

**NSC3270 / NSC5270**  
**Computational Neuroscience**

Tu/Th 9:35-10:50am  
Featheringill Hall 129

Professor Thomas Palmeri  
Professor Sean Polyn

## For Today

### Required Readings

Chapter 3 (selected pages) of Churchland, P.S., & Sejnowski, T.J. (2017). *The Computational Brain* (25th Anniversary Edition). MIT Press.

### In-Class Python Code

Homework3.py

Homework3.ipynb

### Info to help with Homework 3

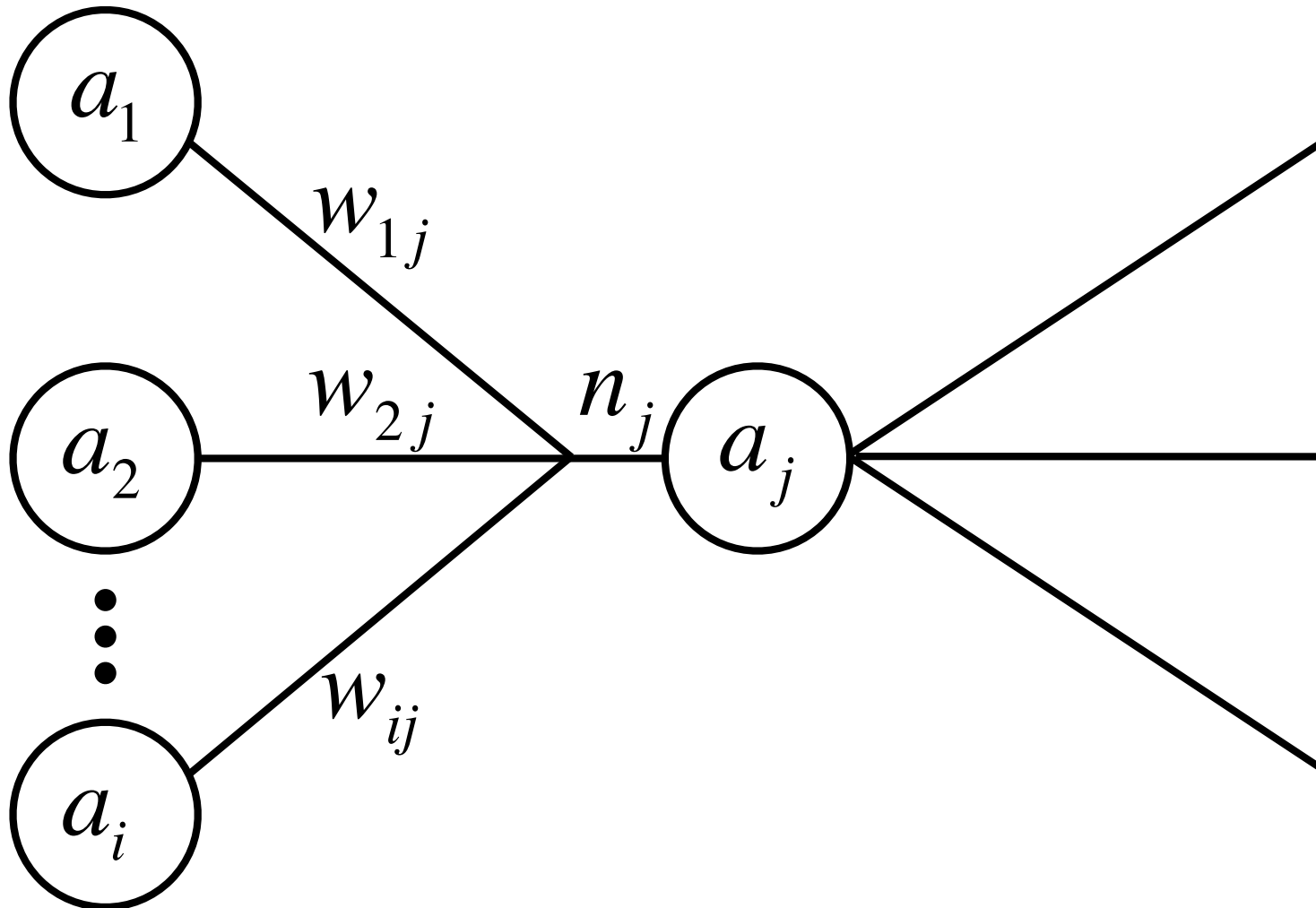
NumpyExamples.ipynb

links on Brightspace

**inputs integrate  
at the cell body  
- they are added  
together**

net input sums the weighted inputs

$$n_j = \sum_i a_i w_{ij}$$



let's take a look at this equation

$$n_j = \sum_i a_i w_{ij}$$

$$a = [a_1, a_2, \dots, a_m]$$
 activation of all the input nodes

$$w_j = [w_{1j}, w_{2j}, \dots, w_{mj}]$$
 all weights going to 2nd layer node j

let's take a look at this equation

$$n_j = \sum_i a_i w_{ij}$$

$$a = [a_1, a_2, \dots, a_m]$$

$$w_j = [w_{1j}, w_{2j}, \dots, w_{mj}]$$

```
import numpy as np
n = 0
for i in np.arange(len(a)):
    n += a[i]*wj[i]
```

let's take a look at this equation

$$n_j = \sum_i a_i w_{ij}$$

$$a = [a_1, a_2, \dots, a_m]$$

$$w_j = [w_{1j}, w_{2j}, \dots, w_{mj}]$$

`n = sum(a*wj)`



element-wise multiplication of numpy arrays  
(different from Matlab, which requires `.*` operator)

let's take a look at this equation

$$n_j = \sum_i a_i w_{ij}$$

$$a = [a_1, a_2, \dots, a_m]$$

$$w_j = [w_{1j}, w_{2j}, \dots, w_{mj}]$$

$$n_j = a \cdot w_j$$

```
import numpy as np  
n = np.dot(a, wj)
```

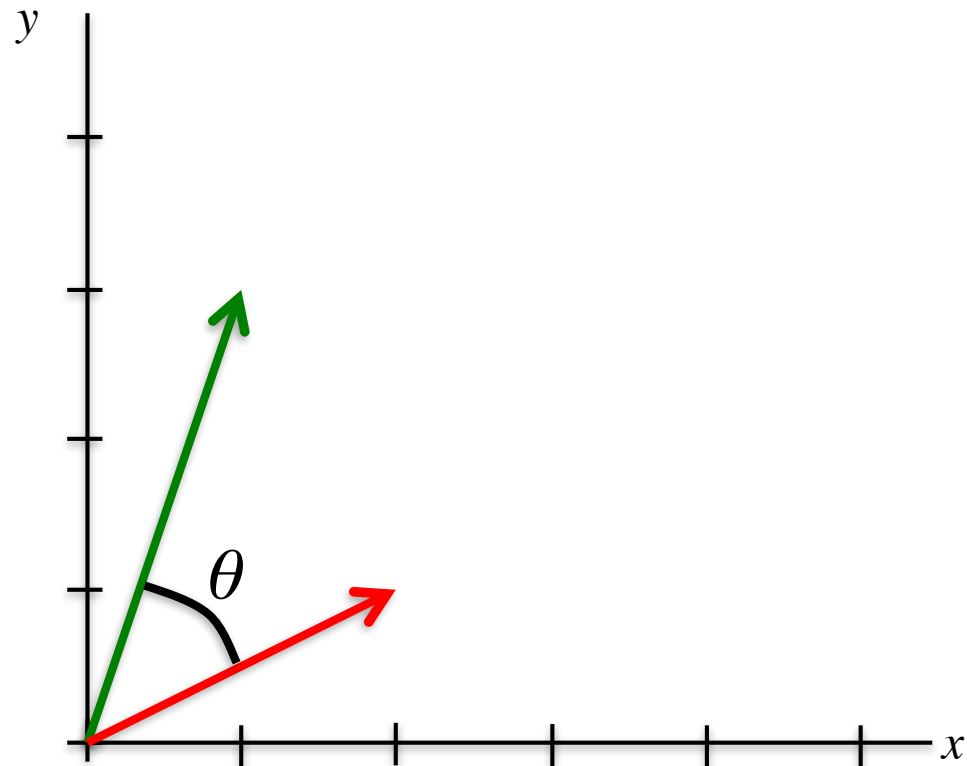
dot product

# dot product

“similarity” between two vectors

```
>>> a = [1, 3]
```

```
>>> wj = [2, 1]
```





# dot product

angle between two vectors ...

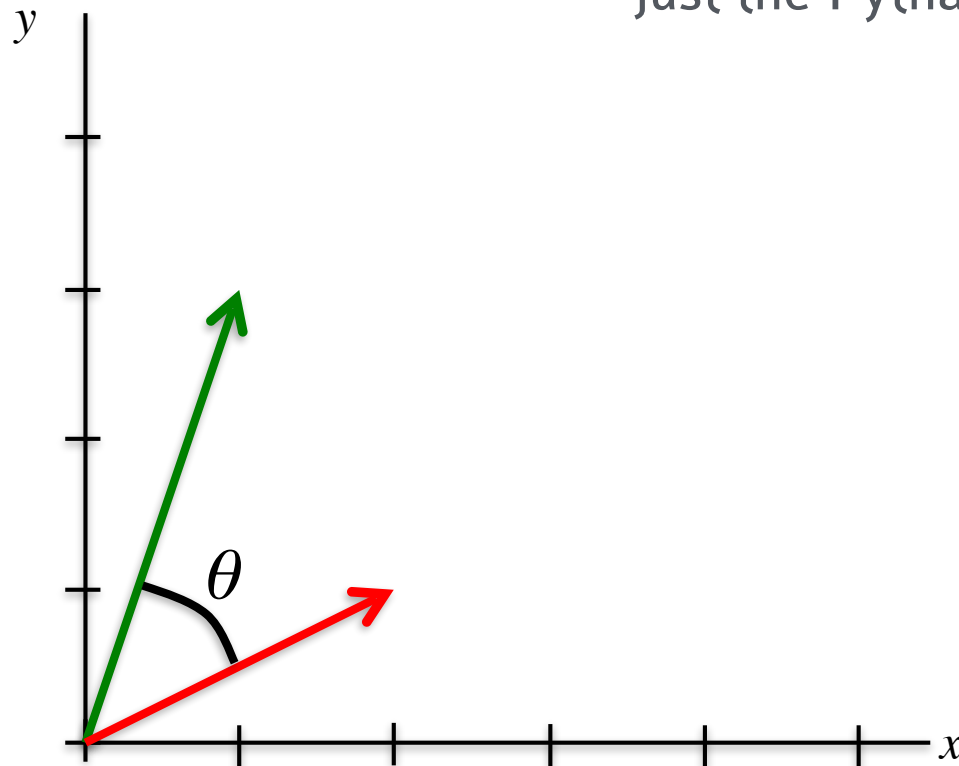
$$\cos(\theta) = \frac{a \cdot w_j}{\|a\| \|w_j\|}$$

← dot product

← norm

$$\|a\| = \sqrt{a \cdot a}$$

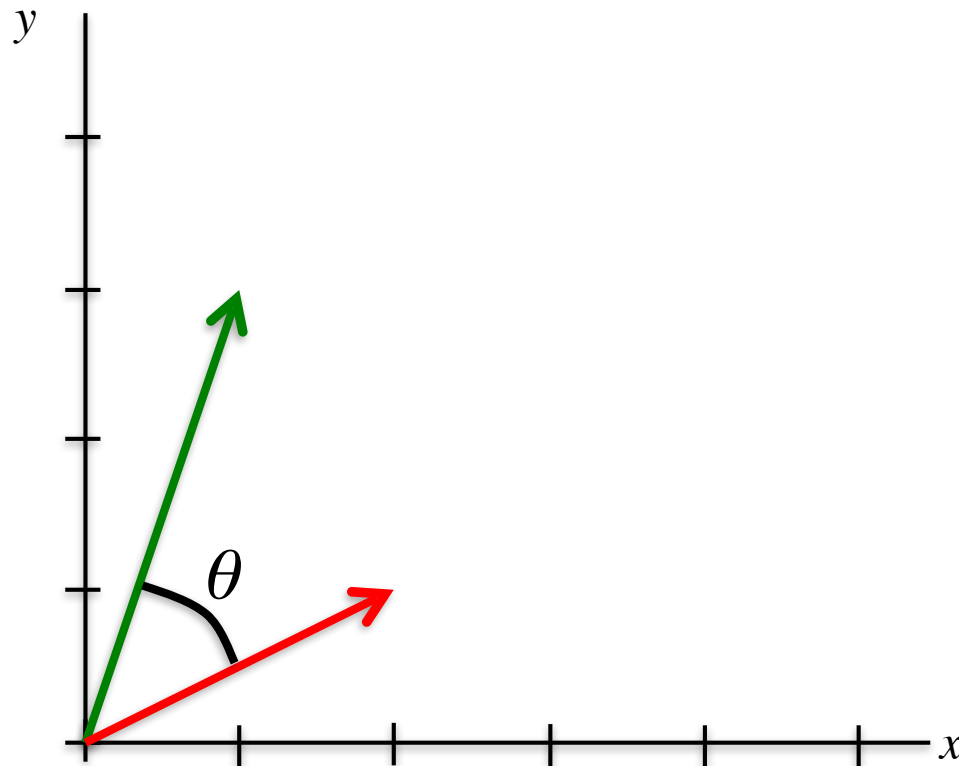
just the Pythagorean theorem



## dot product

```
>>> theta = m.degrees(m.acos(np.dot(a,wj) /  
    (np.linalg.norm(a)*np.linalg.norm(wj))))
```

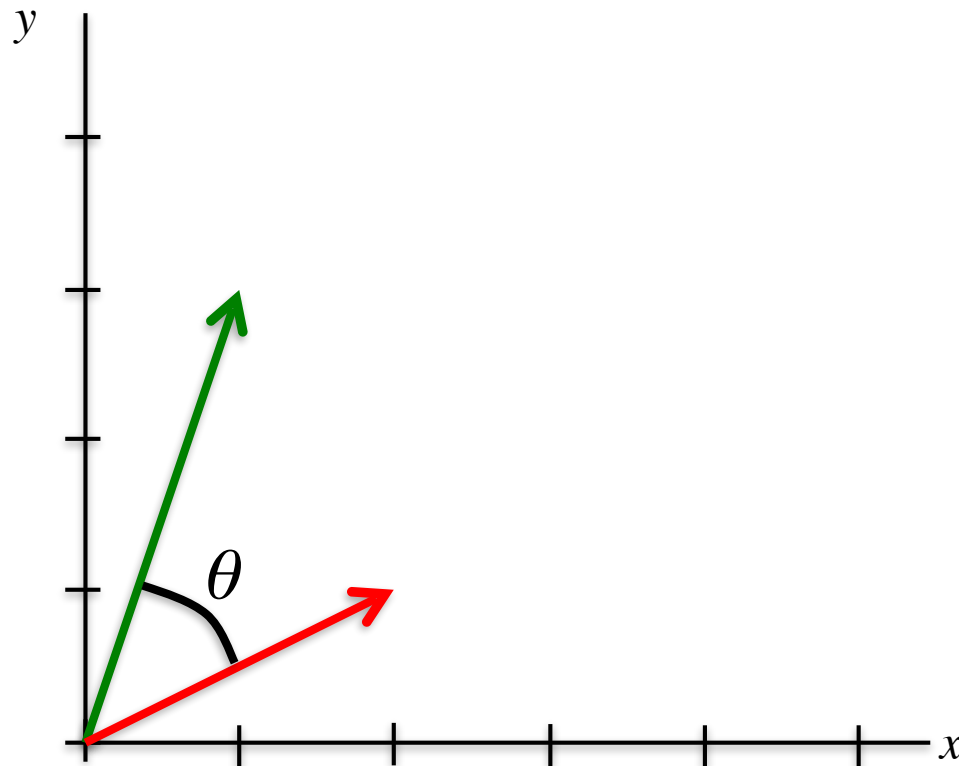
$$\cos(\theta) = \frac{a \cdot w_j}{\|a\| \|w_j\|}$$



## dot product

```
>>> theta = m.degrees(m.acos(np.dot(a,wj) /  
    (np.dot(a,a)*np.dot(wj,wj))))
```

$$\cos(\theta) = \frac{a \cdot w_j}{\|a\| \|w_j\|}$$

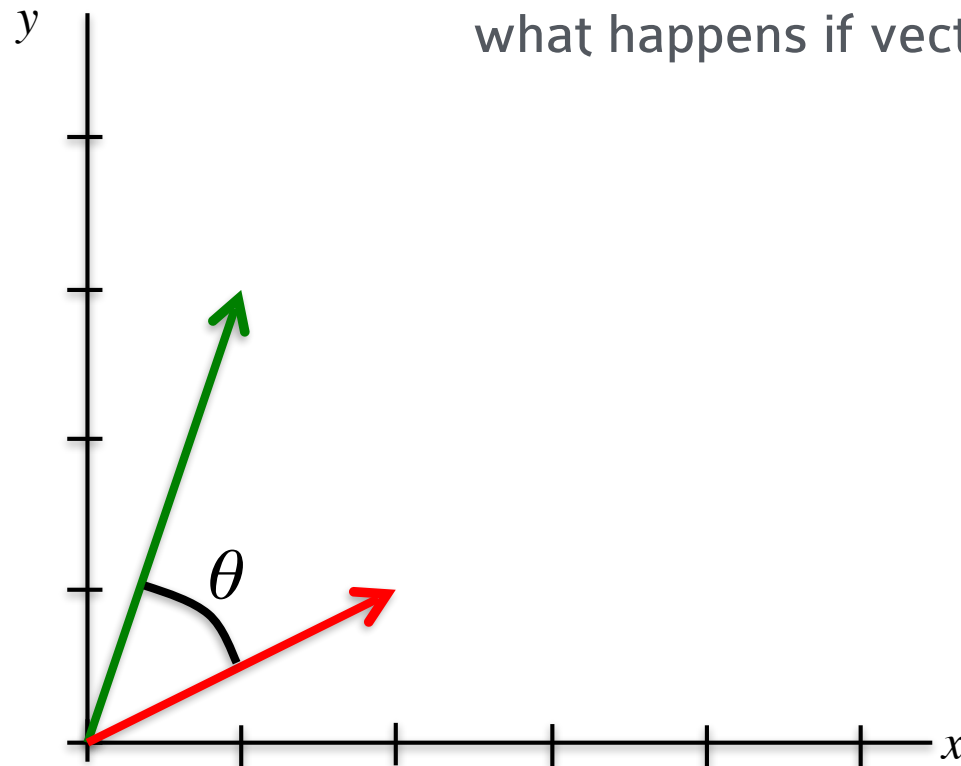


# dot product

product of the lengths and the angle

$$a \cdot w_j = \|a\| \|w_j\| \cos(\theta)$$

dot product	length $a$	length $w_j$	cos angle
----------------	---------------	-----------------	--------------



what happens if vectors are orthogonal?

# dot product

product of the lengths and the angle

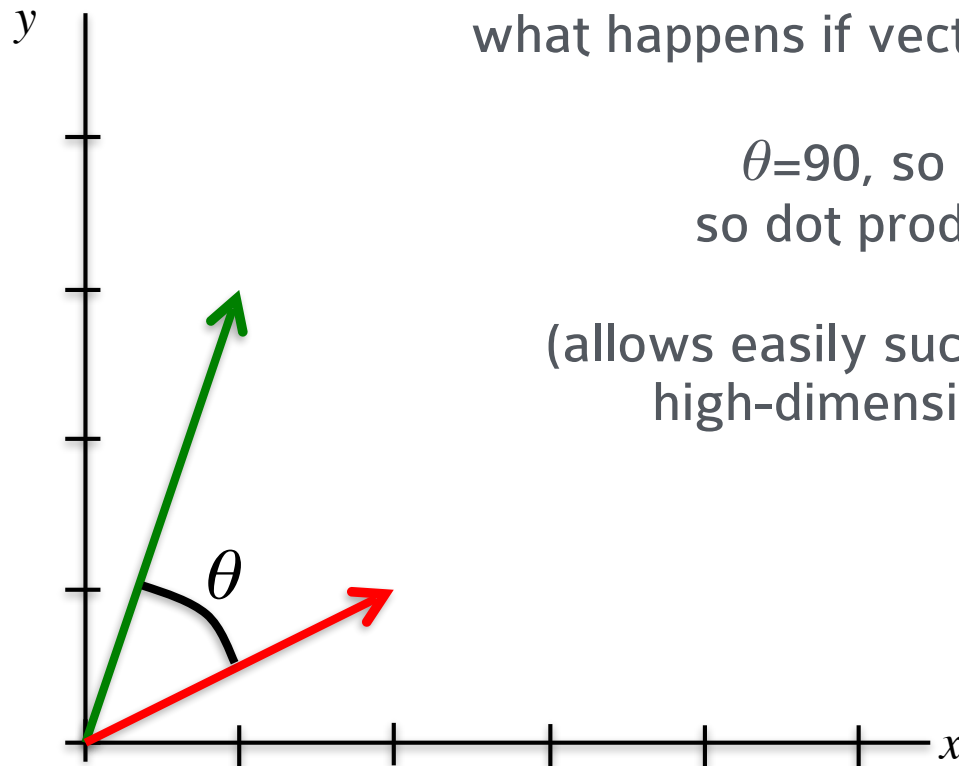
$$a \cdot w_j = \|a\| \|w_j\| \cos(\theta)$$

dot  
product

length  
 $a$

length  
 $w_j$

cos  
angle



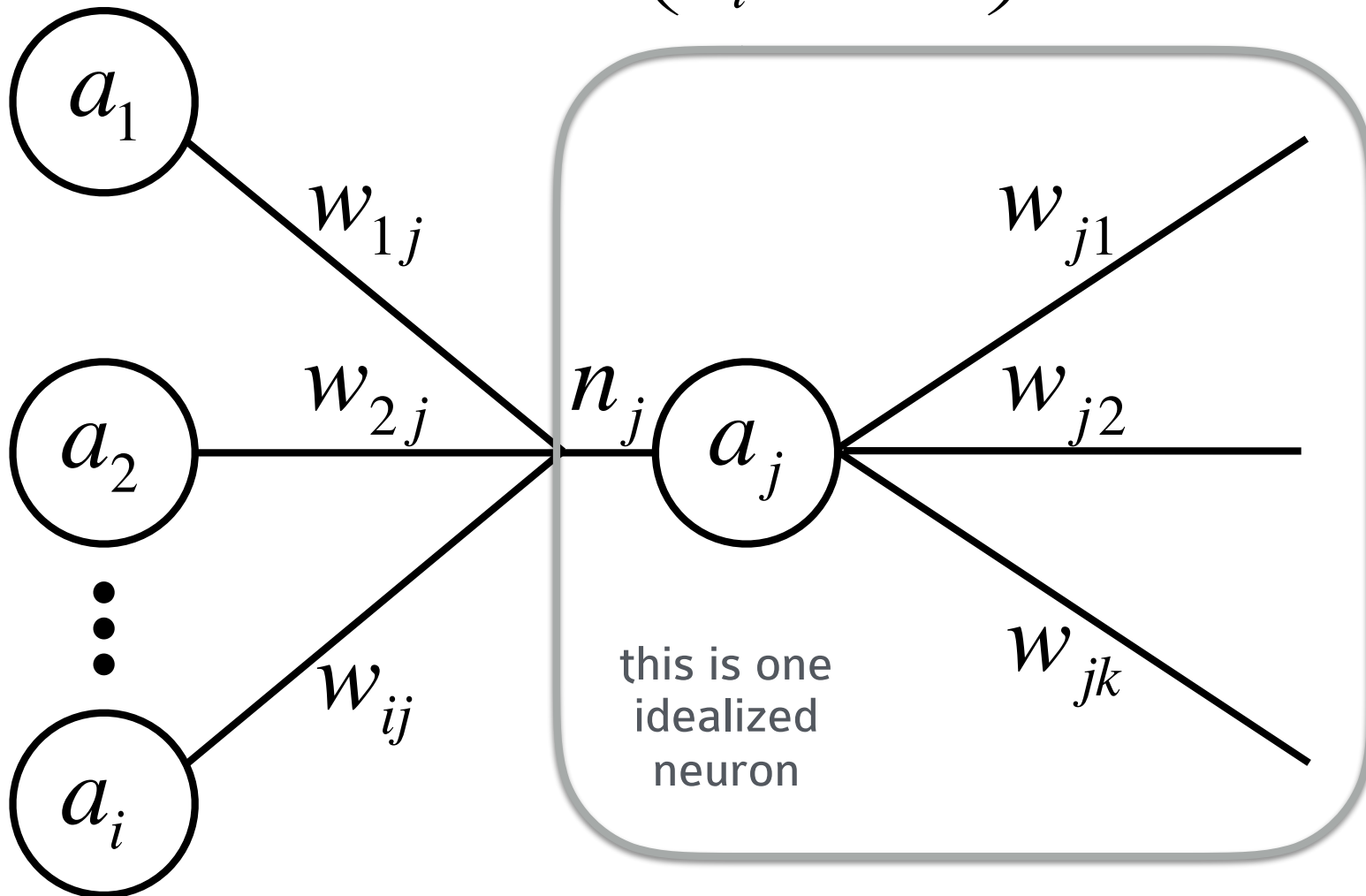
what happens if vectors are orthogonal?

