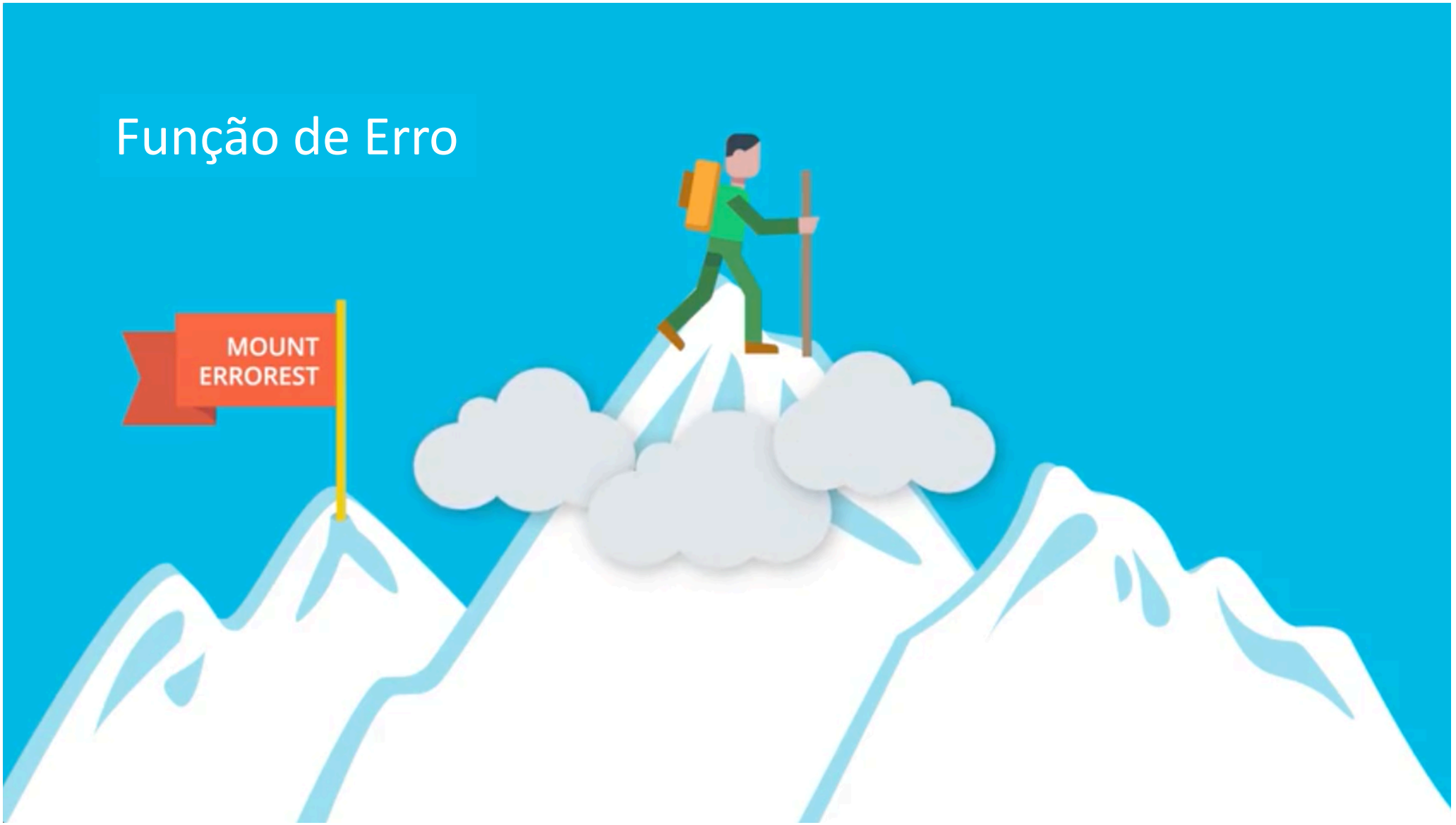
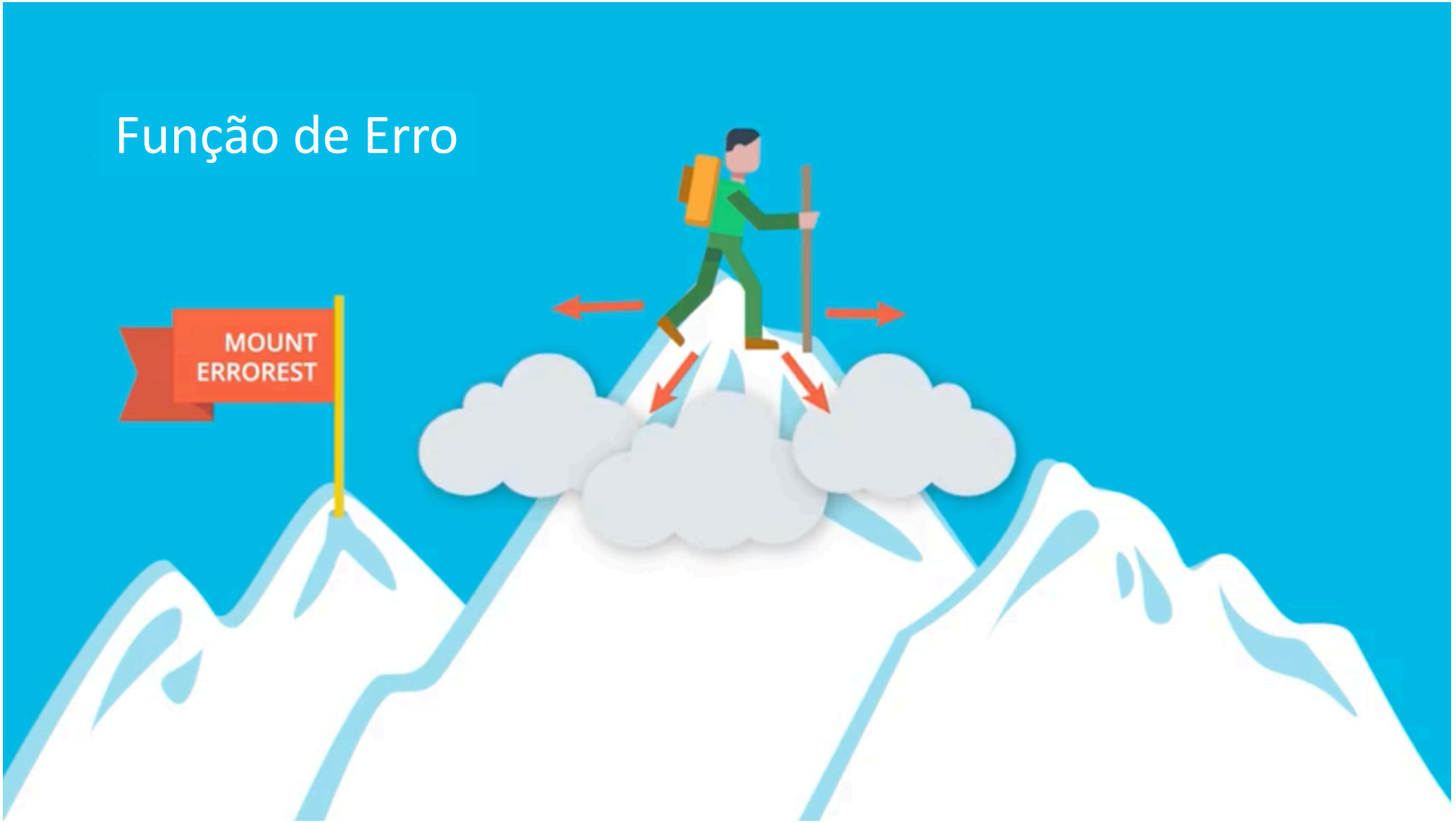
FILIPE ROLIM CORDEIRO (FILIPE.ROLIM@GMAIL.COM)

Função de Erro

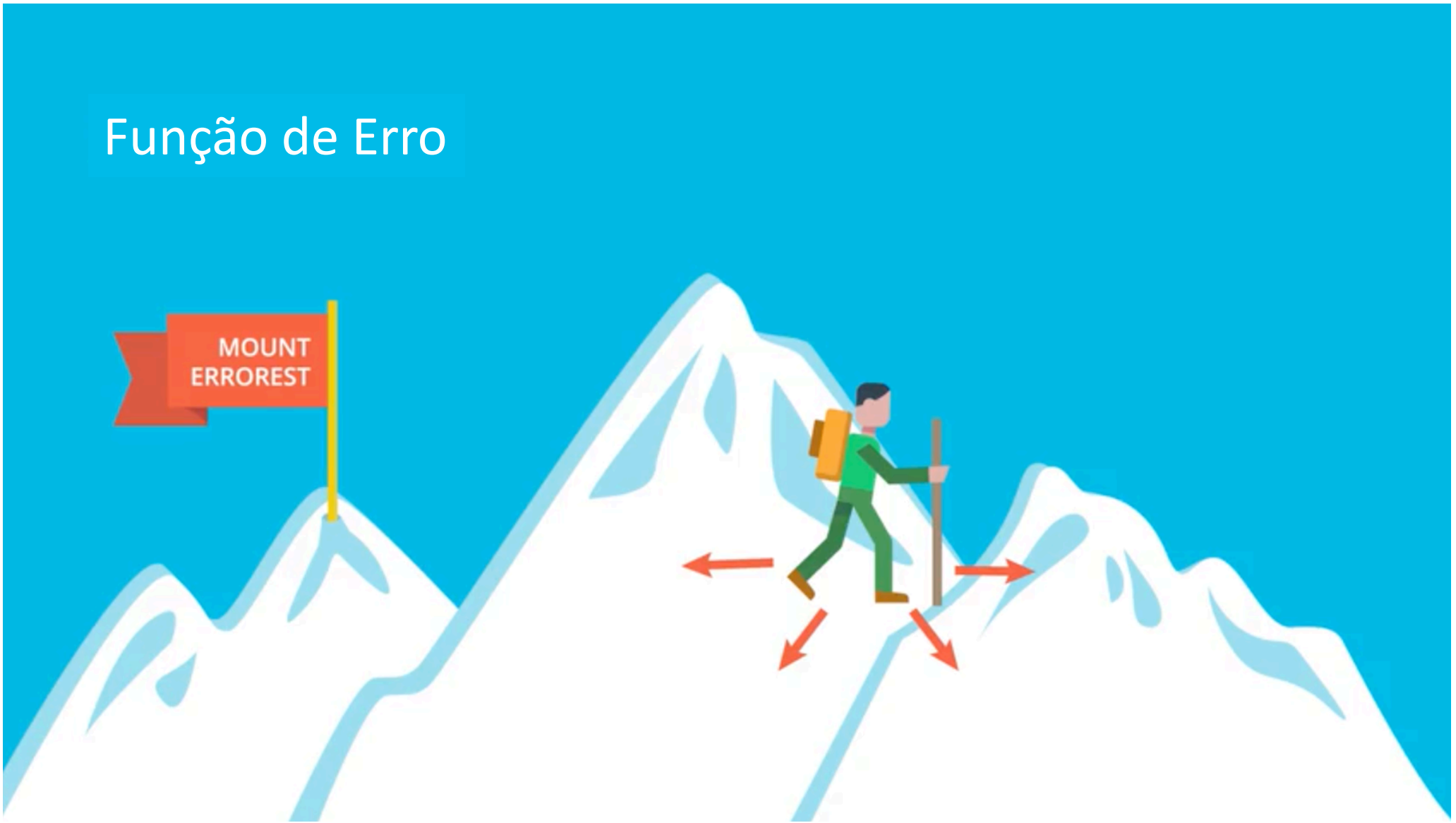
Função de Erro



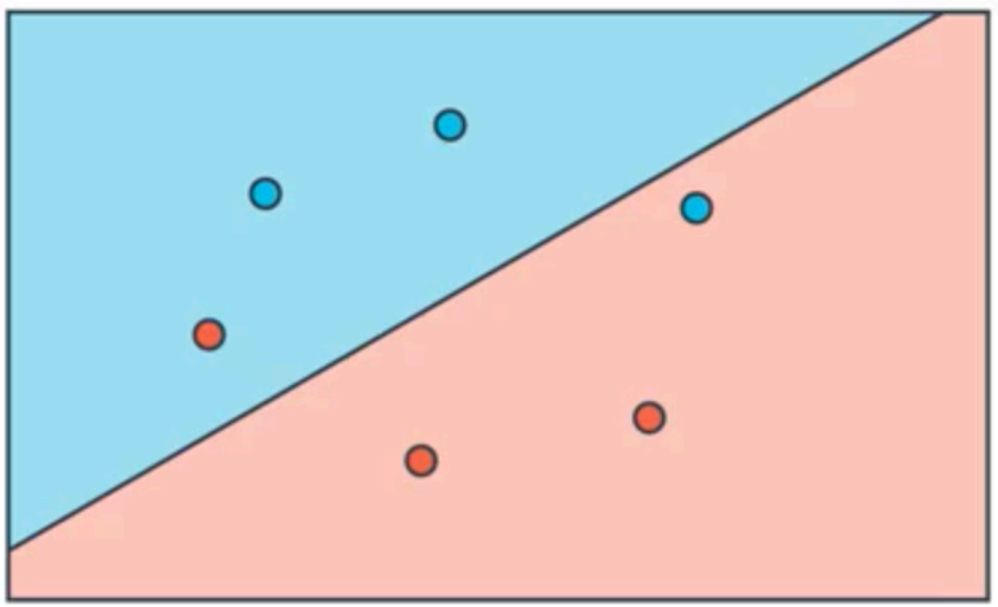
Função de Erro



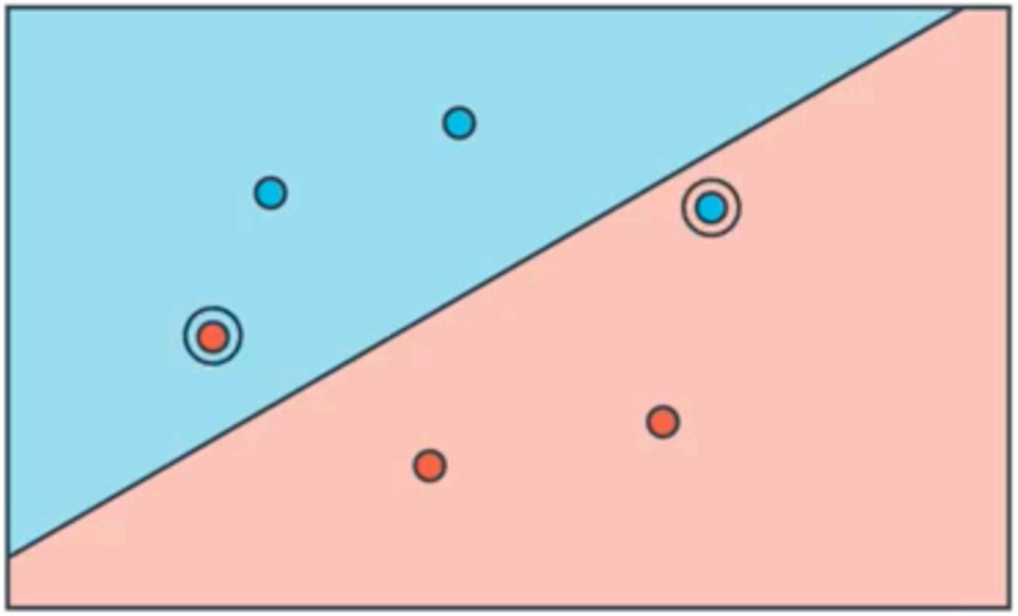
Função de Erro



- O quão errado é o modelo?

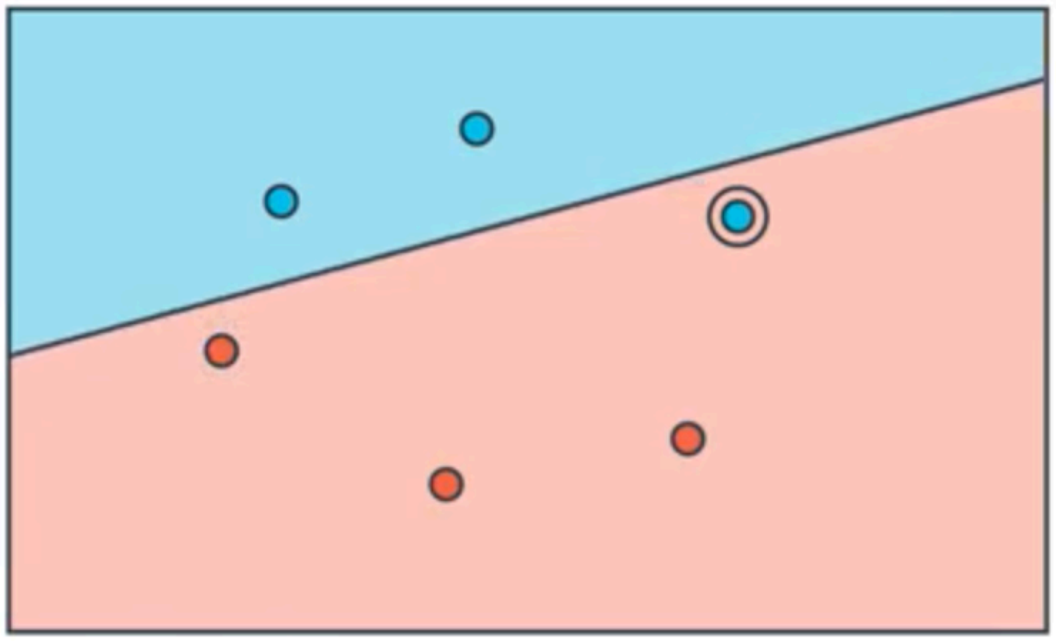


- O quão errado é o modelo?



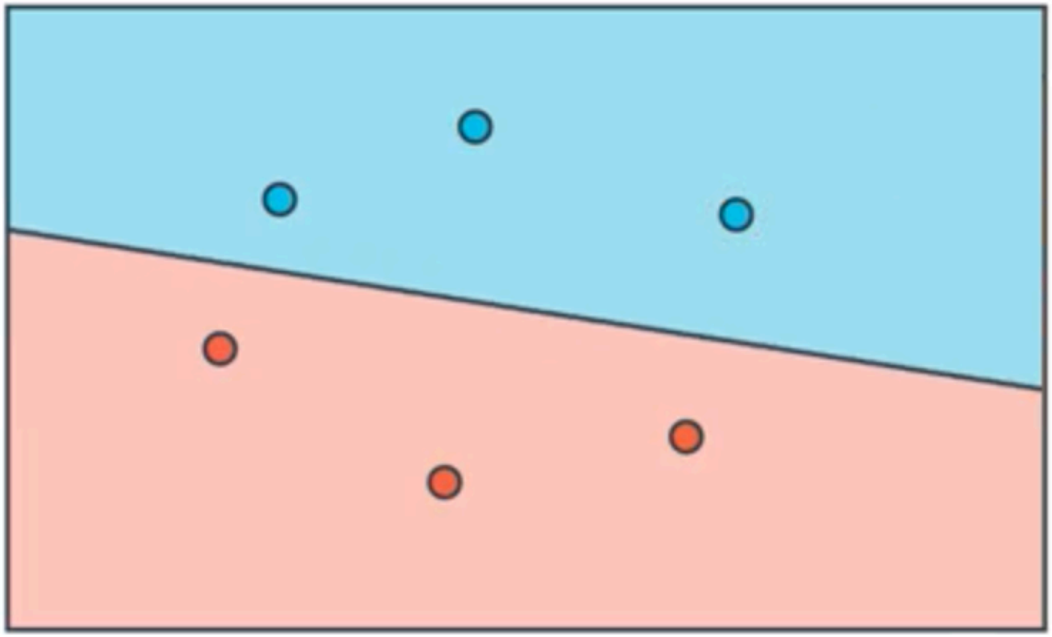
2 erros

- O quão errado é o modelo?



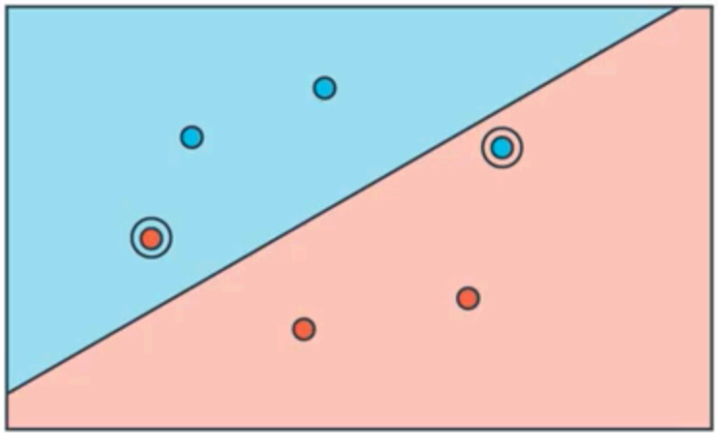
1 erro

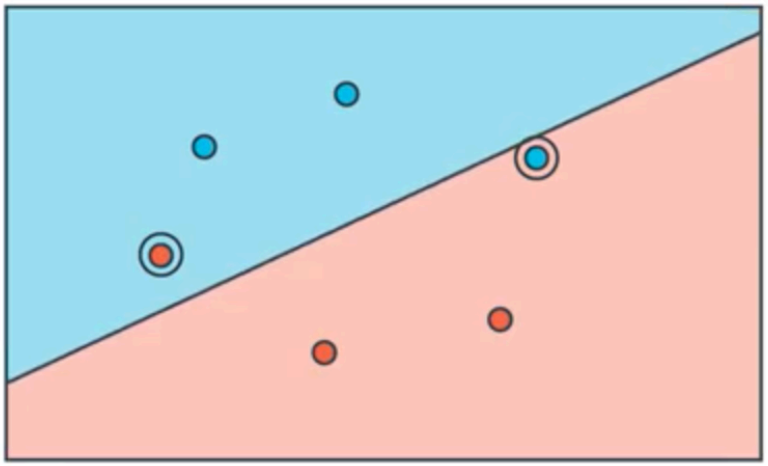
- O quão errado é o modelo?

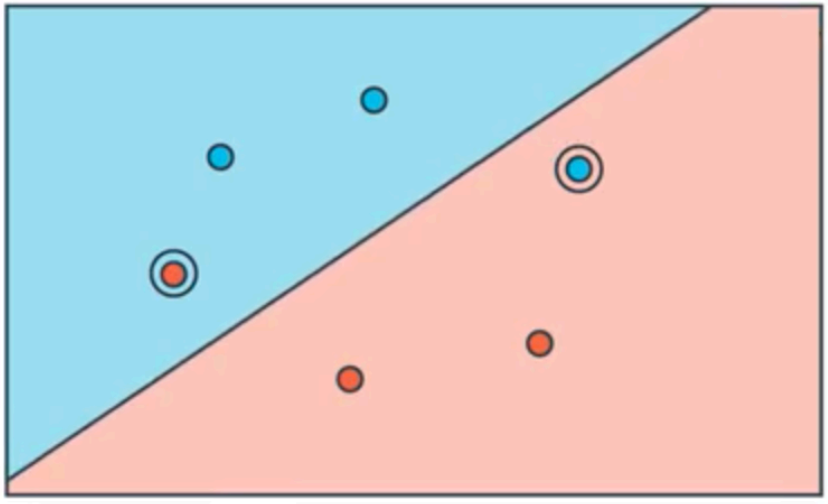


0 erros

- Problema!

