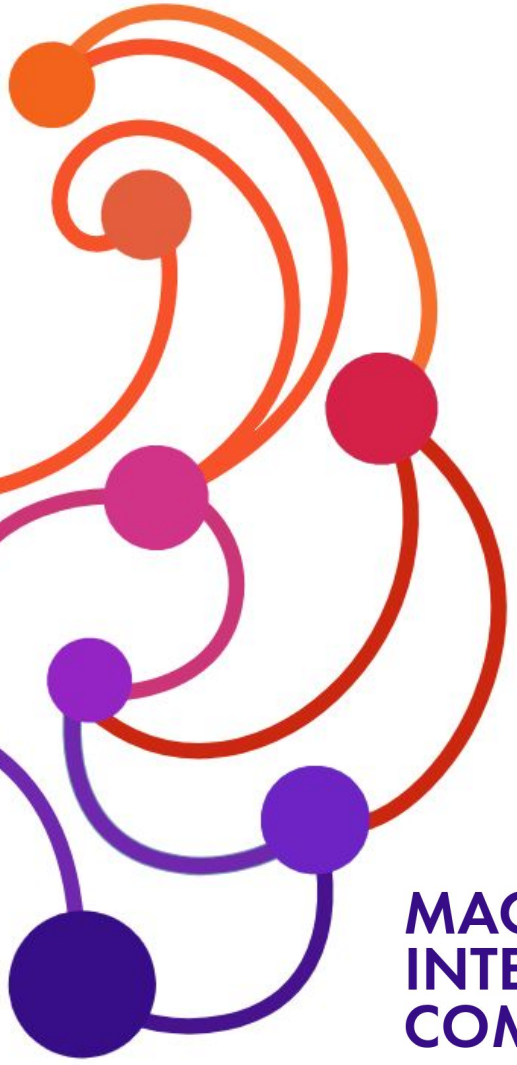
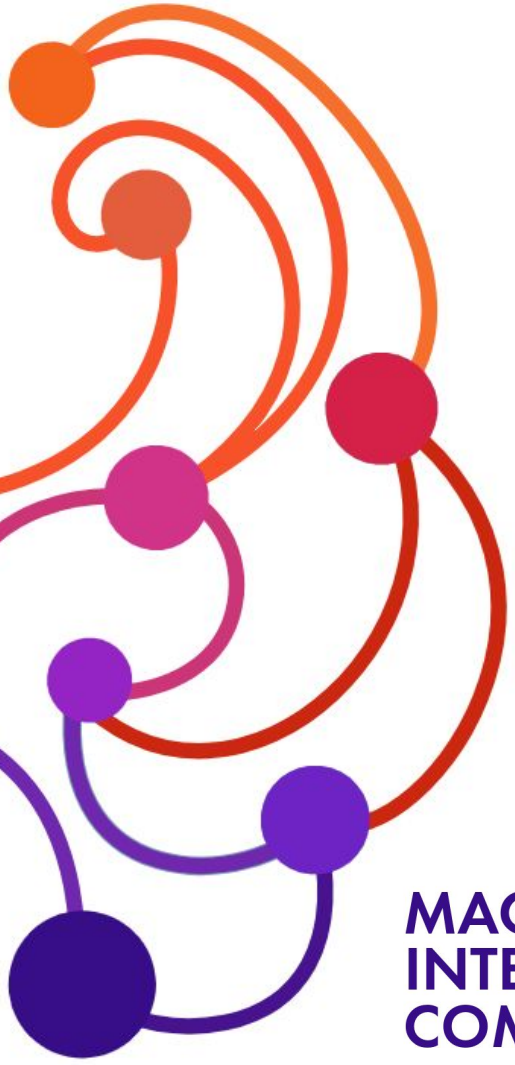


Intro to Deep Learning

Sign-in Sheet with links to deep learning worksheet

bit.ly/bumicspring2019ws01

MACHINE
INTELLIGENCE
COMMUNITY



Intro to Deep Learning

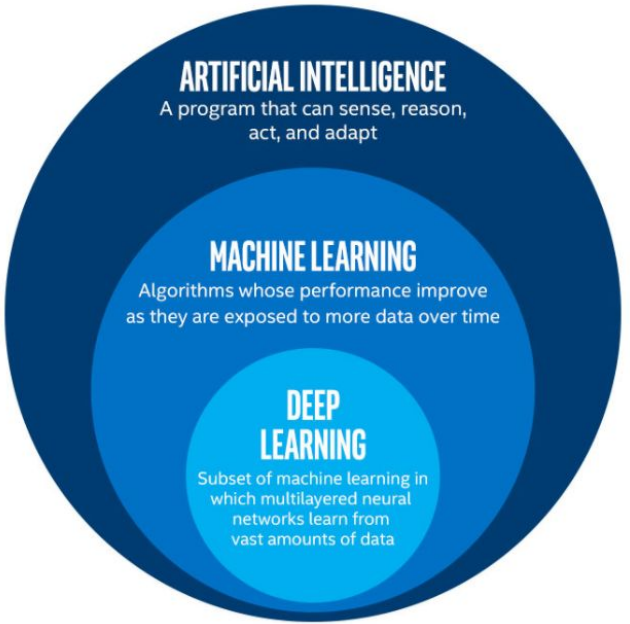
Darcy, Deren, Jennifer, Julius

MACHINE
INTELLIGENCE
COMMUNITY

2/1/2019

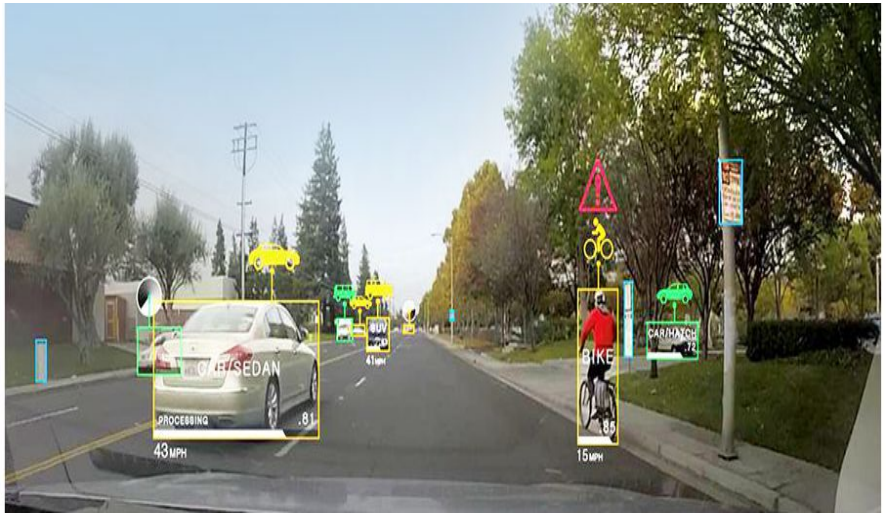
What is deep learning?

- Subfield of traditional machine learning
- Inspired by the structure and function of the brain
  - Called artificial neural networks
- Basis for recent advances in artificial intelligence and advanced models



Motivation

1. Cool things using deep learning
    a. Computer Vision
        i. Tesla recognizing items on a street
    b. Text generation
        i. An algorithm was trained to create a new Shakespeare piece
    c. Image recognition
        i. Classifying what a certain picture contains
        ii. Facebook photo tagging
    d. Many more...

