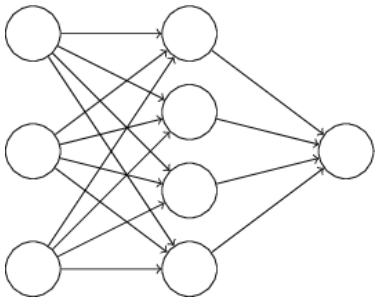
# Introduction to Artificial Neural Networks

*Prepared for PyData Denver*

by

Ryan Arredondo

03/08/2017



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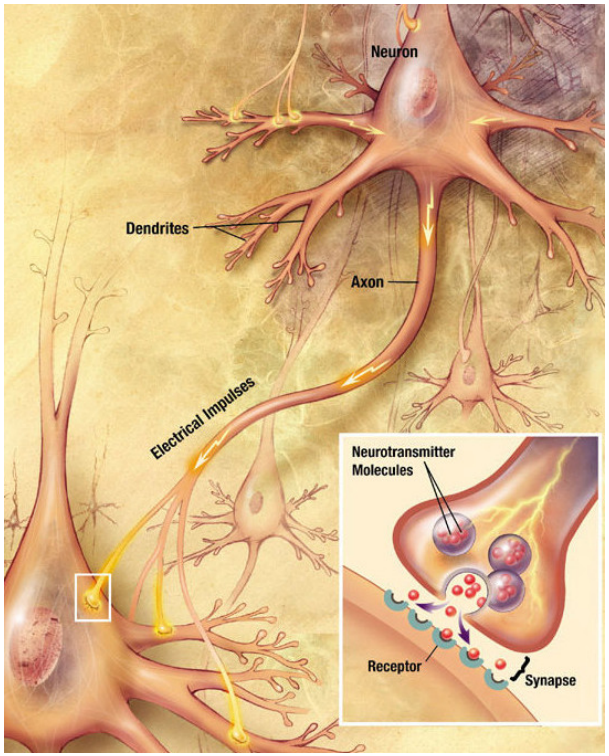
# Biologically Motivated

- Artificial neural networks were motivated by models of how learning could happen in the brain.




Source: http://www.nia.nih.gov/alzheimers/publication/alzheimers-disease-unraveling-mystery/preface

# First Wave (1940s – 1960s)

## Linear Models

Models computed a linear function

$$f(x, w) = x_1 w_1 + x_2 w_2 + \cdots + x_n w_n$$

from an input $x$ and a set of weights $w$.

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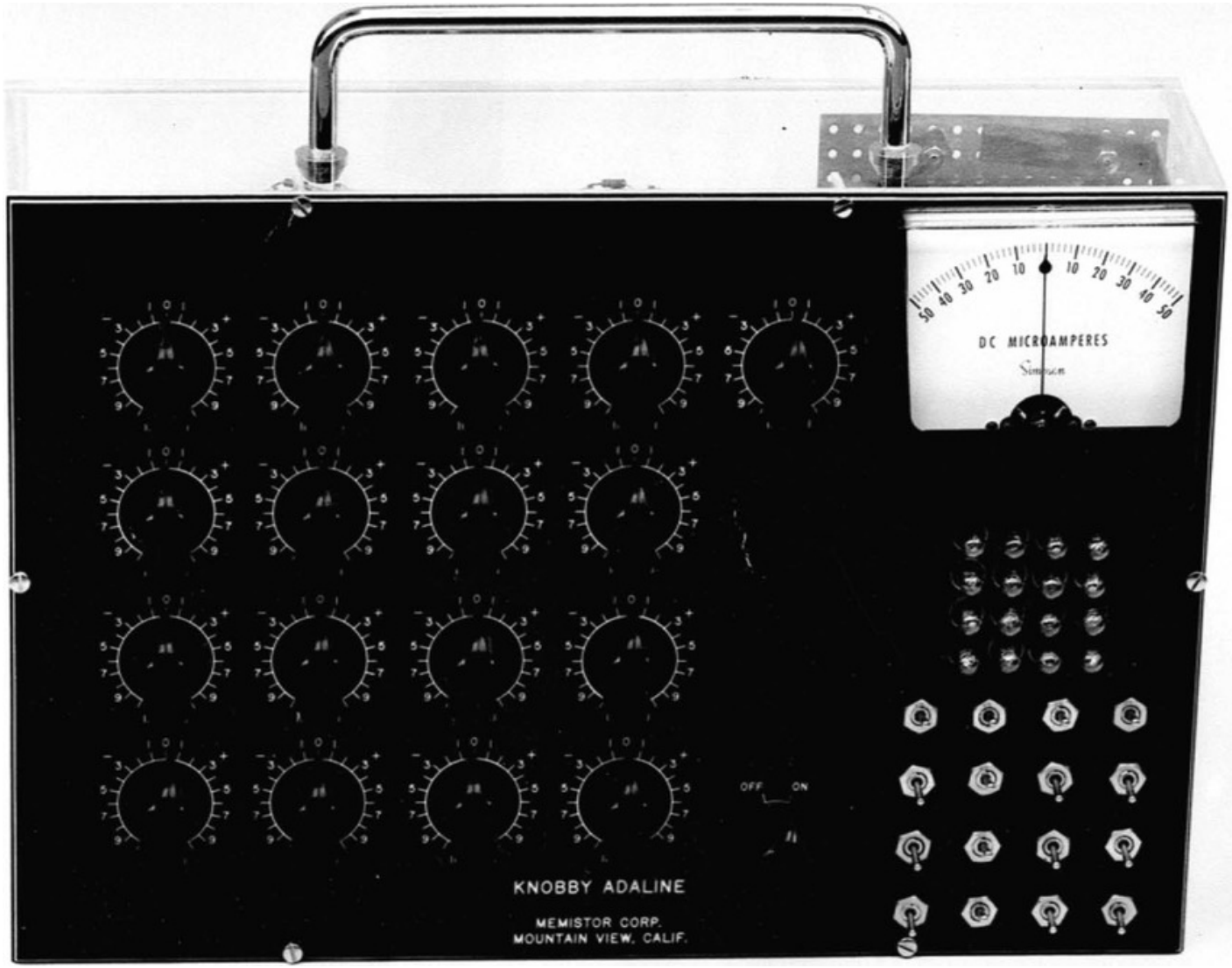
- **(1960) Widrow and Hoff's adaptive linear neuron:** trained using a special case of stochastic gradient descent




ADALINE. An adaptive linear neuron.

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- **Distributed representation:** the inputs should have many features, and the features should be representative of many inputs
- **Backpropagation:** Algorithm to train neural networks. Is still the dominant approach today.

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- **Increasing model sizes.** Models double in size every $\sim$2.4 years.
- **Increasing accuracy and complexity.** Significant drops in the error rate for object and speech recognition problems using NNs.

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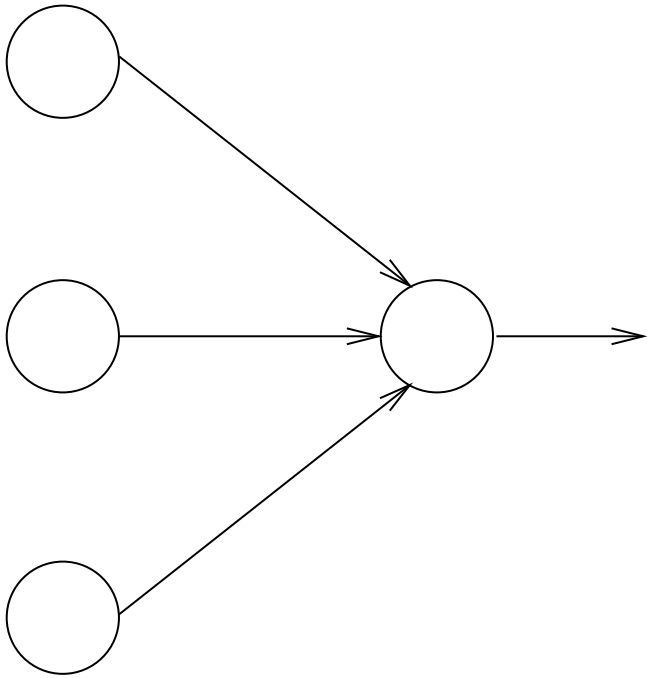
# The Simplest Neural Network

Sinlge-layer perceptron:



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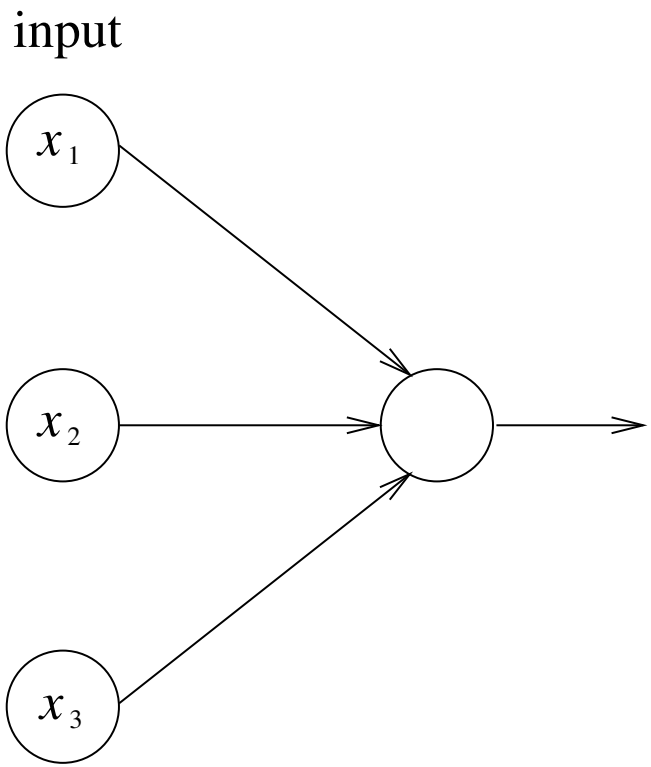

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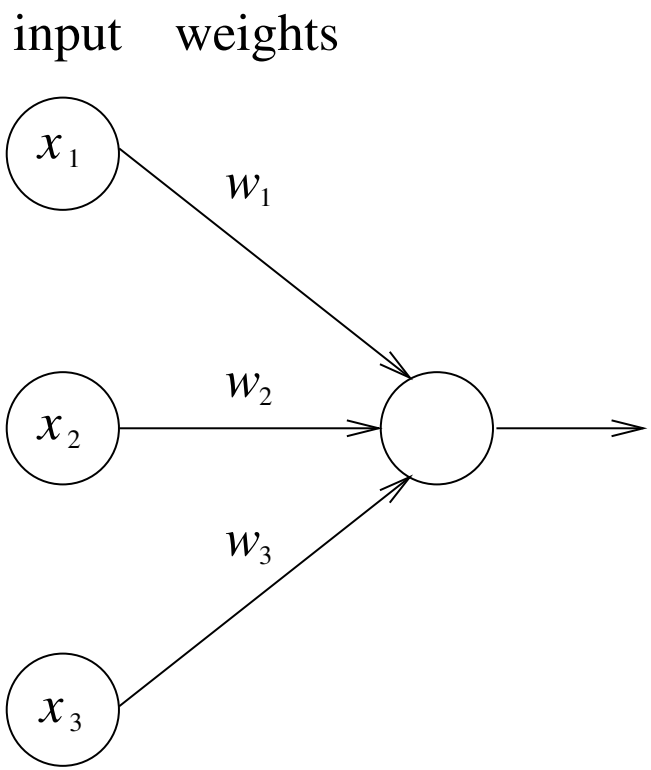

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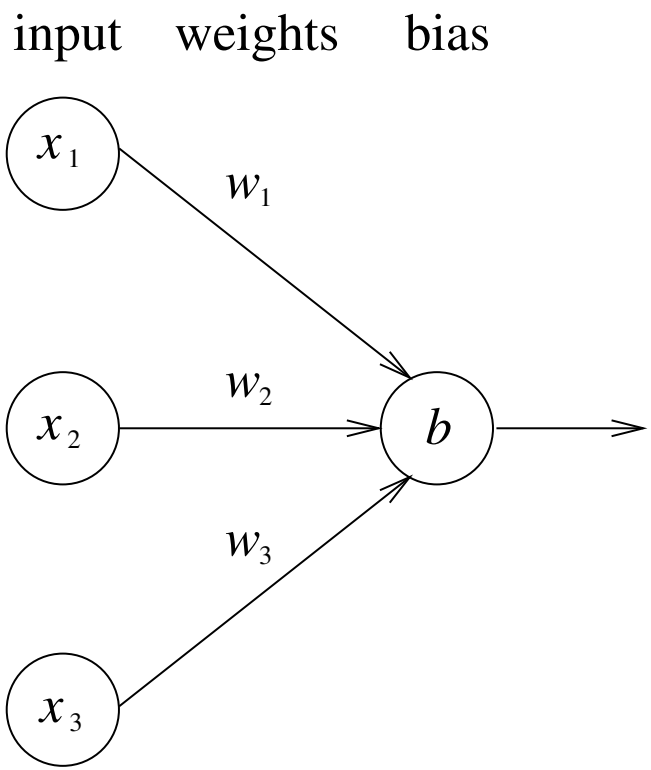

