

# Neural Networks, Tensorflow, and Keras

DATA 607 — Session 7 — 18/03/2019

Perceptron and logistic regression classifiers have linear decision boundaries.

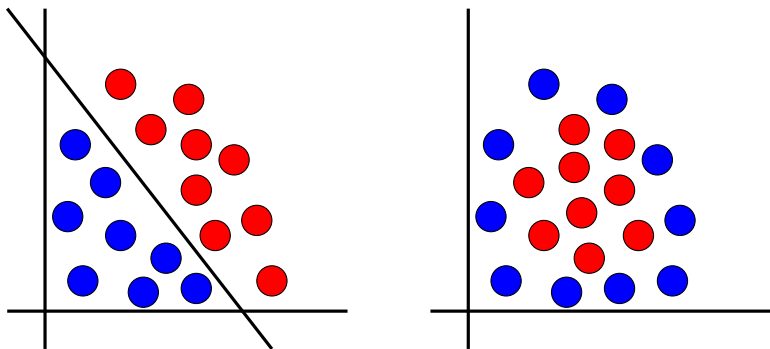


Figure: Linearly separable, not linearly separable

Perceptron, logistic regression **can** learn:

$$f : \{(0, 0), (1, 0), (1, 1), (0, 1)\} \longrightarrow \{0, 1\}$$

$$f(0, 0) = 1, \quad f(1, 0) = f(1, 1) = f(0, 1) = 0$$

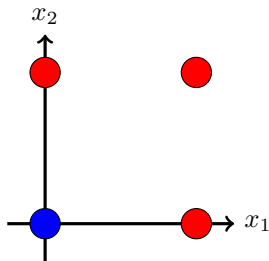


Figure: Graph of  $f$

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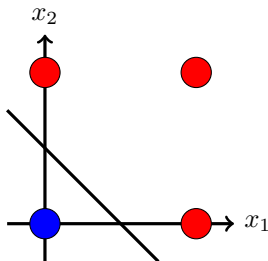
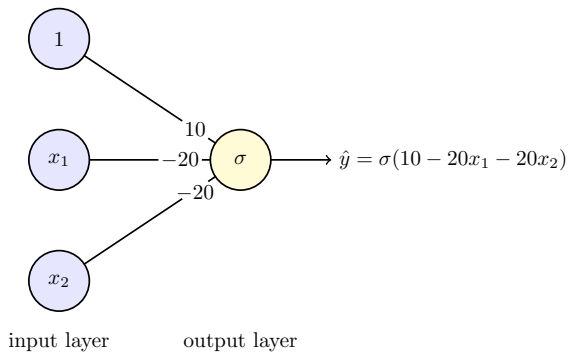


Figure: Graph of  $f$



$x_1$	$x_2$	$\hat{y}$
0	0	$\sigma(10) \approx 1$
1	0	$\sigma(-10) \approx 0$
0	1	$\sigma(-10) \approx 0$
1	1	$\sigma(-30) \approx 0$

Perceptron, logistic regression **can't** learn...

$$f : \{(0, 0), (1, 0), (1, 1), (0, 1)\} \longrightarrow \{0, 1\}$$

$$f(0, 0) = f(1, 1) = 1, \quad f(1, 0) = f(0, 1) = 0$$

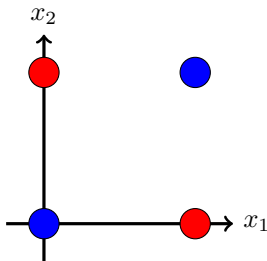
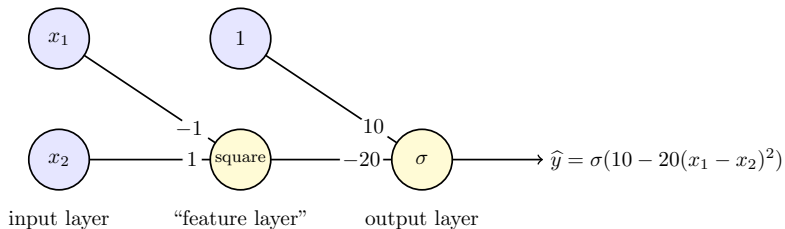


Figure: Graph of  $f$

... unless we introduce new features.



$x_1$	$x_2$	$\hat{y}$
0	0	$\sigma(10) \approx 1$
1	0	$\sigma(-10) \approx 0$
0	1	$\sigma(-10) \approx 0$
1	1	$\sigma(10) \approx 1$

# What is a neural network?

A neural network consists of **neurons** or **units**. Neurons have **inputs**, **outputs**, and **activations**. Connections between these neurons have **weights**. Neurons are organized into **layers**. **Hidden layers** are sandwiched between an **input layer** and an **output layer**.

