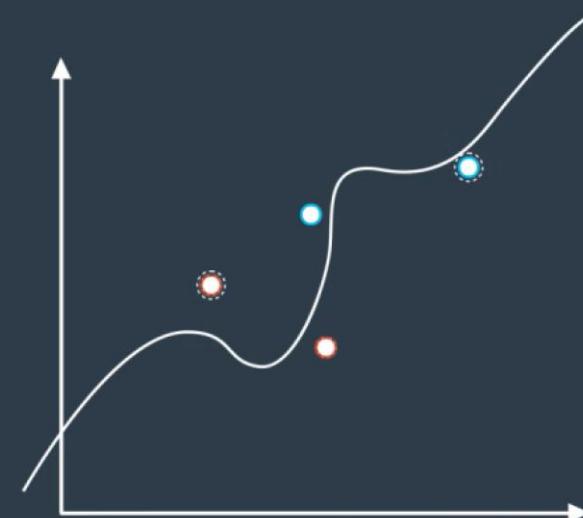
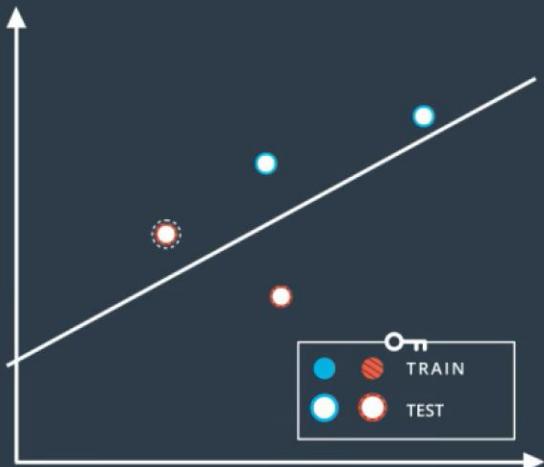
# Redes Neurais – Testing

WHY TESTING?



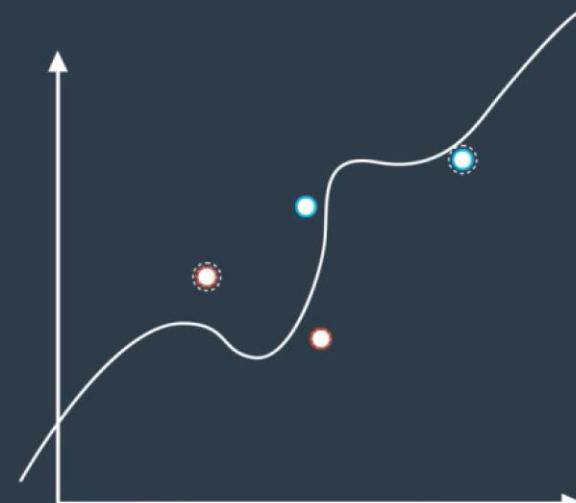
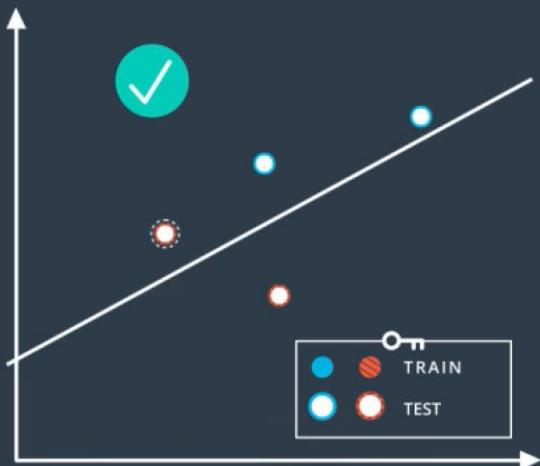
# Redes Neurais – Testing

WHY TESTING?

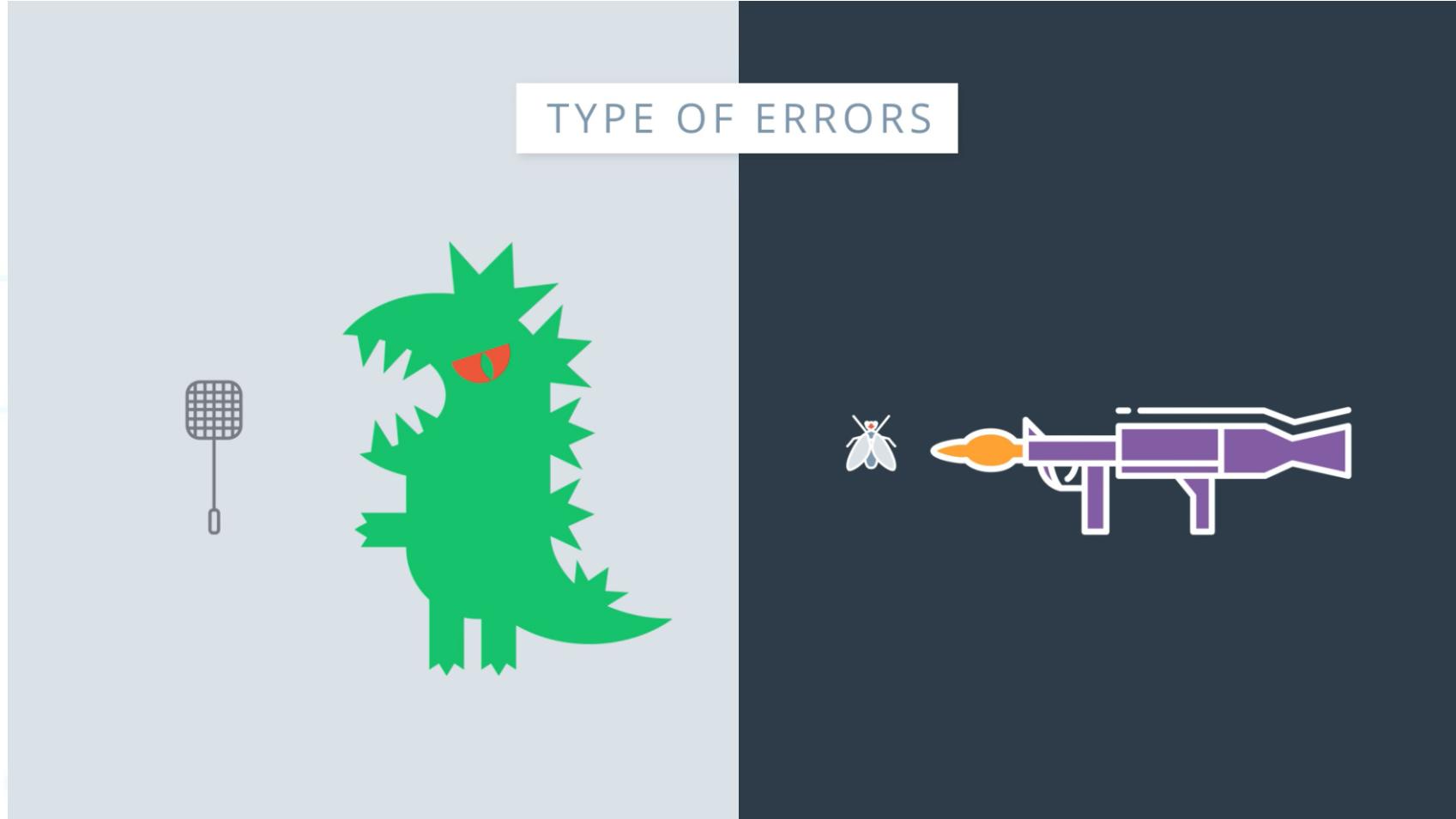


# Redes Neurais – Testing

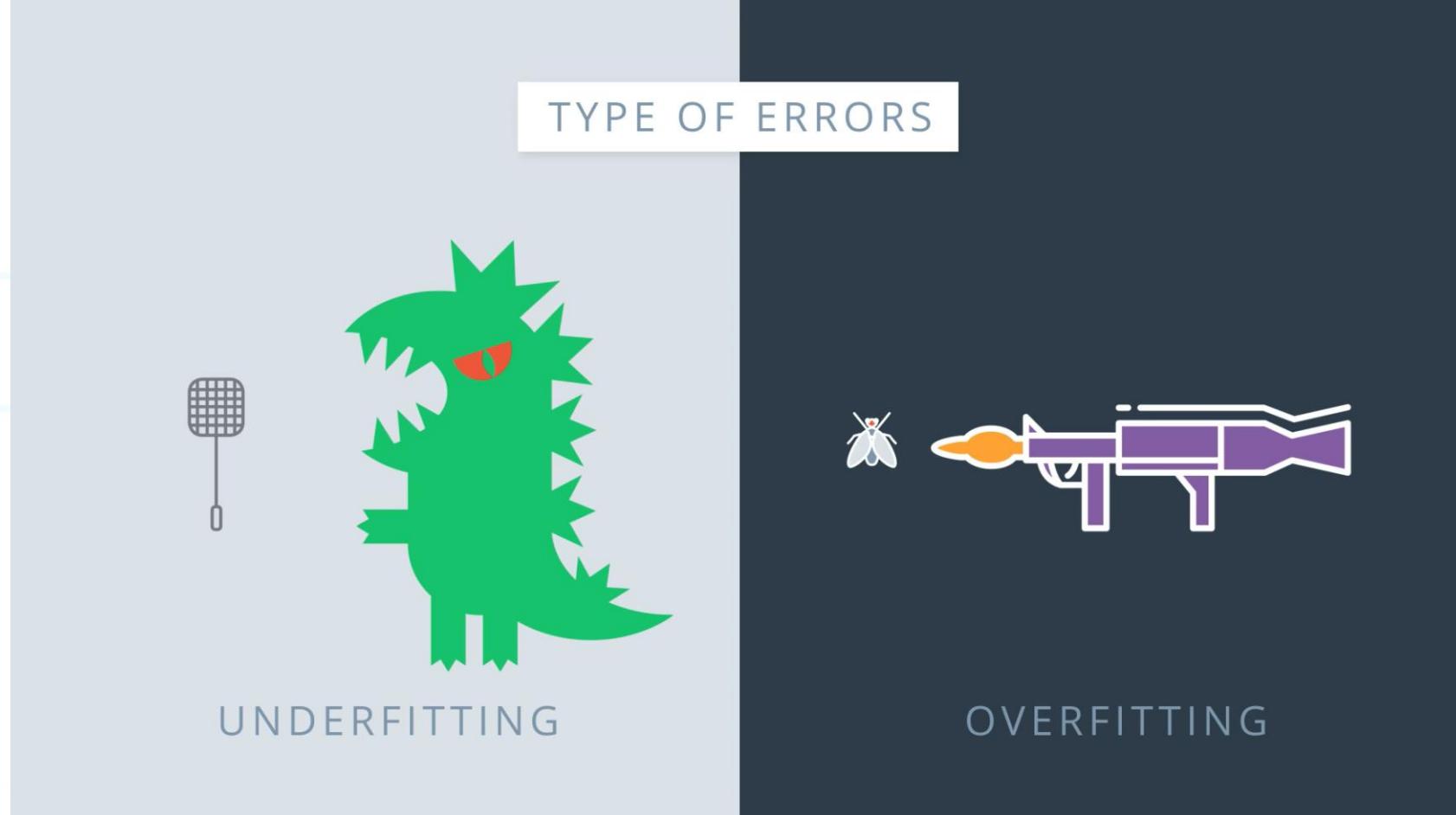
WHY TESTING?



# Redes Neurais – Overfitting and Underfitting



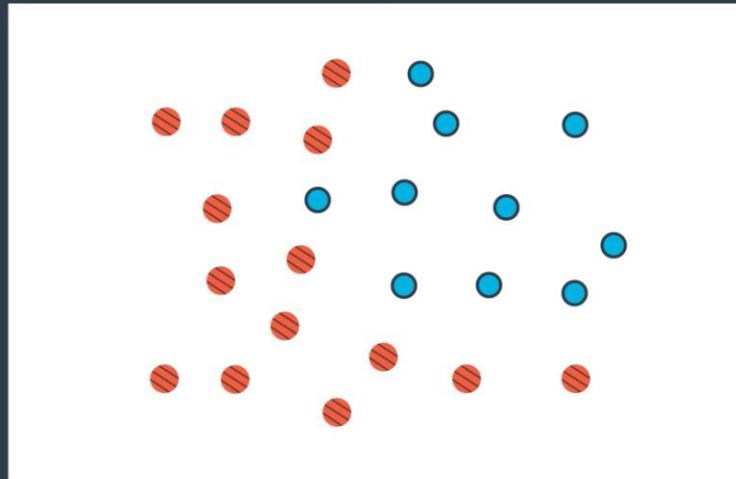
# Redes Neurais – Overfitting and Underfitting



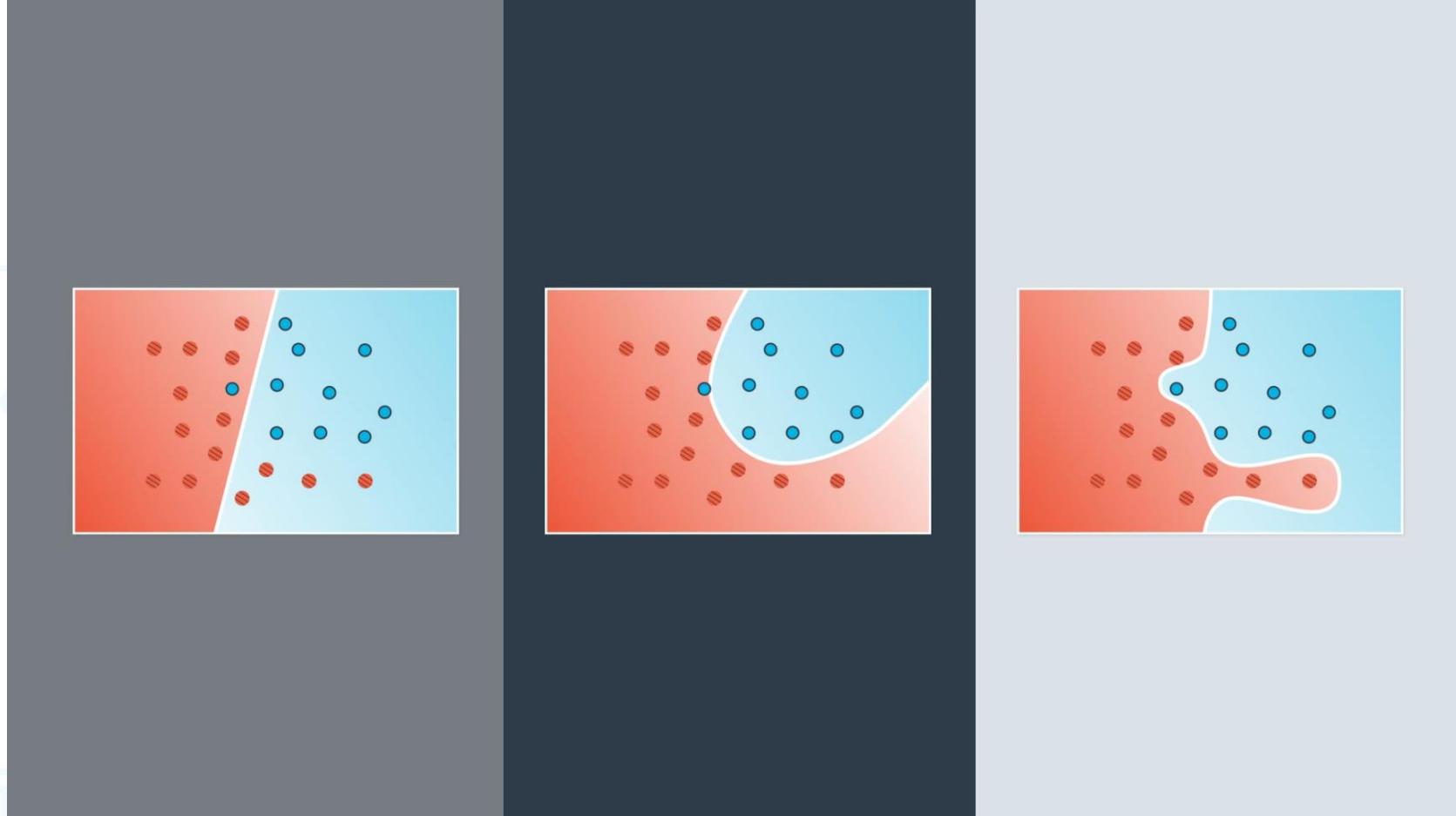
# Redes Neurais – Overfitting and Underfitting



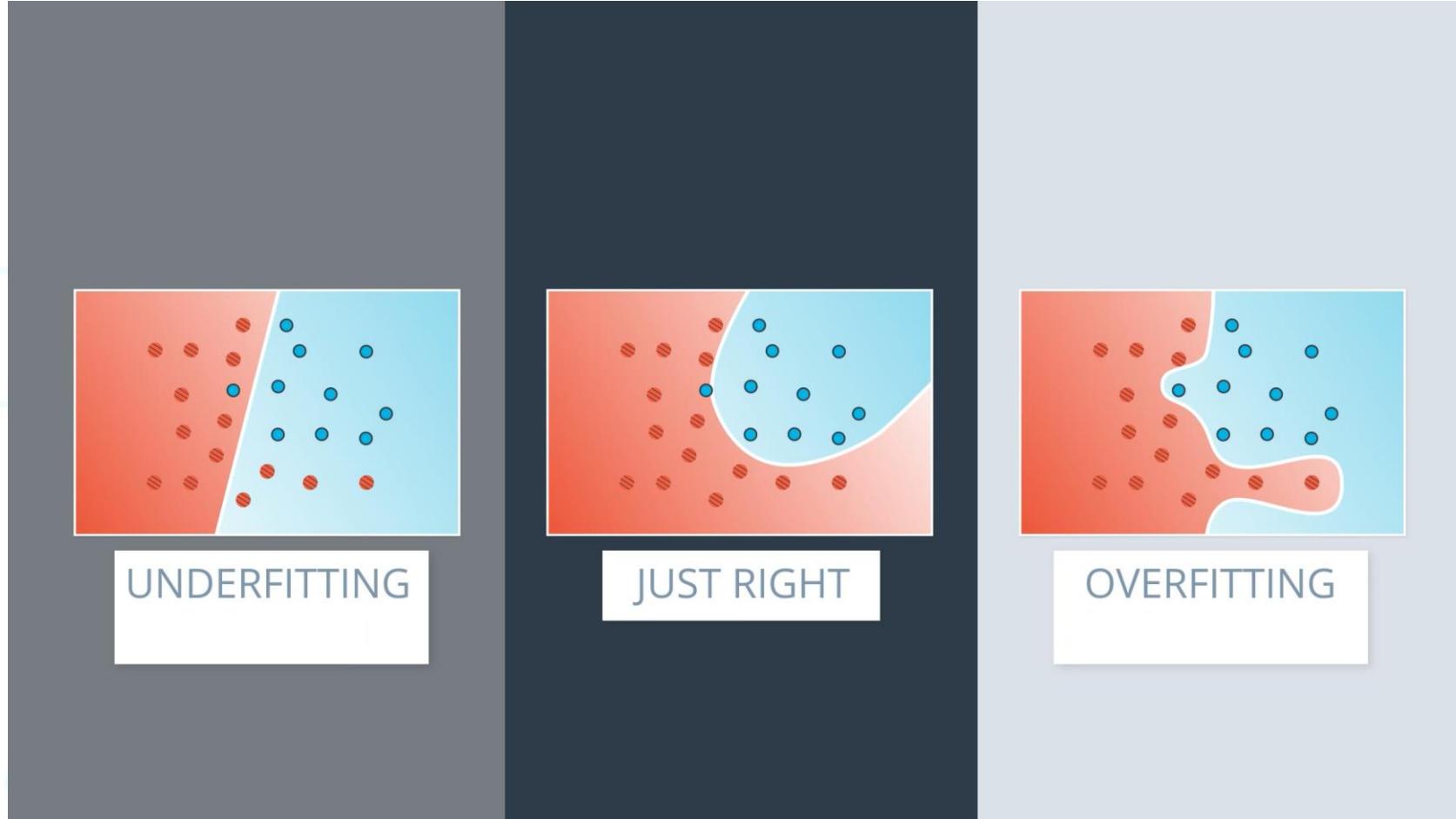
# Redes Neurais – Overfitting and Underfitting