$\theta=90$ , so  $\cos(\theta)=0$   
so dot product is zero

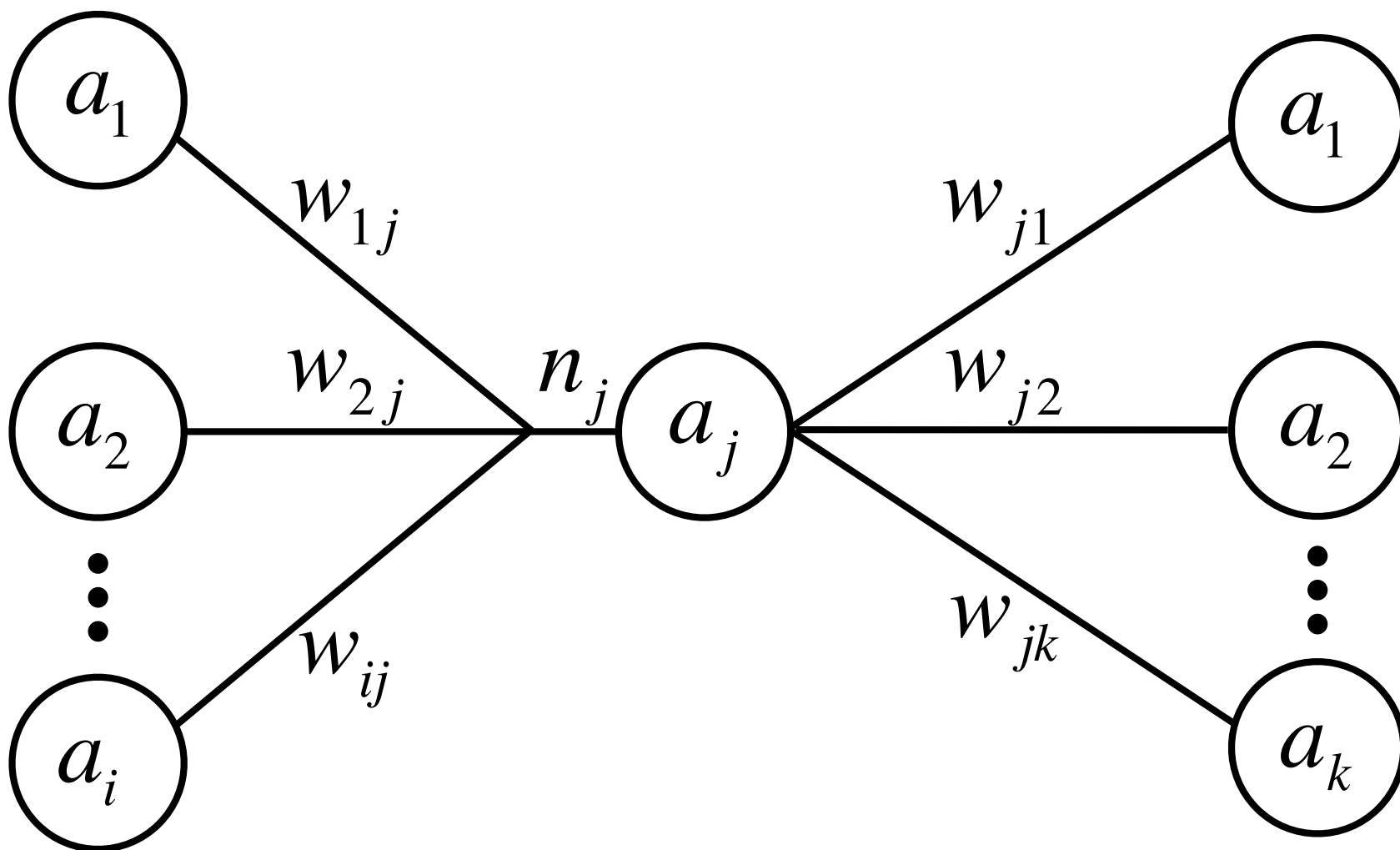
(allows easily such computation in  
high-dimensional spaces)

activation equation

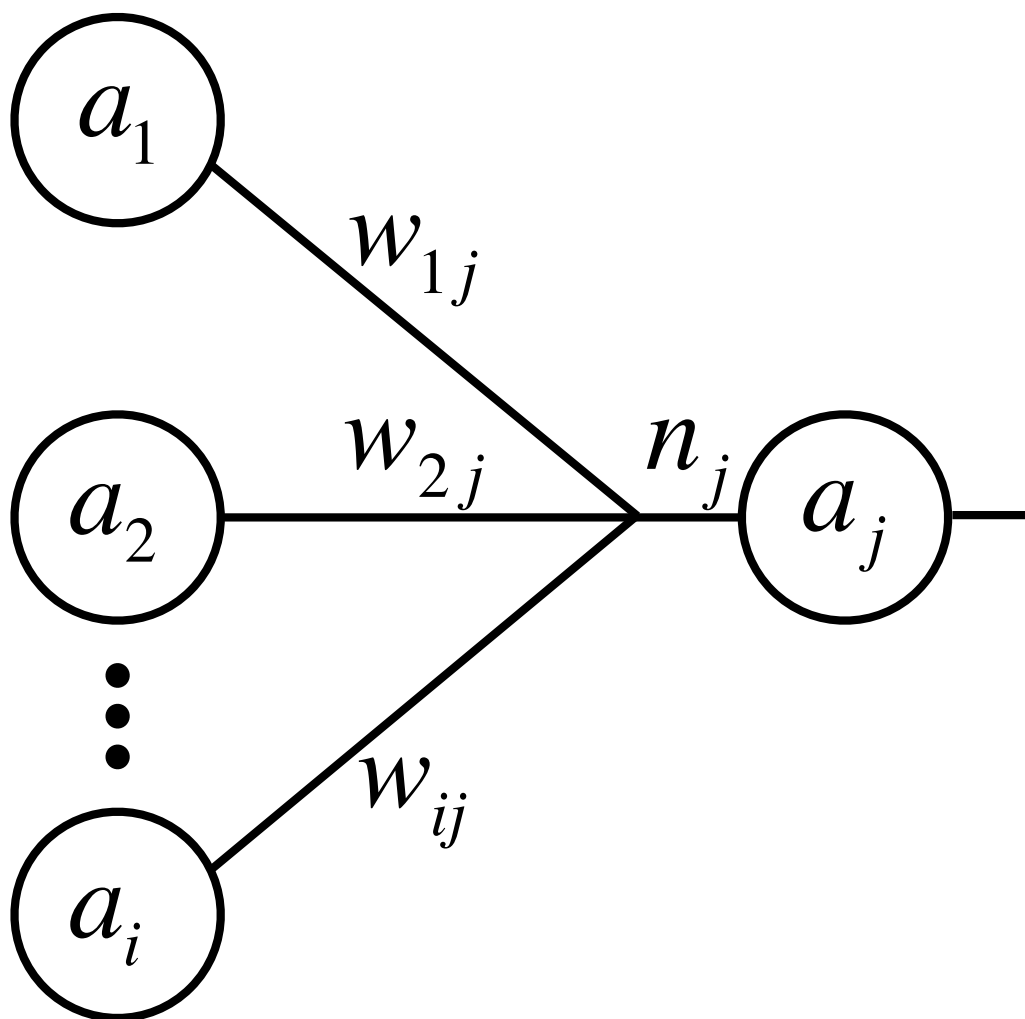
$$a_j = f\left(\sum_i a_i w_{ij}\right)$$



**Idealized Neuron**

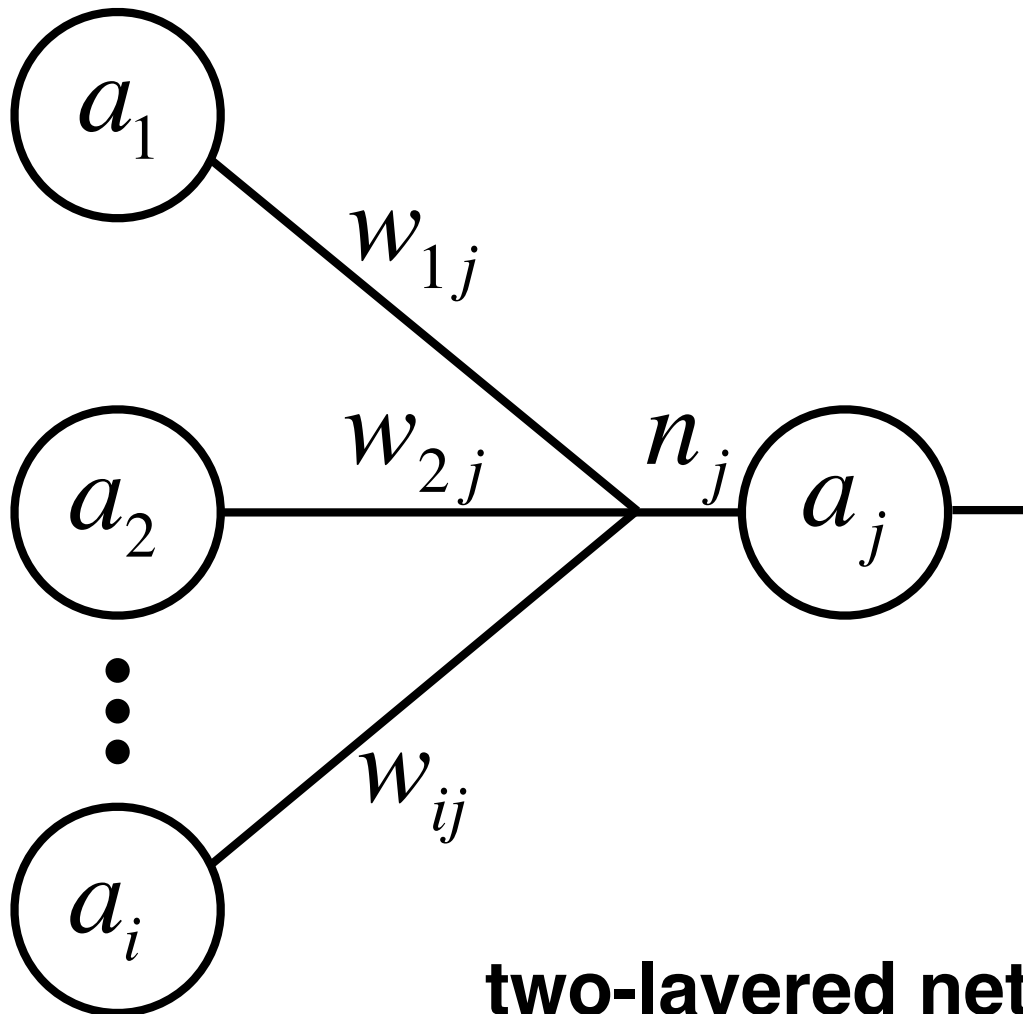


**Multi-layered network**



**single-layered network**

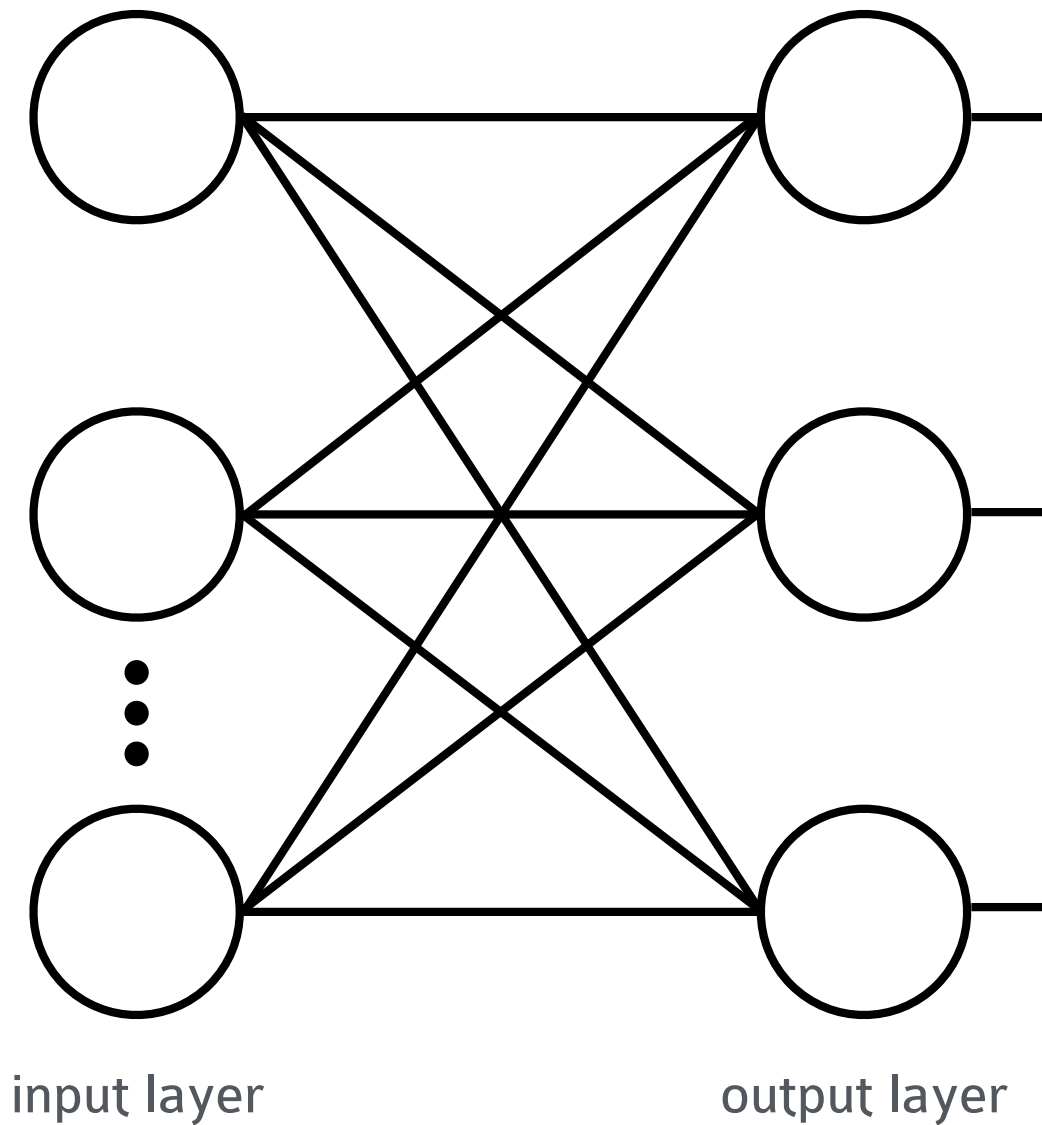




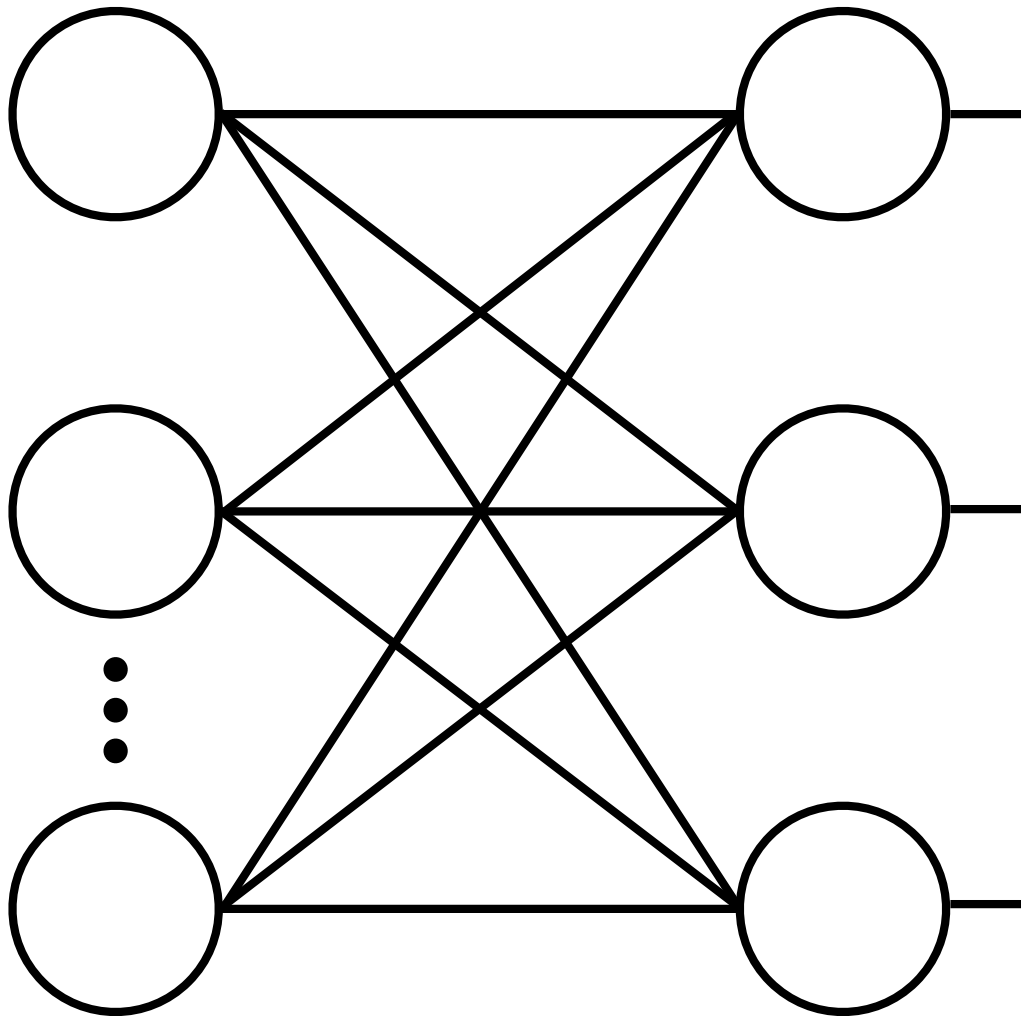
**two-layered network**  
**~~single-layered network~~**

the terminology  
may vary

# fully-interconnected two-layer network



**fully-interconnected**  
**~~two-layer network~~**  
**single-layer network**

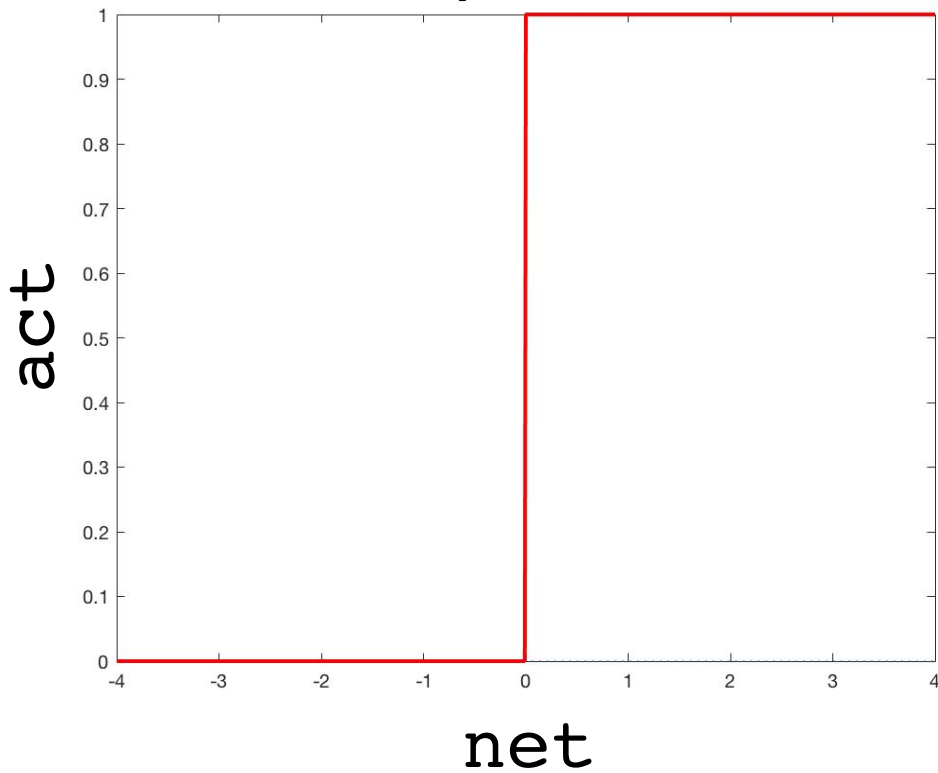


input layer

output layer

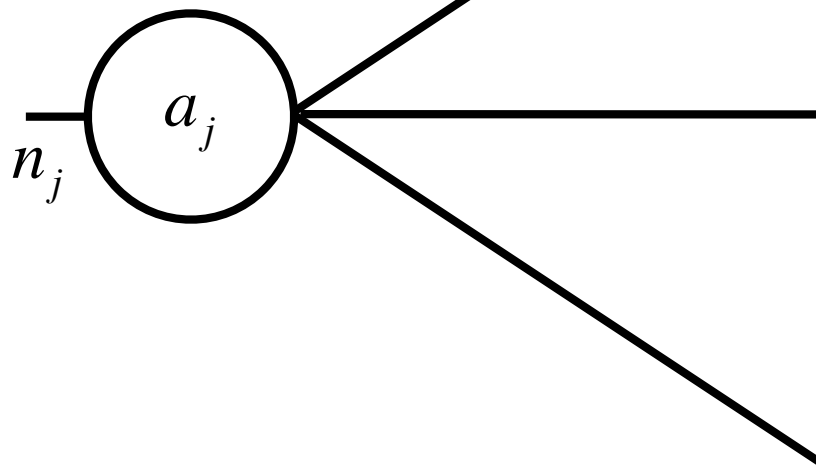


**Step Function**

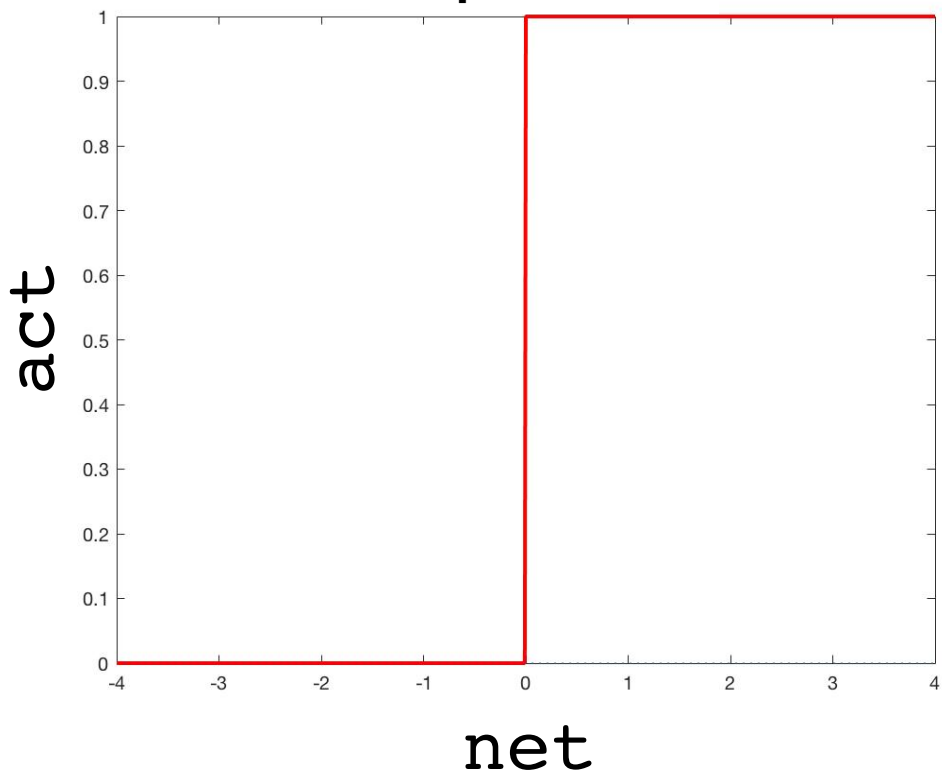


**neurons have a  
nonlinear  
response function**

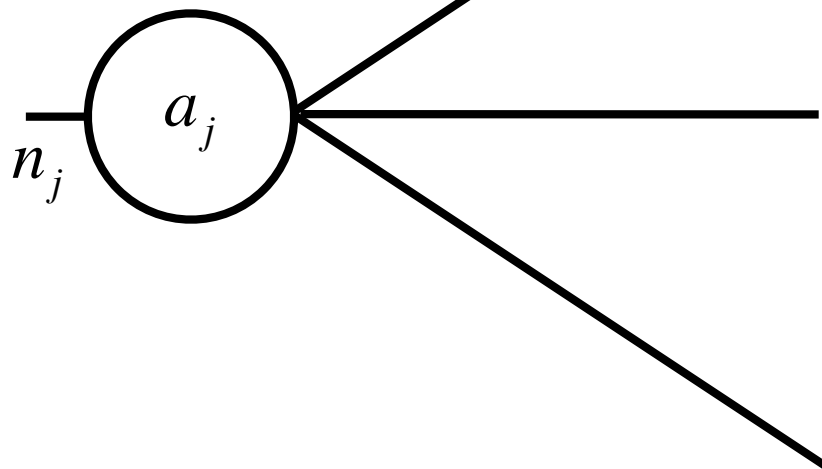
$$a_j = \begin{cases} 0 & \text{if } n_j \leq 0 \\ 1 & \text{otherwise} \end{cases}$$



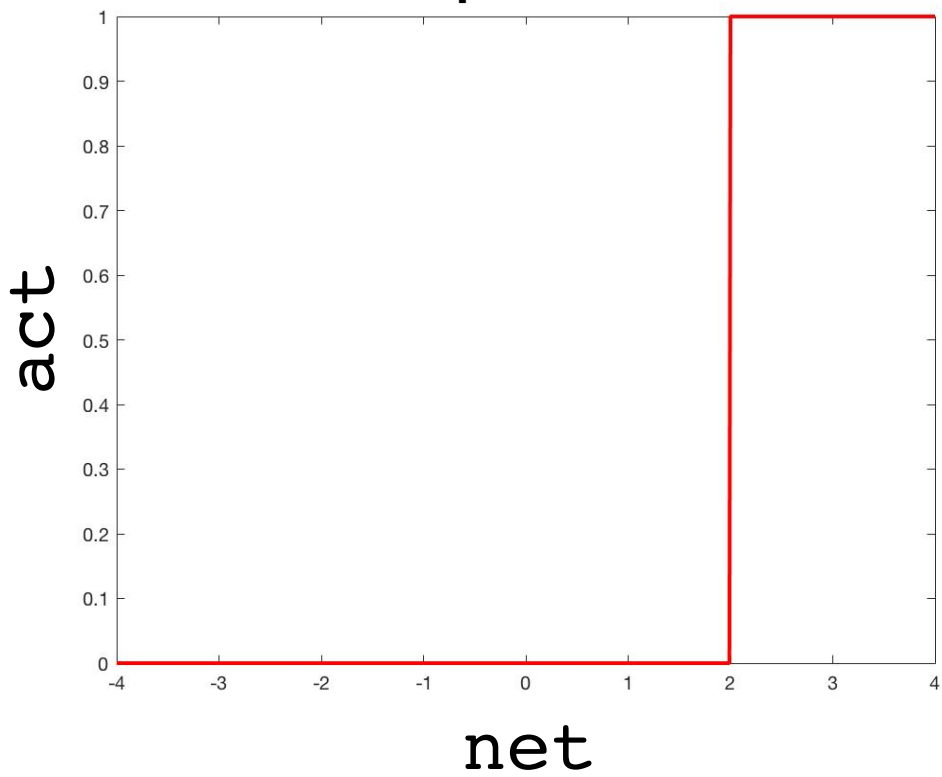
Step Function



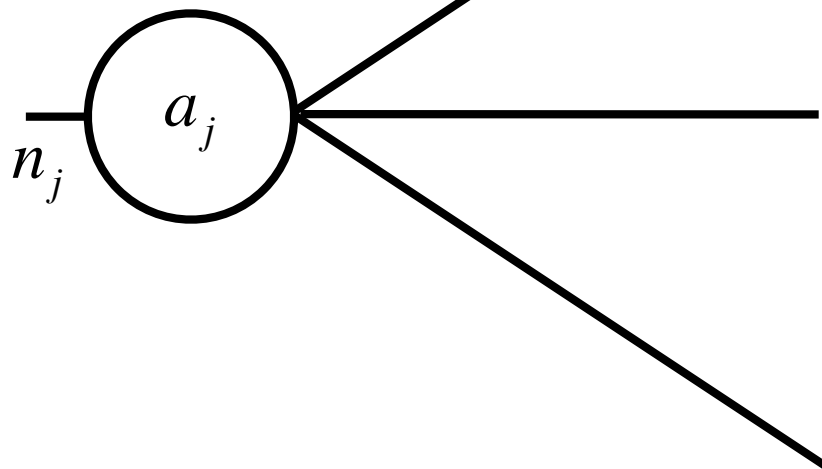
$$a_j = \begin{cases} 0 & \text{if } n_j \leq 0 \\ 1 & \text{otherwise} \end{cases}$$



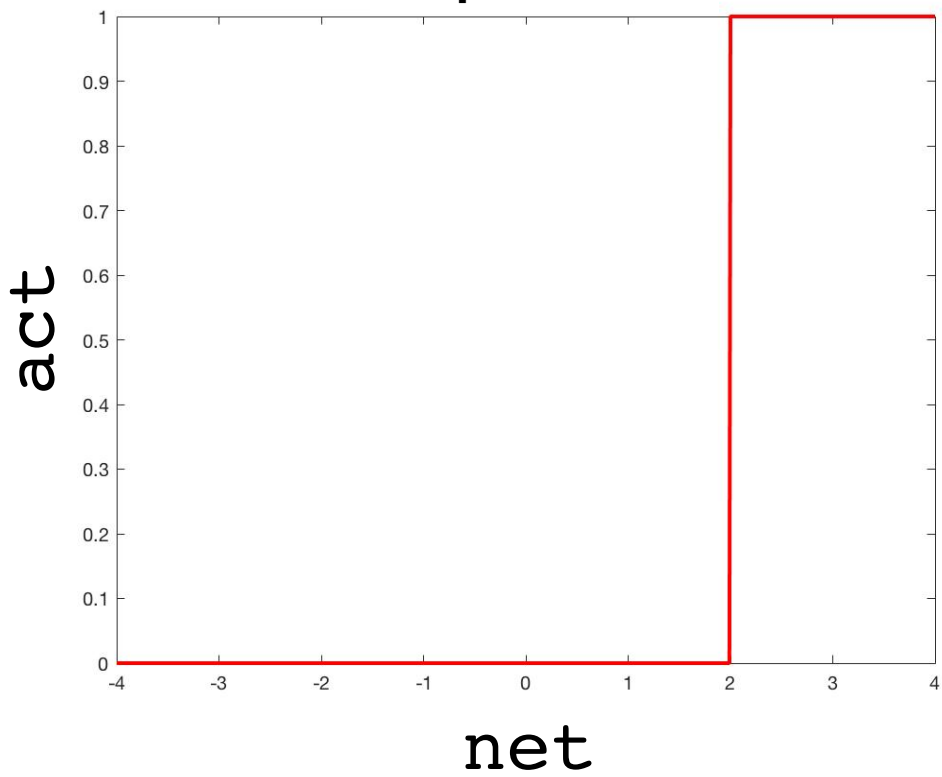
Step Function



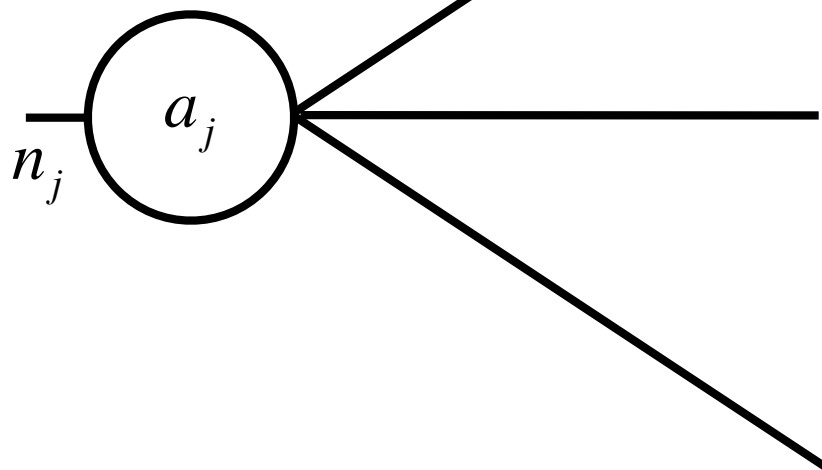
$$a_j = \begin{cases} 0 & \text{if } n_j \leq 2 \\ 1 & \text{otherwise} \end{cases}$$