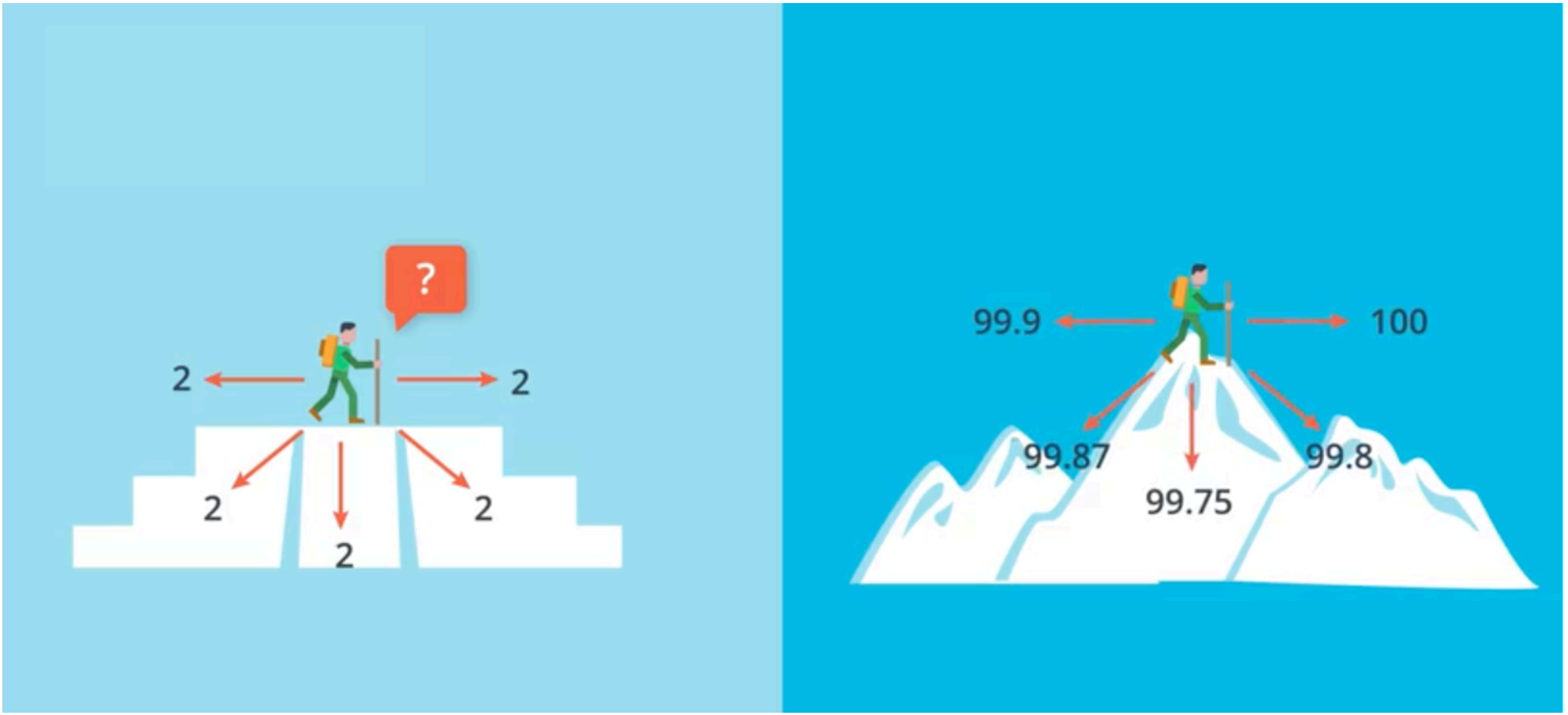




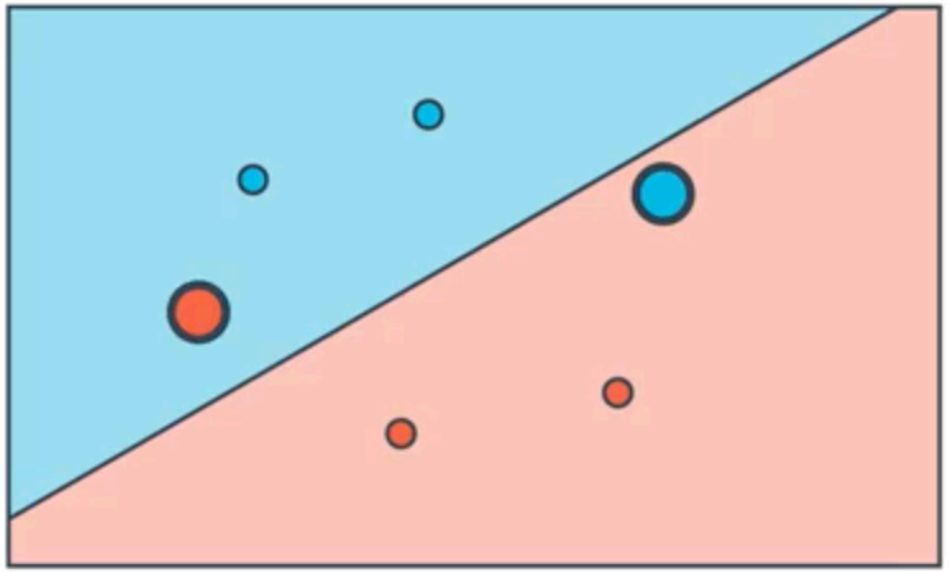


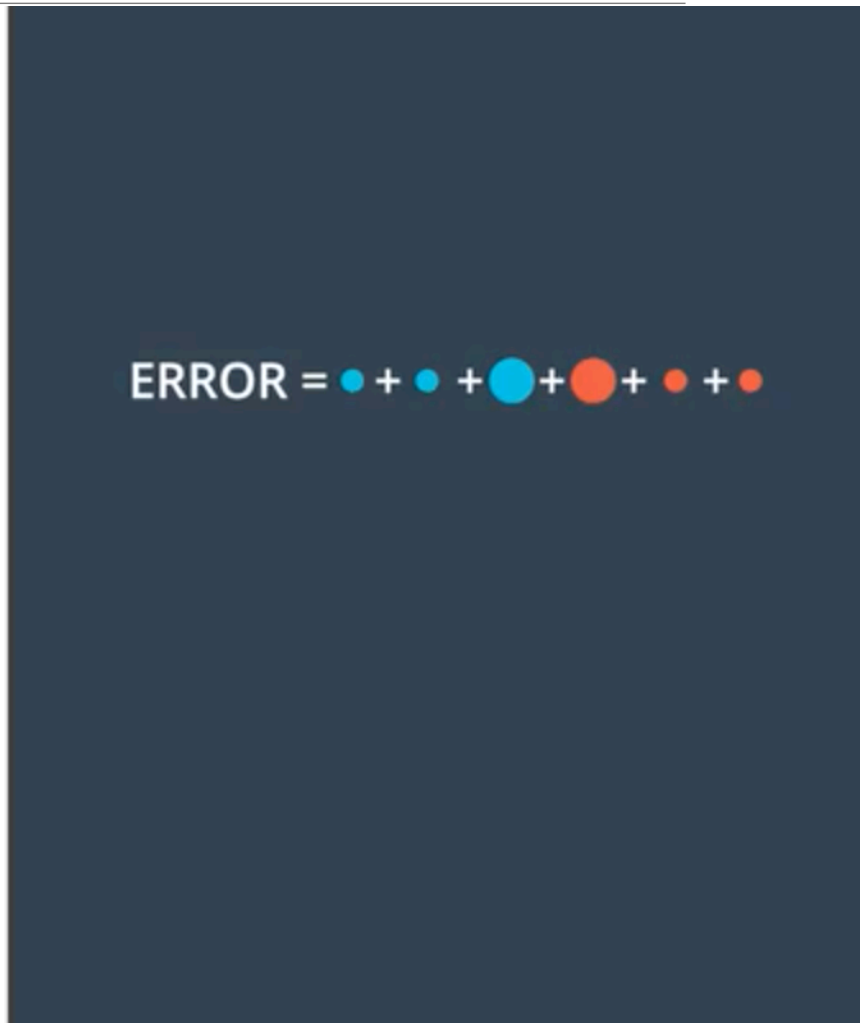
2 erros

Discreto vs Contínuo

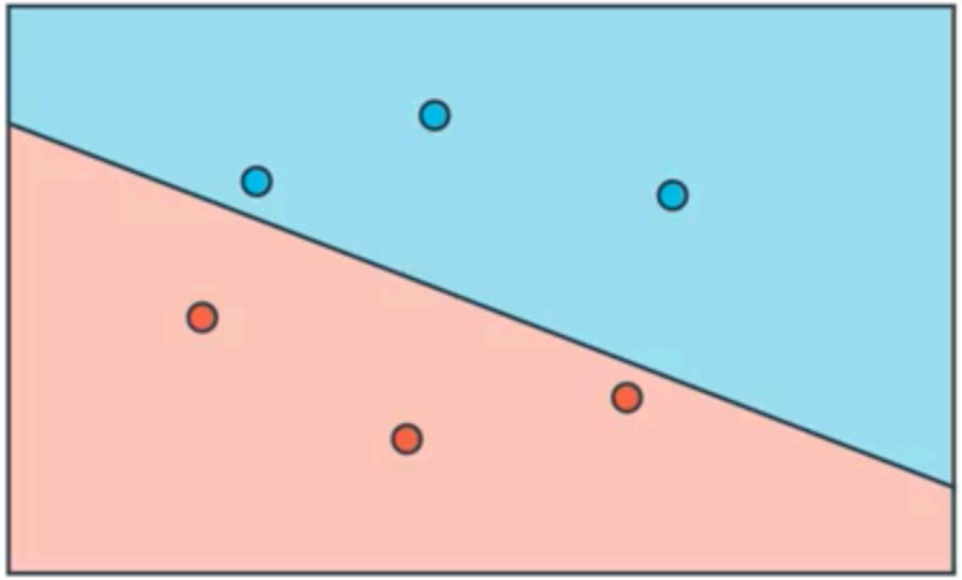


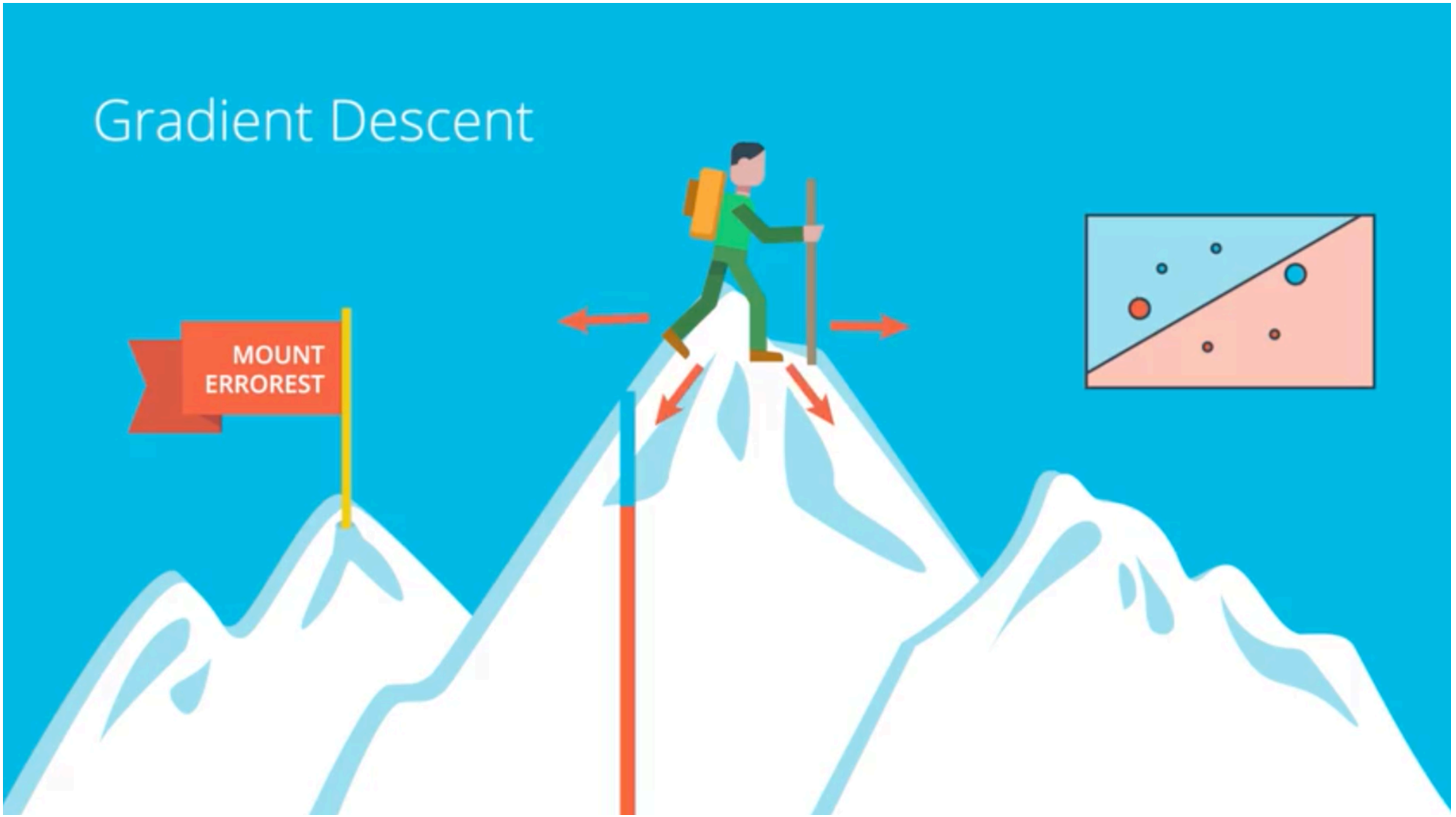
Função de Erro

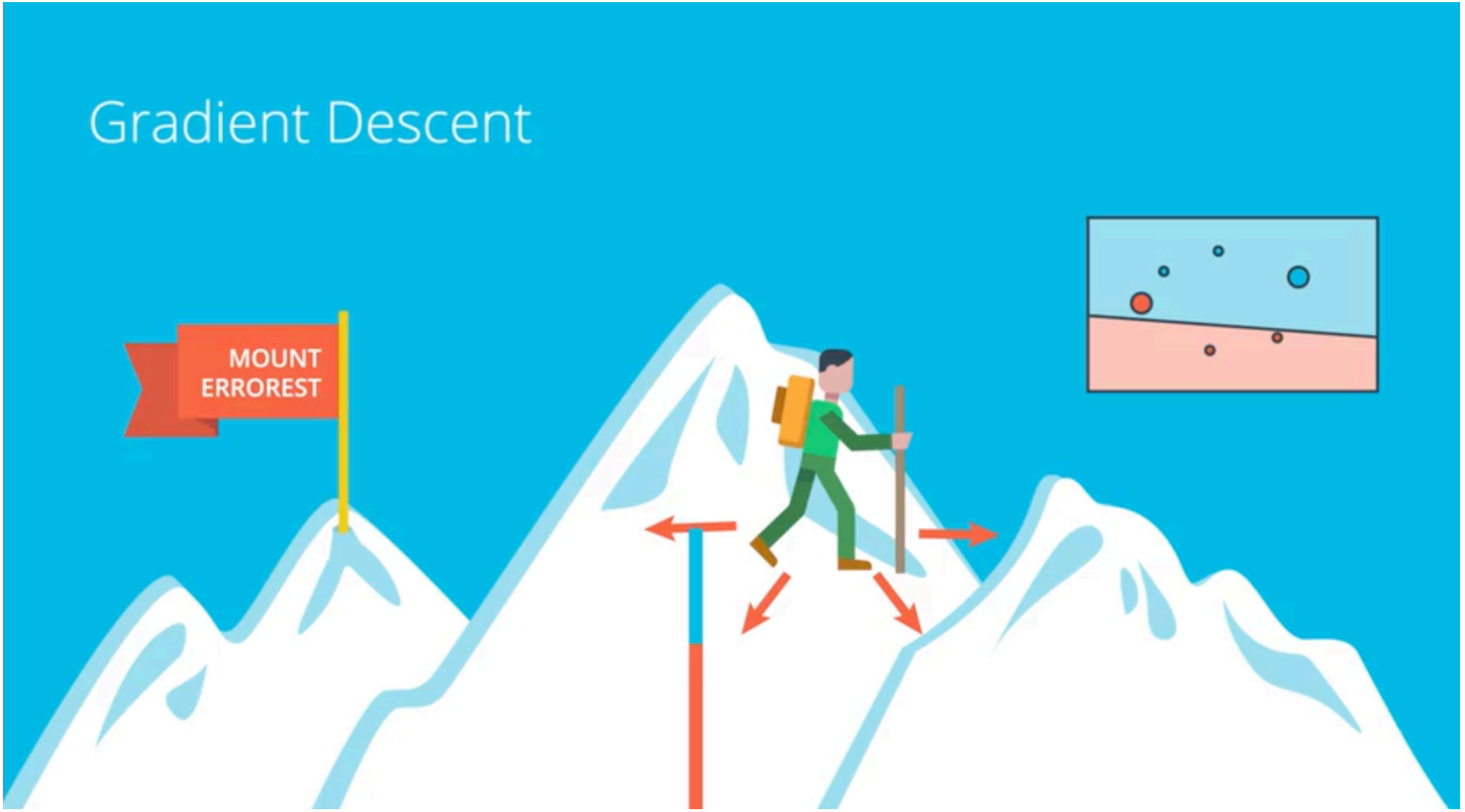


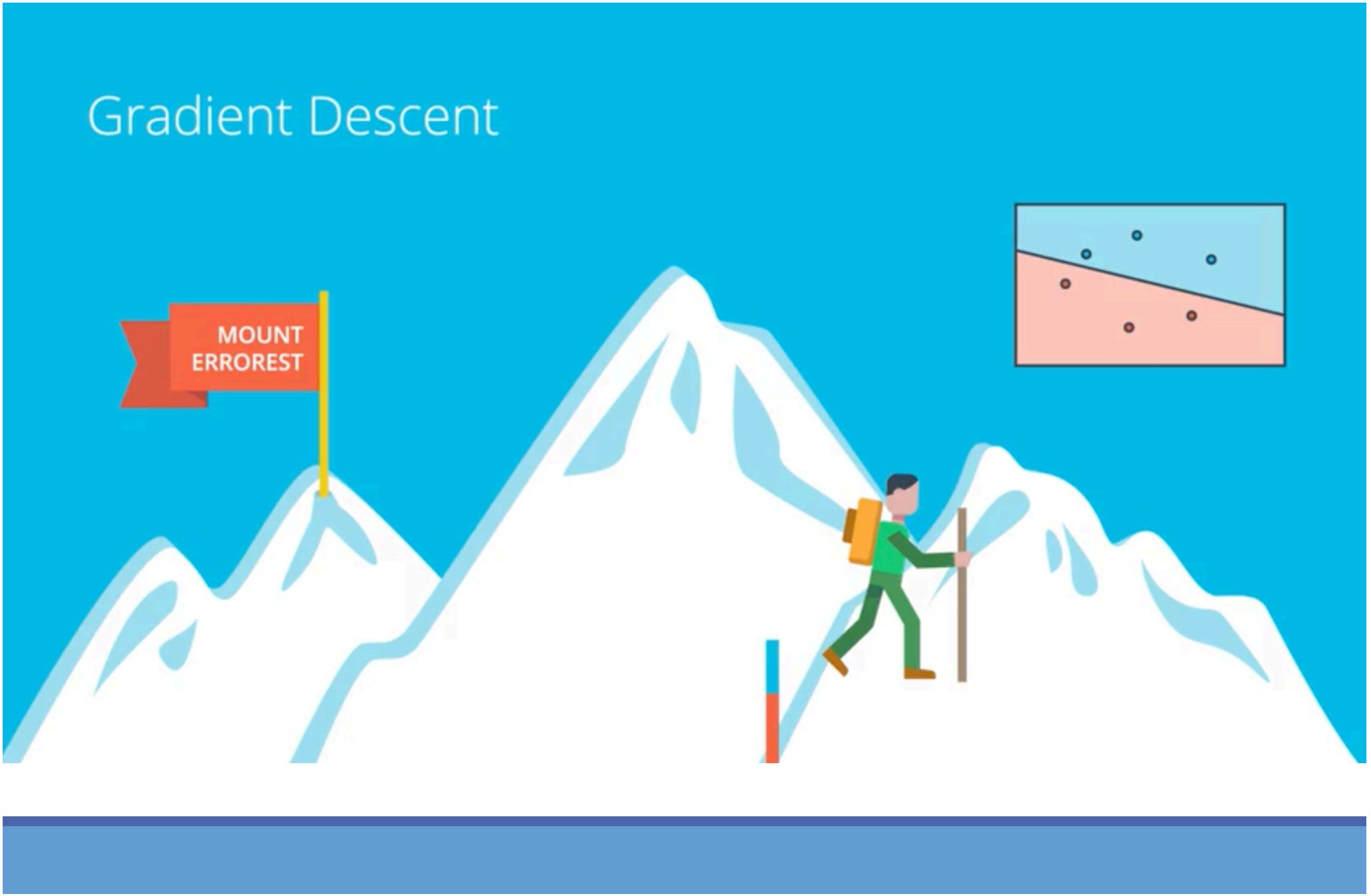


Função de Erro

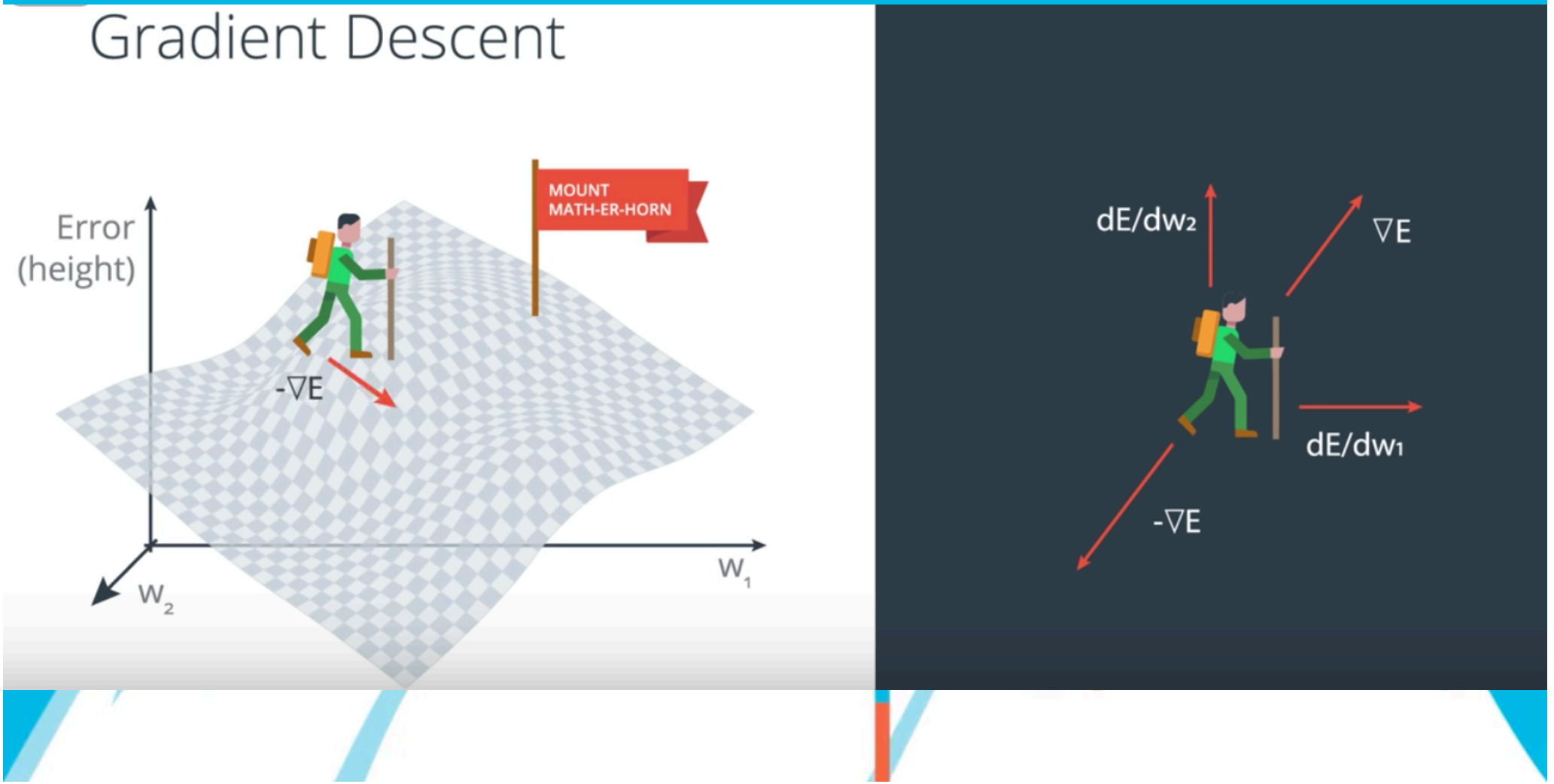



Gradient Descent
MOUNT
ERROREST

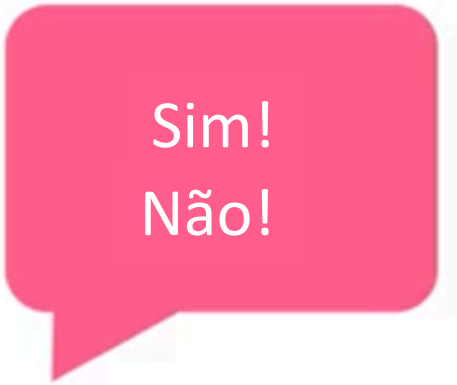

Gradient Descent
MOUNT
ERROREST


Gradient Descent
MOUNT
ERROREST

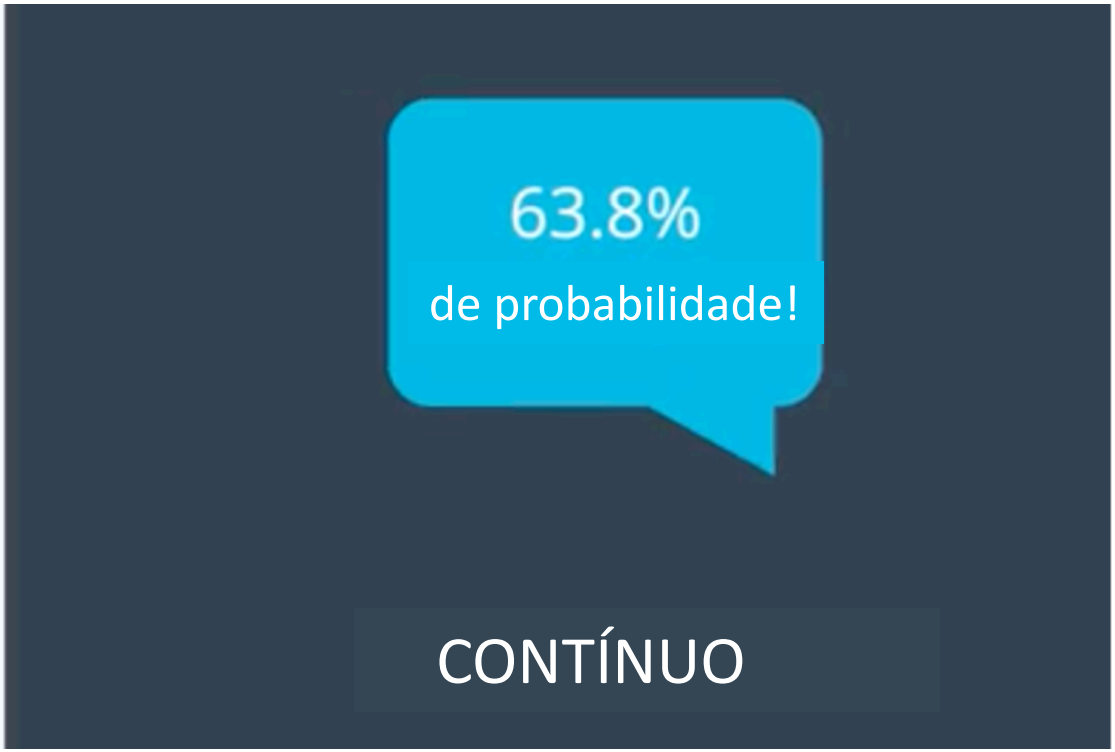
Gradient Descent



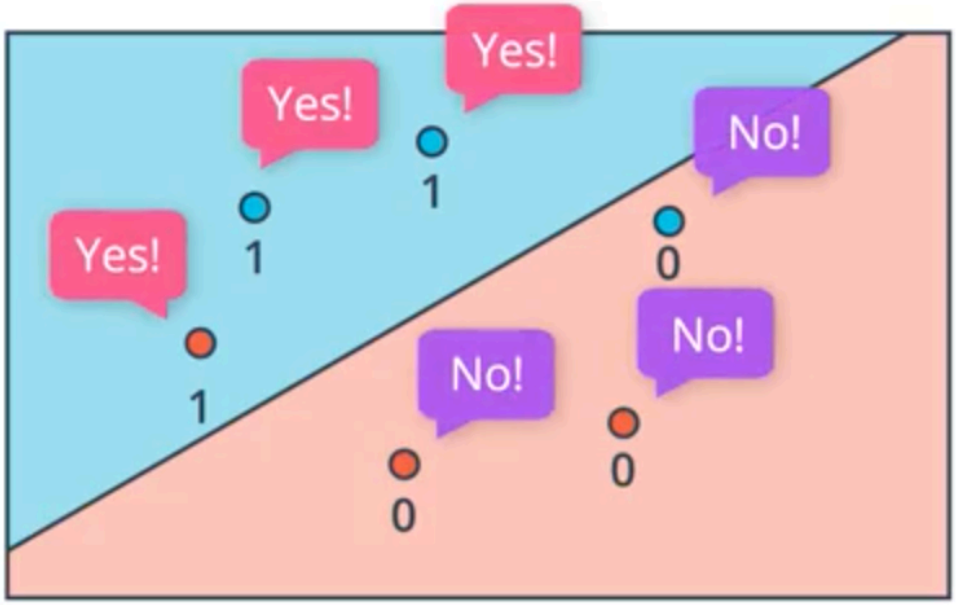
Predições – Discreta vs Contínua



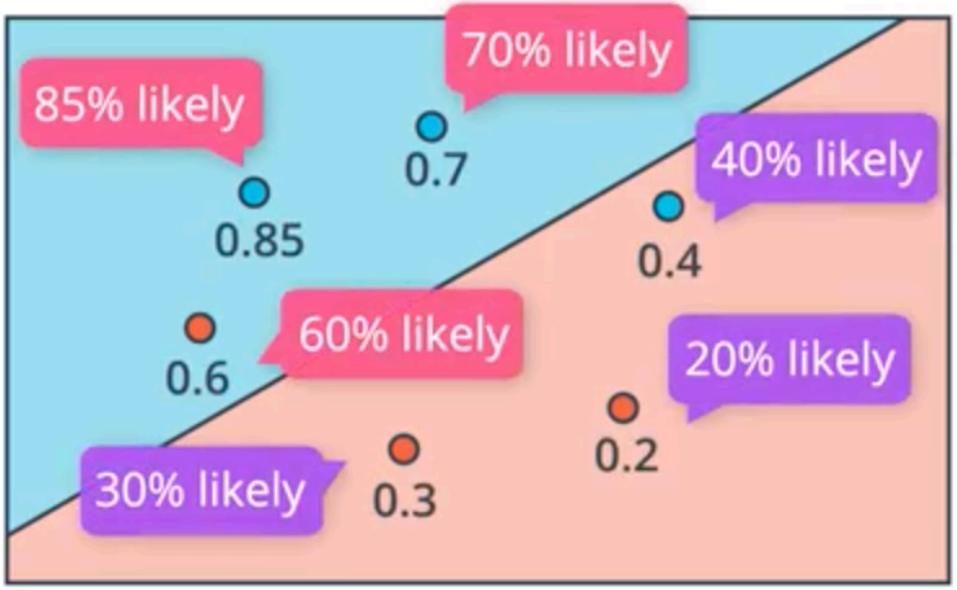
DISCRETO



Predições

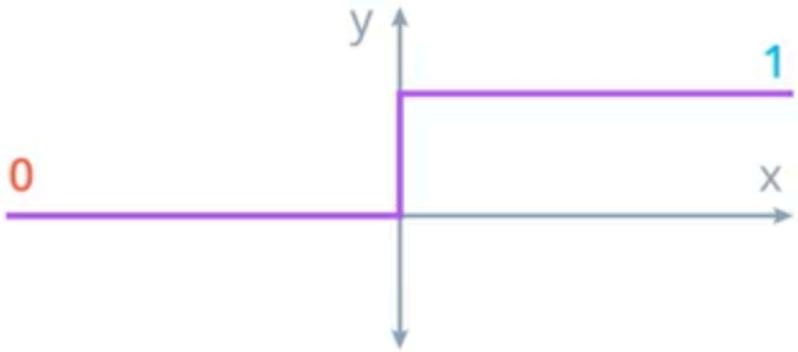


DISCRETO



CONTÍNUO

Funções de Ativação



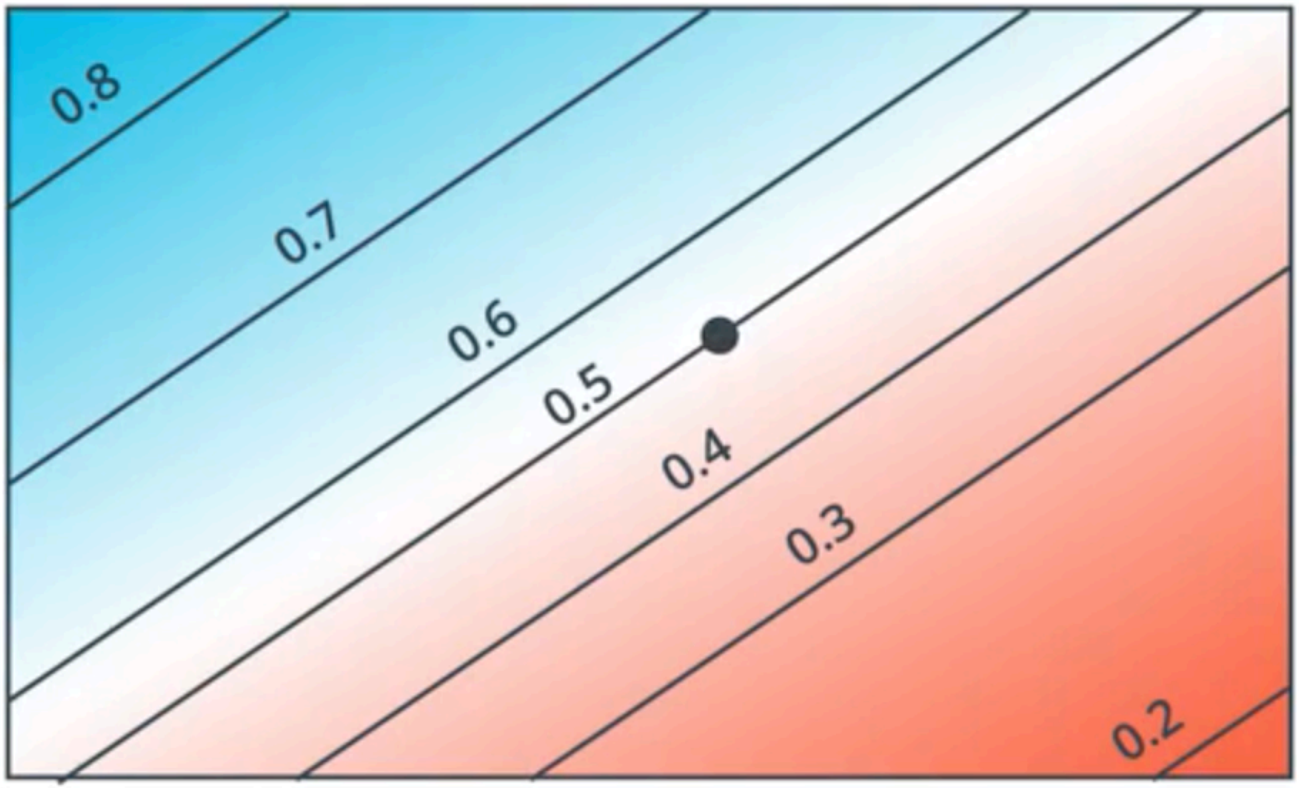
DISCRETO:
Função Degrau

$$y = \begin{cases} 1 \text{ if } x \geq 0 \\ 0 \text{ if } x < 0 \end{cases}$$

CONTÍNUO
Função Sigmoide

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

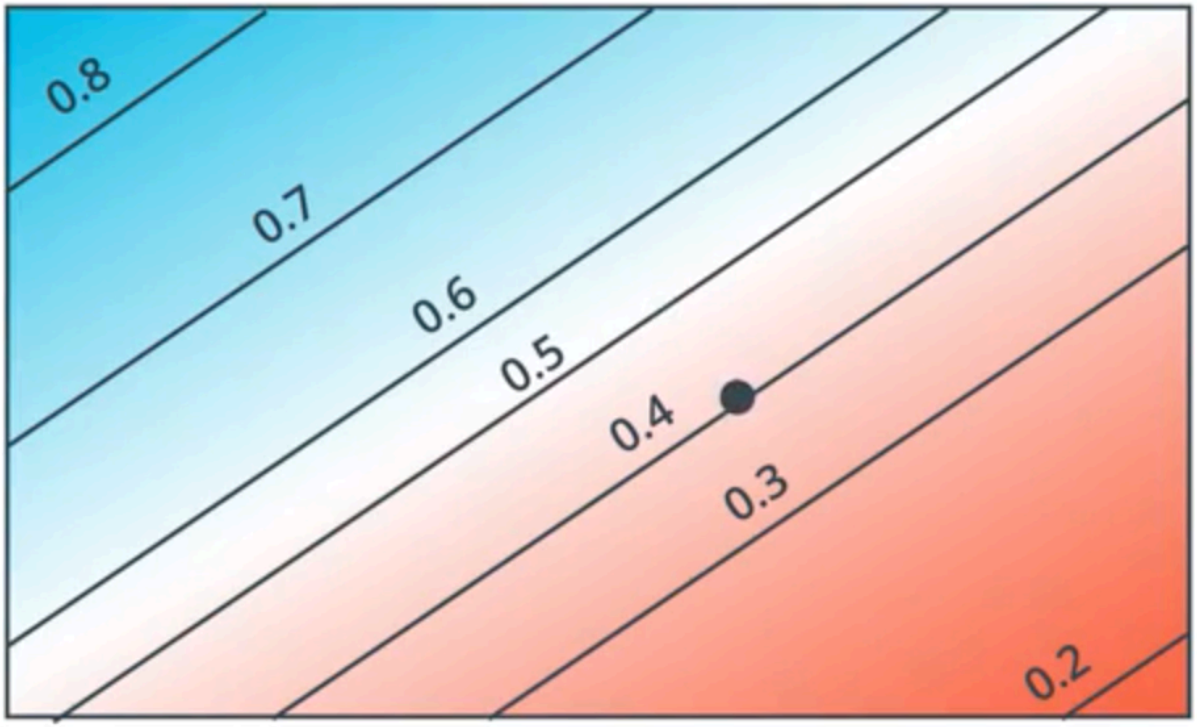
Predições



P(BLUE) = 0.5

P(RED) = 0.5

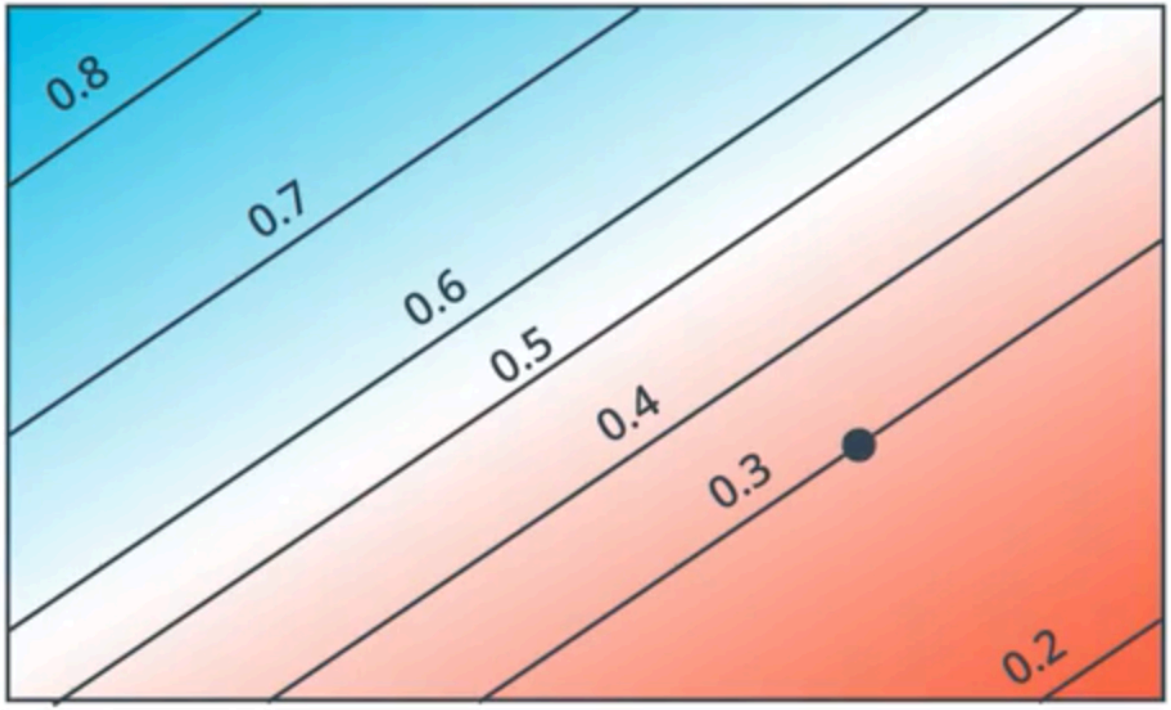
Predições



P(BLUE) = 0.4

P(RED) = 0.6