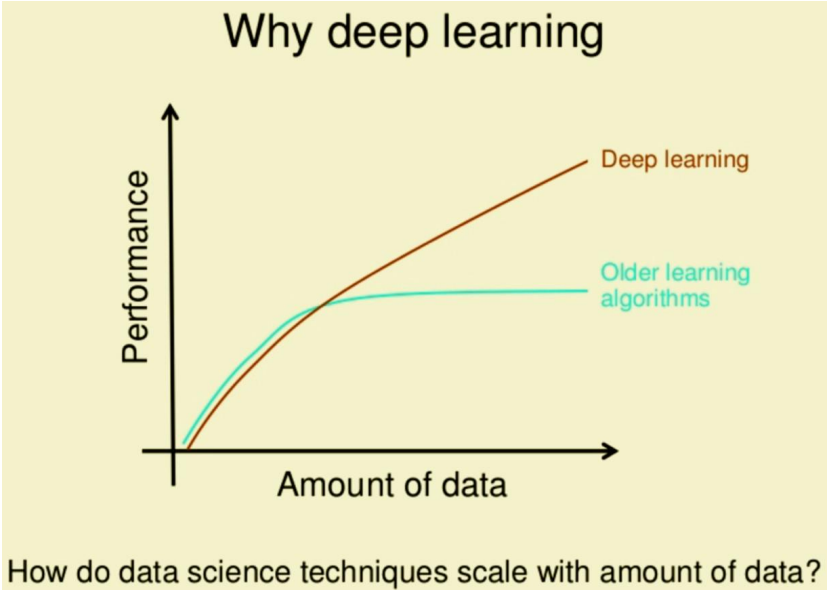


Google Alphastar

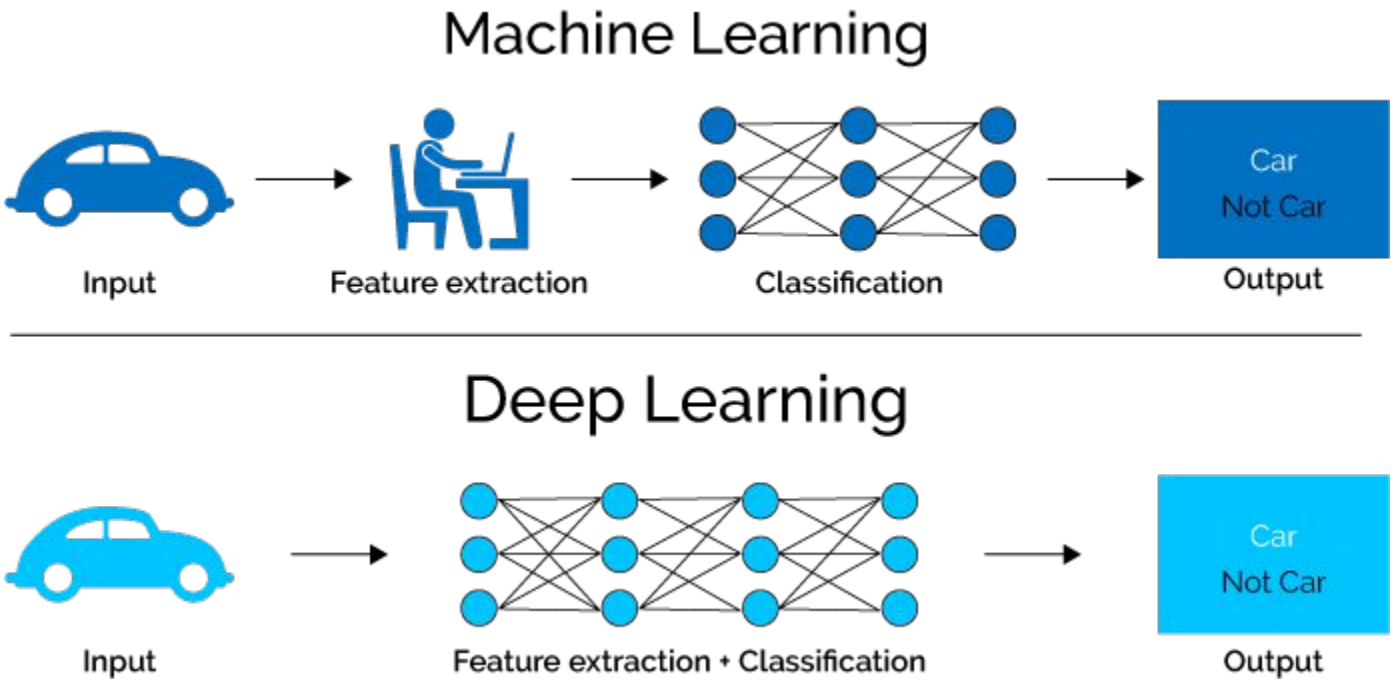
- Starcraft bot using deep learning
- Supervised learning by examples from humans
  - Then self play using a combination of deep learning and reinforcement learning
  - Played different types of deep learning algorithms

What is deep learning

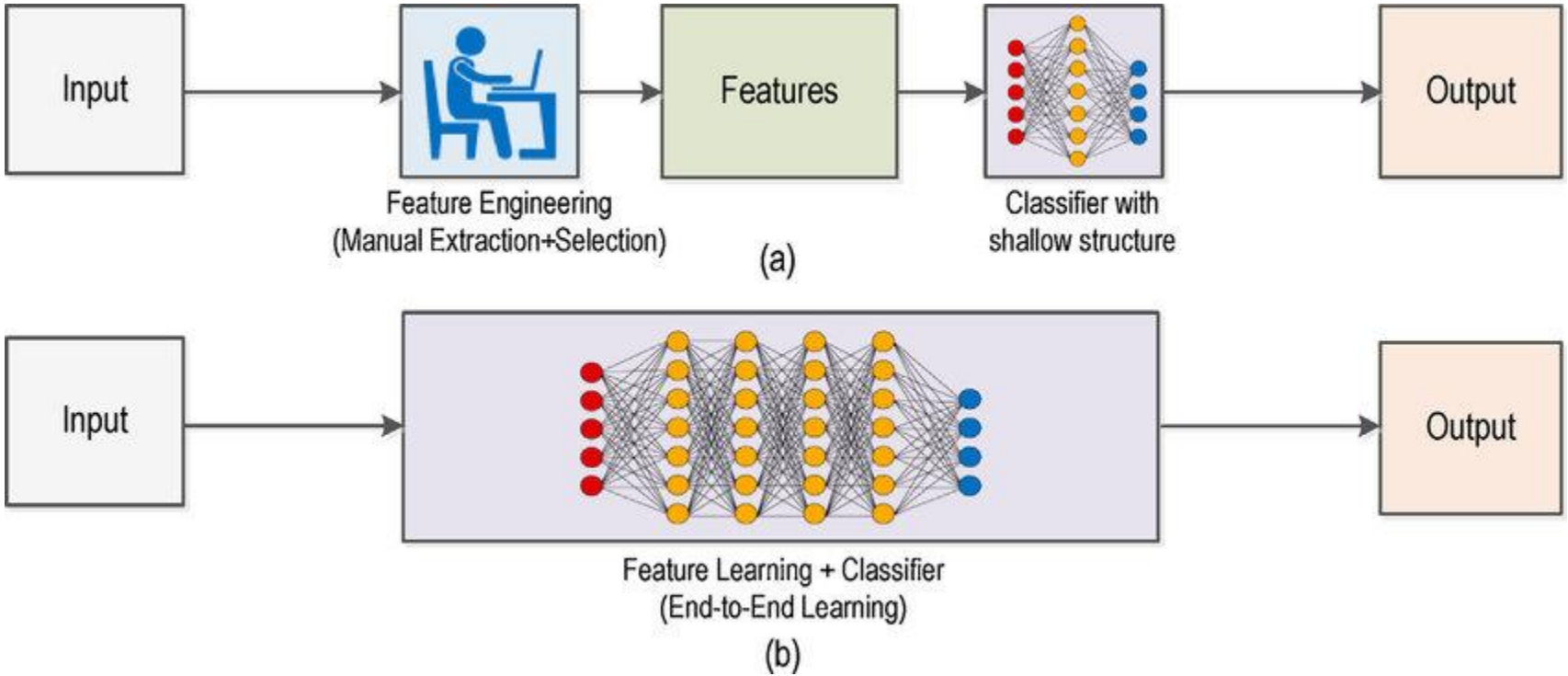
1. **Deep learning is a subset of machine learning**
    a. Both deal with data
        i. Deep learning performs better with larger amounts of data
        ii. Deep learning requires strong computation units such as GPU's



