

# Machine Learning for Physicists Lecture 1

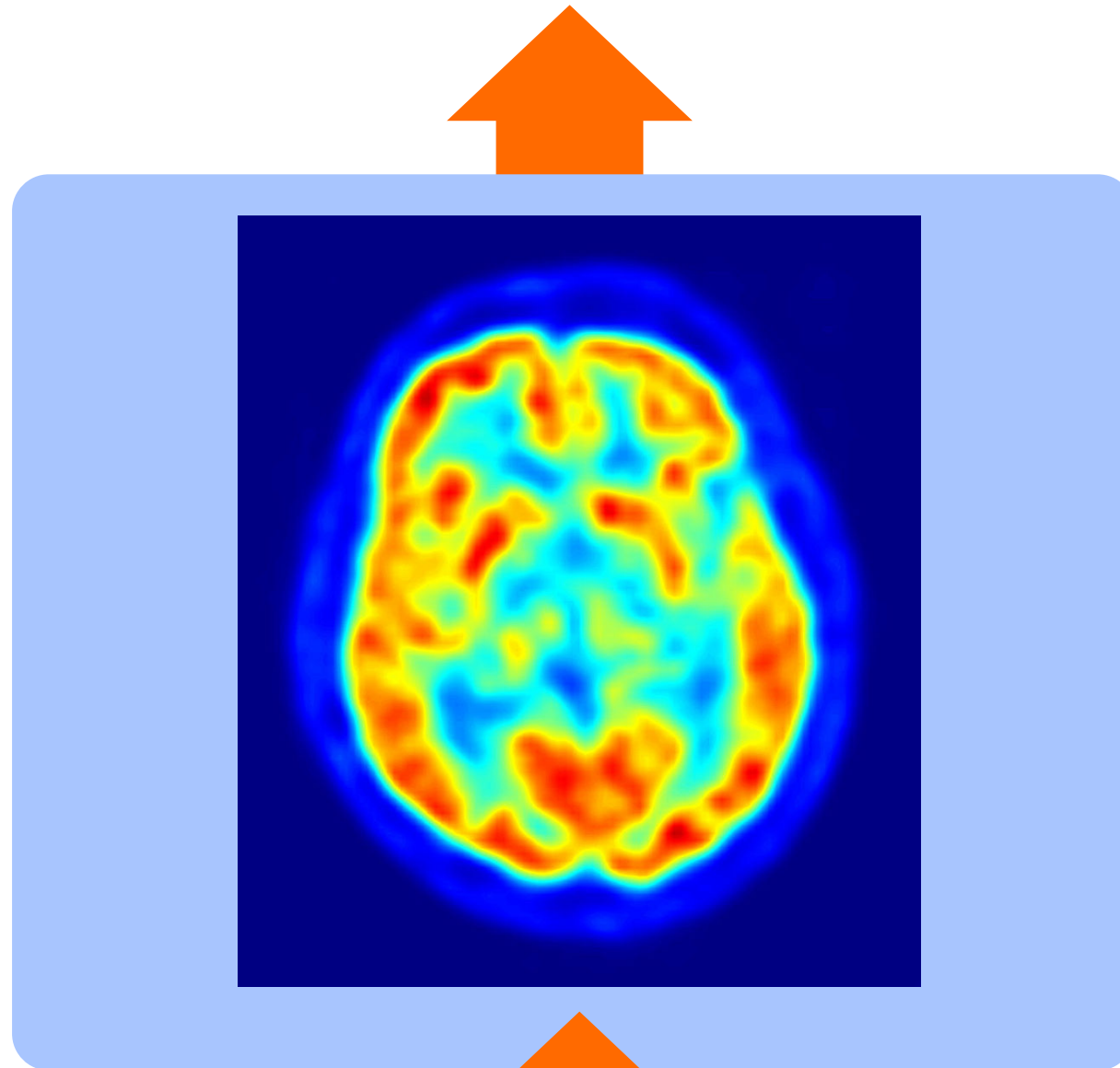
Summer 2017

University of Erlangen-Nuremberg

Florian Marquardt

(Image generated by a net with 20 hidden layers)

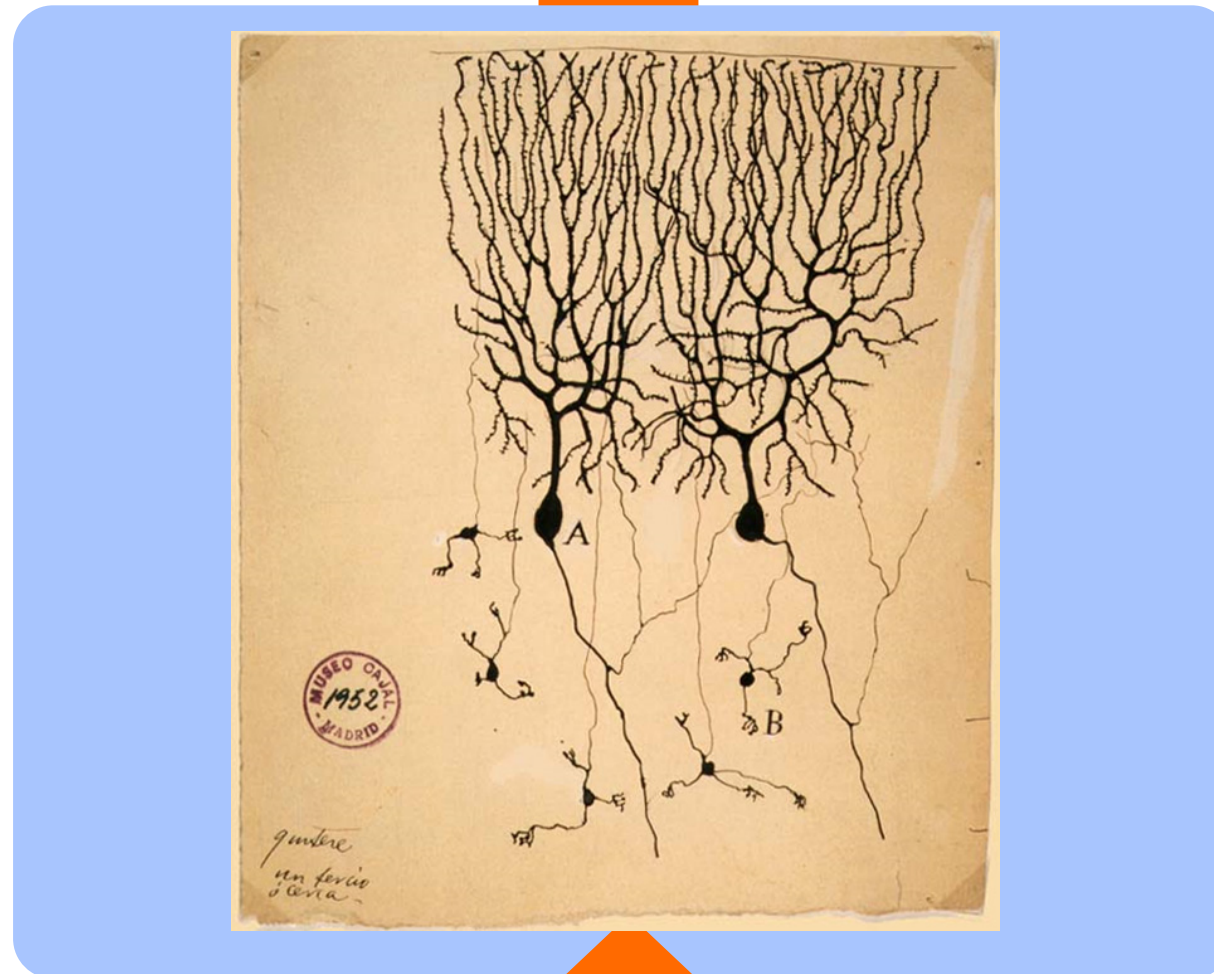
OUTPUT



INPUT



OUTPUT



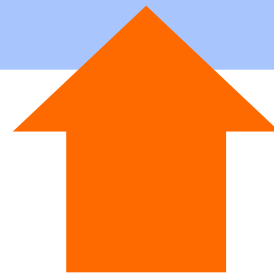
INPUT

(drawing by  
Ramon y Cajal,  
~1900)