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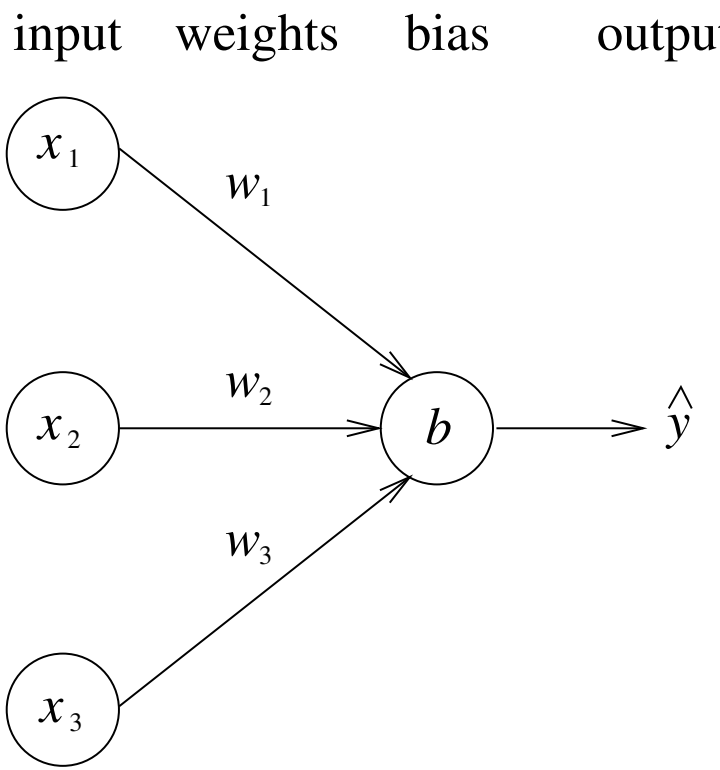

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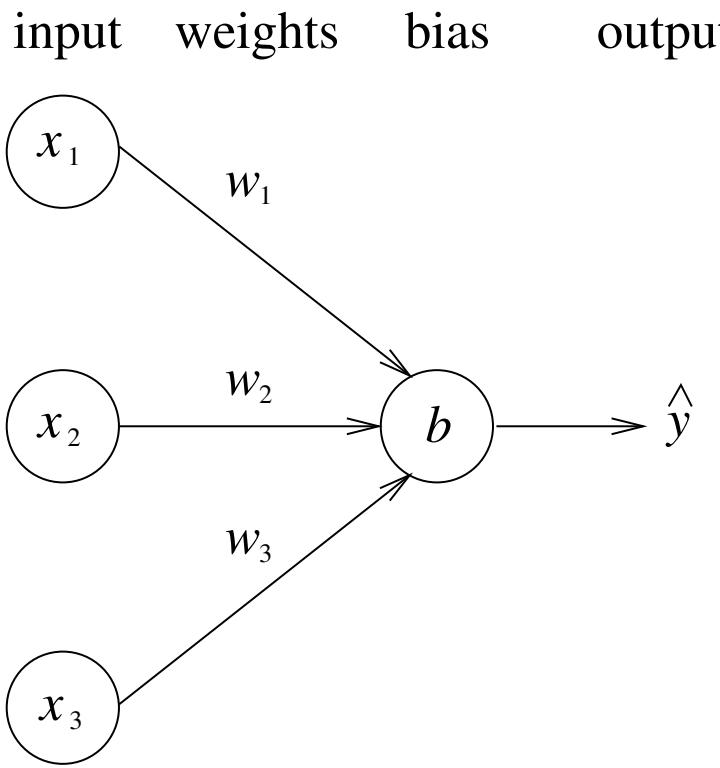
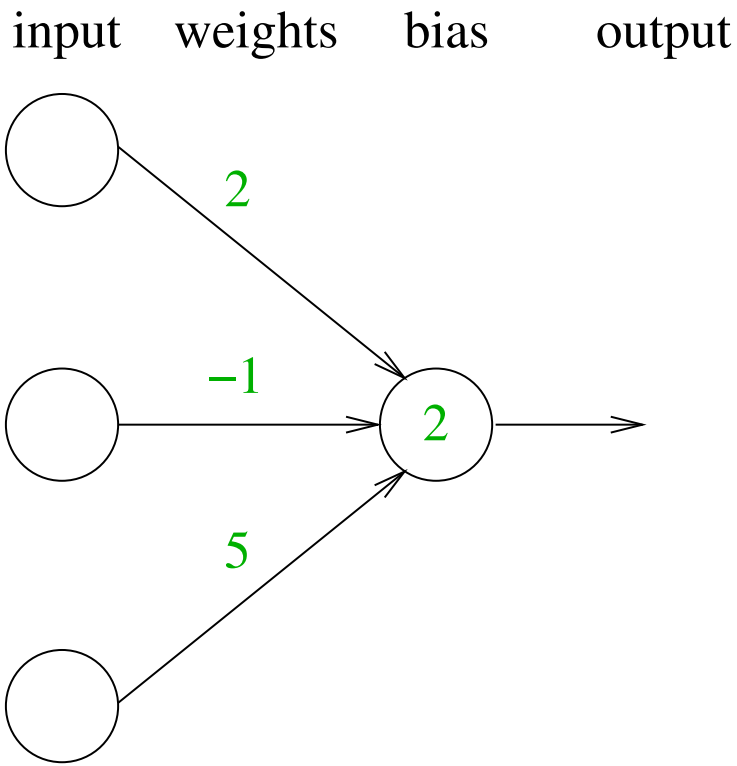



$$\hat{y} = \begin{cases} 0 & \text{if } \sum x_i w_i + b \leq 0 \\ 1 & \text{if } \sum x_i w_i + b > 0 \end{cases}$$

# The Simplest Neural Network Example



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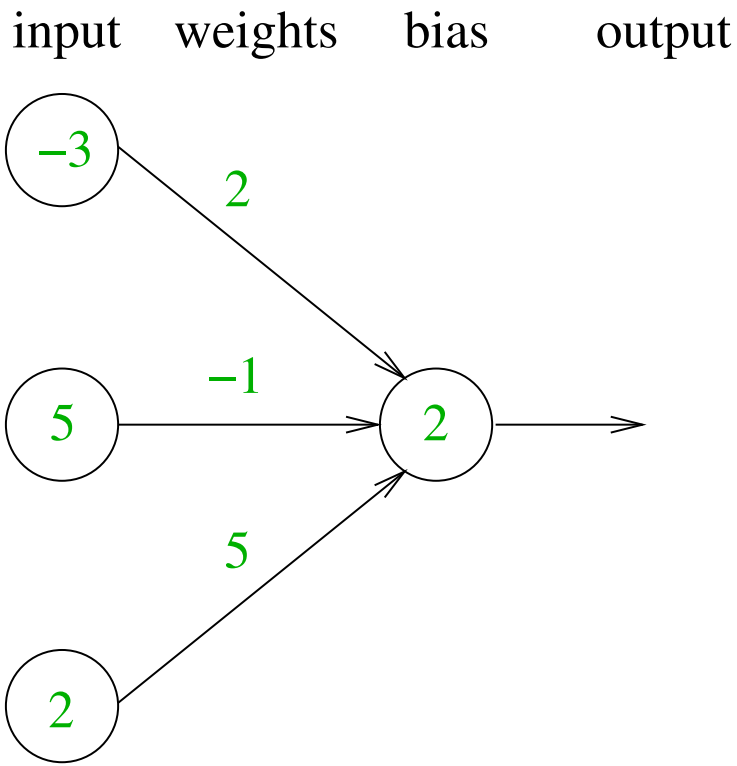

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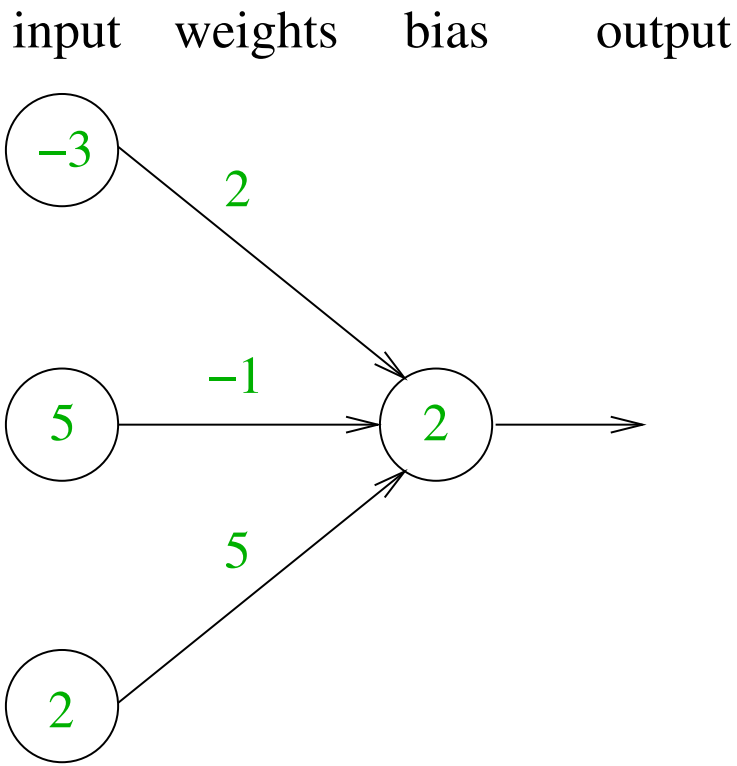


$$\sum x_i w_i + b = (-3) \times 2 + 5 \times (-1) + 2 \times 5 + 2$$

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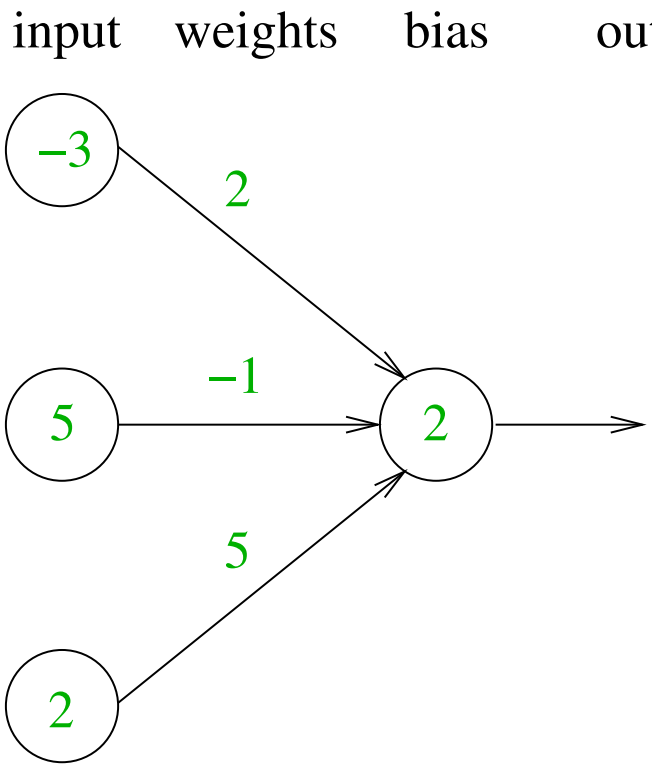