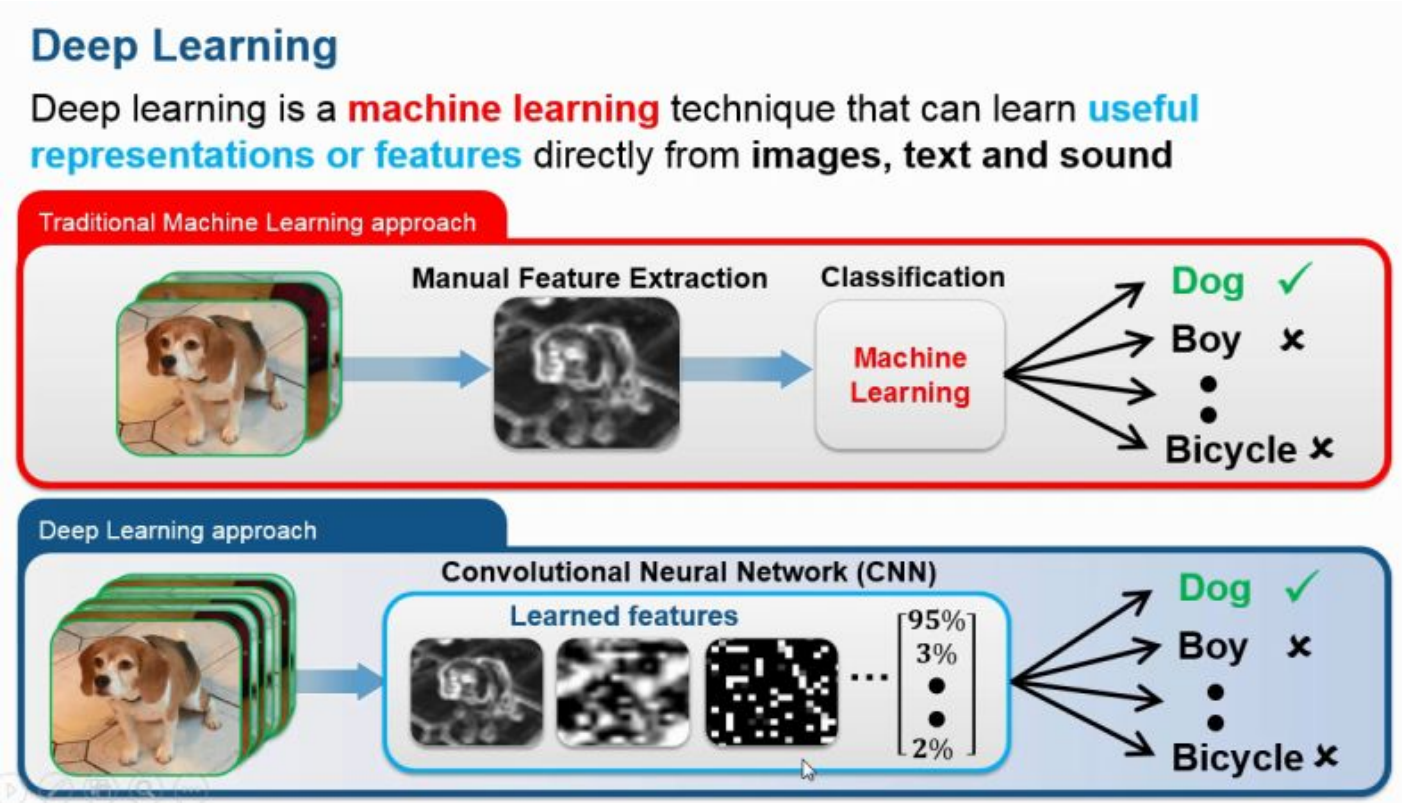
What is deep learning - Classifications



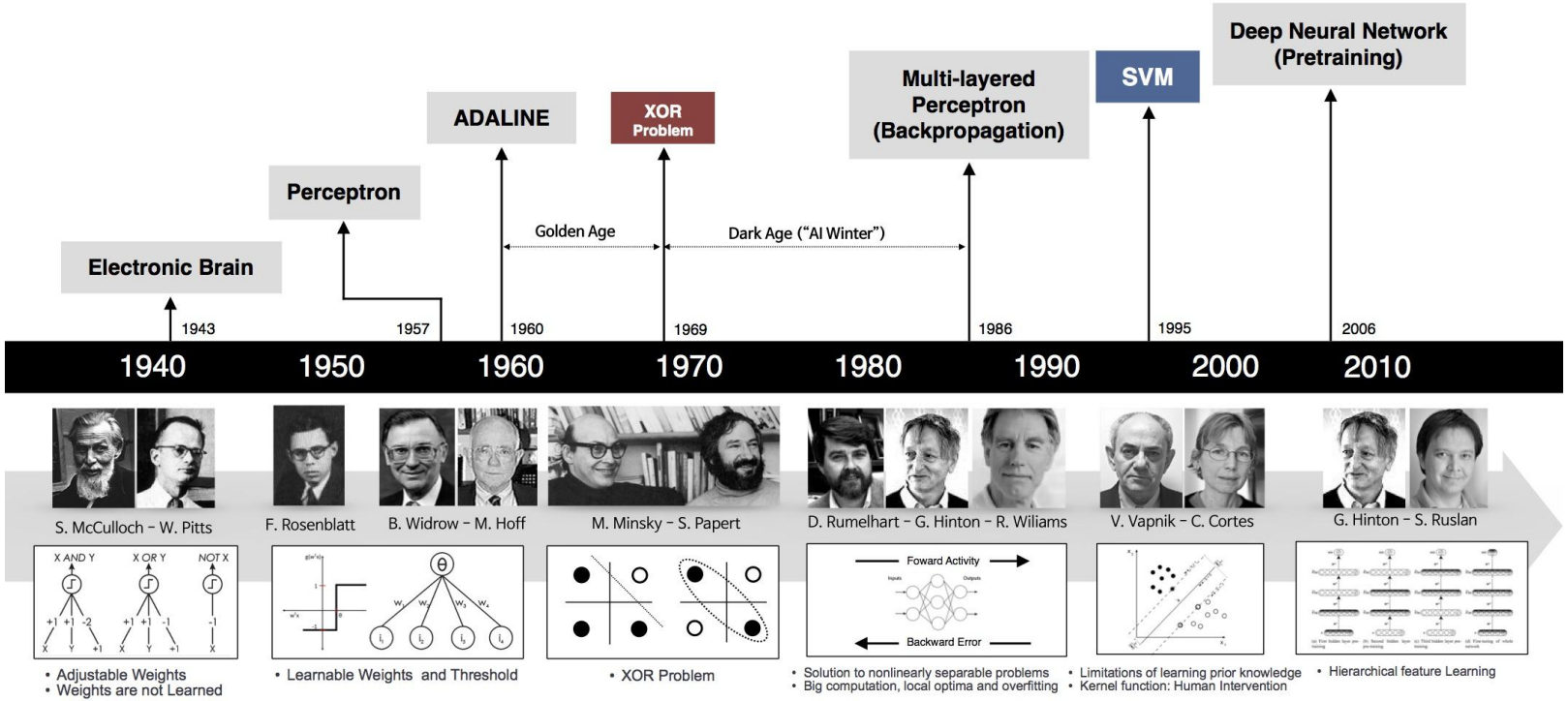
What is deep learning - Classifications cont.



What is deep learning - Classifications cont.

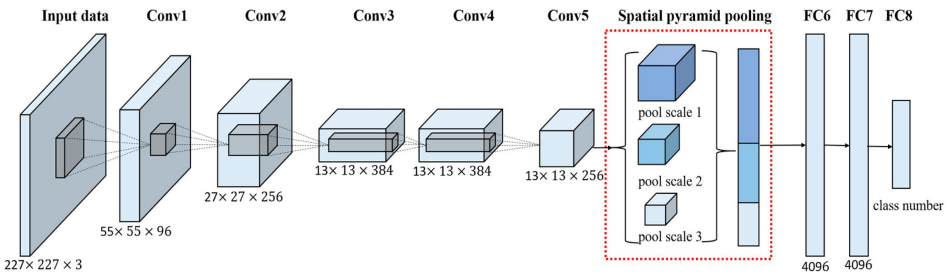


History of Deep Learning

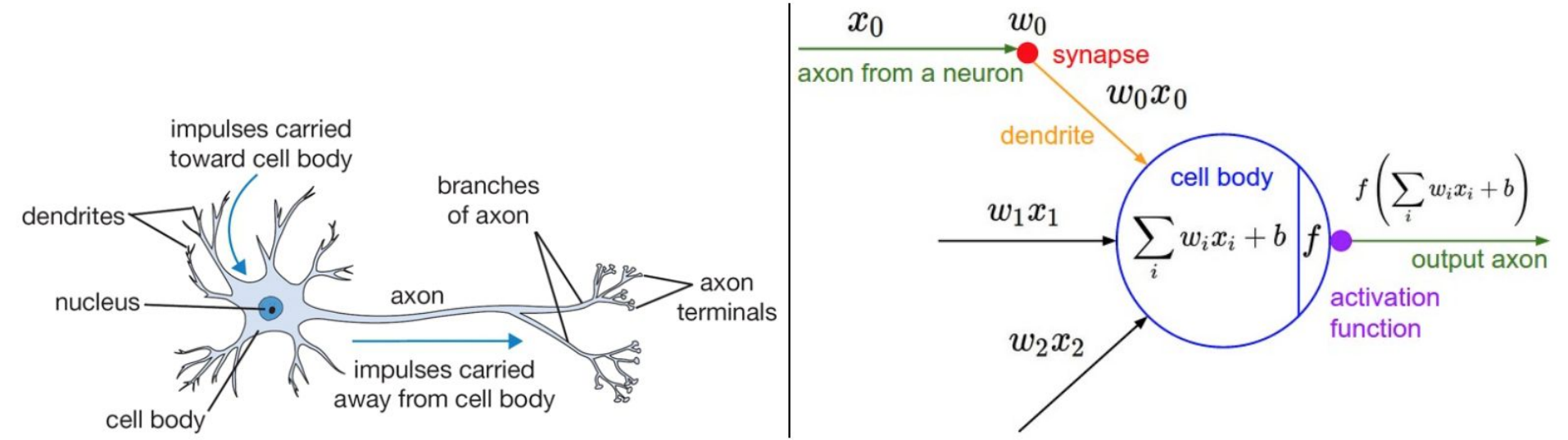


AlexNet

- One of the first neural networks designed by a former Google employee
- Convolutional Neural Network
- Image classification
- Large impact on deep learning
  - Spread the use of CNN's which accelerated deep learning
  - Cited over 30,000 times



Biological Neuron vs. Artificial Neuron

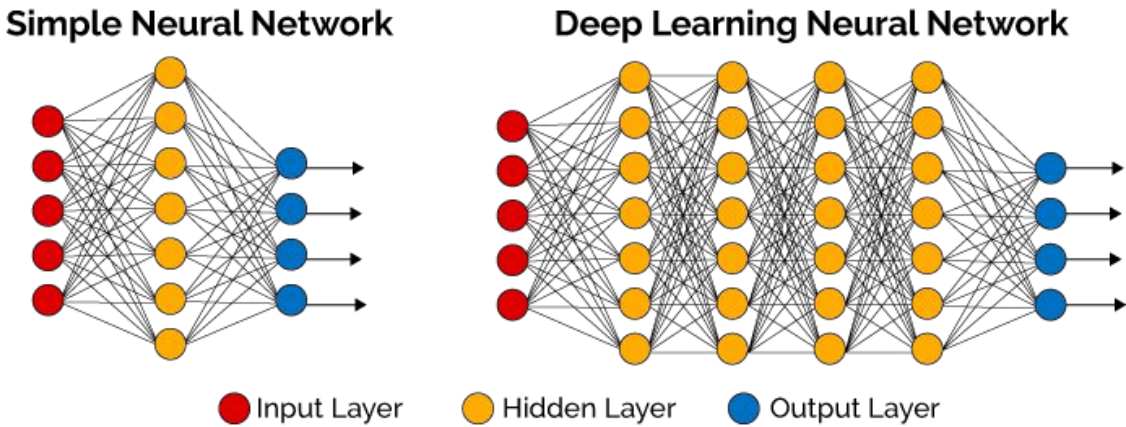


A cartoon drawing of a biological neuron (left) and its mathematical model (right).