Linear regression, logistic regression, and perceptron classification are all neural networks, degenerate in the sense that they have no hidden layers.



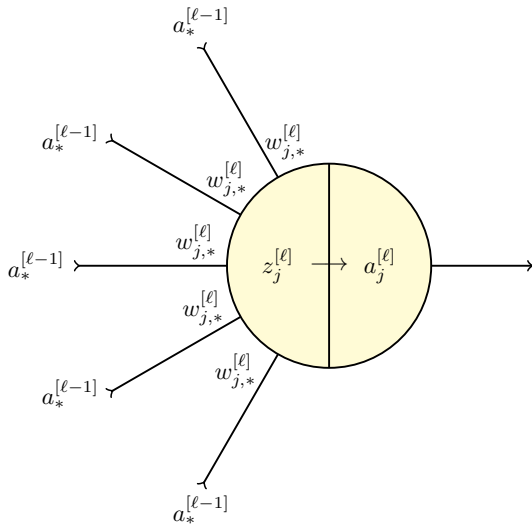
More formally, a neural network is a function

$$N : \mathbb{R}^p \longrightarrow \mathbb{R}^q$$

constructed in a particular way.

depth of network (number of layers):  $d$   
 number of neurons in layer  $\ell$ :  $p_\ell$   
 activation (output) of neuron  $k$  in layer  $\ell$ :  $a_k^{[\ell]}$   
 bias of neuron  $k$  in layer  $\ell$ :  $b_k^{[\ell]}$   
 weight of the connection between neuron  $j$   
 in layer  $\ell$  and neuron  $i$  in layer  $\ell + 1$ :  $w_{ij}^{[\ell]}$   
 activation function in layer  $\ell$ :  $h$

$$a_i^{[\ell+1]} = h\left(z_i^{[\ell+1]}\right), \quad \text{where} \quad z_i^{[\ell+1]} = b_i^{[\ell]} + \sum_{j=1}^{p_\ell} w_{ij}^{[\ell]} a_j^{[\ell]}$$



$$z_j^{[l]} = \sum_i w_{j,i}^{[l]} a_i^{[l-1]}$$

$$a_j^{[l]} = A_\ell(z_j^{[l]})$$

Figure: A hidden or output unit

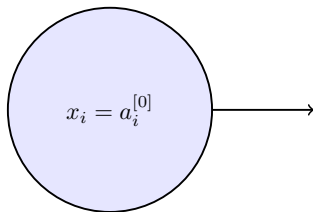


Figure: An input unit

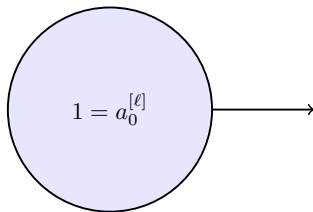


Figure: A bias unit

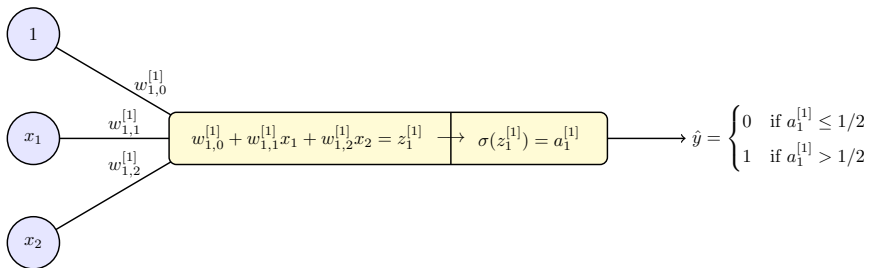


Figure: Logistic regression

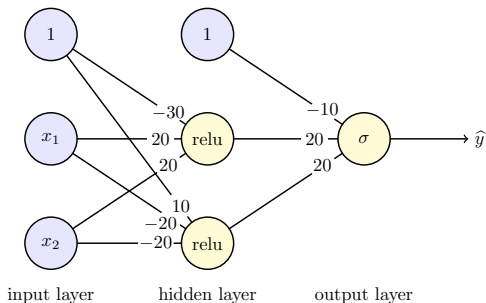


Figure: Learning XOR

$x_1$	$x_2$	$z_1^{[1]}$	$z_2^{[1]}$	$a_1^{[1]}$	$a_2^{[1]}$	$z_1^{[2]}$	$a_1^{[2]}$	$\hat{y}$
0	0	-30	-10	0	10	190	1.00	1
0	1	-10	-10	0	0	-10	0.00	0
1	0	-10	-10	0	0	-10	0.00	0
1	1	-10	-10	10	0	190	1.00	1