Step Function

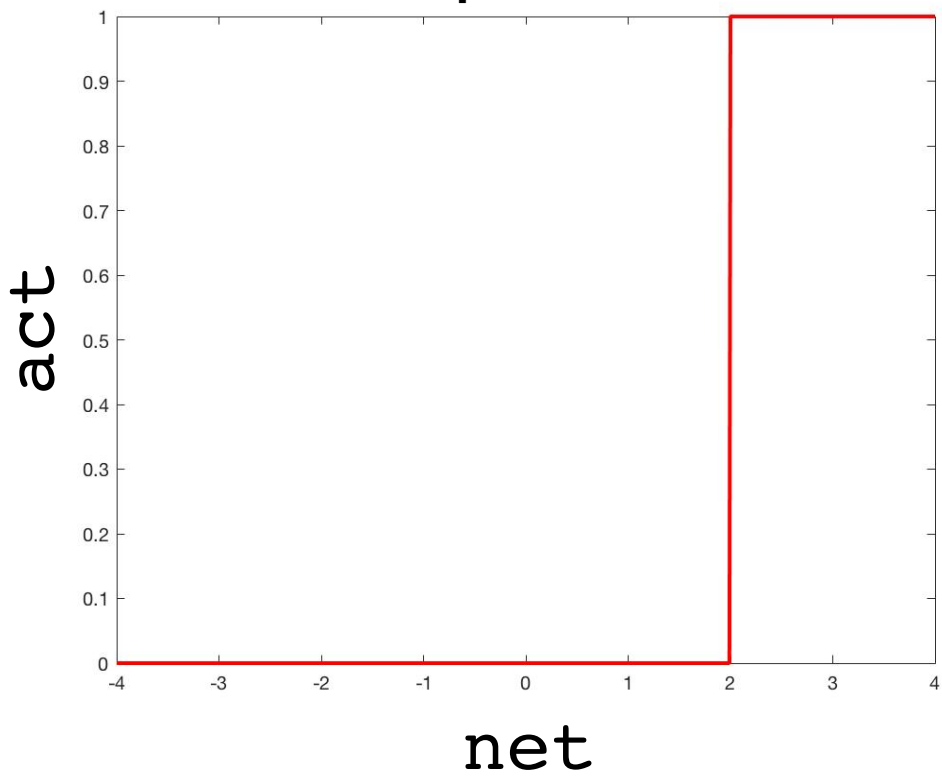


$$a_j = \begin{cases} 0 & \text{if } n_j - 2 \leq 0 \\ 1 & \text{otherwise} \end{cases}$$

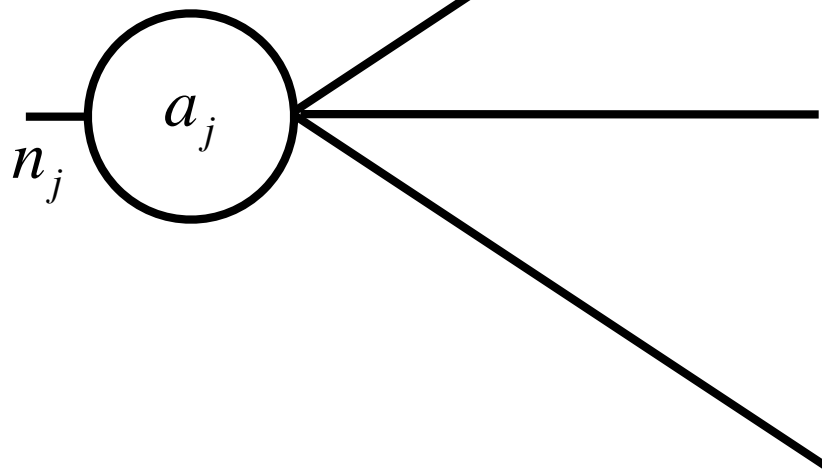




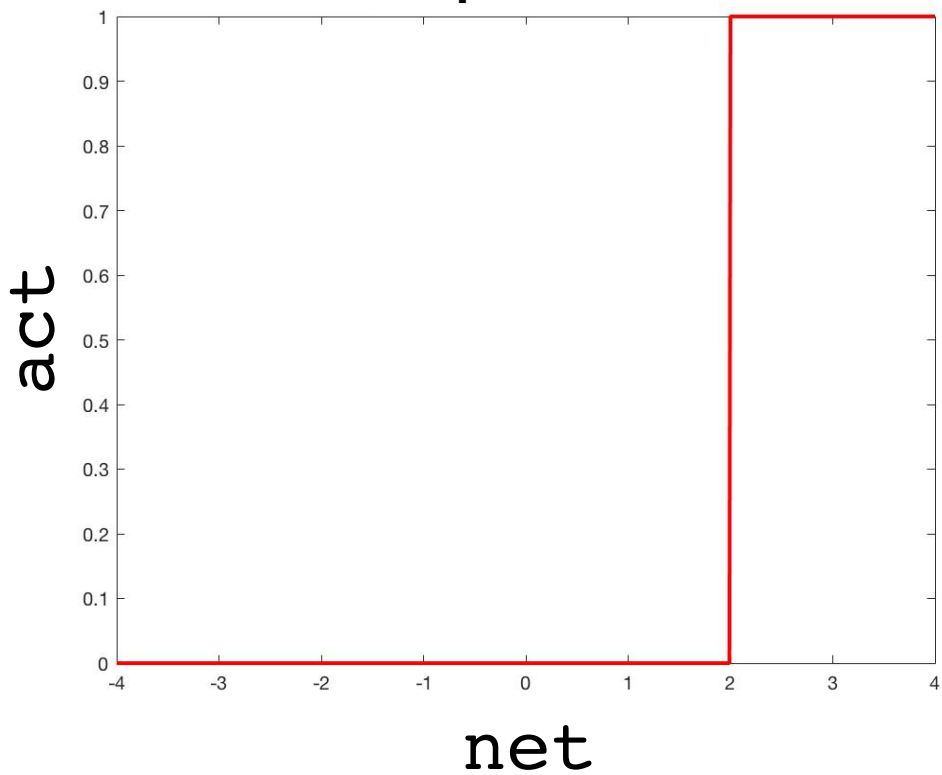
Step Function



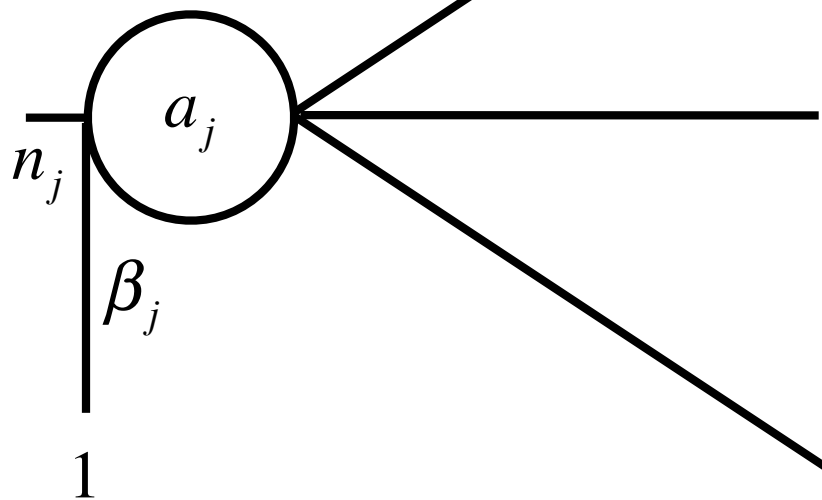
$$a_j = \begin{cases} 0 & \text{if } n_j + (-2) \times 1 \leq 0 \\ 1 & \text{otherwise} \end{cases}$$

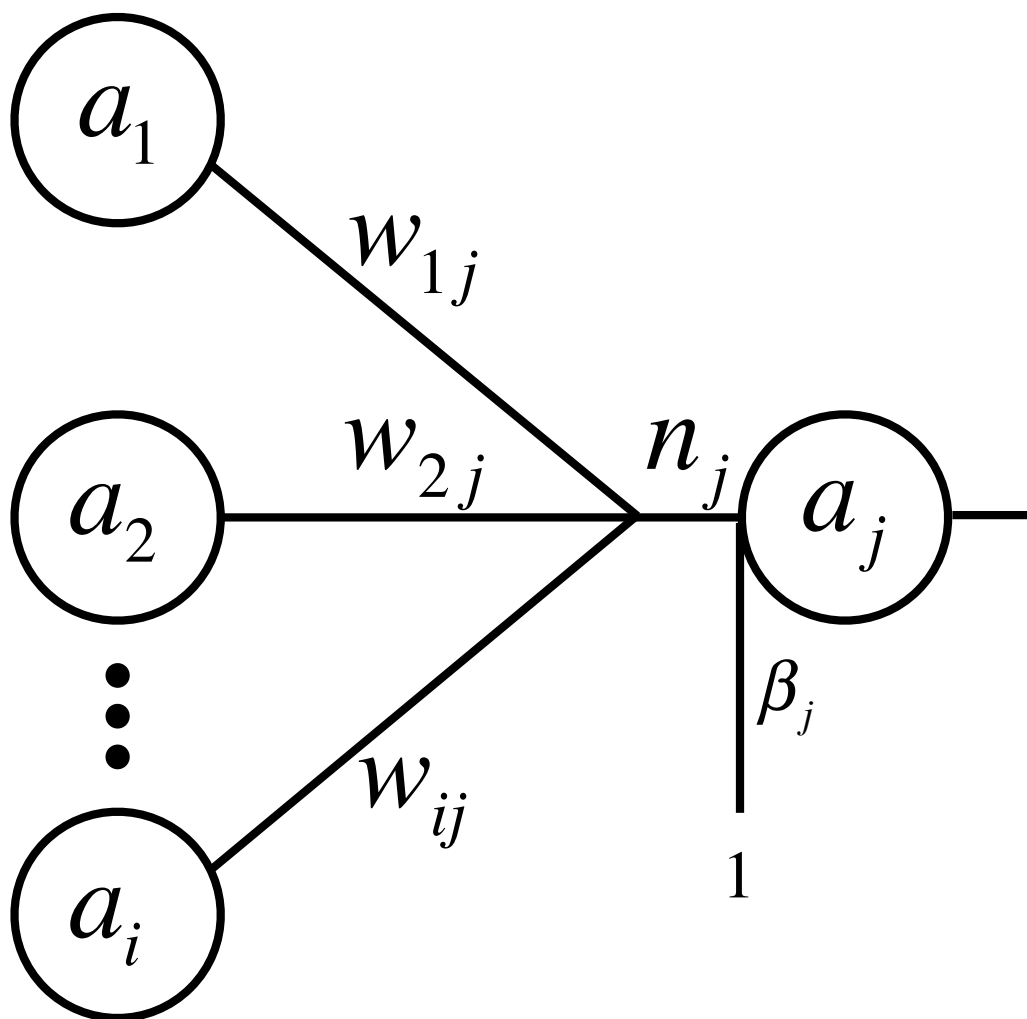


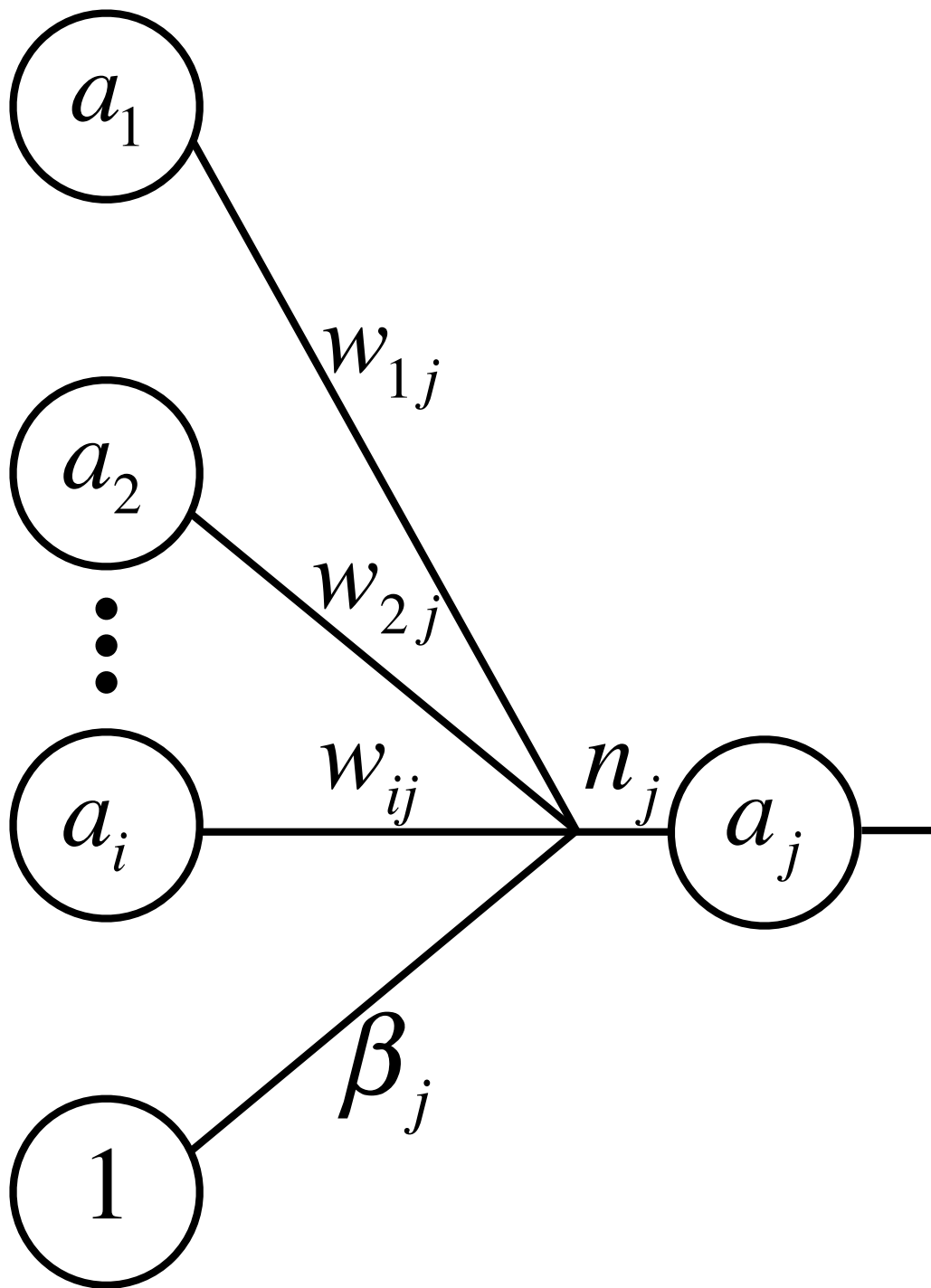
Step Function



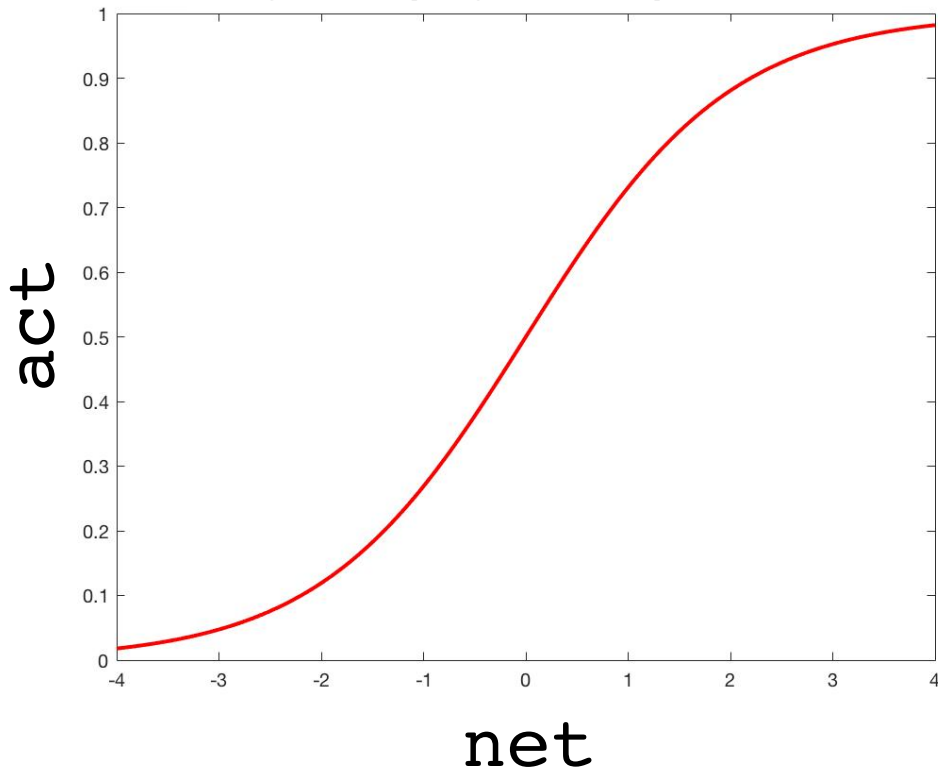
$$a_j = \begin{cases} 0 & \text{if } n_j + (\beta_j) \times 1 \leq 0 \\ 1 & \text{otherwise} \end{cases}$$