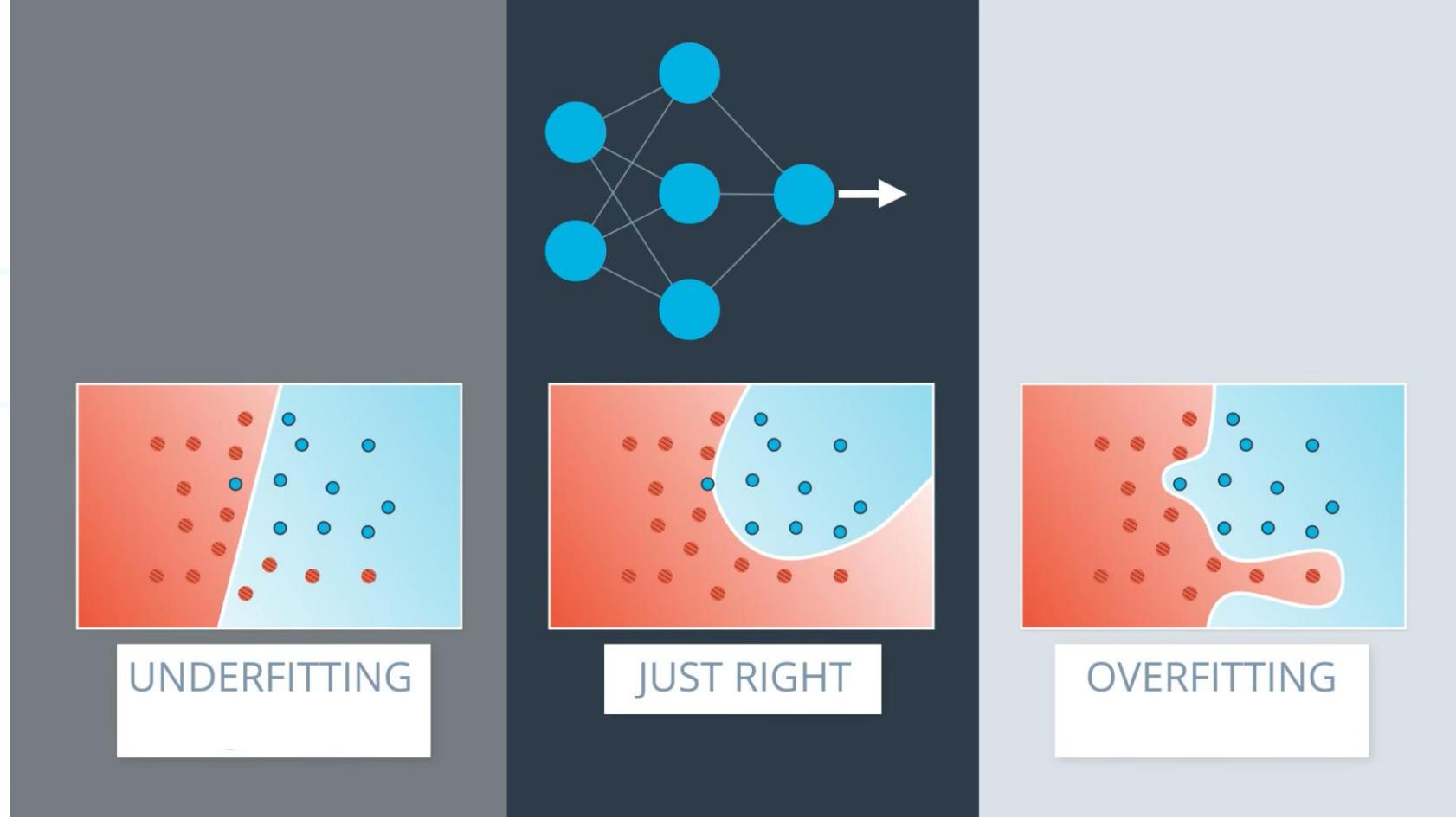
# Redes Neurais – Overfitting and Underfitting



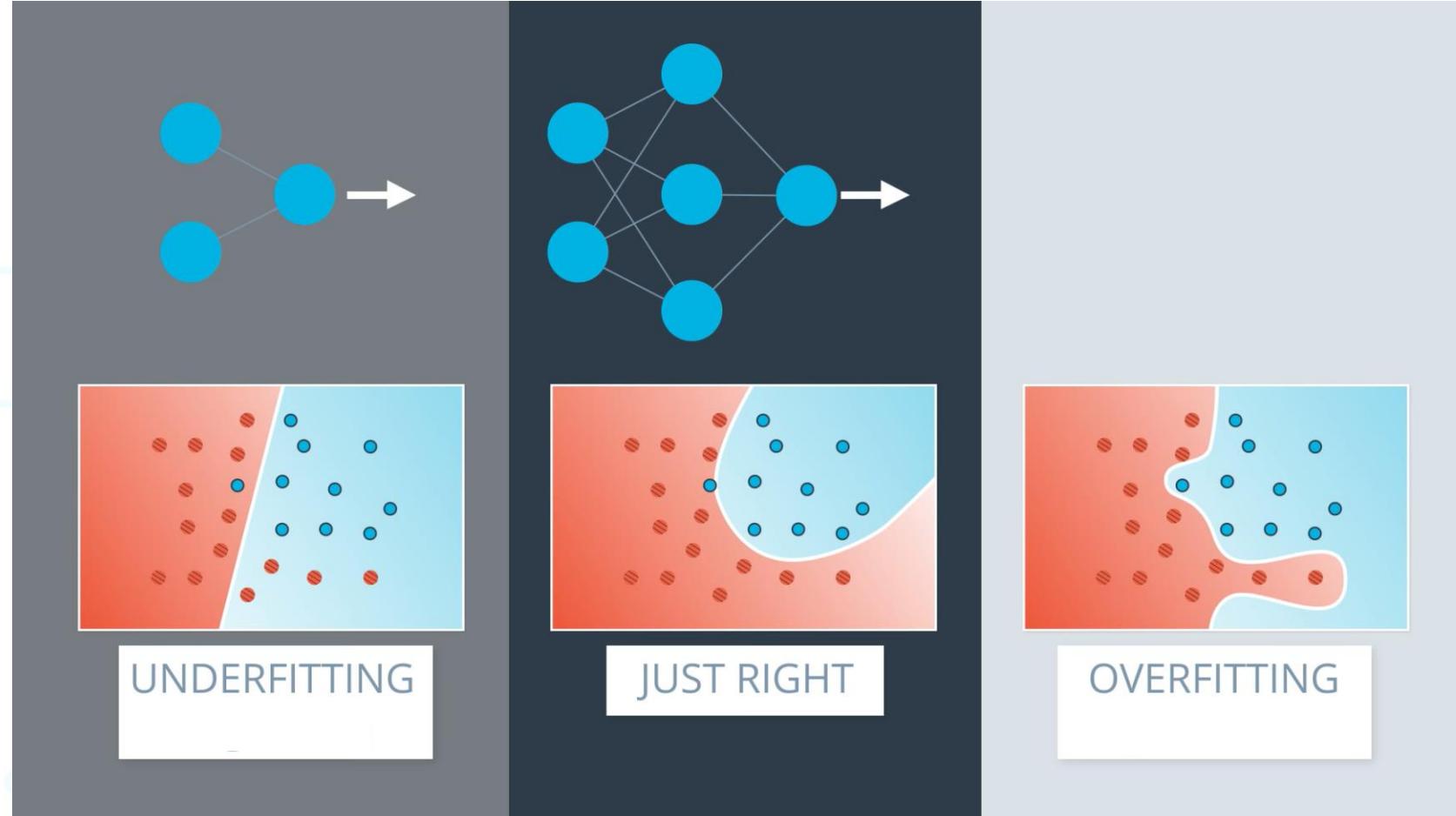
# Redes Neurais – Overfitting and Underfitting



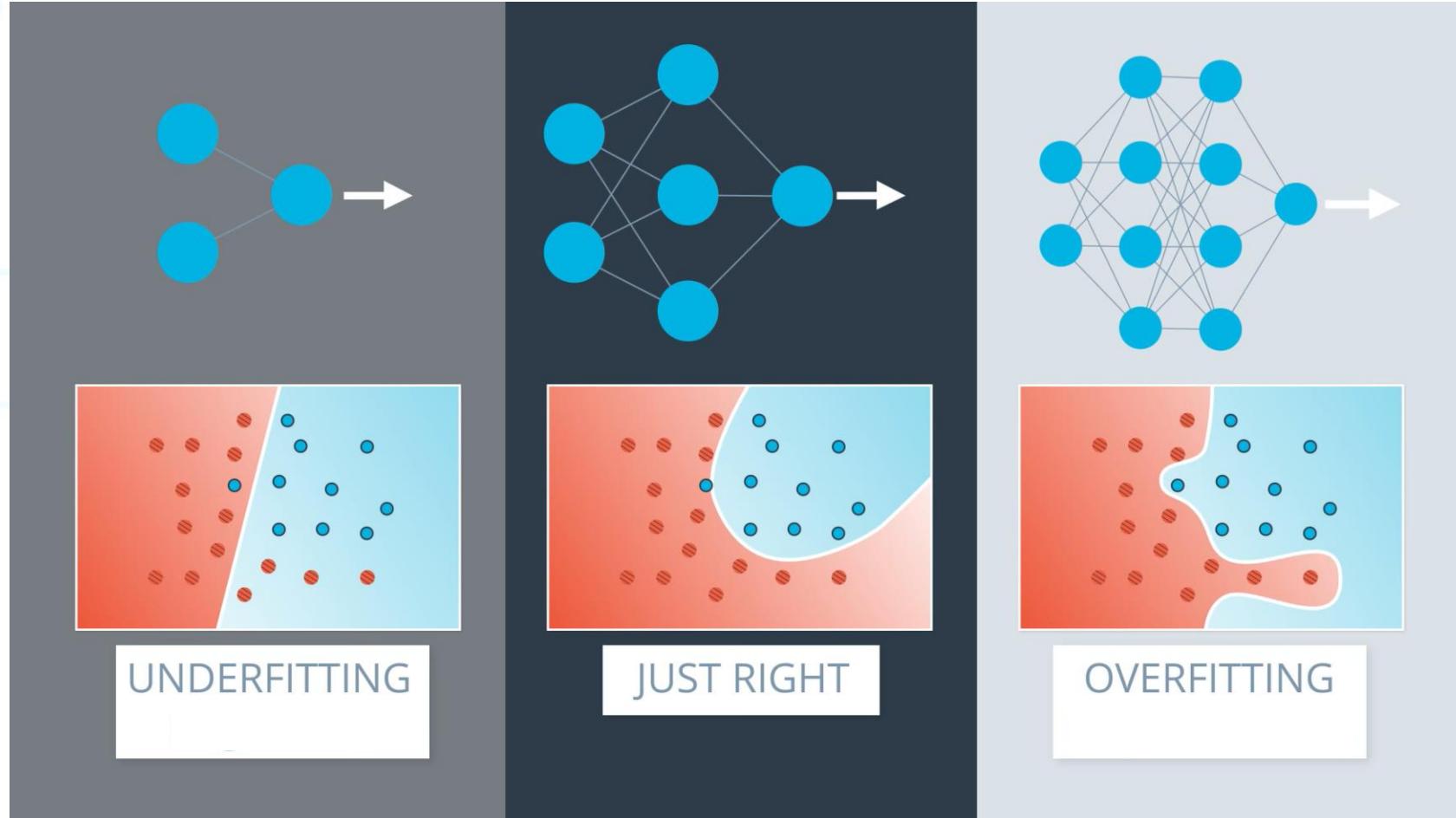
# Redes Neurais – Overfitting and Underfitting



# Redes Neurais – Overfitting and Underfitting

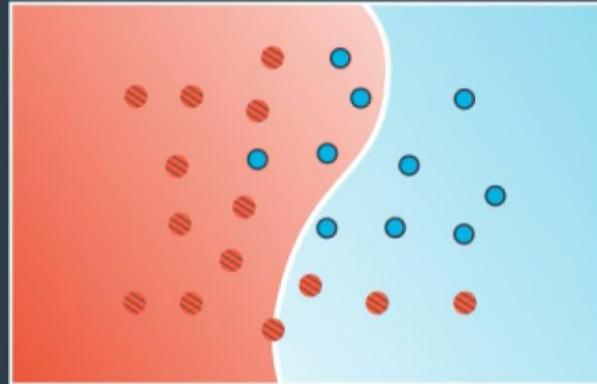


# Redes Neurais – Overfitting and Underfitting



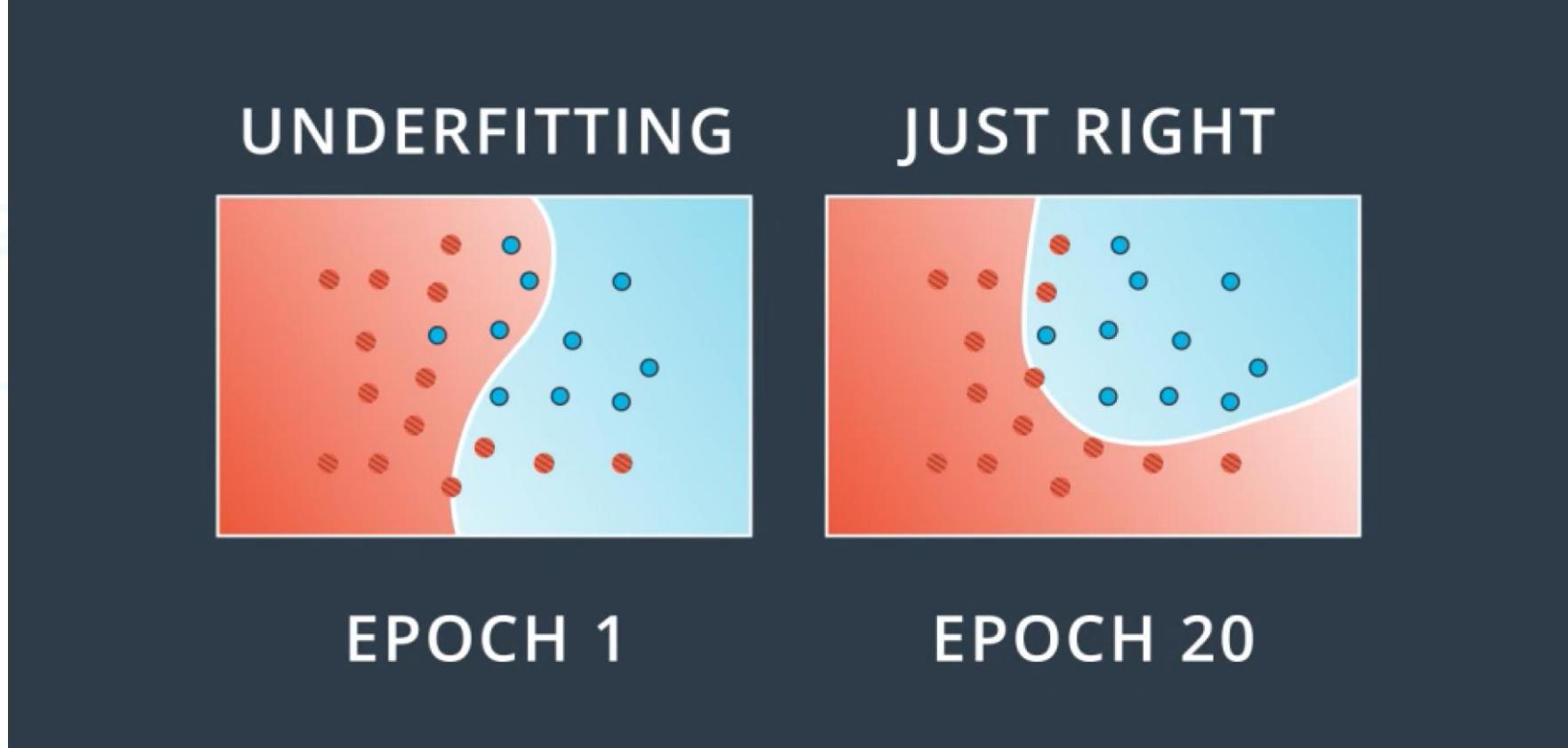
# Redes Neurais – Model Complexity Graph