OUTPUT



**Artificial  
Neural Network**

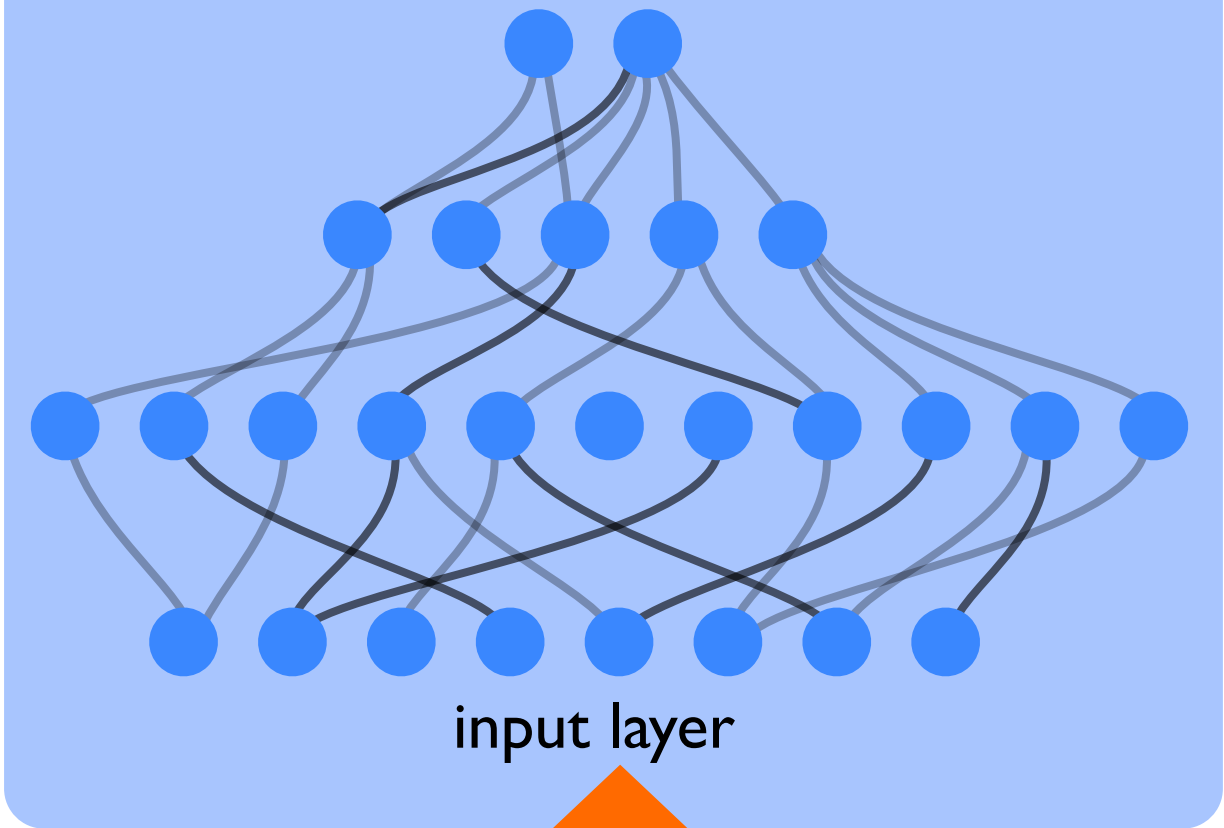


INPUT

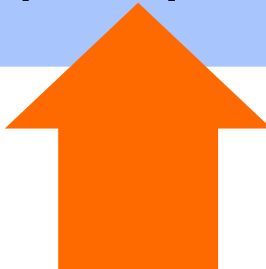
OUTPUT



output layer

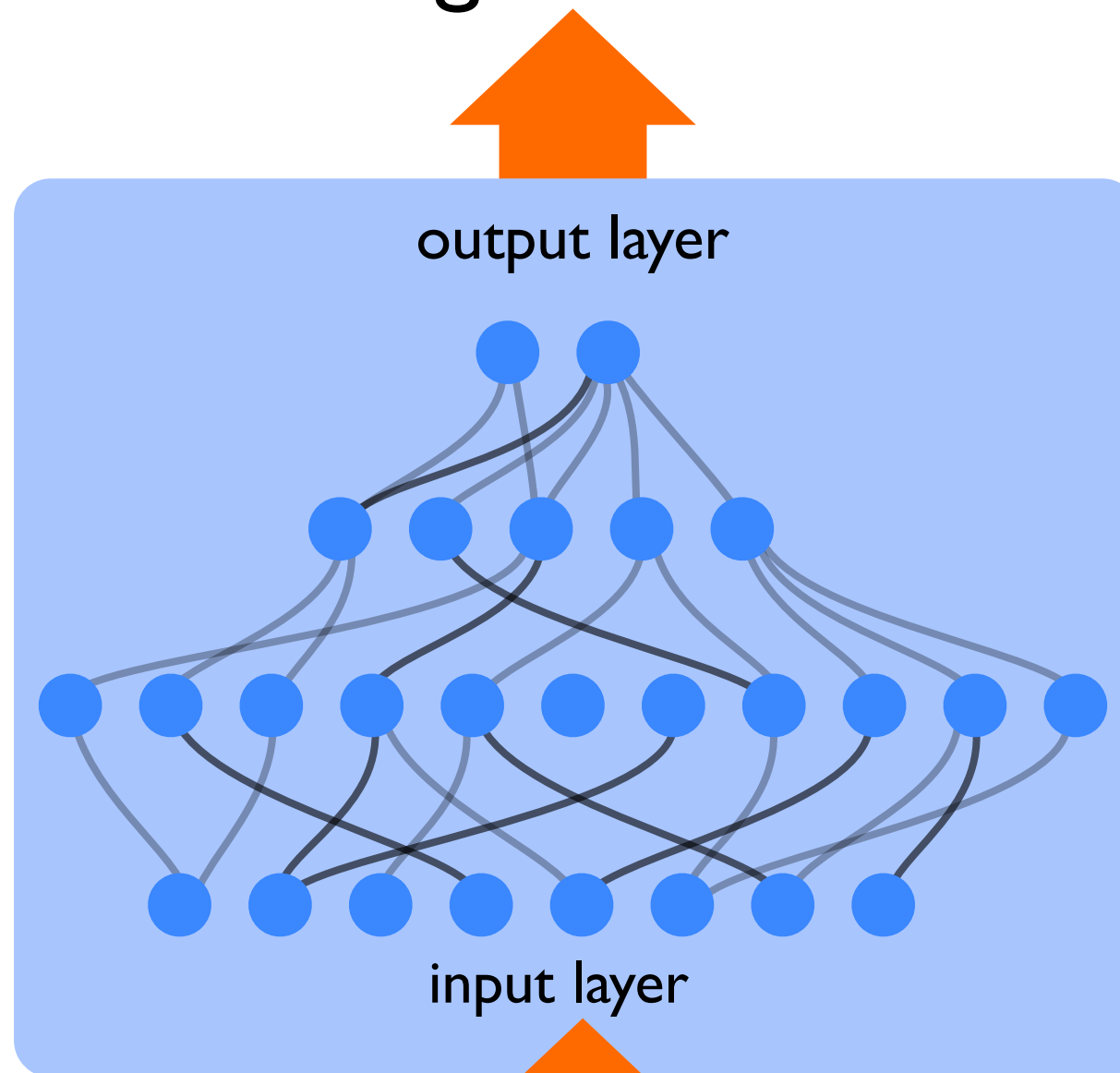


input layer



INPUT

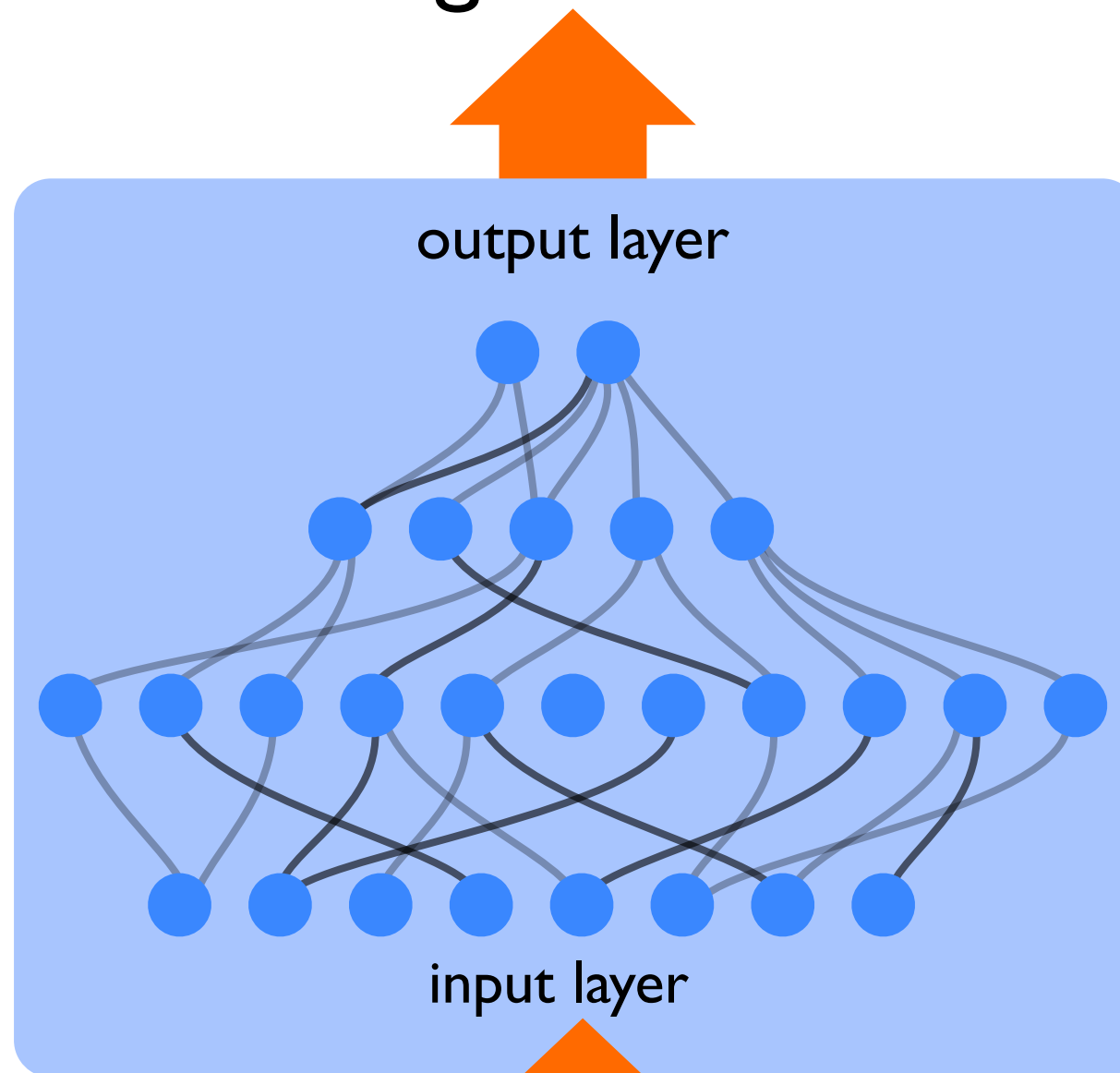
“light bulb”



(this particular picture  
has never been seen  
before!)

(Picture:Wikimedia Commons)

“light bulb”



(training images)



(Picture:Wikimedia Commons)