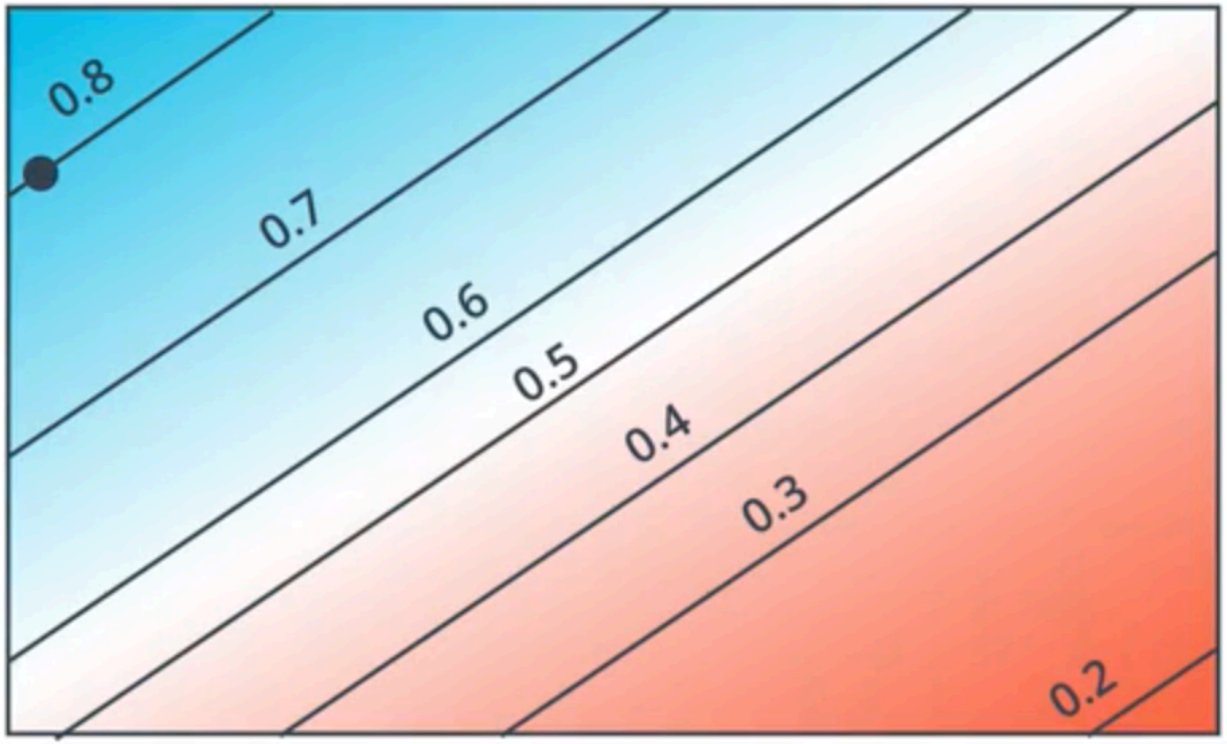
Predicões



P(BLUE) = 0.3

P(RED) = 0.7

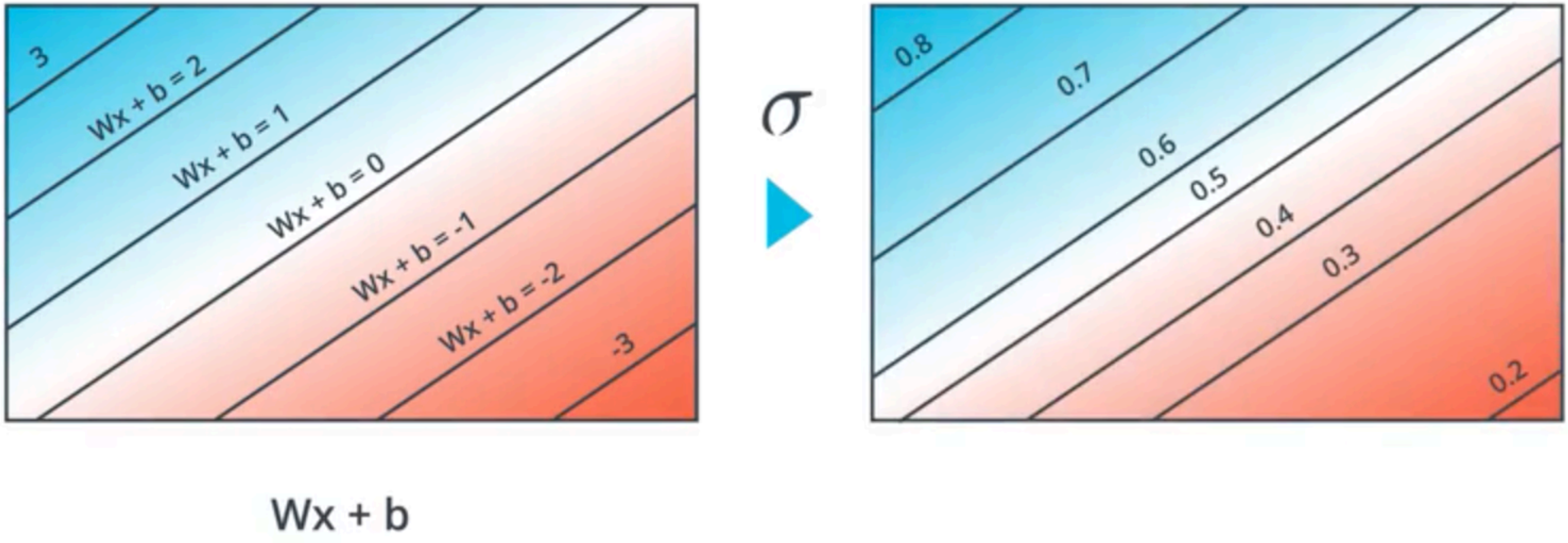
Predições



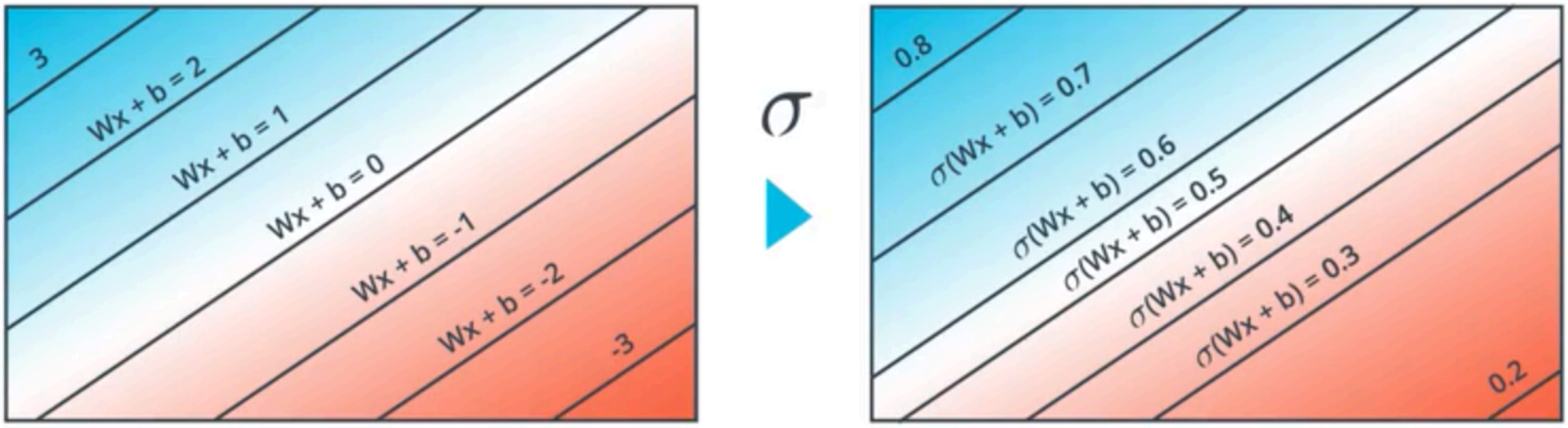
P(BLUE) = 0.8

P(RED) = 0.2

Predições

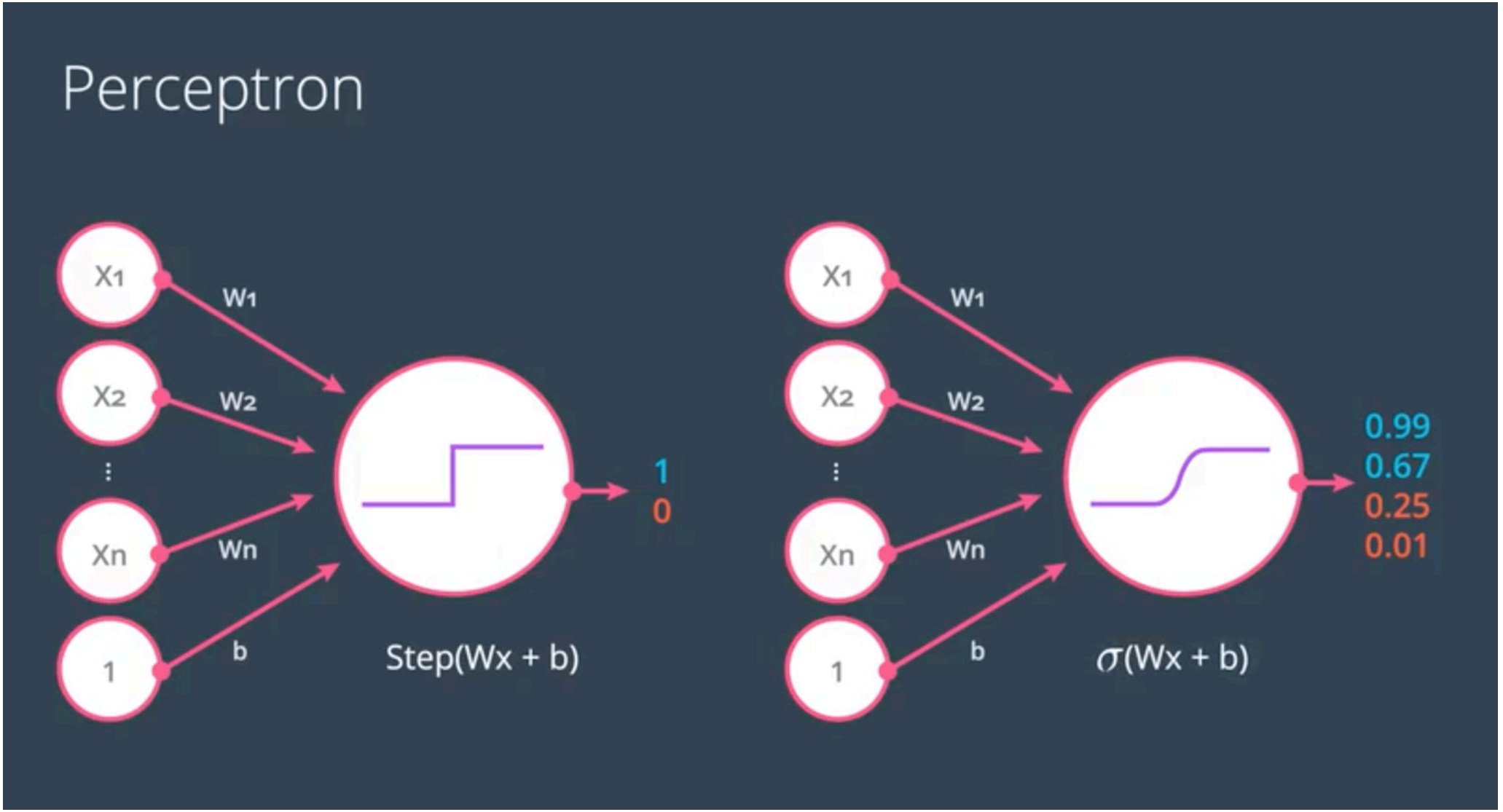


Predições

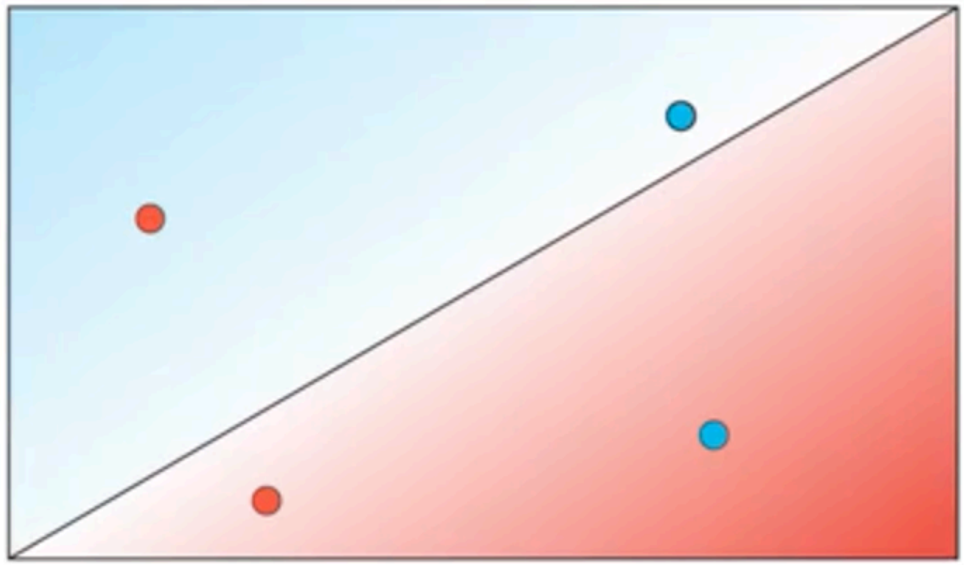


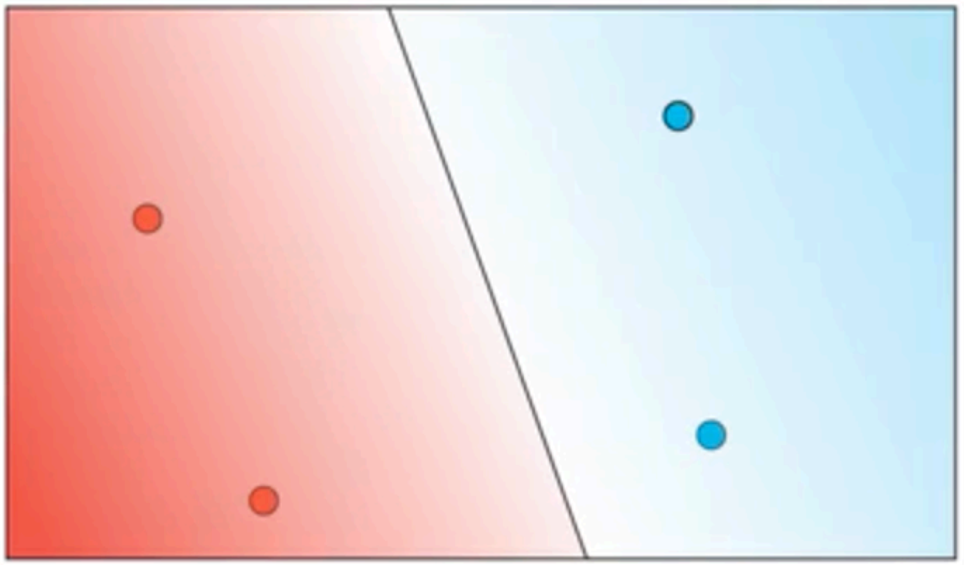
$Wx + b$

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

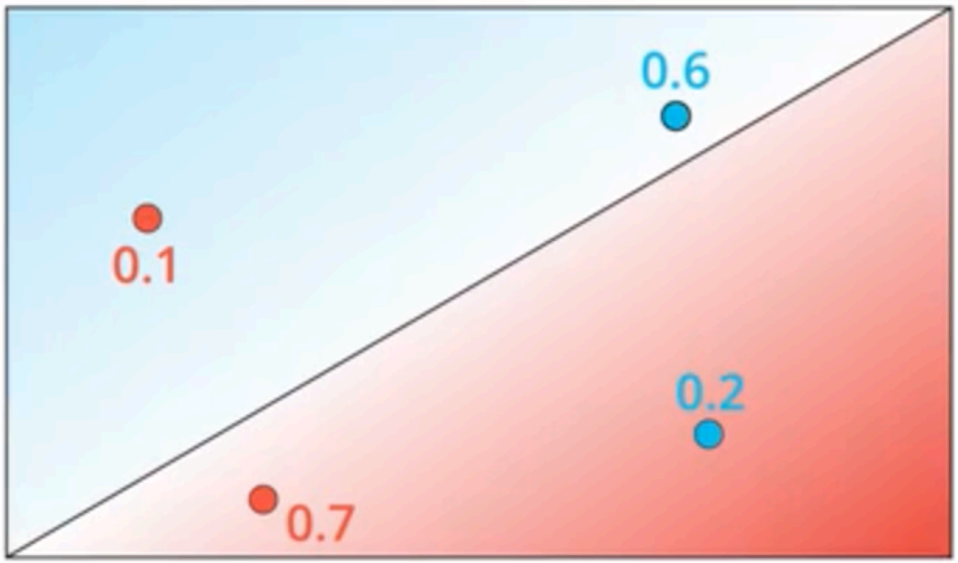

Perceptron
X1
X2
Xn
1
W1
W2
Wn
b
Step(Wx + b)
1
0
X1
X2
Xn
1
W1
W2
Wn
b
σ(Wx + b)
0.99
0.67
0.25
0.01

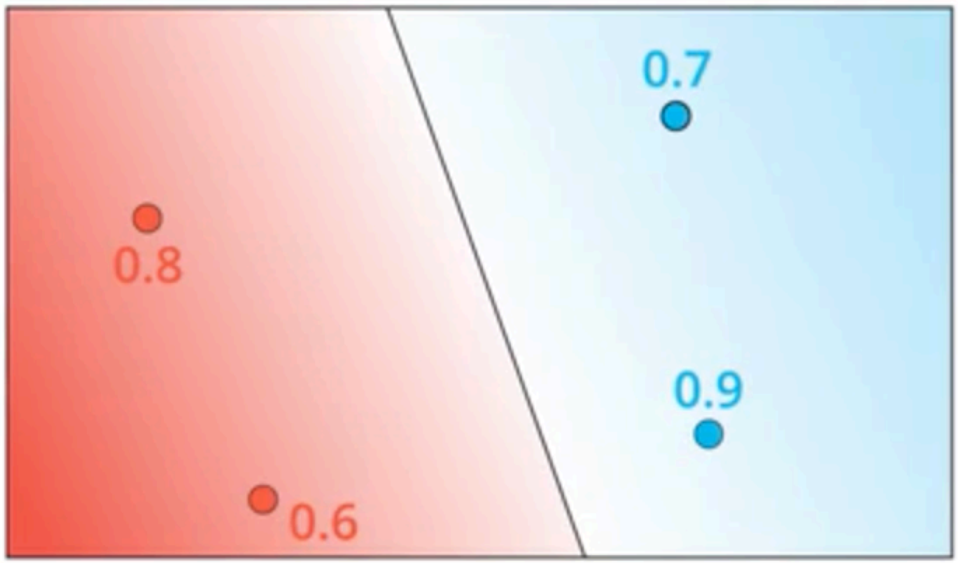
Qual desses modelos é melhor?



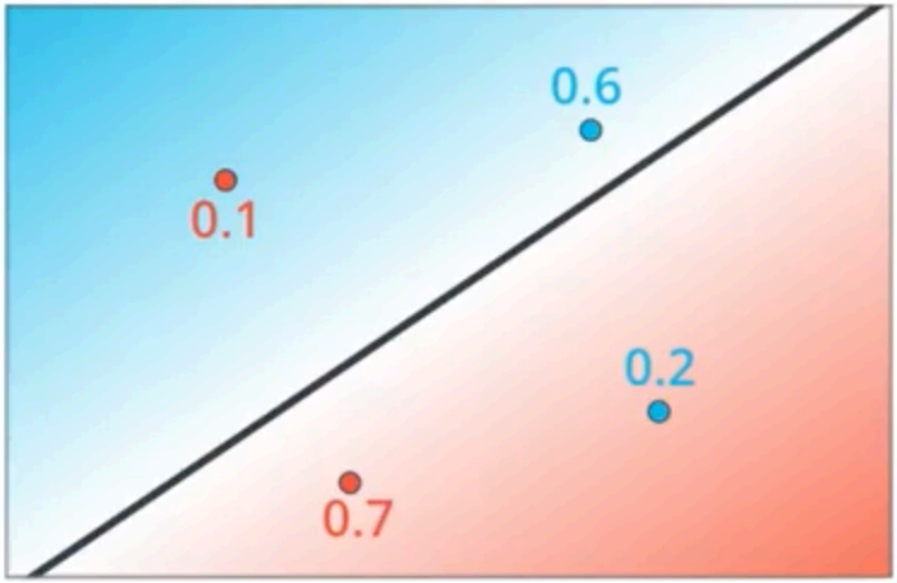


Qual desses modelos é melhor?

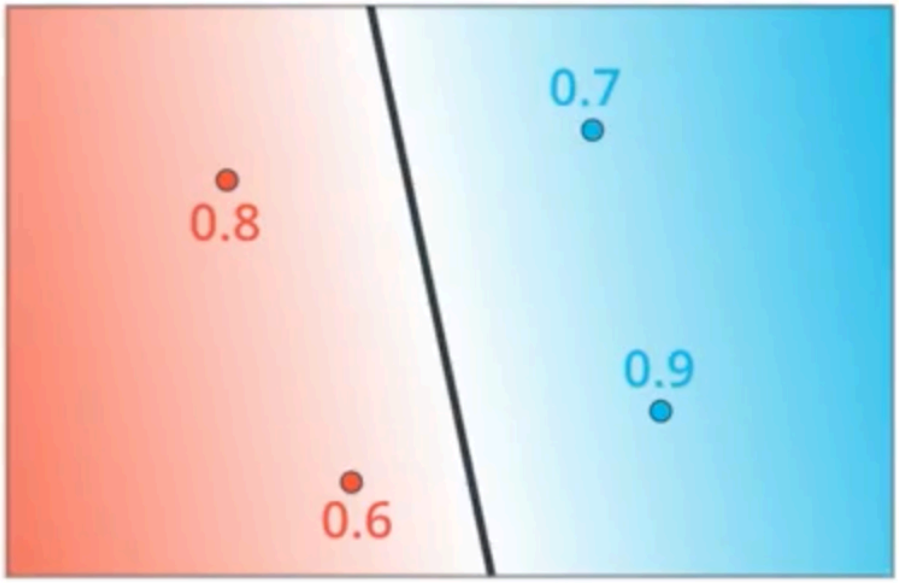




Qual desses modelos é melhor?

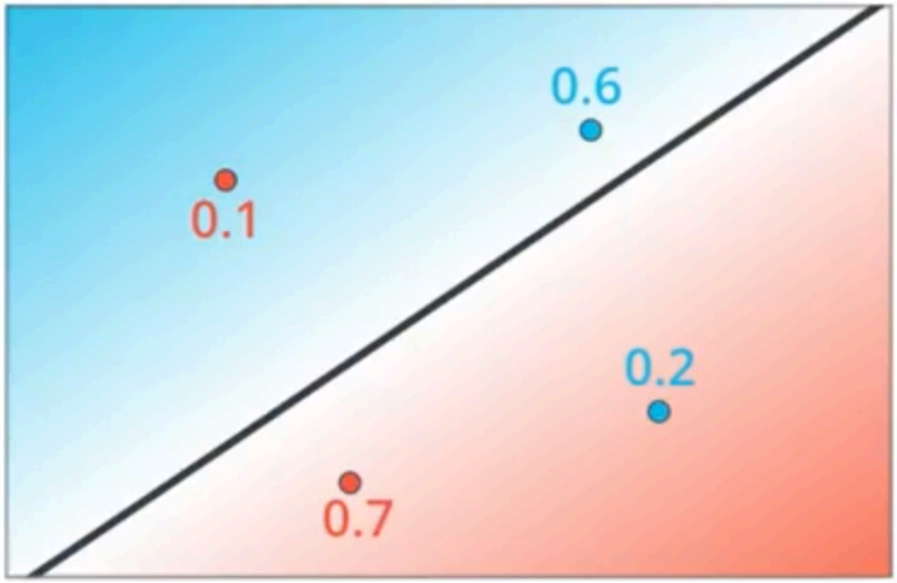


0.6*0.2*0.1*0.7 = 0.0084

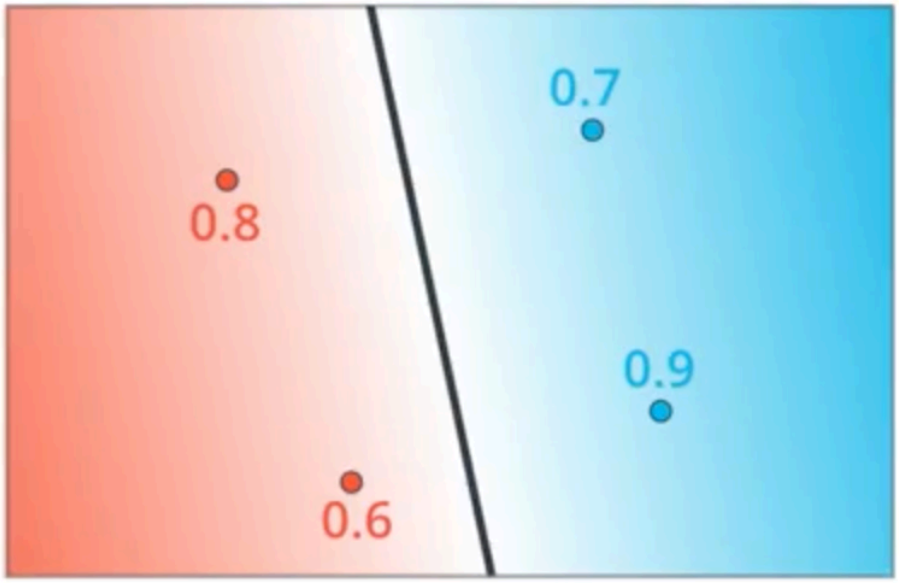


0.7*0.9*0.8*0.6 = 0.3024

Qual desses modelos é melhor?



0.6*0.2*0.1*0.7 = 0.0084



0.7*0.9*0.8*0.6 = 0.3024

Máxima Verossimilhança (Maximum Likelihood)

Problema

$0.6*0.2*0.1*0.7 = 0.0084$

$0.7*0.9*0.8*0.6 = 0.3024$

Qual Função usar?

- sin ○
- cos ○
- log ○
- exp ○

Problema

$0.6*0.2*0.1*0.7 = 0.0084$

$0.7*0.9*0.8*0.6 = 0.3024$

Qual Função usar?