What is a neural network?

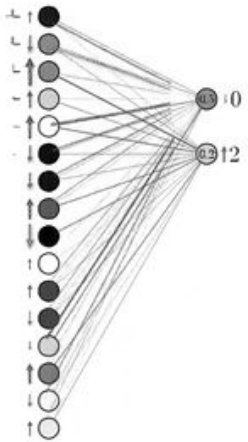
- A neural network (NN) has 3 types of layers:
  - Input
  - Hidden
  - Output

- Deep neural networks (DNN) usually has more hidden layers
  - Still has same 3 types of layers

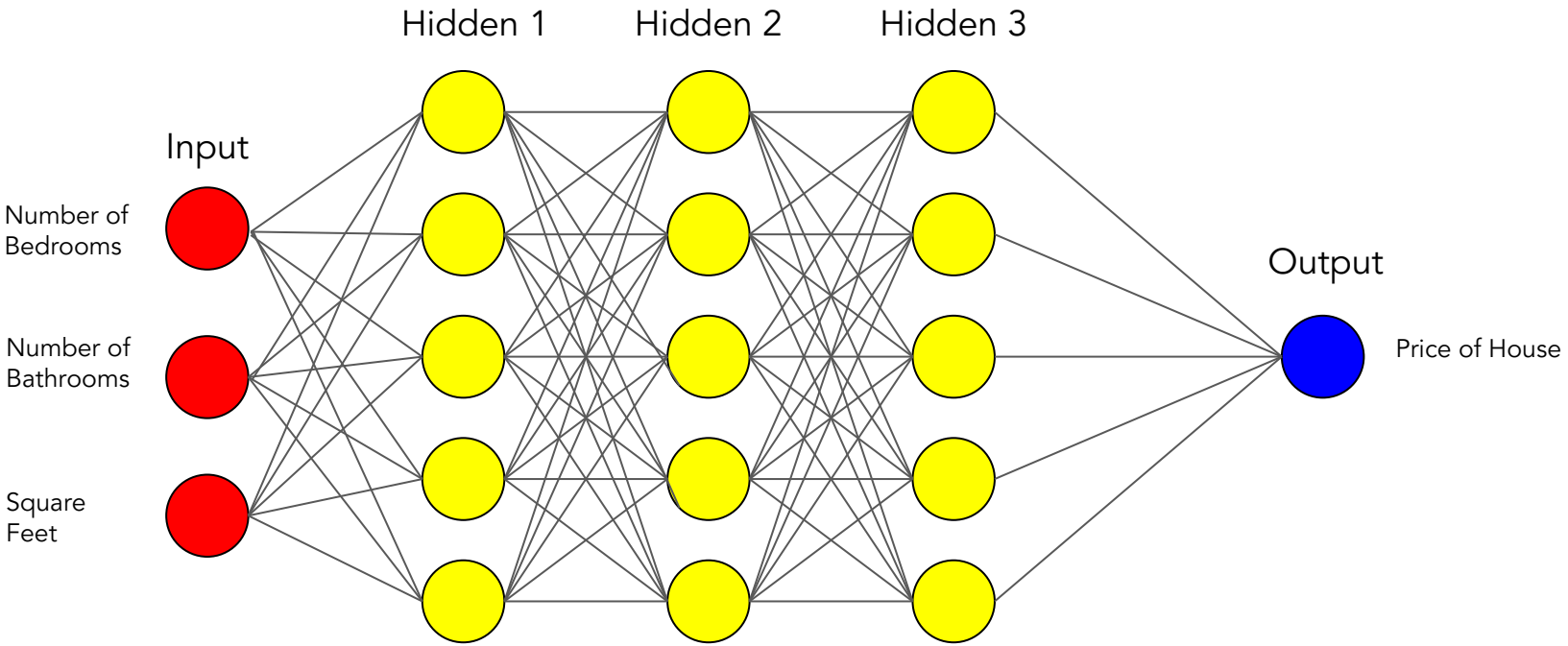


Three steps to training a neural network

1. Forward propagation
    a. Push example through the network to get a predicted output
2. Compute the cost
    a. Calculate difference between predicted output and actual data
3. Backward propagation
    a. Push back the derivative of the error and apply to each weight, such that next time it will result in a lower error



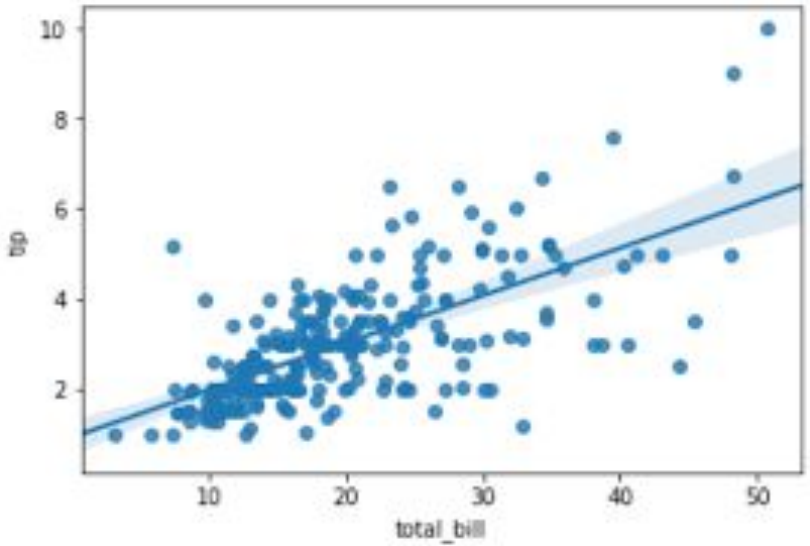
Example Neural Net - House Price



Building up to Neural Networks

Regression

Linear Regression



$$y = mx + b$$

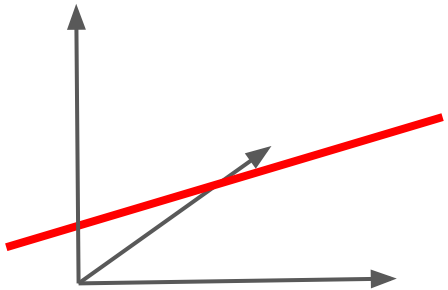
Linear Regression

Say you want to predict house prices given some features about the house

$$x_1 = 5(bedrooms), x_2 = 3(bathrooms), x_3 = 3000(squarefeet)$$

Then the house price could be:

$$z = 5w_1 + 3w_2 + 3000w_3 + b$$



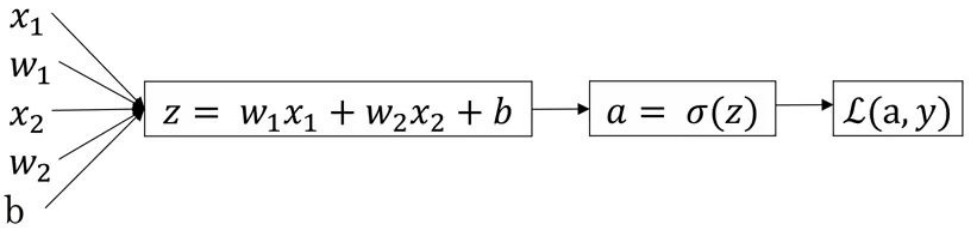
Logistic Regression

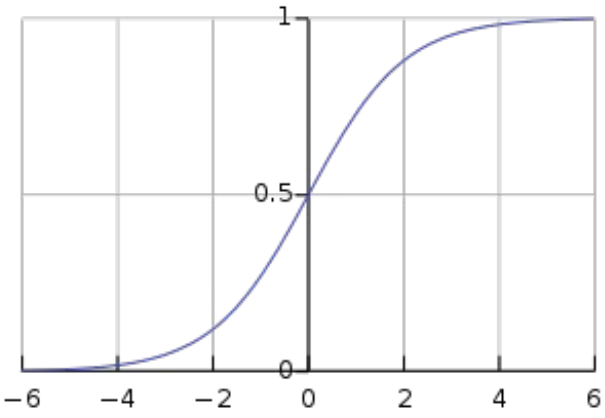
1. **Has a linear combination / made up of weights and a bias**

$$z = w_1 x_1 + w_2 x_2 + \ldots + w_n x_n + b$$

2. **Is fed through an activation function (such as a sigmoid function)**

$$a = \hat{y} = \sigma(z)$$





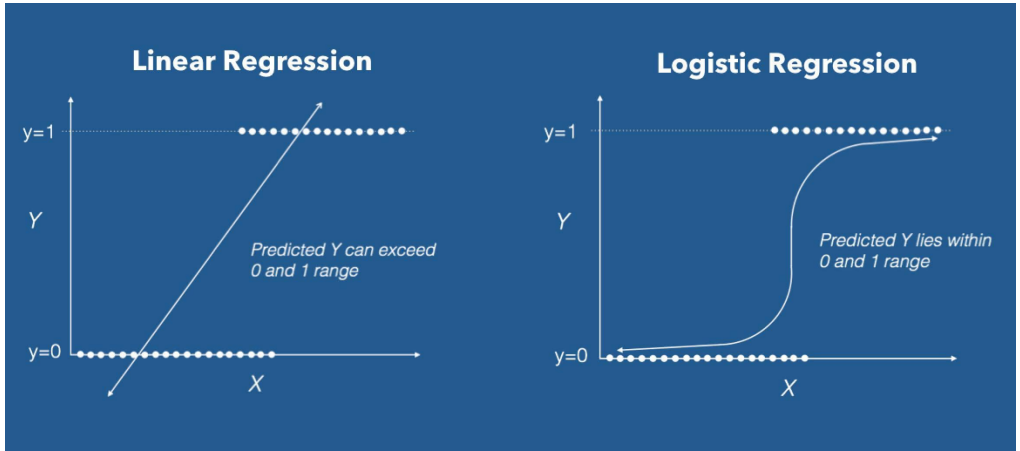
Logistic Regression (example)

Now say we want to determine if we can afford the house or not.