UNDERFITTING



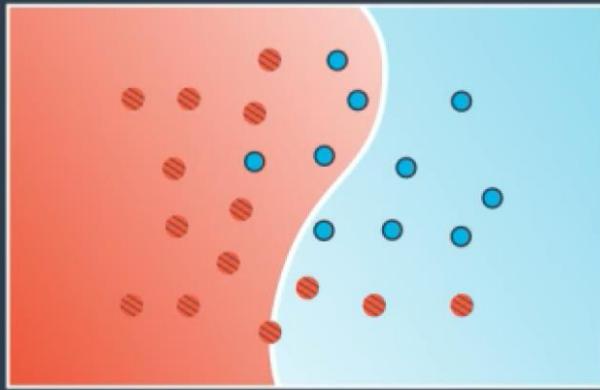
EPOCH 1

# Redes Neurais – Model Complexity Graph

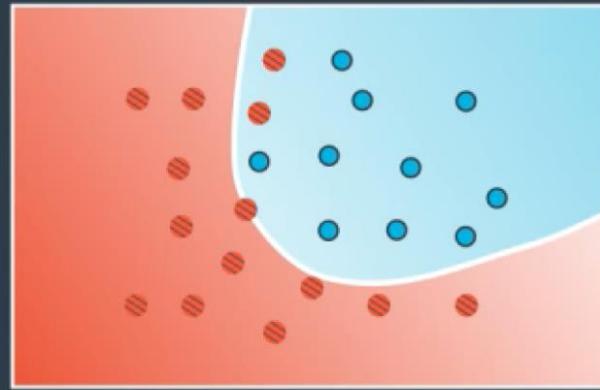


# Redes Neurais – Model Complexity Graph

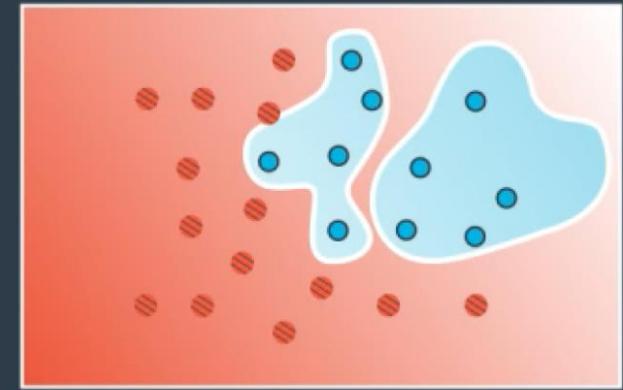
UNDERFITTING



JUST RIGHT



OVERFITTING



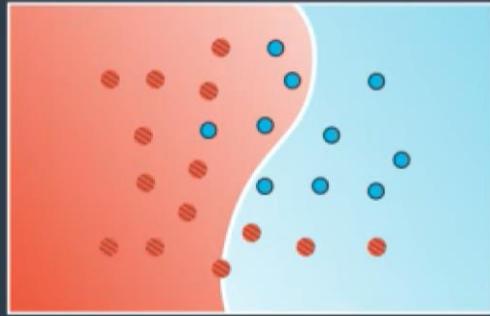
EPOCH 1

EPOCH 20

EPOCH 100

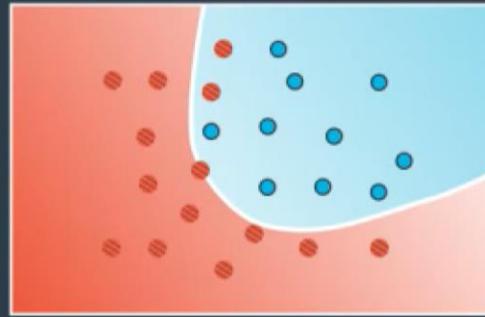
# Redes Neurais – Model Complexity Graph

UNDERFITTING



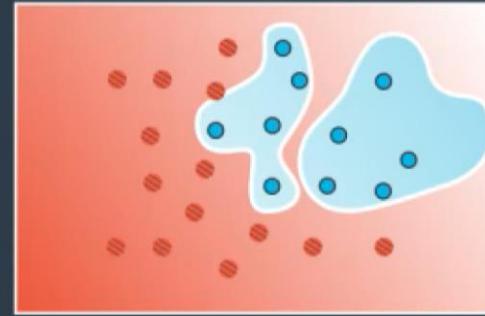
EPOCH 1

JUST RIGHT



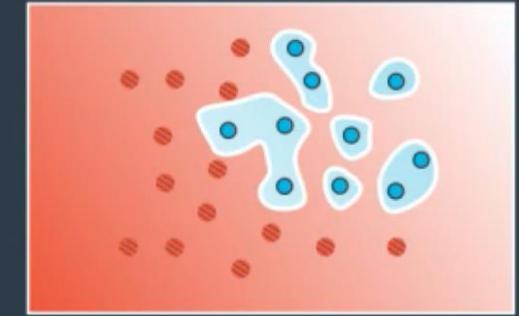
EPOCH 20

OVERFITTING



EPOCH 100

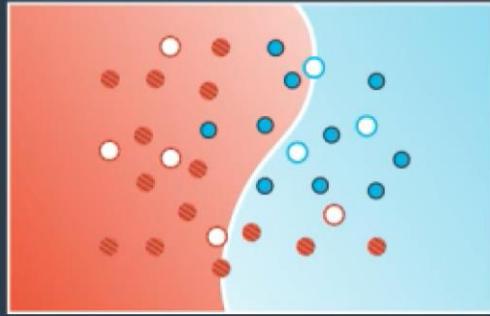
OVERFITTING



EPOCH 600

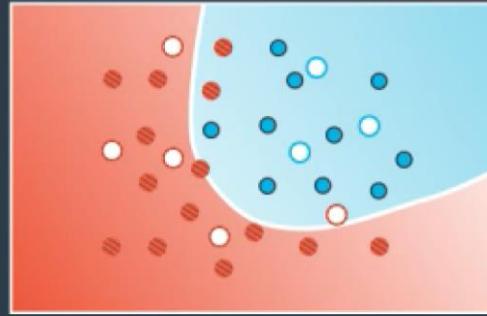
# Redes Neurais – Model Complexity Graph

UNDERFITTING



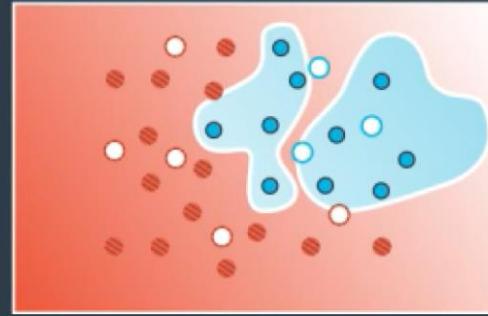
EPOCH 1

JUST RIGHT



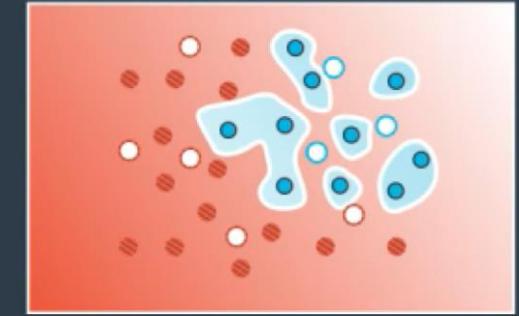
EPOCH 20

OVERFITTING



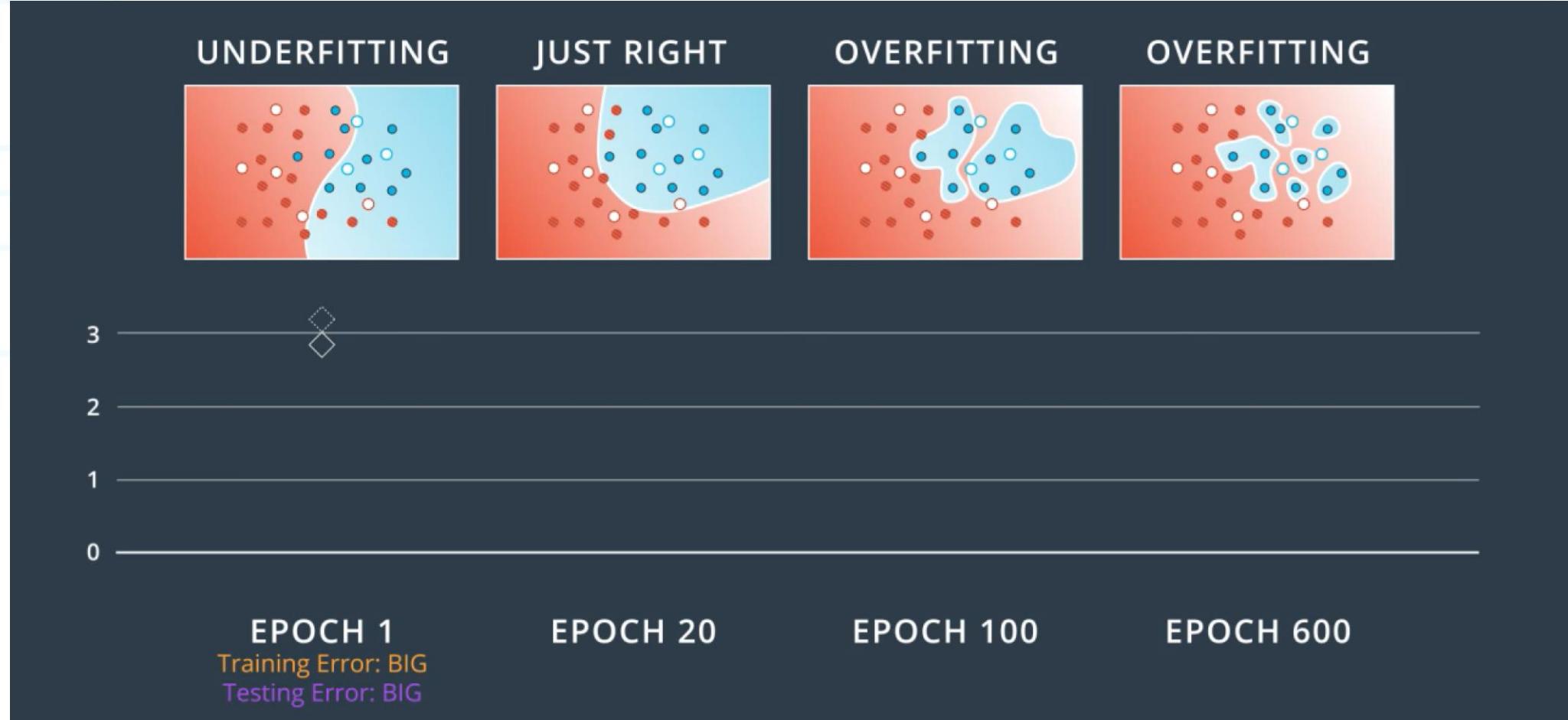
EPOCH 100

OVERFITTING



EPOCH 600

# Redes Neurais – Model Complexity Graph



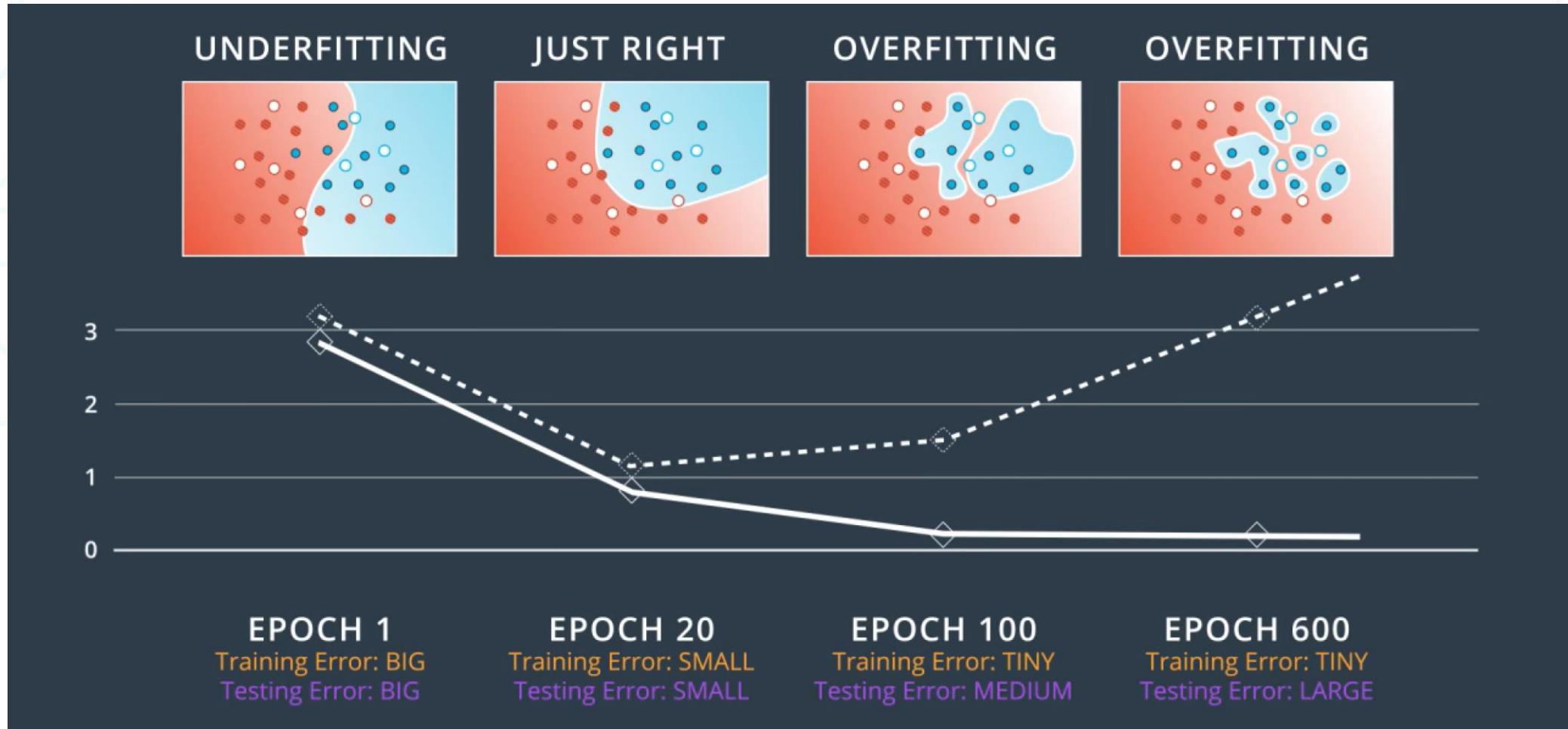
# Redes Neurais – Model Complexity Graph



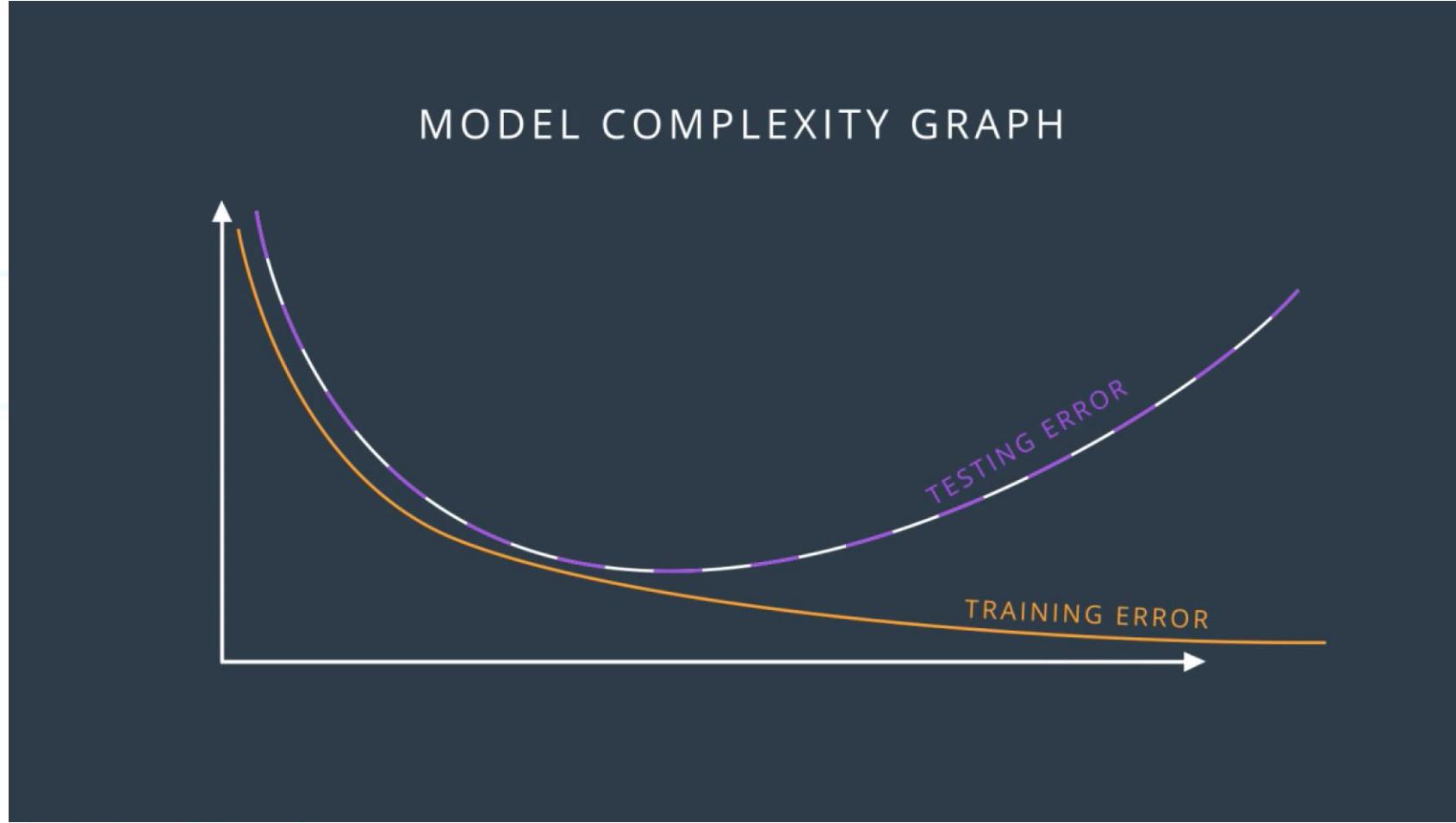
# Redes Neurais – Model Complexity Graph