- sin ○
- cos ○
- log ●
- exp ○

$\log(ab) = \log(a) + \log(b)$

Produtos

$0.6 * 0.2 * 0.1 * 0.7 = 0.0084$

$0.7 * 0.9 * 0.8 * 0.6 = 0.3024$

Produtos

$$0.6 * 0.2 * 0.1 * 0.7 = 0.0084$$

$$\ln(0.6) + \ln(0.2) + \ln(0.1) + \ln(0.7)$$

$$-0.51 \quad -1.61 \quad -2.3 \quad -0.36$$

$$0.7 * 0.9 * 0.8 * 0.6 = 0.3024$$

$$\ln(0.7) + \ln(0.9) + \ln(0.8) + \ln(0.6)$$

$$-0.36 \quad -0.1 \quad -.22 \quad -0.51$$

Produtos

$0.6 * 0.2 * 0.1 * 0.7 = 0.0084$

$\ln(0.6) + \ln(0.2) + \ln(0.1) + \ln(0.7)$

$-0.51 \quad -1.61 \quad -2.3 \quad -0.36$

$-\ln(0.6) - \ln(0.2) - \ln(0.1) - \ln(0.7) = 4.8$

$0.51 \quad 1.61 \quad 2.3 \quad 0.36$

$0.7 * 0.9 * 0.8 * 0.6 = 0.3024$

$\ln(0.7) + \ln(0.9) + \ln(0.8) + \ln(0.6)$

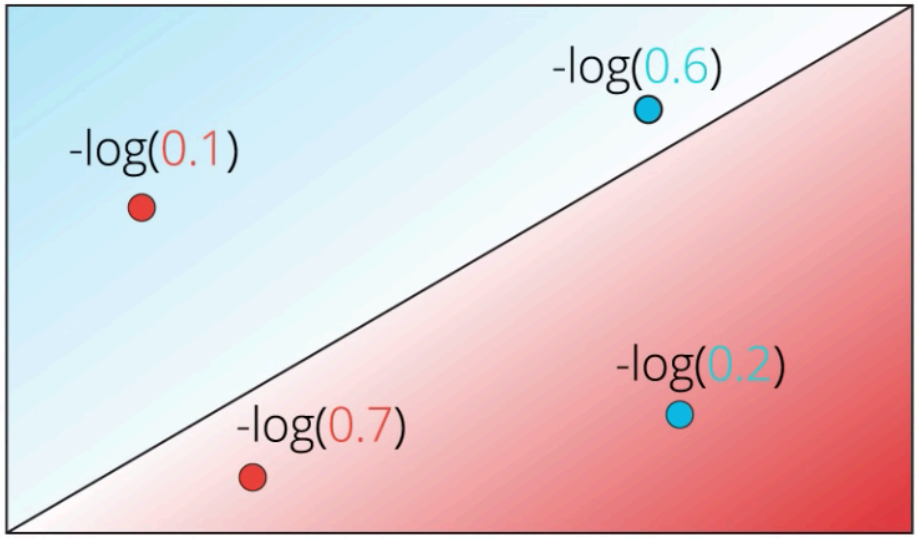
$-0.36 \quad -0.1 \quad -.22 \quad -0.51$

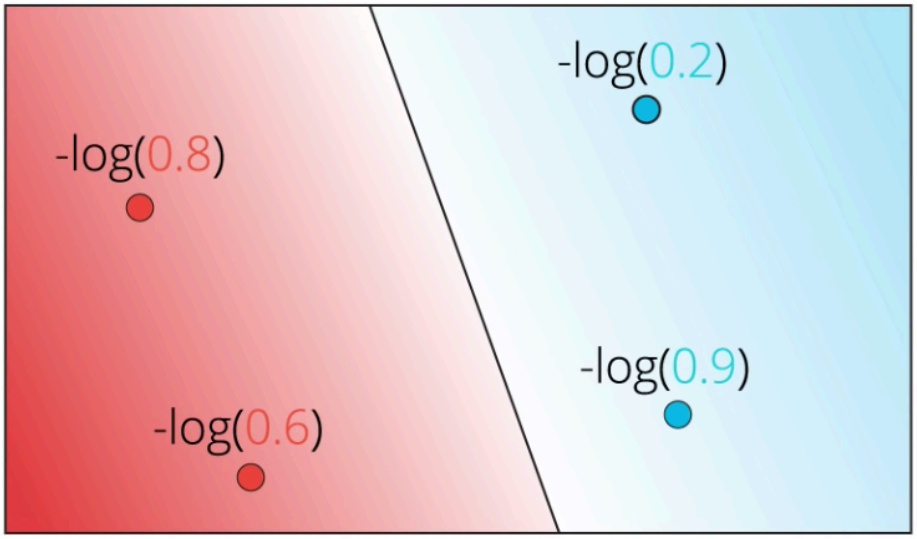
$-\ln(0.7) - \ln(0.9) - \ln(0.8) - \ln(0.6) = 1.2$

$0.36 \quad 0.1 \quad .22 \quad 0.51$

Cross Entropy

Cross Entropia





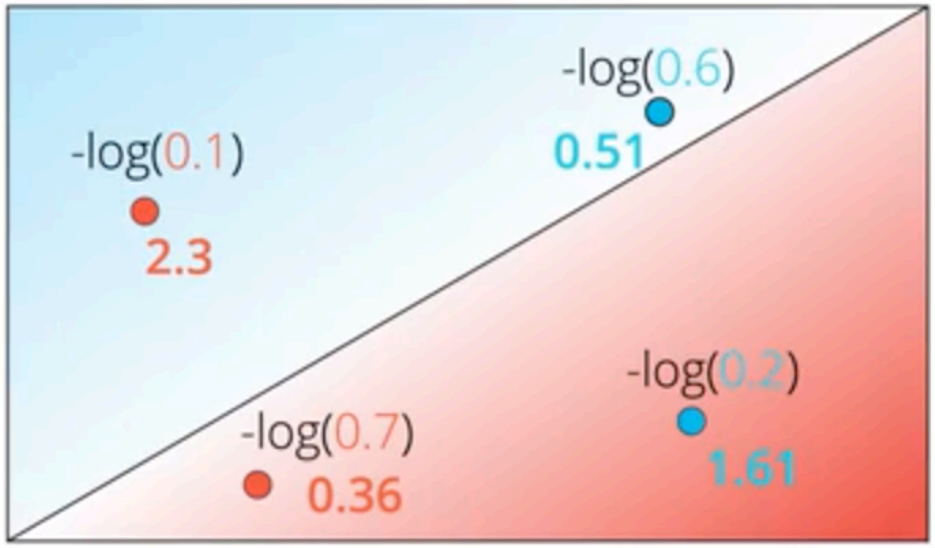
0.6 * 0.2 * 0.1 * 0.7 = 0.0084

-log(0.6) - log(0.2) - log(0.1) - log(0.7) = 4.8

0.7 * 0.9 * 0.8 * 0.6 = 0.3024

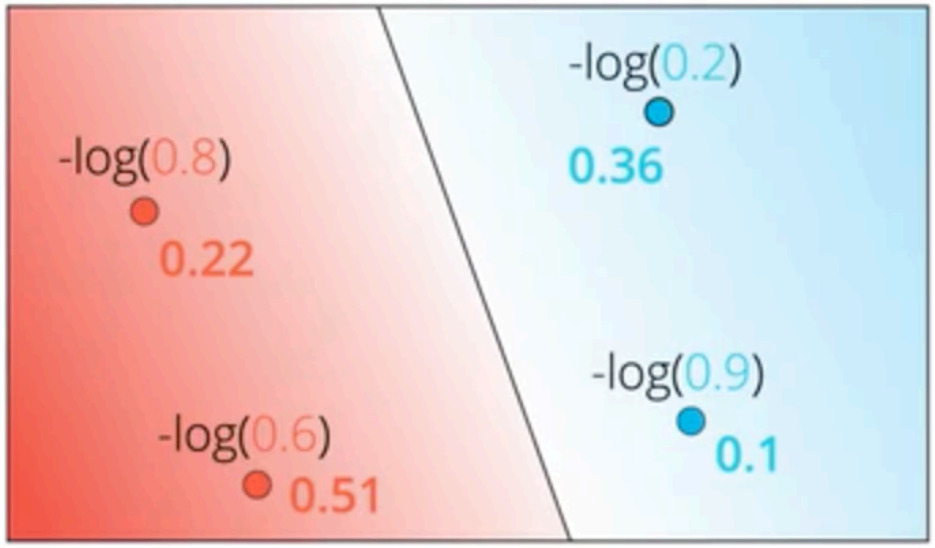
-log(0.7) - log(0.9) - log(0.8) - log(0.6) = 1.2

Cross Entropia



$0.6 * 0.2 * 0.1 * 0.7 = 0.0084$

$-\log(0.6) - \log(0.2) - \log(0.1) - \log(0.7) = 4.8$

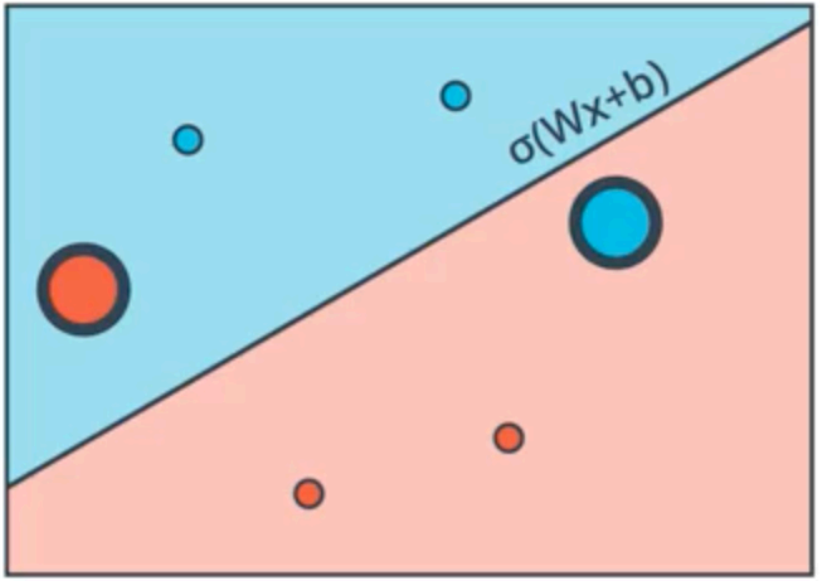


$0.7 * 0.9 * 0.8 * 0.6 = 0.3024$

$-\log(0.7) - \log(0.9) - \log(0.8) - \log(0.6) = 1.2$

Objetivo: Minimizar a Cross Entropia

Objetivo: Minimizar Função de Erro



$$E(W,b) = -\frac{1}{m}\sum_{i=1}^{m} (1-y_i)\ln(1-\sigma(Wx^{(i)}+b)) + y_i \ln(\sigma(Wx^{(i)}+b))$$

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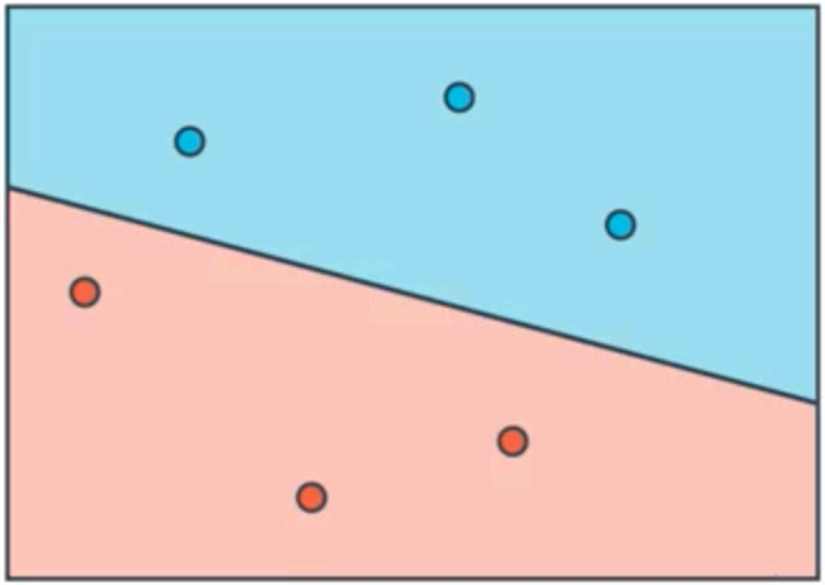
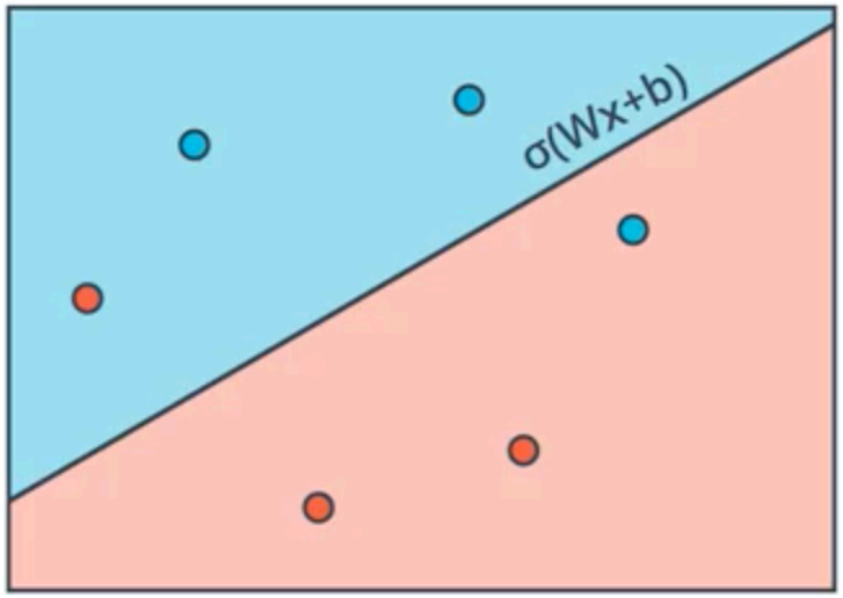


$$E(W,b) = -\frac{1}{m}\sum_{i=1}^{m} (1-y_i)\ln(1-\sigma(Wx^{(i)}+b)) + y_i \ln(\sigma(Wx^{(i)}+b))$$

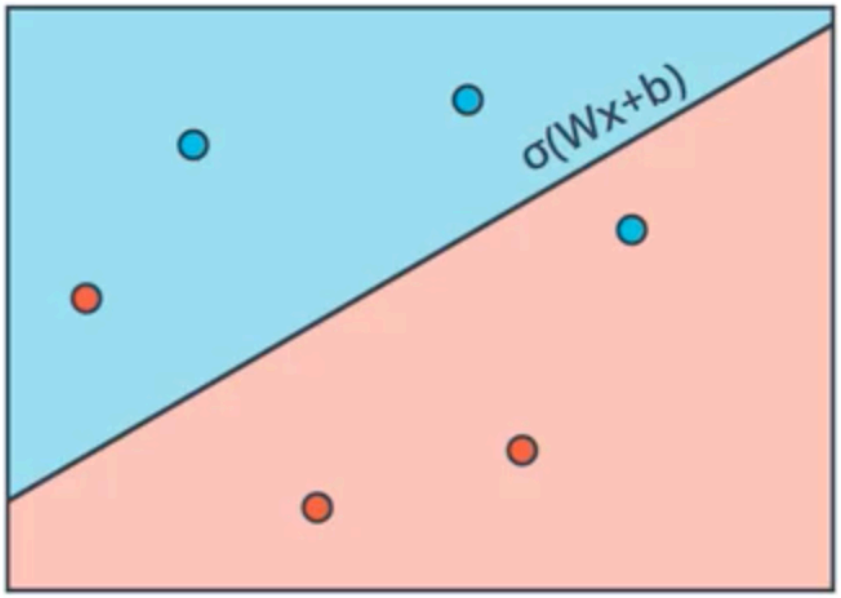
Algoritmo Gradiente Descendente



1. Comece com pesos aleatórios: :

   $w_1, \ldots, w_n, b$

Algoritmo Gradiente Descendente

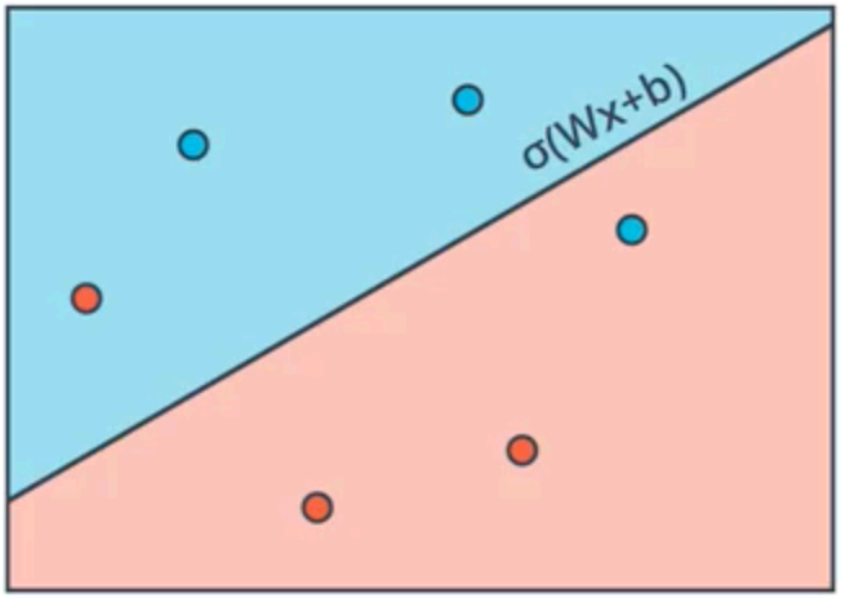


1. Comece com pesos aleatórios: :

   $w_1, \ldots, w_n, b$

2. Para cada ponto $(x_1, \ldots, x_n)$:
   2.1 Para i=1...n
      2.1.1 Atualiza $w_i' \leftarrow w_i - \alpha \, \partial E / \partial w_i$
      2.1.2 Atualiza b'$\leftarrow b - \alpha \, \partial E / \partial b$

Algoritmo Gradiente Descendente



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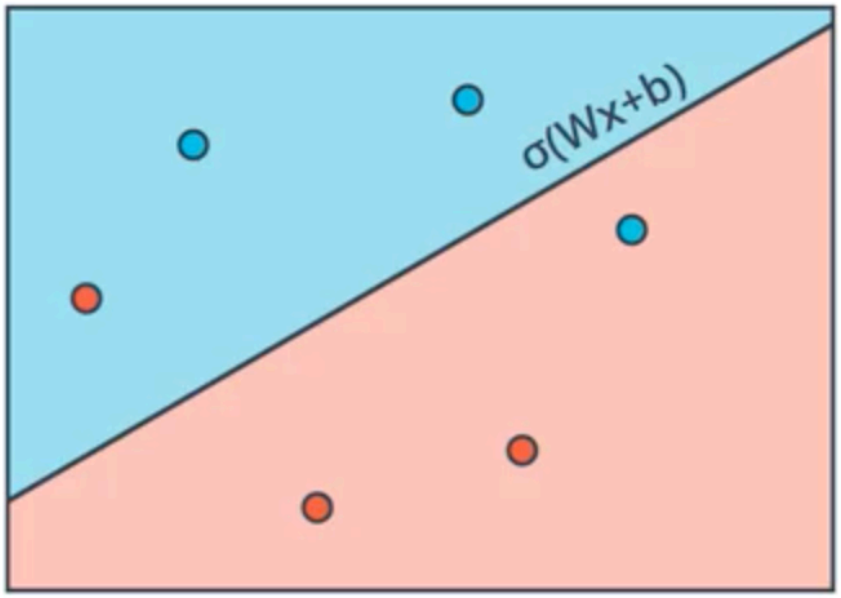
   2.1 Para i=1...n
      2.1.1 Atualiza $w_i' \leftarrow w_i - \alpha\ (\hat{y} - y)x_i$
      2.1.2 Atualiza b'$\leftarrow b - \alpha(\hat{y} - y)$

Algoritmo Gradiente Descendente



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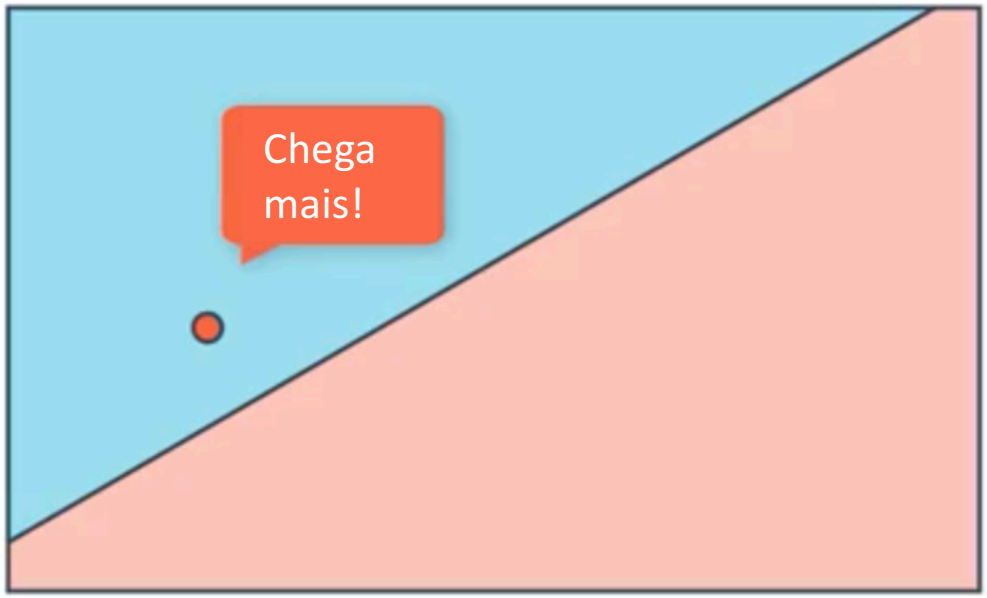
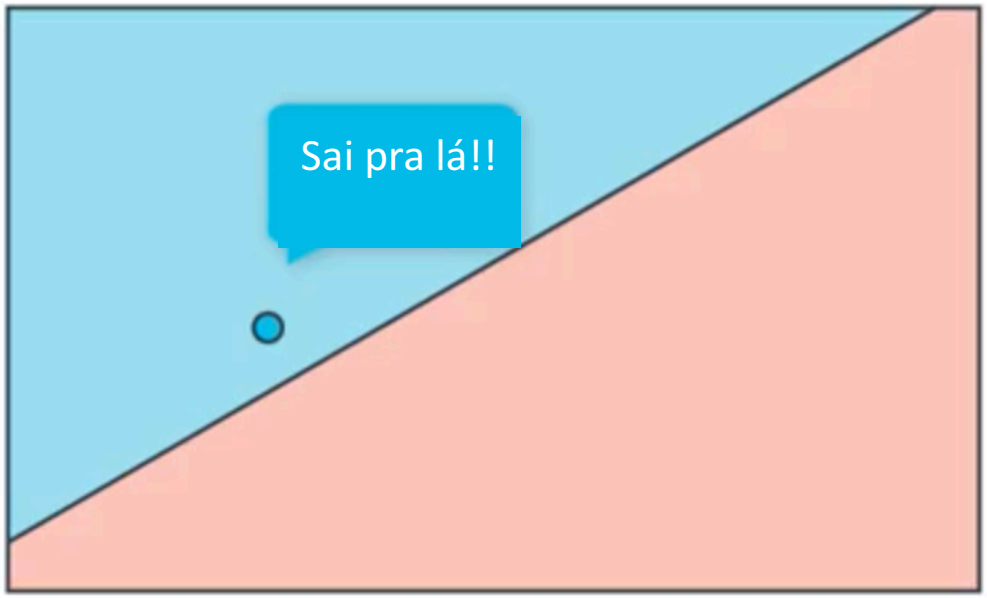
3. Repetir até erro ser pequeno

Perceptron vs Gradiente Descendente



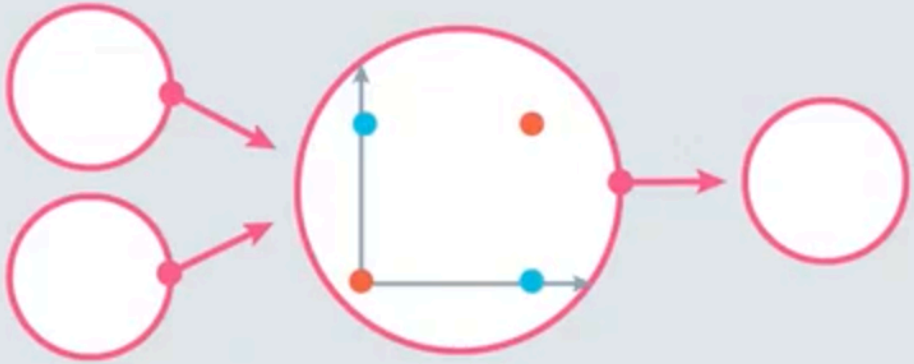


Exercício

- Implementar algoritmo de Gradiente Descendente.
  - ex_gradient_descent.ipynb

XOR Perceptron

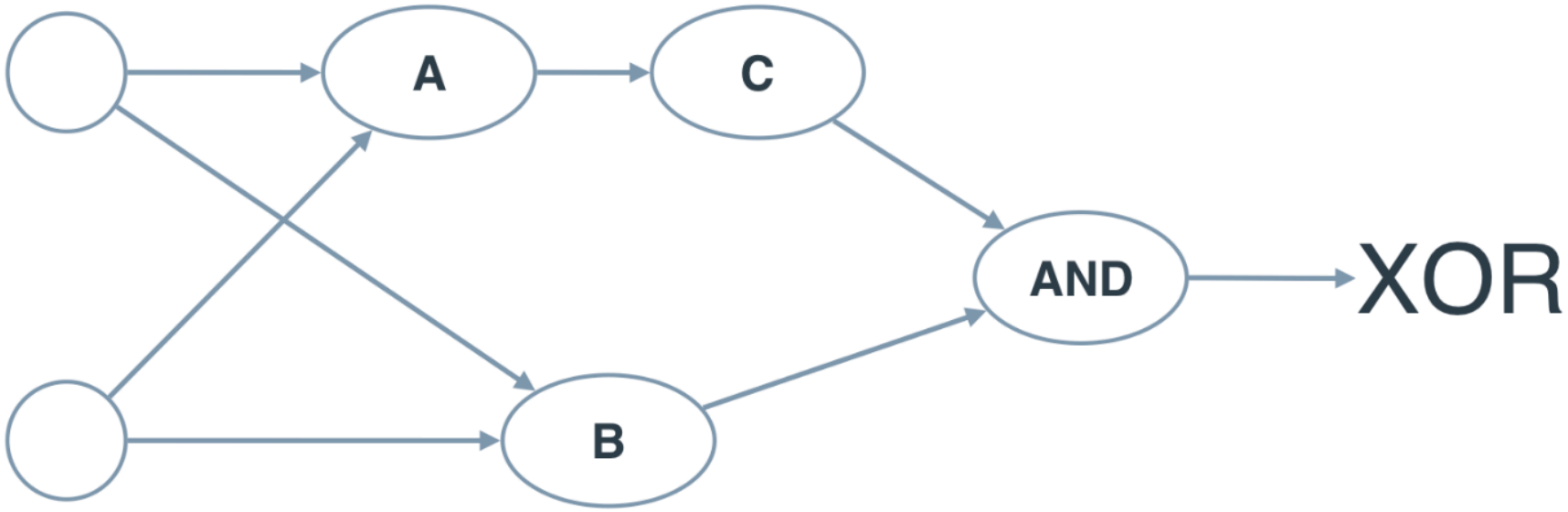
IN	IN	OUT
✓	✓	✗
✓	✗	✓
✗	✓	✓
✗	✗	✗



IN	IN	OUT
1	1	0
1	0	1
0	1	1
0	0	0

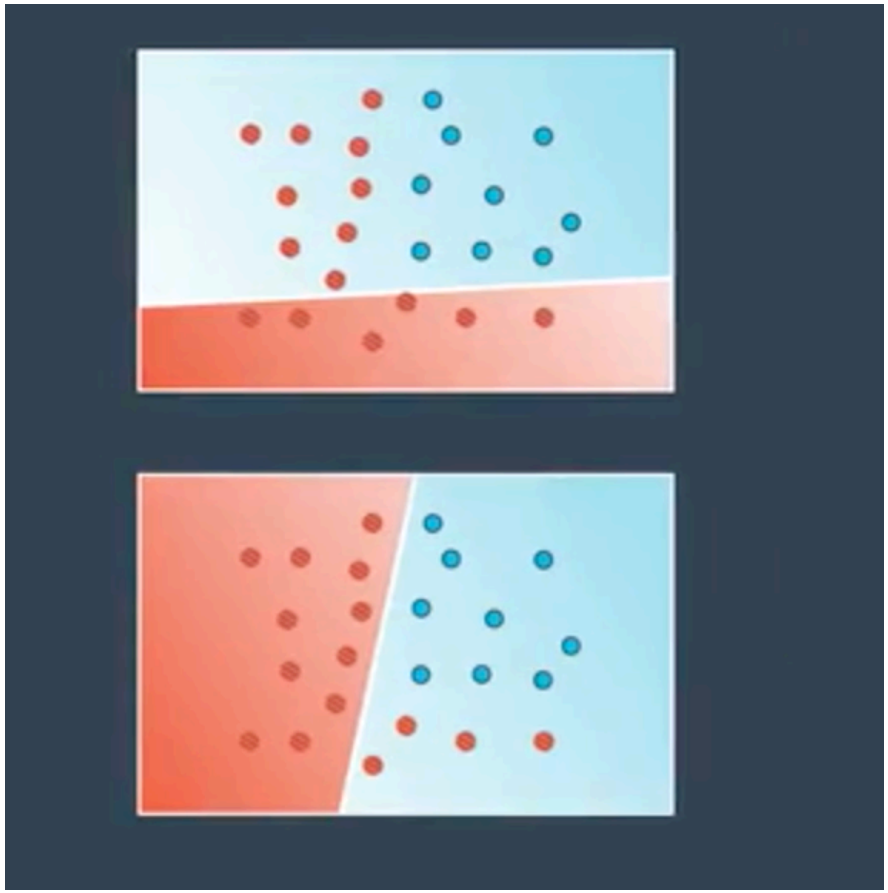
Quiz – Construir um XOR MultiLayer Perceptron

- A rede neural abaixo contêm 3 perceptrons, A, B, e C. O último (AND) foi fornecido. A entrada da rede neural é através do primeiro nó. A saída é pelo último nó.
- O perceptron multi-camadas abaixo calcula a operação XOR. Cada perceptron é um operação lógica de AND, OR e NOT. Diga os operações de cada perceptron para calcular o XOR.