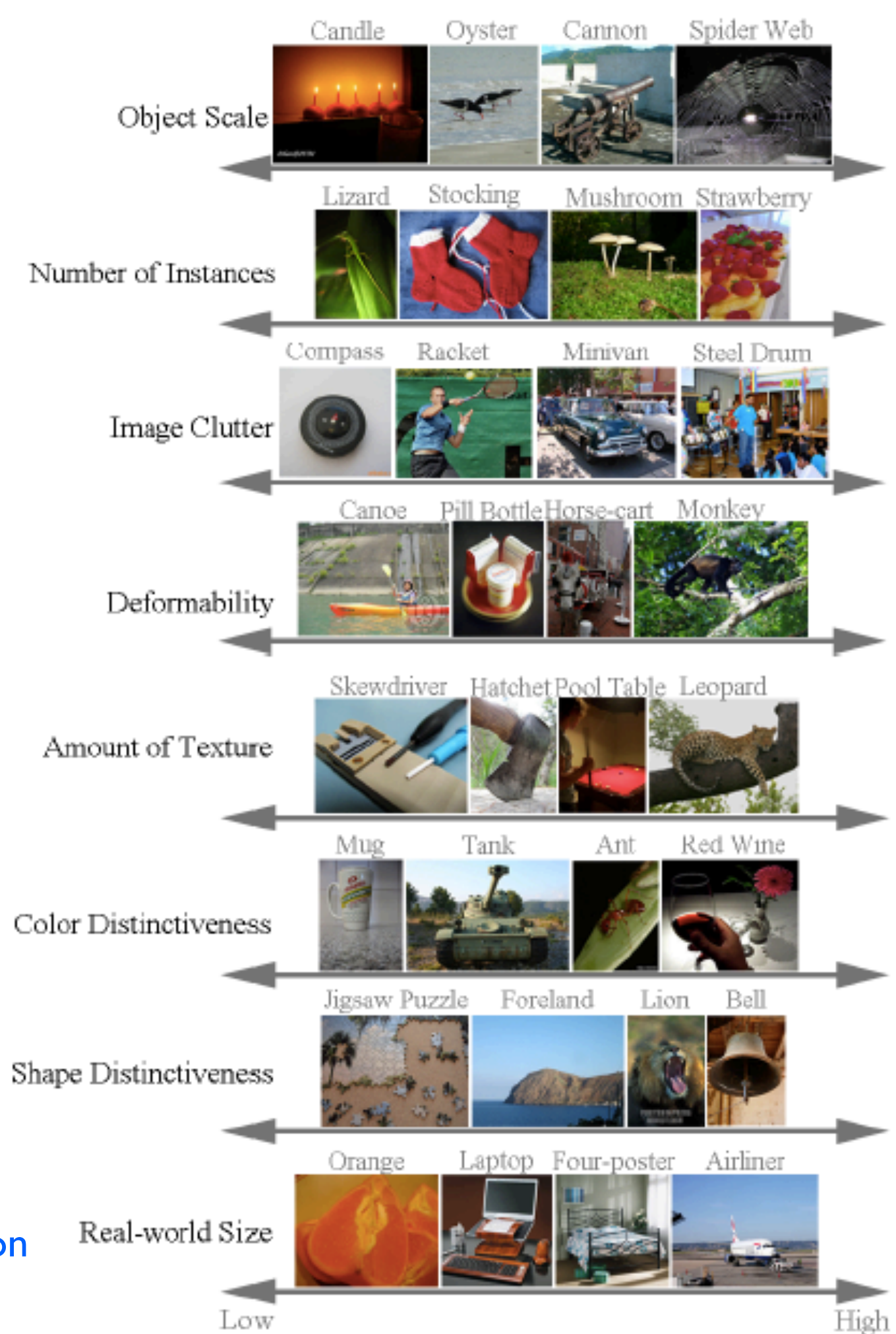
# ImageNet competition

1.2 million training pictures  
(annotated by humans)

1000 object classes

2012: A deep neural network beats  
competition clearly (16%  
error rate; since then  
rapid decrease of error  
rate, down to about 7%)

Picture: “ImageNet Large Scale Visual Recognition  
Challenge”, Russakovsky et al. 2014





# **Example applications of (deep) neural networks** (see links on website)

e.g. <http://machinelearningmastery.com/inspirational-applications-deep-learning/>

Recognize images

Describe images in sentences

Colorize images

Translate languages (French to Spanish, etc.)

Answer questions about a brief text

Play video games & board games at superhuman level

(in physics:)

predict properties of materials

classify phases of matter

represent quantum wave functions

# Lectures Outline

- Basic structure of artificial neural networks
- Training a network (backpropagation)
- Exploiting translational invariance in image processing (convolutional networks)
- Unsupervised learning of essential features (autoencoders)
- Learning temporal data, e.g. sentences (recurrent networks)
- Learning a probability distribution (Boltzmann machine)
- Learning from rare rewards (reinforcement learning)
- Further tricks and concepts
- Modern applications to physics and science

## Lecture

**Learning by doing!**

- Basic structure of neural networks
- Training a neural network (backpropagation)
- Exploring rotational invariance in image processing (convolutional neural networks)
- Unsupervised learning of essential features (autoencoders)
- Learning temporal data, e.g. sentences (recurrent neural networks)
- Learning a probability distribution (Boltzmann machine)
- Learning from rare rewards (reinforcement learning)
- Further tricks and concepts
- Modern applications to physics and science

Python

Keras  
package for  
Python

# Homework

Homework: (usually) explore via programming

We provide feedback if desired

No regular tutorial sessions

[http://www.thp2.nat.uni-erlangen.de/index.php/  
2017\\_Machine\\_Learning\\_for\\_Physicists\\_by\\_Florian\\_Marquardt](http://www.thp2.nat.uni-erlangen.de/index.php/2017_Machine_Learning_for_Physicists_by_Florian_Marquardt)



# Homework

First homework:

1. Install python & keras on your computer (see lecture homepage); questions will be resolved after second lecture **THIS IS IMPORTANT!**
2. Brainstorm: “Which problems could you address using neural networks?”

Next time: “installation party” after the lecture

Bring your laptop, if available (or ask questions)

Mo	Tu	We	Th	Fr
8.			11.	
	May			
22.				
29.				

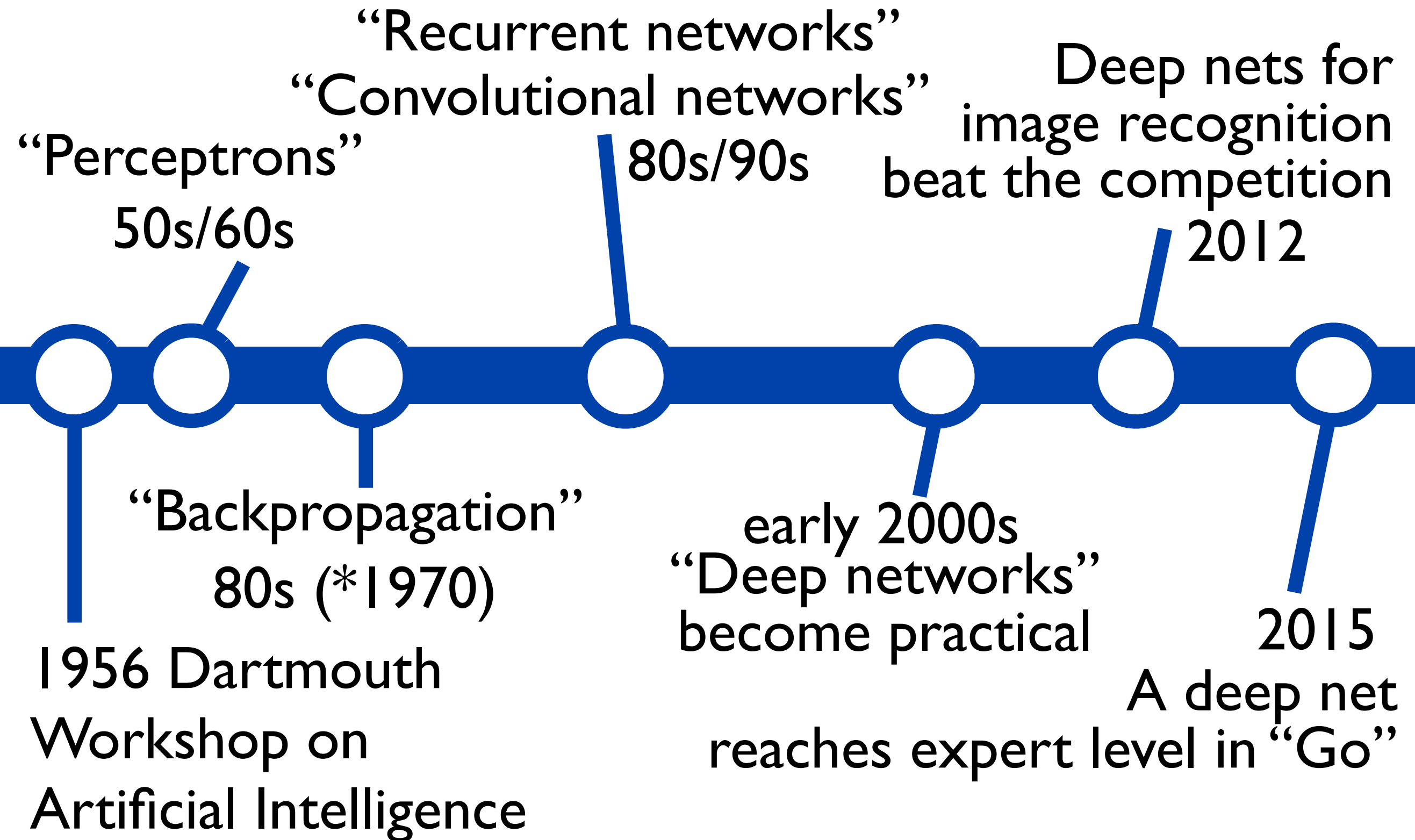
Mo	Tu	We	Th
3.			6.
10.			
17.		July	
24.			

Mo	Tu	We	Th	Fr
			1.	
			8.	
	June			
19.				
26.			29.	

Machine Learning  
Lecture Schedule  
(Summer 2017)

Mo/Th 18-20

# Very brief history of artificial neural networks



Lots of tutorials/info on the web...

recommend:

online book by Nielsen ("**Neural Networks and Deep Learning**") at <https://neuralnetworksanddeeplearning.com>

much more detailed book:

**“Deep Learning”** by Goodfellow, Bengio, Courville; MIT press; see also <http://www.deeplearningbook.org>

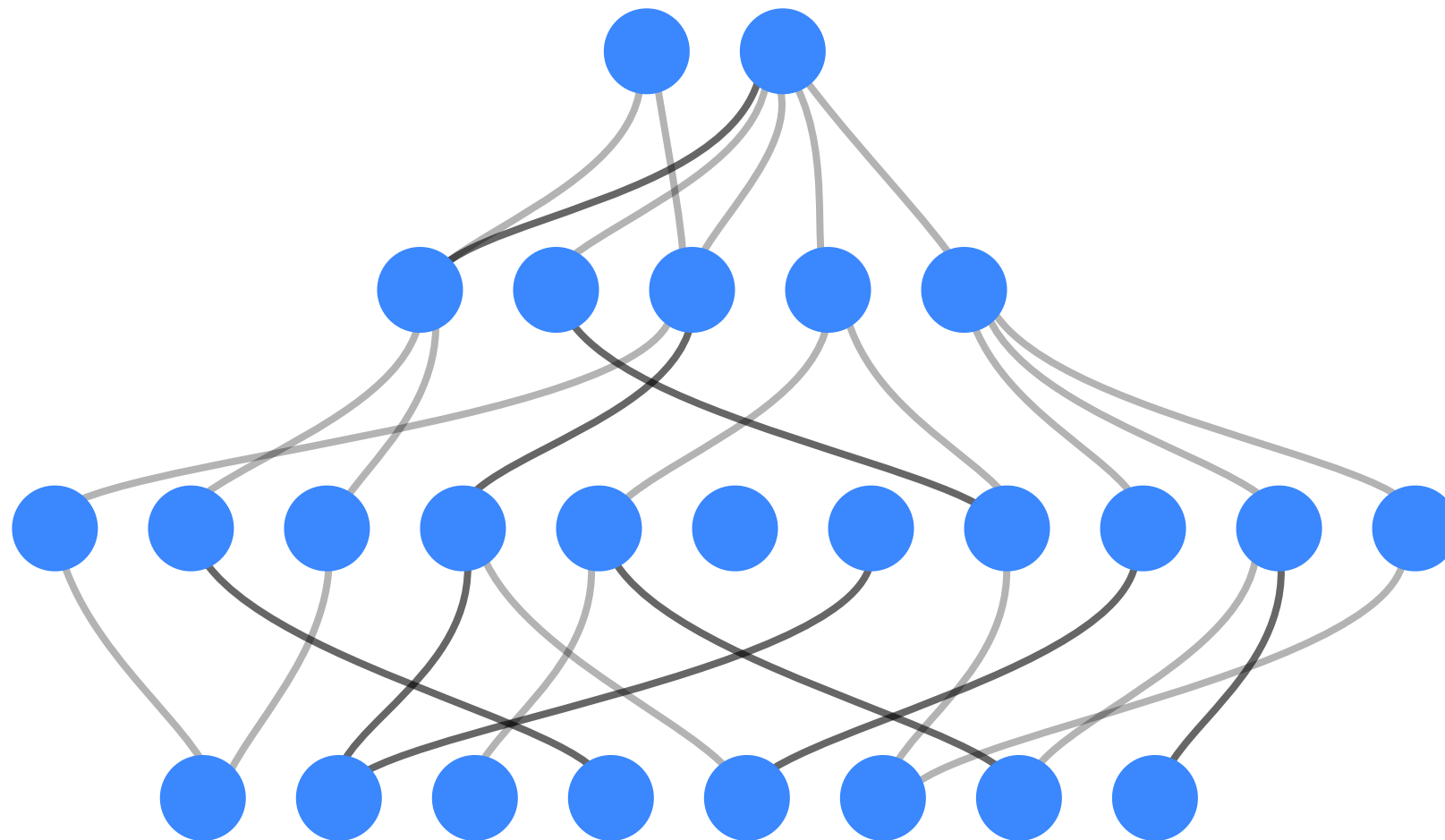
Software –

here: python & keras (builds on theano)