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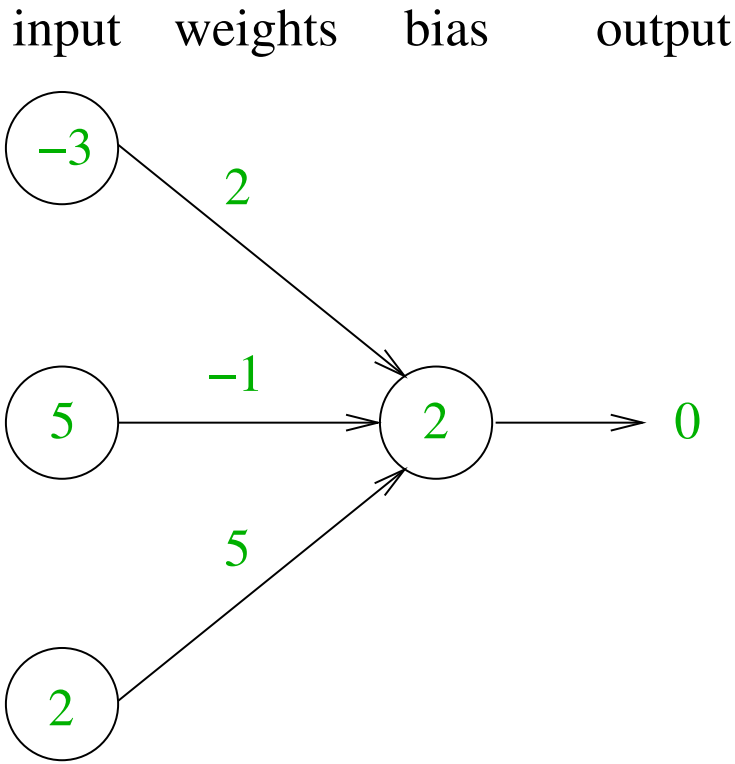


$$\sum x_i w_i + b = (-3) \times 2 + 5 \times (-1) + 2 \times 5 + 2 = -1 \quad \Longrightarrow \quad y = 0$$

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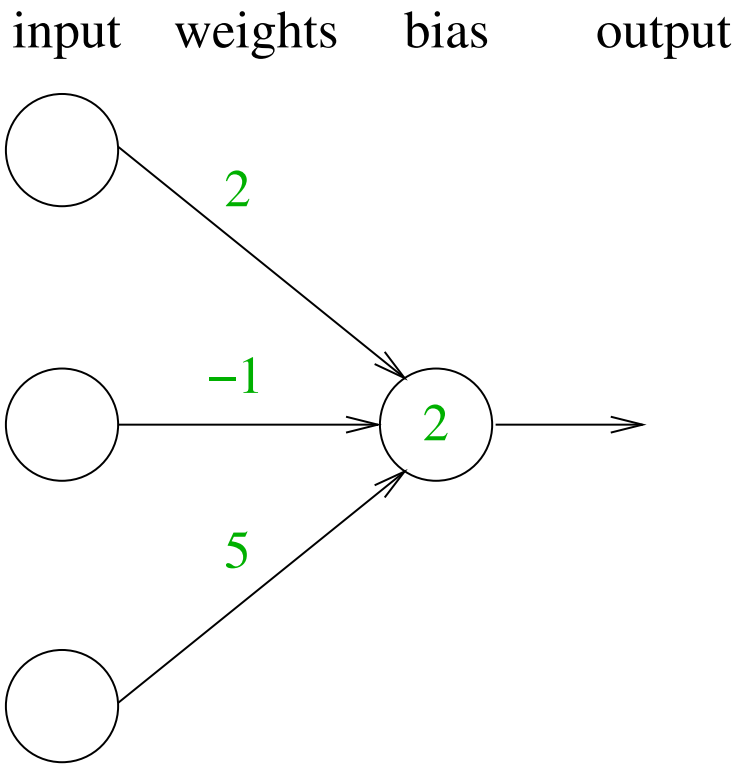

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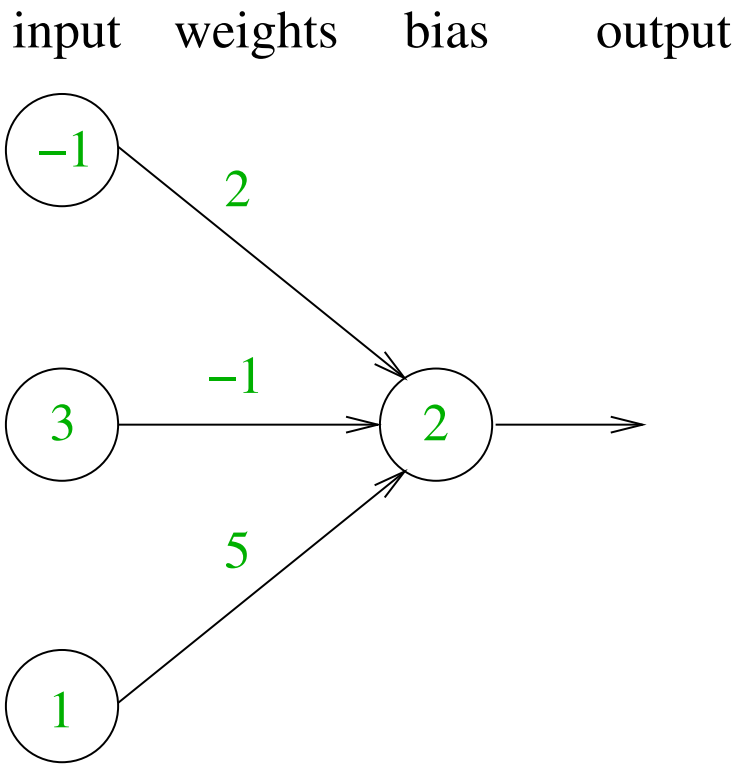

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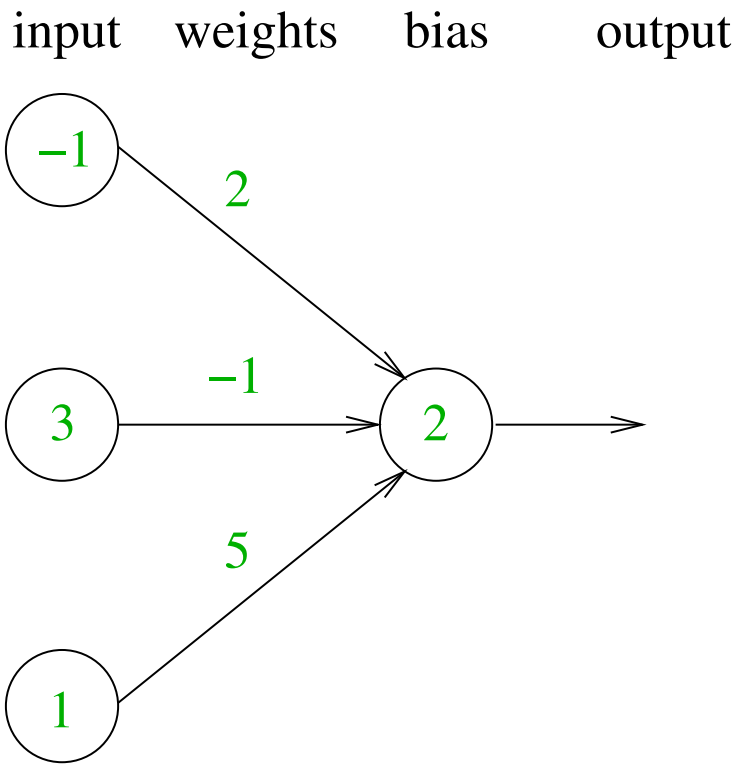


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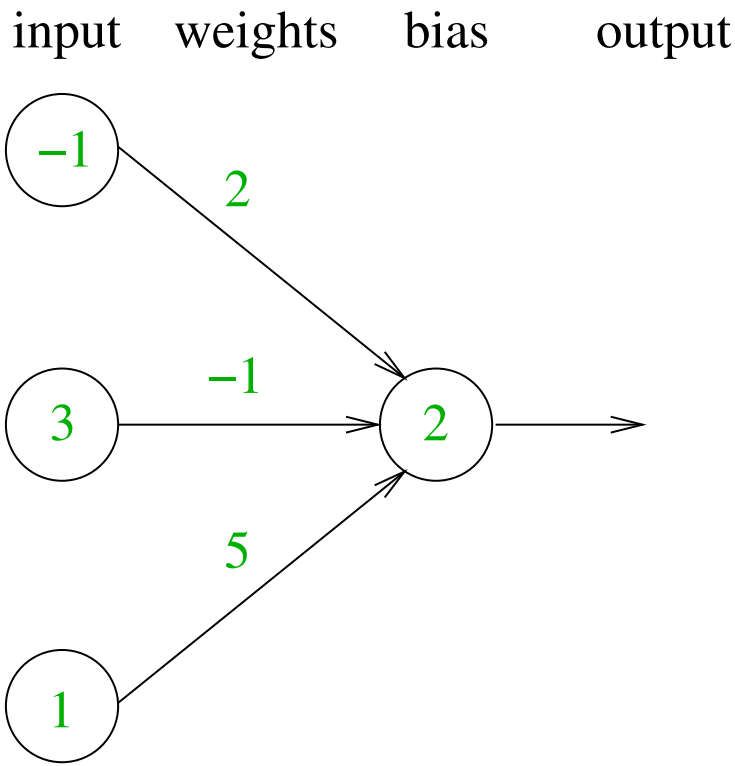


$$\sum x_i w_i + b = (-1) \times 2 + 3 \times (-1) + 1 \times 5 + 2 = 2$$

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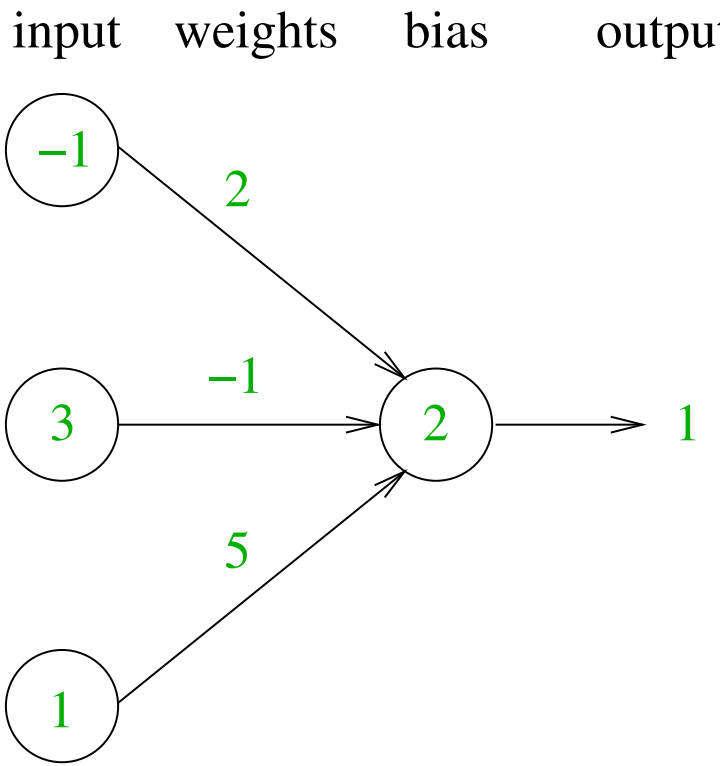
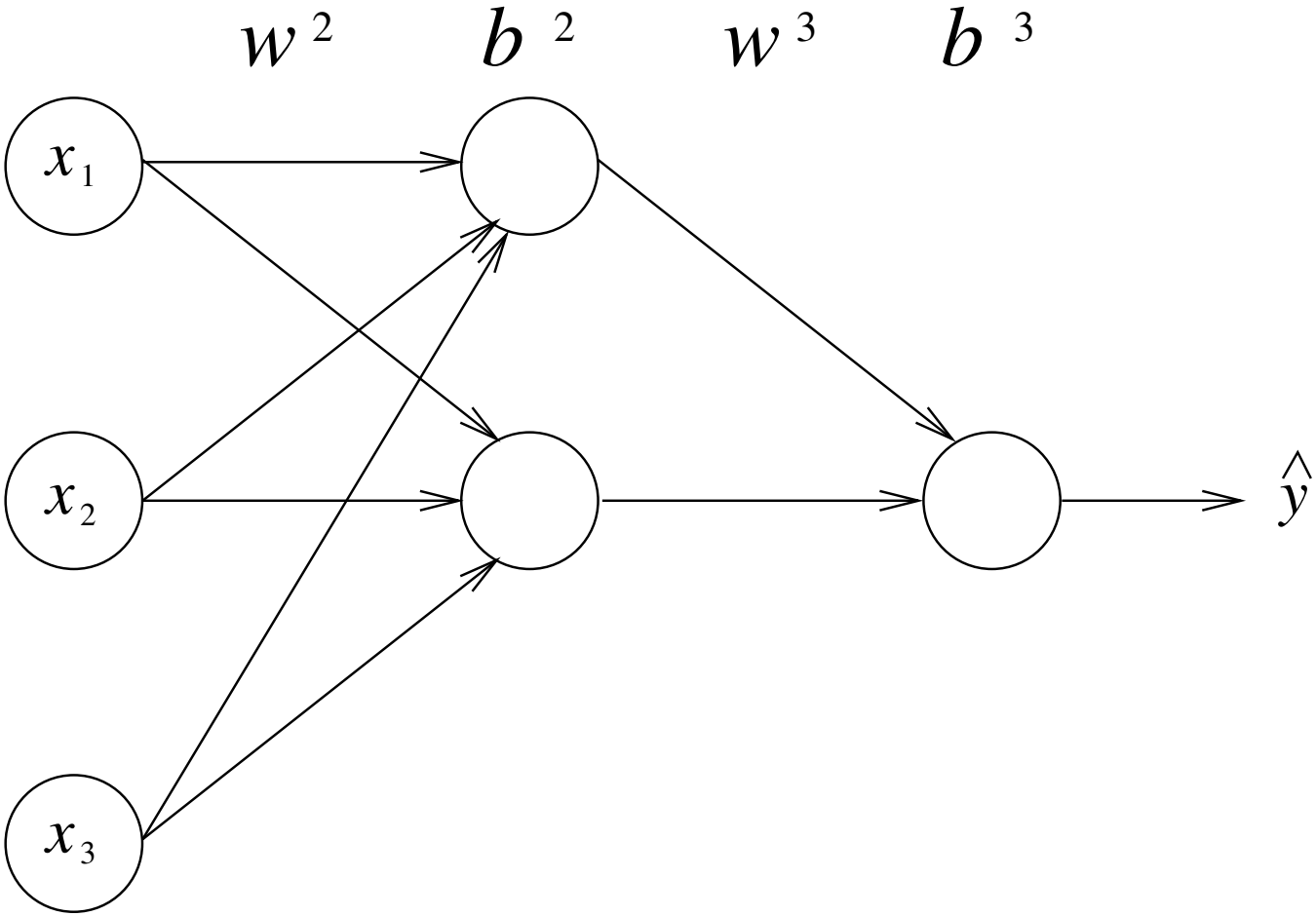