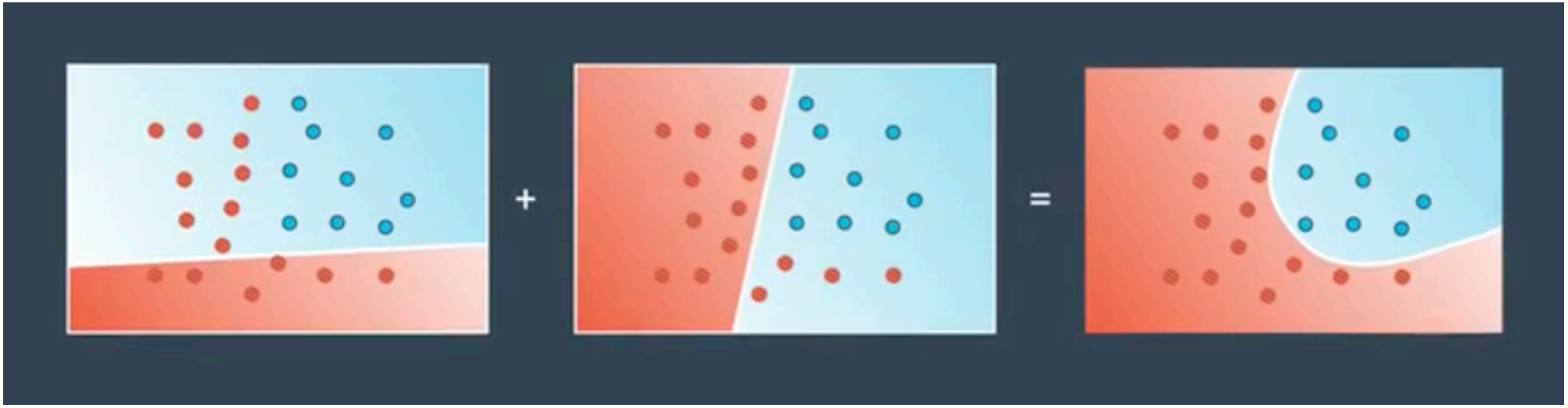


Regiões Não Lineares

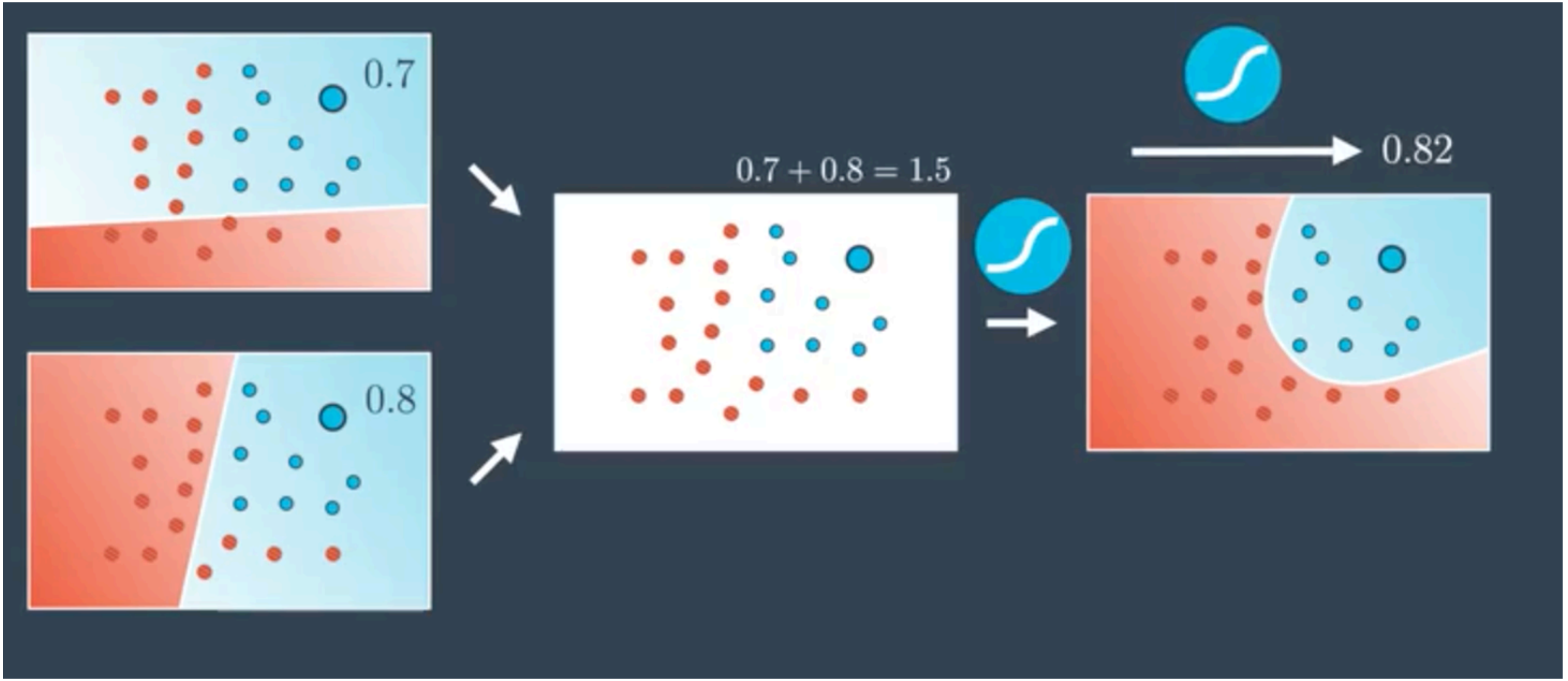
Combinando Regiões



Combinando Regiões



Combinando Regiões



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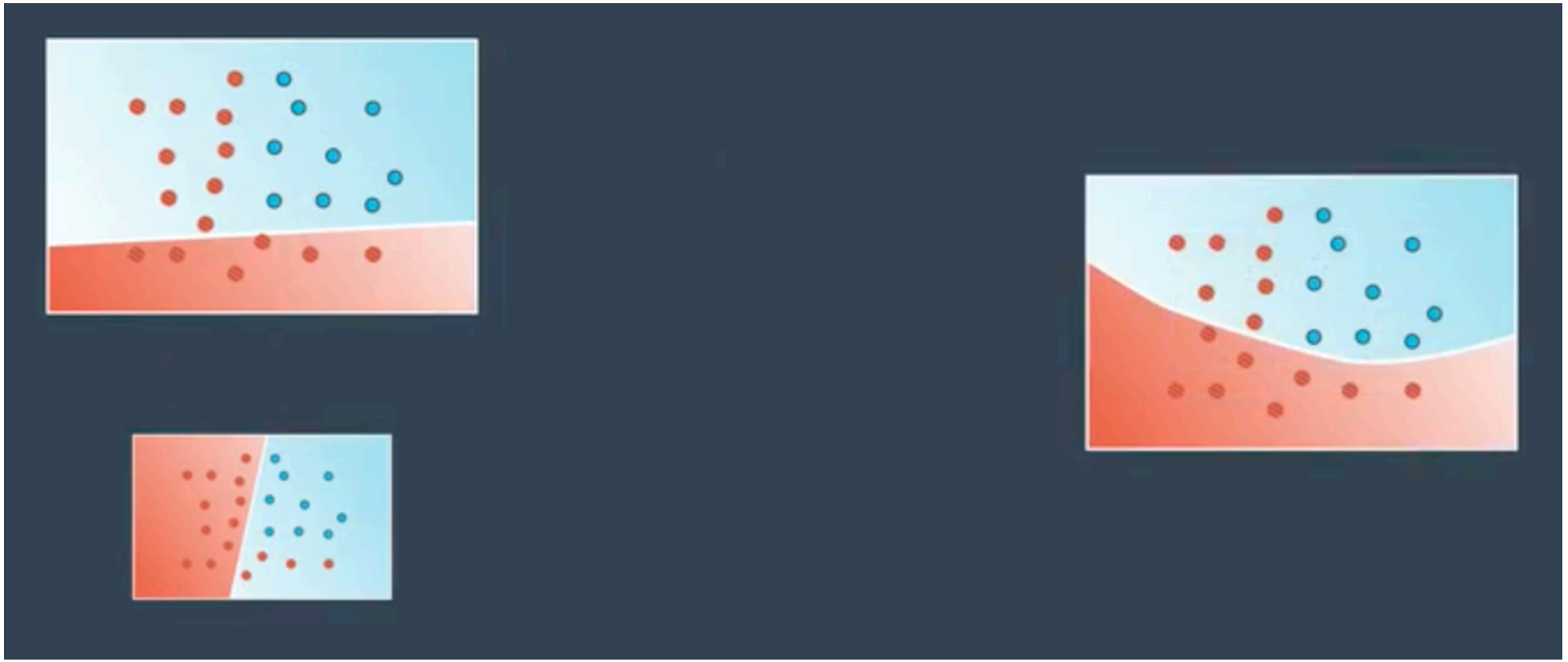
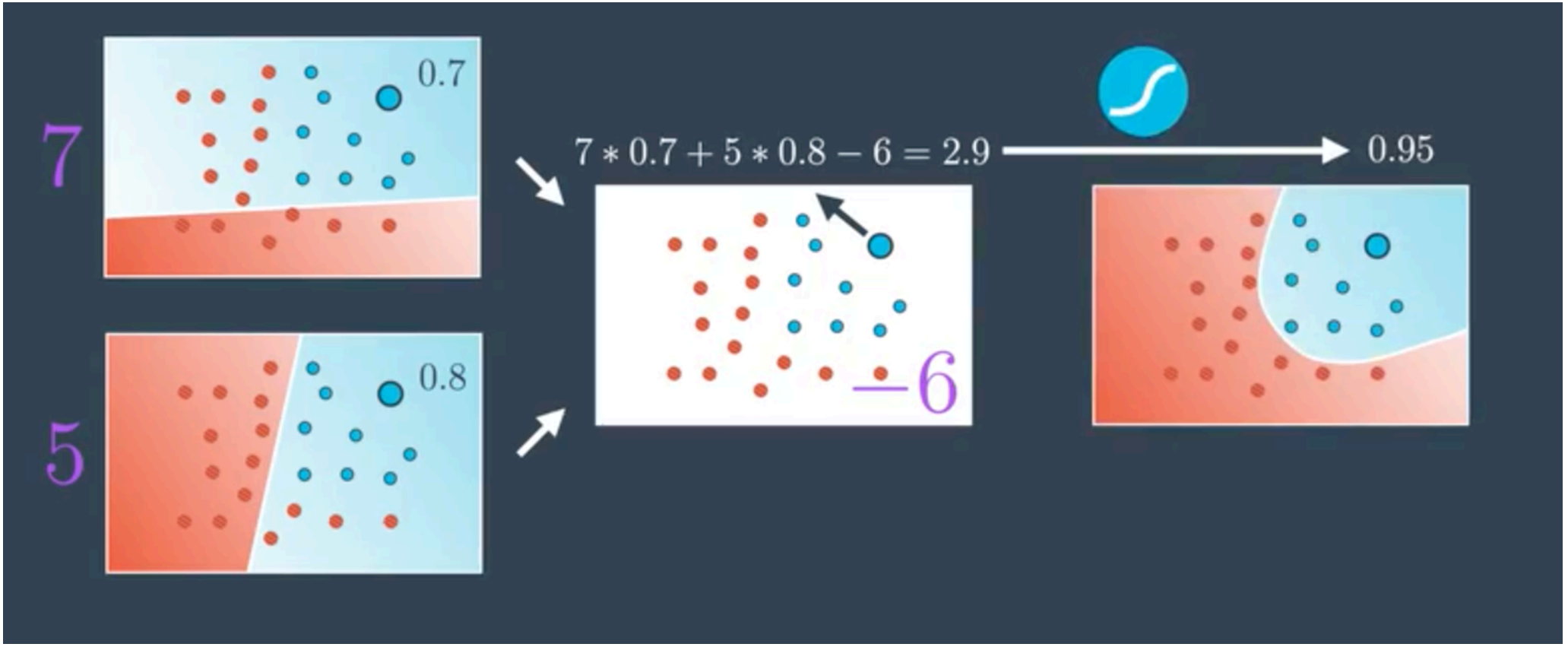
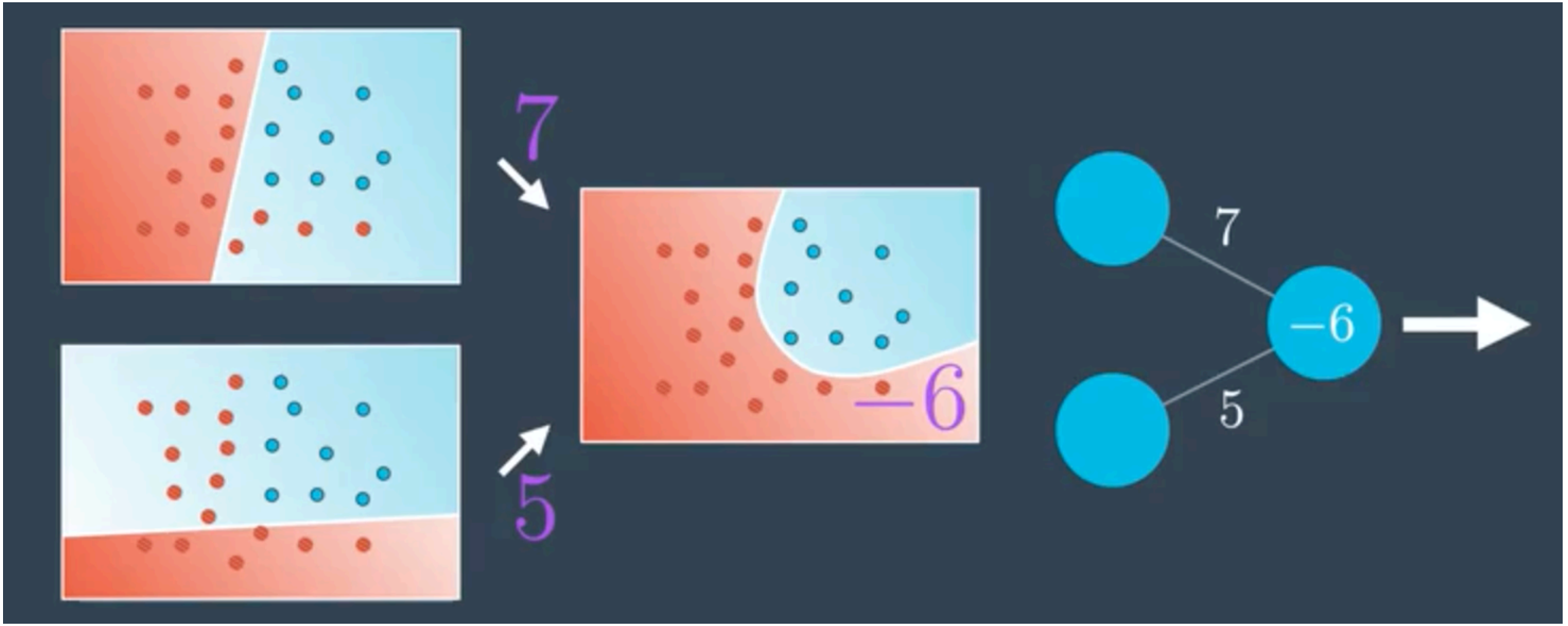