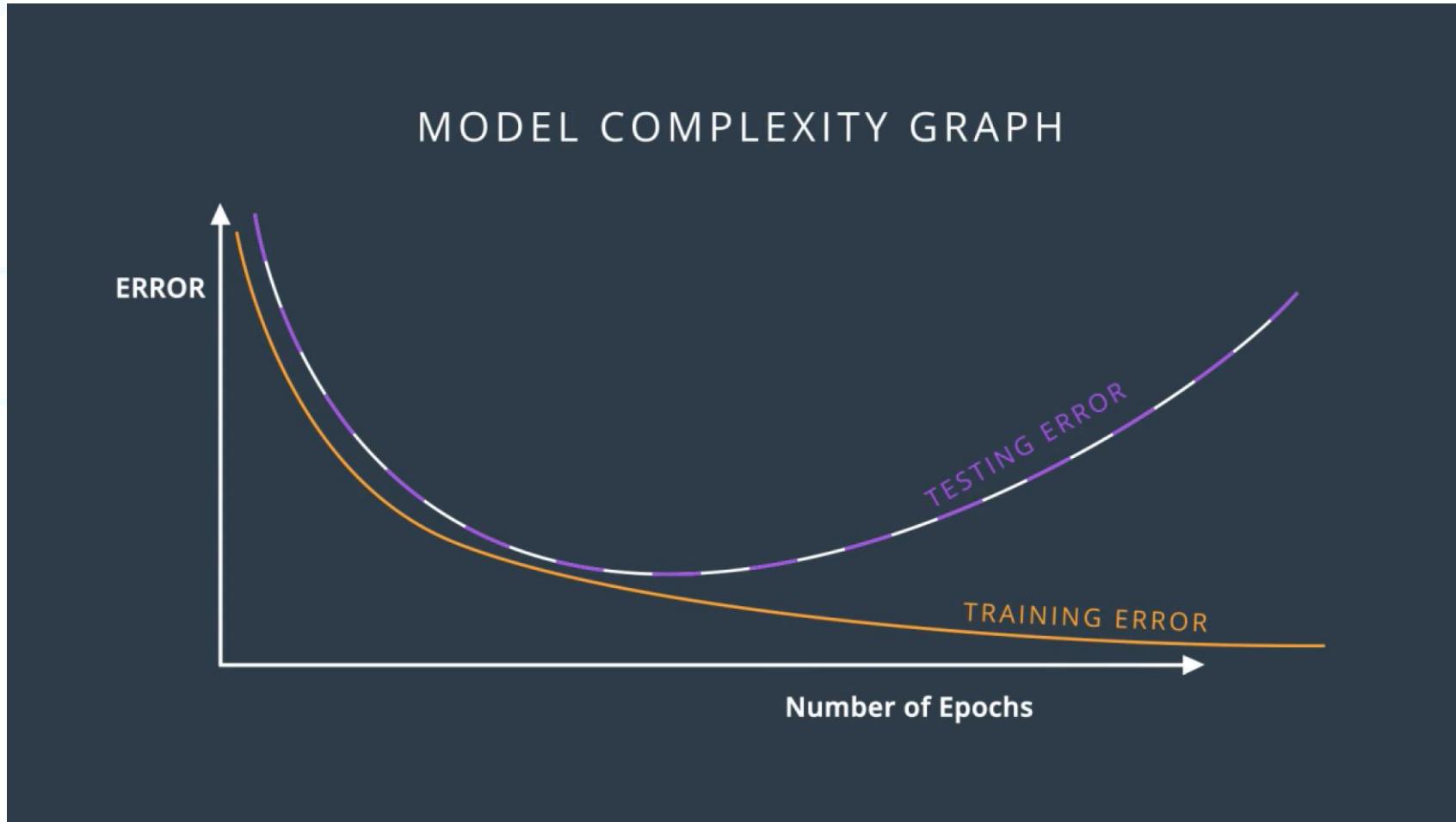
# Redes Neurais – Model Complexity Graph



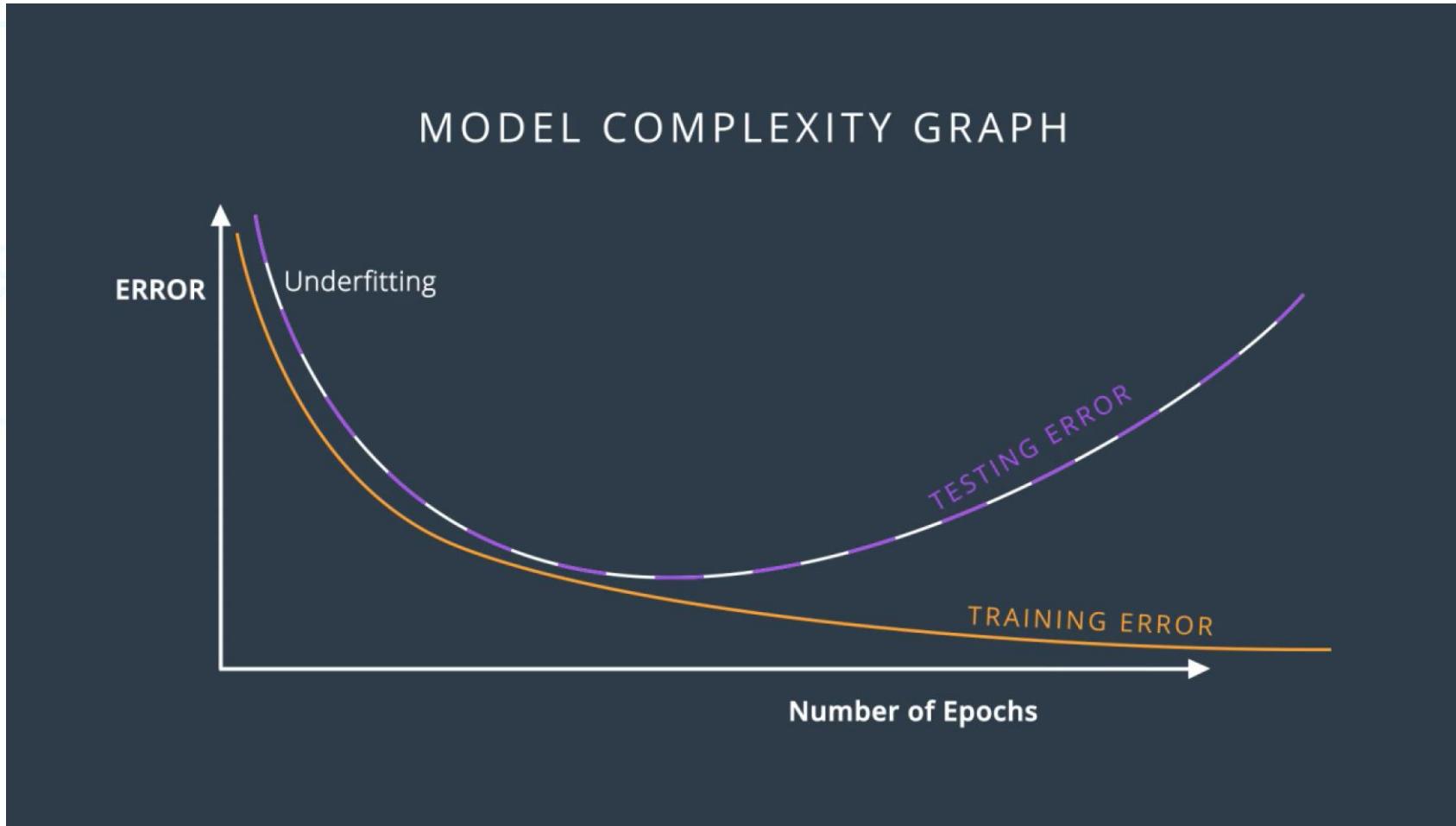
# Redes Neurais – Model Complexity Graph



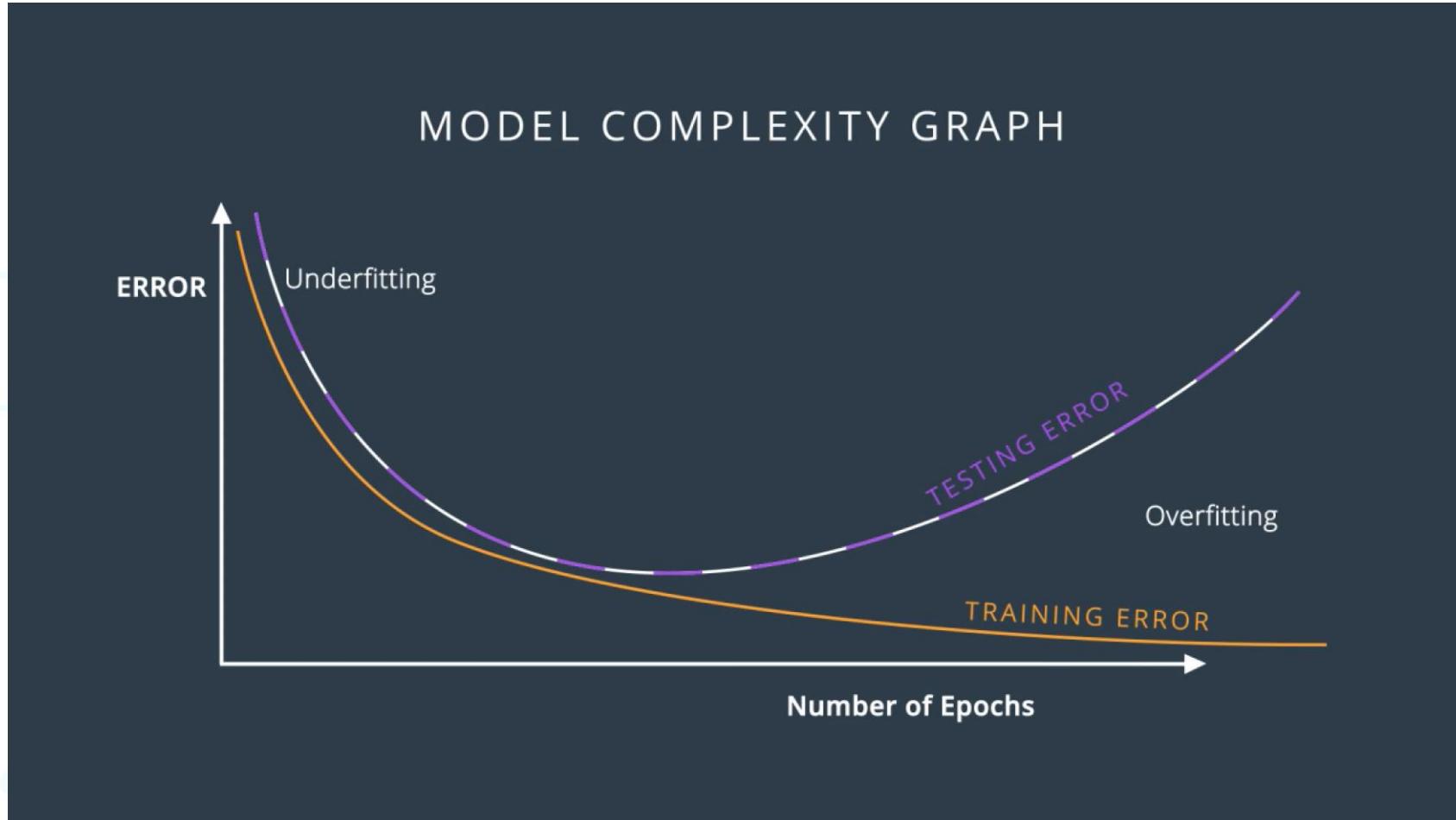
# Redes Neurais – Model Complexity Graph



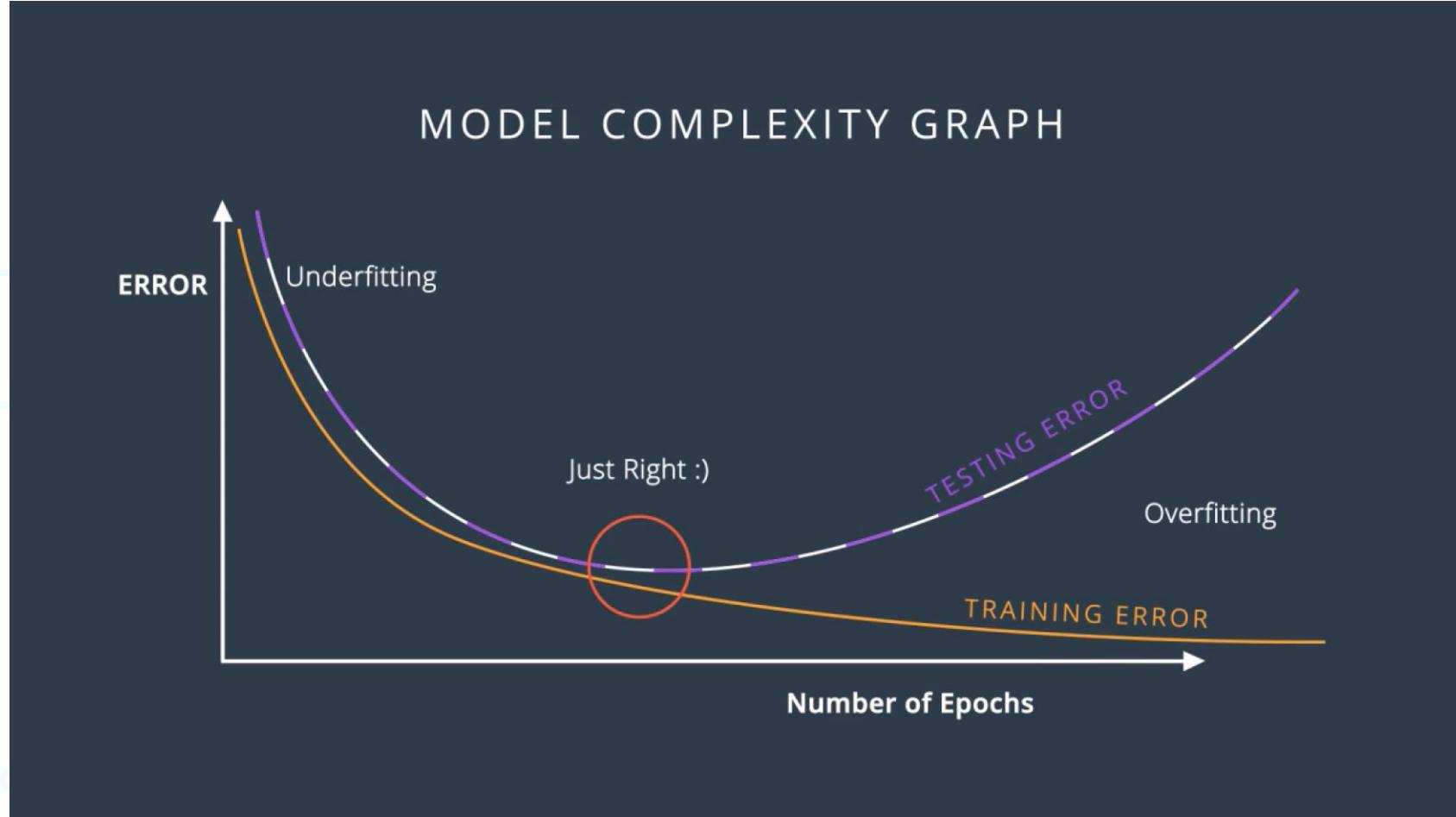
# Redes Neurais – Model Complexity Graph



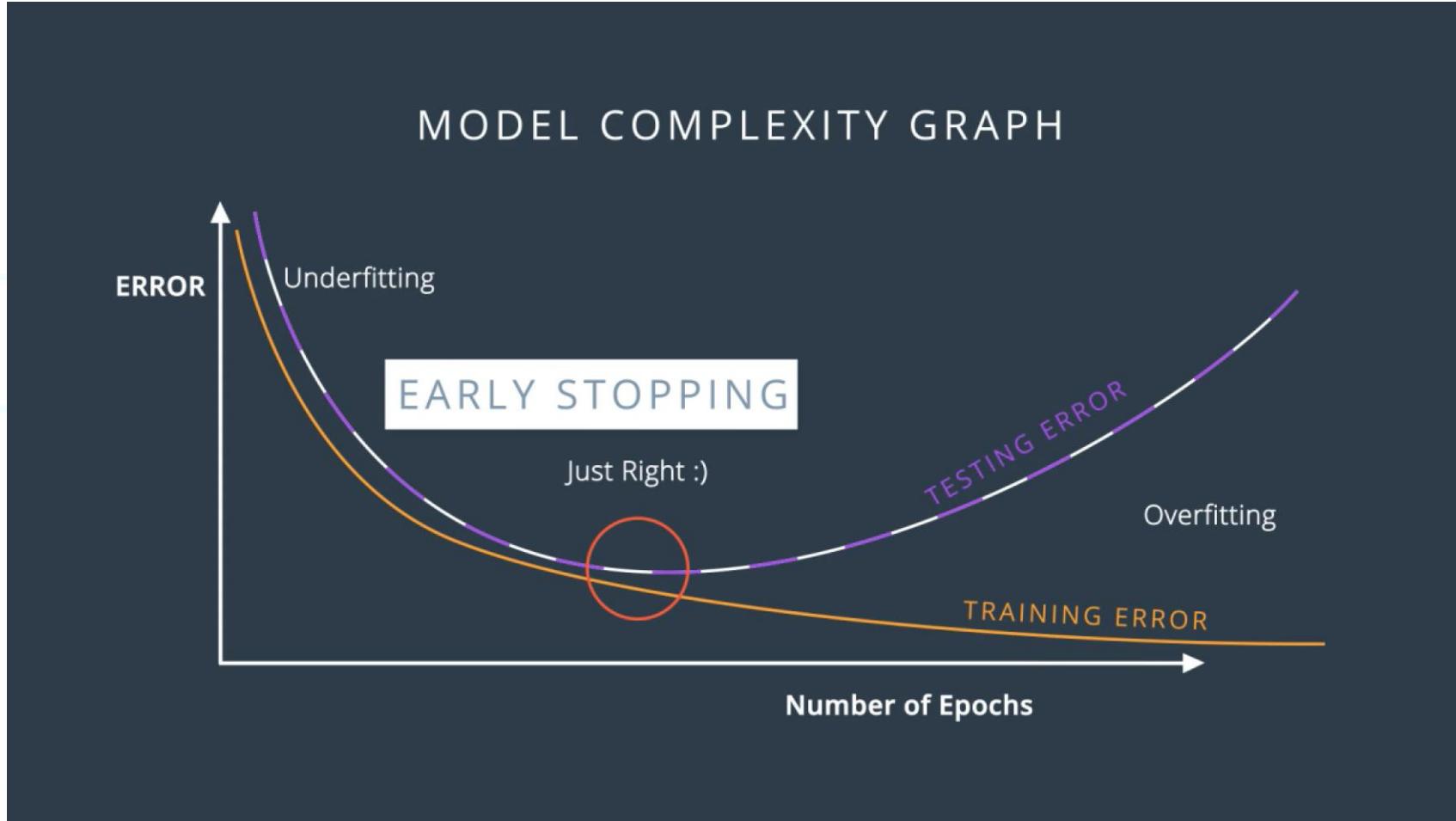
# Redes Neurais – Model Complexity Graph