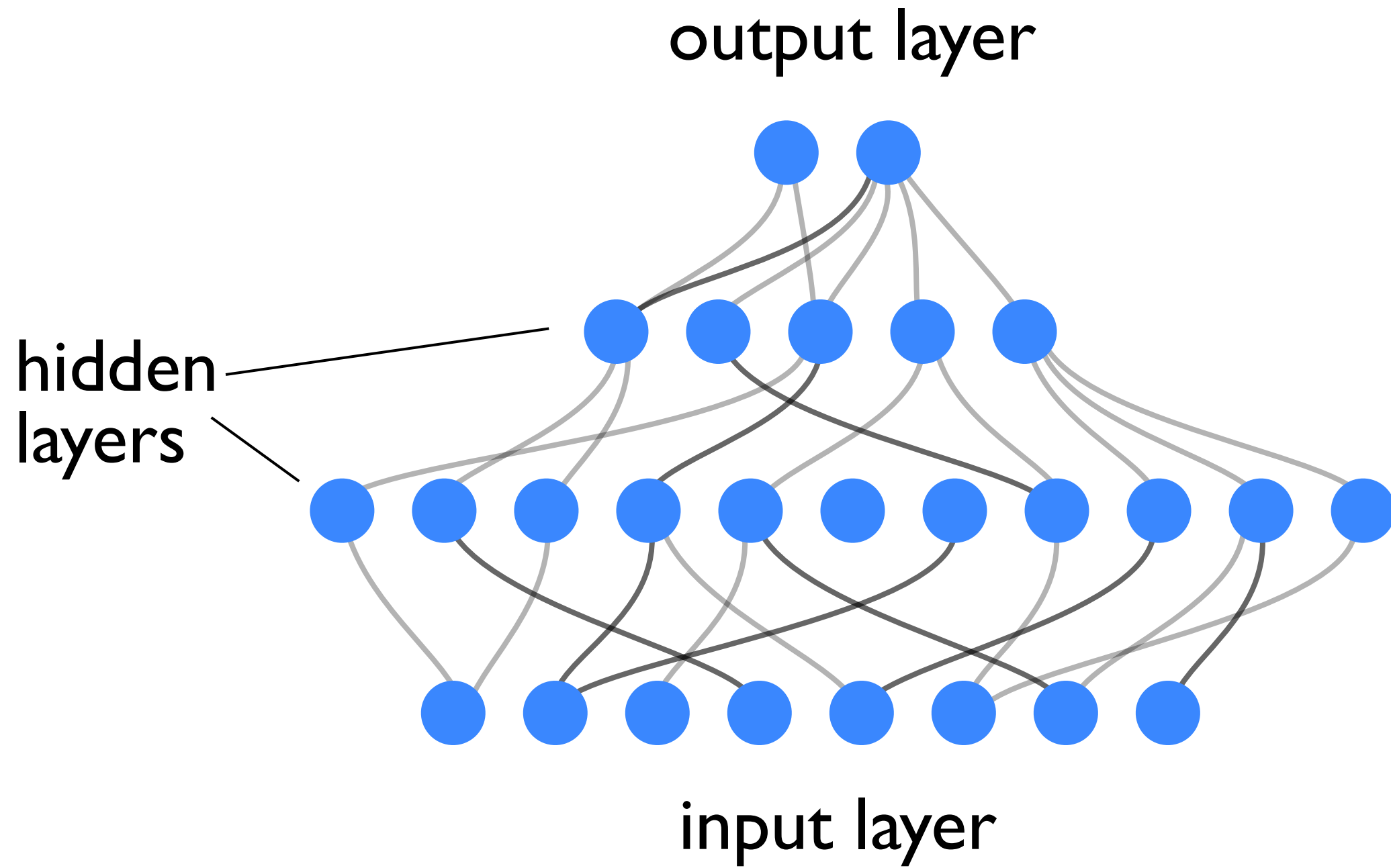


# A neural network

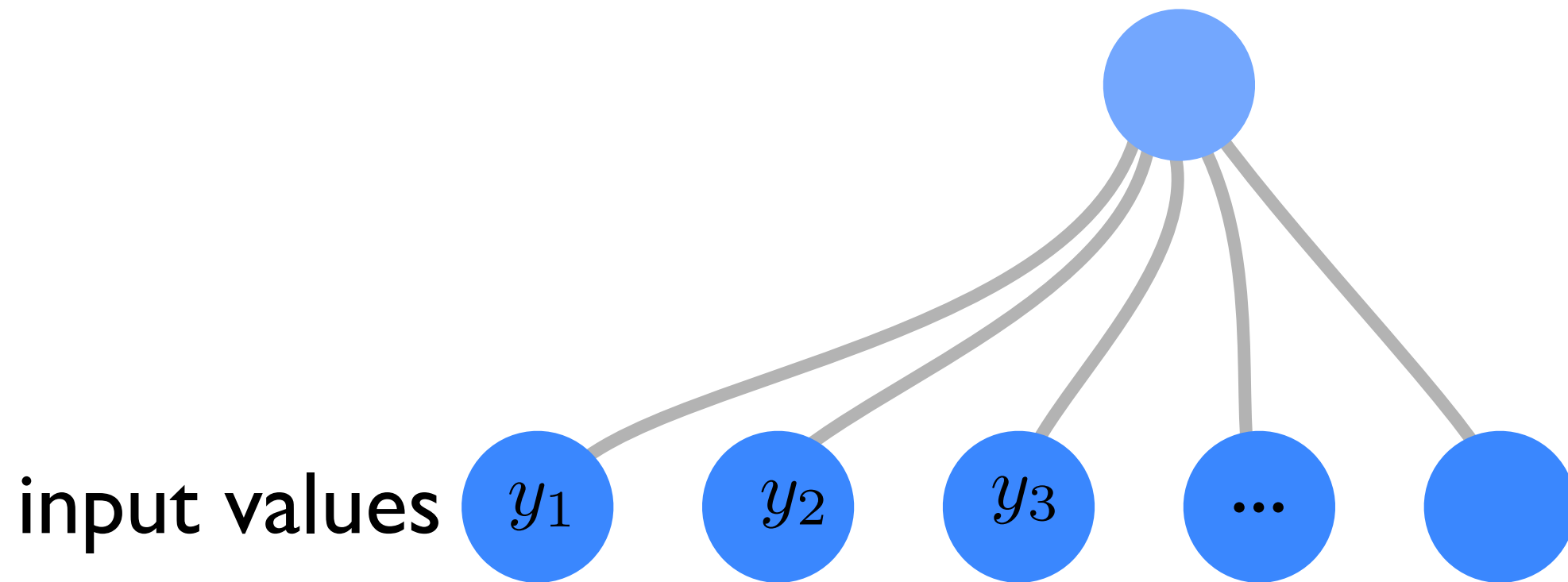
= a nonlinear function (of many variables) that depends on many parameters



# A neural network



output of a neuron =  
nonlinear function of  
weighted sum of inputs



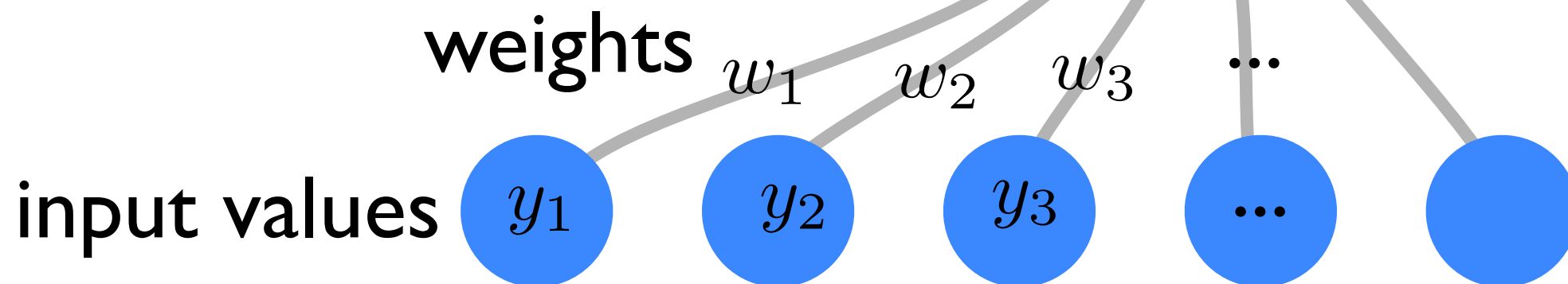
output of a neuron =  
nonlinear function of  
weighted sum of inputs

weighted sum

$$z = \sum_j w_j y_j + b$$

(offset, "bias")