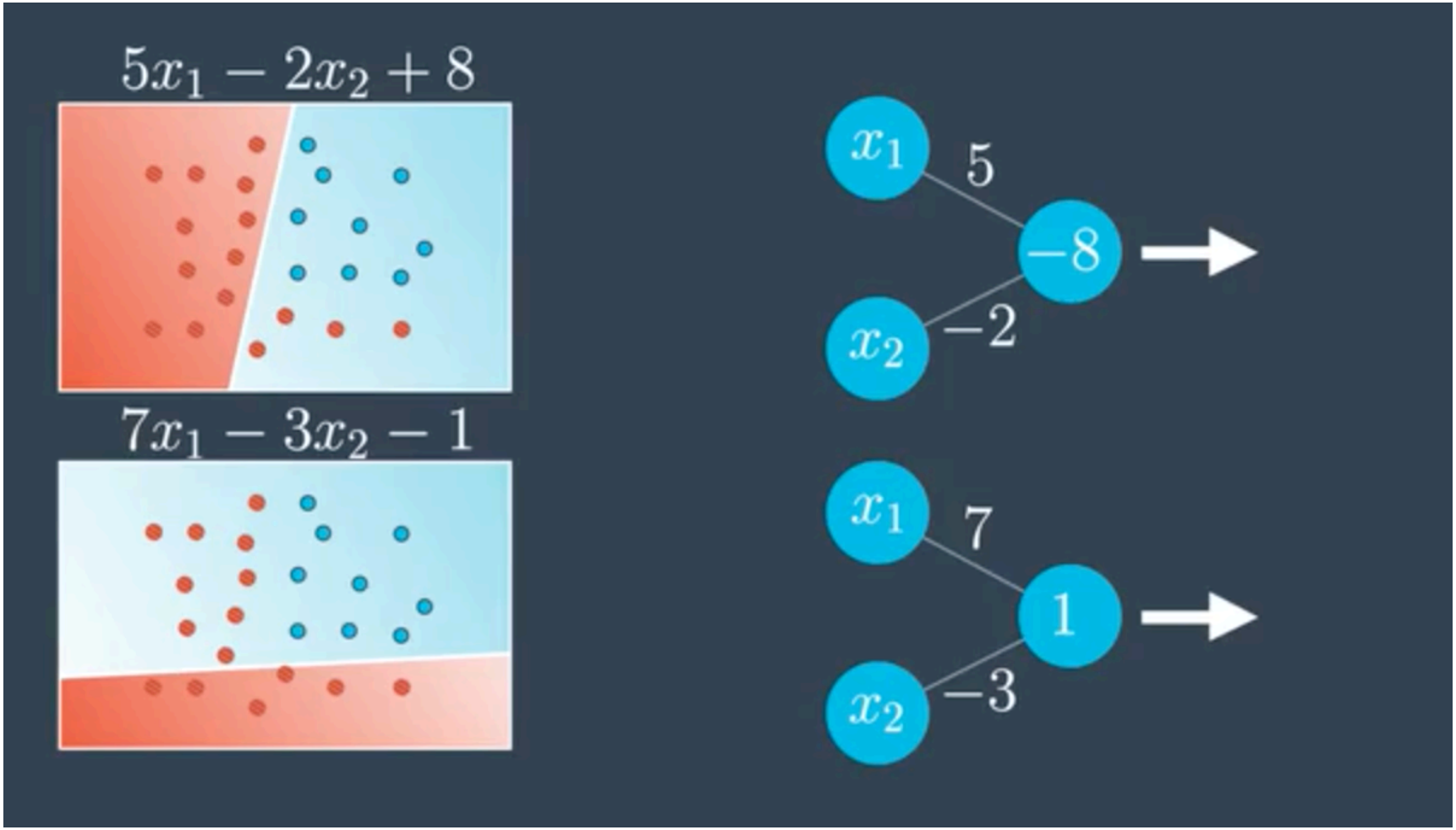
Combinando Regiões



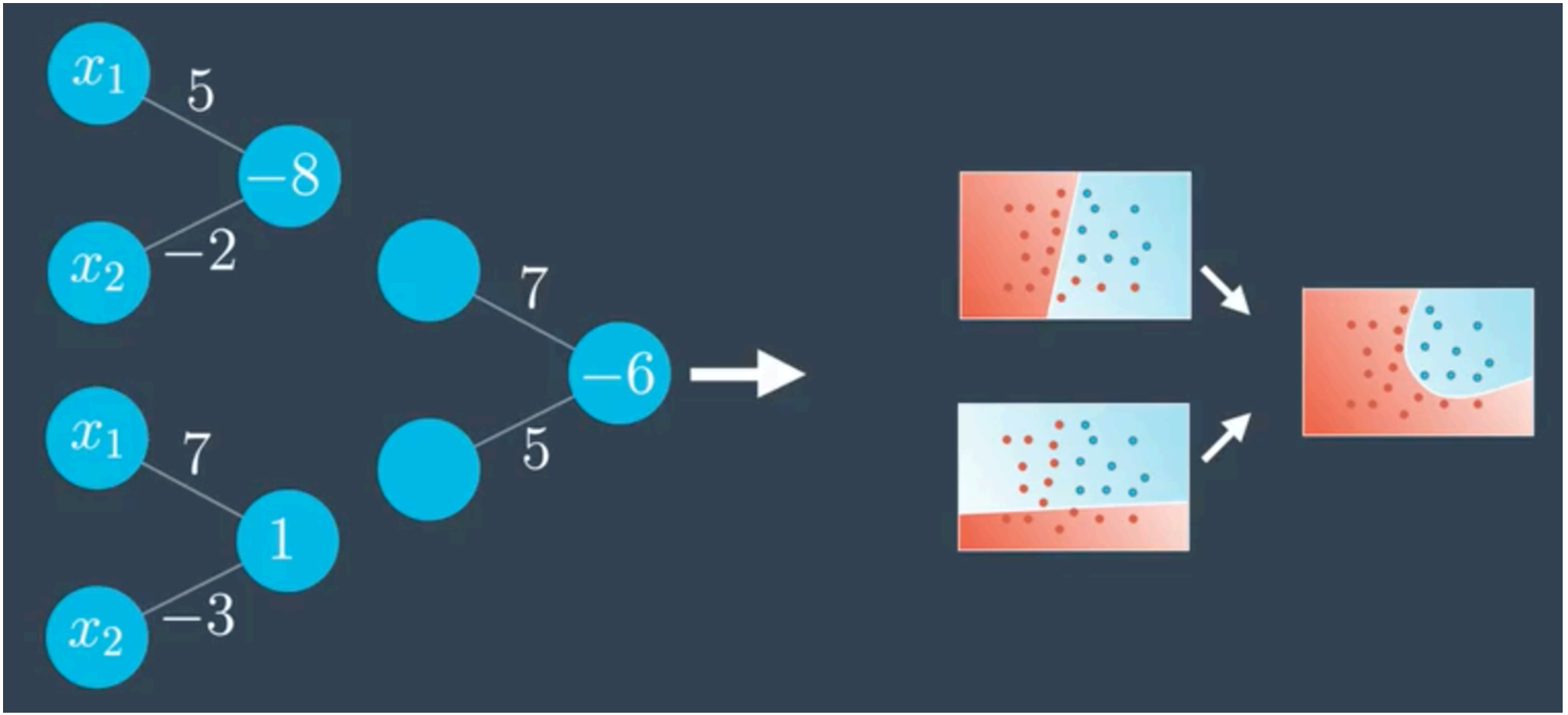
Combinando Regiões



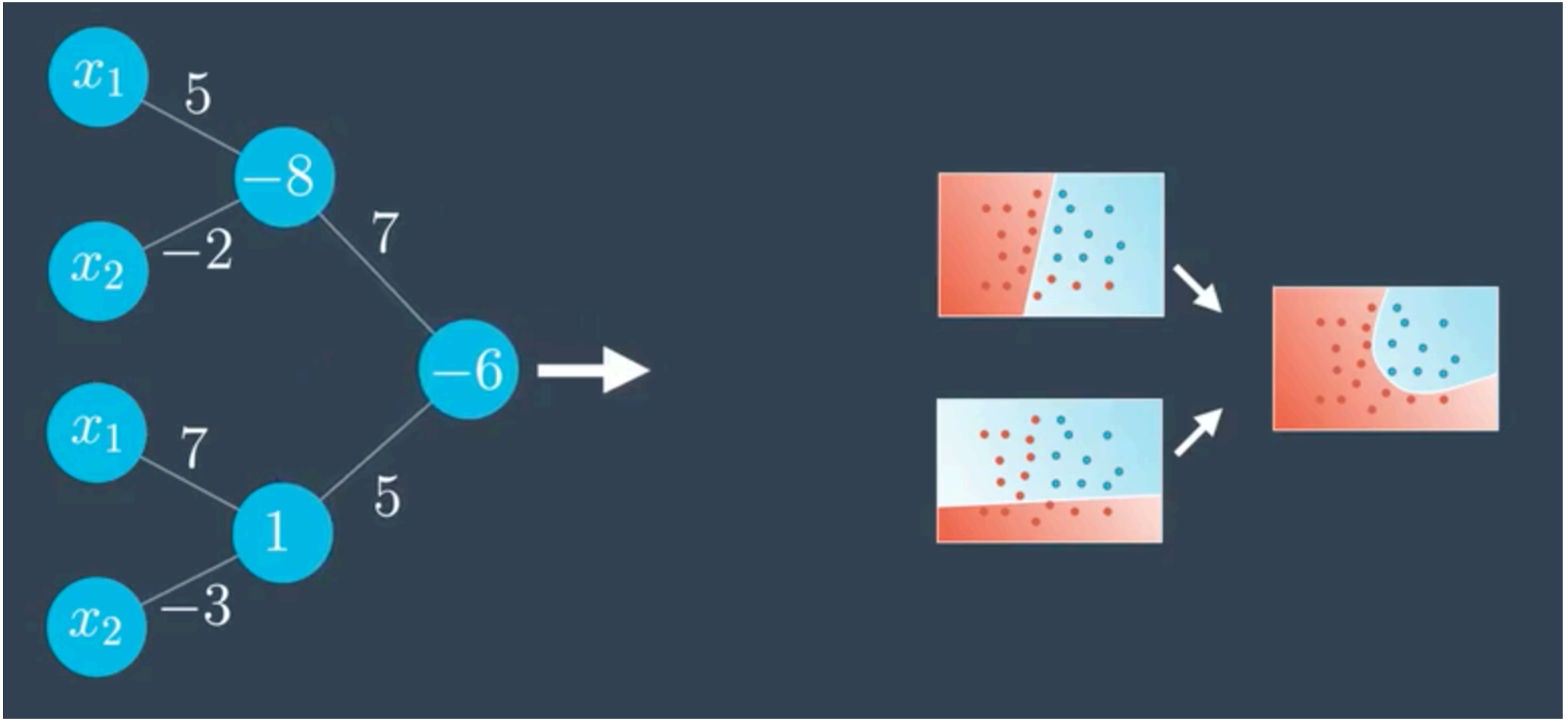
Combinando Regiões



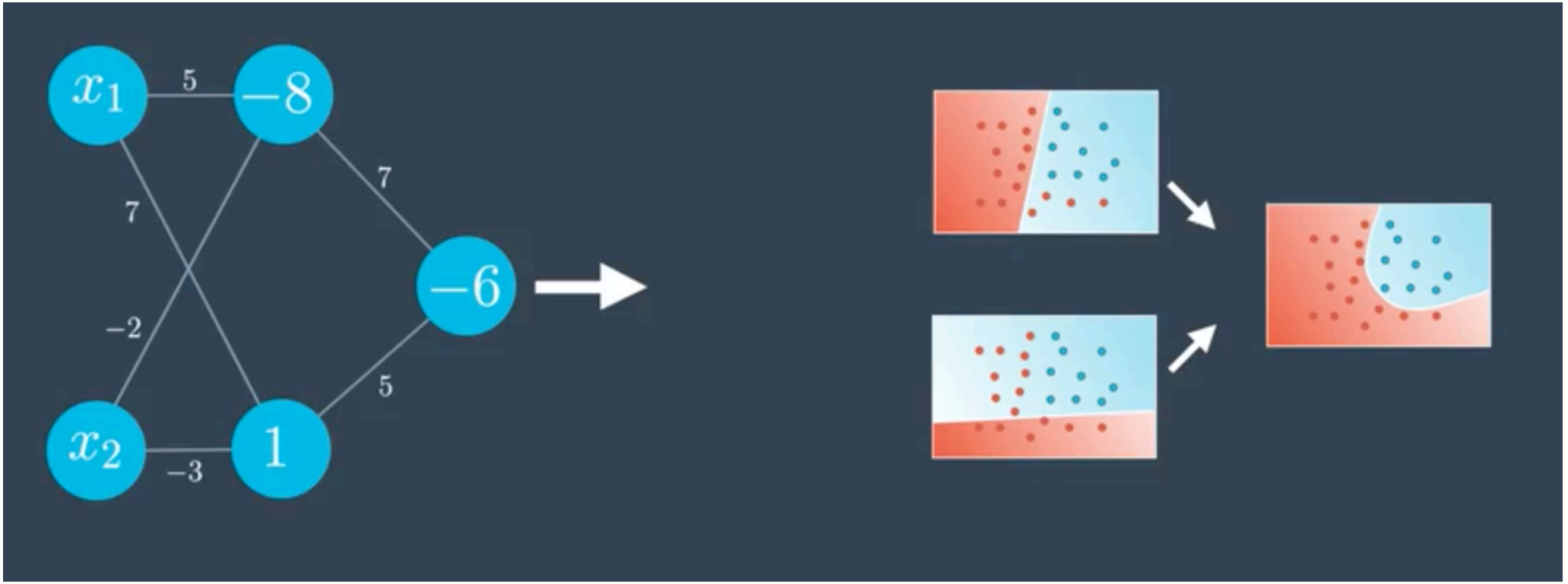
Combinando Regiões



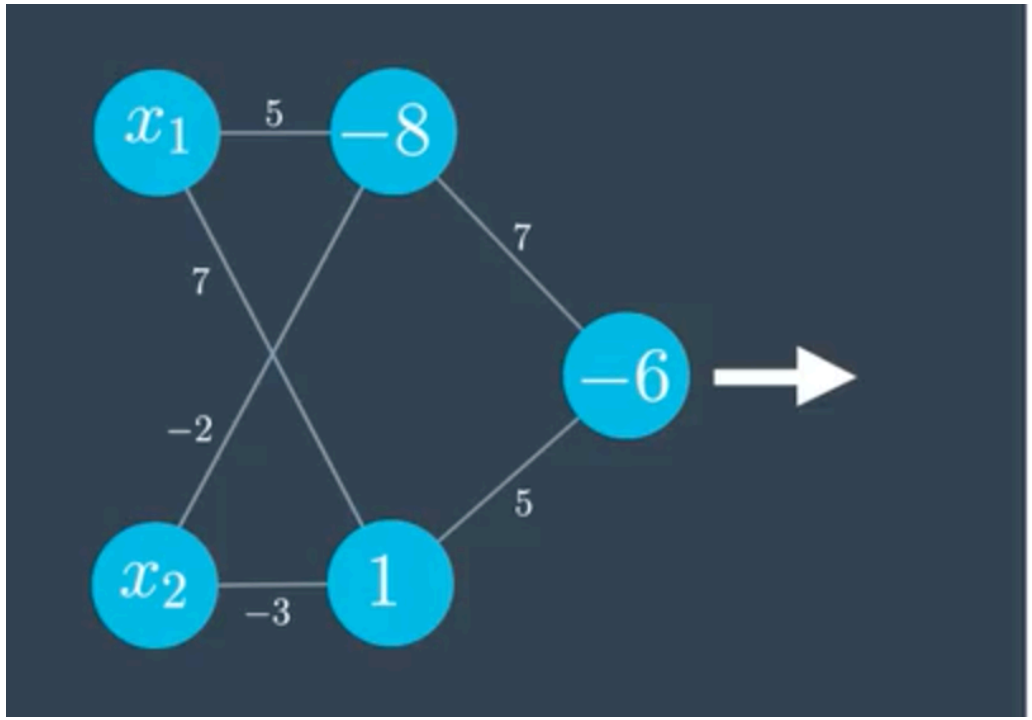
Combinando Regiões

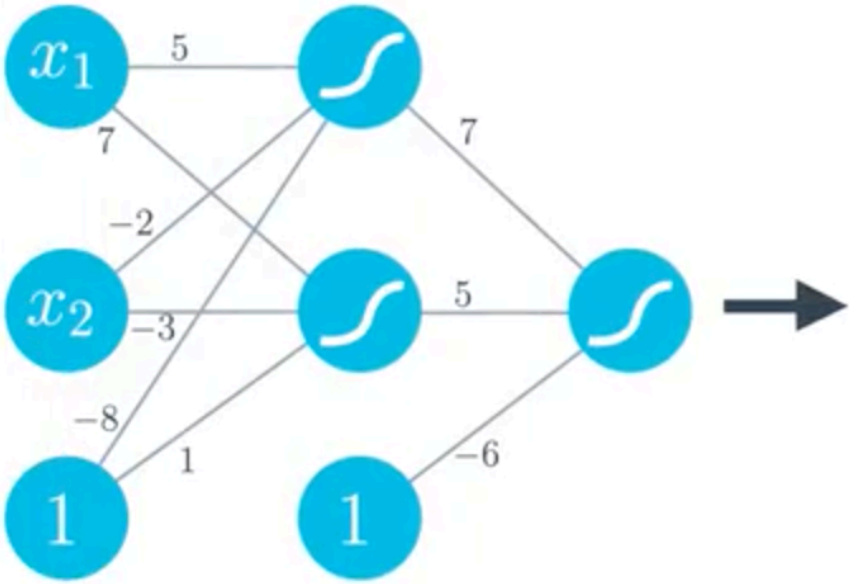


Combinando Regiões

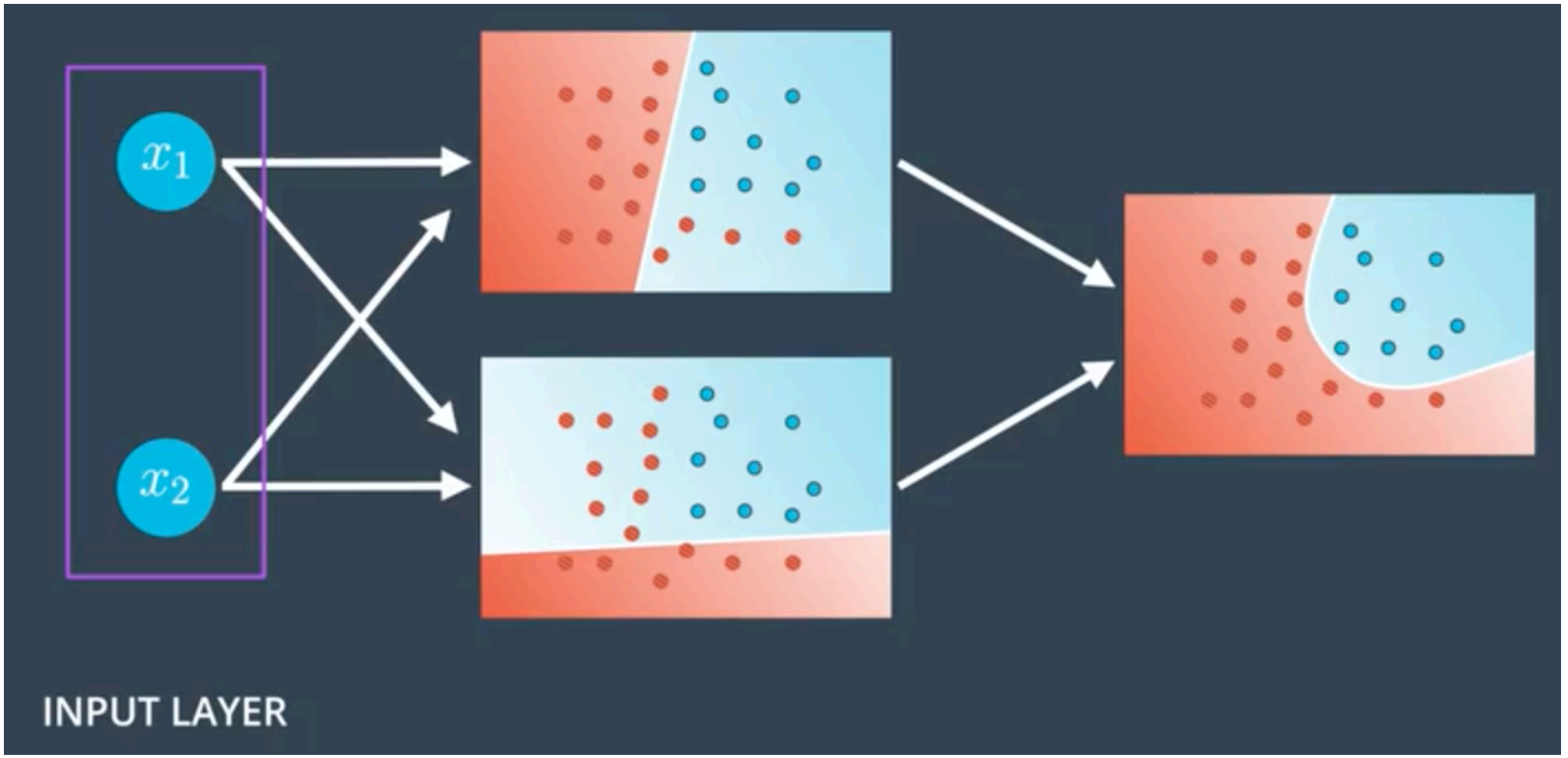


Combinando Regiões

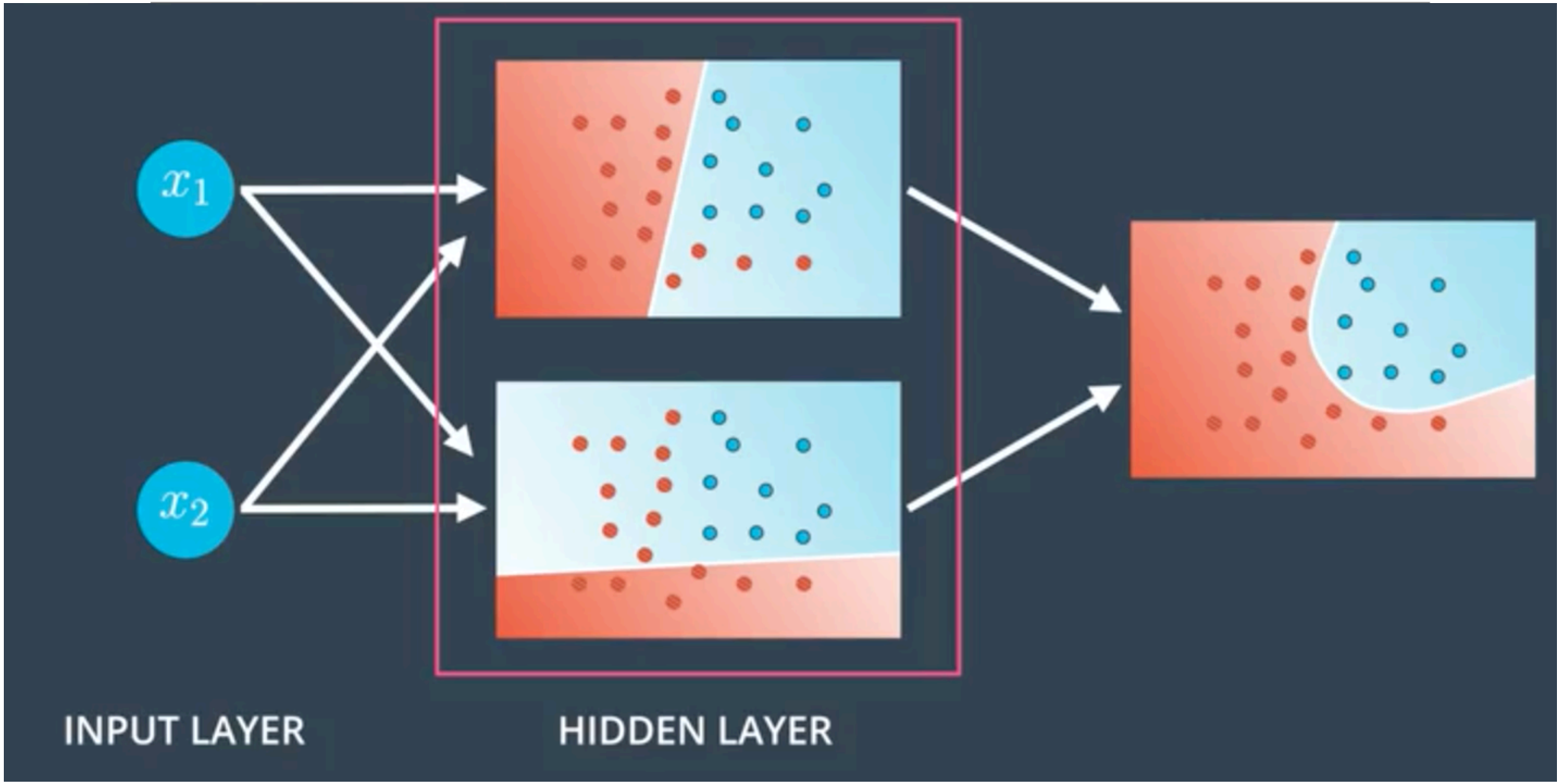




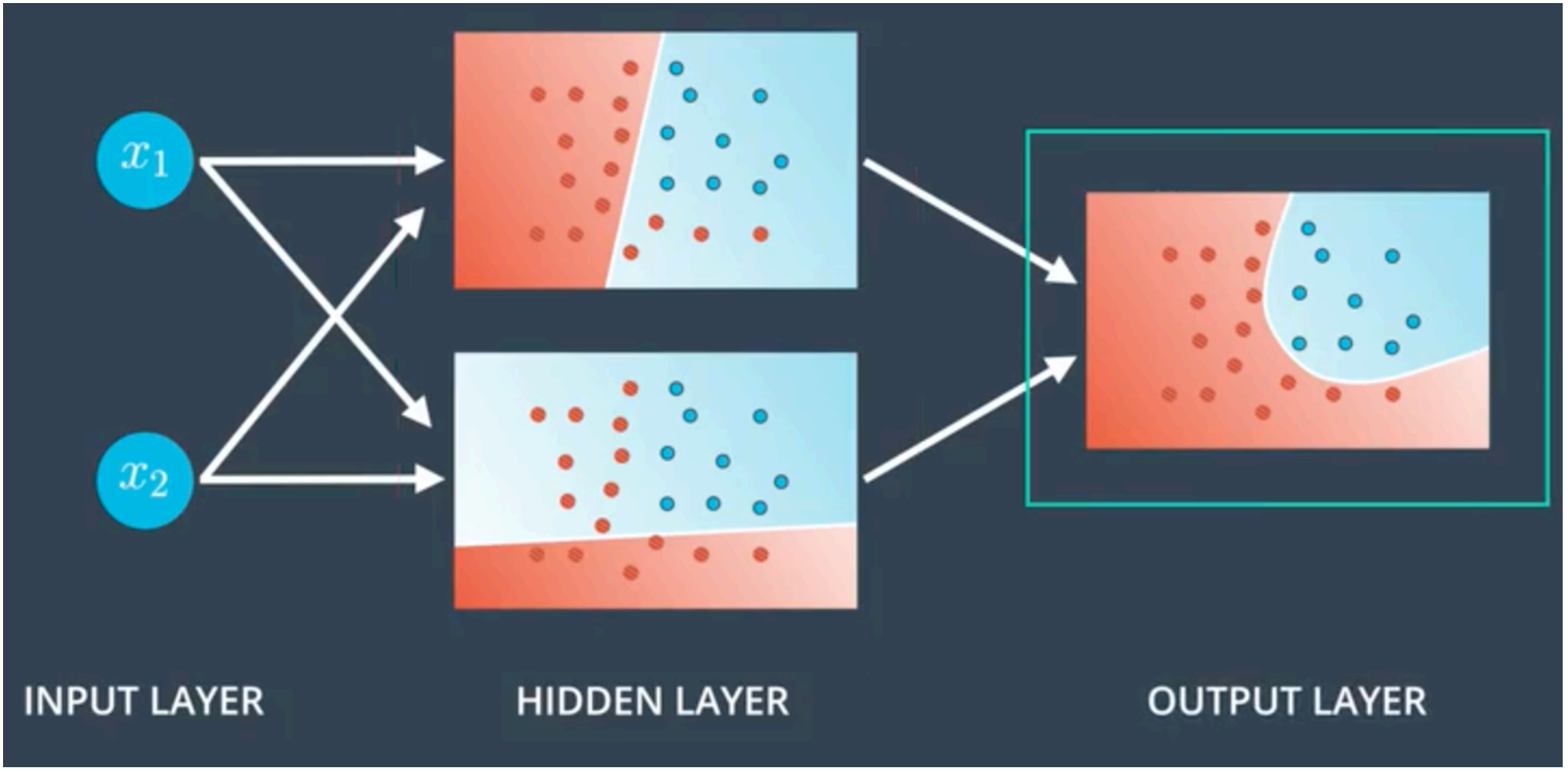
Multilayer Perceptron (MLP)

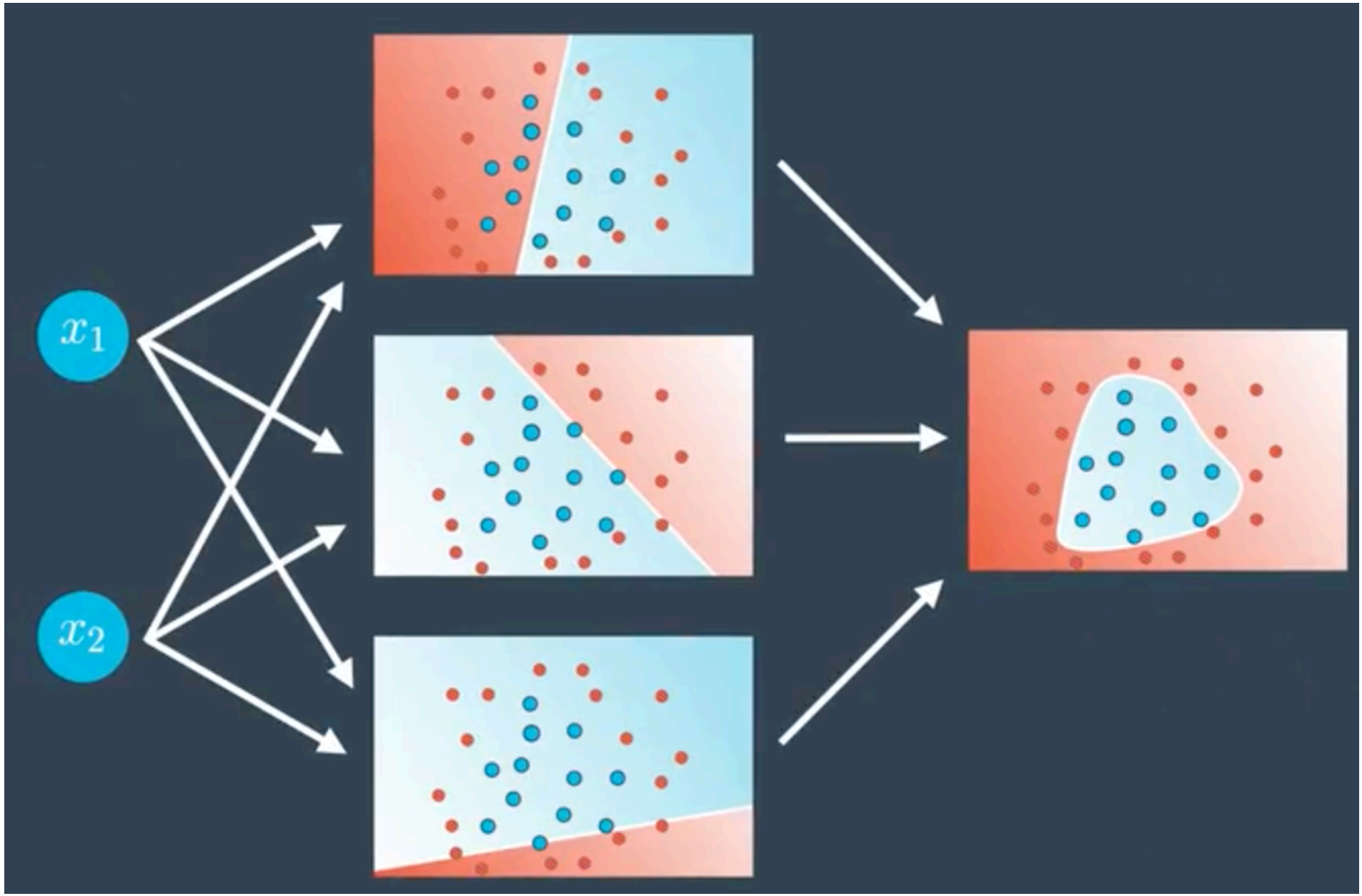


Multilayer Perceptron (MLP)

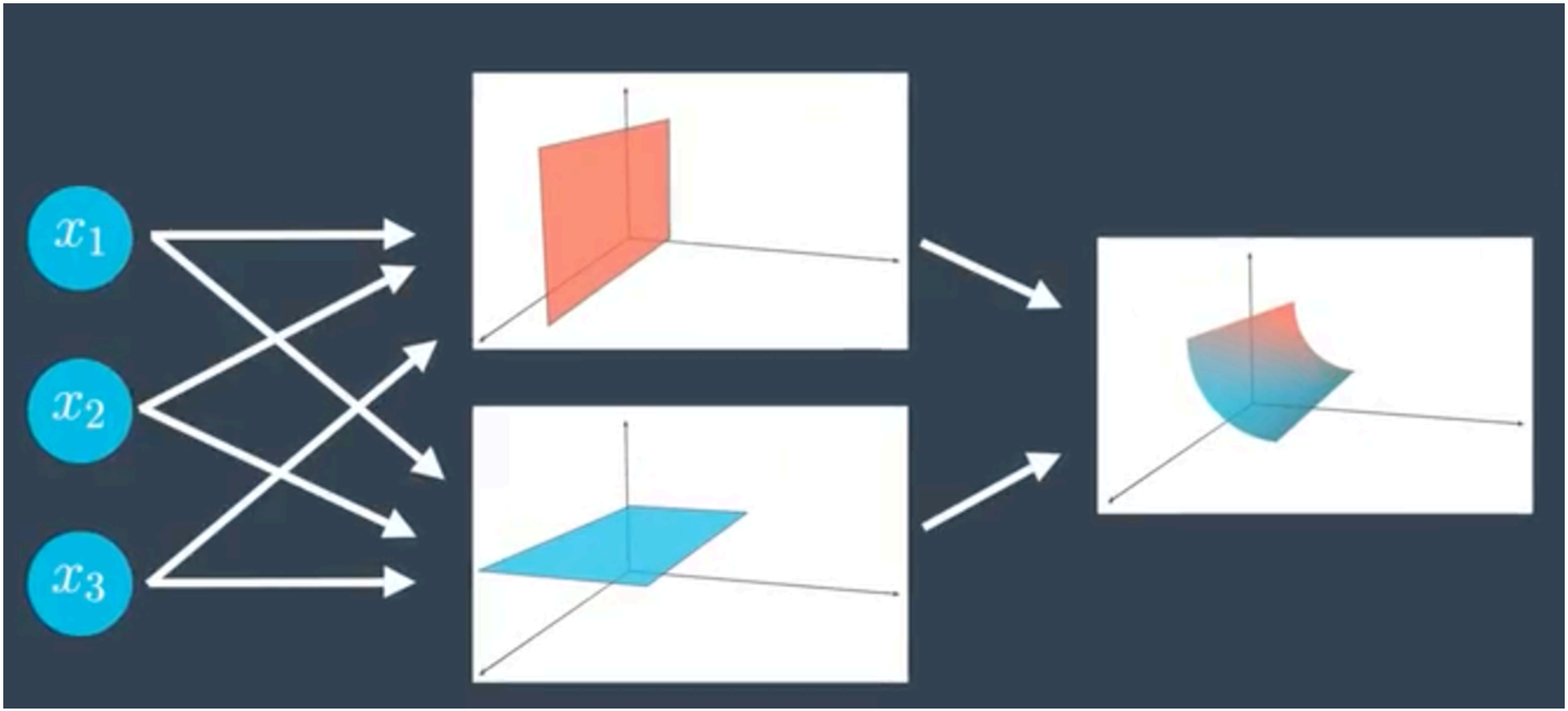


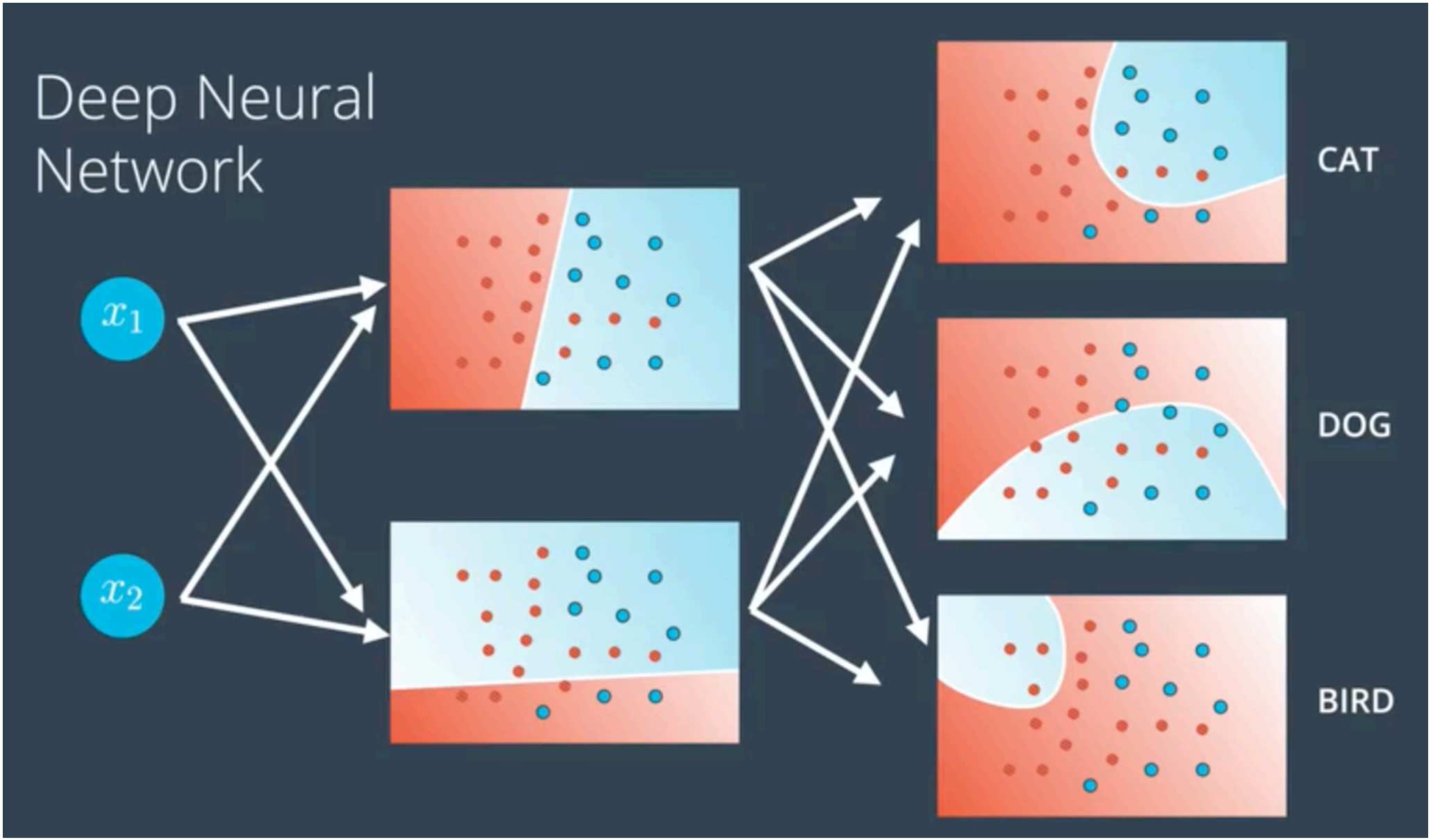
Multilayer Perceptron (MLP)

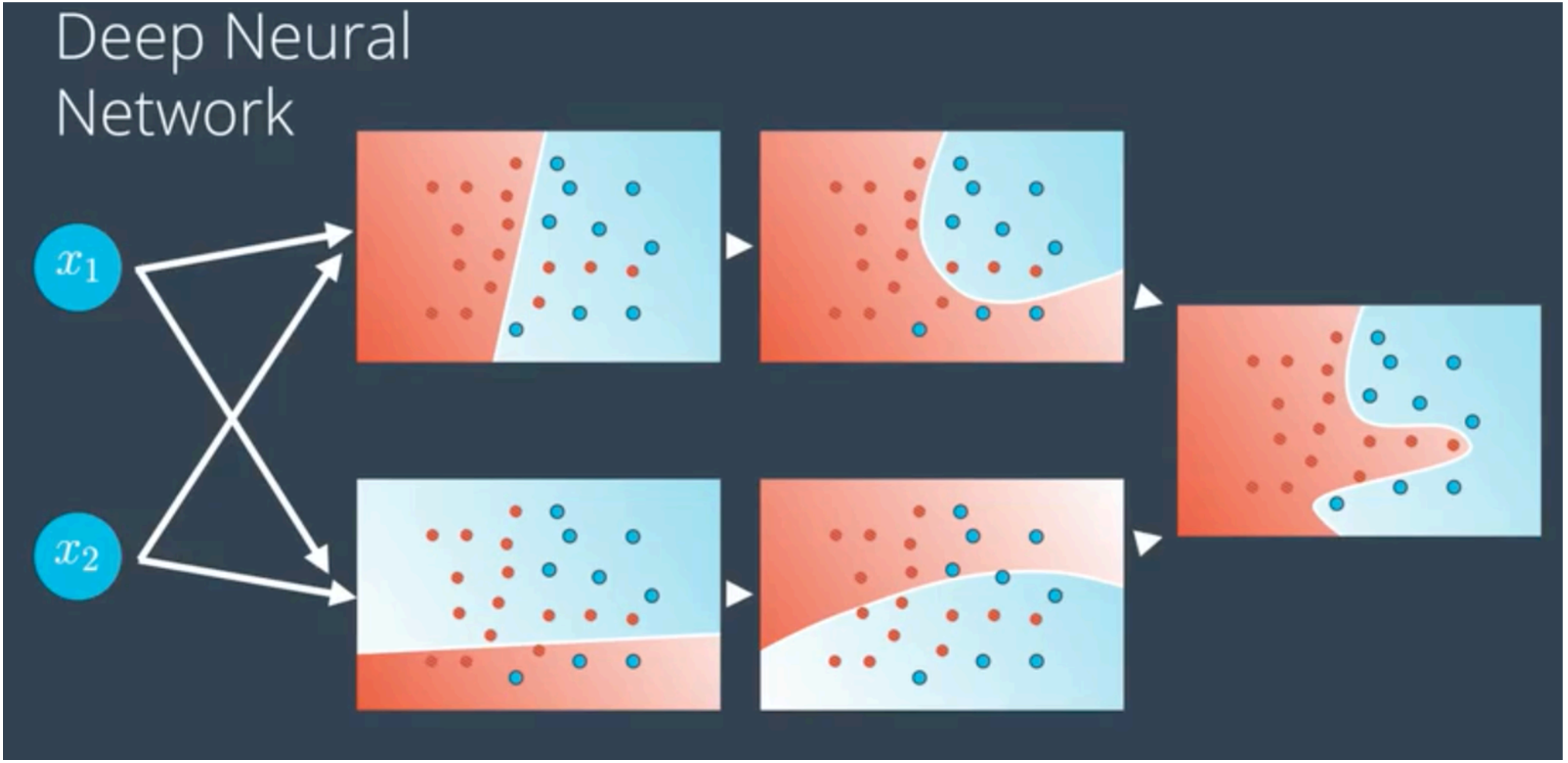


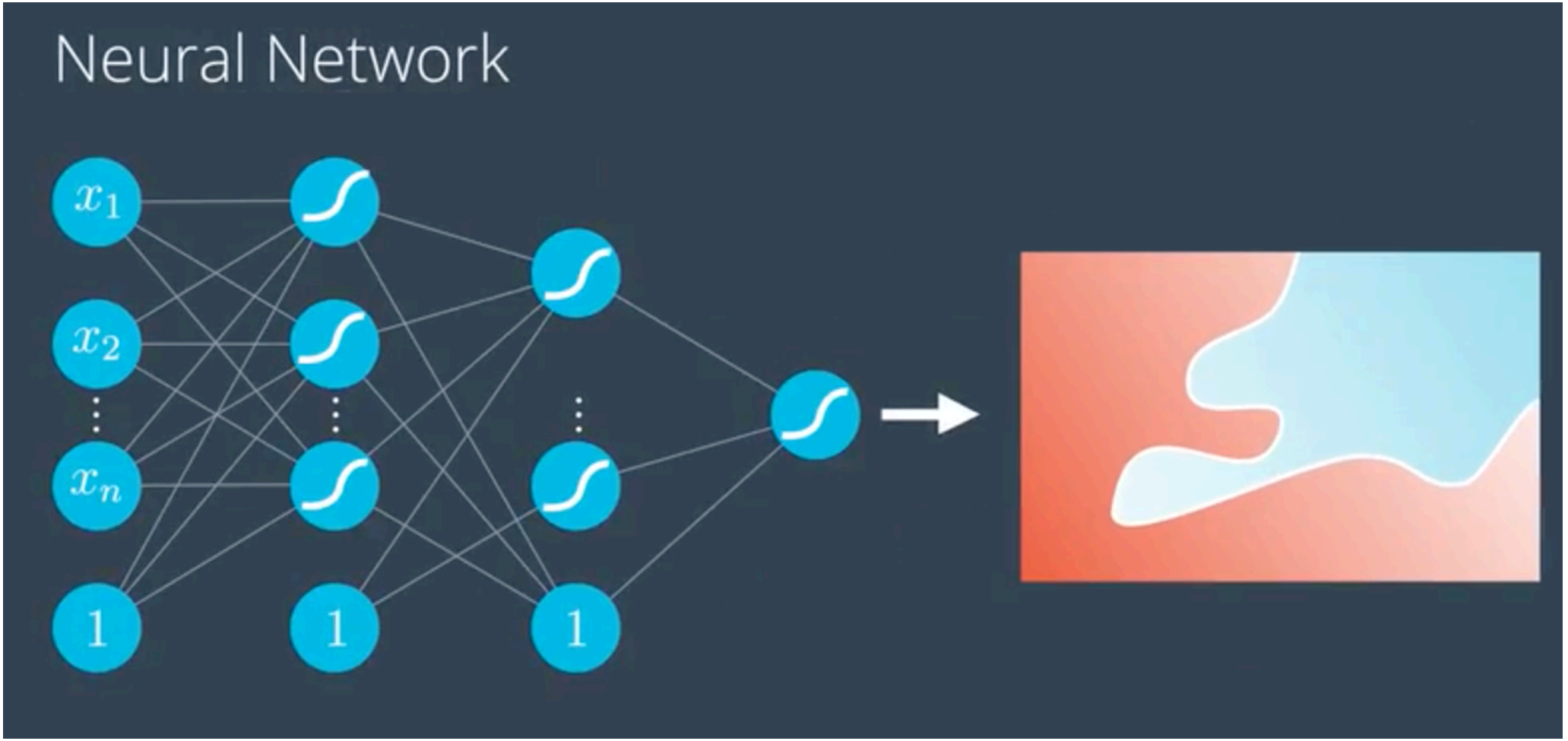

x_1
x_2

Multilayer Perceptron (MLP)