# Redes Neurais – Model Complexity Graph

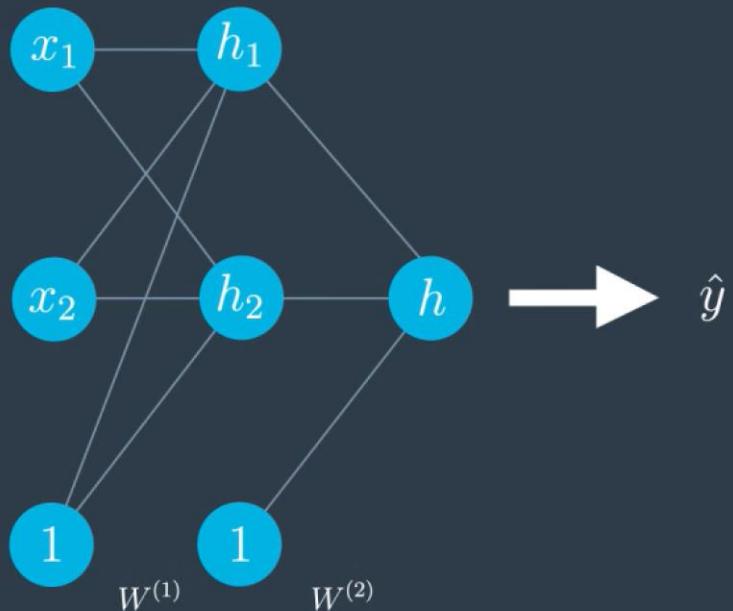


# Redes Neurais – Model Complexity Graph



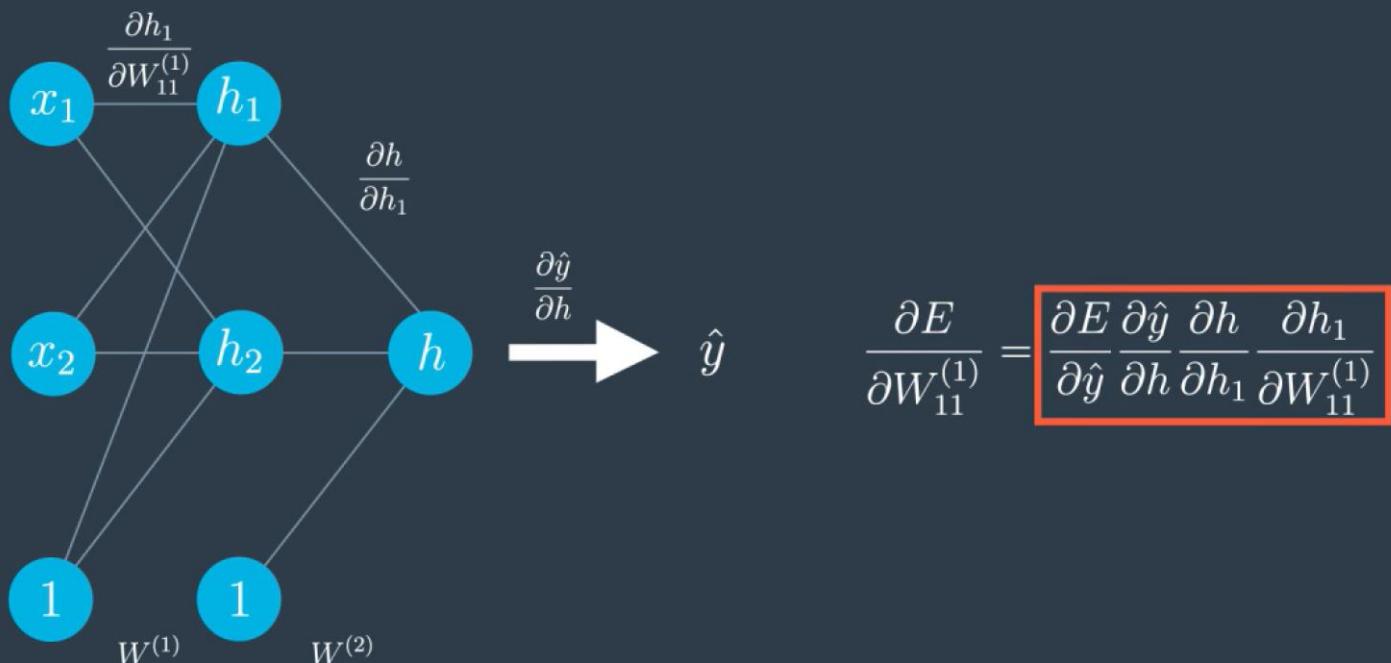
# Vanishing Gradient

BACKPROPAGATION



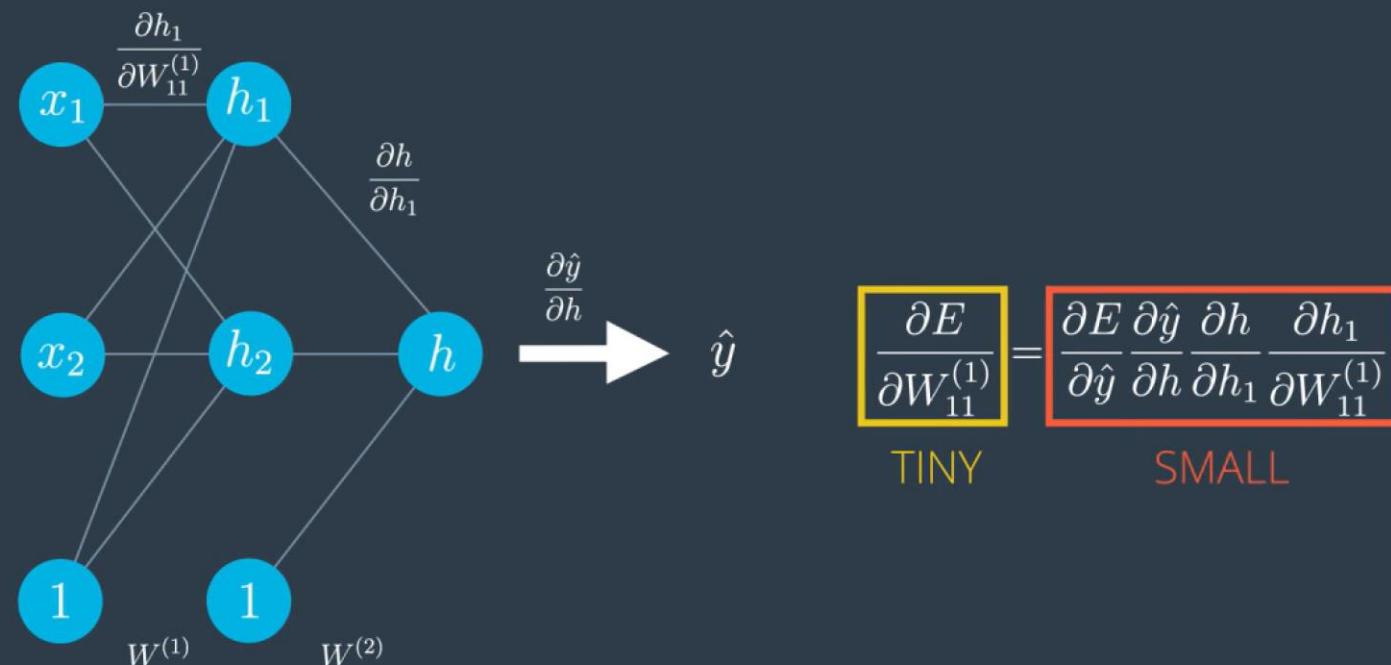
# Vanishing Gradient

BACKPROPAGATION



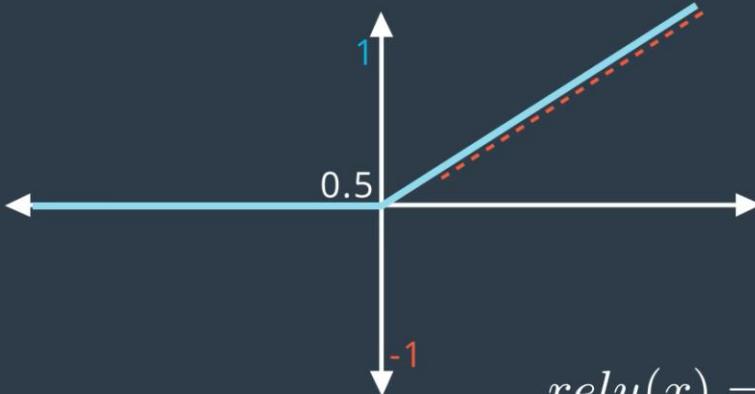
# Vanishing Gradient

BACKPROPAGATION



# Funções de Ativação

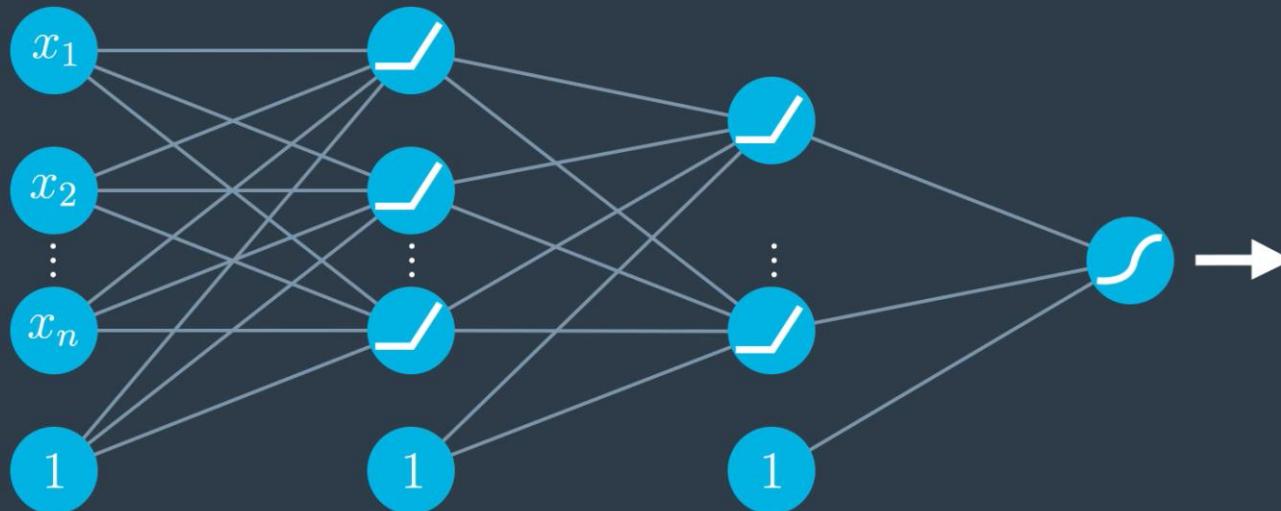
RECTIFIED LINEAR UNIT (ReLU)



$$relu(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

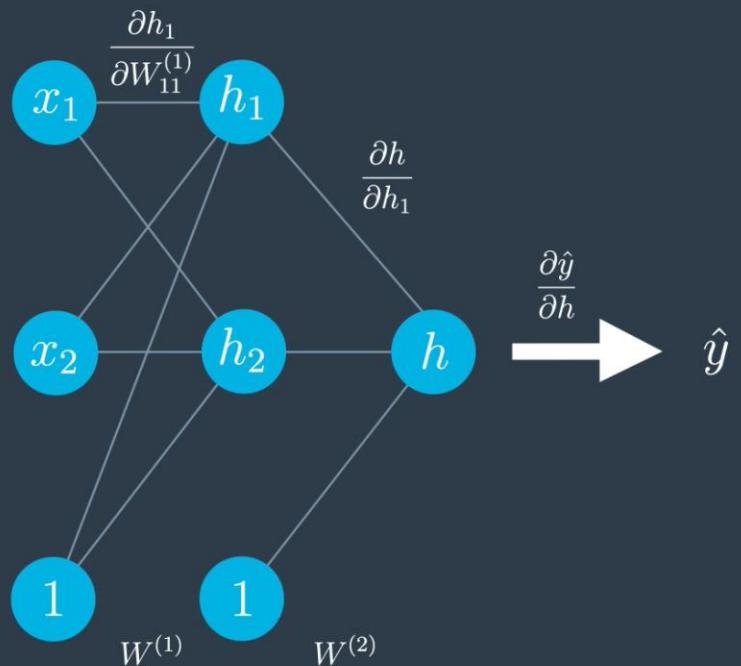
# Funções de Ativação

MULTI-LAYER PERCEPTRON



# Funções de Ativação

## BACKPROPAGATION

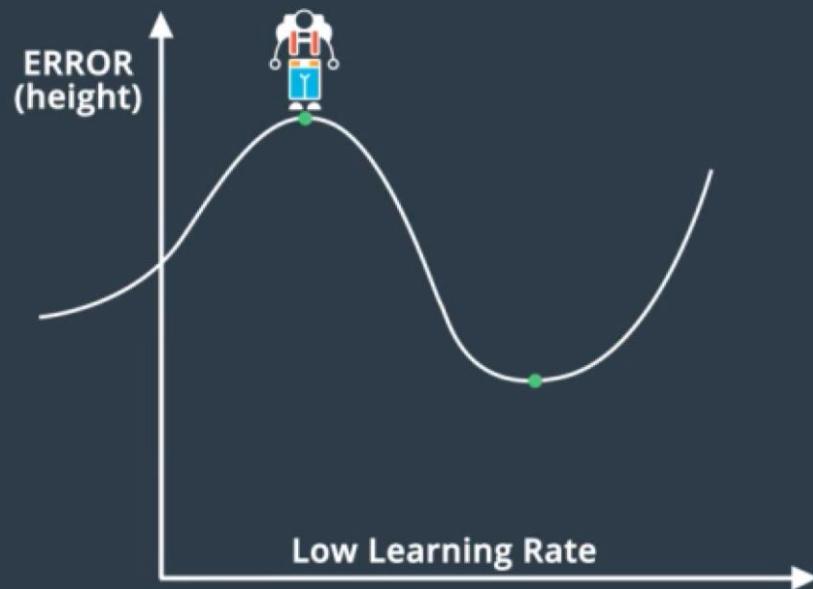
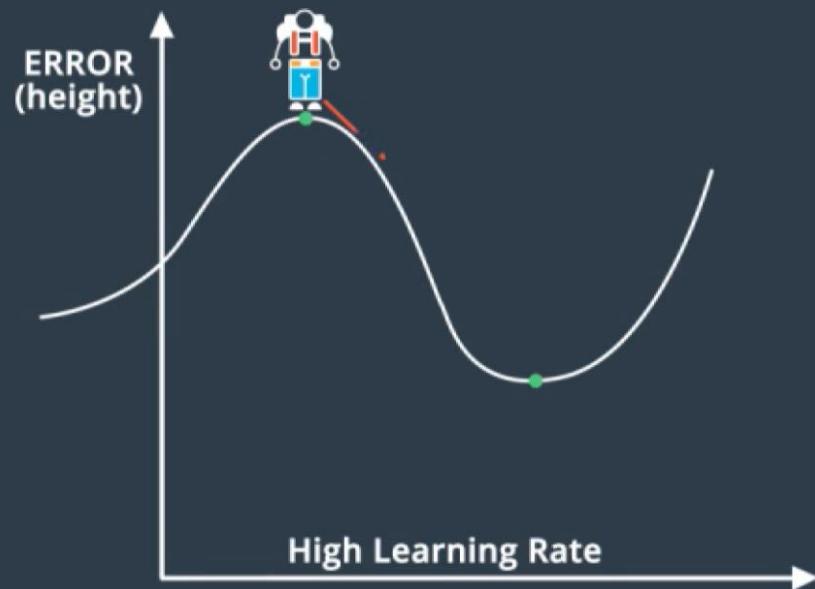


$$\boxed{\frac{\partial E}{\partial W_{11}^{(1)}}} = \boxed{\frac{\partial E}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial h} \frac{\partial h}{\partial h_1} \frac{\partial h_1}{\partial W_{11}^{(1)}}}$$

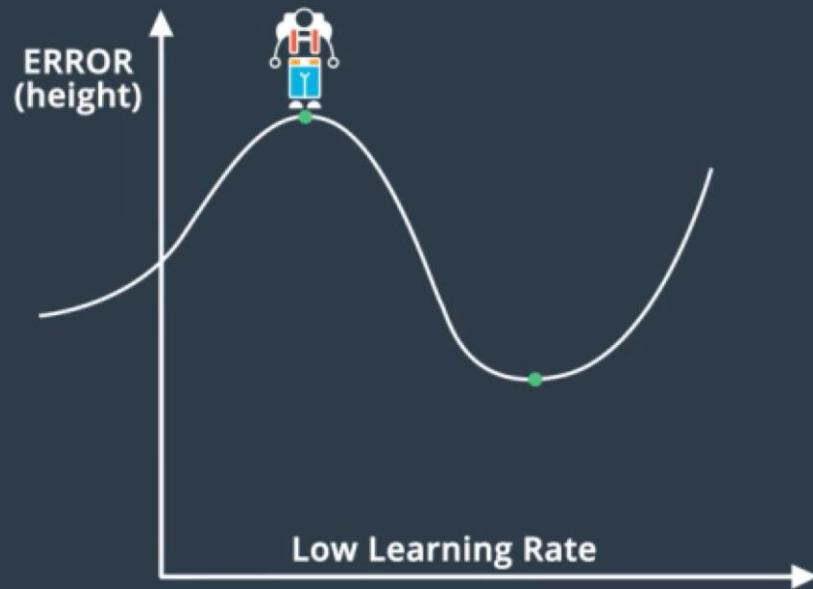
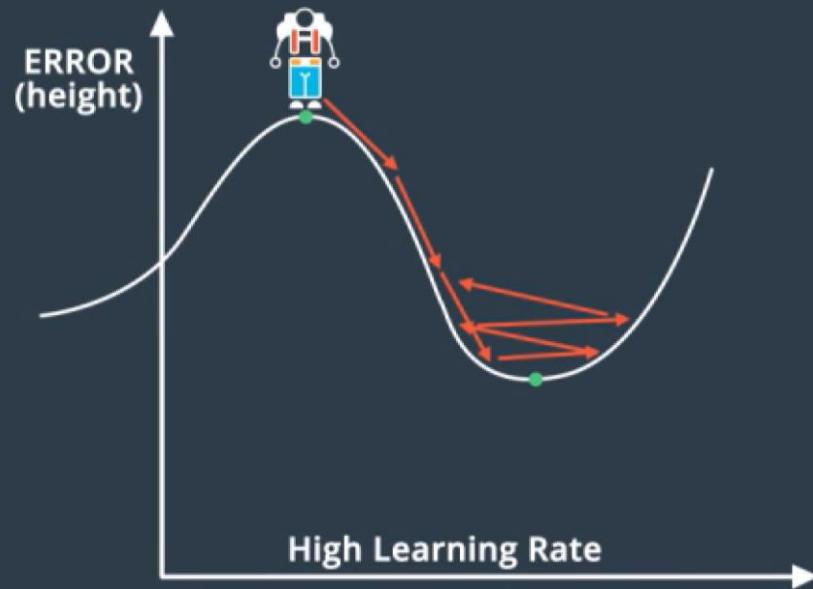
OK!