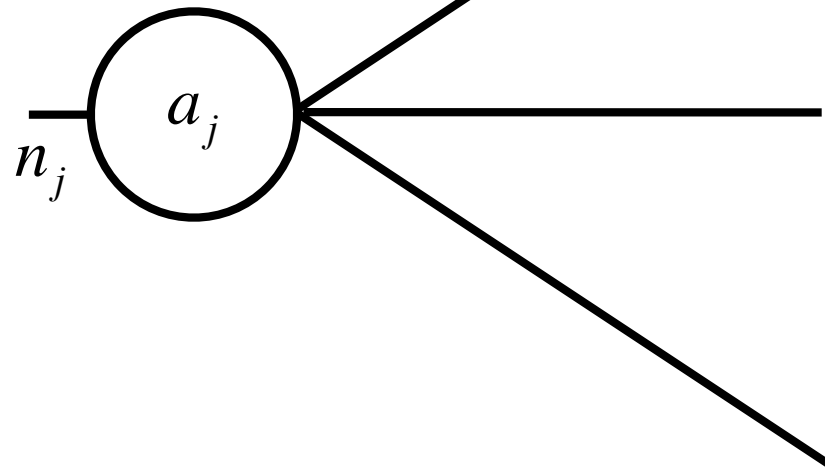
## Logistic (Sigmoidal) Function



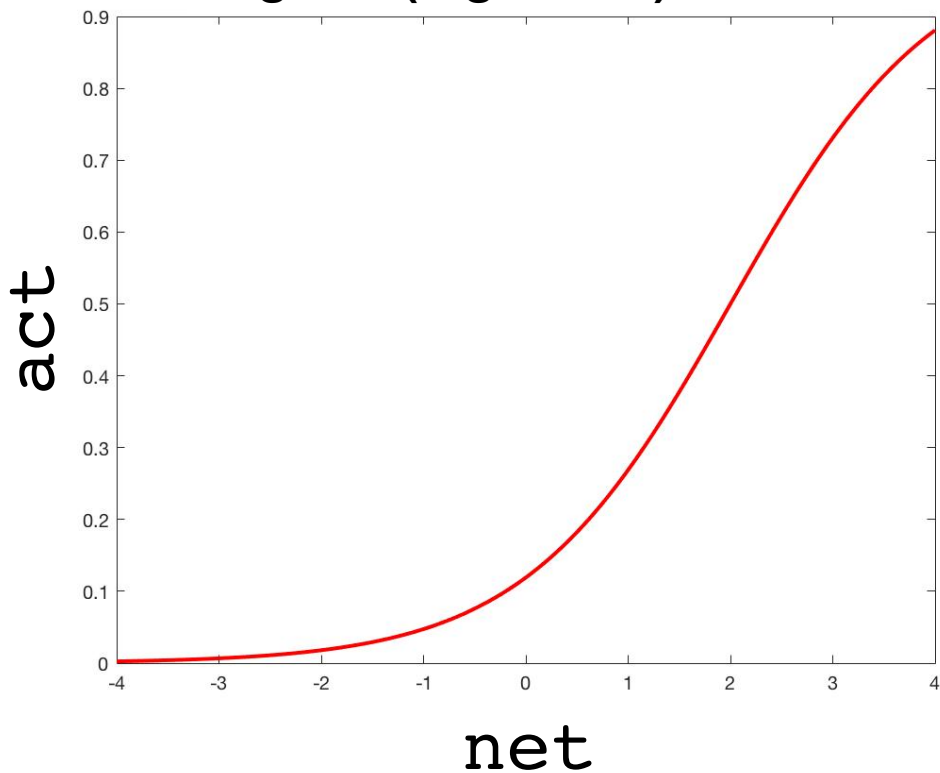
$$a_j = \frac{1}{1 + \exp(-n_j)}$$

from homework

$$a_j = \frac{L}{1 + \exp(-k(n_j - \theta_j))}$$



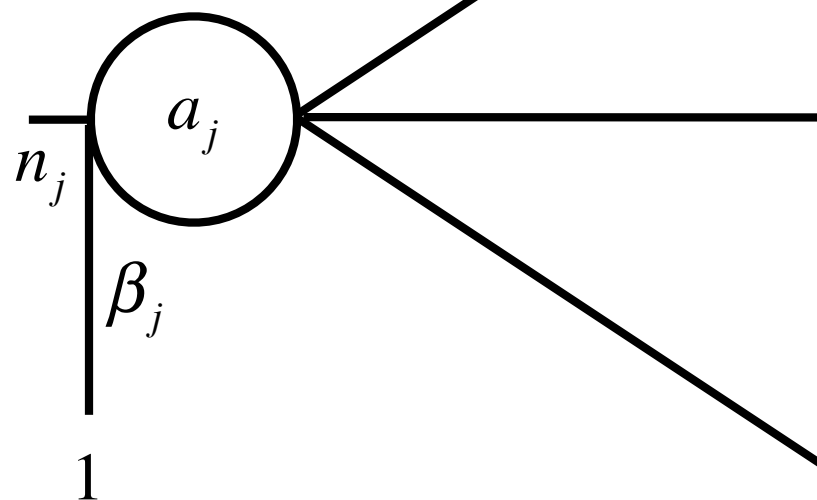
# Logistic (Sigmoidal) Function



$$a_j = \frac{1}{1 + \exp(-(n_j + \beta_j))}$$

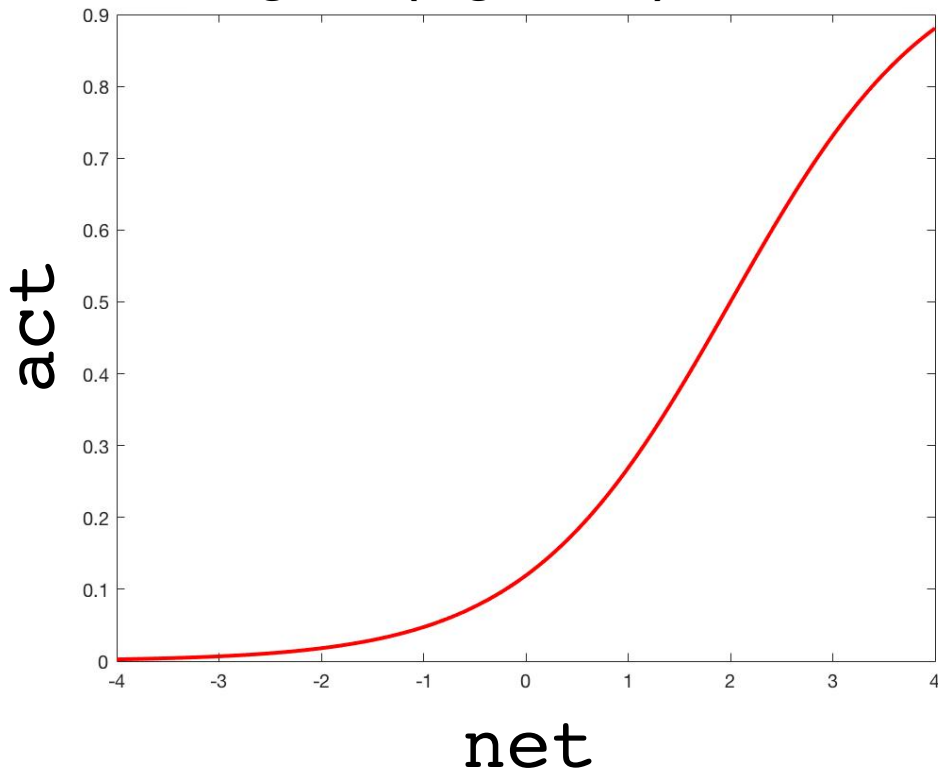
from homework

$$a_j = \frac{L}{1 + \exp(-k(n_j - (-\beta_j)))}$$



# Idealized Neuron

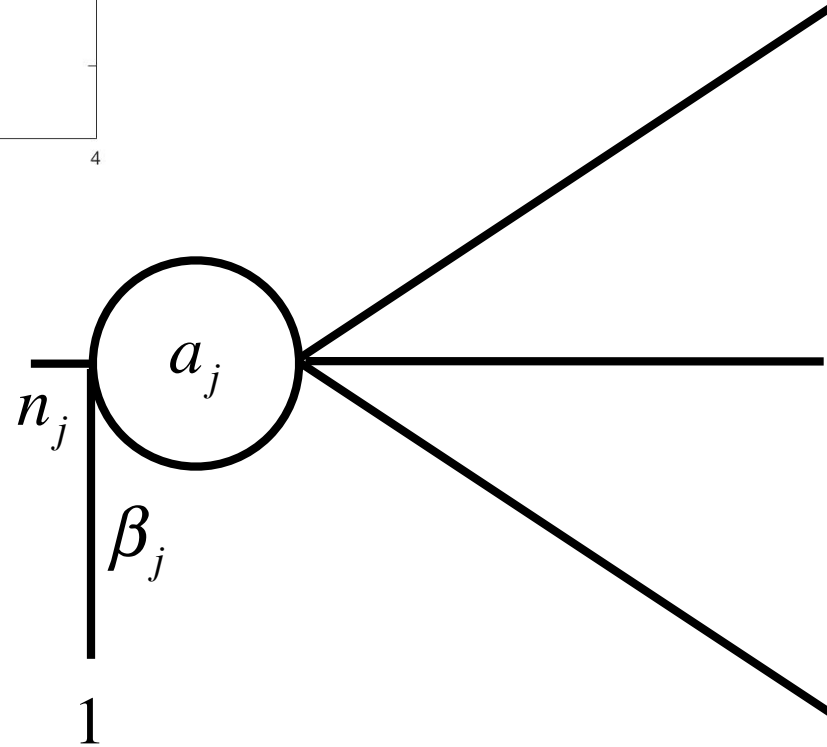
## Logistic (Sigmoidal) Function



$$a_j = \frac{1}{1 + \exp(-(n_j + \beta_j))}$$

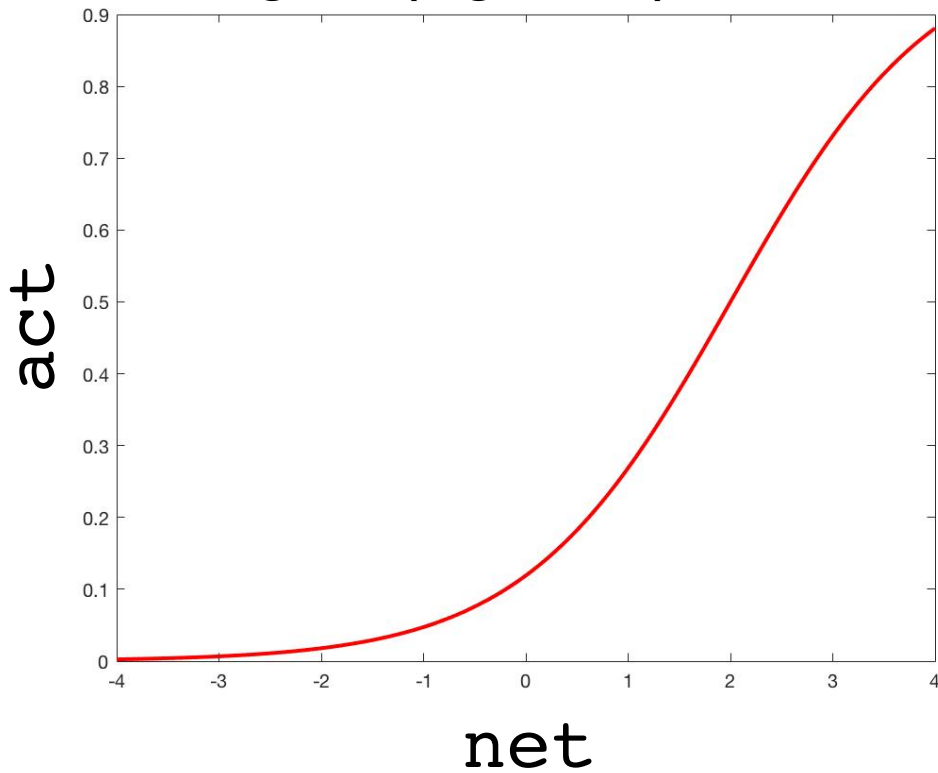
from homework

$$a_j = \frac{L}{1 + \exp(-k(n_j - (-\beta_j)))}$$



k term is like multiplying all input weights and bias by k

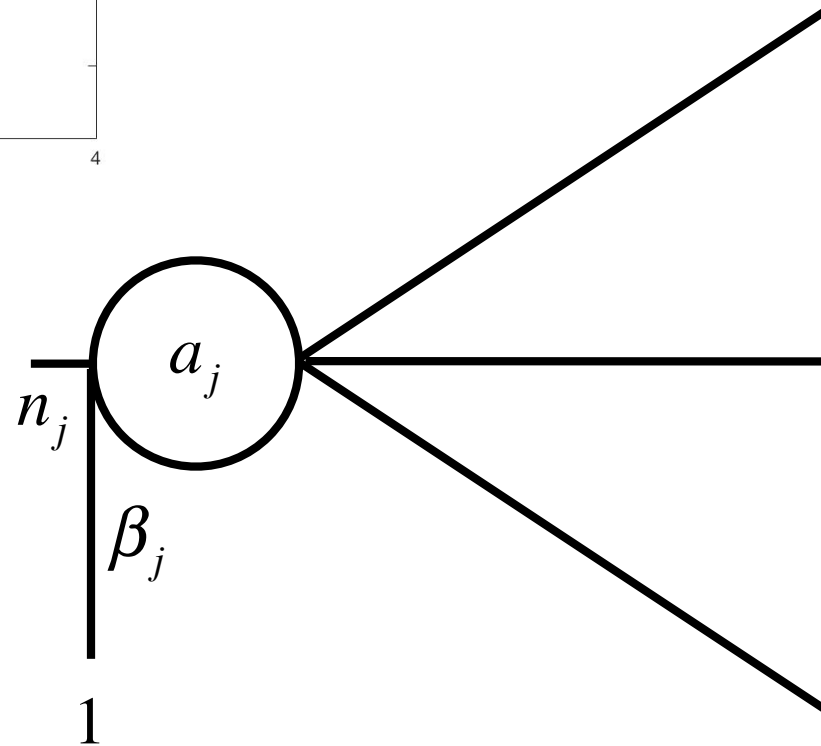
## Logistic (Sigmoidal) Function



$$a_j = \frac{1}{1 + \exp(-(n_j + \beta_j))}$$

from homework

$$a_j = \frac{L}{1 + \exp(-k(n_j - (-\beta_j)))}$$

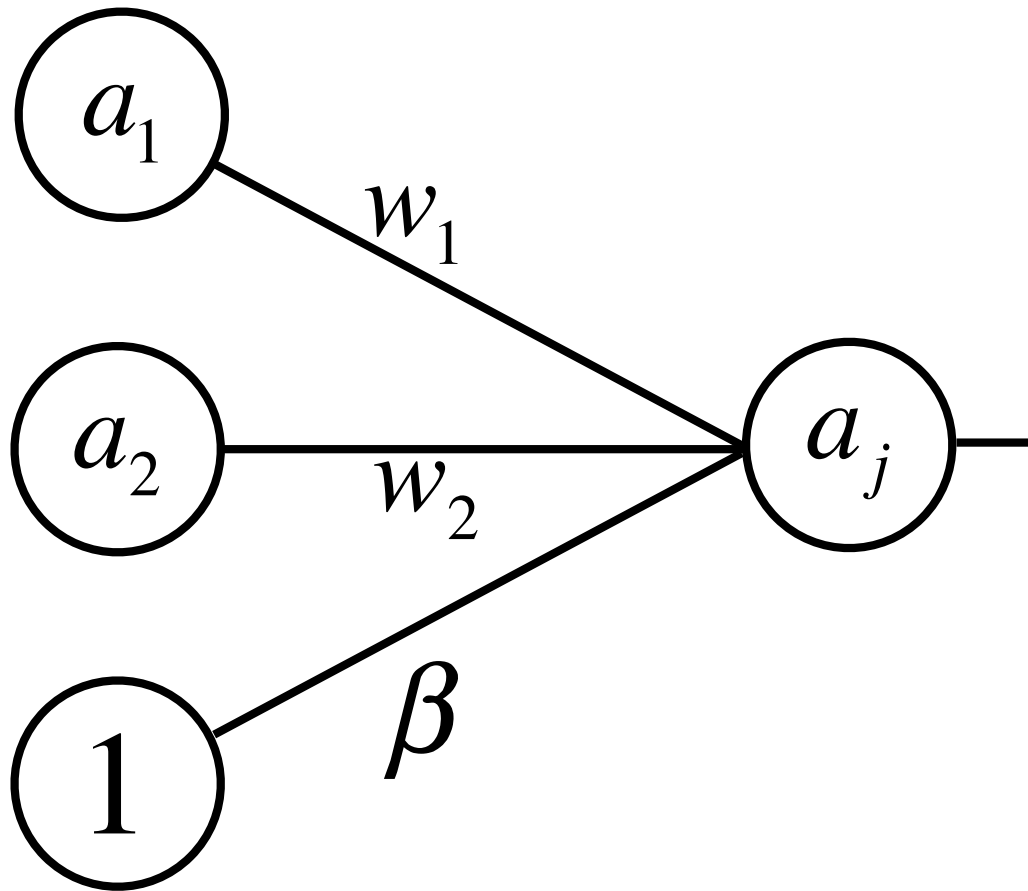


L term is like multiplying all output weights by L





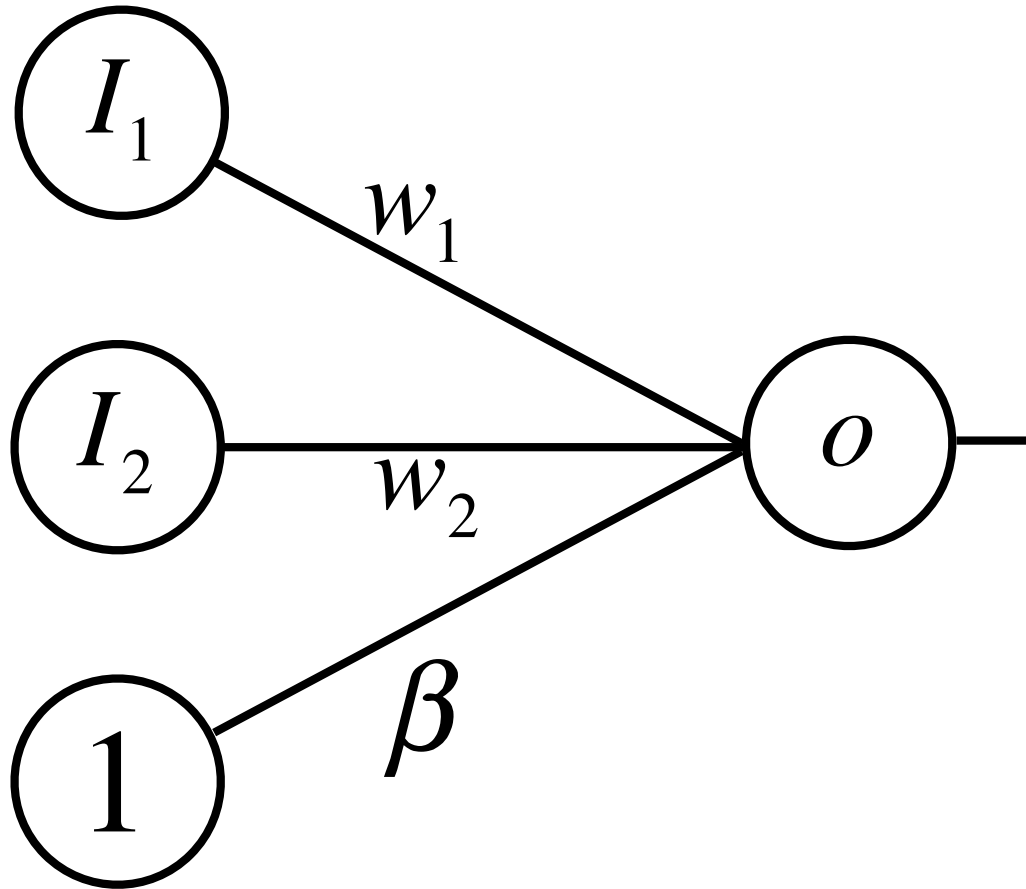
# Example of a Simple Neural Network



# Example of a Simple Neural Network

inputs can be  
sensory, perceptual,  
or abstract features

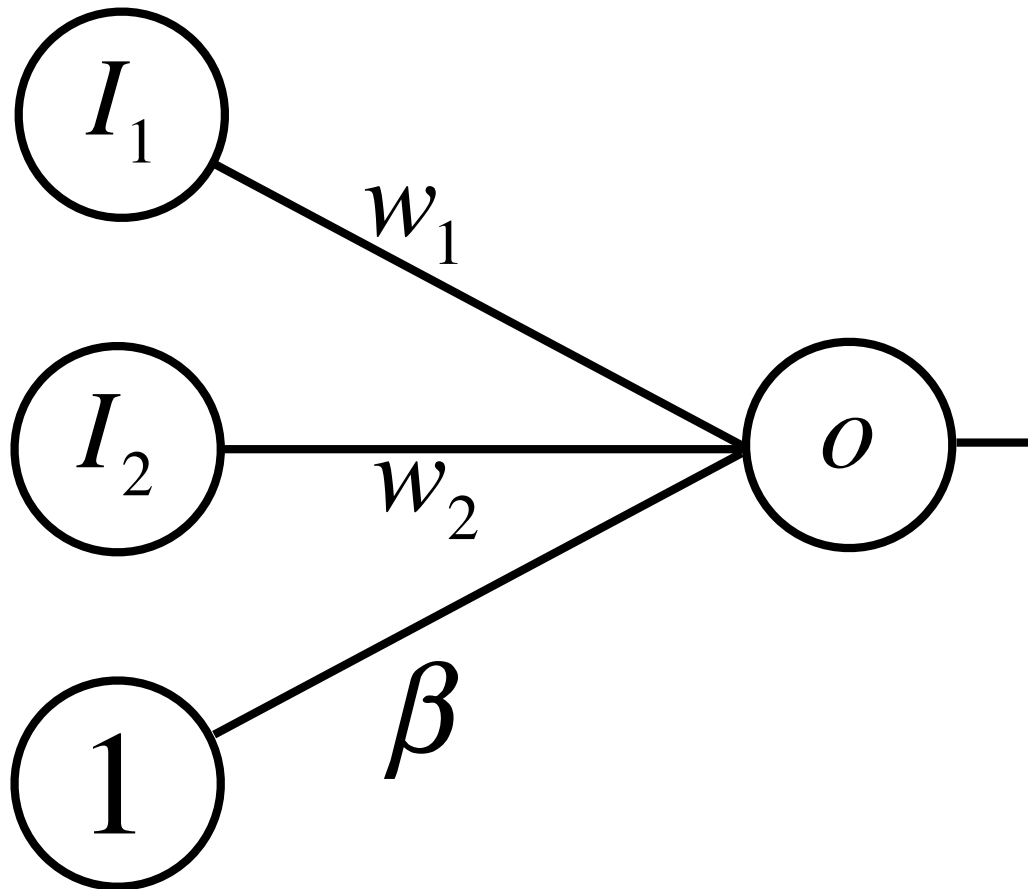
they can be  
discrete or  
continuous values



$I_1$	$I_2$	$o$
0	0	0
1	0	0
0	1	0
1	1	1

what is this  
computation?

# Example of a Simple Neural Network



$I_1$	$I_2$	$o$
0	0	0
1	0	0
0	1	0
1	1	1

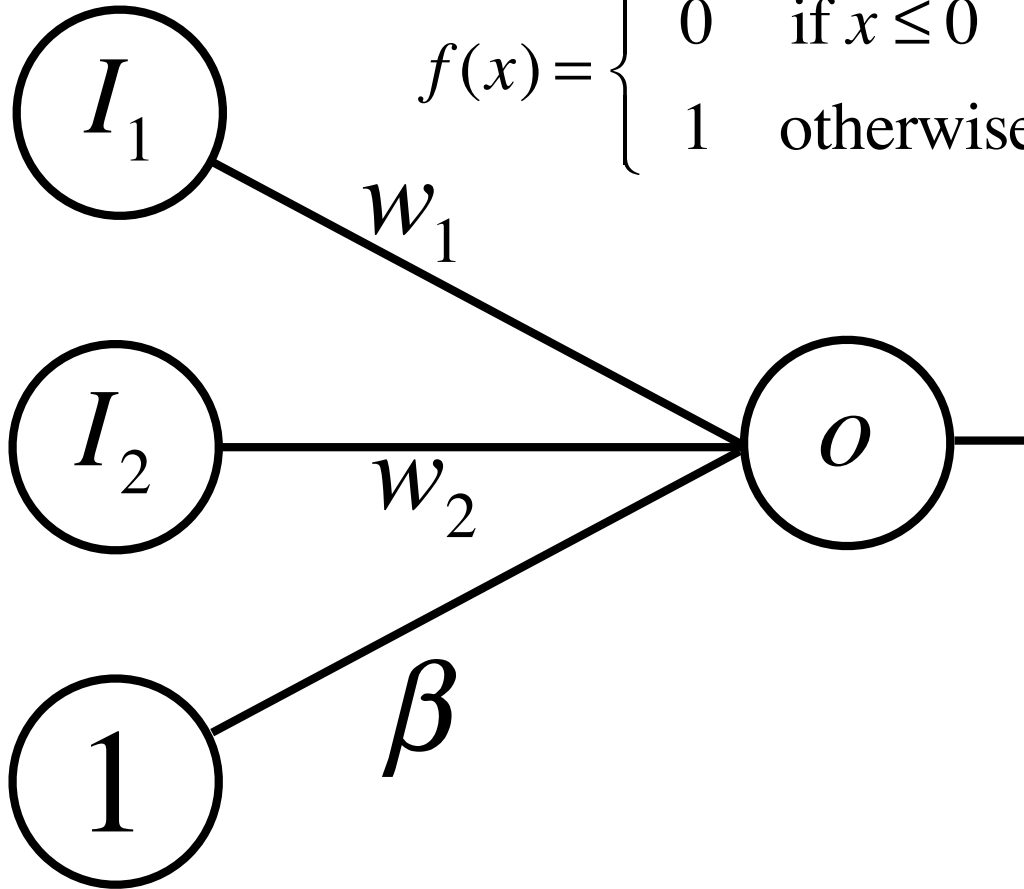
logical  
AND

# Example of a Simple Neural Network

$$o = f\left(\sum_i I_i w_i + \beta\right)$$

what values of  $w_1$ ,  $w_2$ , and  $\beta$

$$f(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 1 & \text{otherwise} \end{cases}$$



$I_1$	$I_2$	$o$
0	0	0
1	0	0
0	1	0
1	1	1

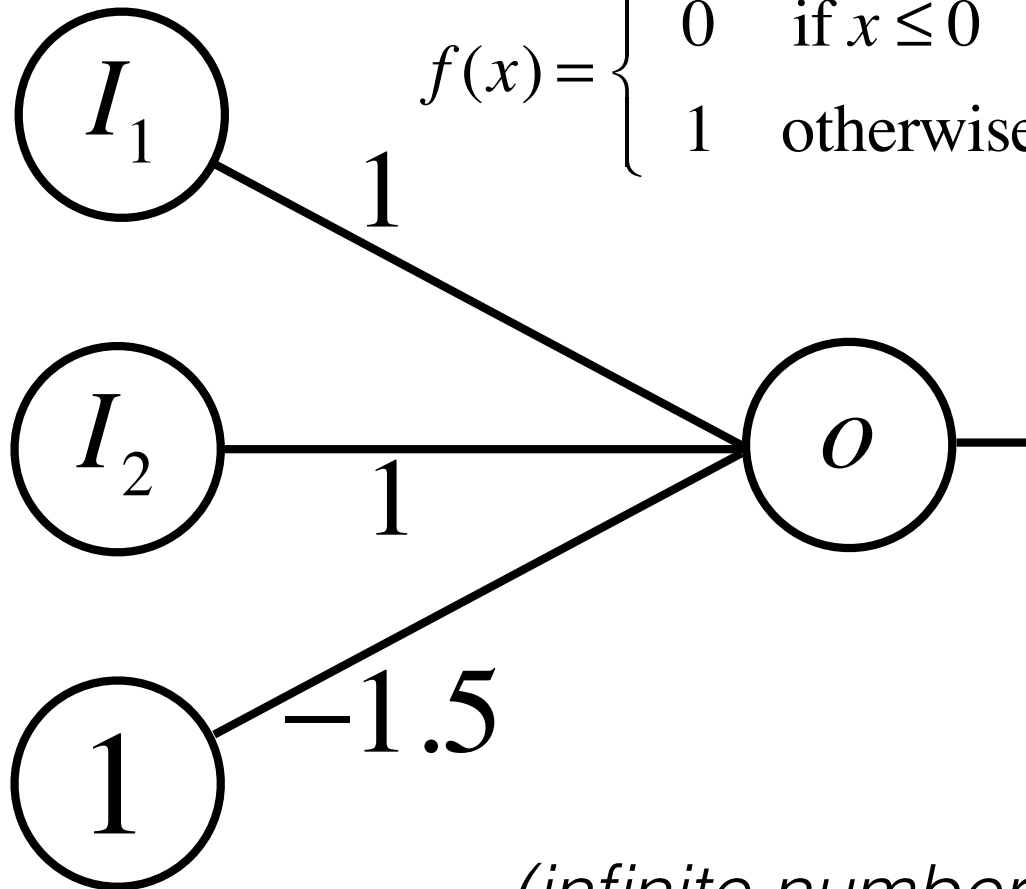
logical  
AND

# Example of a Simple Neural Network

$$o = f\left(\sum_i I_i w_i + \beta\right)$$

what values of  $w_1$ ,  $w_2$ , and  $\beta$

$$f(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 1 & \text{otherwise} \end{cases}$$

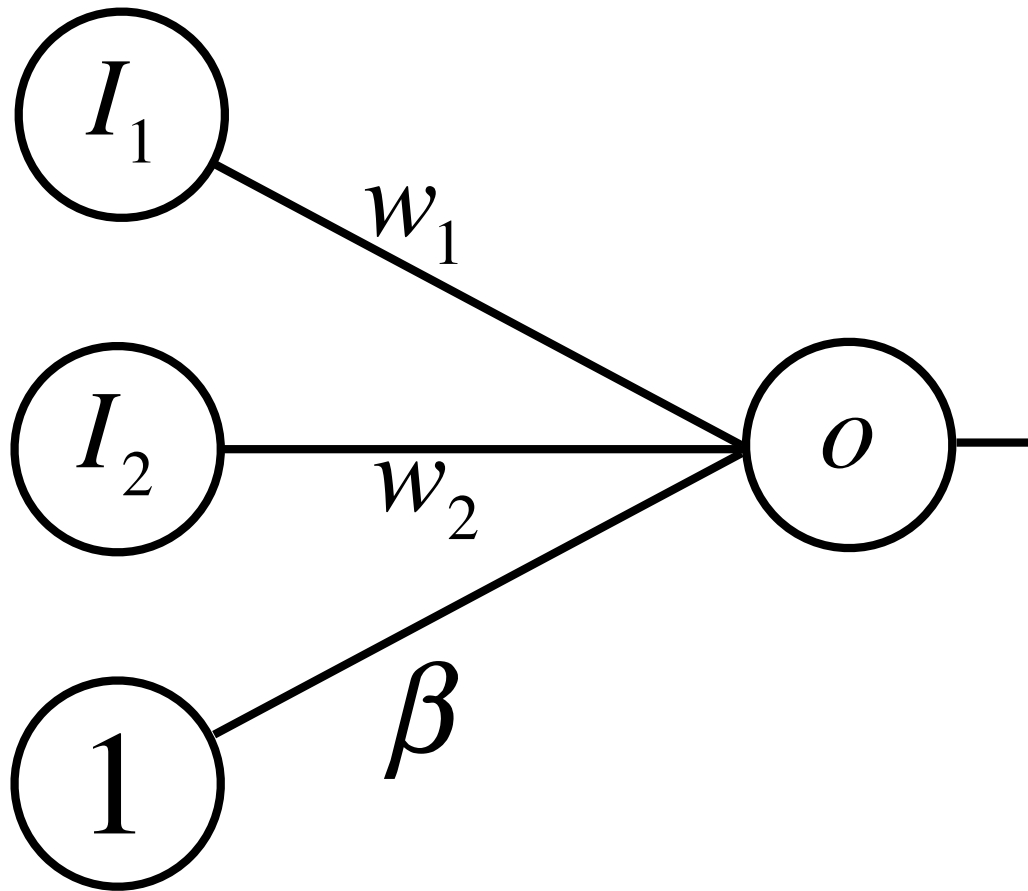


*(infinite number of solutions)*

$I_1$	$I_2$	$o$
0	0	0
1	0	0
0	1	0
1	1	1

logical  
AND

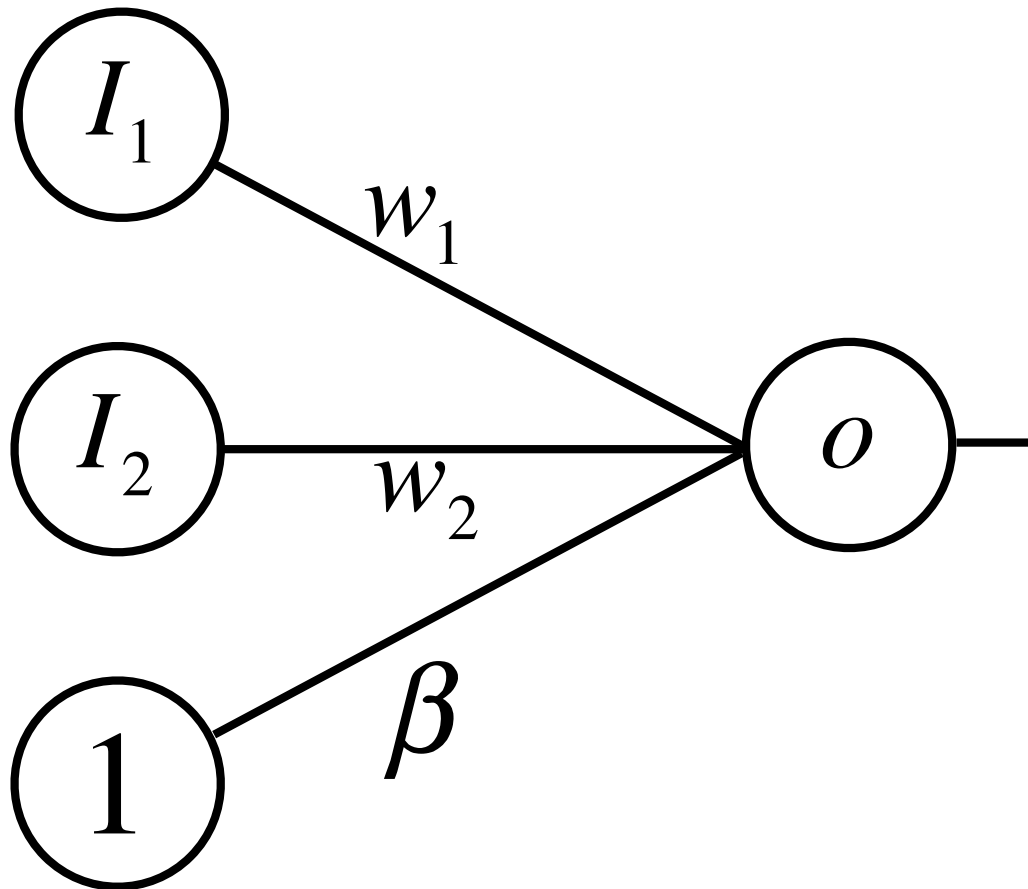
## Example of a Simple Neural Network



$I_1$	$I_2$	$o$
0	0	0
1	0	1
0	1	1
1	1	1

what is this  
computation?