$$\sum x_i w_i + b = (-1) \times 2 + 3 \times (-1) + 1 \times 5 + 2 = 2 \implies y = 1$$

# More Complex Networks



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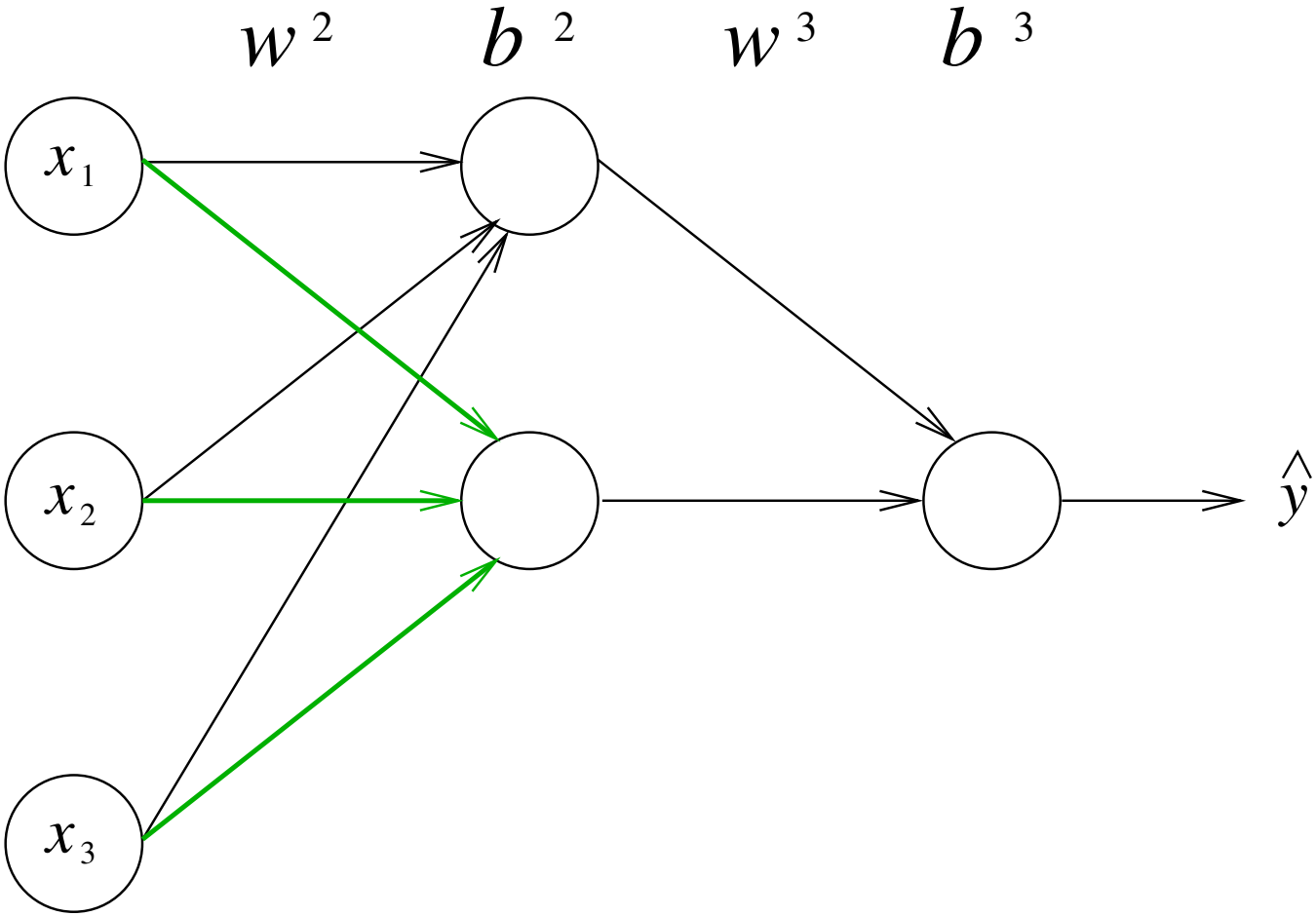

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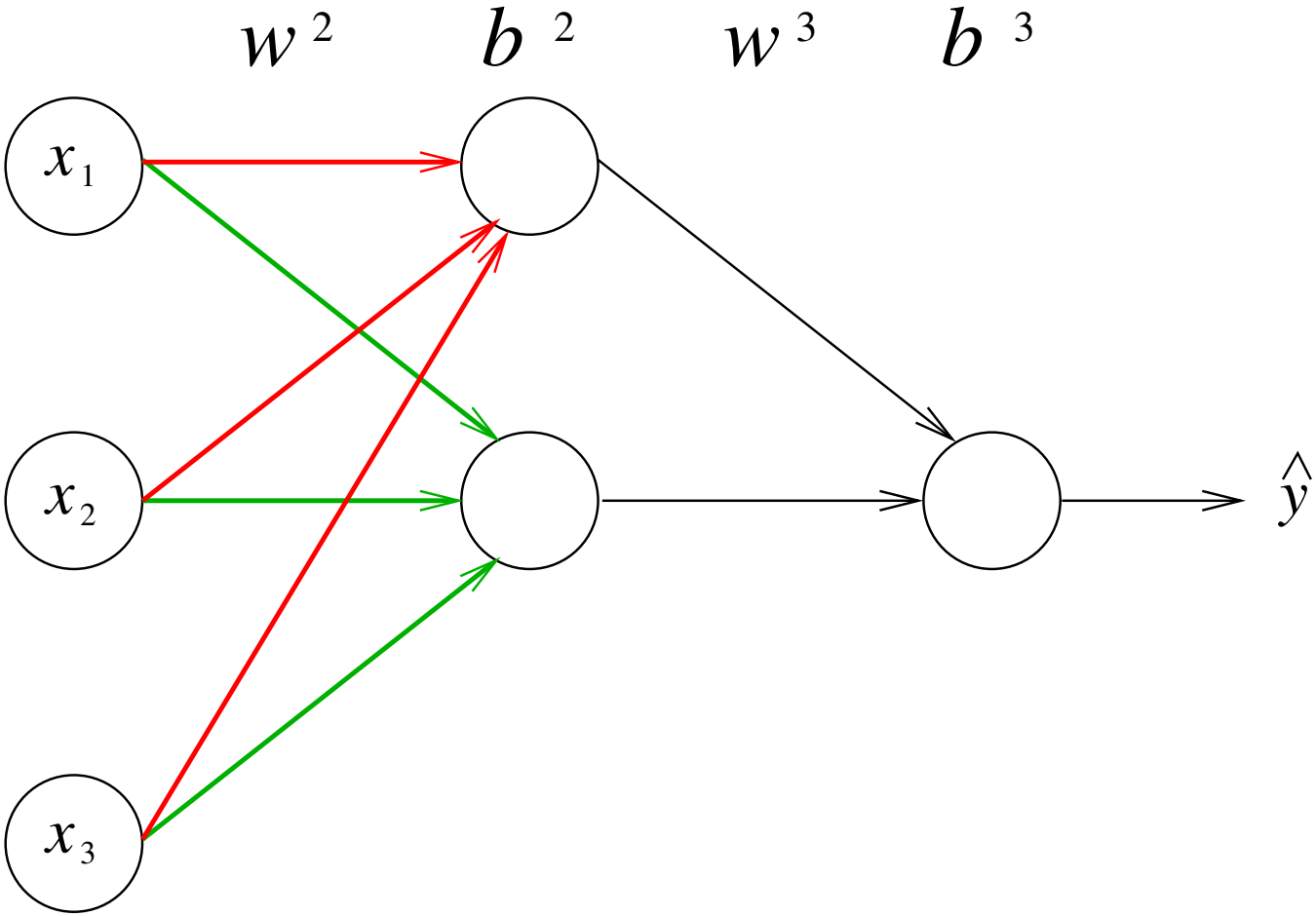

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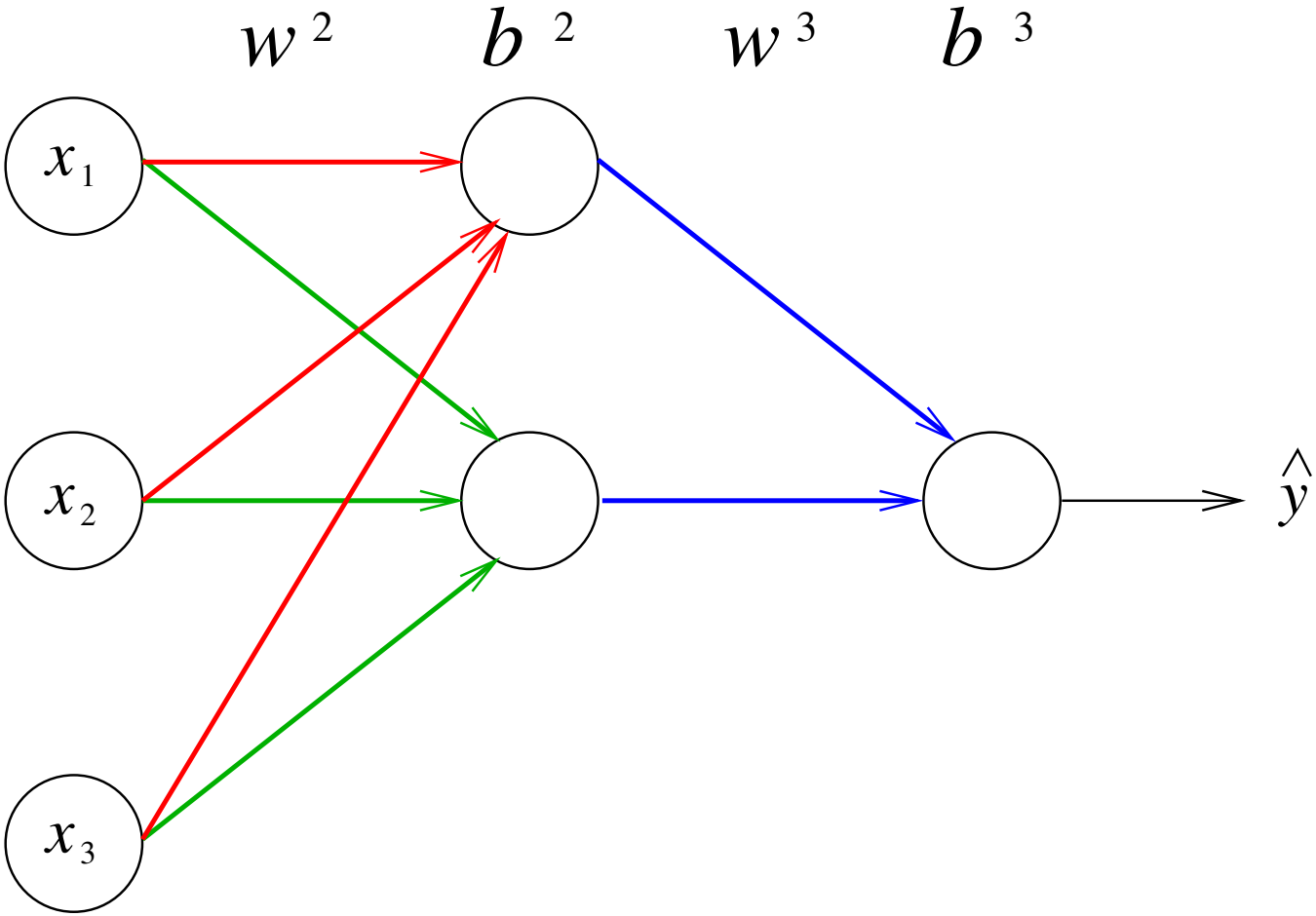