OK

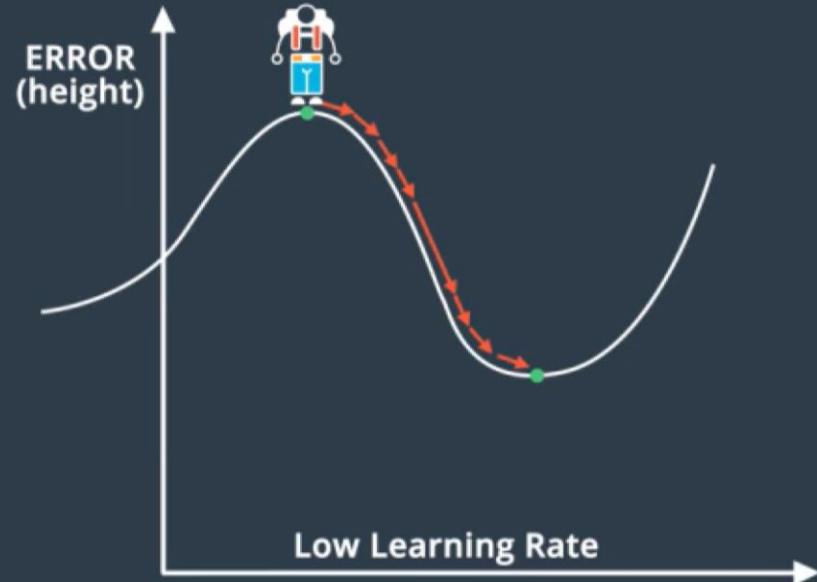
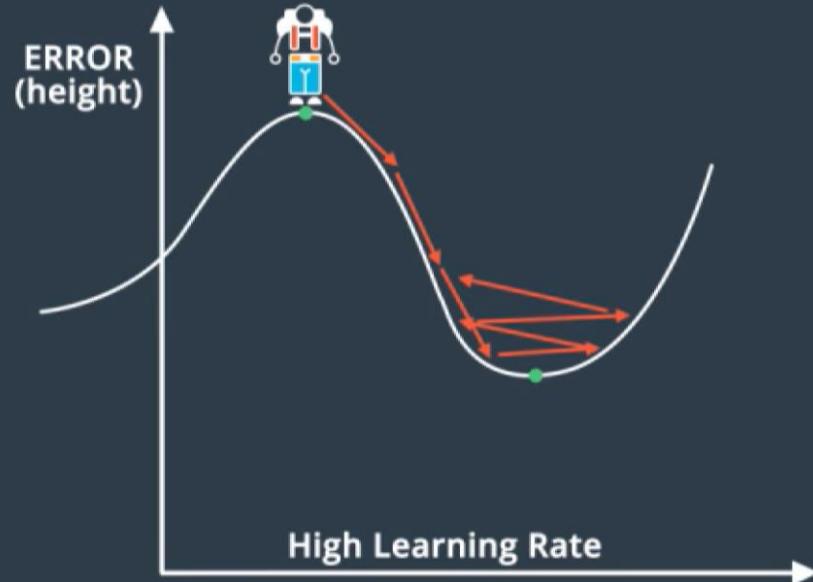
# Learning Rate