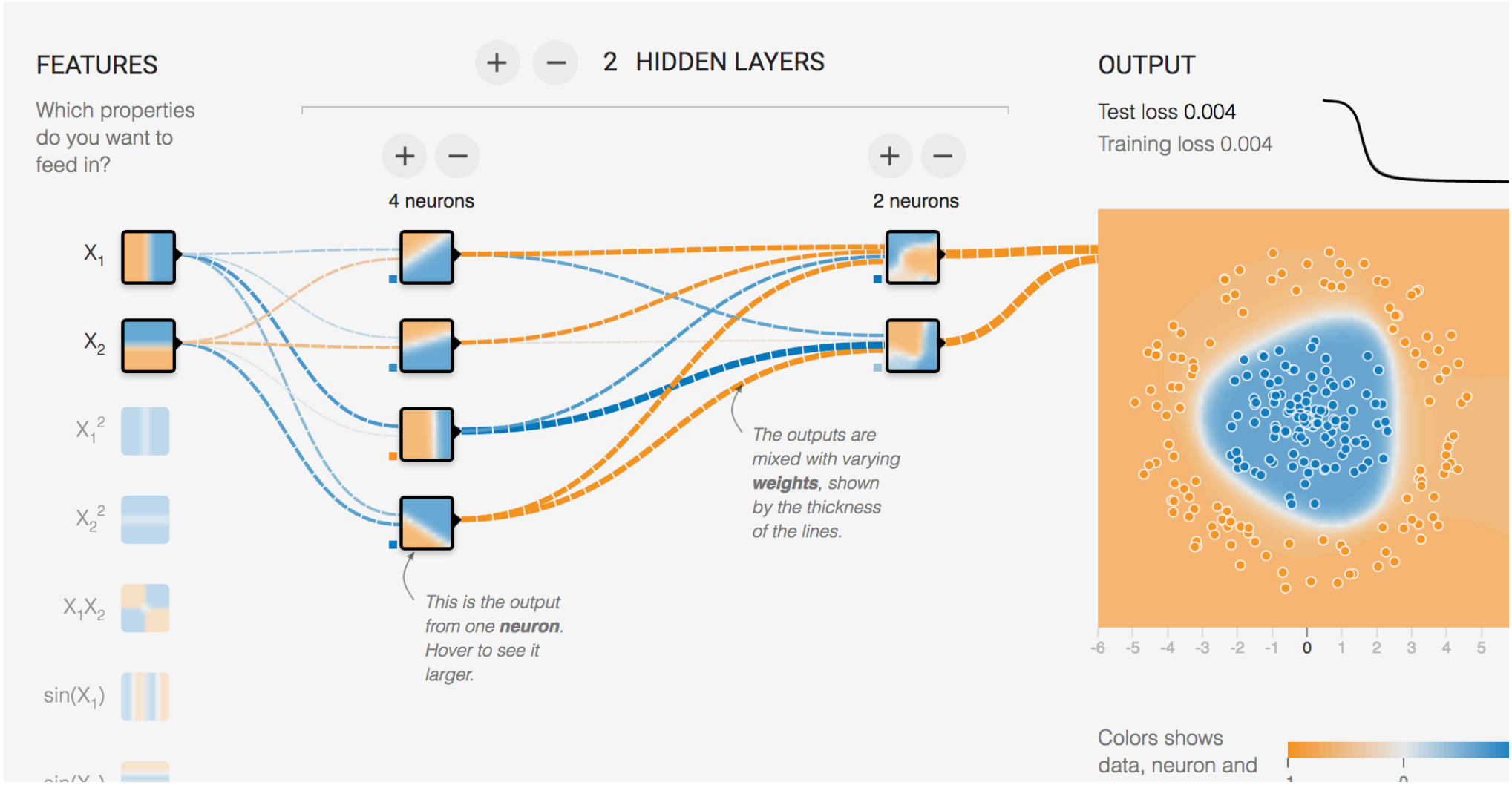

Deep Neural Network
x_1
x_2
CAT
DOG
BIRD


Deep Neural Network
x_1
x_2

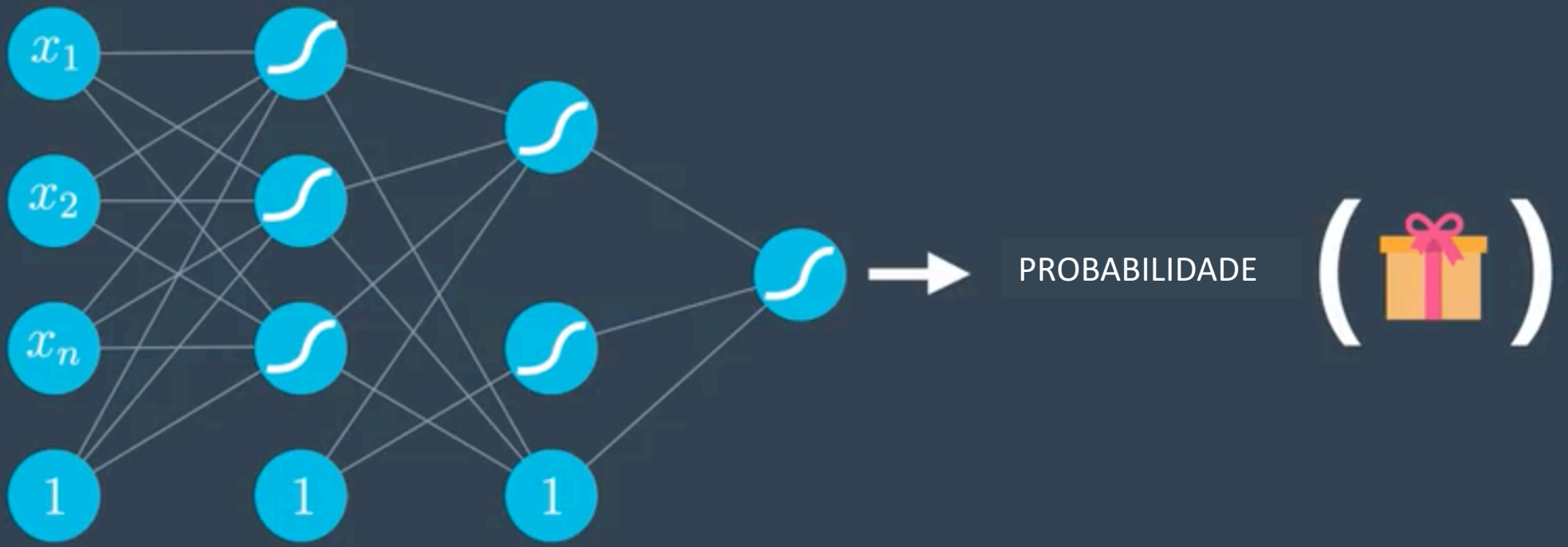

Neural Network
x_1
x_2
x_n
1
1
1

Exercicio

- http://playground.tensorflow.org



Classificação Binária



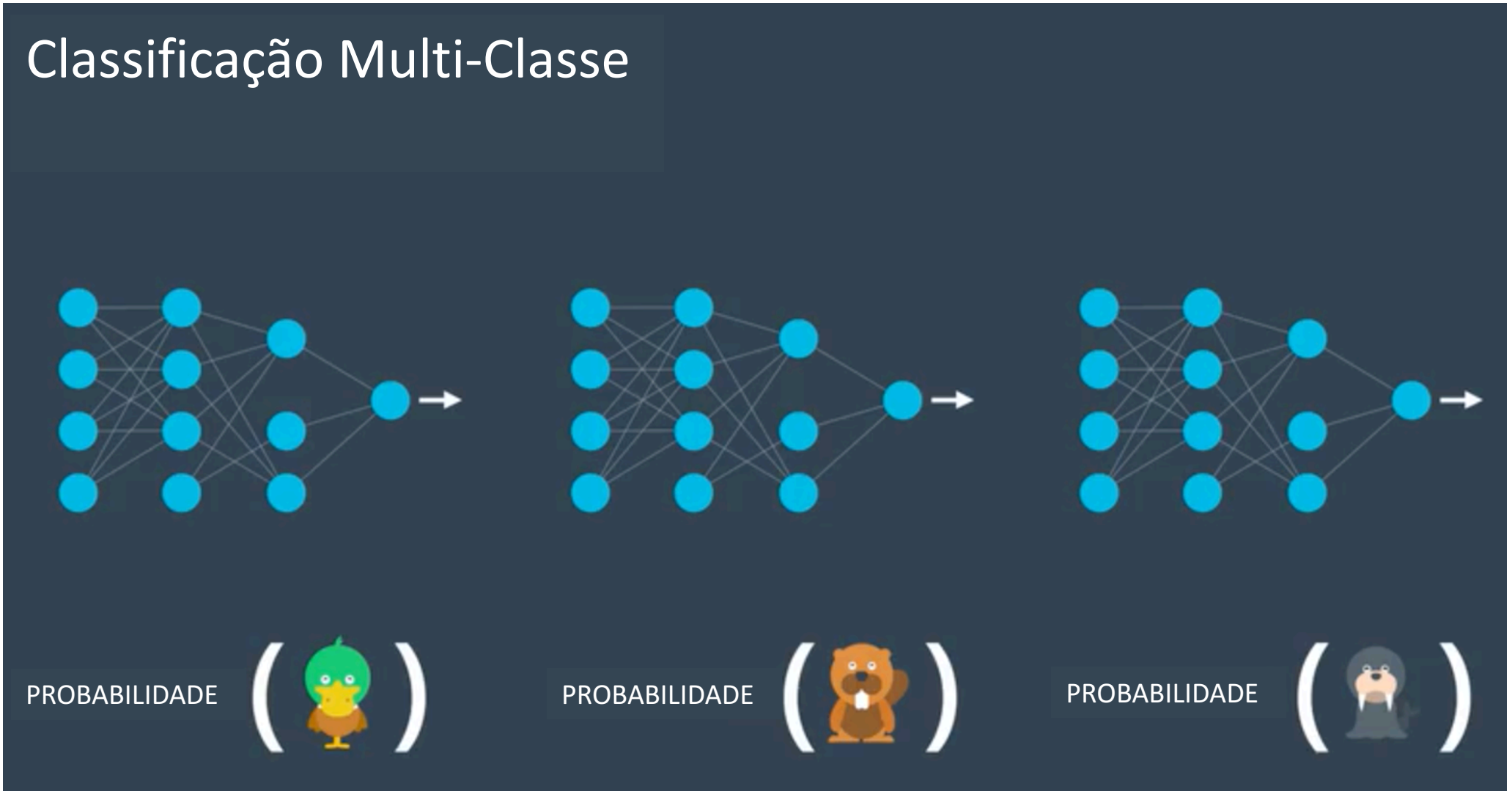
Classificação Multi-Classe

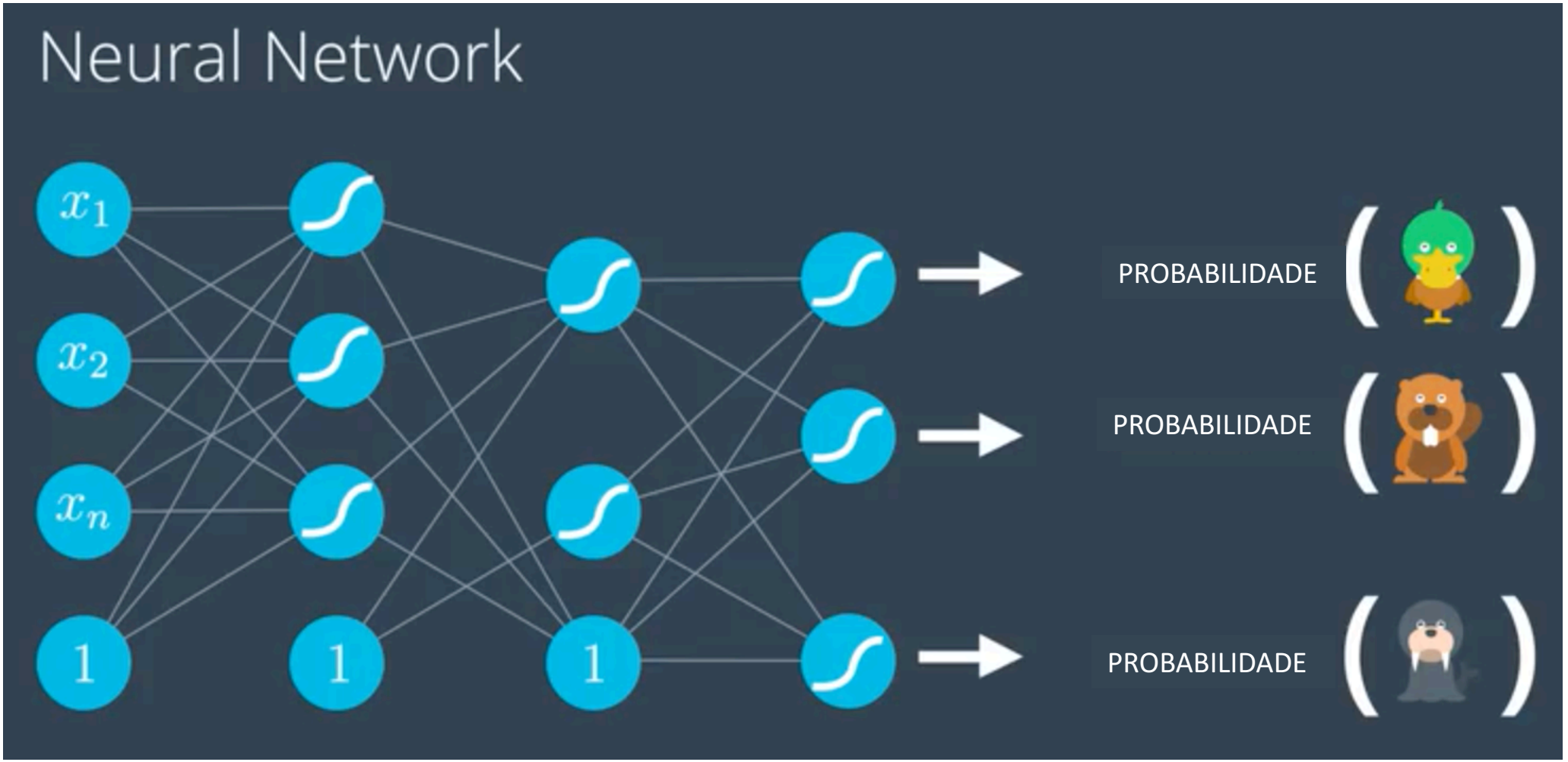
Pato

Castor

Morsa

Classificação Multi-Classe




Neural Network
x_1
x_2
x_n
1
1
1
PROBABILIDADE
PROBABILIDADE
PROBABILIDADE

Classificação Multi-Classe

P(Pato)=
0.67

P(Castor)=
0.24

P(Morsa)=
0.09

Função Softmax

$$P(classe\ i) = \frac{e^{z_i}}{e^{z_1} + \cdots + e^{z_n}}$$

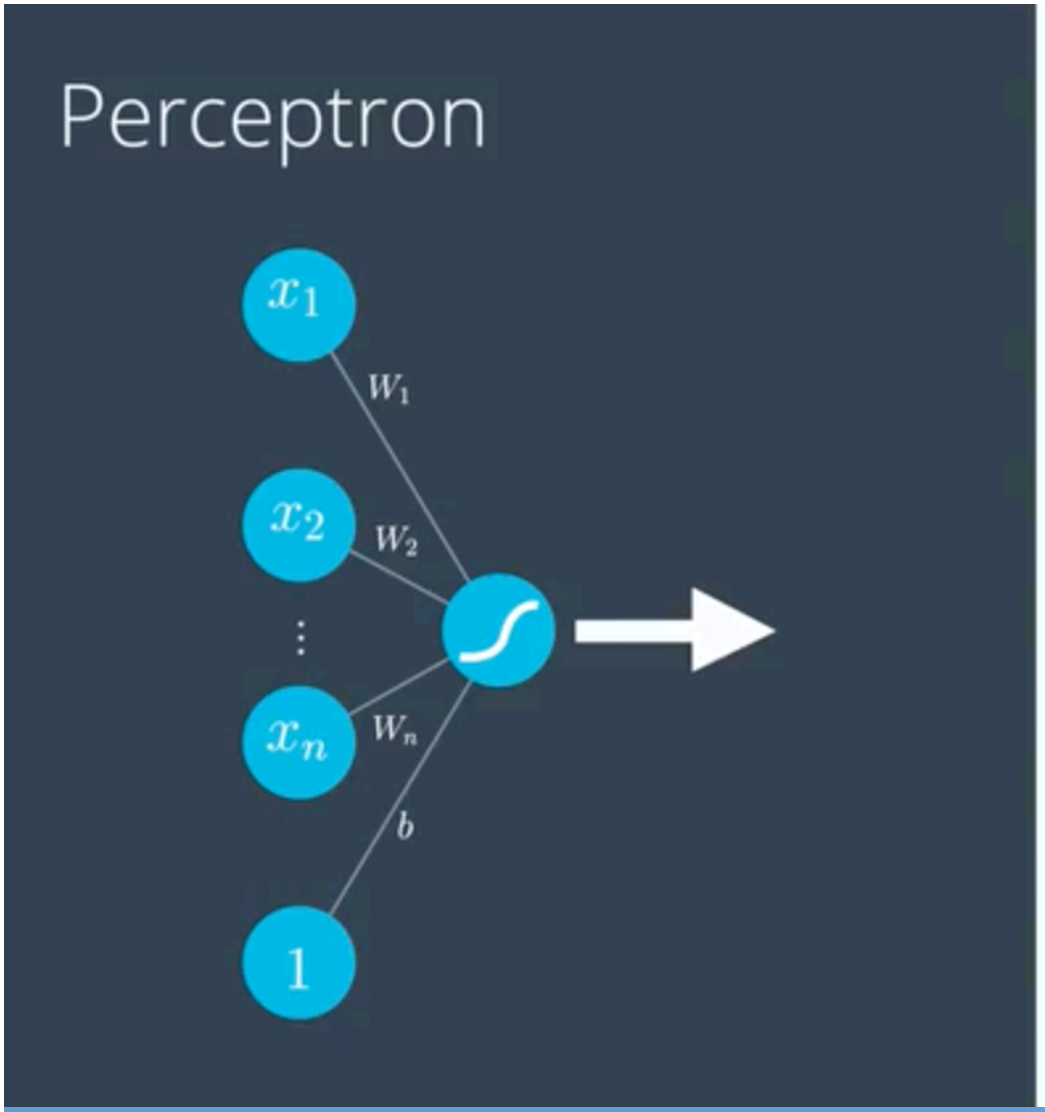
z_i= resultado do somatório do neurônio, antes de aplicar a função de ativação

$$\frac{e^2}{e^2 + e^1 + e^0} = 0.67$$ P(Pato)

$$\frac{e^1}{e^2 + e^1 + e^0} = 0.24$$ P(Castor)

$$\frac{e^0}{e^2 + e^1 + e^0} = 0.09$$ P(Morsa)

Revisando

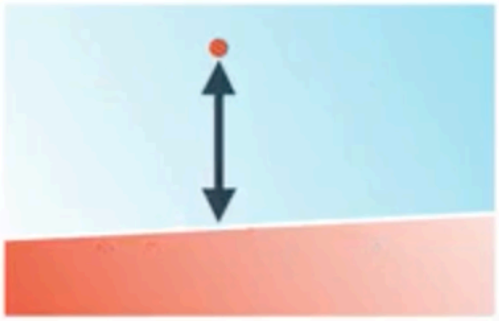


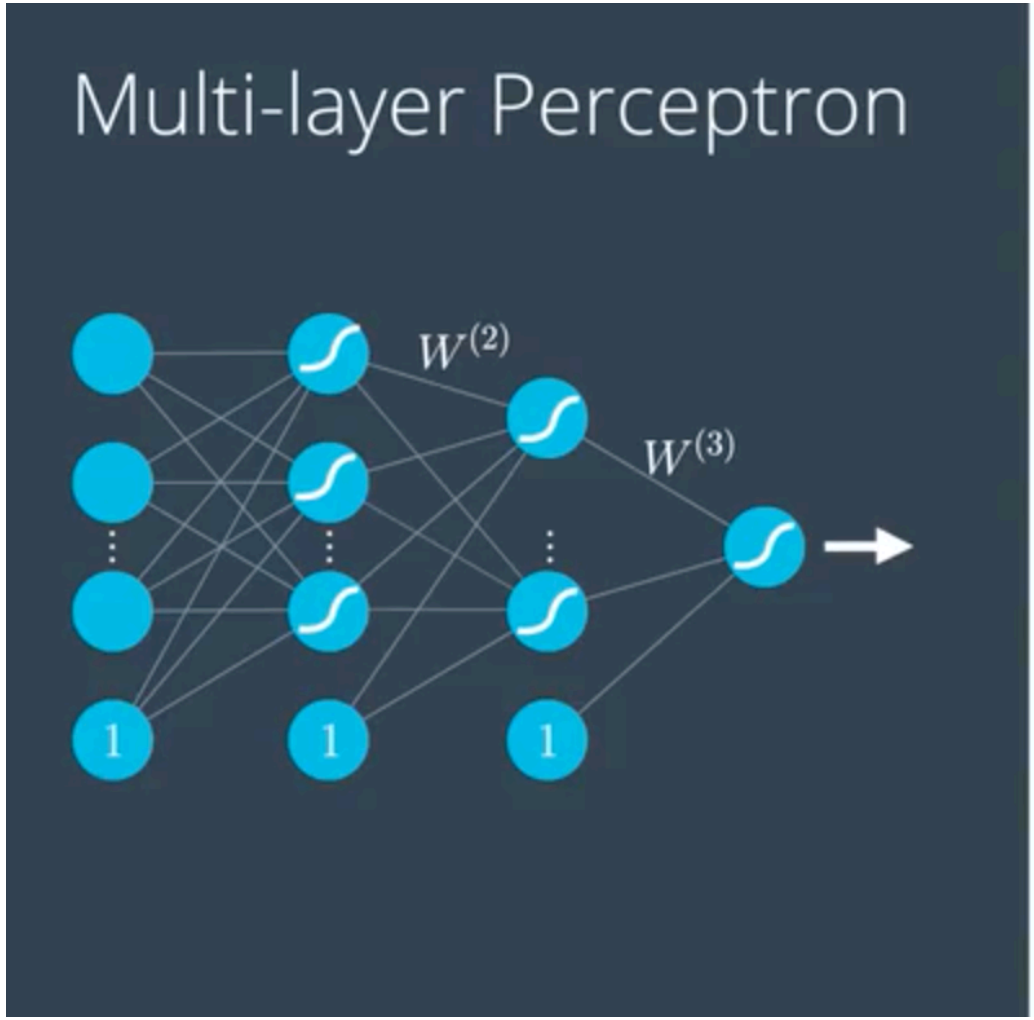
PREDIÇÃO

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

FUNÇÃO DE ERRO

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



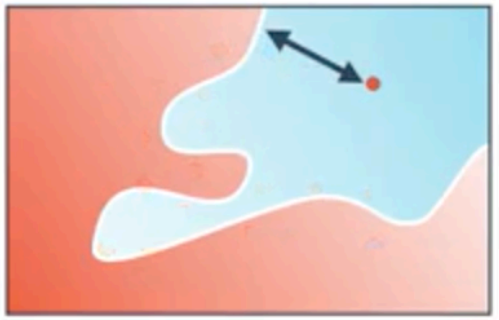


PREDIÇÃO

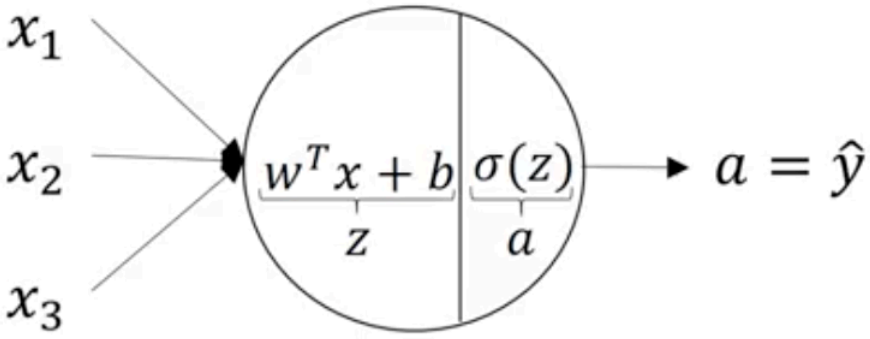
?

FUNÇÃO DE ERRO

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

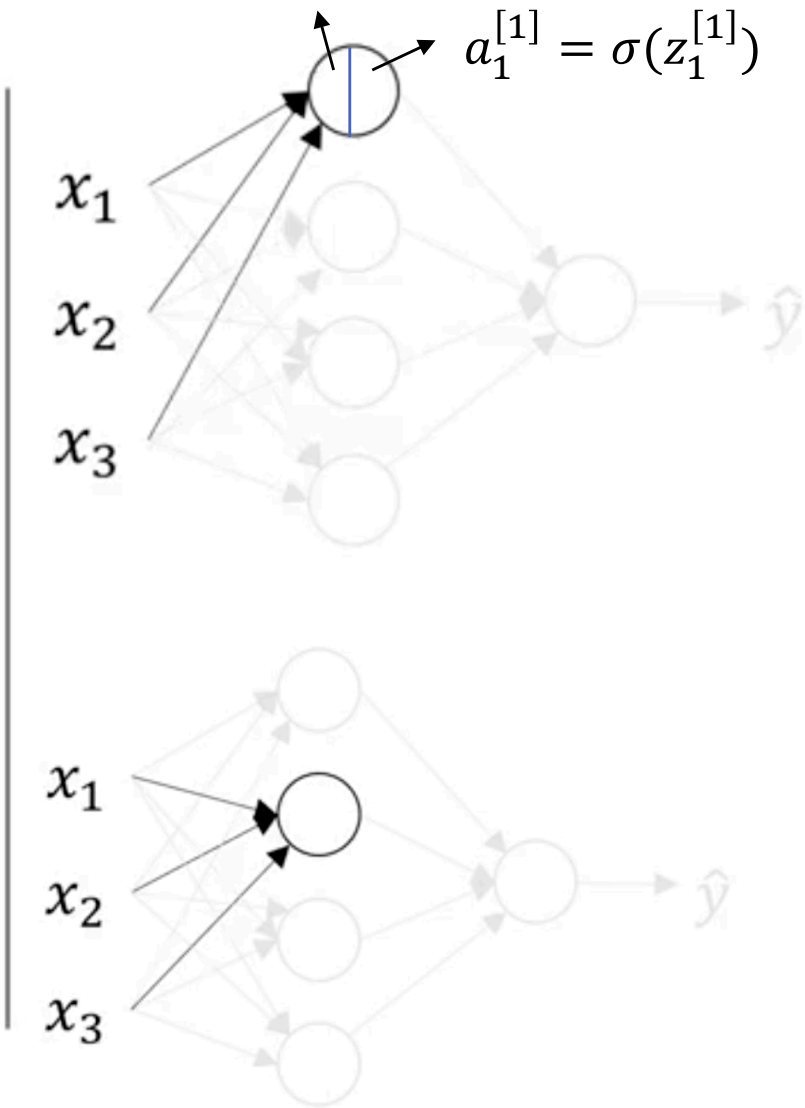


Representação

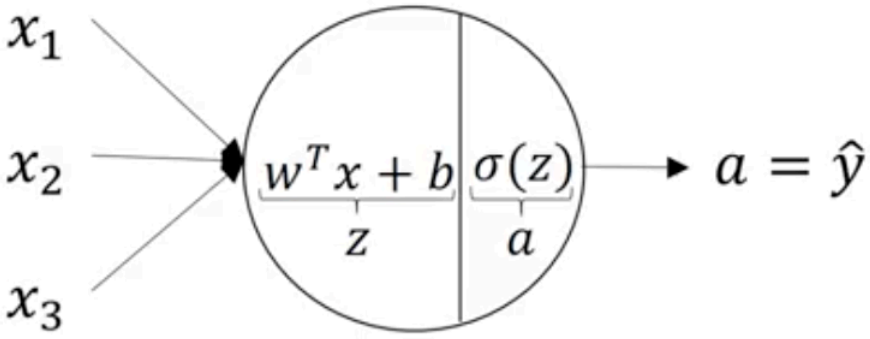


$$z = w^T x + b$$

$$a = \sigma(z)$$

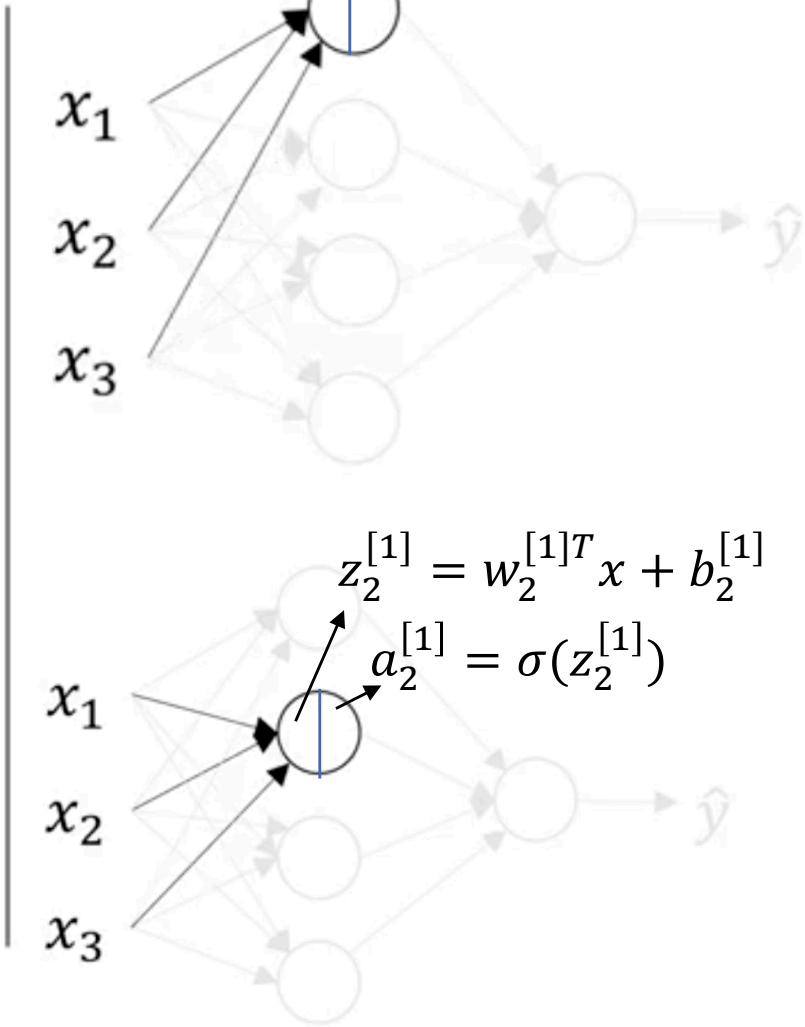


Representação

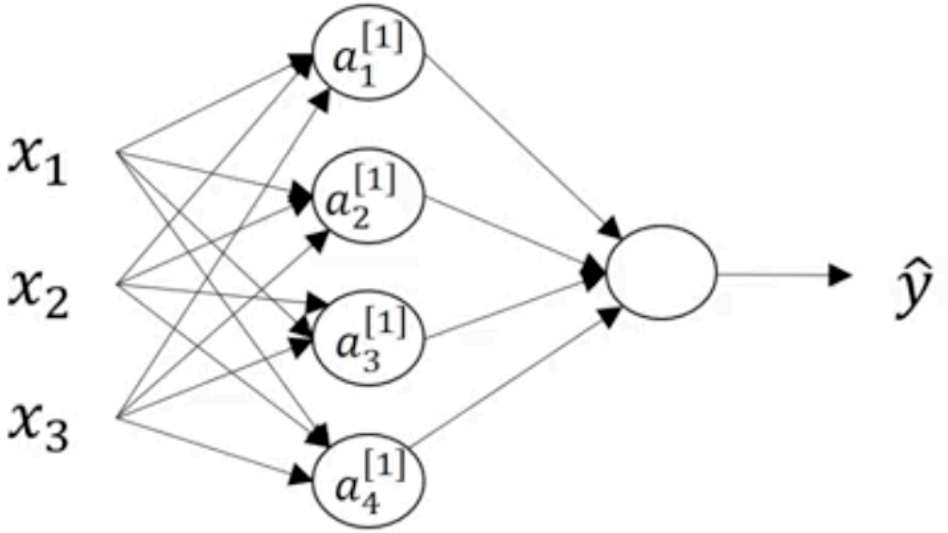


$$z = w^T x + b$$

$$a = \sigma(z)$$

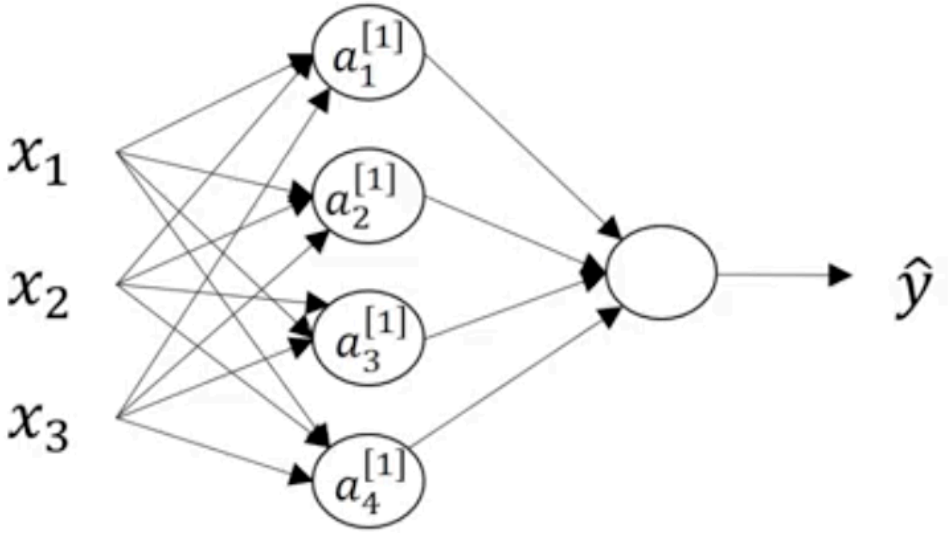


Representação



$$z_1^{[1]} = w_1^{[1]T} x + b_1^{[1]}, a_1^{[1]} = \sigma(z_1^{[1]})$$
$$z_2^{[1]} = w_2^{[1]T} x + b_2^{[1]}, a_2^{[1]} = \sigma(z_2^{[1]})$$
$$z_3^{[1]} = w_3^{[1]T} x + b_3^{[1]}, a_3^{[1]} = \sigma(z_3^{[1]})$$
$$z_4^{[1]} = w_4^{[1]T} x + b_4^{[1]}, a_3^{[1]} = \sigma(z_4^{[1]})$$