output value





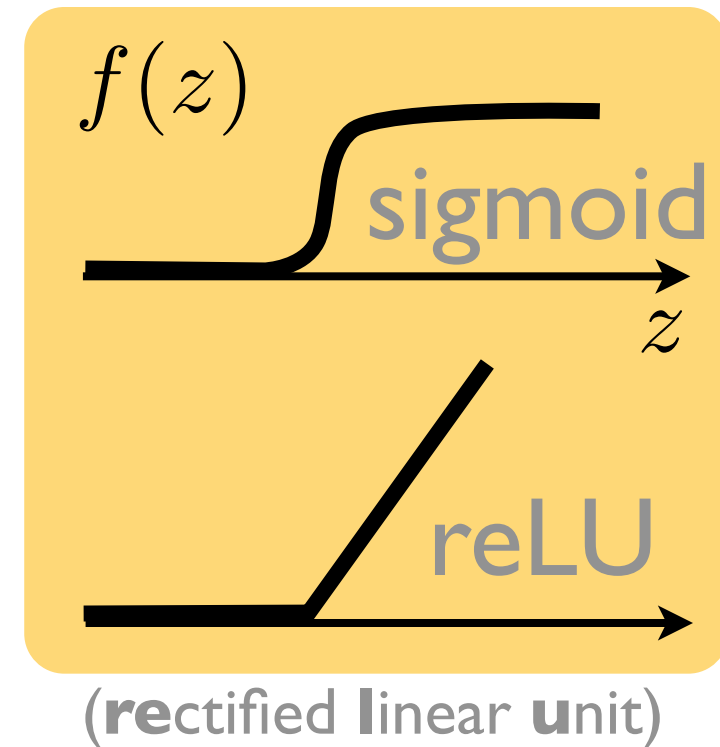
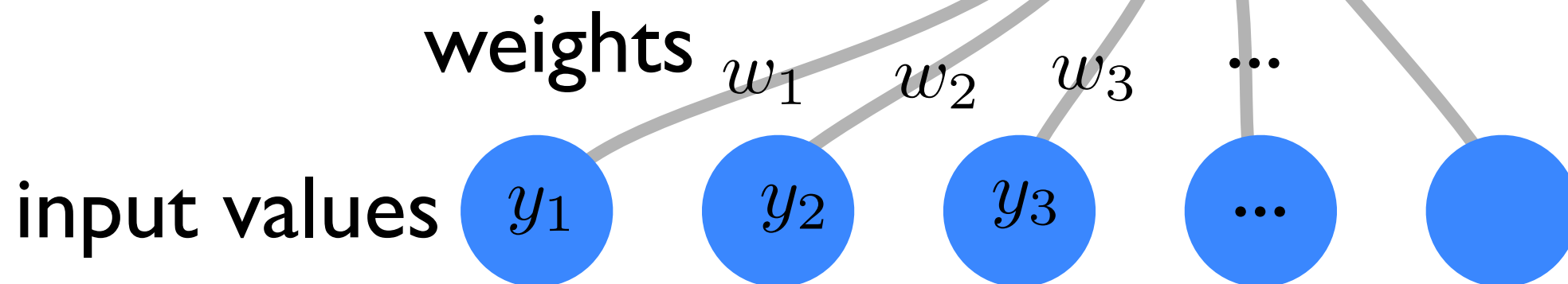
output of a neuron =  
nonlinear function of  
weighted sum of inputs

weighted sum

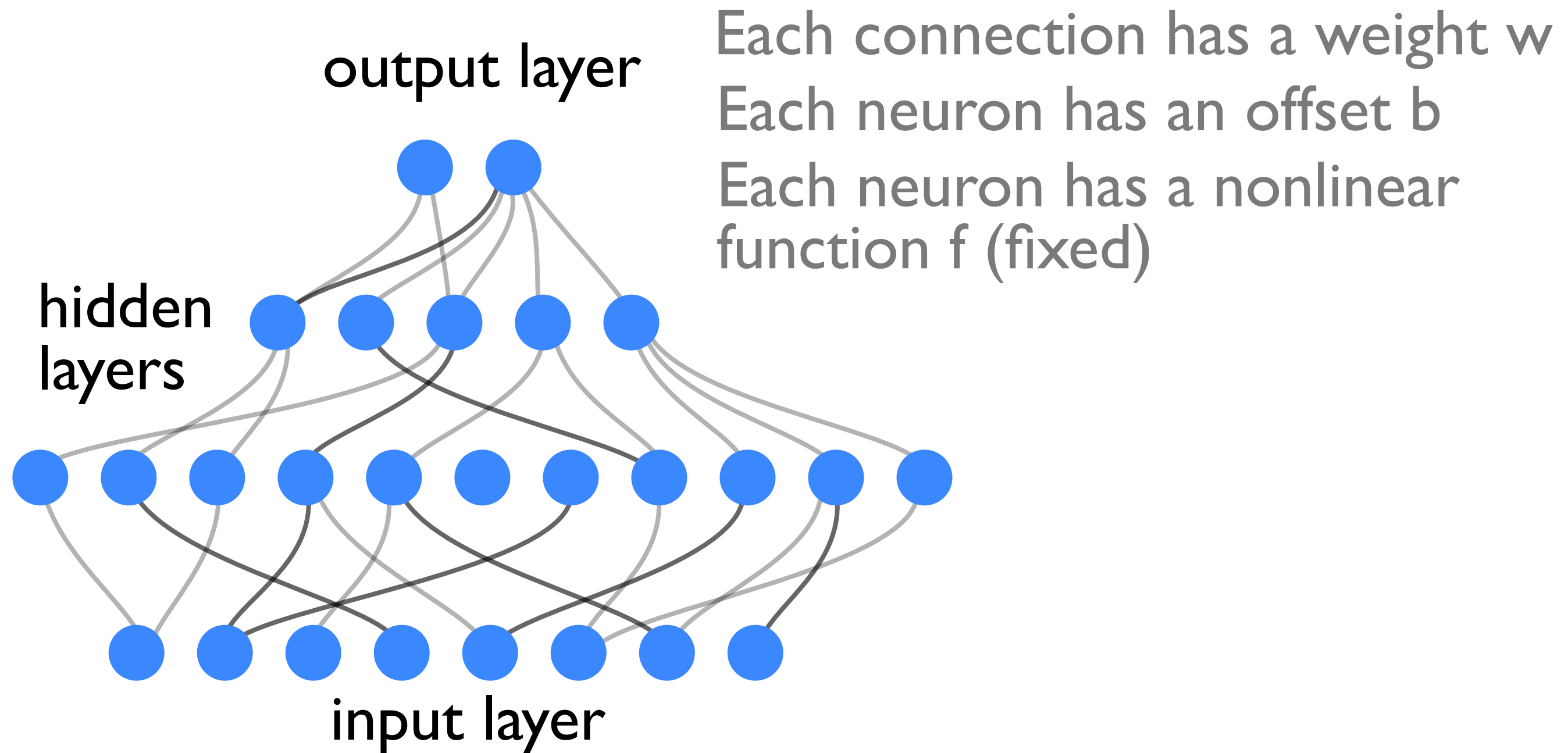
$$z = \sum_j w_j y_j + b$$

(offset, "bias")