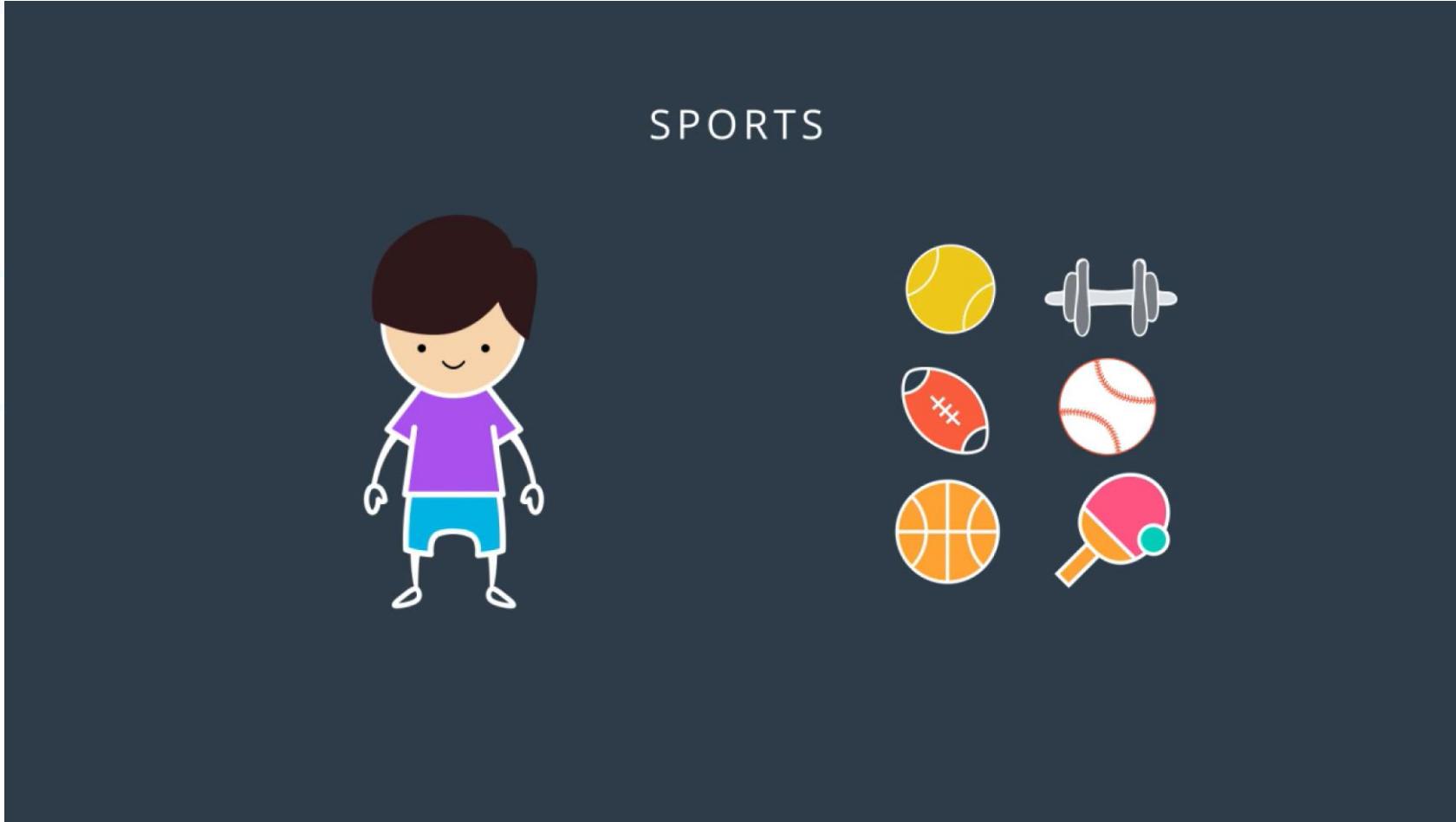
# Learning Rate



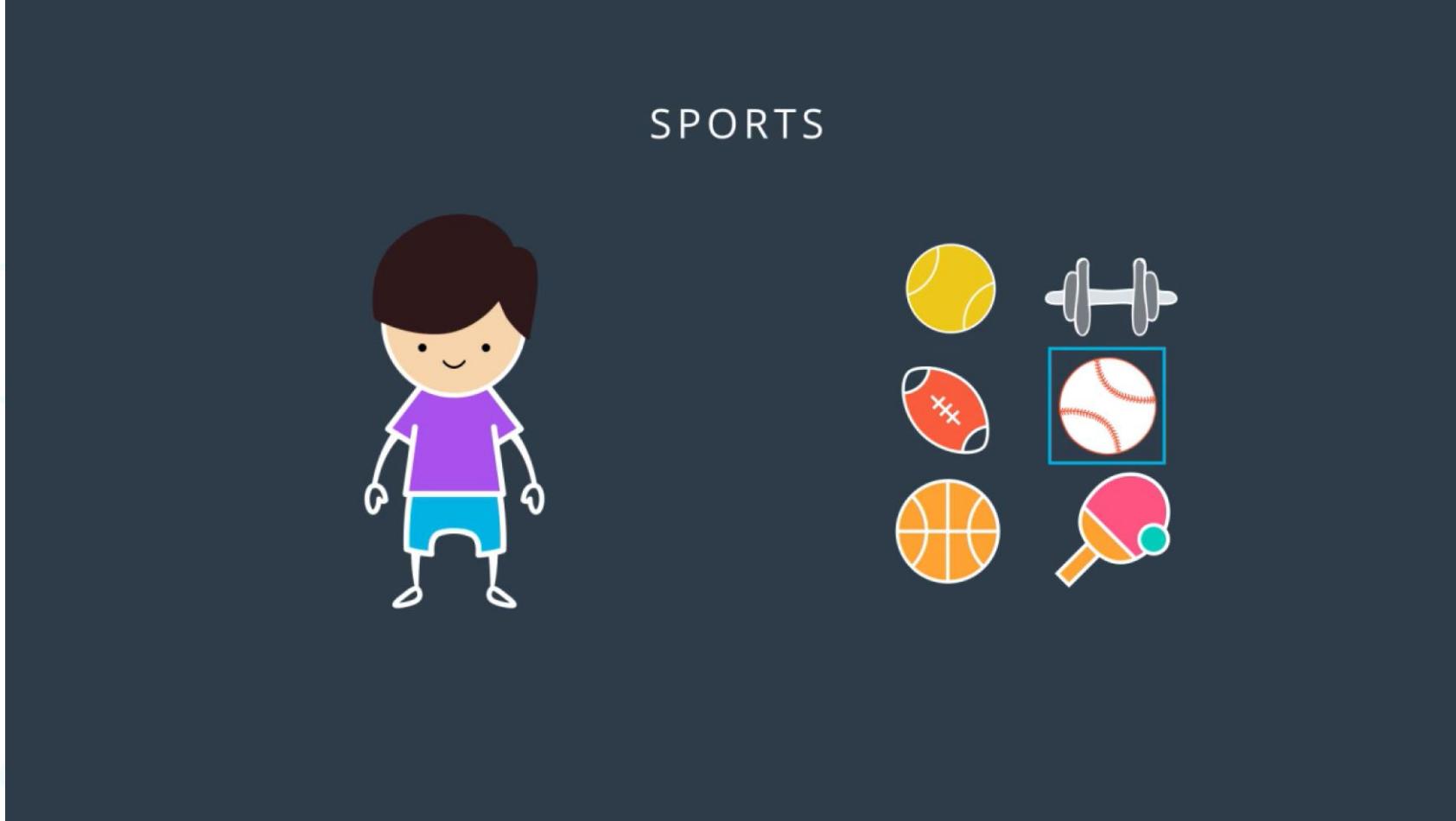
# Learning Rate



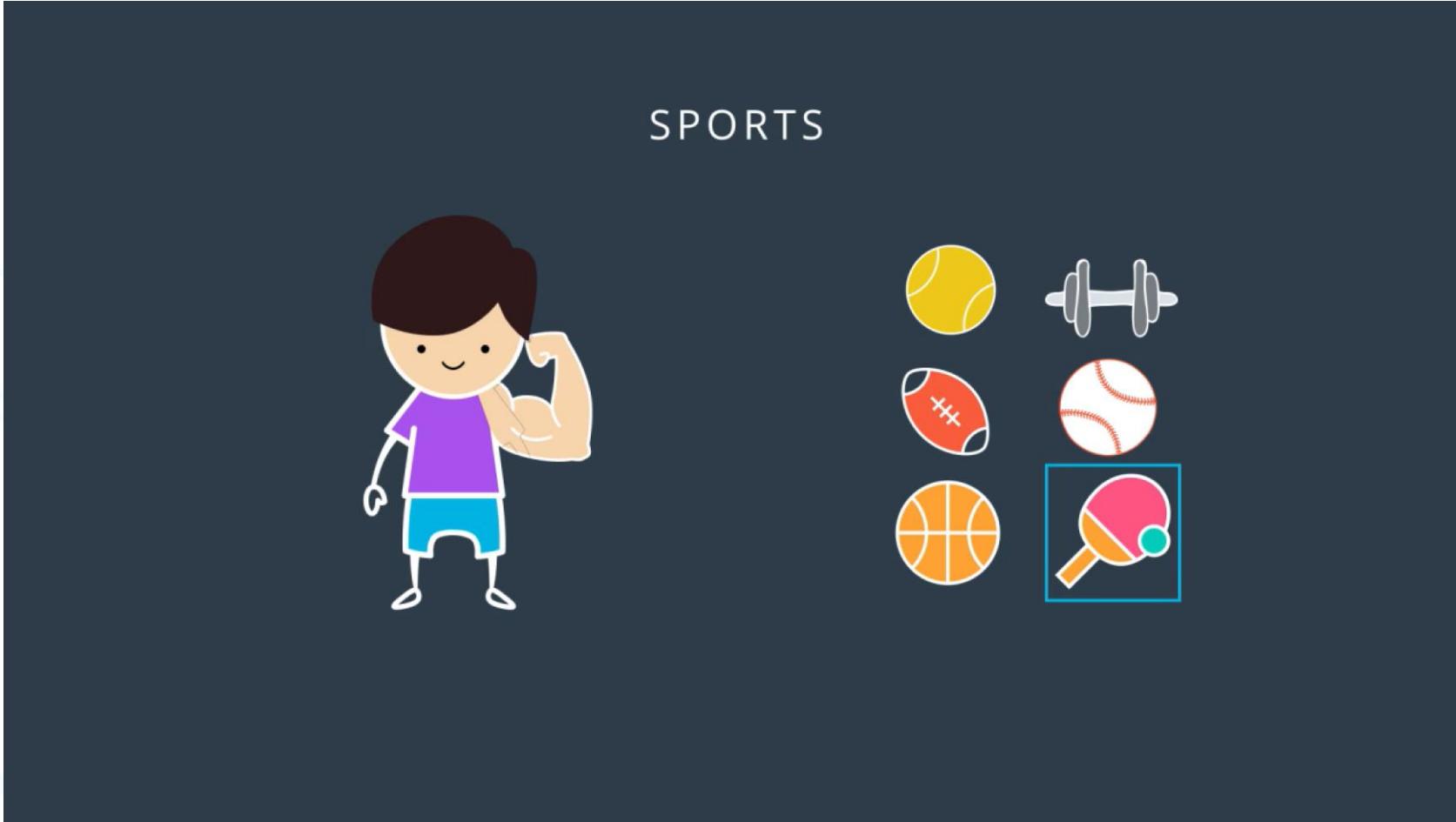
# Redes Neurais – Dropout



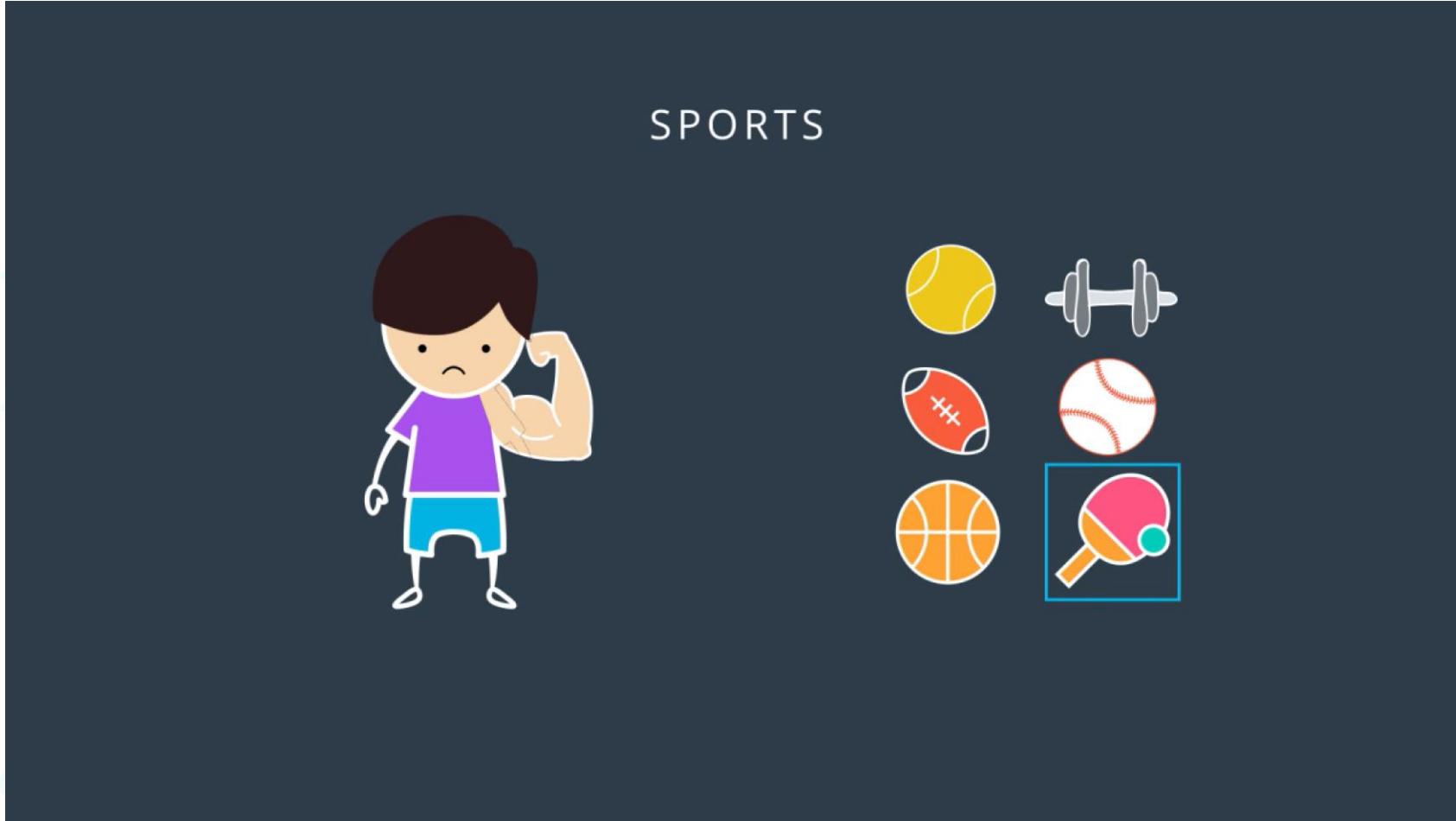
# Redes Neurais – Dropout



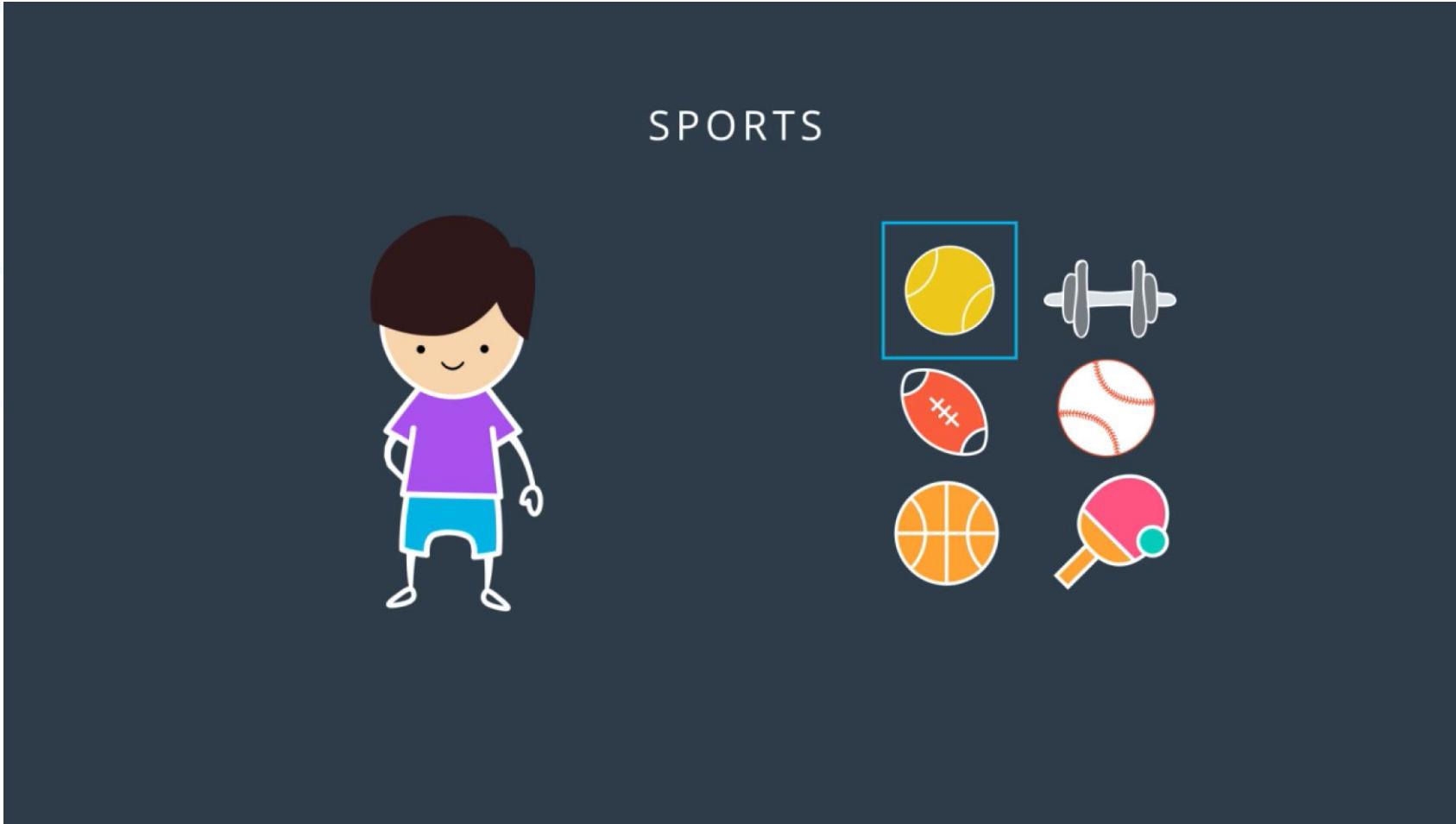
# Redes Neurais – Dropout



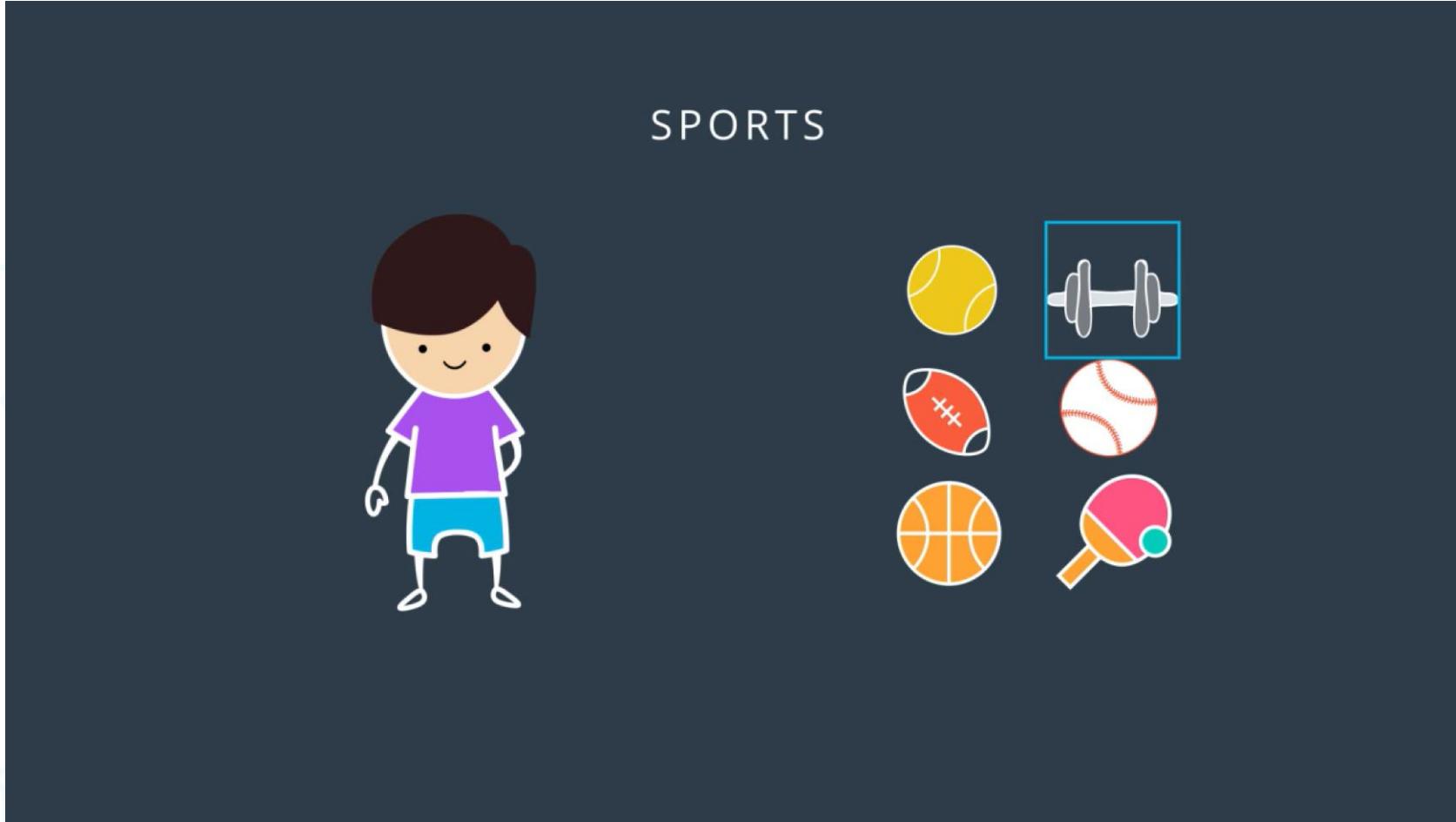
# Redes Neurais – Dropout



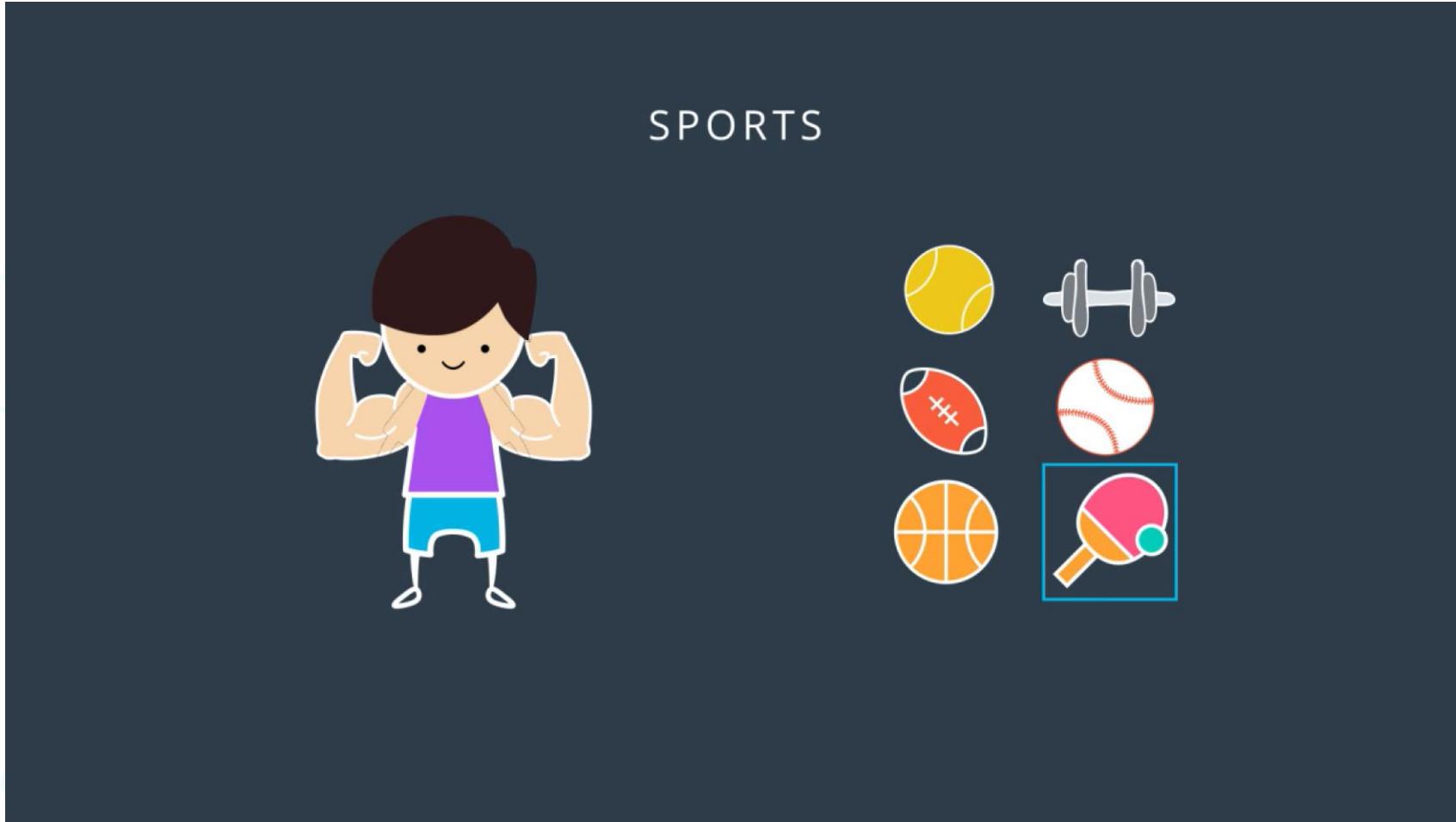
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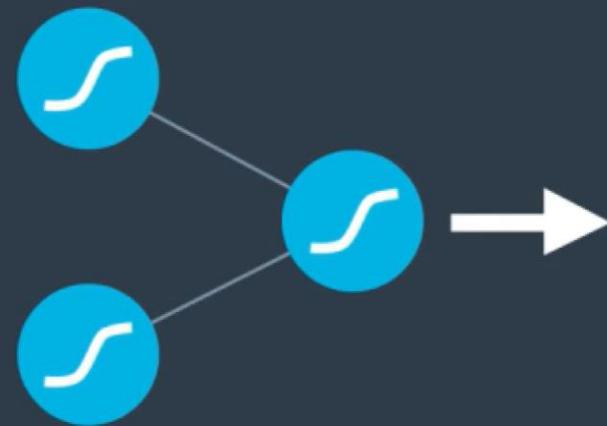
# Redes Neurais – Dropout