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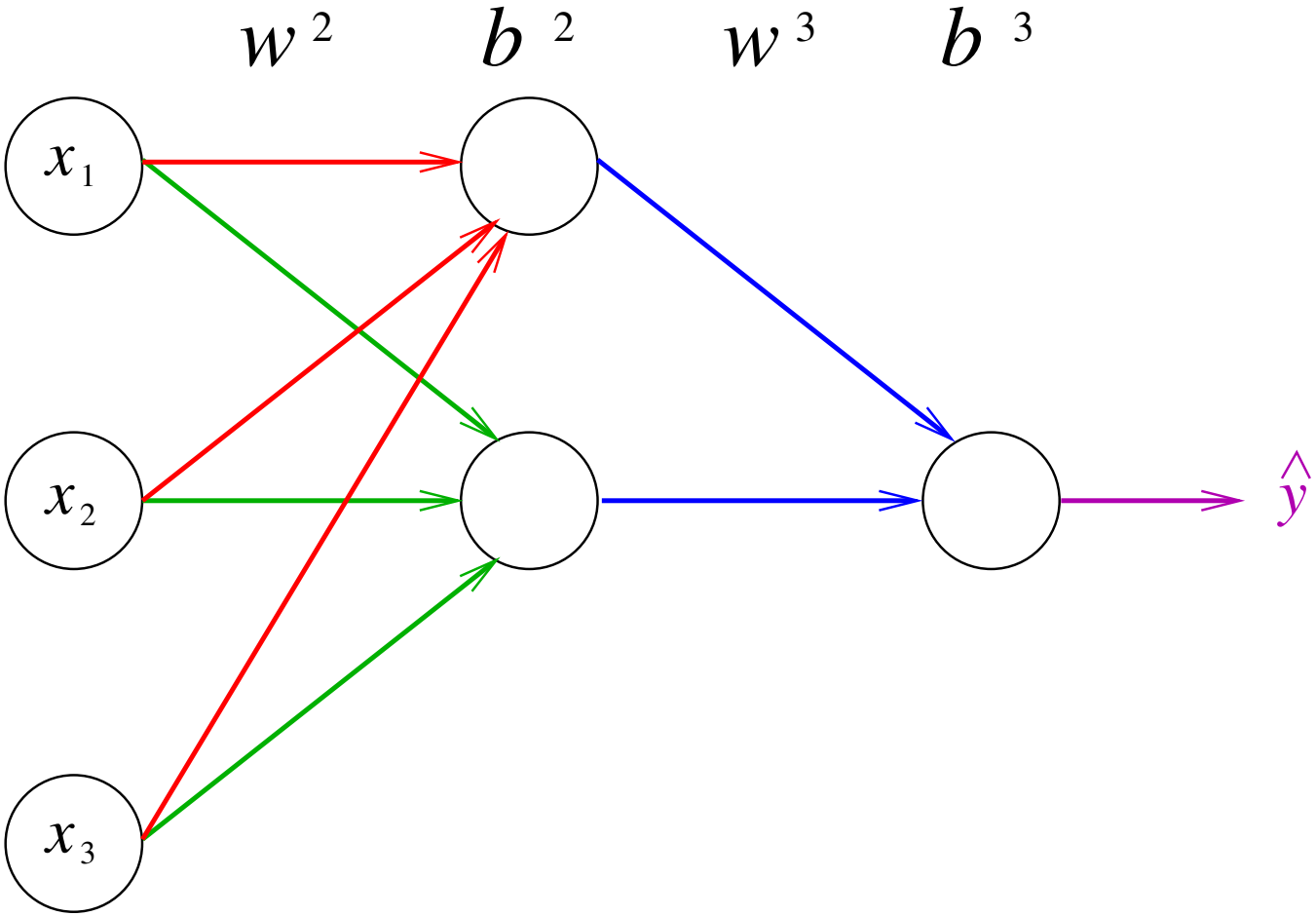

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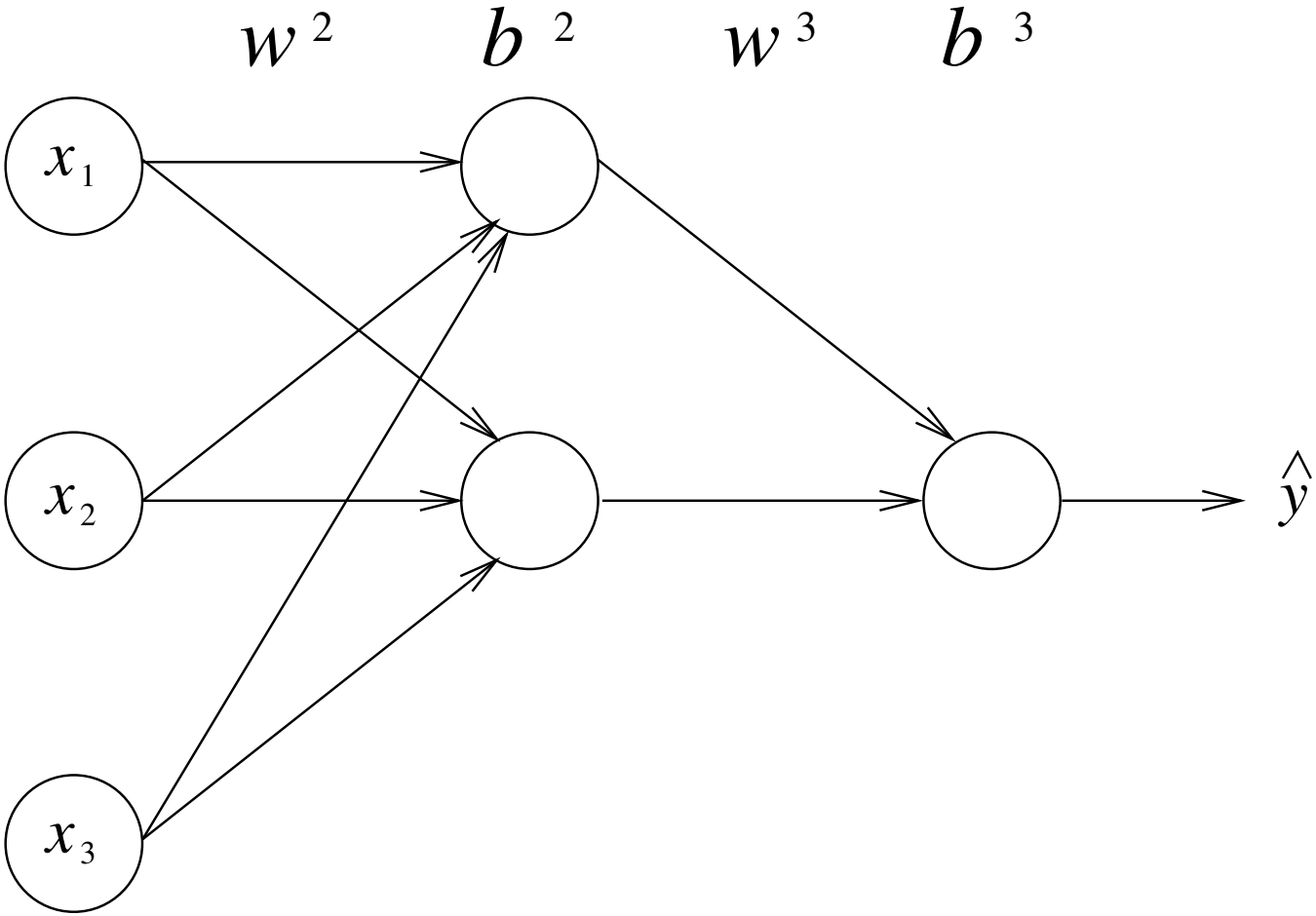

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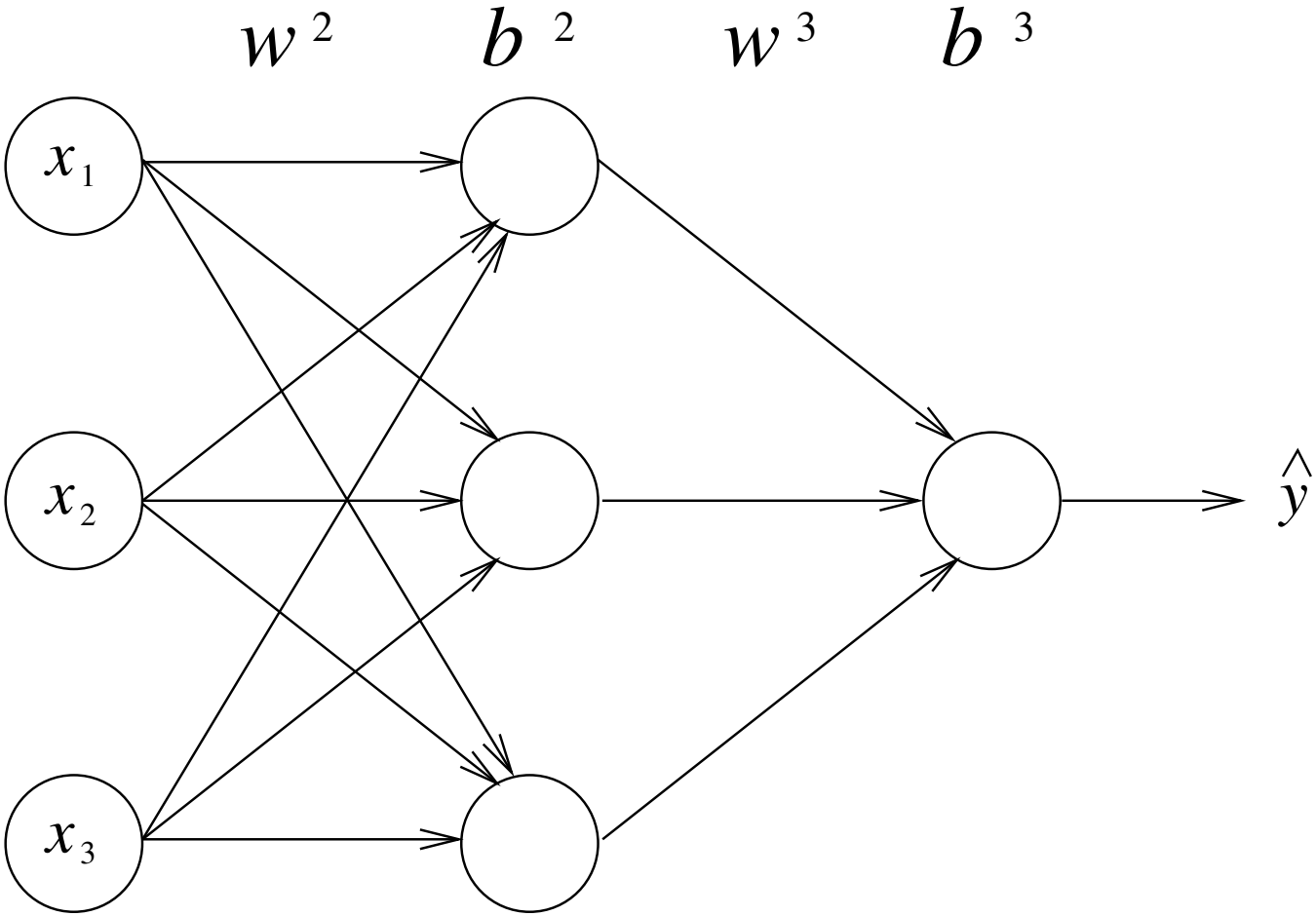