output value

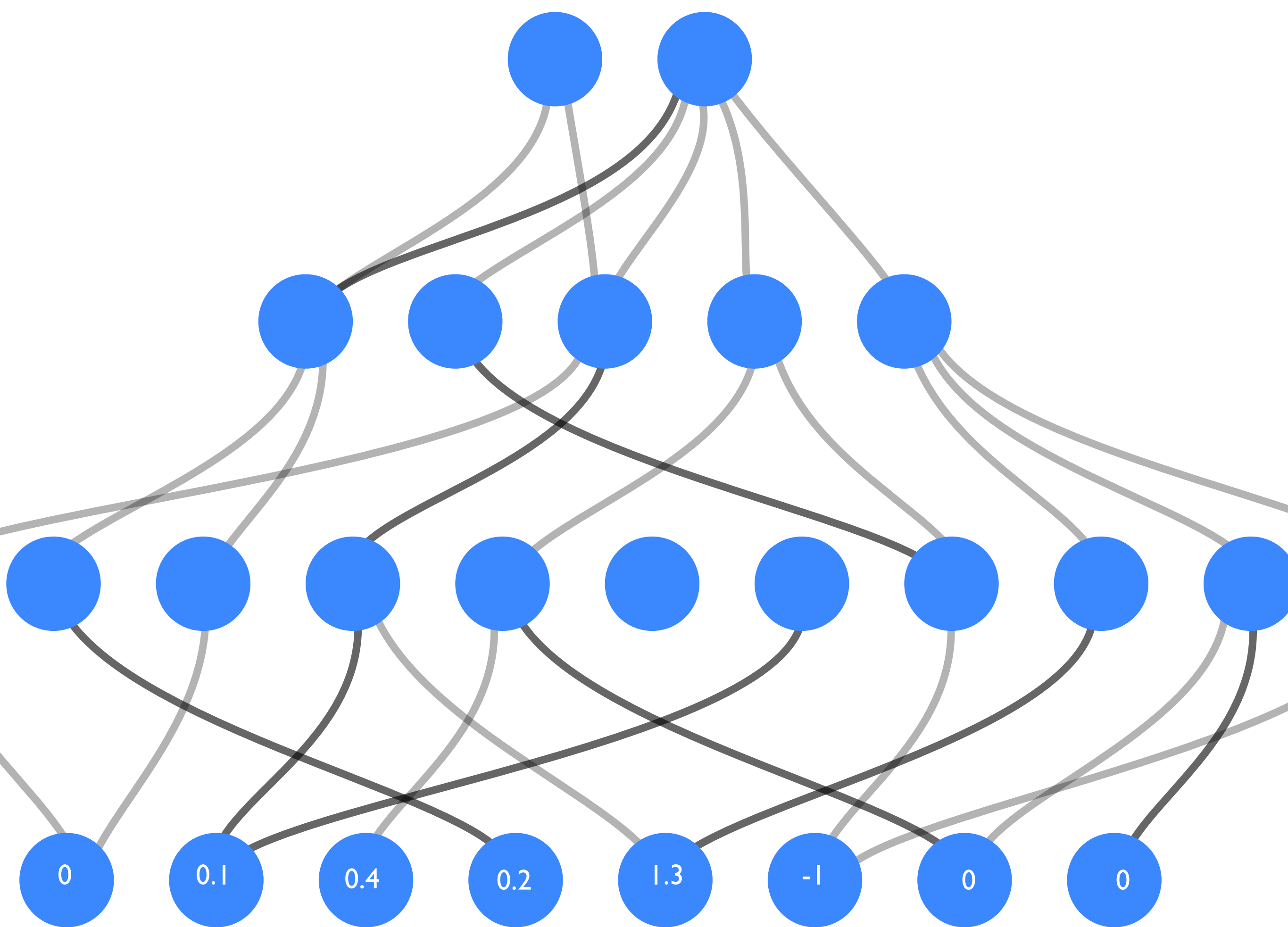


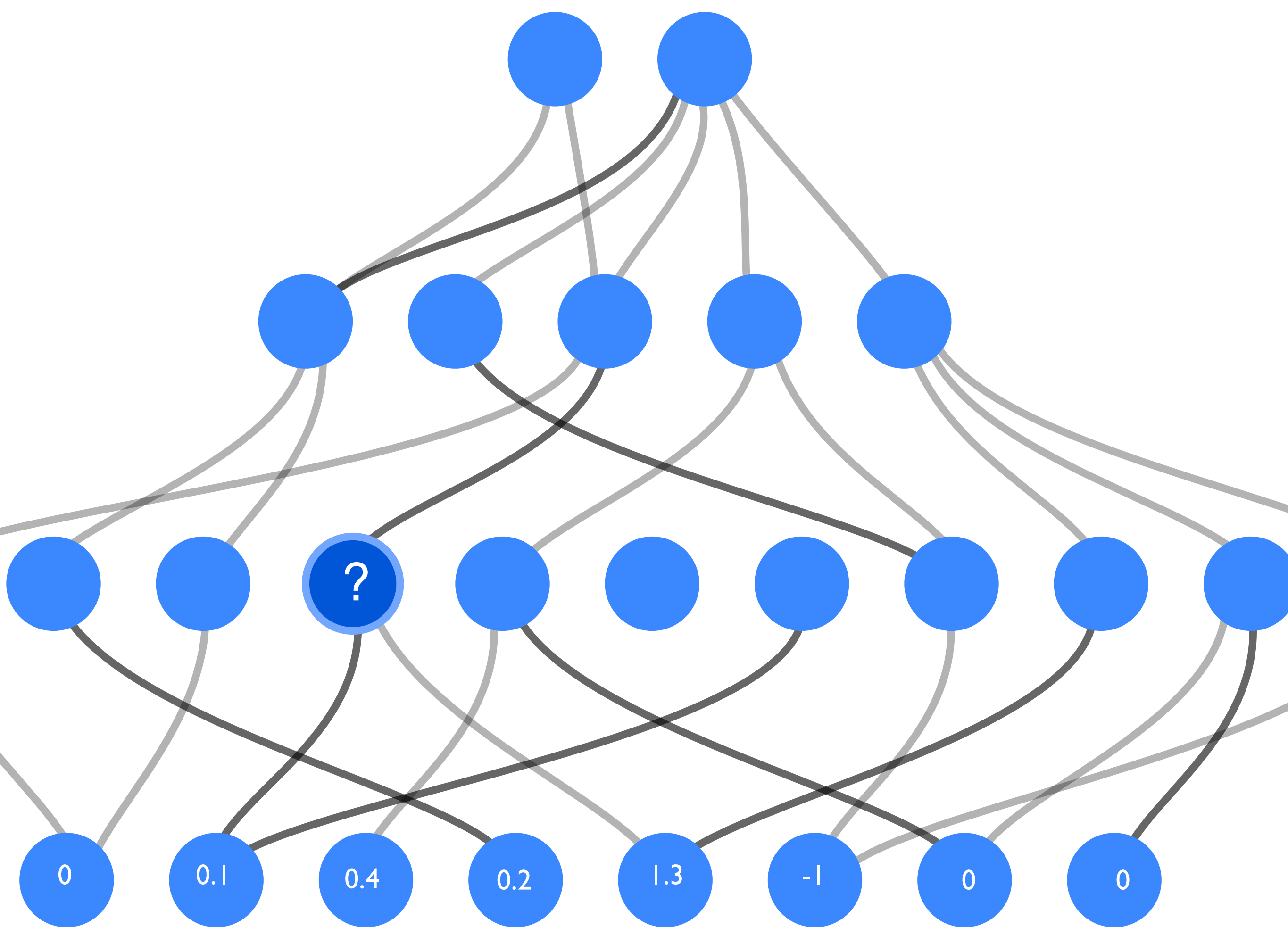
# A neural network



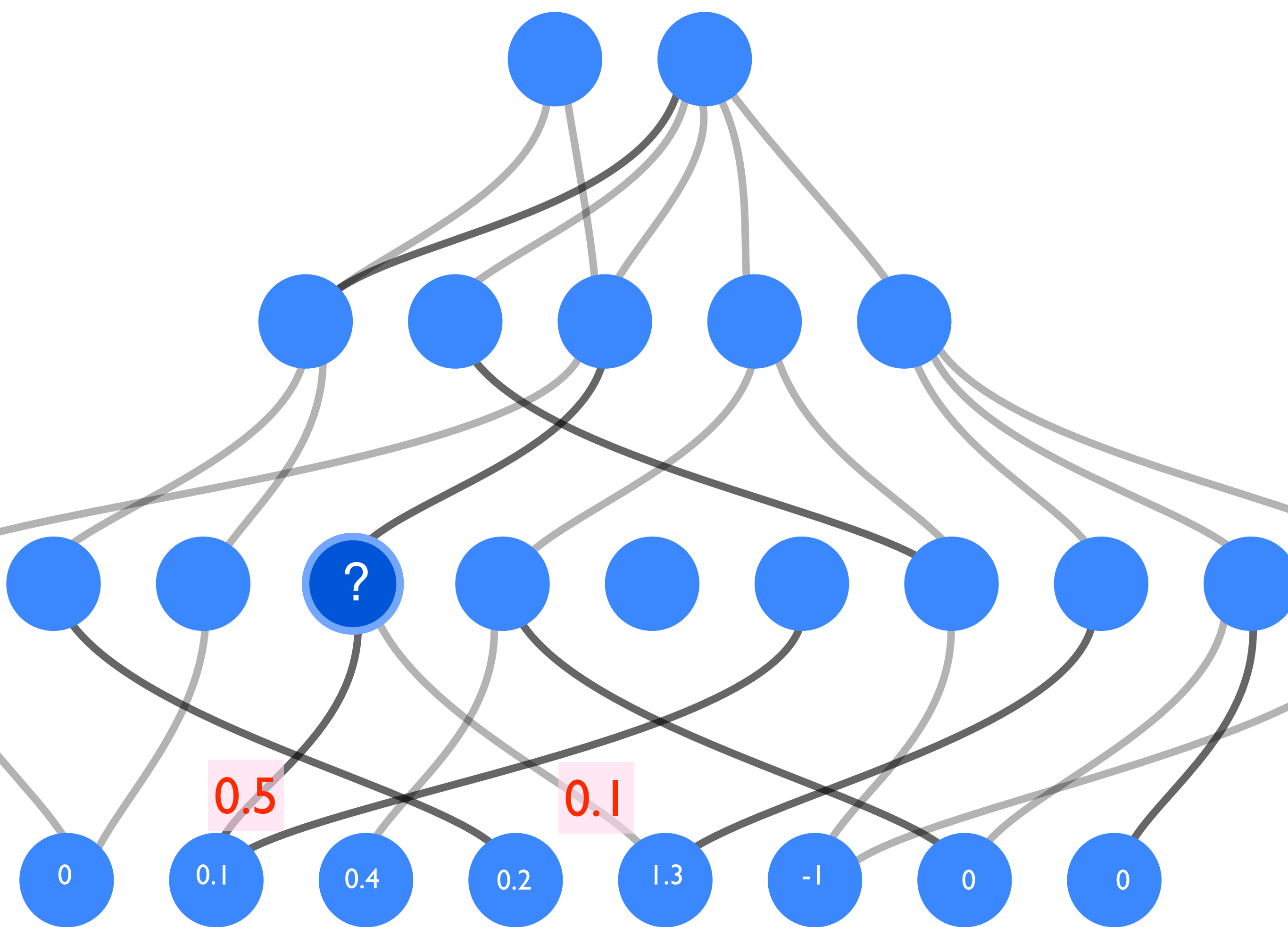
Each connection has a weight  $w$   
Each neuron has an offset  $b$   
Each neuron has a nonlinear function  $f$  (fixed)

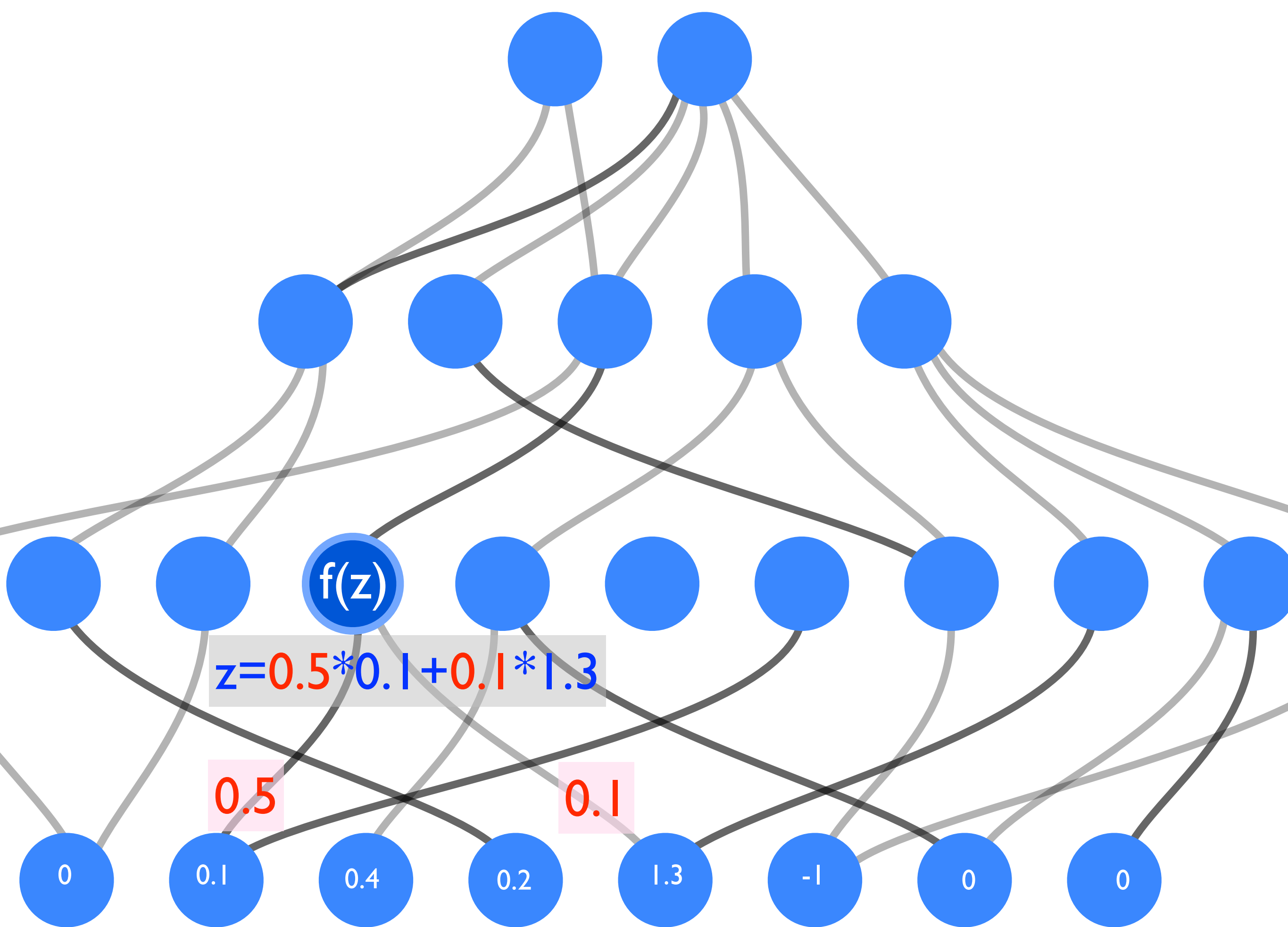
The values of input layer neurons are fed into the network from the outside