# Example of a Simple Neural Network



$I_1$	$I_2$	$o$
0	0	0
1	0	1
0	1	1
1	1	1

logical  
OR

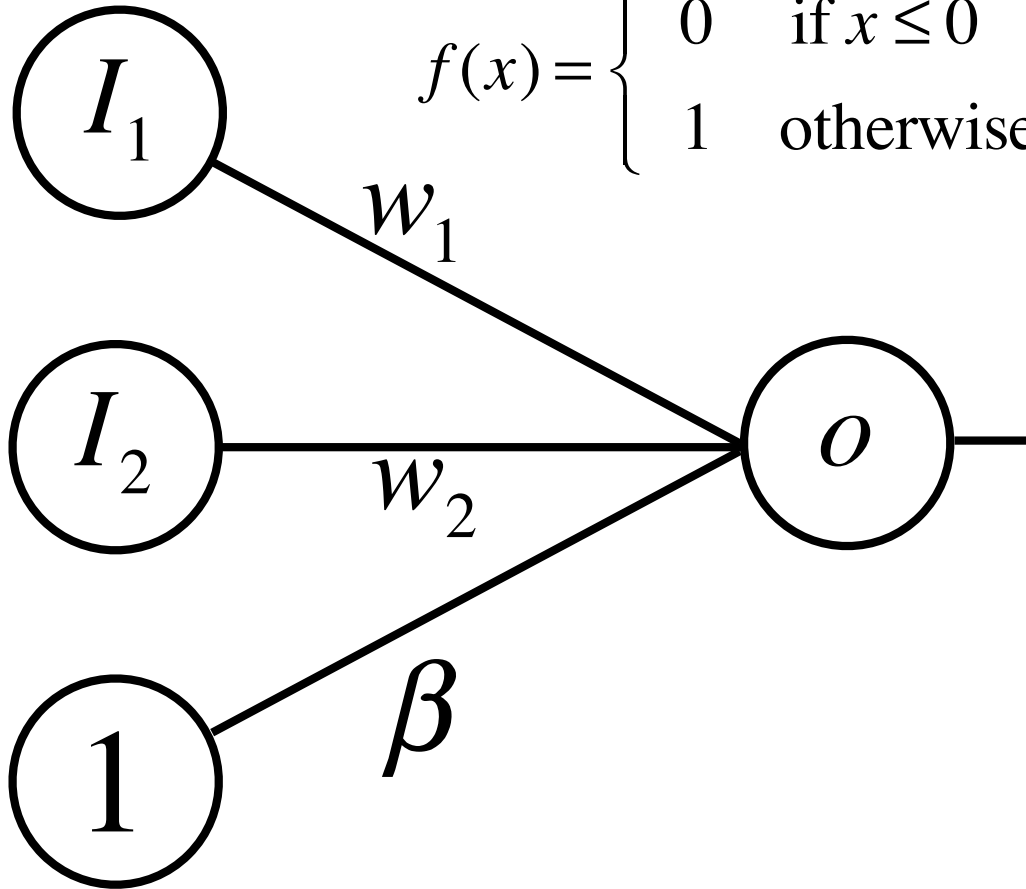


# Example of a Simple Neural Network

$$o = f\left(\sum_i I_i w_i + \beta\right)$$

what values of  $w_1$ ,  $w_2$ , and  $\beta$

$$f(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 1 & \text{otherwise} \end{cases}$$



$I_1$	$I_2$	$o$
0	0	0
1	0	1
0	1	1
1	1	1

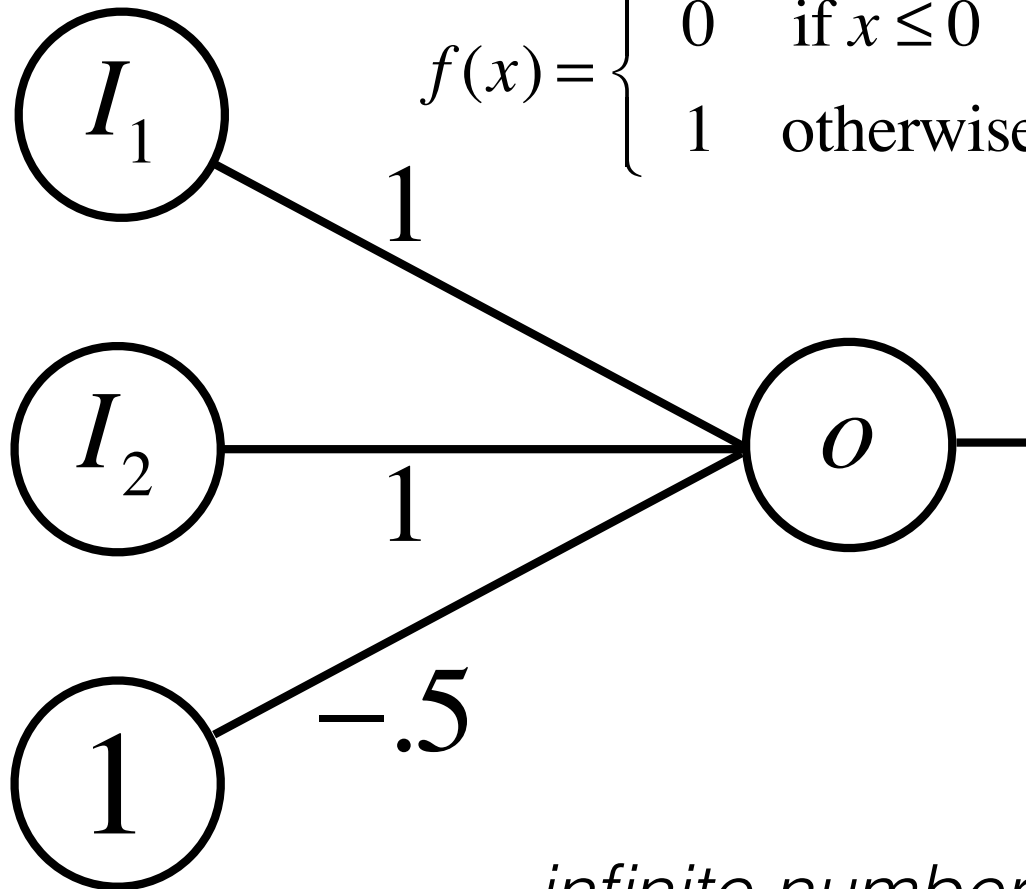
logical  
OR

# Example of a Simple Neural Network

$$o = f\left(\sum_i I_i w_i + \beta\right)$$

what values of  $w_1$ ,  $w_2$ , and  $\beta$

$$f(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 1 & \text{otherwise} \end{cases}$$

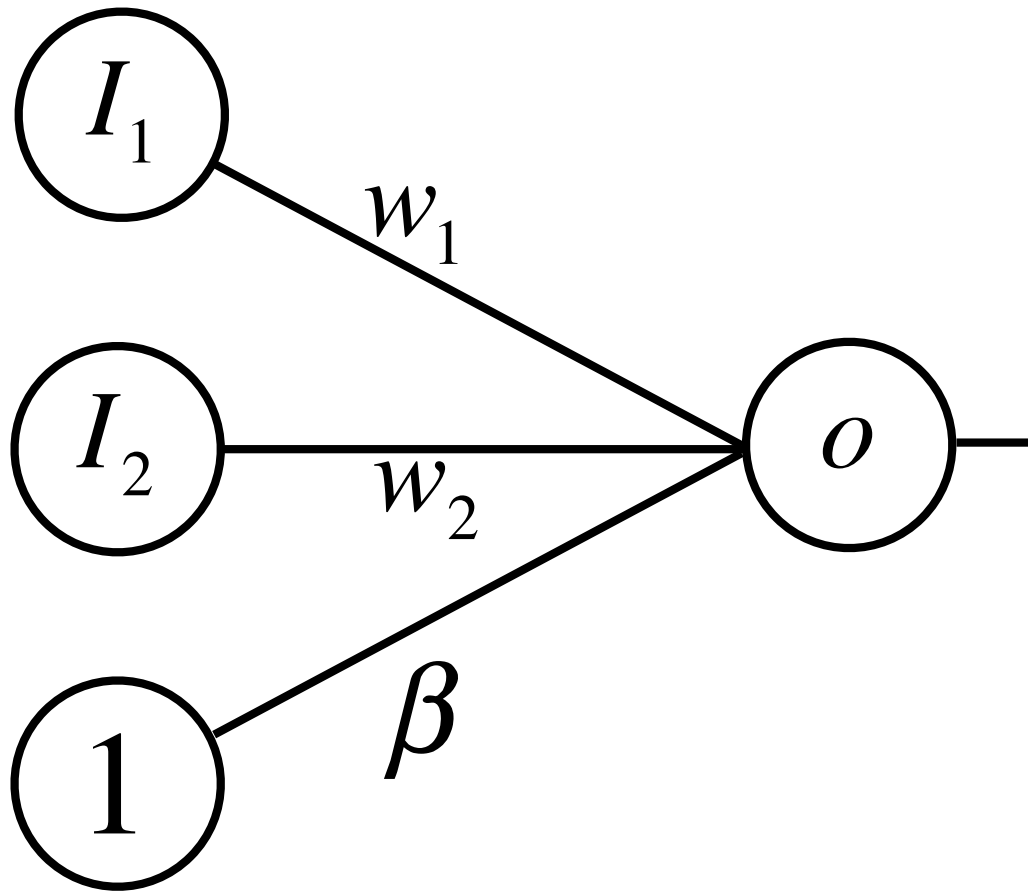


*infinite number of solutions*

$I_1$	$I_2$	$o$
0	0	0
1	0	1
0	1	1
1	1	1

logical  
OR

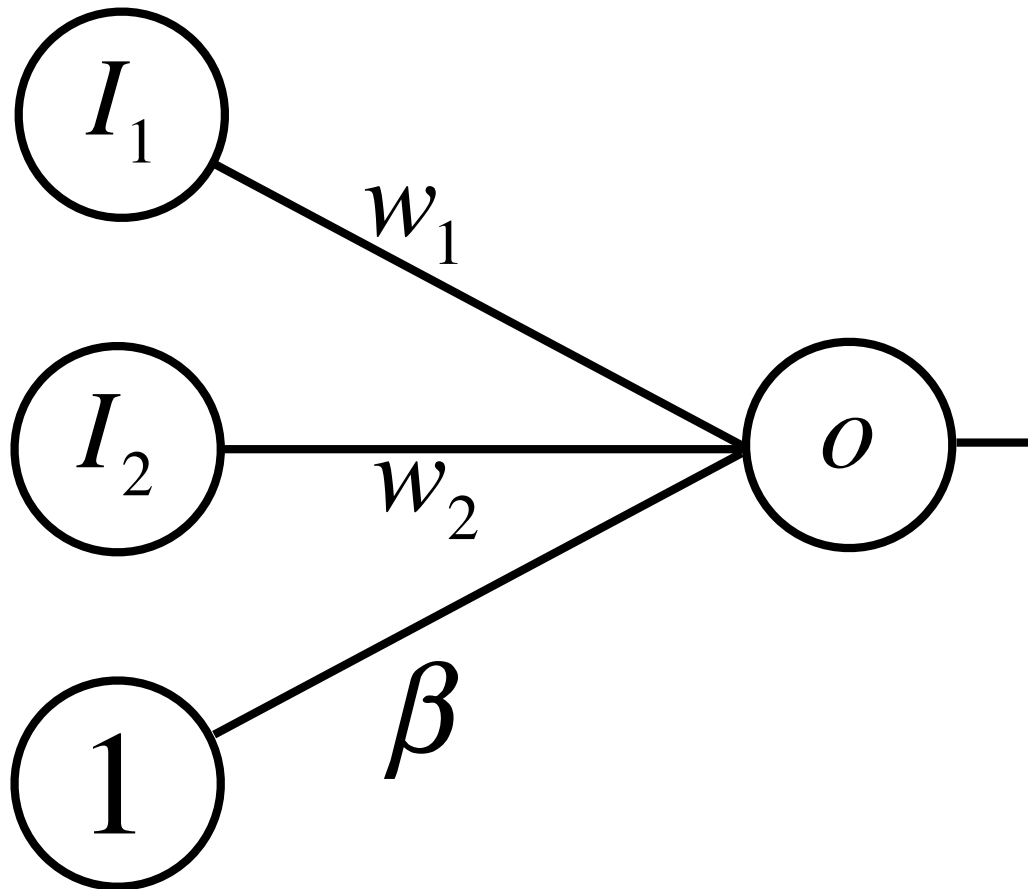
## Example of a Simple Neural Network



$I_1$	$I_2$	$o$
0	0	1
1	0	0
0	1	0
1	1	1

what is this  
computation?

# Example of a Simple Neural Network



$I_1$	$I_2$	$o$
0	0	0
1	0	1
0	1	1
1	1	0

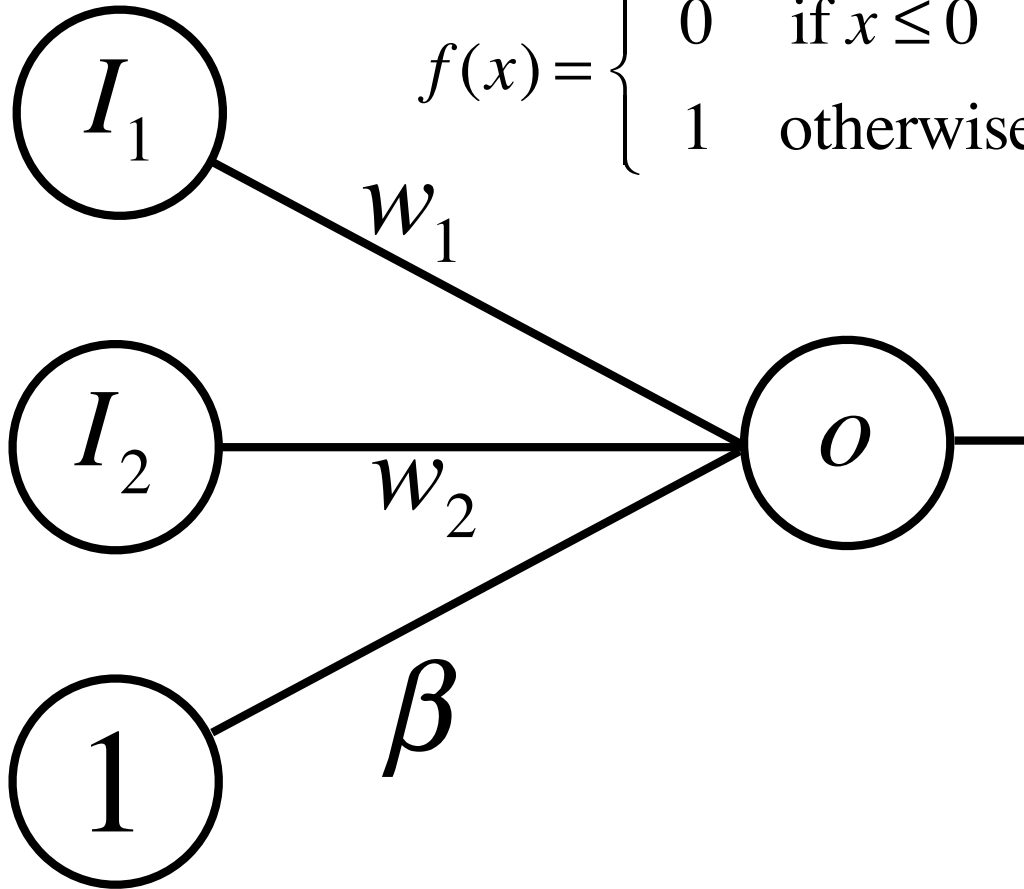
logical  
XOR

# Example of a Simple Neural Network

$$o = f\left(\sum_i I_i w_i + \beta\right)$$

what values of  $w_1$ ,  $w_2$ , and  $\beta$

$$f(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 1 & \text{otherwise} \end{cases}$$



$I_1$	$I_2$	$o$
0	0	0
1	0	1
0	1	1
1	1	0

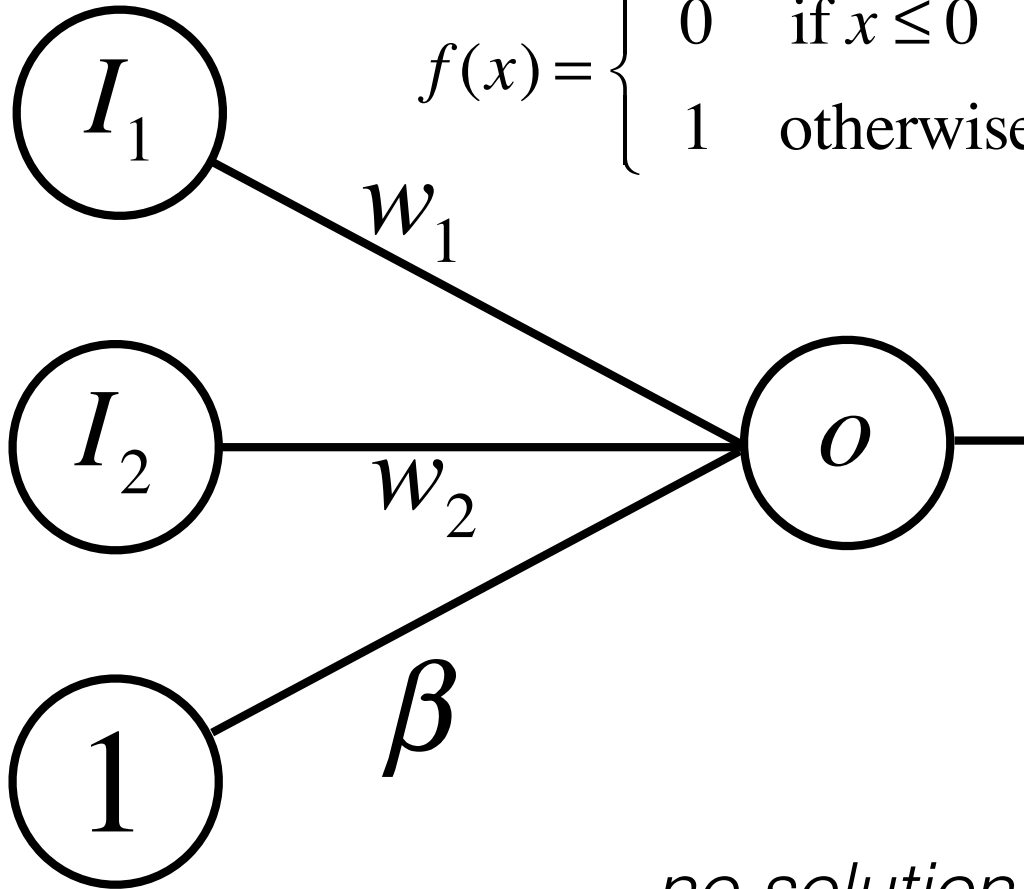
logical  
XOR

# Example of a Simple Neural Network

$$o = f\left(\sum_i I_i w_i + \beta\right)$$

what values of  $w_1$ ,  $w_2$ , and  $\beta$

$$f(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 1 & \text{otherwise} \end{cases}$$



$I_1$	$I_2$	$o$
0	0	0
1	0	1
0	1	1
1	1	0

logical  
XOR

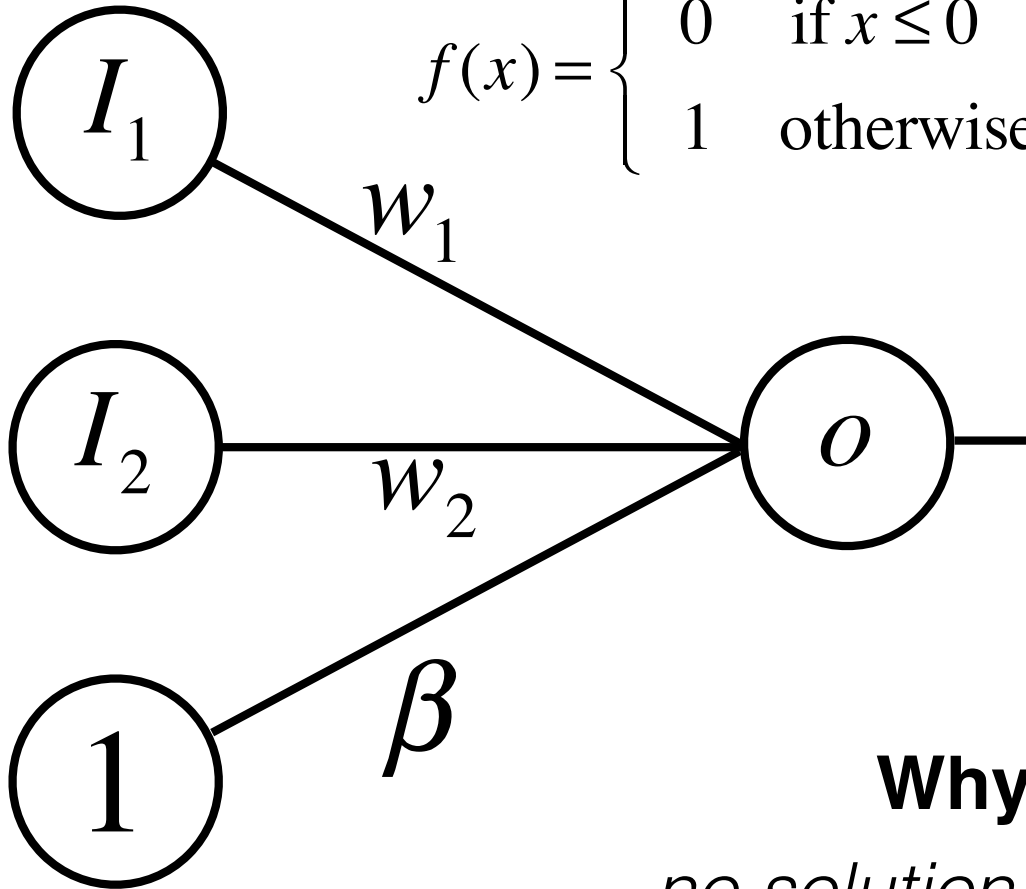
*no solution exists!!!*

# Example of a Simple Neural Network

$$o = f\left(\sum_i I_i w_i + \beta\right)$$

what values of  $w_1$ ,  $w_2$ , and  $\beta$

$$f(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 1 & \text{otherwise} \end{cases}$$



$I_1$	$I_2$	$o$
0	0	0
1	0	1
0	1	1
1	1	0

logical  
XOR

**Why?**

*no solution exists!!!*



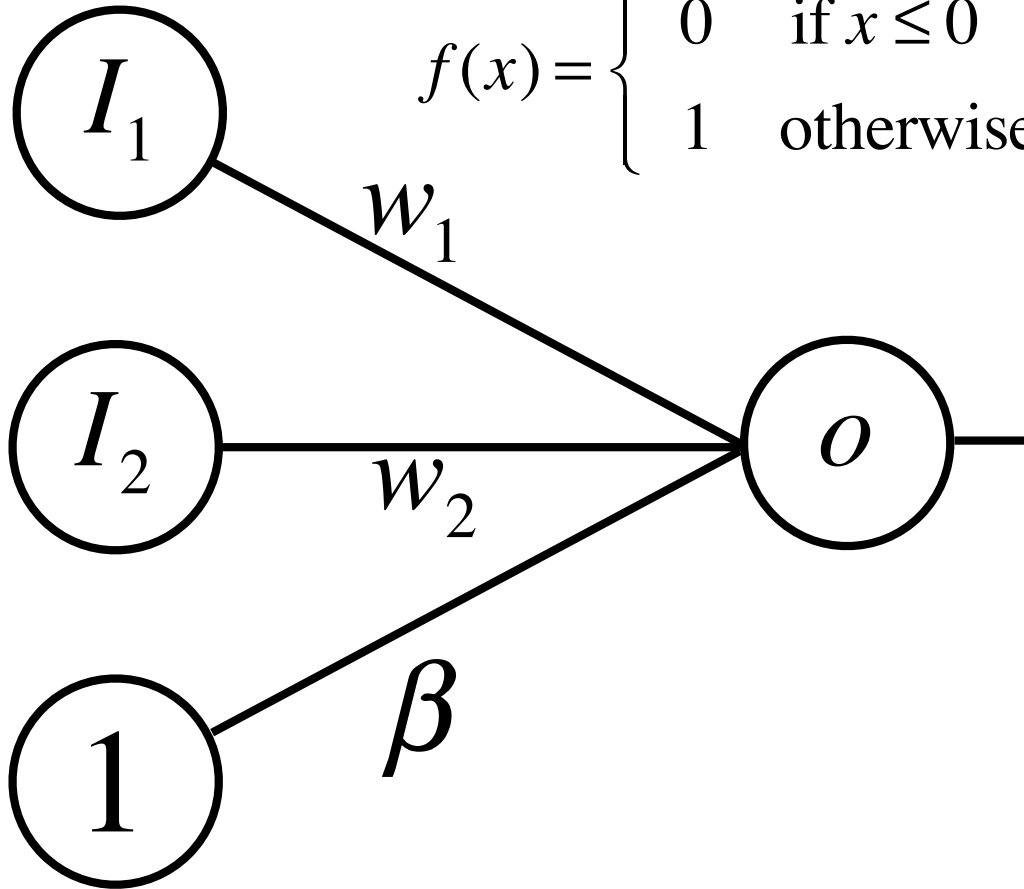


# Example of a Simple Neural Network

$$o = f\left(\sum_i I_i w_i + \beta\right)$$

what values of  $w_1$ ,  $w_2$ , and  $\beta$

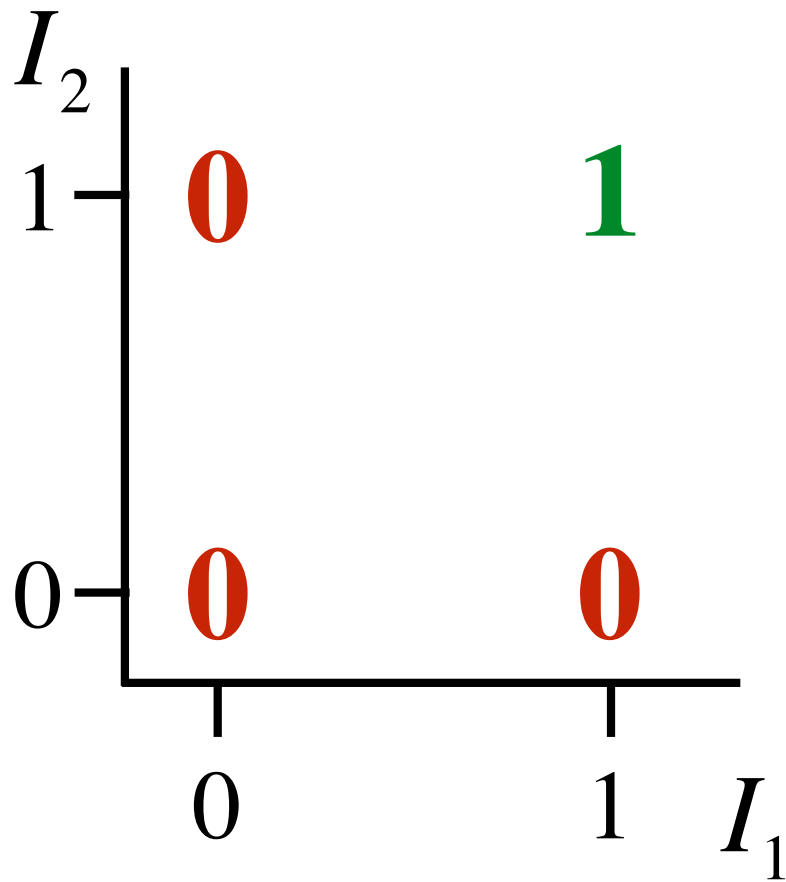
$$f(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 1 & \text{otherwise} \end{cases}$$