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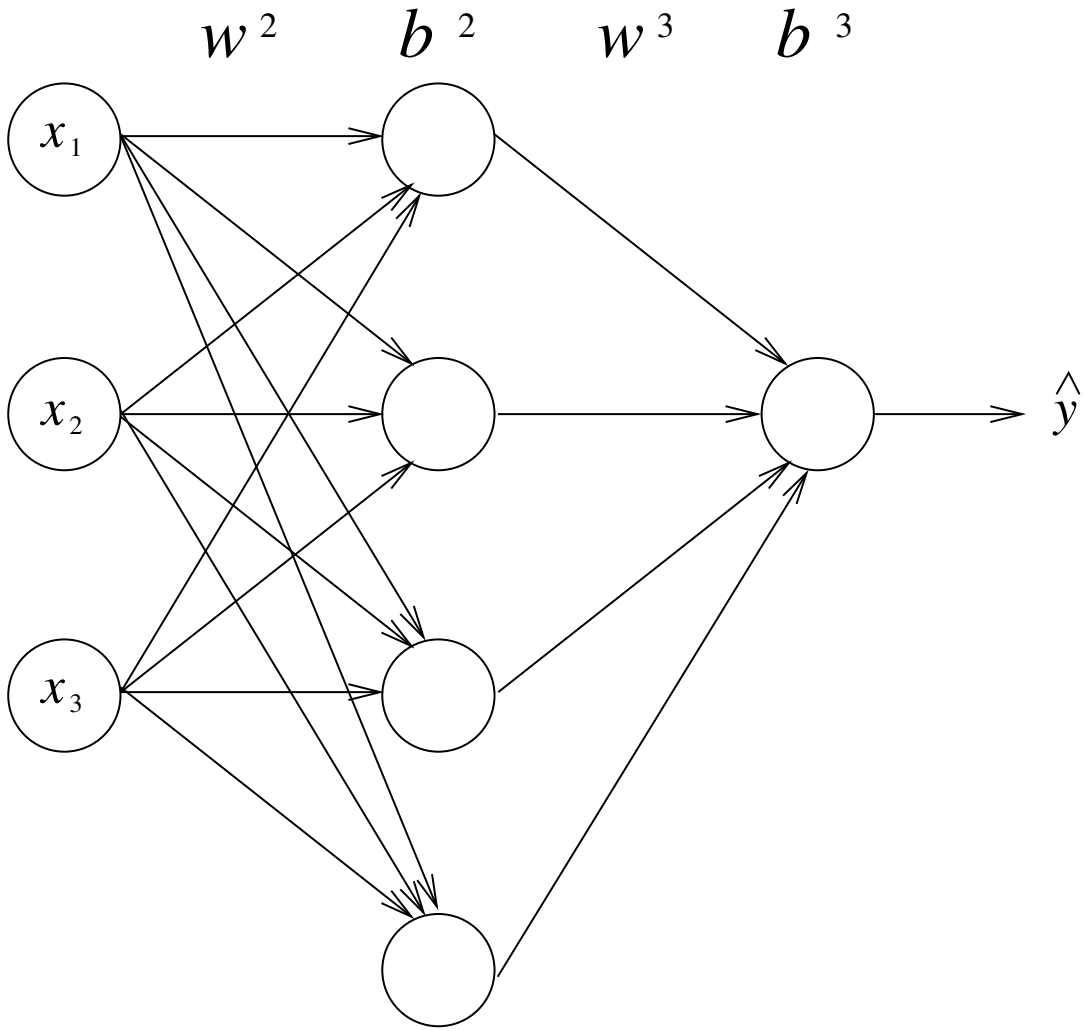

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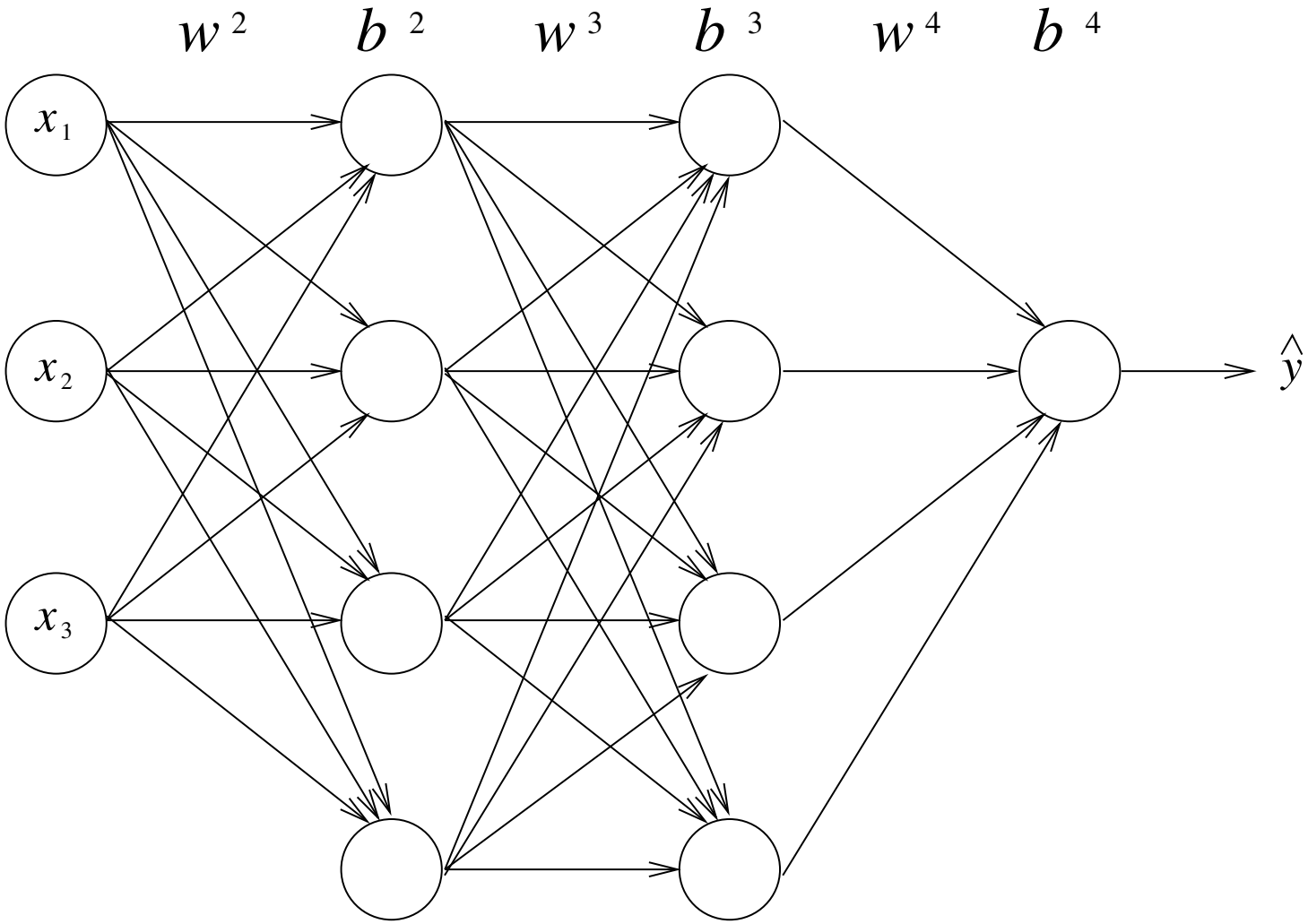

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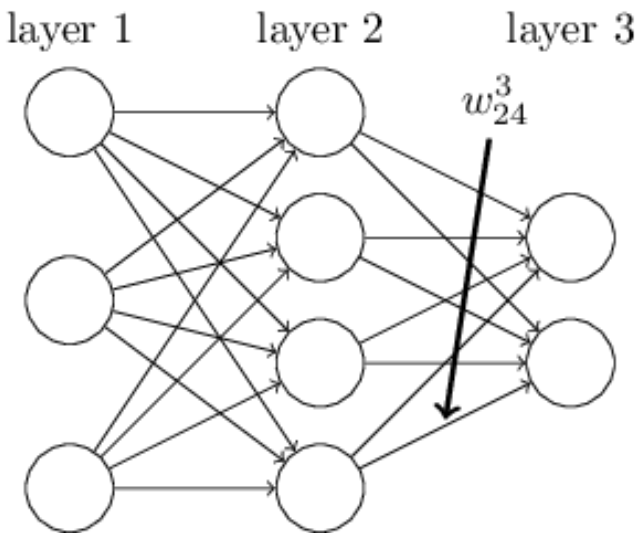