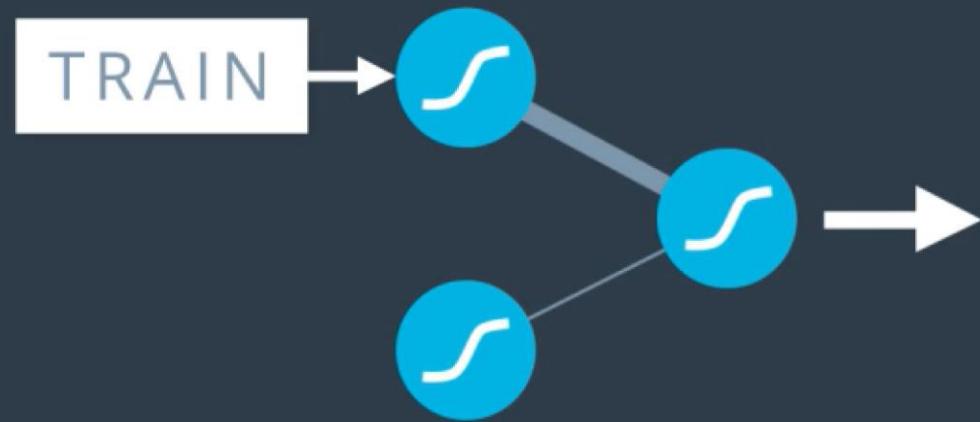
# Redes Neurais – Dropout



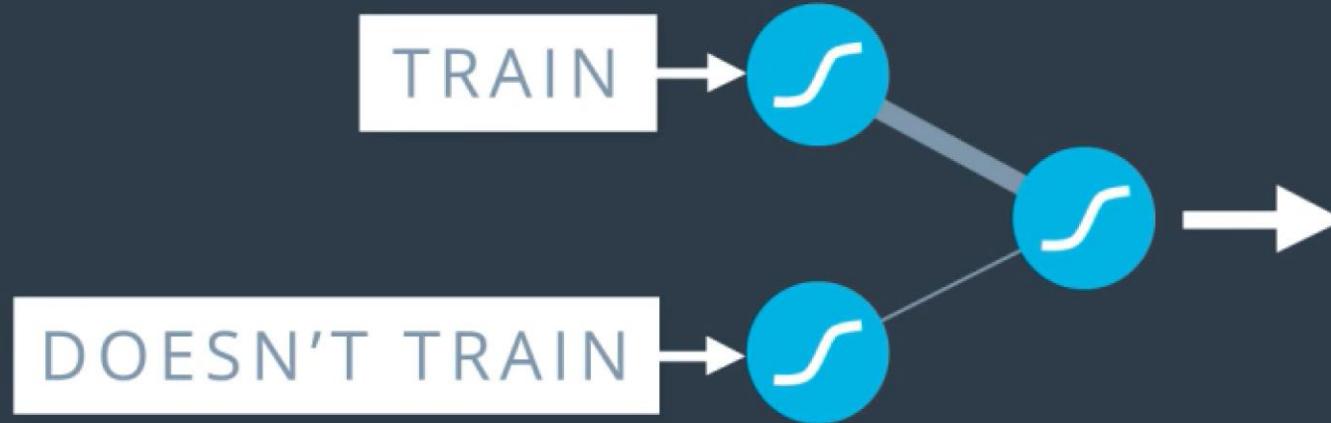
# Redes Neurais – Dropout



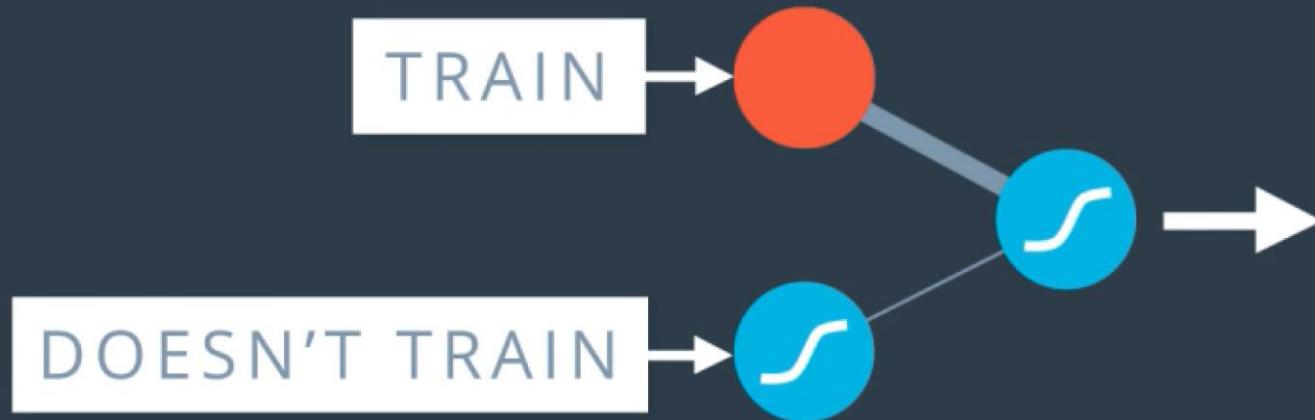
# Redes Neurais – Dropout



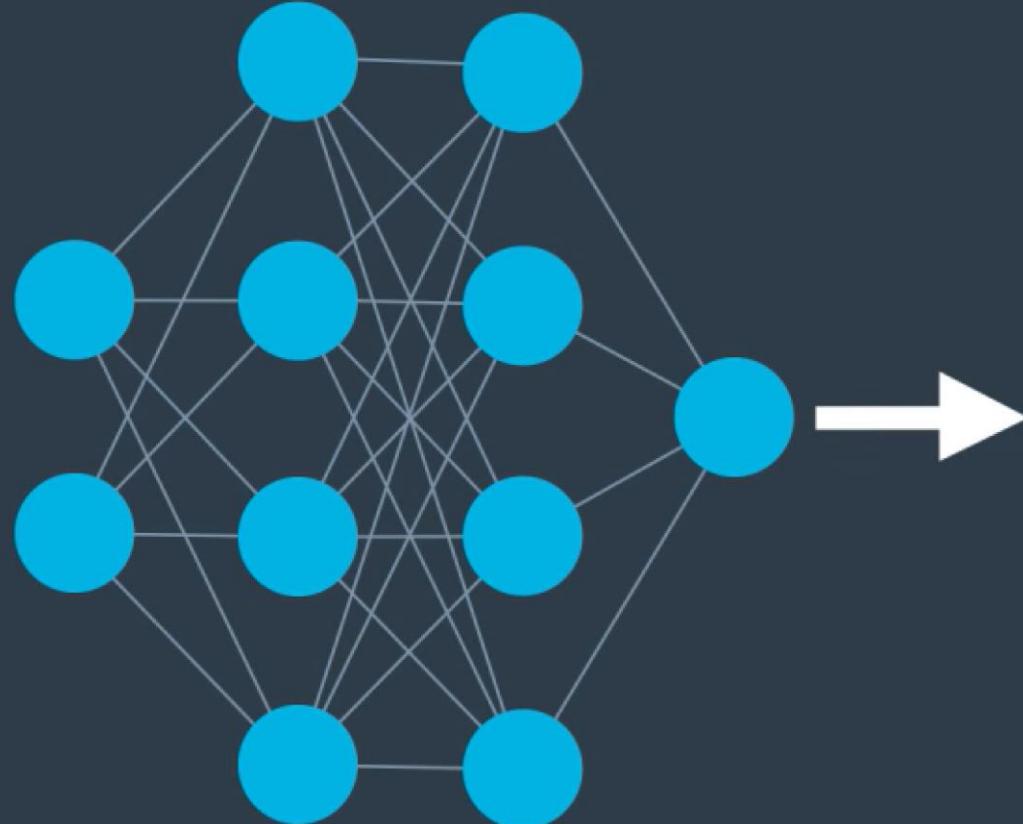
# Redes Neurais – Dropout



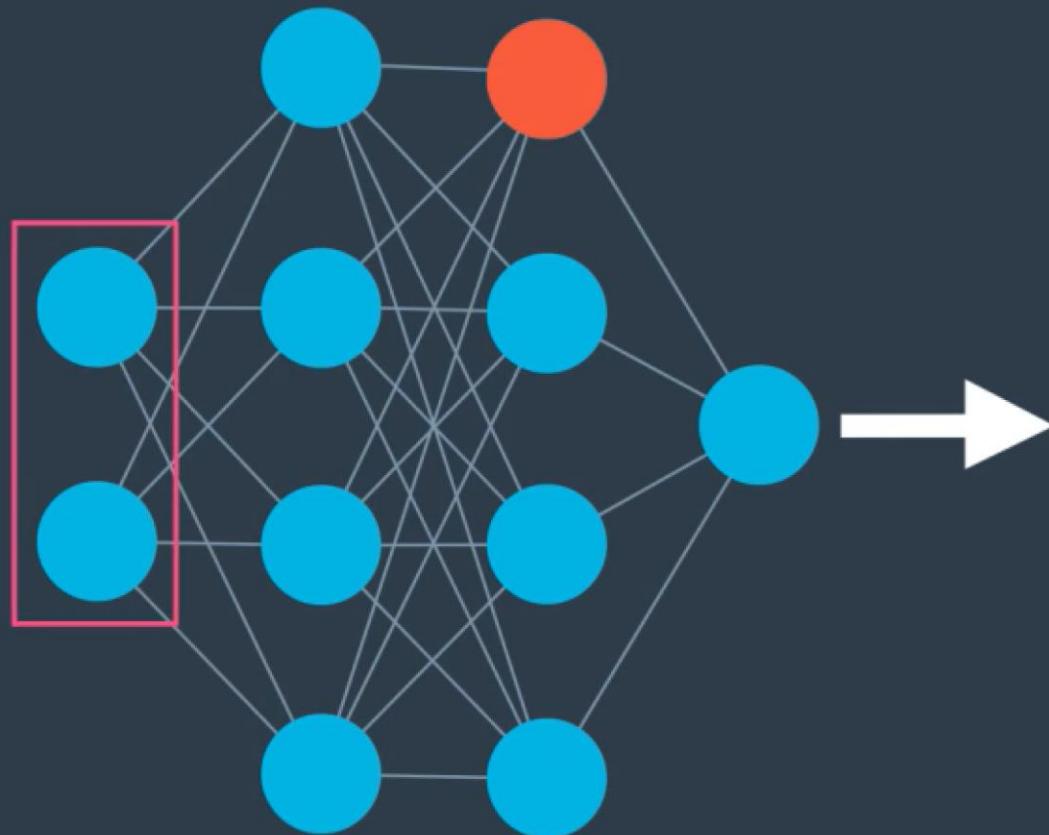
# Redes Neurais – Dropout



# Redes Neurais – Dropout

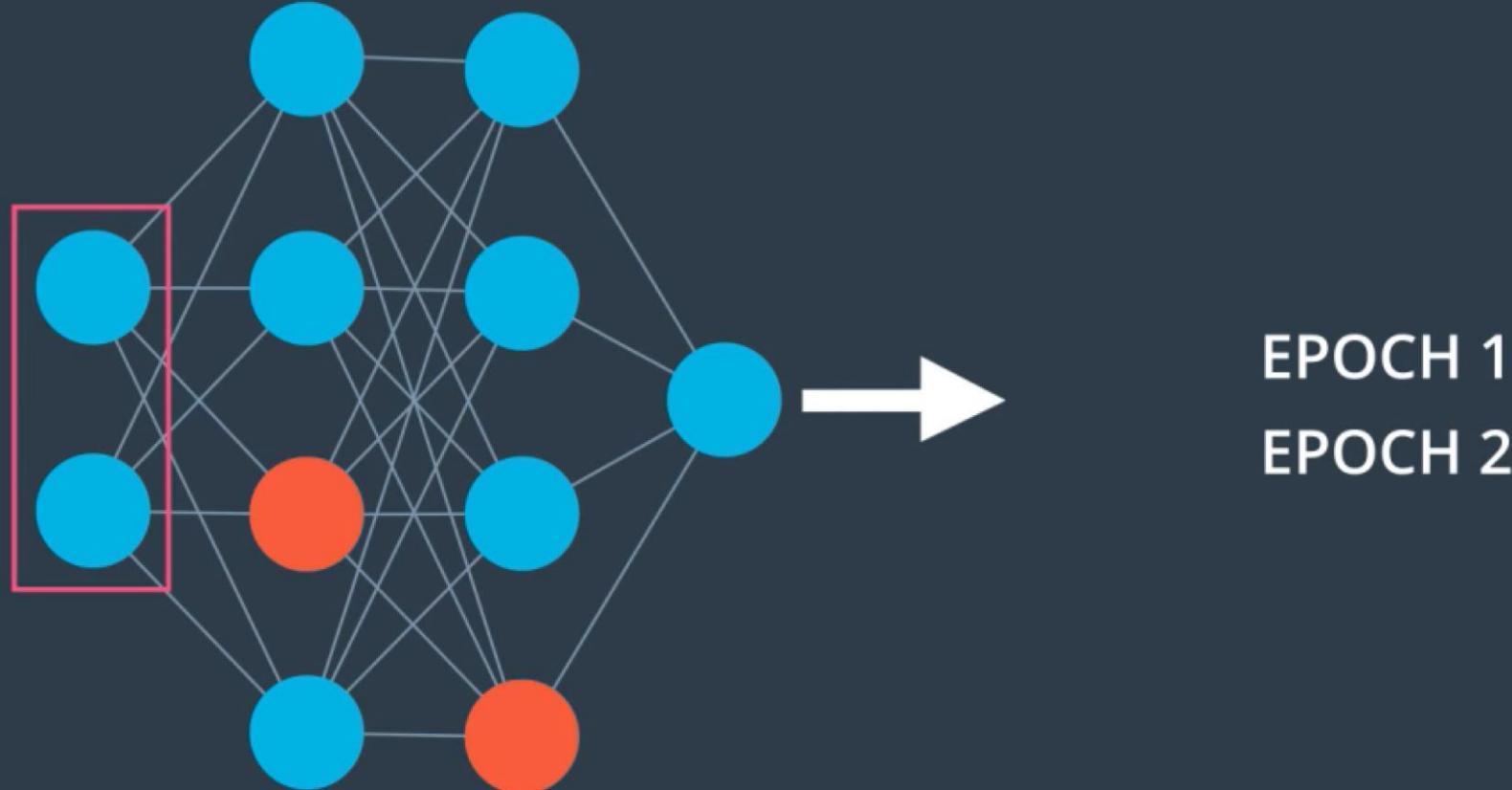


# Redes Neurais – Dropout

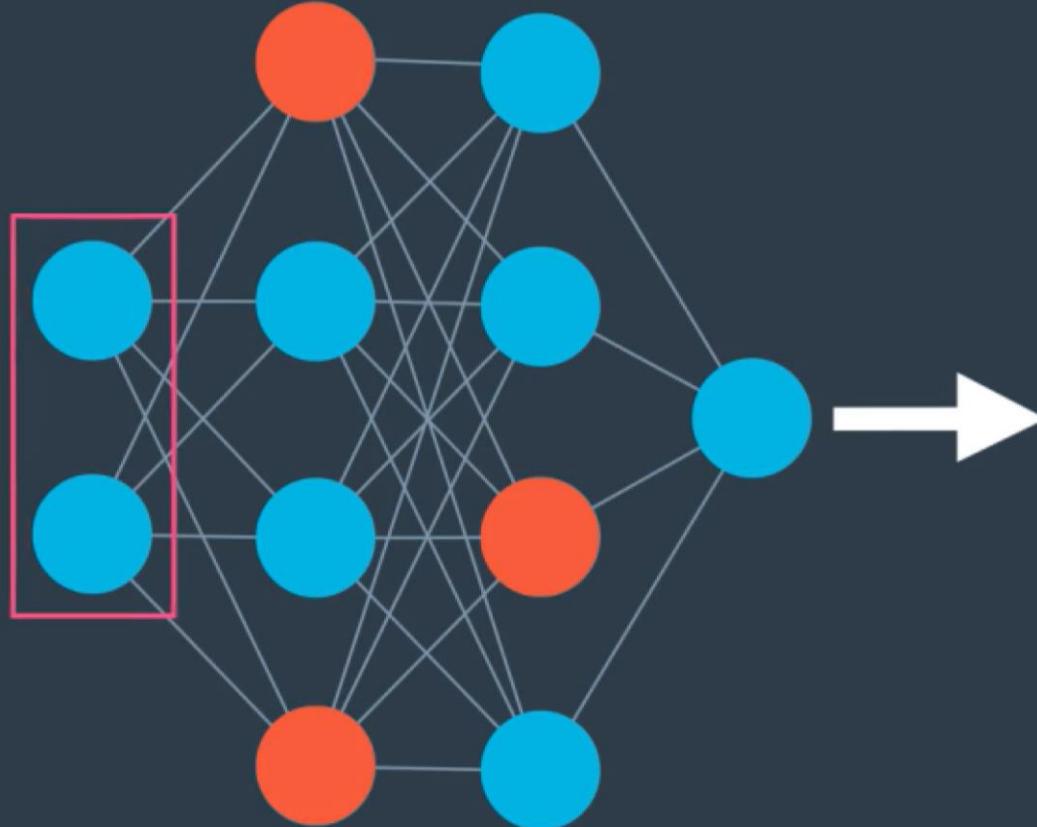


EPOCH 1

# Redes Neurais – Dropout

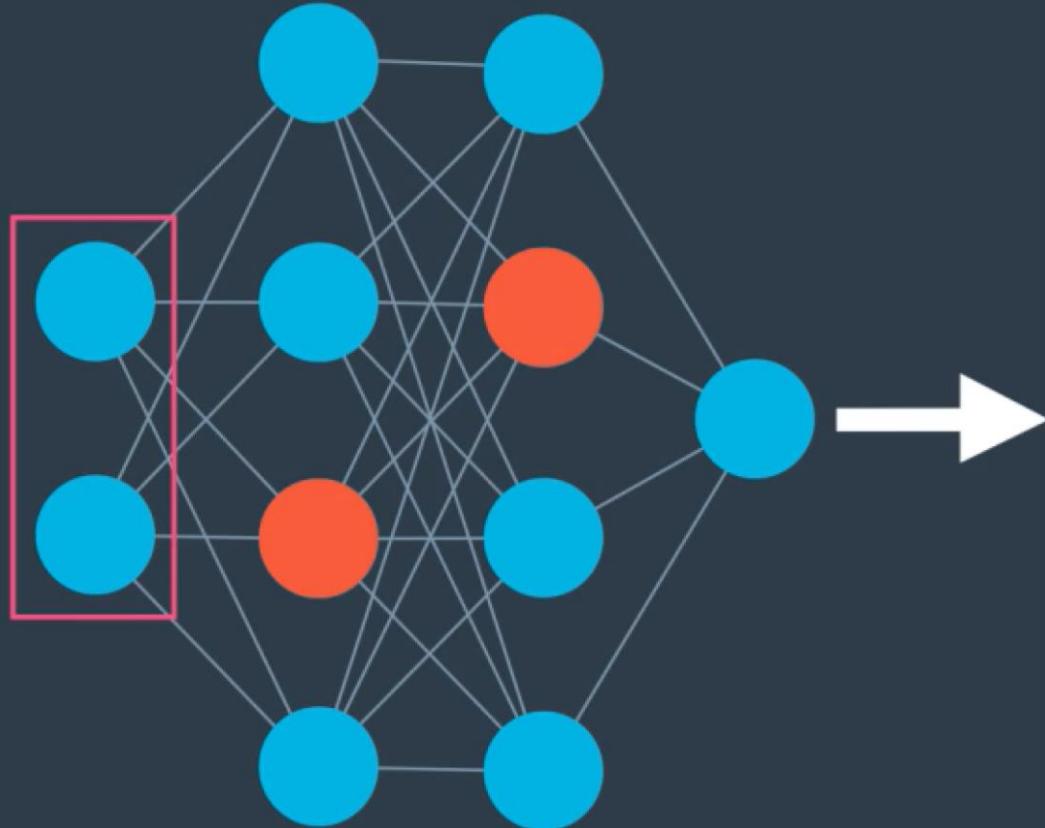


# Redes Neurais – Dropout



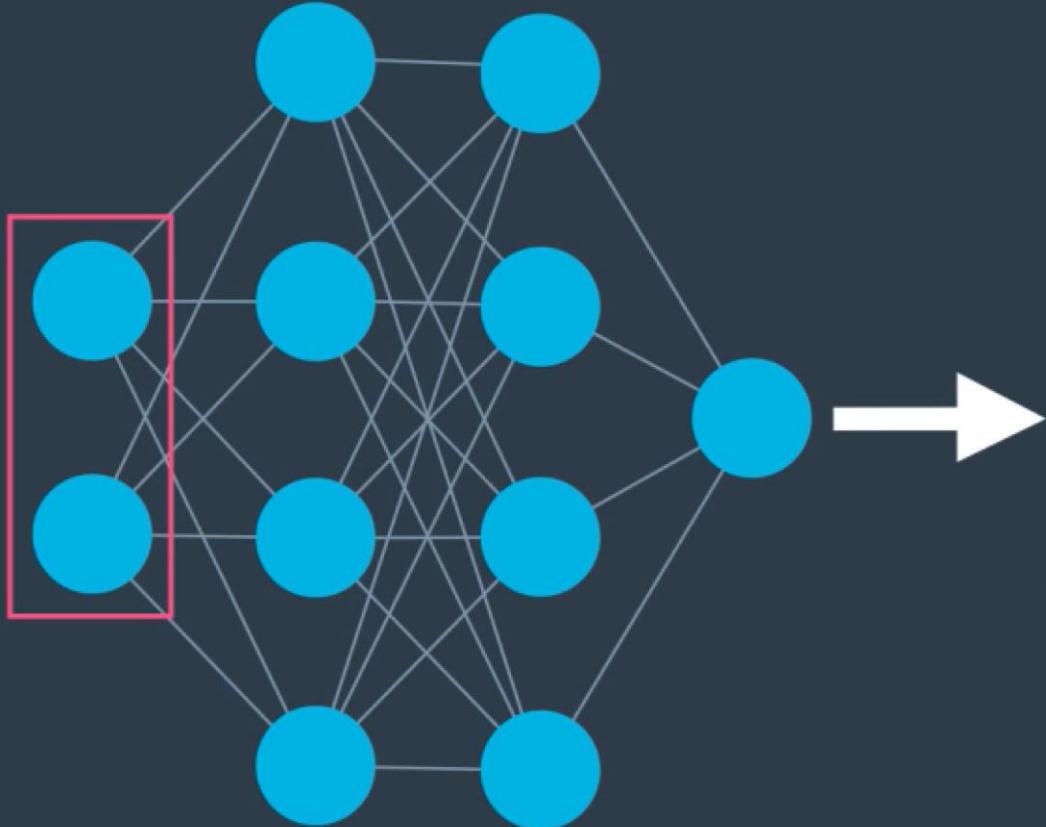
EPOCH 1  
EPOCH 2  
EPOCH 3

# Redes Neurais – Dropout



EPOCH 1  
EPOCH 2  
EPOCH 3  
EPOCH 4

# Redes Neurais – Dropout



EPOCH 1

EPOCH 2

EPOCH 3

EPOCH 4

...

**PROBABILITY EACH NODE  
WILL BE DROPPED = 0.2**

# Thanks !



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