$I_1$	$I_2$	$o$
0	0	0
1	0	0
0	1	0
1	1	1

logical  
AND

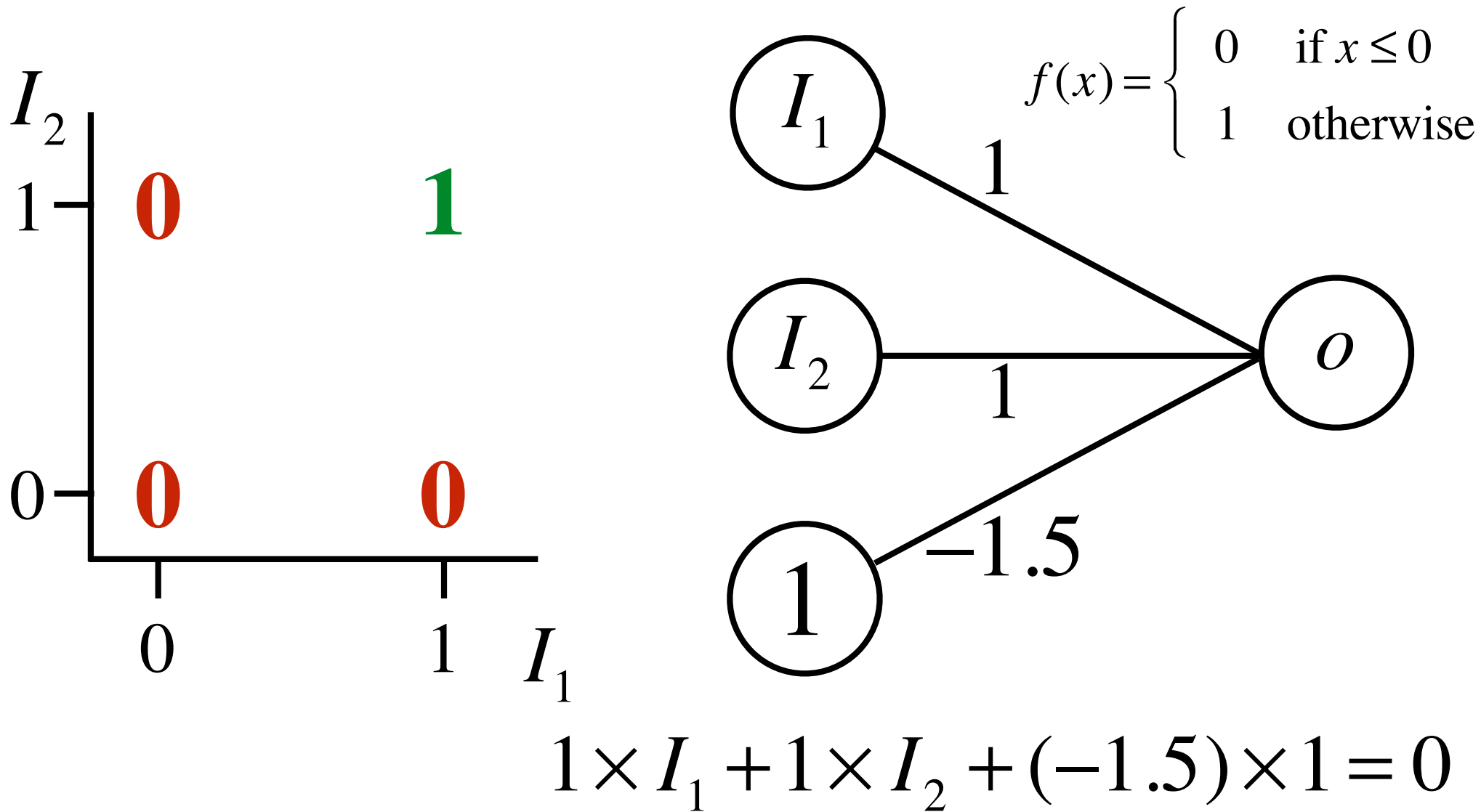
# Example of a Simple Neural Network



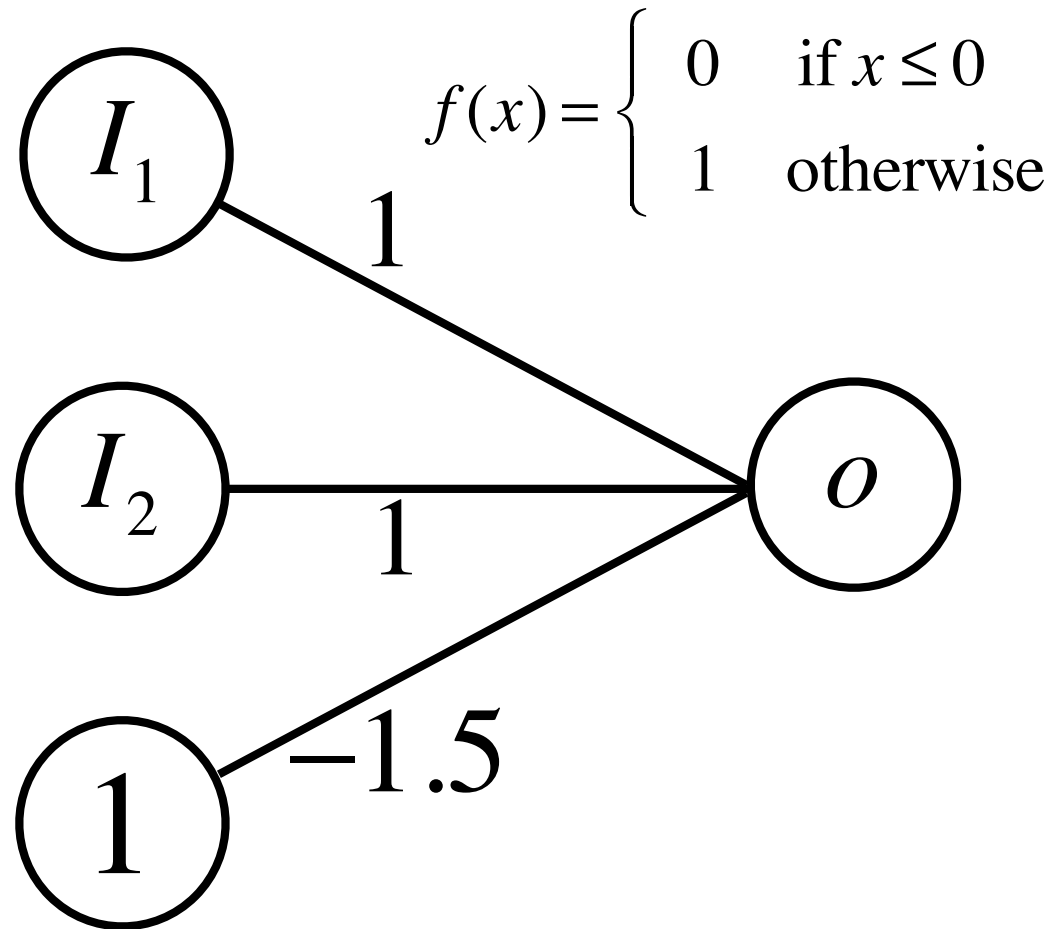
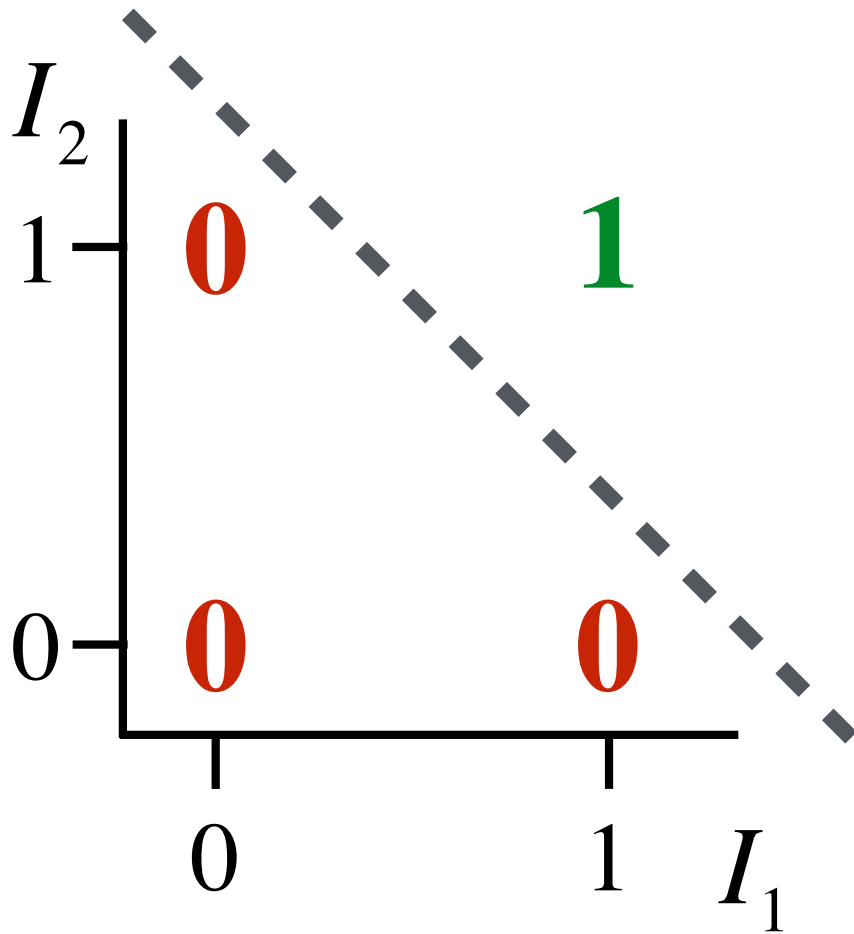
$I_1$	$I_2$	$o$
0	0	0
1	0	0
0	1	0
1	1	1

logical  
AND

# Example of a Simple Neural Network



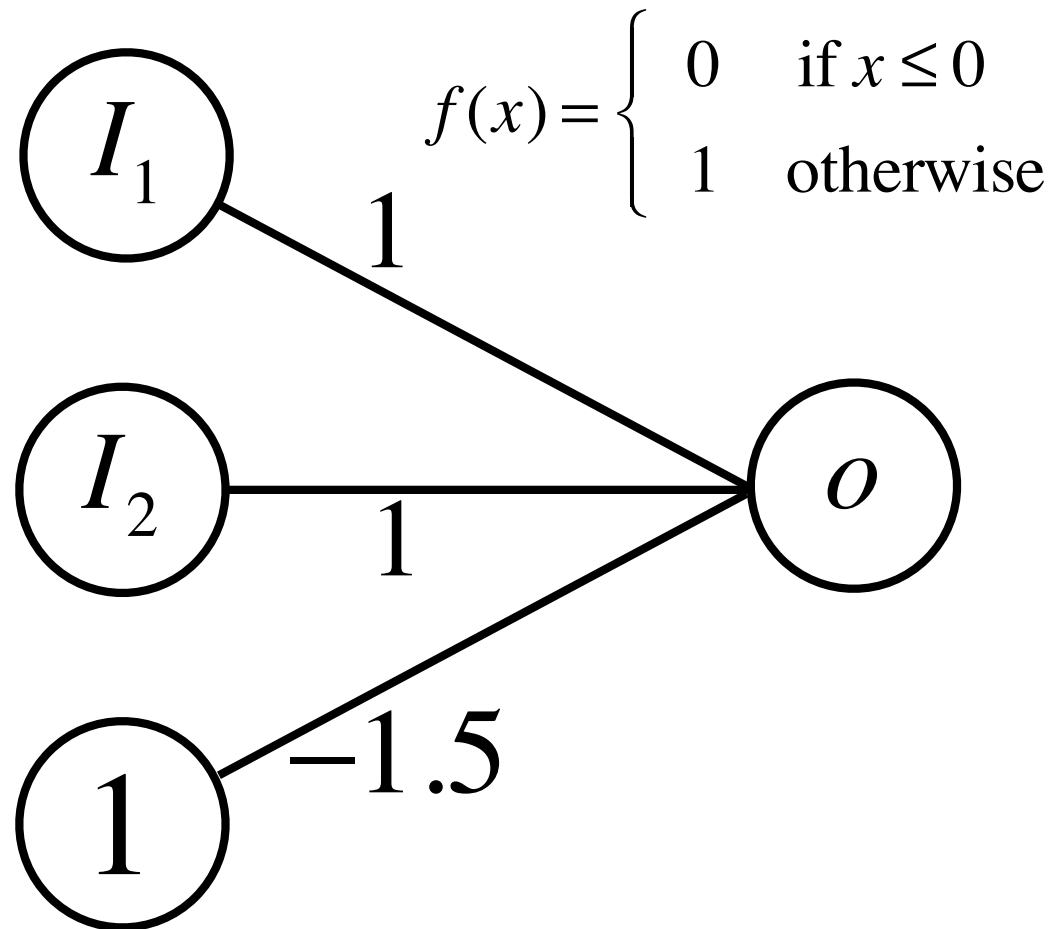
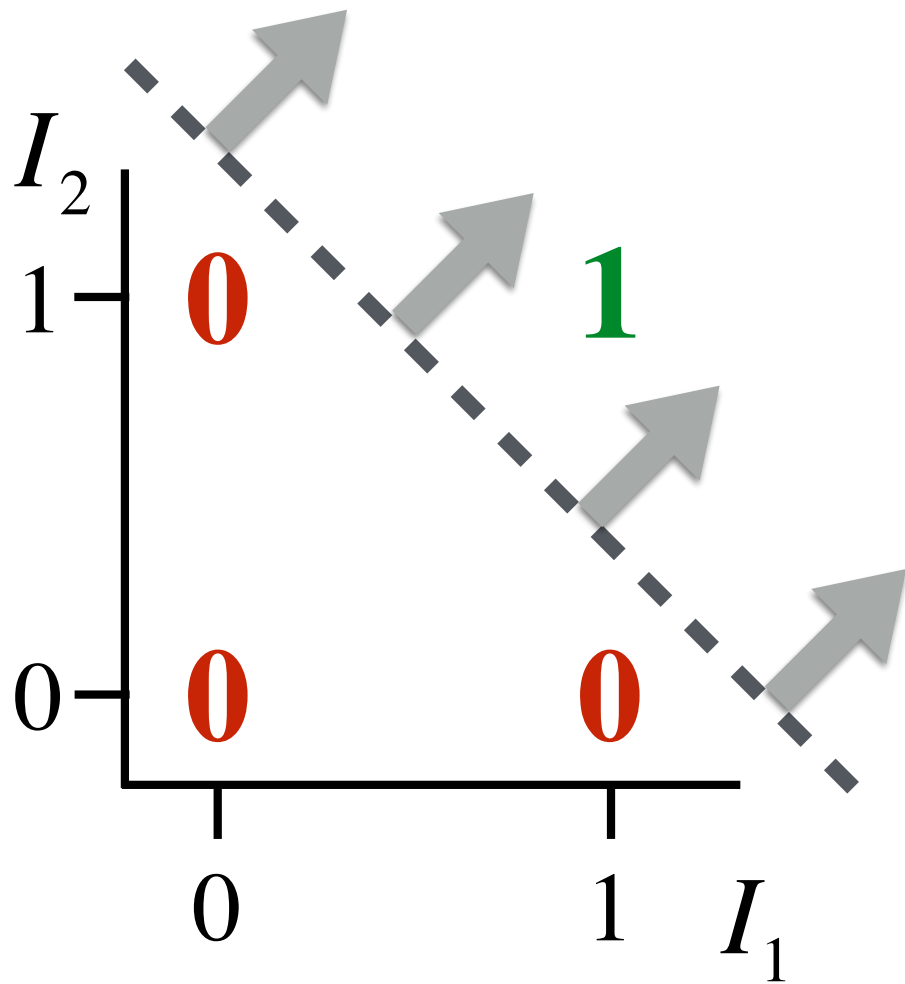
# Example of a Simple Neural Network



$$I_1 + I_2 - 1.5 = 0$$

$$I_2 = -I_1 + 1.5$$

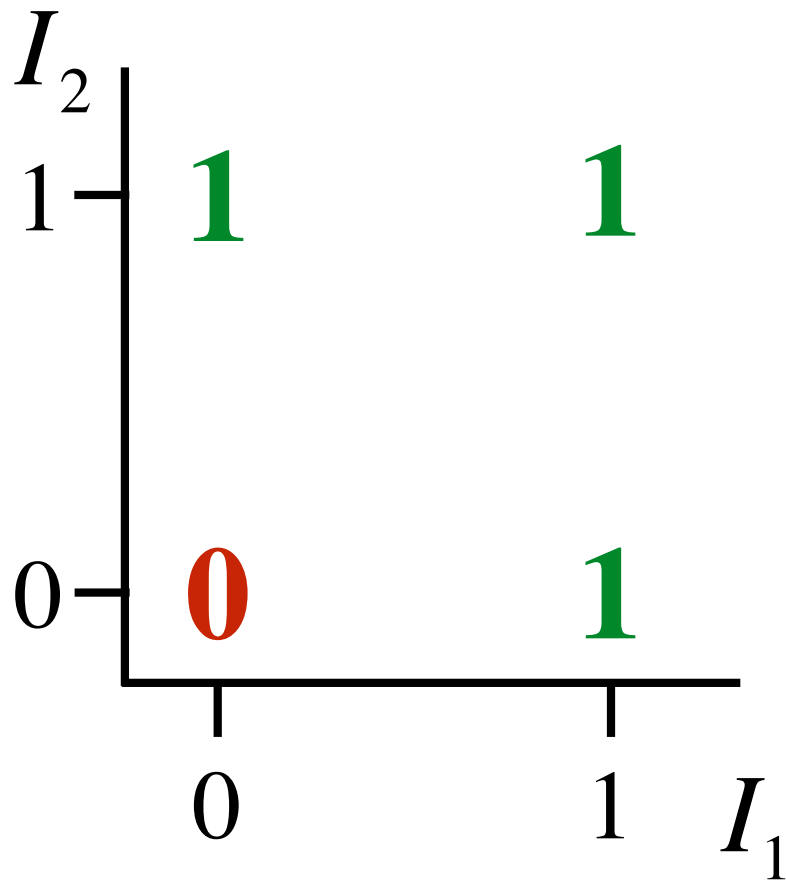
# Example of a Simple Neural Network



$$I_1 + I_2 - 1.5 = 0$$

$$I_2 = -I_1 + 1.5$$

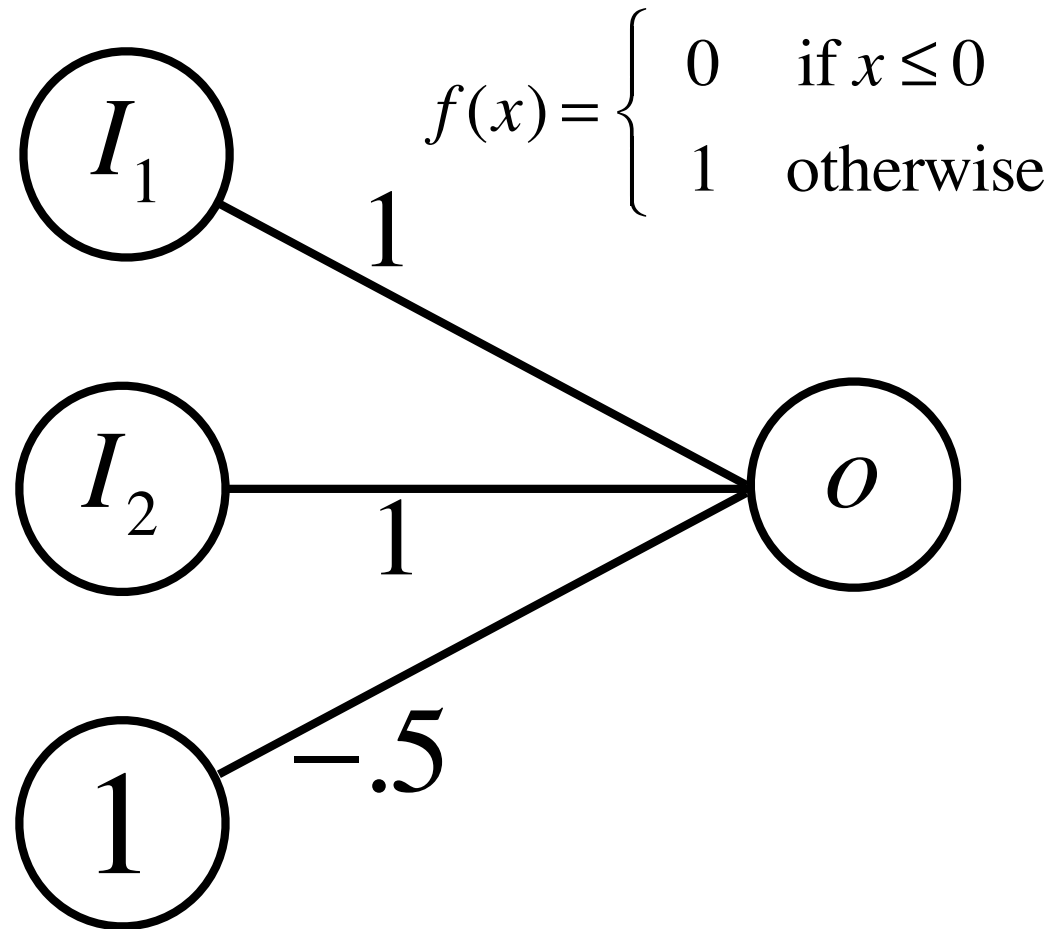
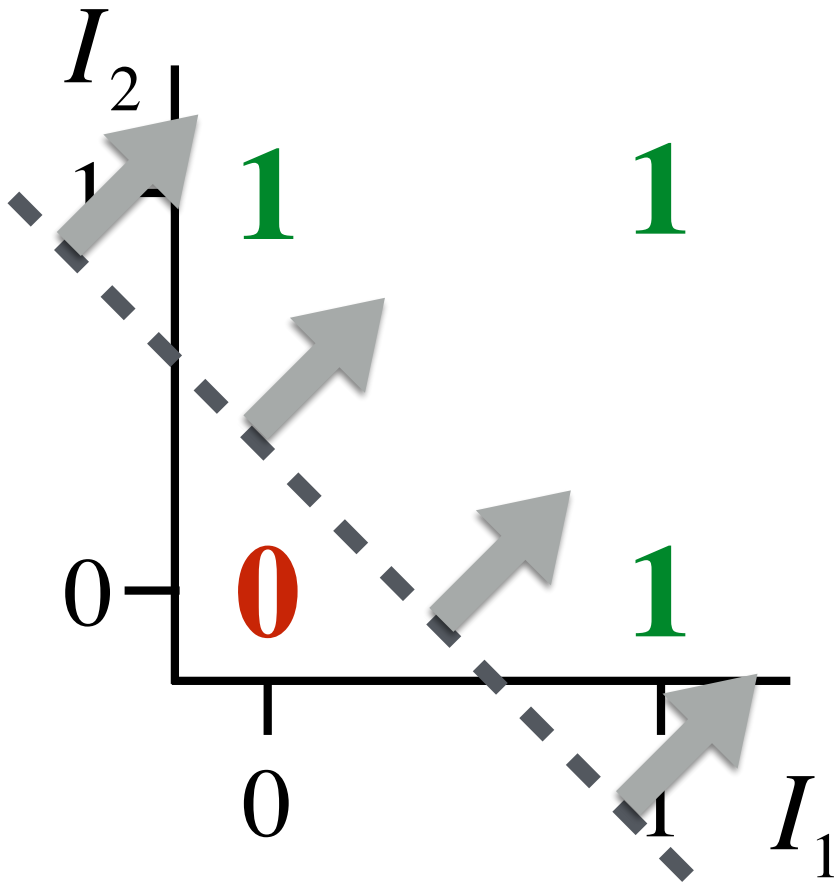
# Example of a Simple Neural Network



$I_1$	$I_2$	$o$
0	0	0
1	0	1
0	1	1
1	1	1

logical  
OR

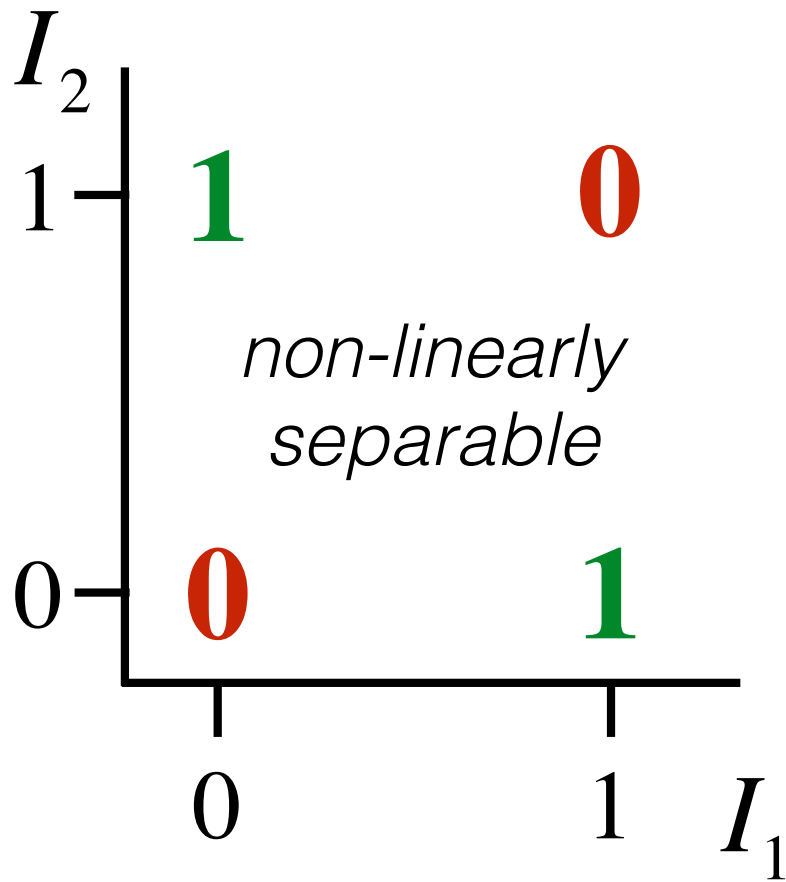
# Example of a Simple Neural Network



$$1 \times I_1 + 1 \times I_2 - .5 = 0$$

$$I_2 = -I_1 + .5$$

# Example of a Simple Neural Network

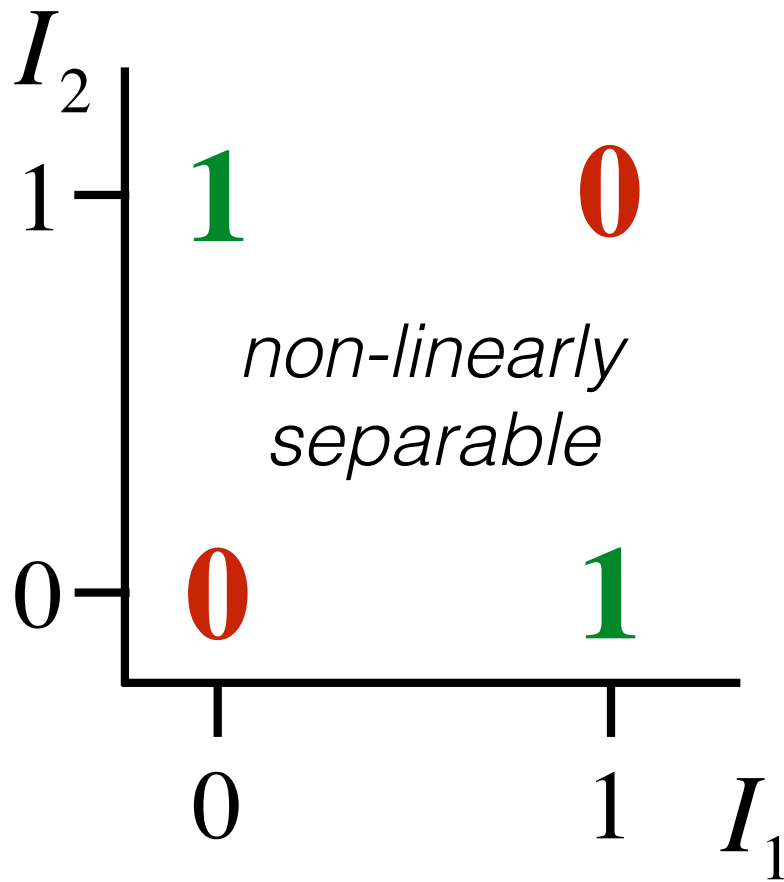


$I_1$	$I_2$	$o$
0	0	0
1	0	1
0	1	1
1	1	0

logical XOR



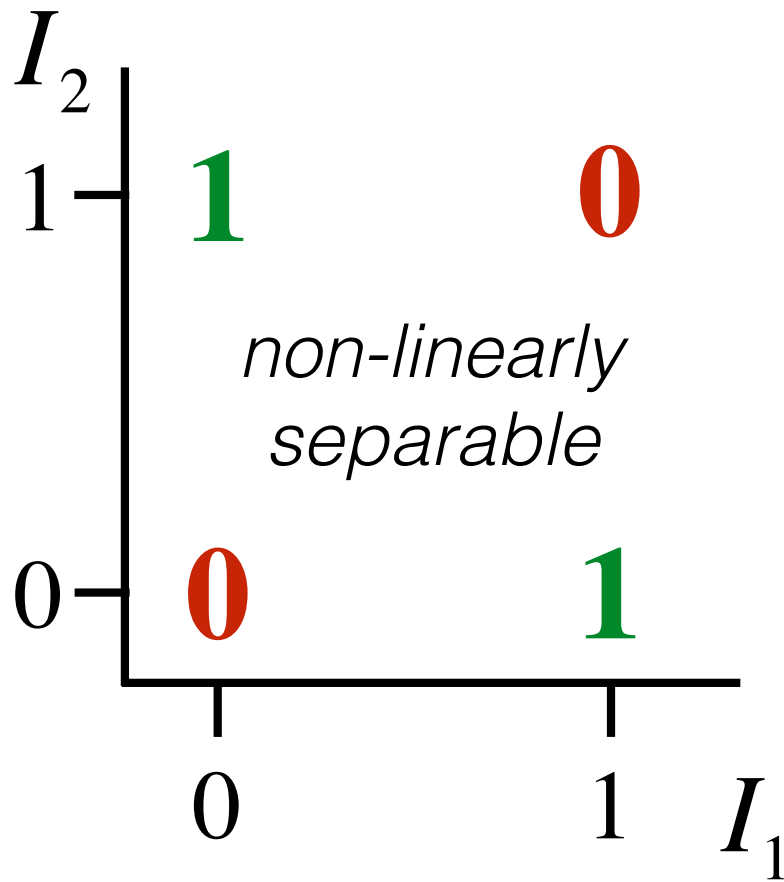
# Example of a Simple Neural Network



	$I_1$	$I_2$	$o$
$w_1 \times 0 + w_2 \times 0 + \beta < 0$	1	0	1
	0	1	1
	1	1	0

logical XOR

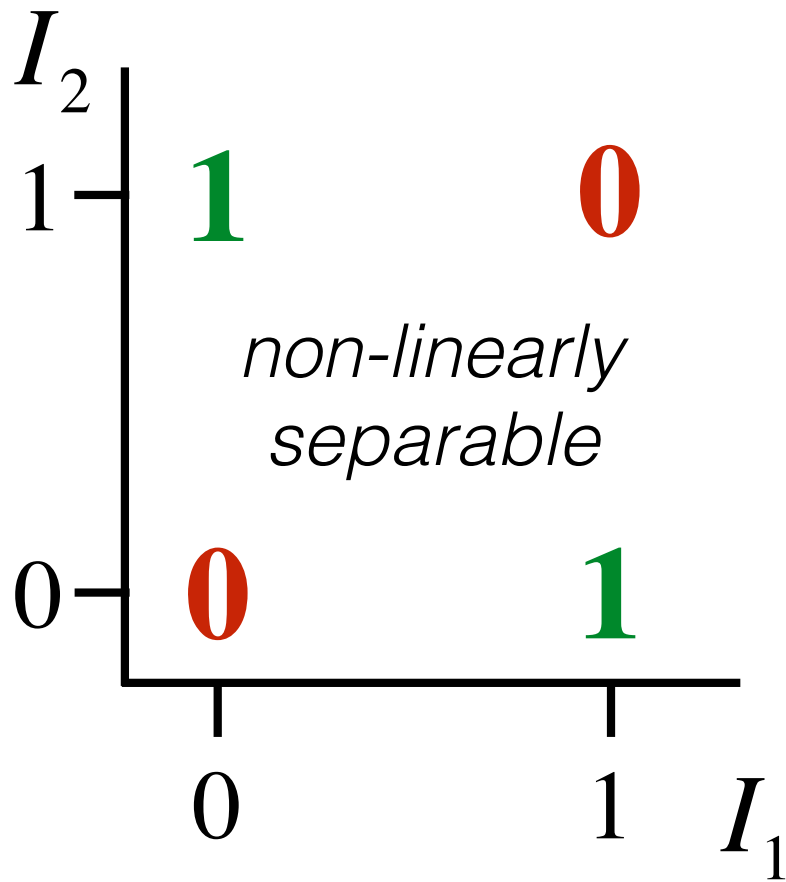
# Example of a Simple Neural Network



$I_1$	$I_2$	$o$
$w_1 \times 0 + w_2 \times 0 + \beta < 0$		
$w_1 \times 1 + w_2 \times 0 + \beta \geq 0$		
0	1	0
1	1	1