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# Implementing the Network Object

```
class Network(object):

    def __init__(self, sizes):
        self.num_layers = len(sizes)
        self.biases = [np.random.randn(y, 1) for y in sizes[1:]]
        self.weights = [np.random.randn(y, x)
                        for x, y in zip(sizes[:-1], sizes[1:])]
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```

## Example

`Network([3, 4, 4, 1])` initializes a neural network with 3 input neurons, two hidden layers with 4 neurons each, and 1 output neuron.

# Objective of Neural Networks

## Cost function

Let $(x, y)$ be a record from our training set of size $m$ and let $\hat{y}(x)$ be the predicted output for the input $x$.

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(Mean Squared Error *or* Quadratic Cost Function)

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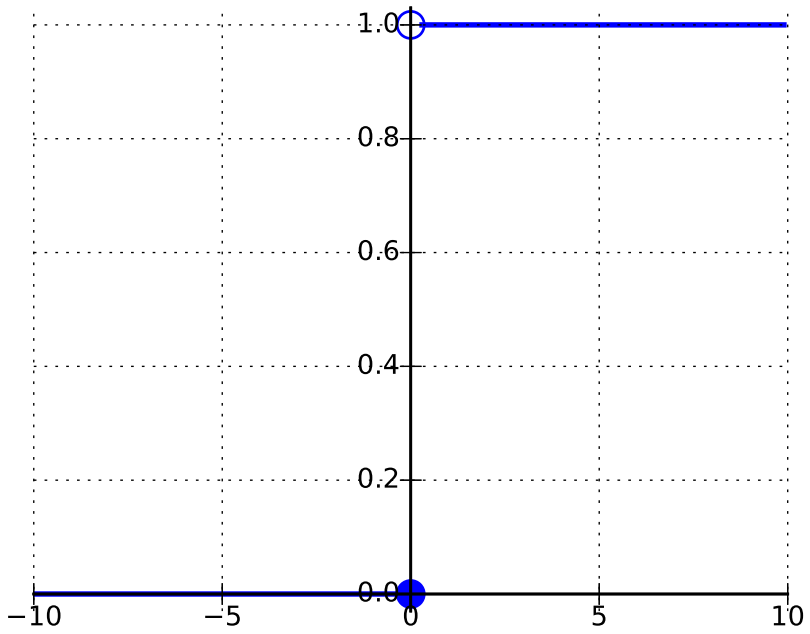
## Objective

Find weights $w^2, \ldots, w^L$ and biases $b^2, \ldots, b^L$ that minimize the Cost.

# A Better Activation Function

Consider the perceptron function:




Perceptron

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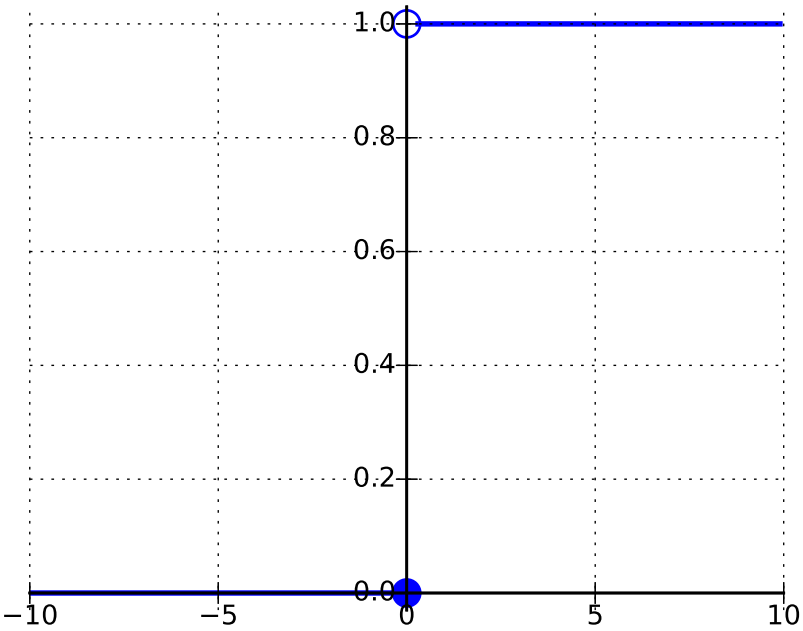
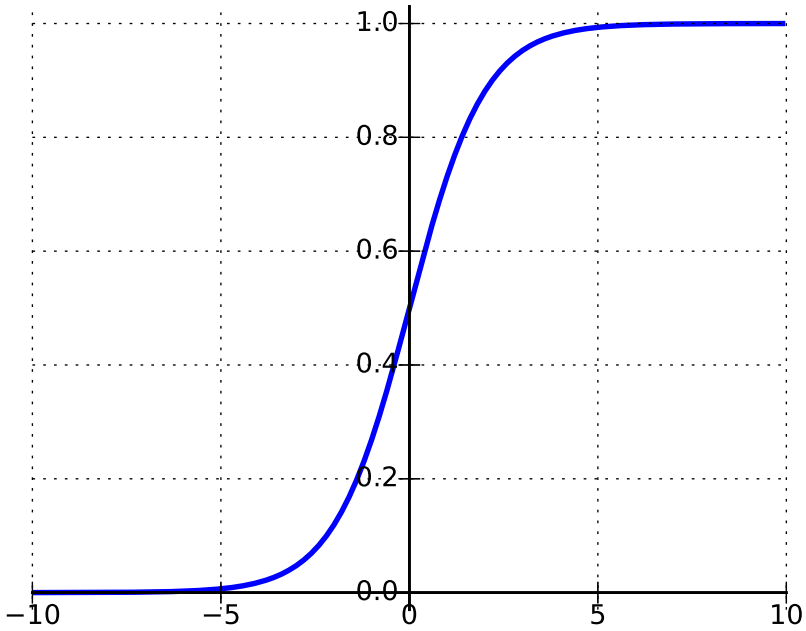


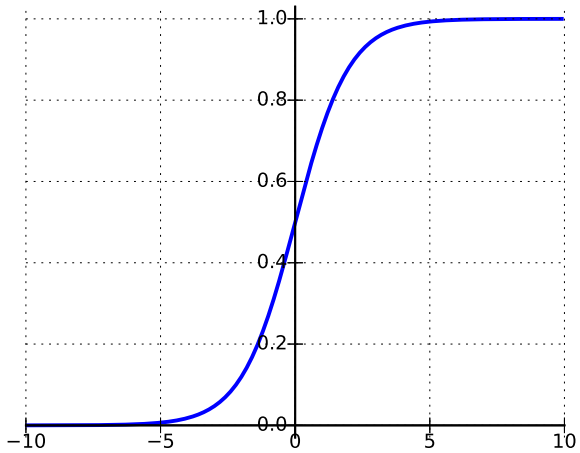

Perceptron

A continuous function is better:




Sigmoid

# Sigmoid Activation Function



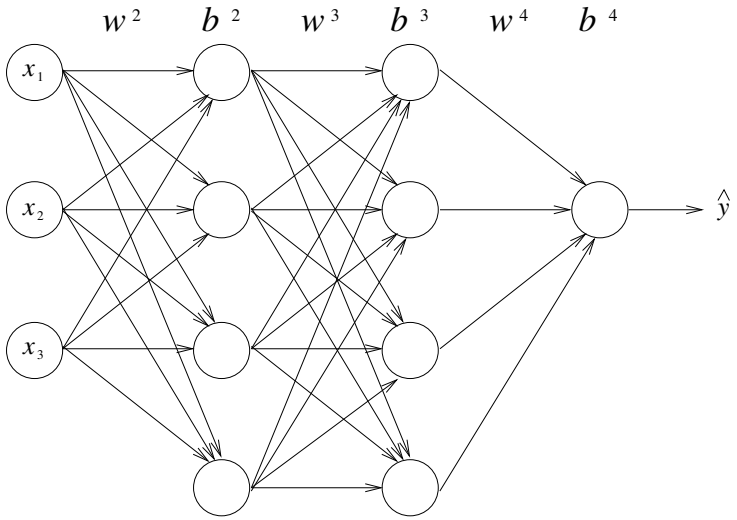

## Sigmoid

The **sigmoid (logistic) function** is defined to be

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

The function can output any number in the range 0-1 (not inclusive).

# Feedforward in a Neural Network



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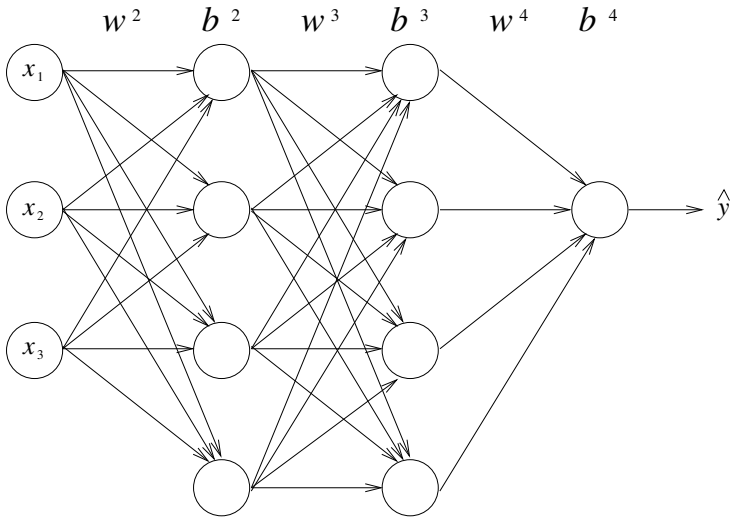
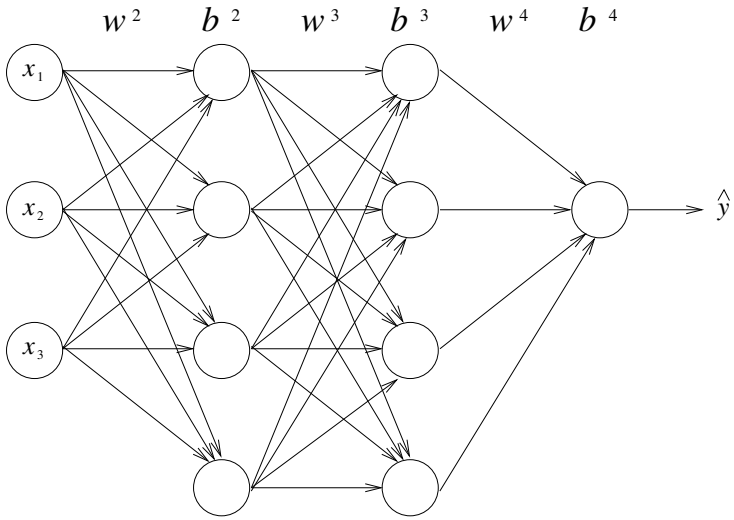



## Feed forward process

For an input $x$, the network predicts an output $\hat{y}(x)$

# Feedforward in a Neural Network

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1. Set $a = x$

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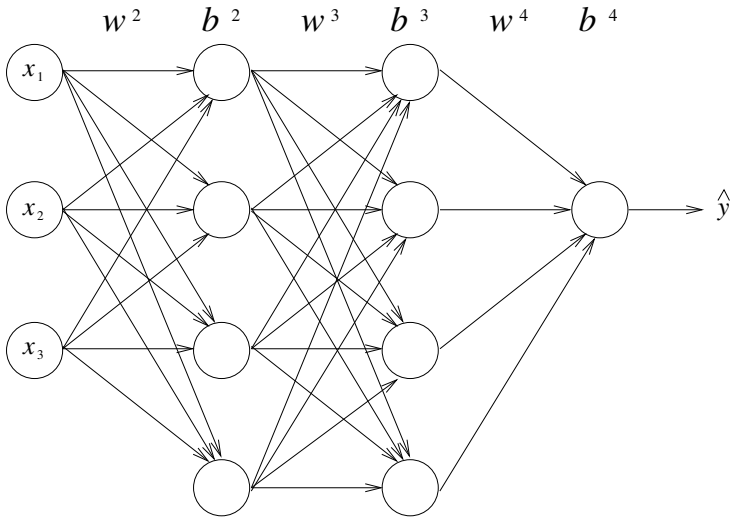


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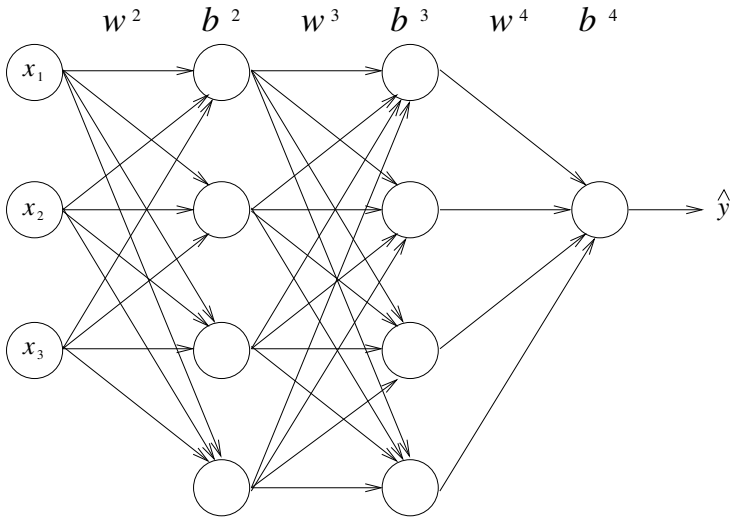


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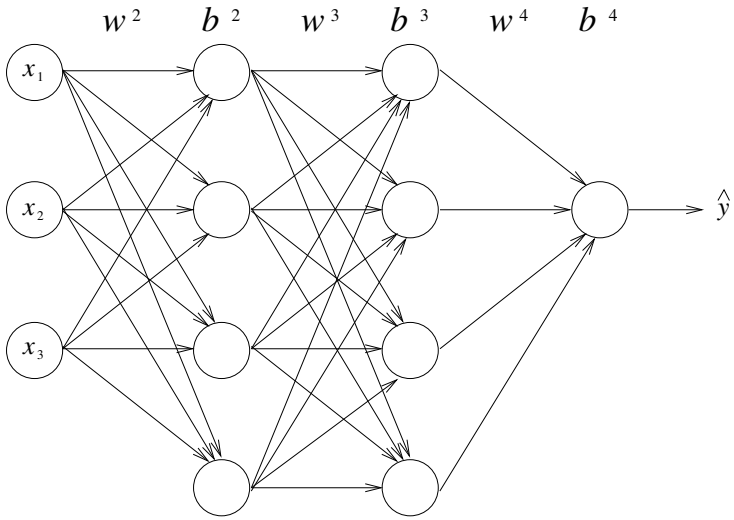


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2. Set $a \leftarrow a' = \sigma(w^\ell a + b^\ell)$ for $\ell = 2 \ldots 4$ or, $\ell = 2 \ldots L$
3. Output $\hat{y}(x) = a$

# Implementing Feed Forward and Sigmoid

```
class Network(object):
...
    def feedforward(self, x):
        a = x
        for w, b in zip(self.weights, self.biases):
            a = sigmoid(np.dot(w, a)+b)
        return a