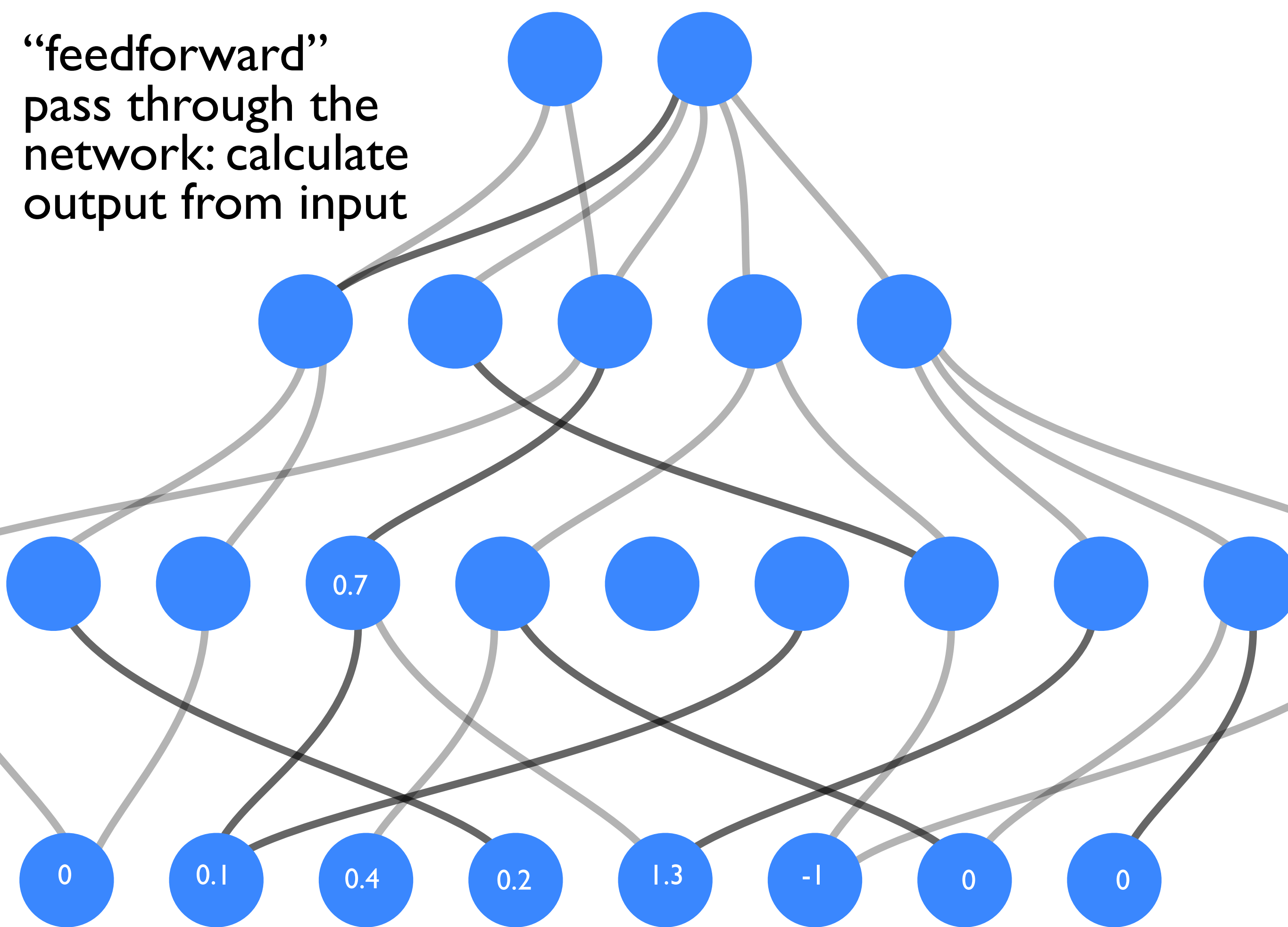




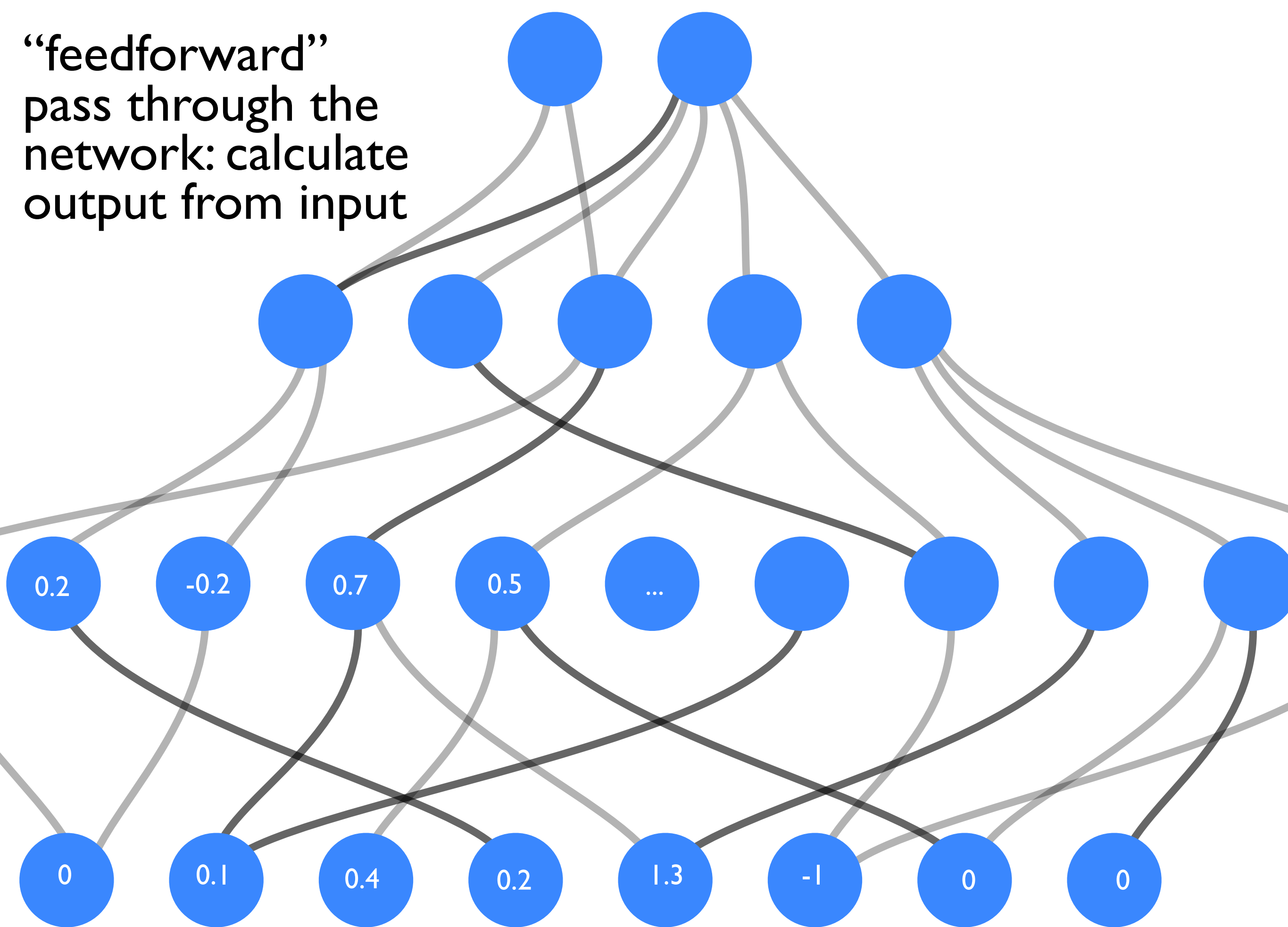




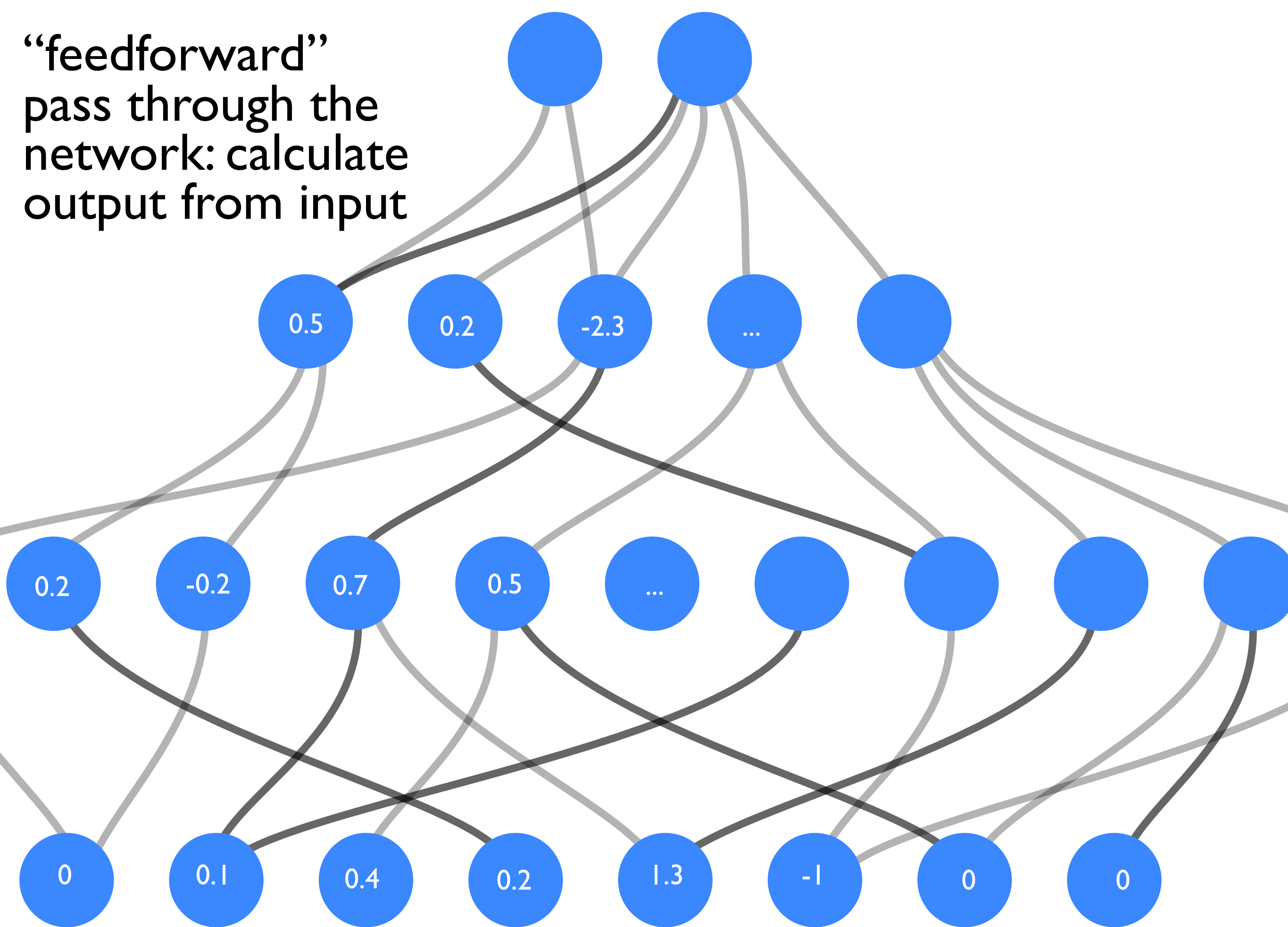
“feedforward”  
pass through the  
network: calculate  
output from input