In this case we would use a sigmoid function to output values between 0 or 1.

This can be a metric of how affordable the house is.

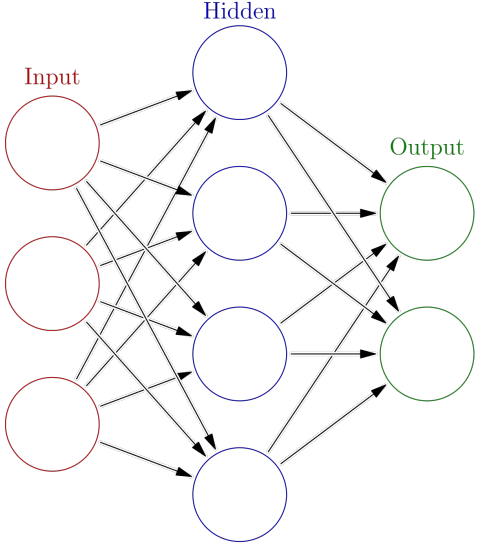
$$a = y = \sigma(z)$$



Shallow Neural Networks

The foundation of new AI

Shallow Neural Networks



1. **Now let's add more activations**
   a. This results in a hidden layer
2. **Each activation takes in inputs from the previous layer**
   a. $a^{[l]} = g(z^{[l]}) = g(w_1 a_1^{[l-1]} + w_2 a_2^{[l-1]} + \ldots + w_n a_n^{[l-1]} + b)$
   b. This occurs for every activation in one layer
3. **Adding another layer means we can learn more complicated functions**

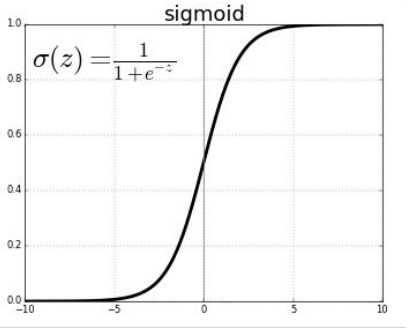
Shallow Neural Networks (example)

Say you want to predict if it is worth going to class or not

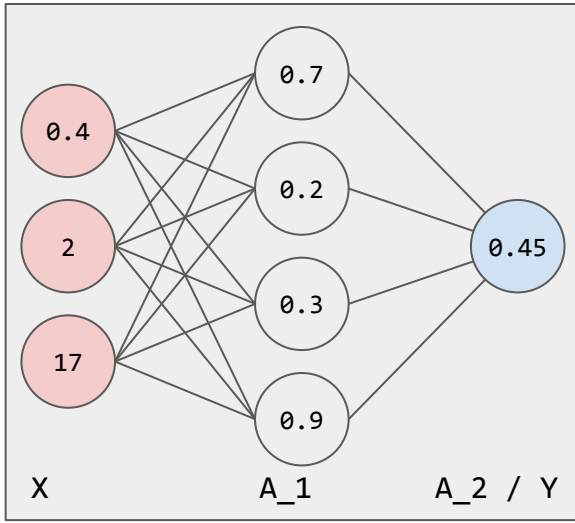
$$X = \begin{bmatrix} \text{difficulty of material} \\ \text{number of assignments due} \\ \text{days until midterm} \end{bmatrix} \qquad Y = \left[\text{probability of going to class}\right]$$

$$a_i^{[1]} = g(z) = g(w_1 x_1 + w_2 x_2 + w_3 x_3 + b)$$

$$a^{[2]} = g(w_1 a_1^{[1]} + w_2 a_2^{[1]} + w_3 a_3^{[1]} + w_4 a_4^{[1]} + b)$$

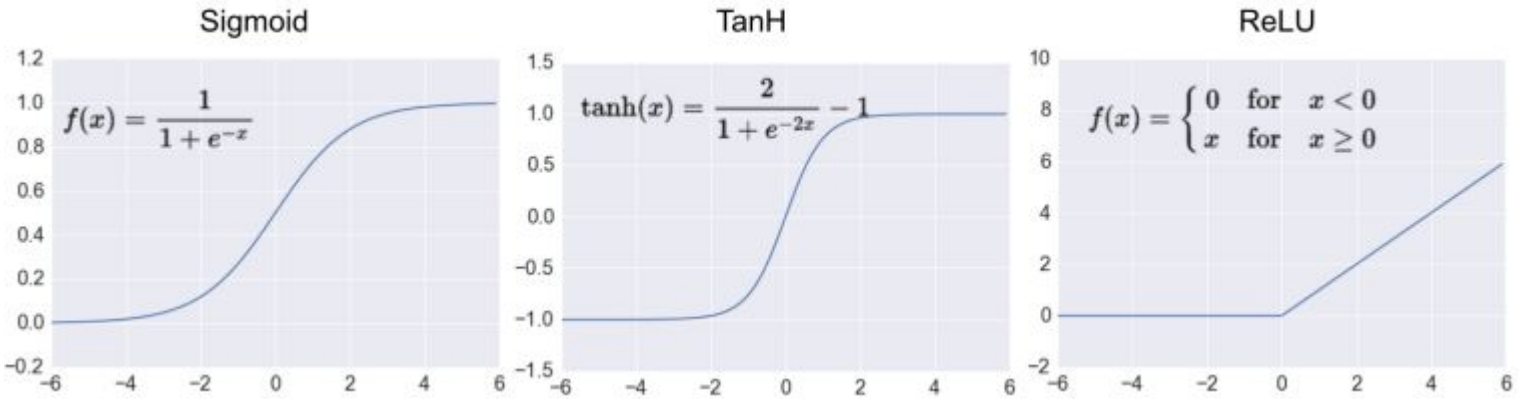


$g(x)$ **is an activation function**



Activation functions

1. **Sigmoid: output is between 0,1**
2. **Tanh: output is between -1,1**
3. **ReLu: output is positive real numbers**



Activation functions

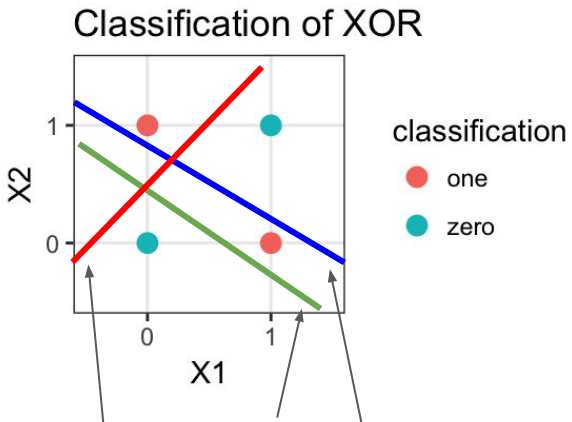
1. If we removed the activation function from our algorithm that can be called a linear activation function.
2. Linear activation function will output linear activations
    a. Whatever hidden layers you add, the activation will be always linear like logistic regression (So its useless in a lot of complex problems)
3. You might use linear activation function in one place - in the output layer if the output is real numbers (regression problem). But even in this case if the output value is non-negative you could use RELU instead.

Why do you need nonlinear activation functions?

XOR Problem

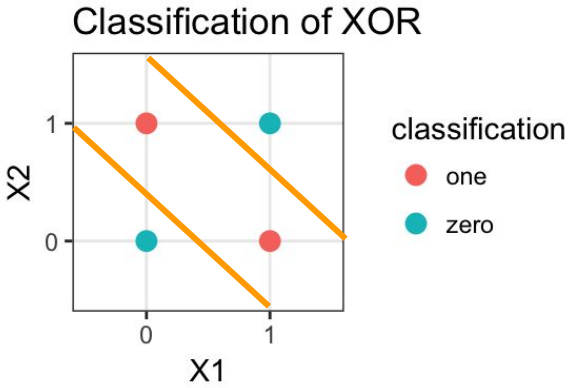
There is no way to correctly classify all inputs with a linear decision boundary