...
def sigmoid(z):
    return 1.0/(1.0+np.exp(-z))

def sigmoid_prime(z):
    return sigmoid(z)*(1-sigmoid(z))
```

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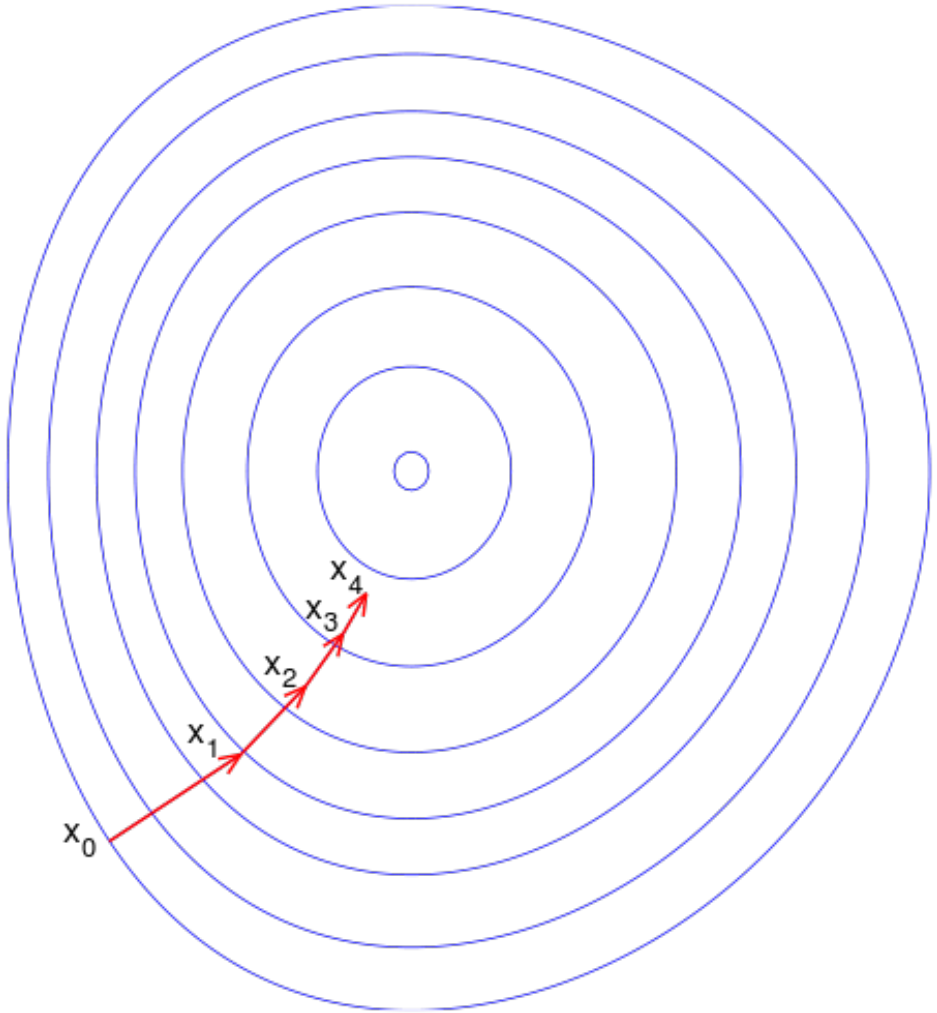
# Intuition for gradient descent



# General algorithm

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- $w \leftarrow w' = w - \eta \frac{\partial E}{\partial w}$
- $b \leftarrow b' = b - \eta \frac{\partial E}{\partial b}$

Eta ($\eta$) is the **learning rate**

# Implementing Gradient Descent

```
class Network(object):
...
    def SGD(self, training_data, iters, eta):
        for j in range(iters):
            for x, y in training_data:
                delta_w, delta_b = self.backprop(x, y)
                self.weights = [w-eta*dw
                        for w, dw in zip(self.weights, delta_w)]
                self.biases = [b-eta*db
                        for b, db in zip(self.biases, delta_b)]
```

# Implementing Gradient Descent

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class Network(object):
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                self.biases = [b-eta*db
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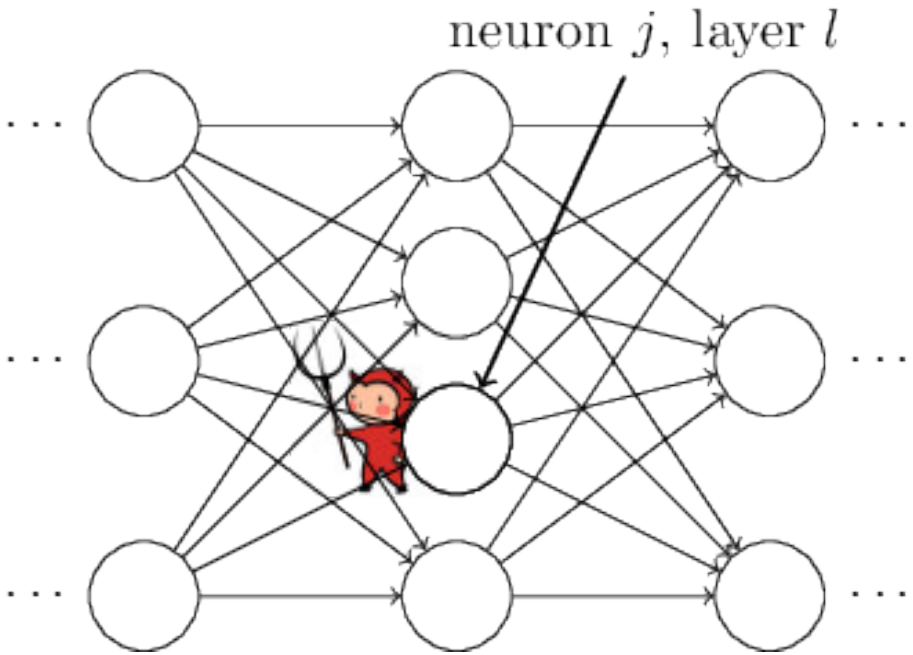
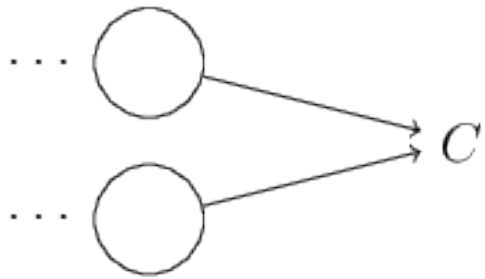
```

## Stochastic Gradient Descent

The above implementation is called **Stochastic Gradient Descent**. We get the `delta_w, delta_b` from a single training example $(x, y)$.

# Backpropagation Intuition




Source: http://neuralnetworksanddeeplearning.com/chap2.html

# Backpropagation

## Equations

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3. $$\frac{\partial E}{\partial w^{\ell}_{jk}} = \frac{\partial E}{\partial(\text{input; layer } \ell)} \times (\text{output; layer } \ell - 1)$$

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3. $$\frac{\partial E}{\partial w^{\ell}_{jk}} = \frac{\partial E}{\partial(\text{input; layer } \ell)} \times (\text{output; layer } \ell - 1)$$
4. $$\frac{\partial E}{\partial b^{\ell}_{j}} = \frac{\partial E}{\partial(\text{input; layer } \ell)}$$

# Backpropagation Implementation

```
class Network(object):
...
    def backprop(self, x, y):
        delta_w = [np.zeros(w.shape) for w in self.weights]
        delta_b = [np.zeros(b.shape) for b in self.biases]
        # Feed it forward
        layer_out = [x] # Stores output from all layers
        layer_in_prime = [] # Stores sigmoid' of input to all layers
        for w, b in zip(self.weights, self.biases):
            z = np.dot(w, layer_out[-1])+b # Get input to next layer
            layer_out.append(sigmoid(z))
            layer_in_prime.append(sigmoid_prime(z))
        # Take it back
        delta = (layer_out[-1]-y) * layer_in_prime[-1]
        delta_w[-1] = np.dot(delta, layer_out[-2].transpose())
        delta_b[-1] = delta
        for l in range(2, self.num_layers):
            sp = layer_in_prime[-l]
            delta = np.dot(self.weights[-l+1].transpose(), delta)*sp
            delta_w[-l] = np.dot(delta, layer_out[-l-1].transpose())
            delta_b[-l] = delta
        return delta_w, delta_b
```

# First Equation

1. $$\frac{\partial E}{\partial(\text{input; final layer})} = (\hat{y}(x) - y) \times \sigma'(\text{input; final layer})$$

```
def backprop(self, x, y):
...
    layer_out = [x] # Stores output from all layers
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...
    delta = (layer_out[-1]-y) * layer_in_prime[-1]
```

# Second Equation

2. $$\frac{\partial E}{\partial(\text{input; layer } \ell)} = w^{\ell+1}\left(\frac{\partial E}{\partial(\text{input; layer } \ell+1)}\right) \odot \sigma'(\text{input; layer } \ell)$$

```
def backprop(self, x, y):
...
    layer_in_prime = [] # Stores sigmoid' of input to all layers
...
    for l in range(2, self.num_layers):
        sp = layer_in_prime[-l]
        delta = np.dot(self.weights[-l+1].transpose(), delta) * sp
```

# Third Equation

3. $$\frac{\partial E}{\partial w_{jk}^{\ell}} = \frac{\partial E}{\partial (\text{input; layer } \ell)} \times (\text{output; layer } \ell - 1)$$

```
def backprop(self, x, y):
...
    layer_out = [x] # Stores output from all layers
...
    delta_w[-1] = np.dot(delta, layer_out[-2].transpose())
    for l in range(2, self.num_layers):
    ...
        delta_w[-l] = np.dot(delta, layer_out[-l-1].transpose())
```

# Fourth Equation

4. $$\frac{\partial E}{\partial b_j^\ell} = \frac{\partial E}{\partial(\text{input; layer } \ell)}$$

```
def backprop(self, x, y):
...
    delta_b[-1] = delta
    for l in range(2, self.num_layers):
    ...
        delta_b[-l] = delta
```

# Code

Let's run the code:

https://github.com/rarredon/PyDataTalk/blob/master/src/Intro%20to%20Neural%20Networks%20Talk.ipynb

# Table of Contents

# A New Error Function

## Cross-Entropy Function

Let $(x, y)$ be a record from our training set of size $m$ and let $\hat{y}(x)$ be the predicted output for the input $x$.

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Let $(x, y)$ be a record from our training set of size $m$ and let $\hat{y}(x)$ be the predicted output for the input $x$.

$$E = -\frac{1}{m}\sum_{x}[y \ln(\hat{y}) + (1-y)\ln(1-\hat{y})]$$

# Cross-entropy effects on Backpropagation

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becomes

1. $$\frac{\partial E}{\partial(\text{input; final layer})} = (\hat{y}(x) - y)$$

# Cross-Entropy Implementation

In the code we change

```
def backprop(self, x, y):
...
    delta = (layer_out[-1]-y) * layer_in_prime[-1]
```

to

```
def backprop(self, x, y):
...
    delta = (layer_out[-1]-y)
```

# Regularization

## $L_2$ Regularization

To keep weights small, while minimizing the cost, we alter the cost:

- $E = -\frac{1}{m}\sum_x [y \ln(\hat{y}(x)) + (1-y)\ln(1-\hat{y}(x))] + \frac{\lambda}{2m}\sum_w w^2$

# Effect of $L_2$ Regularization Gradient Descent

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1. $w \leftarrow w' = \left(1 - \frac{\eta\lambda}{m}\right) w - \eta \frac{\partial E}{\partial w}$

# Cross-Entropy Implementation

In the code we change

```
def SGD(self, training_data, iters, eta):
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            self.weights = [w-eta*dw
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            self.biases = [b-eta*db
                    for b, db in zip(self.biases, delta_b)]
```

to

```
def SGD(self, training_data, iters, eta):
...
            self.weights = [(1-eta*(lmbda/m))w-eta*dw
                    for w, dw in zip(self.weights, delta_w)]
            self.biases = [b-eta*db
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```

# Other ways to avoid overfitting

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- **Dropout method:** train several networks with some of the nerurons missing and then combine these into one network.
- **More data:** Obtain more data or artificially create more data.

# Faster computational speeds

## Mini-batch Stochastic Gradient Descent

## Weight initialization

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Update the weights and biases for a mini-batch:

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- Weights initialized using standard normal distribution.

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## Weight initialization

- Weights initialized using standard normal distribution.
- Better results if variance is inversely propotional to the number input neurons, i.e., $\sigma^2 = 1/n_{\text{in}}$.

# Other Optimization Methods

## Variations on Gradient Descent Algorithm

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- Hessian Technique

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For a reference that introduces and compares these methods see "Efficient BackProp" by LeCun et. al.

# Table of Contents

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- **network size:** Number of layers and number of neurons in each.

# MNIST Best Results

## Deep, yet Simple

In a 2010 paper, "Deep, Big, Simple Neural Networks Excel on Handwritten Digit Recognition", the authors trained a network whose hidden layers were $2500, 2000, 1500, 1000,$ and 500 neurons, respectively. Their classification accuracy was a resounding 99.65%.

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## Deep Convolutional

In 2012, the same authors trained a convolutional neural network with a classification accuracy of 99.77%. [a]

[a] http://repository.supsi.ch/5145/1/IDSIA-04-12.pdf

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- Certain techniques have become standard in their use without a theoretical backing or understanding.
- They consistently win the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC).

# Future of Neural Networks

# Future of Neural Networks

?

# References

The following references were a huge help in preparing this talk:


1. Michael A. Nielsen, “Neural Networks and Deep Learning”, Determination Press, 2015. Retrieved from http://neuralnetworksanddeeplearning.com/
2. Ian Goodfellow and Yoshua Bengio and Aaron Courville, “Deep Learning”, MIT Press, 2016. Retrieved from http://www.deeplearningbook.org/

# Thanks!

Many thanks to Chris Luiz and Bob Mickus for organizing the meetup.

Thank you for coming to watch me talk.

Materials available on my github account:

https://github.com/rarredon/PyDataTalk

## Questions?