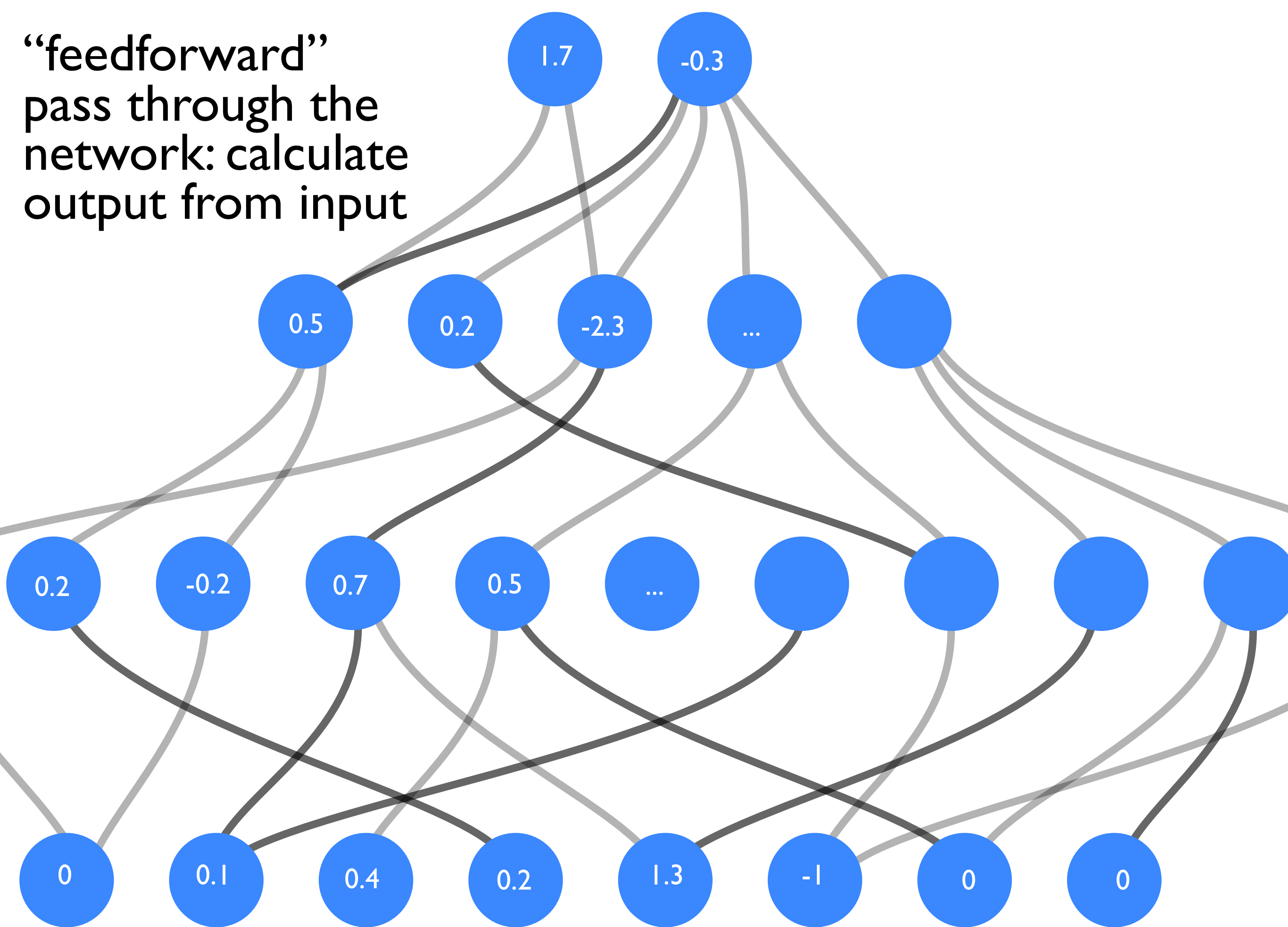
“feedforward”  
pass through the  
network: calculate  
output from input



“feedforward”  
pass through the  
network: calculate  
output from input



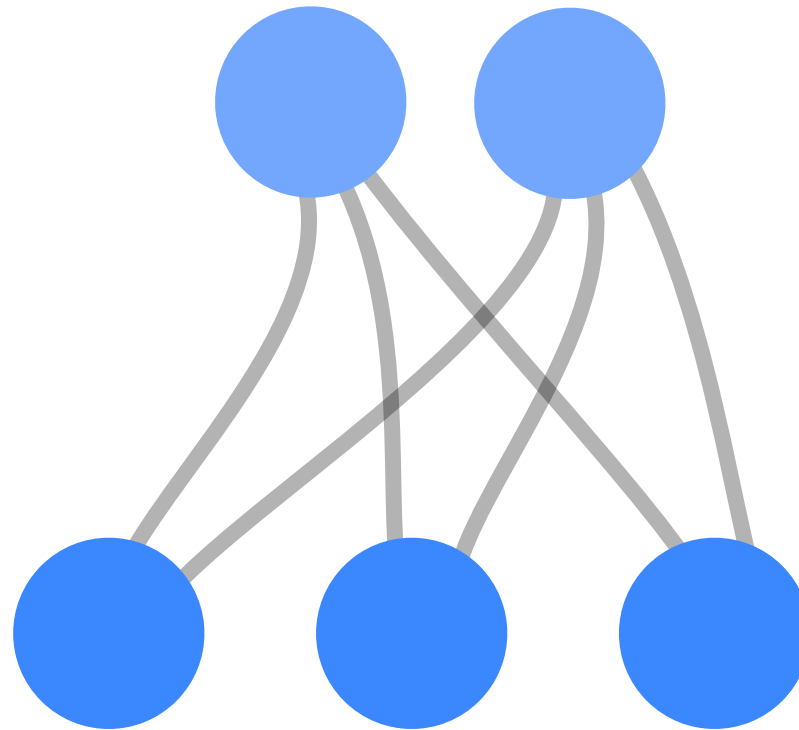
“feedforward”  
pass through the  
network: calculate  
output from input



# One layer

output

input



j=output neuron  
k=input neuron

$$z_j = \sum_k w_{jk} y_k^{\text{in}} + b_j$$

in matrix/vector notation:

$$z = w y^{\text{in}} + b$$

elementwise nonlinear function:

$$y_j^{\text{out}} = f(z_j)$$



```
for j in range(N):  
    do_step(j)  
  
u=dot(M,v)  
  
def f(x):  
    return(sin(x)/x)  
  
x=linspace(-5,5,N)
```

**Anaconda**

**Jupyter**

**Python**

localhost

AnimTestNew MachineLearning\_Basics ipython - matplotlib python inline o... 2017 Machine Learning for Physici...

**jupyter** MachineLearning\_Basics (autosaved)

File Edit View Insert Cell Kernel Help Python [Root]

Code

### A very simple neural network (input to output)

```
In [494]: from numpy import * # get the "numpy" library for linear algebra
```

```
In [495]: N0=3 # input layer size
          N1=2 # output layer size

          w=random.uniform(low=-1,high=+1,size=(N1,N0)) # random weights: N1xN0
          b=random.uniform(low=-1,high=+1,size=N1) # biases: N1 vector
```

```
In [496]: y_in=array([0.2,0.4,-0.1]) # input values
```

```
In [498]: z=dot(w,y_in)+b # result: the vector of 'z' values, length N1
```

Anaconda Jupyter

# python

# A few lines of “python” !

Python code

vector ( $N_{out}$ ) —  **$z = \text{dot}(w, y) + b$**  — vector ( $N_{in}$ )

matrix ( $N_{out} \times N_{in}$ )    vector ( $N_{out}$ )

$$z_j = \sum_k w_{jk} y_k^{\text{in}} + b_j$$

in matrix/vector notation:

$$z = w y^{\text{in}} + b$$

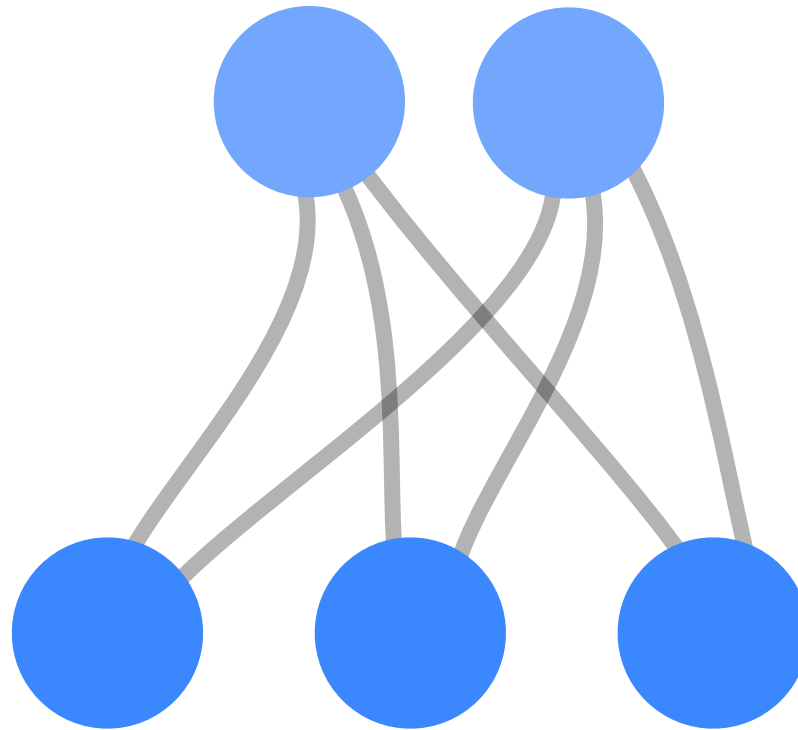
# A few lines of “python” !

output

$N1=2$

input

$N0=3$



Random weights and biases

```
N0=3 # input layer size  
N1=2 # output layer size
```

```
w=random.uniform(low=-1,high=+1,size=(N1,N0)) # random weights: N1xN0  
b=random.uniform(low=-1,high=+1,size=N1) # biases: N1 vector
```

```
y_in=array([0.2,0.4,-0.1]) # input values
```

Input values

```
z=dot(w,y_in)+b # result: the vector of 'z' values, length N1  
y_out=1/(1+exp(-z)) # the sigmoid function (applied elementwise)
```

Apply network!