logical XOR

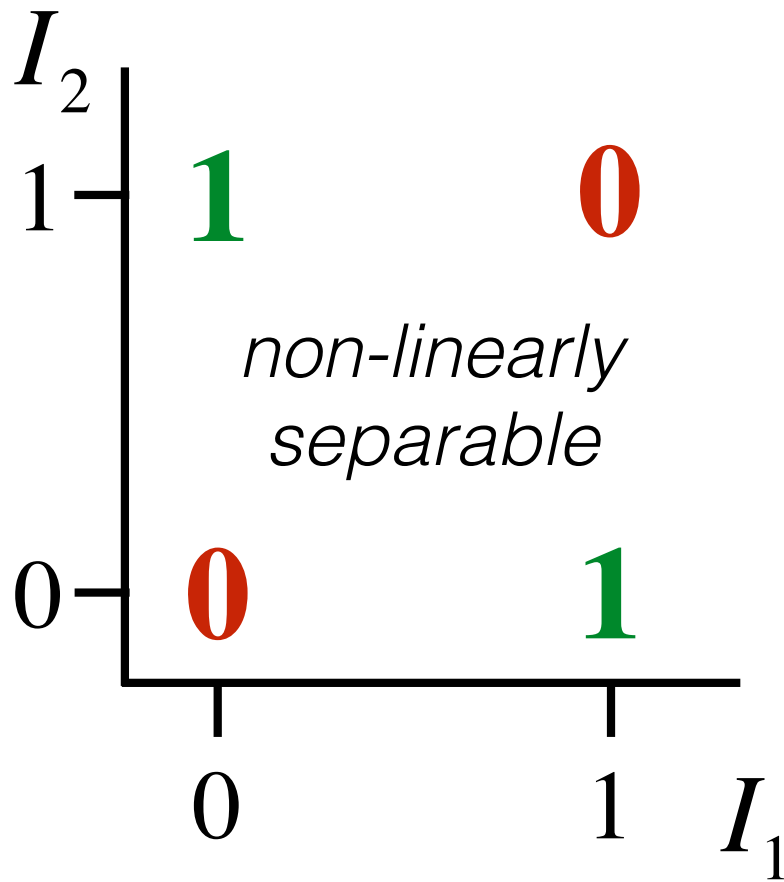
# Example of a Simple Neural Network



$I_1$	$I_2$	$o$
$w_1 \times 0 + w_2 \times 0 + \beta < 0$		
$w_1 \times 1 + w_2 \times 0 + \beta \geq 0$		
$w_1 \times 0 + w_2 \times 1 + \beta \geq 0$		
1	1	1

logical XOR

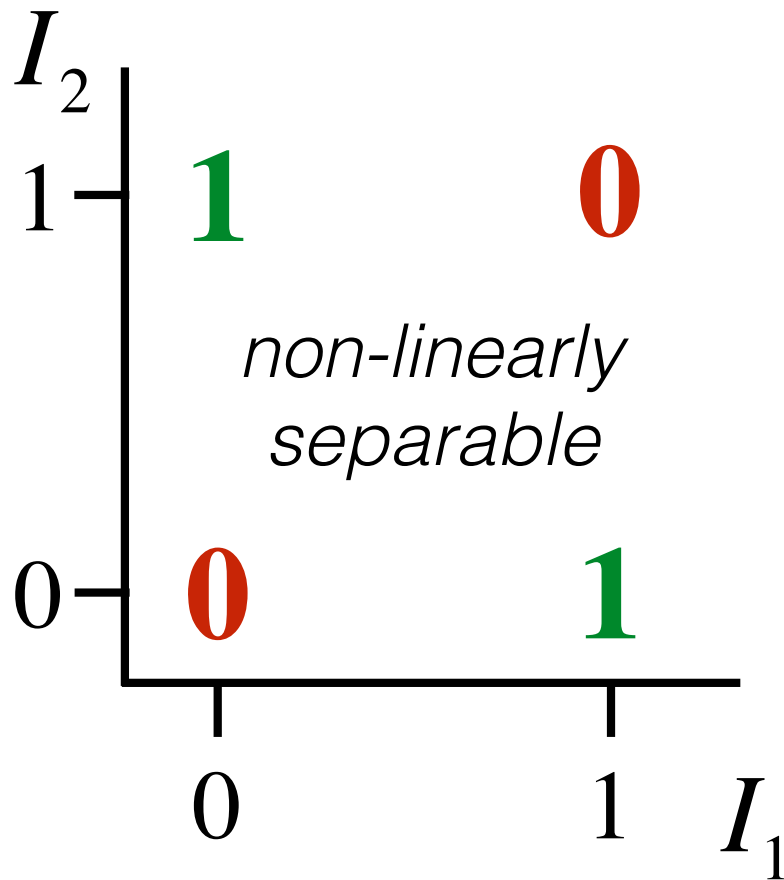
# Example of a Simple Neural Network



$I_1$	$I_2$	$o$
$w_1 \times 0 + w_2 \times 0 + \beta < 0$		
$w_1 \times 1 + w_2 \times 0 + \beta \geq 0$		
$w_1 \times 0 + w_2 \times 1 + \beta \geq 0$		
$w_1 \times 1 + w_2 \times 1 + \beta < 0$		

logical  
XOR

# Example of a Simple Neural Network



$I_1$	$I_2$	$o$
		$\beta < 0$

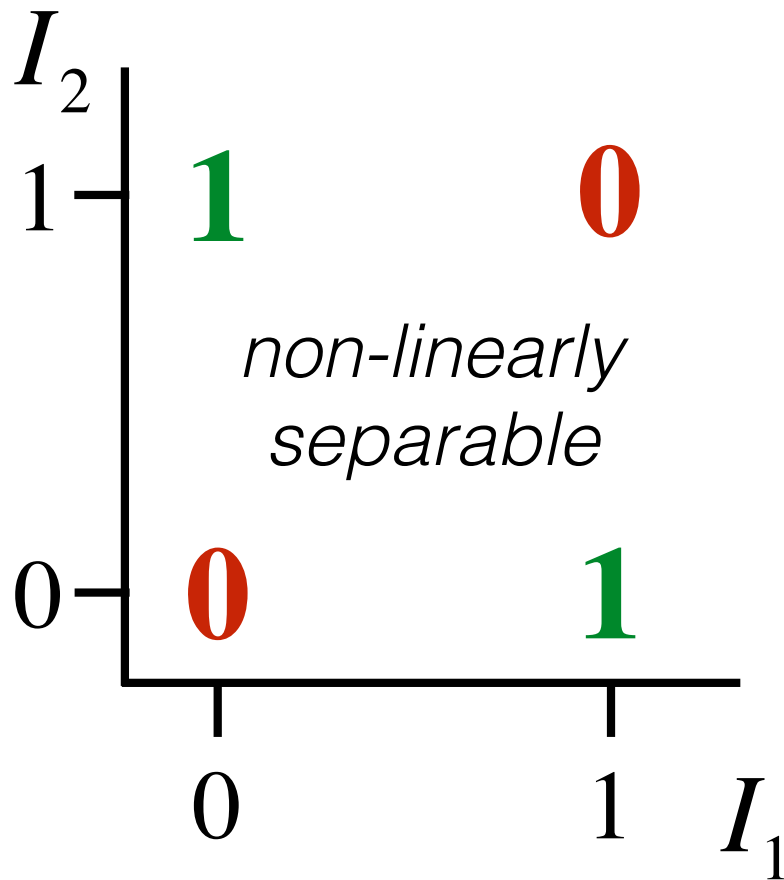
$$w_1 + \beta \geq 0$$

$$w_2 + \beta \geq 0$$

$$w_1 + w_2 + \beta < 0$$

mutually  
contradictory  
(*convince yourself*)

# Example of a Simple Neural Network



$I_1$	$I_2$	$o$
		$\beta < 0$
		$w_1 + \beta \geq 0$
		$w_2 + \beta \geq 0$
		$w_1 + w_2 + \beta < 0$

*networks with multiple layers can solve this!!!  
(the week after next)*



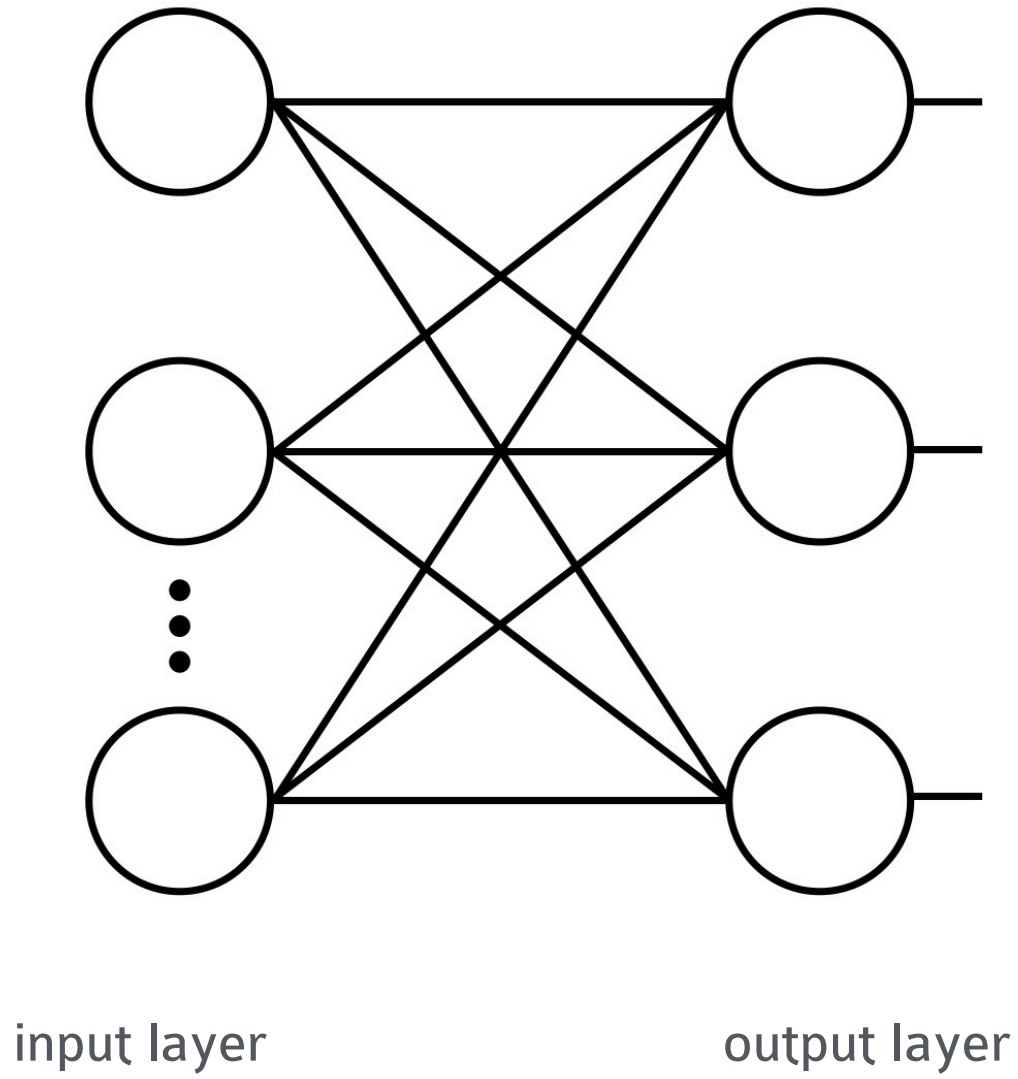
**Example of a Simple Neural Network**

**&**

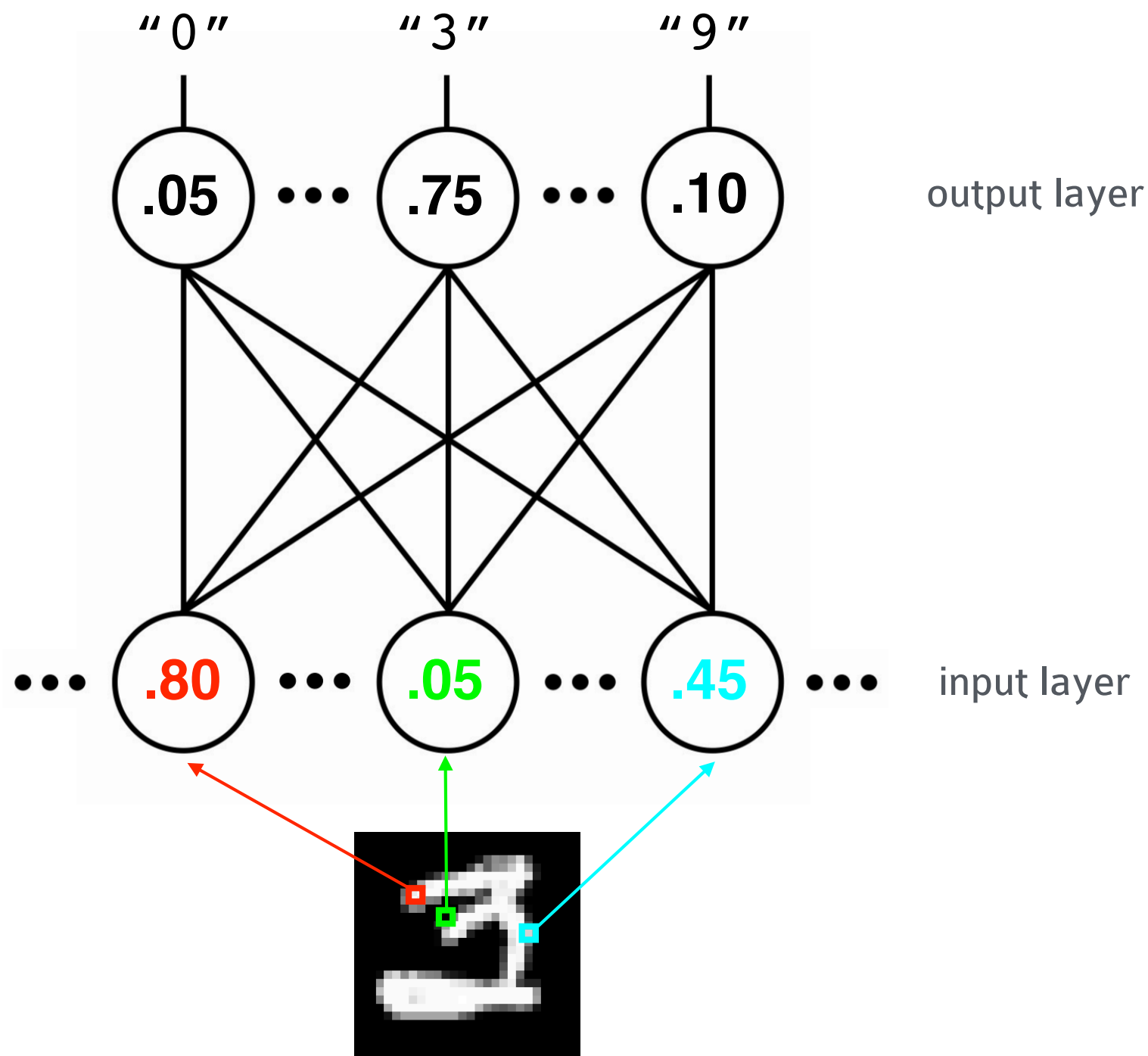
**Background for  
Homework 3**



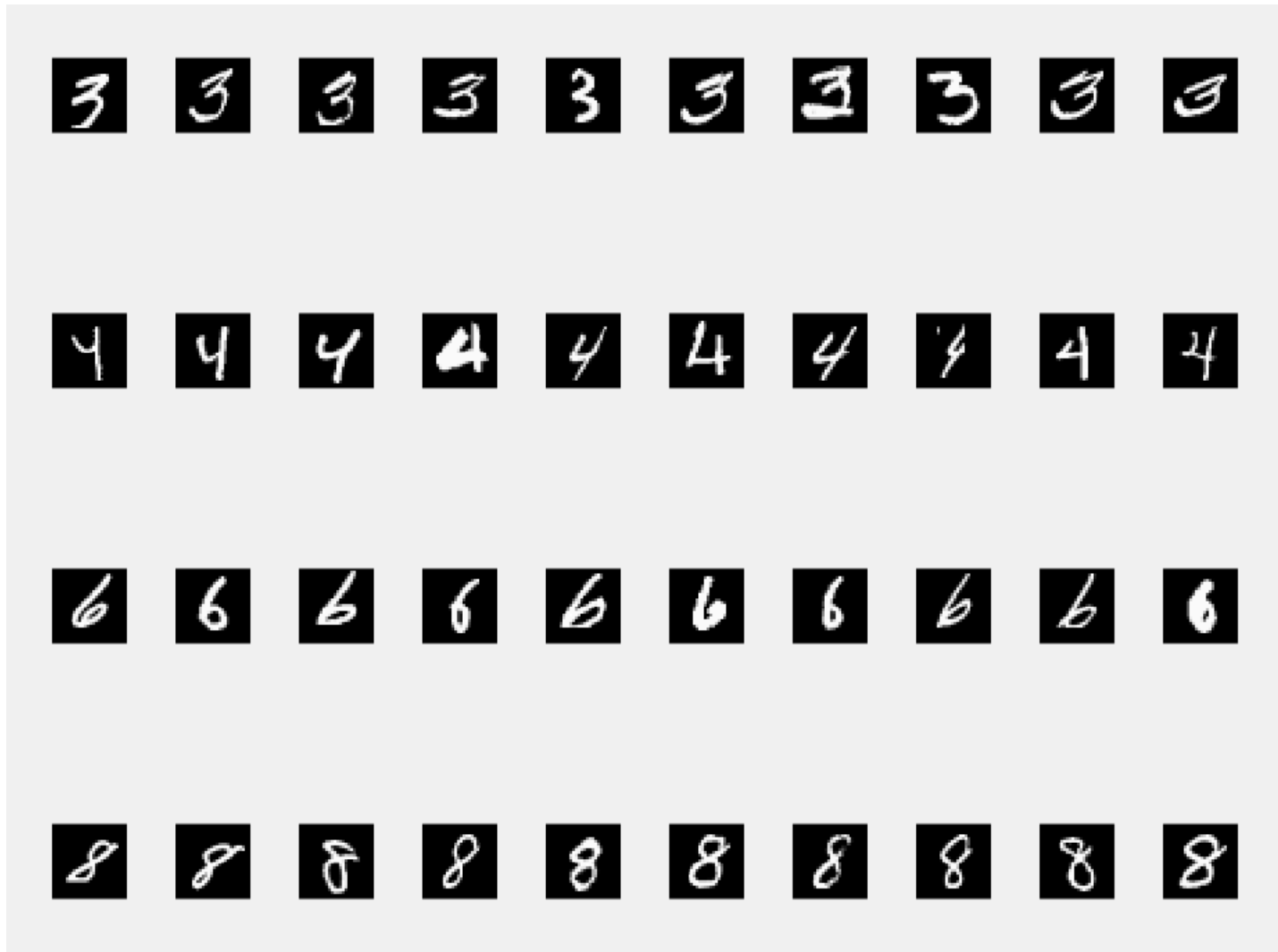
## Example : Visual Digit Classification



$P(\text{classification})$



- more practice using Python
- use a one-layer neural network (input and output layer)



**MNIST** <http://yann.lecun.com/exdb/mnist/>

**see Homework3.ipynb**

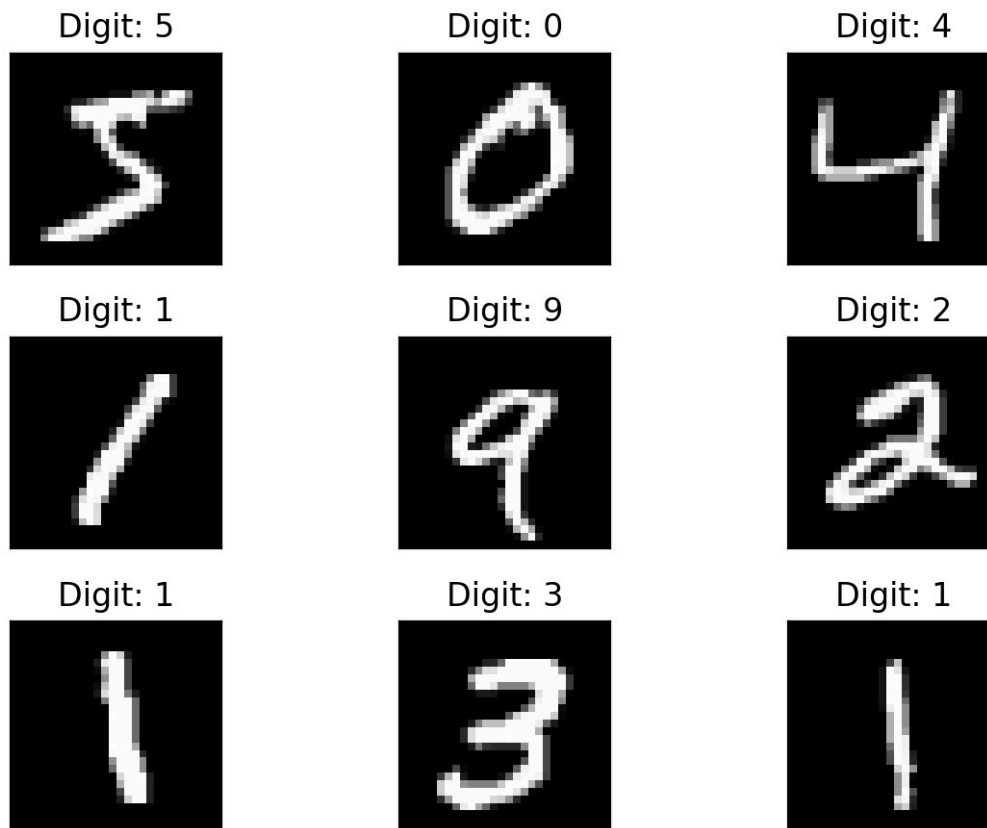
```
from keras.datasets import mnist
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

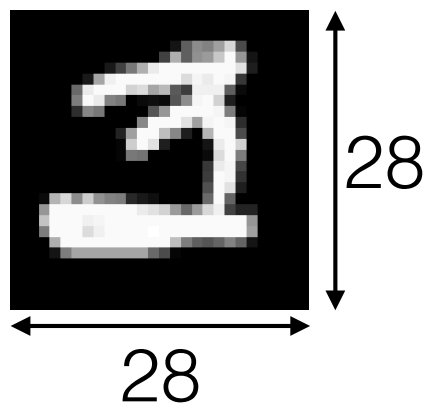
# check out dimensions and types of mnist data
print('Training images shape: ', train_images.shape)
print('Training images type:   ', type(train_images[0][0][0]))
print('Testing images shape:   ', test_images.shape)
print('Testing images type:    ', type(test_images[0][0][0]))
```

```
Training images shape: (60000, 28, 28)
Training images type:  <class 'numpy.uint8'>
Testing images shape:  (10000, 28, 28)
Testing images type:   <class 'numpy.uint8'>
```

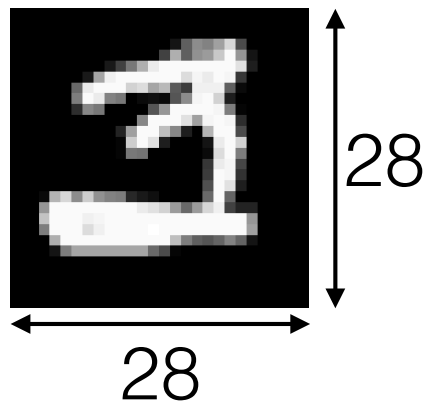
```
import matplotlib.pyplot as plt

# display some digits
fig = plt.figure()
for i in range(9):
    plt.subplot(3,3,i+1)
    plt.tight_layout()
    plt.imshow(train_images[i], cmap='gray', interpolation='none')
    plt.title("Digit: {}".format(train_labels[i]))
    plt.xticks([])
    plt.yticks([])
plt.show()
```





P(classification)

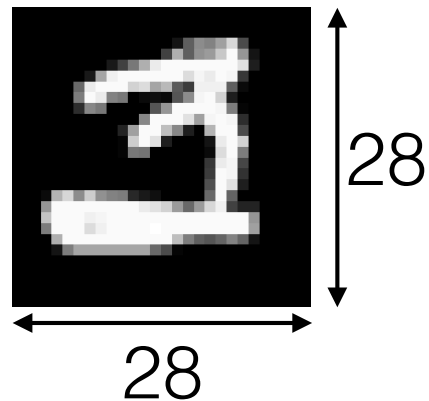
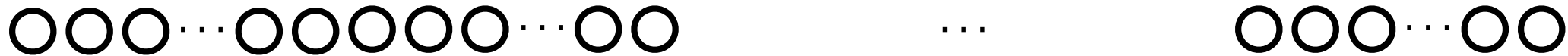




P(classification)



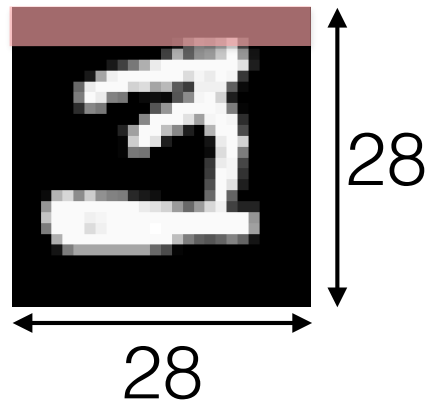
$28 \times 28 = 784$  input units



P(classification)



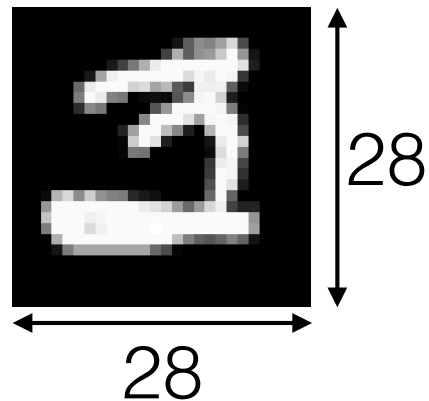
28x28 = 784 input units



P(classification)