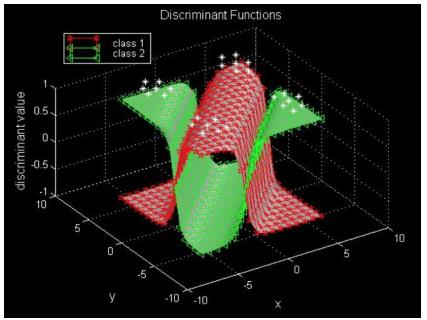
Linear Classifier



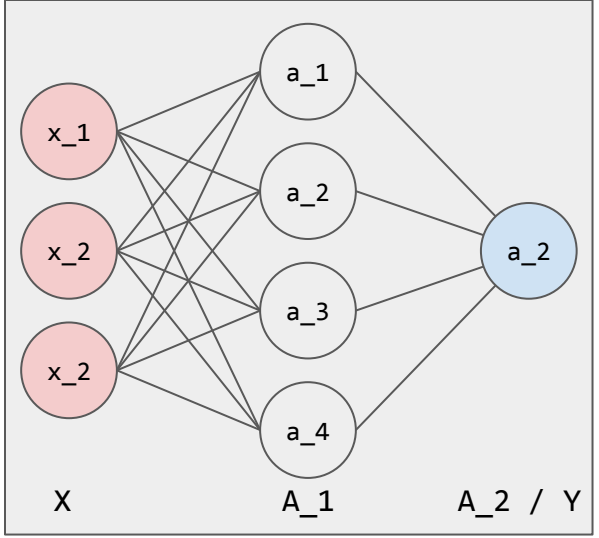
Possible linear decision boundaries

Two Layer Neural Network w/ Sigmoid Activation





Forward Propagation



1. **We've seen neural nets with one pass through, however usually, we have multiple samples.**
2. **One way is to do this iteratively**

```
for each sample i:
     for each layer l:
          for each activation j:
```

$$a_j^{[l]} = g^{[l]}(\sum_k w_{jk}^{[l]} a_k^{[l-1]} + b_j^{[l]}) = g^{[l]}(z_j^{[l]})$$

```
finally, compute the cost
```

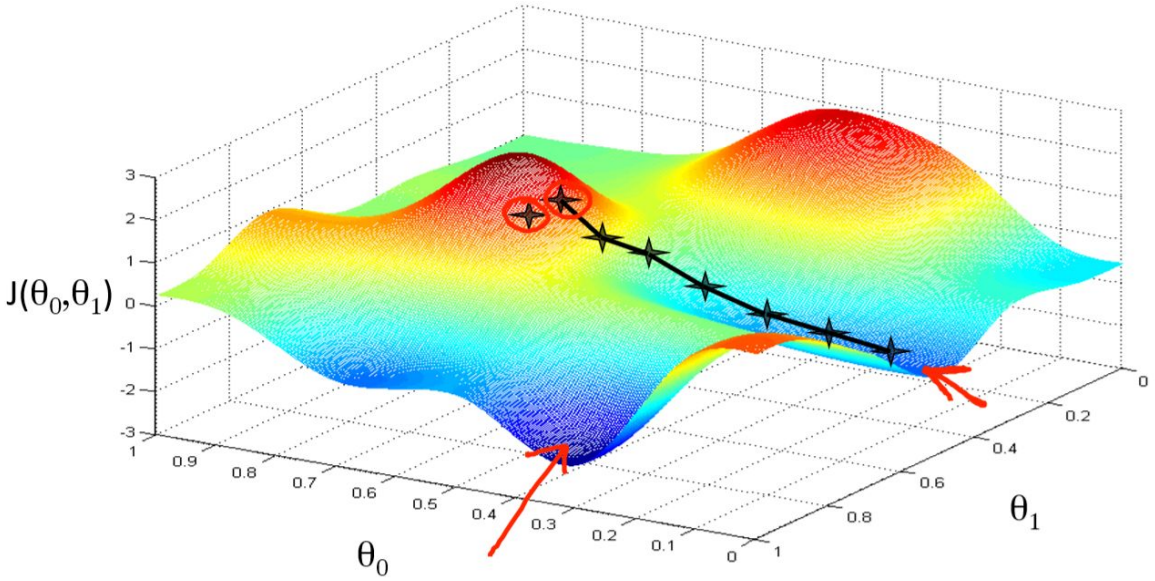
Computing the cost

1. **In order to train our neural network, we need some way to tell us how far off its estimate was from the actual value.**

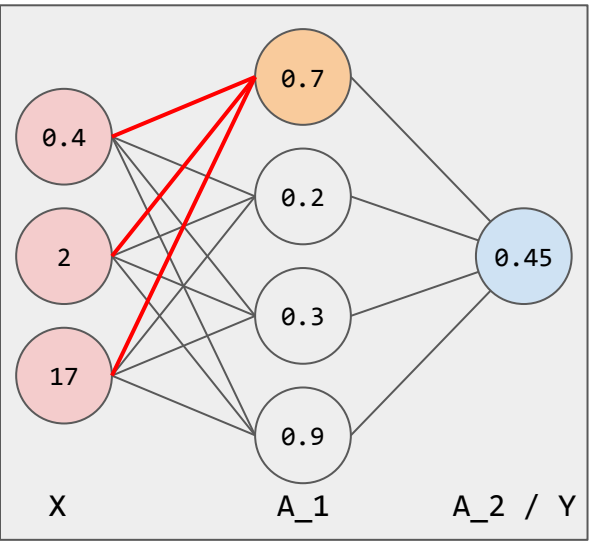
2. **We define the cost function, $J(\hat{y}, y)$ as the sum of losses, $\sum_{i=0}^{m} L(\hat{y}, y)$**
   a. Loss = Error for a single training example
   b. Cost = Sum of all Losses

Computing the cost

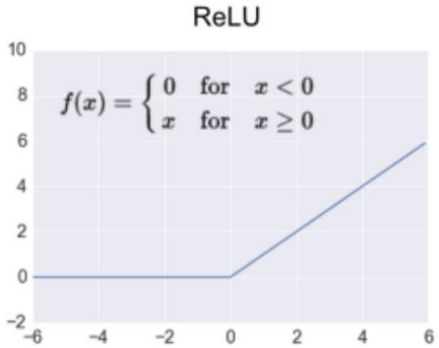
3. Train with gradient descent



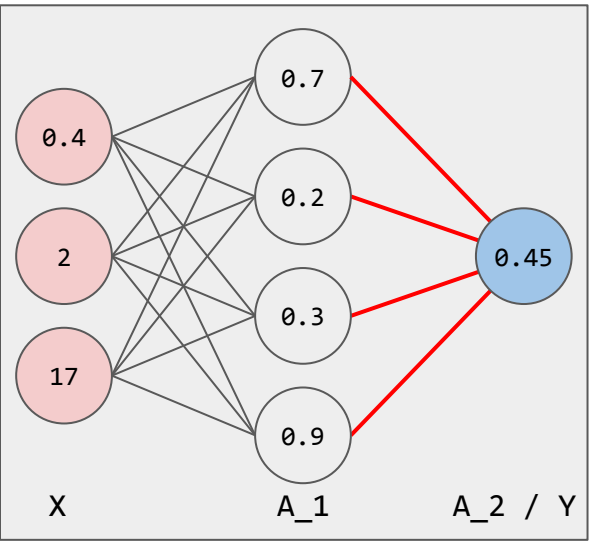
Forward Propagation (example)



$$z_1^{[1]} = w_1^{[1]} x_1 + w_1^{[1]} x_2 + w_3^{[1]} x_3 + b$$
$$= 0.5 * 0.4 + 0.1 \times 2 + 0.0058 \times 17 + 0.2 = 0.7$$
$$a_1^{[1]} = g(0.7) = \mathrm{ReLU}(0.7) = 0.7$$

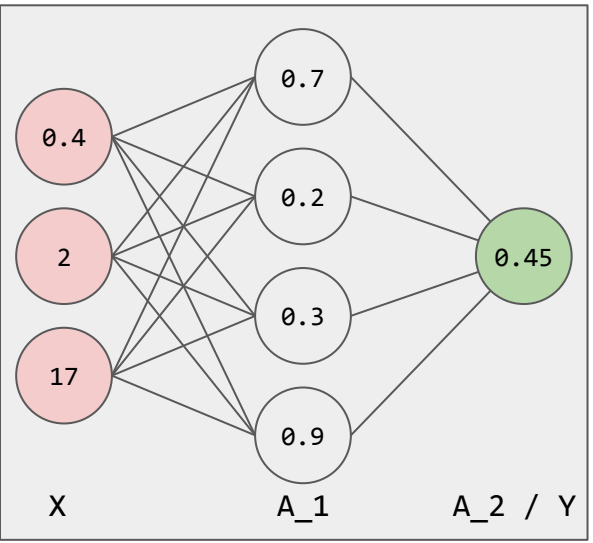


Forward Propagation (example)



$$z_1^{[1]} = w_1^{[1]} x_1 + w_1^{[1]} x_2 + w_3^{[1]} x_3 + b$$
$$= 0.5 * 0.4 + 0.1 \times 2 + 0.0058 \times 17 + 0.2 = 0.7$$
$$a_1^{[1]} = g(0.7) = \mathrm{ReLU}(0.7) = 0.7$$
$$z_1^{[2]} = w_1^{[2]} a_1^{[1]} + w_2^{[2]} a_2^{[1]} + w_3^{[2]} a_3^{[1]} + w_4^{[2]} a_4^{[1]} + b$$