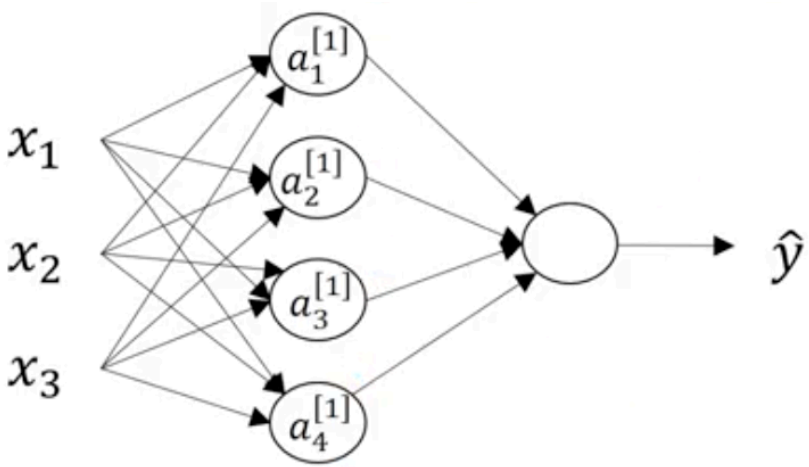
Representação



$$z_1^{[1]} = w_1^{[1]T} x + b_1^{[1]}, a_1^{[1]} = \sigma(z_1^{[1]})$$
$$z_2^{[1]} = w_2^{[1]T} x + b_2^{[1]}, a_2^{[1]} = \sigma(z_2^{[1]})$$
$$z_3^{[1]} = w_3^{[1]T} x + b_3^{[1]}, a_3^{[1]} = \sigma(z_3^{[1]})$$
$$z_4^{[1]} = w_4^{[1]T} x + b_4^{[1]}, a_3^{[1]} = \sigma(z_4^{[1]})$$

$$Z^{[1]} = \underbrace{\begin{bmatrix} - & w_1^{[1]T} & - \\ - & w_2^{[1]T} & - \\ - & w_3^{[1]T} & - \\ - & w_4^{[1]T} & - \end{bmatrix}}_{W^{[1]}} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \underbrace{\begin{bmatrix} b_1^{[1]} \\ b_2^{[1]} \\ b_3^{[1]} \\ b_4^{[1]} \end{bmatrix}}_{b^{[1]}} = \begin{bmatrix} w_1^{[1]T} x + b_1^{[1]} \\ w_2^{[1]T} x + b_2^{[1]} \\ w_3^{[1]T} x + b_3^{[1]} \\ w_4^{[1]T} x + b_4^{[1]} \end{bmatrix} = \begin{bmatrix} z_1^{[1]} \\ z_2^{[1]} \\ z_3^{[1]} \\ z_4^{[1]} \end{bmatrix}$$

Representação



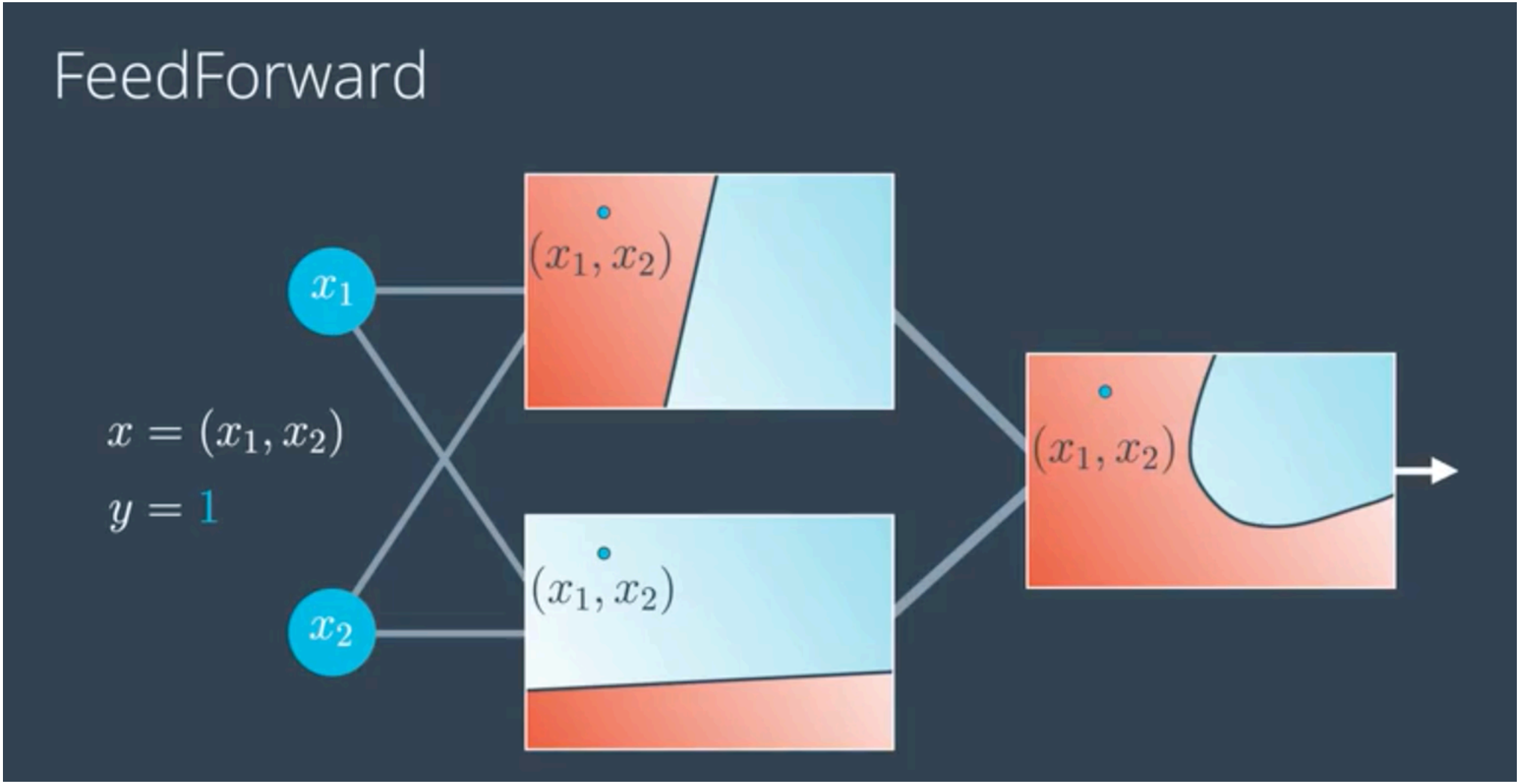
Dada a entrada x:

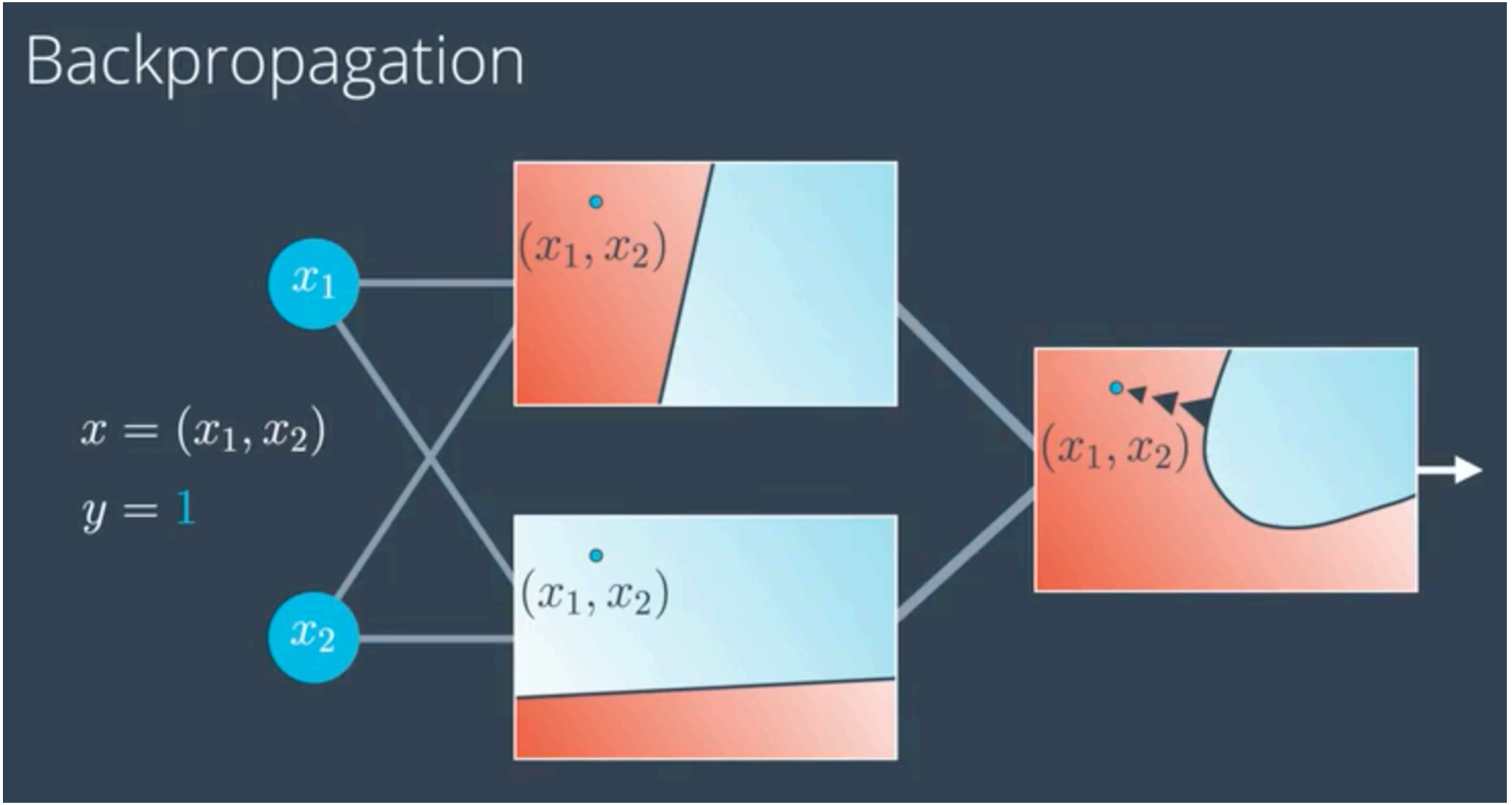
$$z^{[1]} = w^{[1]}x + b^{[1]}$$

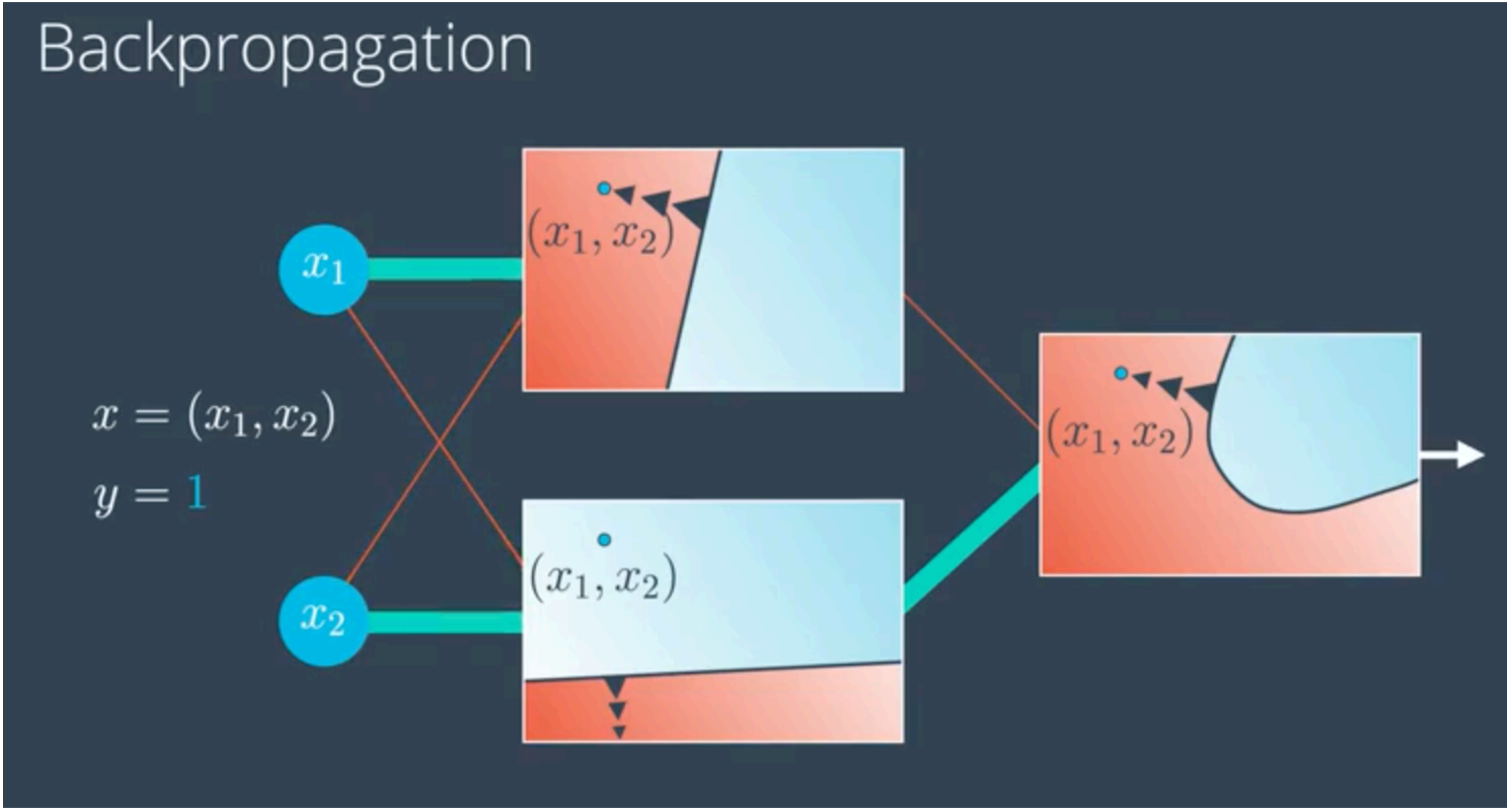
$$a^{[1]} = \sigma(z^{[1]})$$

$$z^{[2]} = w^{[2]}x + b^{[2]}$$

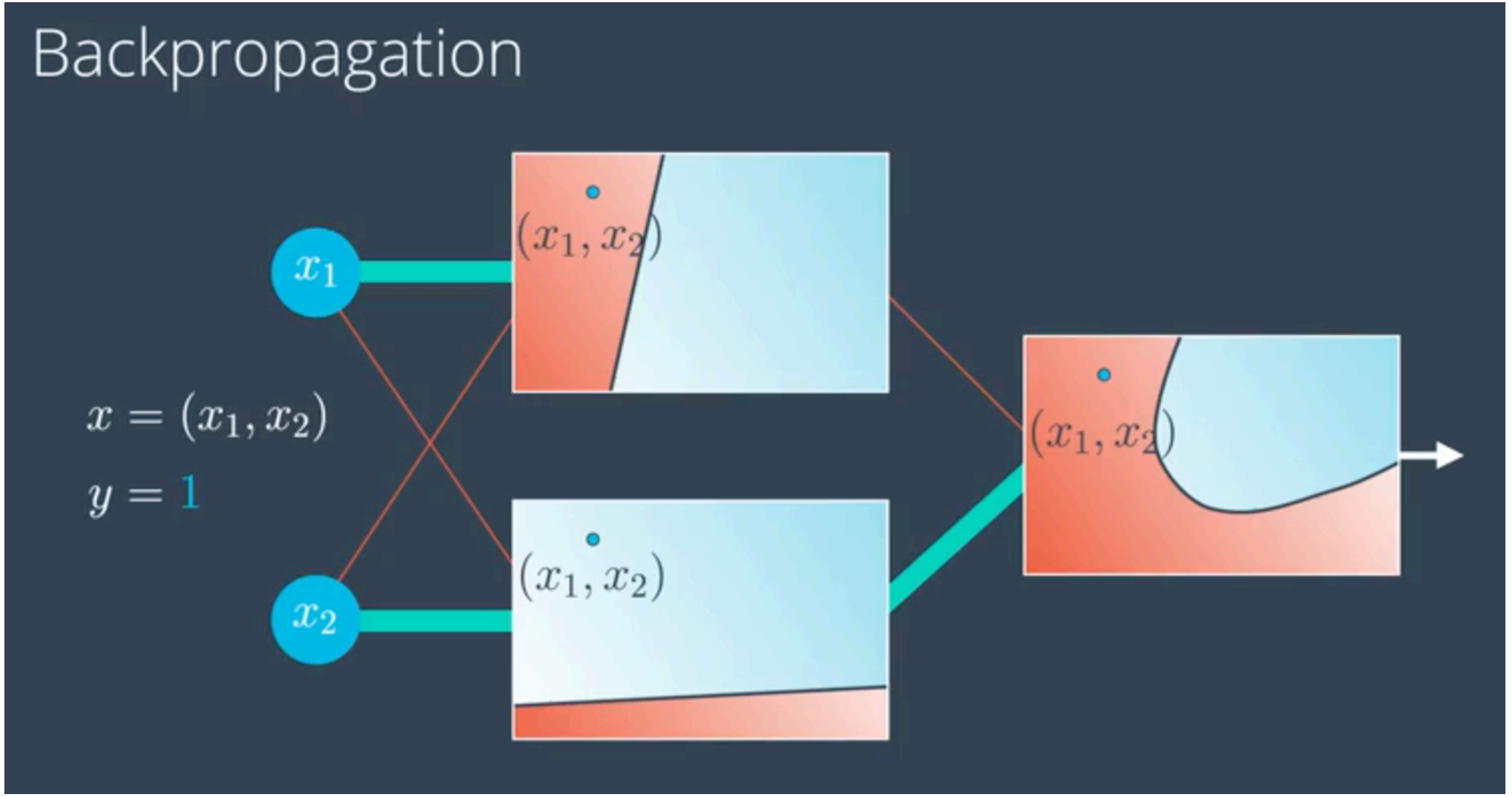
$$a^{[2]} = \sigma(z^{[2]})$$


FeedForward
x_1
x_2
$x = (x_1, x_2)$
$y = 1$
(x_1, x_2)
(x_1, x_2)
(x_1, x_2)


Backpropagation
x_1
x_2
$x = (x_1, x_2)$
$y = 1$
(x_1, x_2)
(x_1, x_2)
(x_1, x_2)


Backpropagation
$x = (x_1, x_2)$
$y = 1$
x_1
x_2
(x_1, x_2)
(x_1, x_2)
(x_1, x_2)

Backpropagation



Exercício

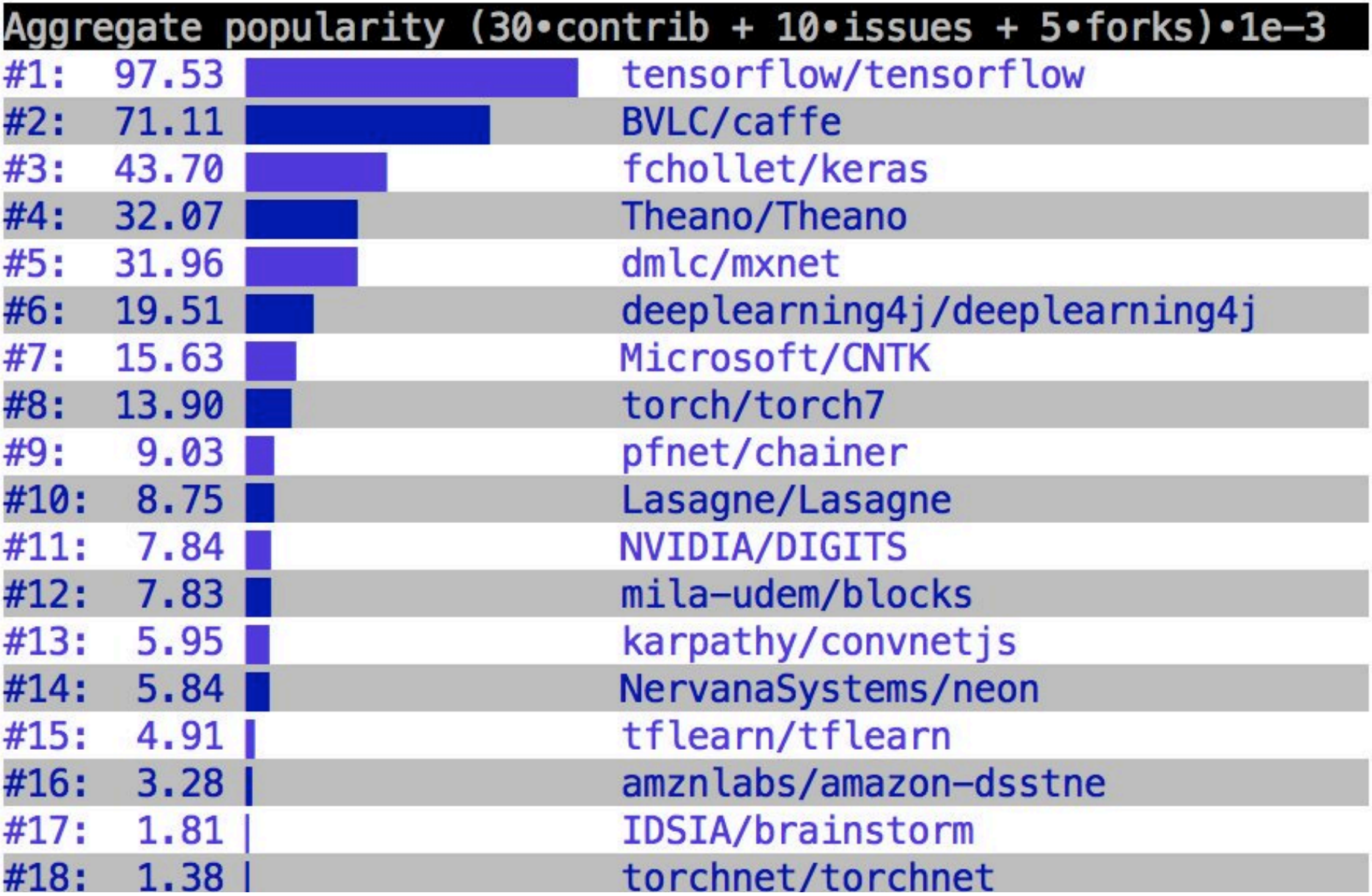
- MLP_code.ipynb

MLP com Keras

Frameworks

DEEPLEARNING4J

Popularidade



	Languages	Tutorials and training materials	CNN modeling capability	RNN modeling capability	Architecture: easy-to-use and modular front end	Speed	Multiple GPU support	Keras compatible
Theano	Python, C++	++	++	++	+	++	+	+
Tensor-Flow	Python	+++	+++	++	+++	++	++	+
Torch	Lua, Python (new)	+	+++	++	++	+++	++	
Caffe	C++	+	++		+	+	+	
MXNet	R, Python, Julia, Scala	++	++	+	++	++	+++	
Neon	Python	+	++	+	+	++	+	
CNTK	C++	+	+	+++	+	++	+	

Keras: High Level Wrapper

Keras é uma camada em cima do *Tensorflow*, que facilita alguns procedimentos

Também suporta *Theano* como backend

```
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.optimizers import SGD

N, D, H = 64, 1000, 100

model = Sequential()
model.add(Dense(input_dim=D, output_dim=H))
model.add(Activation('relu'))
model.add(Dense(input_dim=H, output_dim=D))

optimizer = SGD(lr=1e0)
model.compile(loss='mean_squared_error',
              optimizer=optimizer)

x = np.random.randn(N, D)
y = np.random.randn(N, D)
history = model.fit(x, y, nb_epoch=50,
                    batch_size=N, verbose=0)
```

Keras: High Level Wrapper

Define modelo como uma sequência de camadas

```
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.optimizers import SGD

N, D, H = 64, 1000, 100

model = Sequential()
model.add(Dense(input_dim=D, output_dim=H))
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y = np.random.randn(N, D)
history = model.fit(x, y, nb_epoch=50,
                    batch_size=N, verbose=0)
```

Keras: High Level Wrapper

Define otimizador

```
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.optimizers import SGD

N, D, H = 64, 1000, 100

model = Sequential()
model.add(Dense(input_dim=D, output_dim=H))
model.add(Activation('relu'))
model.add(Dense(input_dim=H, output_dim=D))

optimizer = SGD(lr=1e0)
model.compile(loss='mean_squared_error',
              optimizer=optimizer)

x = np.random.randn(N, D)
y = np.random.randn(N, D)
history = model.fit(x, y, nb_epoch=50,
                    batch_size=N, verbose=0)
```

Keras: High Level Wrapper

Constrói modelo,
especifica função de perda

```
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.optimizers import SGD

N, D, H = 64, 1000, 100

model = Sequential()
model.add(Dense(input_dim=D, output_dim=H))
model.add(Activation('relu'))
model.add(Dense(input_dim=H, output_dim=D))

optimizer = SGD(lr=1e0)
model.compile(loss='mean_squared_error',
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x = np.random.randn(N, D)
y = np.random.randn(N, D)
history = model.fit(x, y, nb_epoch=50,
                    batch_size=N, verbose=0)
```
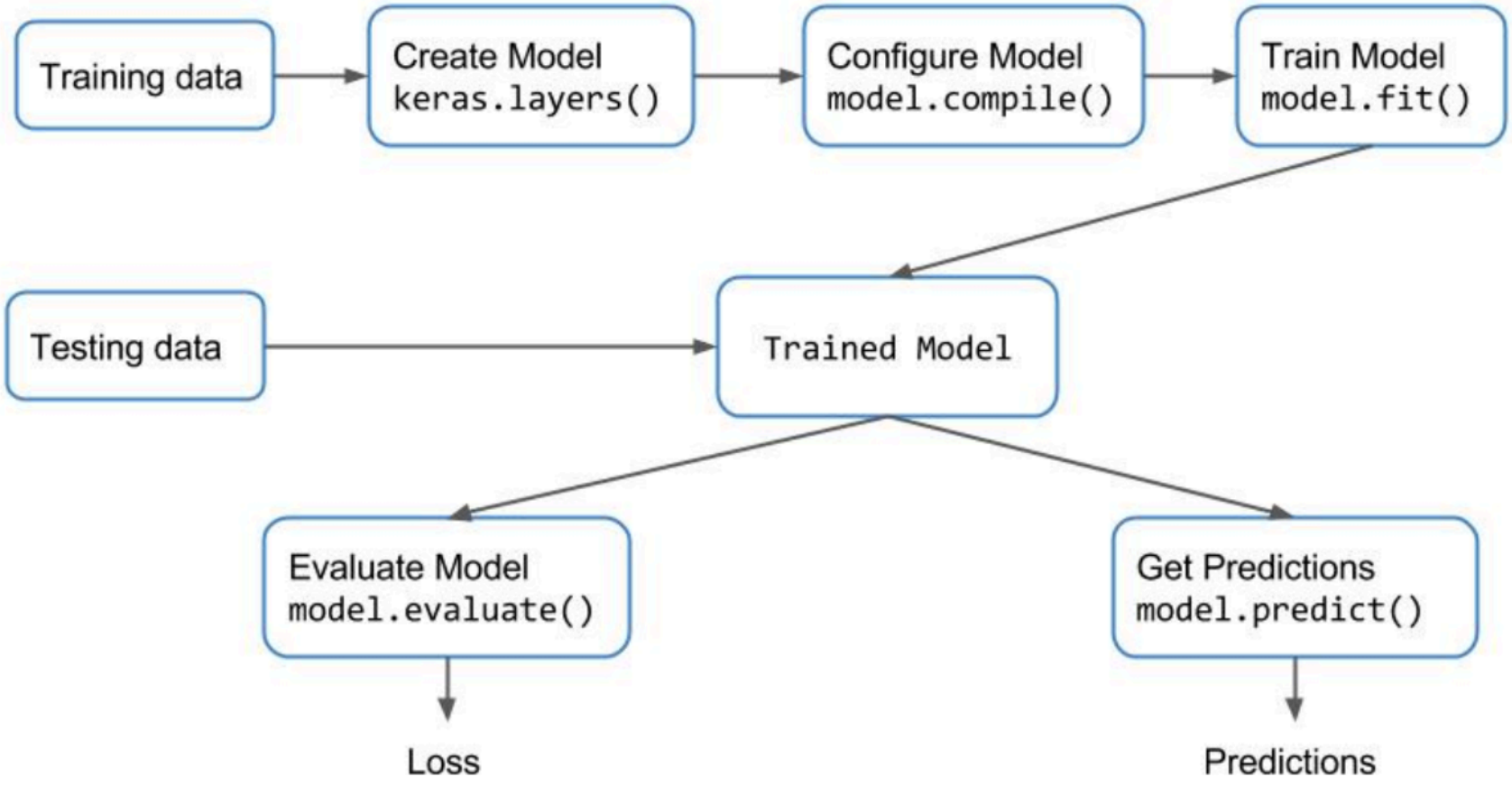

Keras: High Level Wrapper

```
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.optimizers import SGD

N, D, H = 64, 1000, 100

model = Sequential()
model.add(Dense(input_dim=D, output_dim=H))
model.add(Activation('relu'))
model.add(Dense(input_dim=H, output_dim=D))

optimizer = SGD(lr=1e0)
model.compile(loss='mean_squared_error',
              optimizer=optimizer)

x = np.random.randn(N, D)
y = np.random.randn(N, D)
history = model.fit(x, y, nb_epoch=50,
                    batch_size=N, verbose=0)
```

Treina o modelo

Fluxograma Keras



MLP com Keras

- código minist_keras.ipynb

One-hot Encoding

ANIMAL	VALOR
	?
	?
	?
	?
	?

ANIMAL	PATO	CASTOR	MORSA?
	1	0	0
	0	1	0
	1	0	0
	0	0	1
	0	1	0

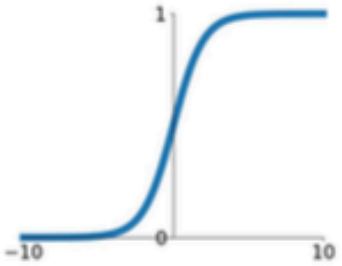
TODO

- Cifar10_keras.ipynb

Funções de Ativação

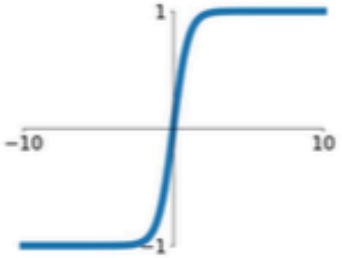
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



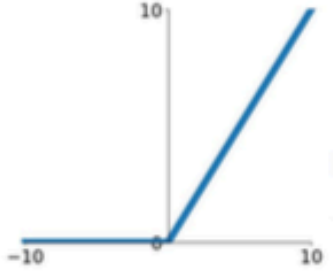
tanh

$$\tanh(x)$$



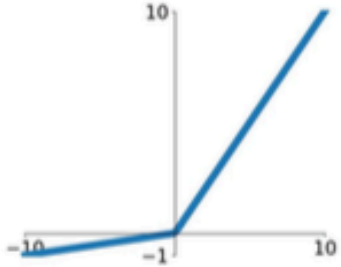
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

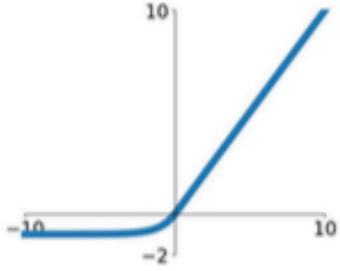


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Histórico das funções de ativação

Name	Formula	Year
none	$y = x$	-
sigmoid	$y = \frac{1}{1+e^{-x}}$	1986
tanh	$y = \frac{e^{2x}-1}{e^{2x}+1}$	1986
ReLU	$y = \max(x, 0)$	2010
(centered) SoftPlus	$y = \ln(e^x + 1) - \ln 2$	2011
LReLU	$y = \max(x, \alpha x), \alpha \approx 0.01$	2011
maxout	$y = \max(W_1 x + b_1, W_2 x + b_2)$	2013
APL	$y = \max(x,0) + \sum_{s=1}^{S} a_i^s \max(0, -x + b_i^s)$	2014
VLReLU	$y = \max(x, \alpha x), \alpha \in 0.1, 0.5$	2014
RReLU	$y = \max(x, \alpha x), \alpha = \text{random}(0.1, 0.5)$	2015
PReLU	$y = \max(x, \alpha x), \alpha$ is learnable	2015
ELU	$y = x$, if $x \geq 0$, else $\alpha(e^x - 1)$	2015


IDEAS
Think?
good
click
Inspiration
CHECK LIST:
- SEO
- 3G / 4G
cloud
SHARE