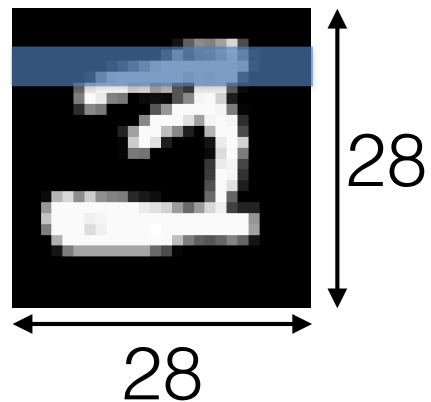
$28 \times 28 = 784$  input units



P(classification)



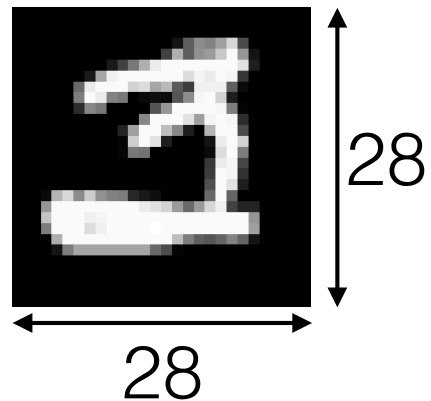
$28 \times 28 = 784$  input units



P(classification)



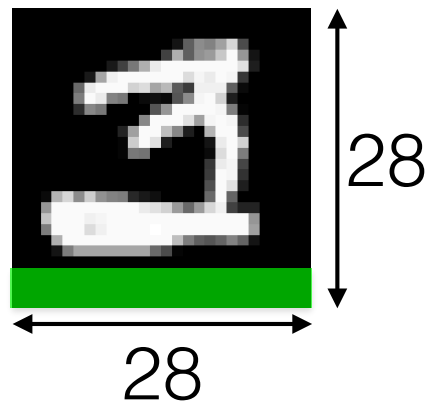
$28 \times 28 = 784$  input units



P(classification)



$28 \times 28 = 784$  input units



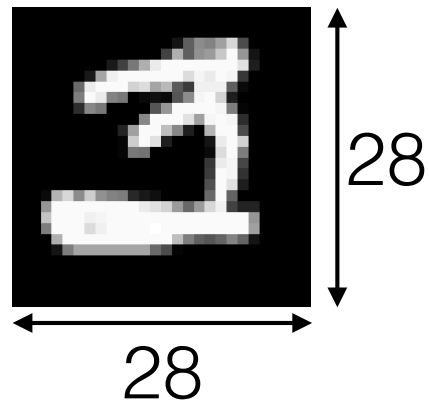
P(classification)



$28 \times 28 = 784$  input units



...



```
# need to reshape and preprocess the training/testing images
sz = train_images.shape[1]
train_images_vec = train_images.reshape((train_images.shape[0], sz * sz))
train_images_vec = train_images_vec.astype('float32') / 255
test_images_vec = test_images.reshape((test_images.shape[0], sz * sz))
test_images_vec = test_images_vec.astype('float32') / 255

# display new input dimensions/type
print('Training images shape: ', train_images_vec.shape)
print('Training images type:  ', type(train_images_vec[0][0]))
```

```
Training images shape: (60000, 784)
Training images type:  <class 'numpy.float32'>
Testing images shape:  (10000, 784)
Testing images type:   <class 'numpy.float32'>
```



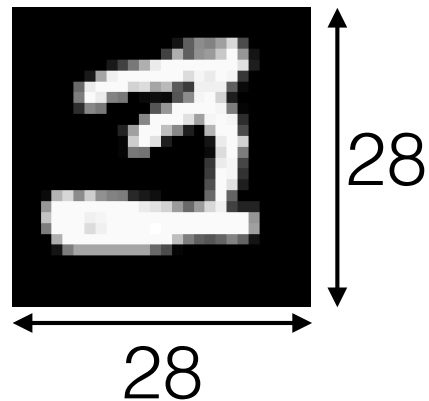
P(classification)



$28 \times 28 = 784$  input units



...



```
print('Training labels shape: ', train_labels.shape)
print('Training labels type:  ', type(train_labels[0]))

# also need to categorically encode the labels
print("First 5 training labels as labels:\n", train_labels[:5])
from keras.utils import to_categorical
train_labels_onehot = to_categorical(train_labels)
test_labels_onehot = to_categorical(test_labels)
print("First 5 training labels as one-hot encoded vectors:\n",
      train_labels_onehot[:5])

# display new output dimensions/type
print('Training labels shape: ', train_labels_onehot.shape)
print('Training labels type:  ', type(train_labels_onehot[0][0]))
```

```
Training labels shape:  (60000,)
Training labels type:   <class 'numpy.uint8'>
```

```
First 5 training labels as labels:
```

```
[5 0 4 1 9]
```

```
First 5 training labels as one-hot encoded vectors:
```

```
[[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

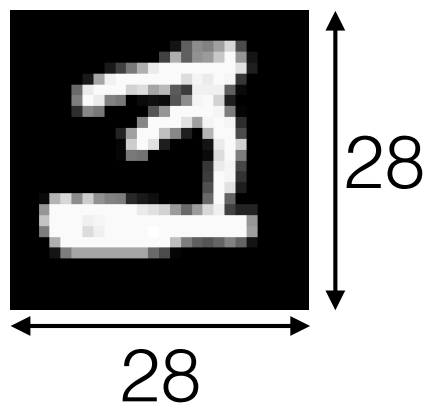
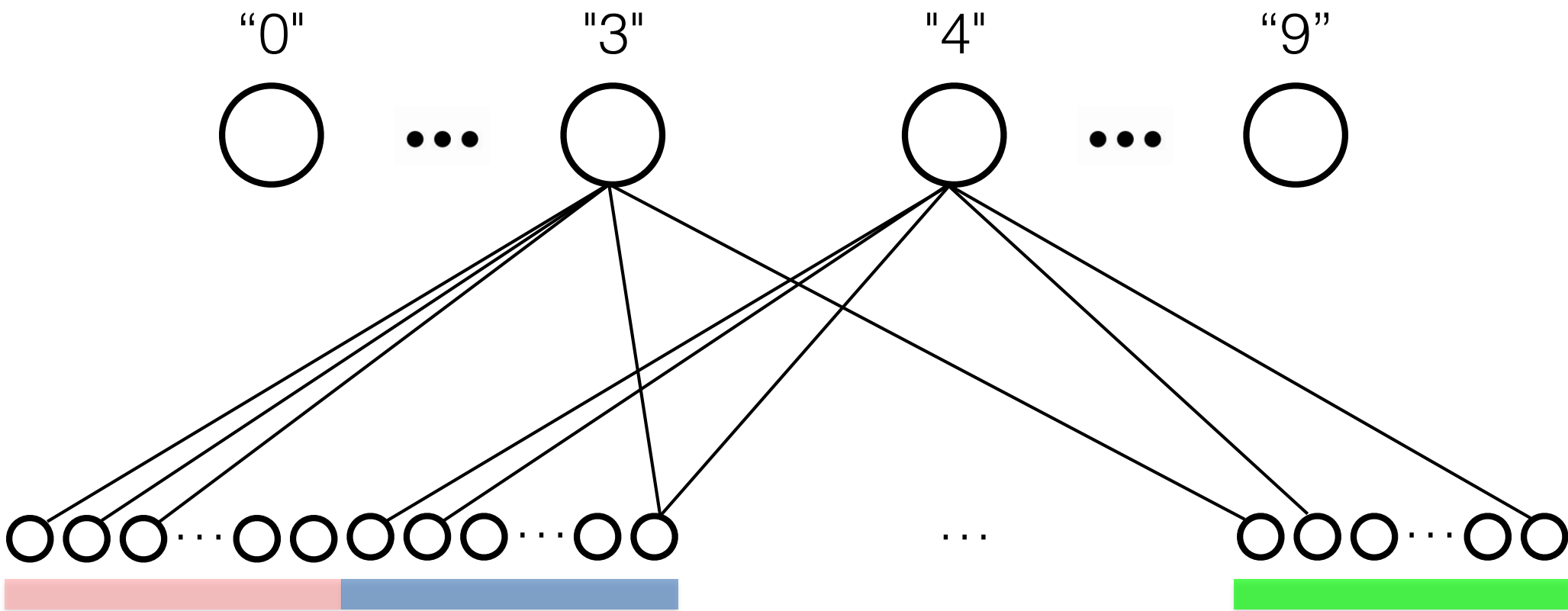
```
[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

```
[0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
```

```
[0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
```

```
[0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]]
```

```
Training labels shape:  (60000, 10)
Training labels type:   <class 'numpy.float32'>
```



```
# import tools for basic keras networks
from keras import models
from keras import layers

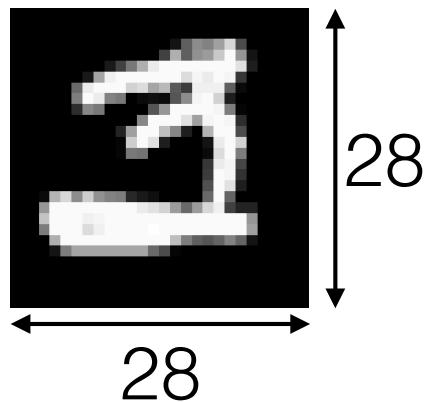
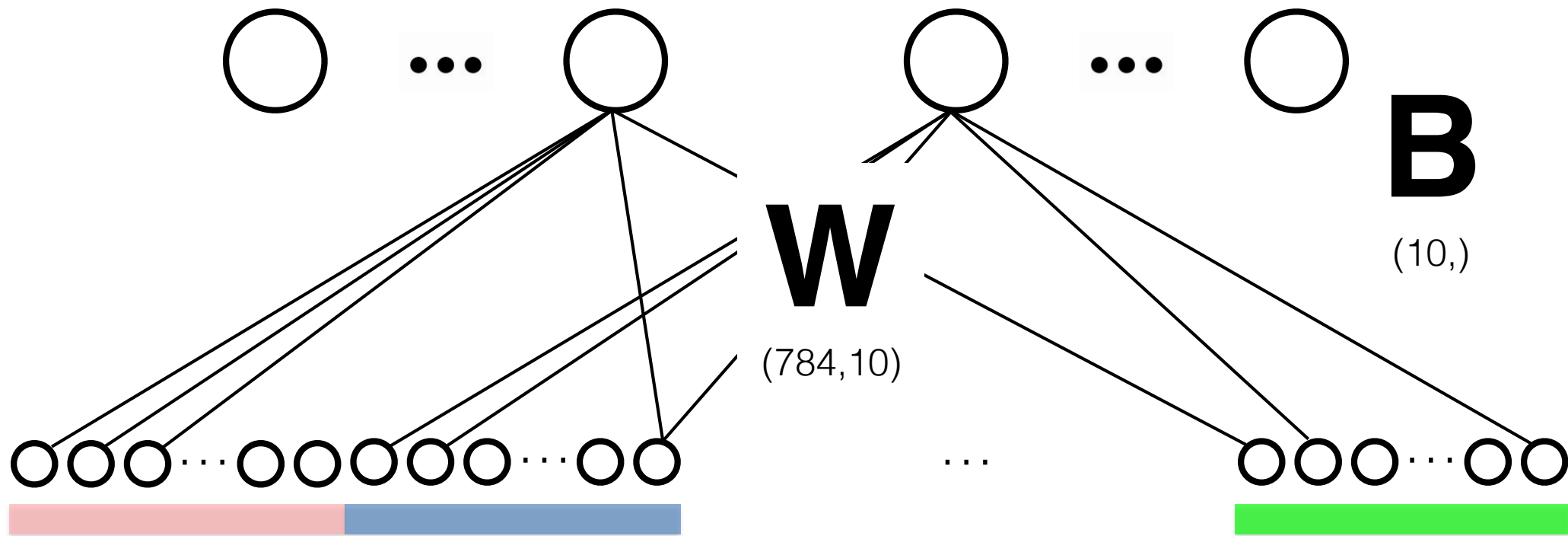
nout = 10
# create architecture of simple neural network model
# input layer : 28*28 = 784 input nodes
# output layer : 10 (nout) output nodes
network = models.Sequential()
network.add(layers.Dense(nout, activation='sigmoid', input_shape=(sz * sz,)))

# compile network
network.compile(optimizer='sgd', loss='mean_squared_error', metrics=[ 'accuracy' ])

# now train the network
history = network.fit(train_images_vec, train_labels_onehot, verbose=False,
                      validation_split=.1, epochs=20, batch_size=128)
```

$$a_j = \frac{1}{1 + \exp(-n_j)}$$

the weights (**W**) and biases (**B**) are learned from training data



## **Homework 3**

see Homework3.py and Homework3.ipynb  
on Brightspace

20 points

Due Thursday January 24th

**## Q1.** The original MNIST test\_labels numpy array contains the digit value associated with the corresponding digit image (test\_images). The output from the network (from out = network.predict(test\_images\_vec) above) contains the activations of the 10 output nodes for every test image presented to the network. Write a function that takes the (10000,10) numpy array of output activations (of type float32) and returns a (10000,) numpy array of discrete digit classification by the network (of type uint8). In other words, create a test\_decisions numpy array of the same size and type as the MNIST test\_labels array you started with. Below you will use both arrays to pull out test images that the network classifies correctly or incorrectly.

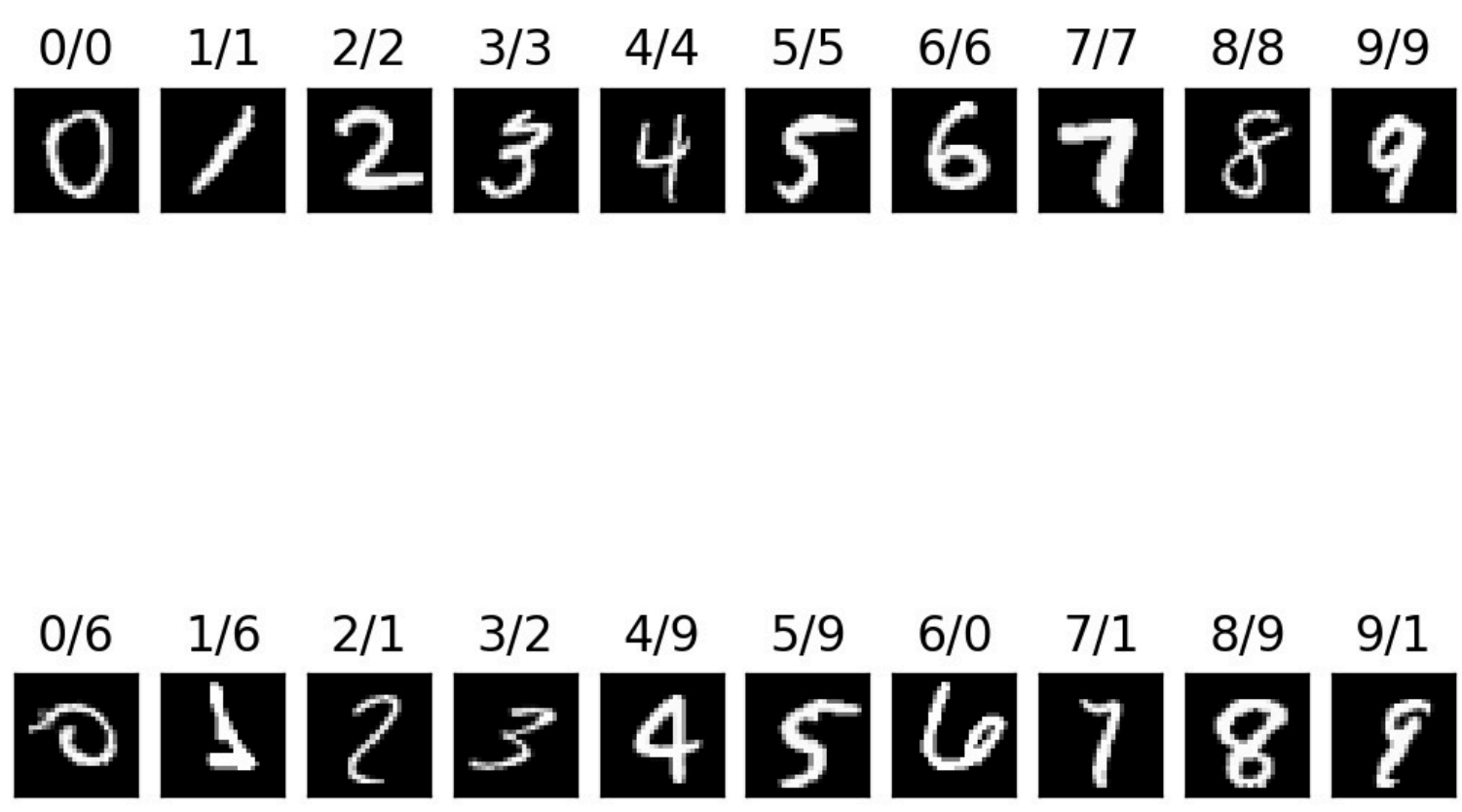
**##**

**##** To turn a numpy array of continuous output activations into a discrete digit classification, just take the maximum output as the "winner" that take all, determining the classification.

**##**

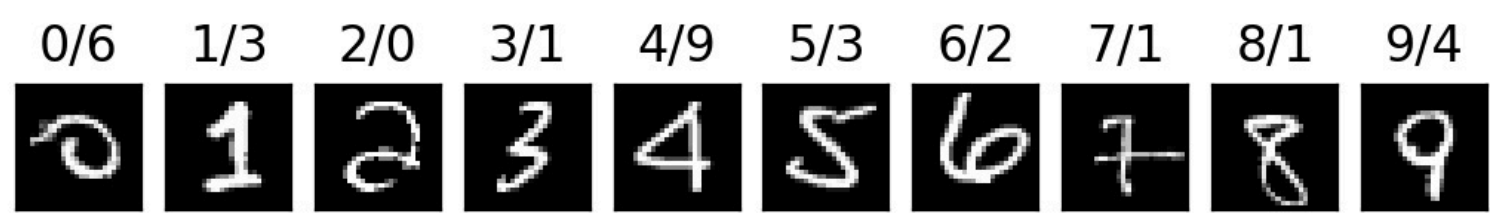
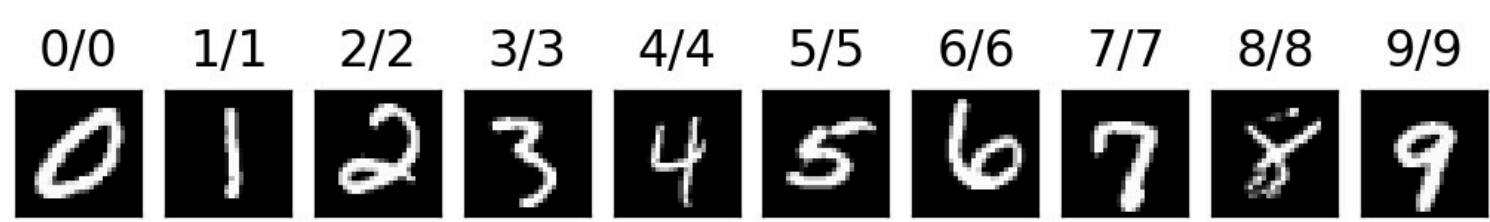
**##** In your function, feel free to use for loops. We are looking to see that you understand how to use the outputs generated by the network, not whether you can program using the most efficient python style.

## **Q2.** Comparing the correct answers (test\_labels) and network classifications  
## (test\_decisions), for each digit 0..9, find one test image (test\_image) that is classified  
## by the network correctly and one test image that is classified by the network incorrectly.  
##  
## Create a 2x10 plot of digit images (feel free to adapt the code above that uses subplot),  
## with a column for each digit 0..9 with the first row showing examples correctly classified  
## (one example for each digit) and the second row showing the examples incorrectly  
## classified (one example for each digit). Each subplot title should show the answer and  
## the classification response (e.g., displaying 4/2 as the title, if the correct answer is 4  
## and the classification was 2).

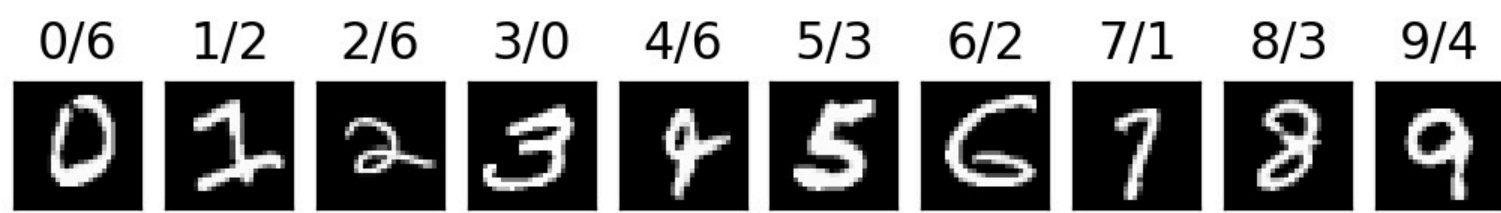
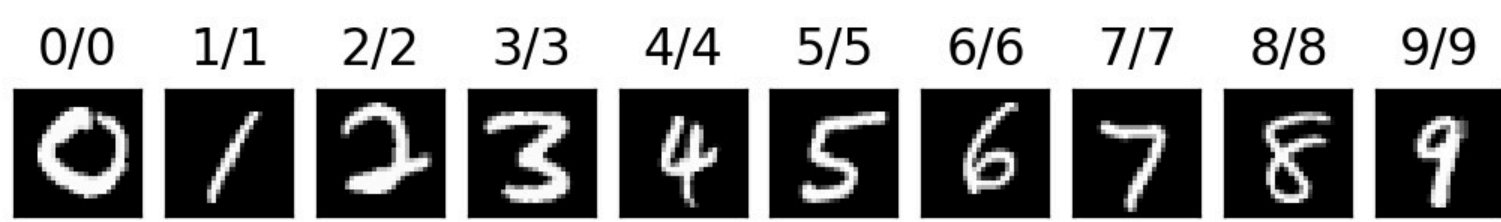




## **Q2.** Comparing the correct answers (test\_labels) and network classifications  
## (test\_decisions), for each digit 0..9, find one test image (test\_image) that is classified  
## by the network correctly and one test image that is classified by the network incorrectly.  
##  
## Create a 2x10 plot of digit images (feel free to adapt the code above that uses subplot),  
## with a column for each digit 0..9 with the first row showing examples correctly classified  
## (one example for each digit) and the second row showing the examples incorrectly  
## classified (one example for each digit). Each subplot title should show the answer and  
## the classification response (e.g., displaying 4/2 as the title, if the correct answer is 4  
## and the classification was 2).

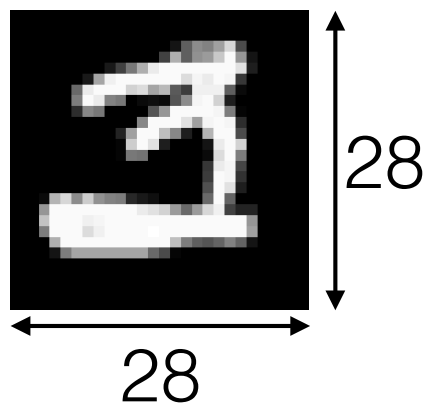
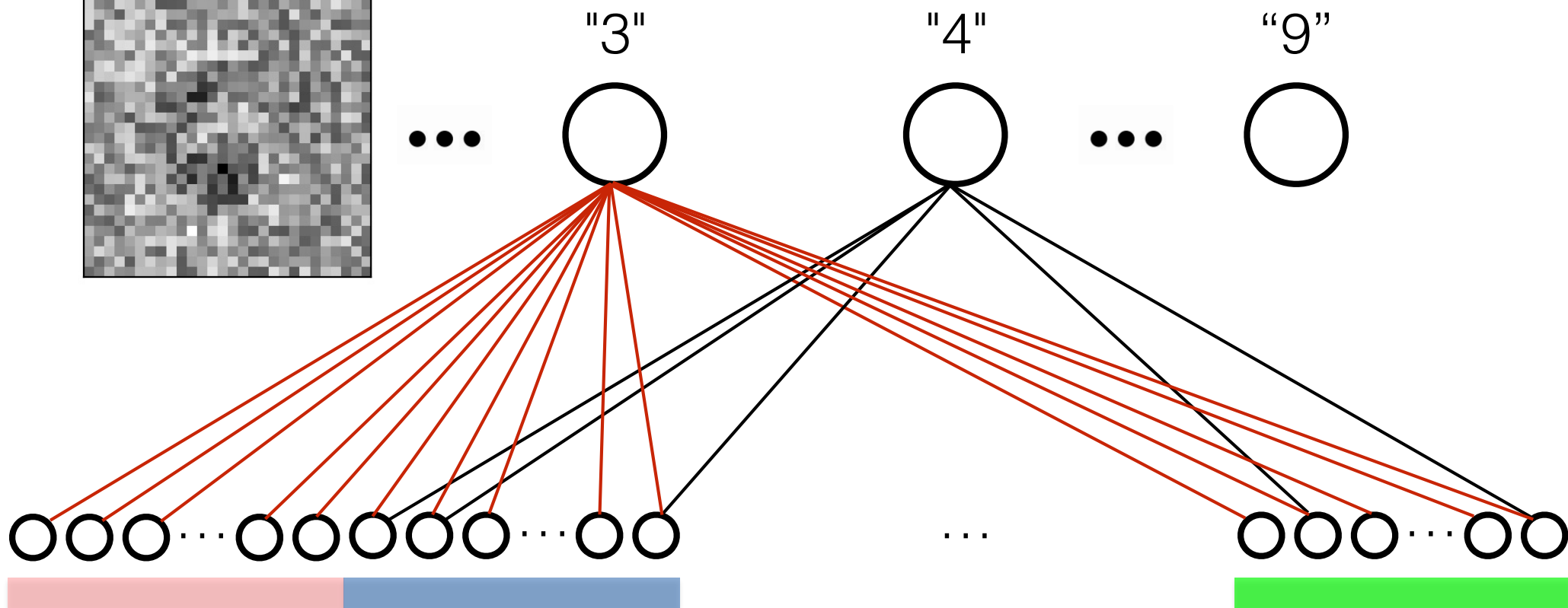
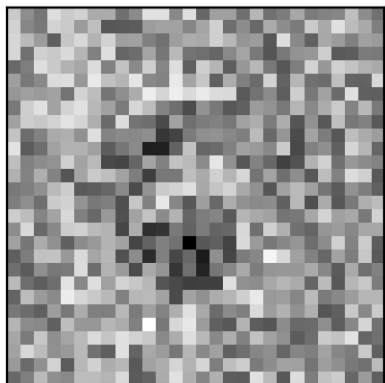


## **Q2.** Comparing the correct answers (test\_labels) and network classifications  
## (test\_decisions), for each digit 0..9, find one test image (test\_image) that is classified  
## by the network correctly and one test image that is classified by the network incorrectly.  
##  
## Create a 2x10 plot of digit images (feel free to adapt the code above that uses subplot),  
## with a column for each digit 0..9 with the first row showing examples correctly classified  
## (one example for each digit) and the second row showing the examples incorrectly  
## classified (one example for each digit). Each subplot title should show the answer and  
## the classification response (e.g., displaying 4/2 as the title, if the correct answer is 4  
## and the classification was 2).



**## Q3.** Create "images" of the connection weight adapting the code used to display the actual digit images. There should be 10 weight images, an image for each set of weight connecting the input layer (784 inputs) to each output node. You will want to reshape the (784,1) vector of weights to a (28,28) image and display the result using imshow().

weights to "3"



```
## Q4. Use the weight matrix (W), bias vector (B), and activation function (simple sigmoid)
## to reproduce in your own code the outputs (out) generated by the network (from
## this out = network.predict(test_images_vec))
##
## The simple sigmoid activation function is defined as follows:
##  $f(x) = 1 / (1 + \exp(-x))$ 
##
## Feel free to use for loops or vector/matrix operations (we will go over the latter in
## in the coming weeks)
##
## Confirm that your output vectors and the keras-produced output vectors are the same
## (within some small epsilon since floating point calculations will often not come out
## exactly the same on computers).
```