Forward Propagation (example)



$$z_1^{[1]} = w_1^{[1]} x_1 + w_1^{[1]} x_2 + w_3^{[1]} x_3 + b$$
$$= 0.5 * 0.4 + 0.1 \times 2 + 0.0058 \times 17 + 0.2 = 0.7$$

$$a_1^{[1]} = g(0.7) = \text{ReLU}(0.7) = 0.7$$

$$z_1^{[2]} = w_1^{[2]} a_1^{[1]} + w_2^{[2]} a_2^{[1]} + w_3^{[2]} a_3^{[1]} + w_4^{[2]} a_4^{[1]} + b$$

$$\hat{y} = a_1^{[2]} = g(z_1^{[2]}) = 0.45$$

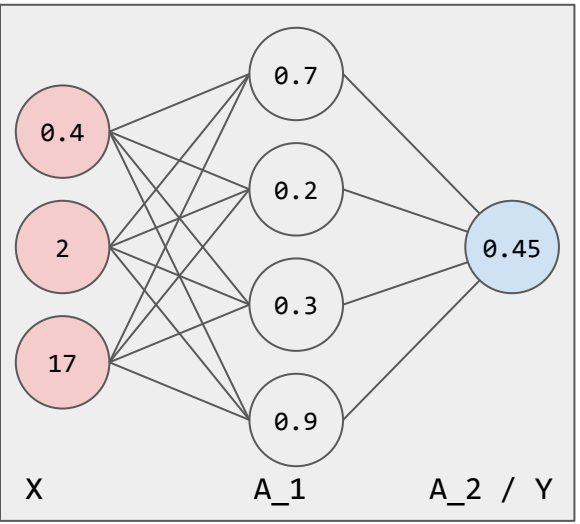
$$y = 1$$

$$L(\hat{y}, y) = -y \log \hat{y} - (1 - y) \log(1 - \hat{y})$$

$$-(1) \log (0.45) - (1 - (1)) \log(1 - (0.45)) = 0.798508$$

Back to the example

Say you want to predict if it is worth going to class or not



$$\hat{y} = a_1^{[2]} = g(z_1^{[2]}) = 0.45$$

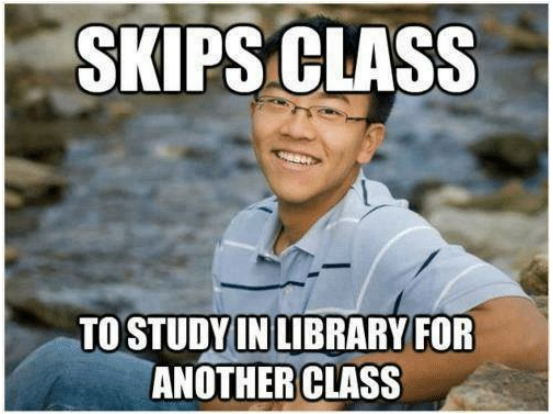
But it turns out midterm material was covered...

$$y = 1$$

Here is his mistake in numerical form

$$L(\hat{y}, y) = 0.798508$$

```
if y > 0.5:
    goto_class()
else:
    skip()
```



Training a network with Calculus

Gradient descent

Terminology for later

Parameters vs Hyperparameters

1. **Parameters are values that are <u>learned</u> through training or backpropagation. (E.g. $W, \quad b$)**
2. **Hyperparameters are values that are <u>set manually</u> without a learning method. (E.g. the learning rate, α)**

Cost Function: revisited

The cost function is the sum of losses for all training examples

- Basically, the combined error for all training examples.

$$J(\hat{y}, y) = \sum_{i=1}^{m} L(\hat{y}^{(i)}, y^{(i)})$$

This is the general form of writing the cost function

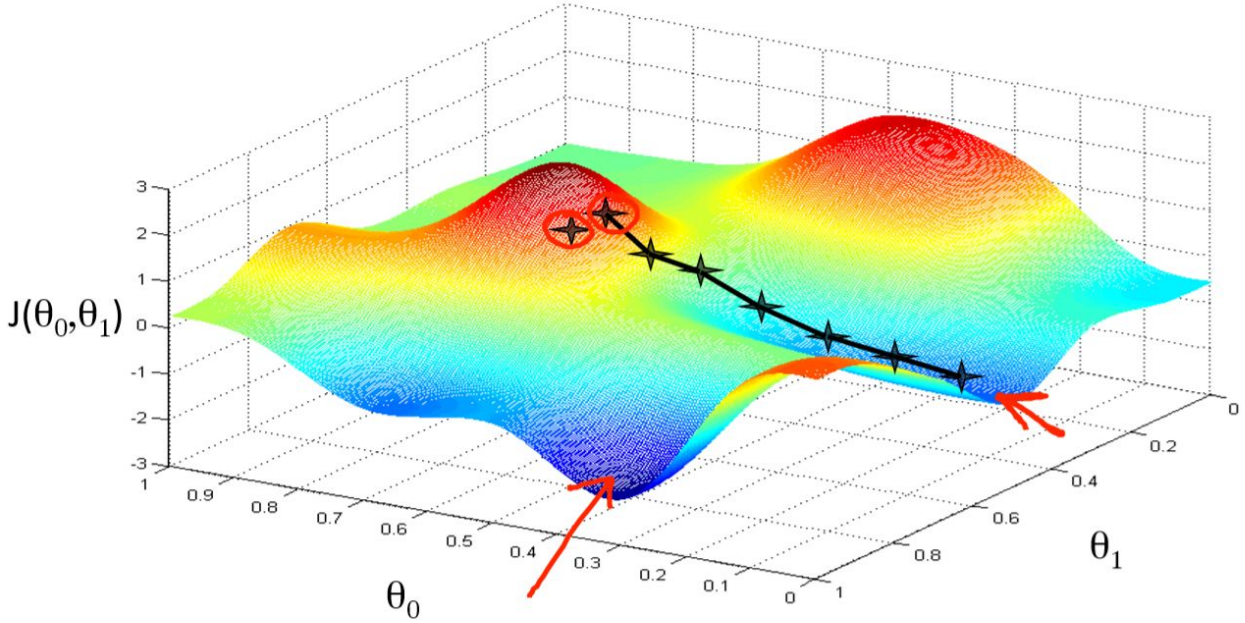
$$J(\theta) = \text{Cost Function}$$

Gradient Descent Summary

1. **Goal: we want to change all of the weights so that our predictions fit the data better**
2. **How: the error between our predicted values and actual values tells us how much we need to change each individual weight (increase or decrease)**
    a. By calculating the derivative from the cost function we get the numerical value of change.
    b. The derivative is equivalent to the slope that that point, and tells us where the error is minimized

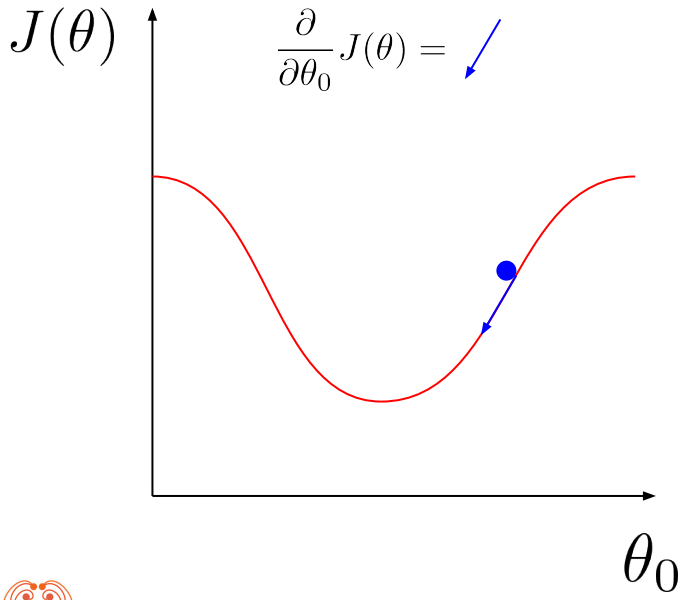
Gradient descent

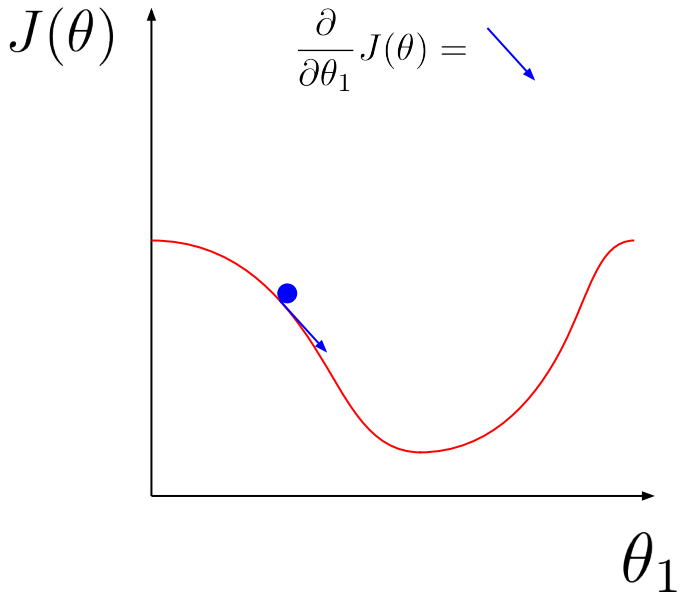
We find the direction of steepest slope, then take one step in that direction.



Gradient descent

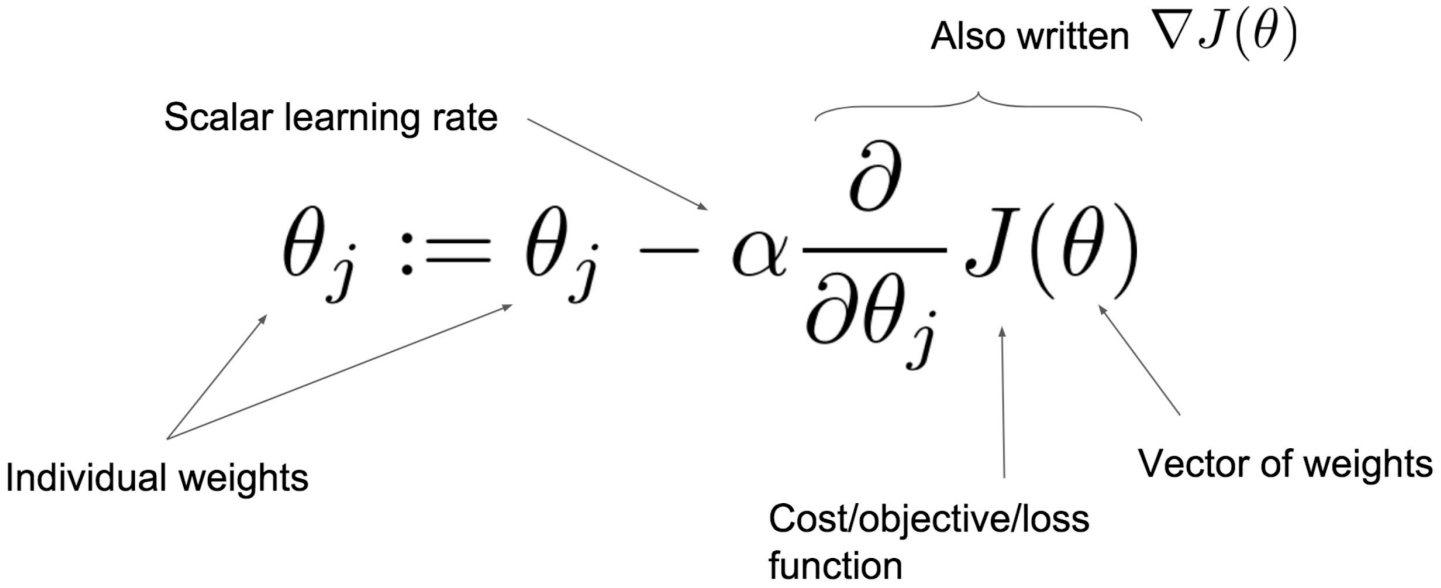
Finding the slope for each individual parameter





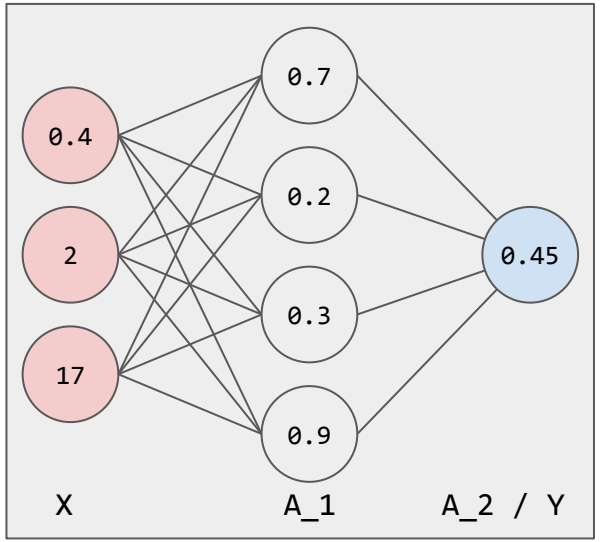
Gradient descent

To find the slope, we compute the derivative of the cost (gradient) with respect to a single parameter.



Gradient descent for Neural Networks

Goal: update the **weights** and **biases** such that the **cost function** will output a smaller value
(i.e. the difference actual and predicted values will be minimized)



Repeat for many iterations (training steps):

Compute forward pass and the cost function, **J**

$$W^{[1]} := W^{[1]} - \alpha \frac{\partial J}{\partial W^{[1]}}$$

$$b^{[1]} := b^{[1]} - \alpha \frac{\partial J}{\partial b^{[1]}}$$

$$W^{[2]} := W^{[2]} - \alpha \frac{\partial J}{\partial W^{[2]}}$$

$$b^{[2]} := b^{[2]} - \alpha \frac{\partial J}{\partial b^{[2]}}$$

Chain Rule

1. To get the direction that a parameter must change in order reduce prediction error, we use the **chain rule** from calculus.

$$\frac{d}{dx} f(g(x)) = f'(g(x))g'(x)$$

$$\frac{\partial J}{\partial W^{[2]}} = \frac{\partial J}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} \frac{\partial z^{[2]}}{\partial W^{[2]}}$$

$$\frac{\partial J}{\partial W^{[1]}} = \frac{\partial J}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} \frac{\partial z^{[2]}}{\partial a^{[1]}} \frac{\partial a^{[1]}}{\partial z^{[1]}} \frac{\partial z^{[1]}}{\partial W^{[1]}}$$

$$J(\hat{y}, y) = \sum_{i=1}^{m} L(\hat{y}^{(i)}, y^{(i)})$$

$$L(\hat{y}, y) = -y \log \hat{y} - (1 - y) \log(1 - \hat{y})$$

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

$$z^{[2]} = W^{[2]} a^{[1]} + b^{[2]}$$

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

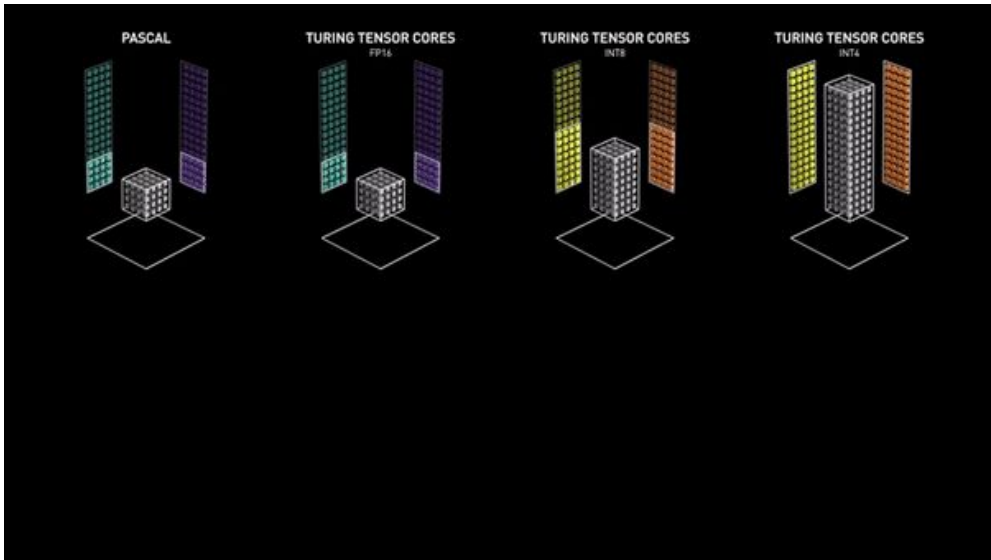
$$z^{[1]} = W^{[1]} x + b^{[1]}$$

Speeding up with Linear Algebra

Vectors and matrices

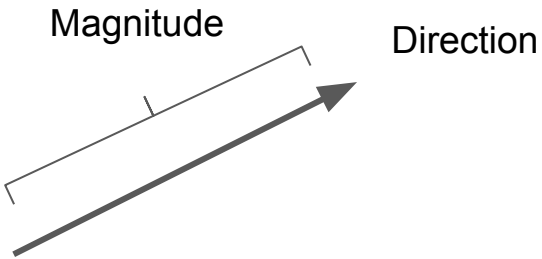
Vectorization

1. Recent models require massive amounts of computational power
2. Therefore obtaining the most efficiency out of your model is crucial
3. Linear algebra libraries are becoming more efficient, and neural networks can benefit from this outcome
   - Matrix multiplication in Numpy
   - Tensor operations in TensorFlow



Vectors and Matrices

Vector



Feature vector

$$x = \begin{bmatrix} 0.4 \\ 2 \\ 17 \end{bmatrix}$$

Matrix

Weight Matrix

$$\begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix}$$

rows

columns

Vectors and Matrices

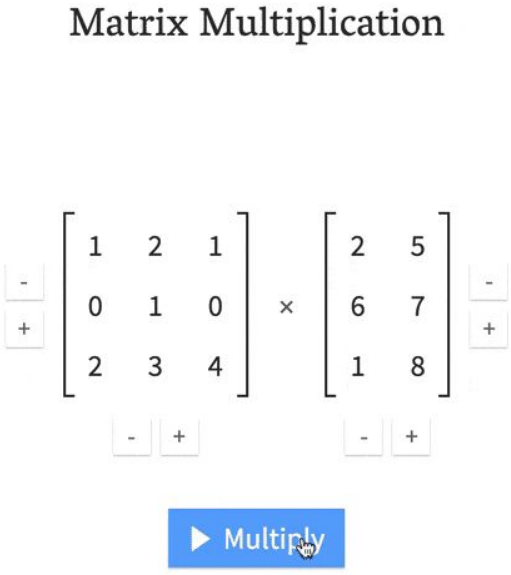
Inner product (dot product)

$$v \cdot w = v^T w = \begin{bmatrix} 1 & 2 & 3 \end{bmatrix} \begin{bmatrix} 4 \\ 1 \\ 3 \end{bmatrix} = 1 \times 4 + 2 \times 1 + 3 \times 3 = 15$$

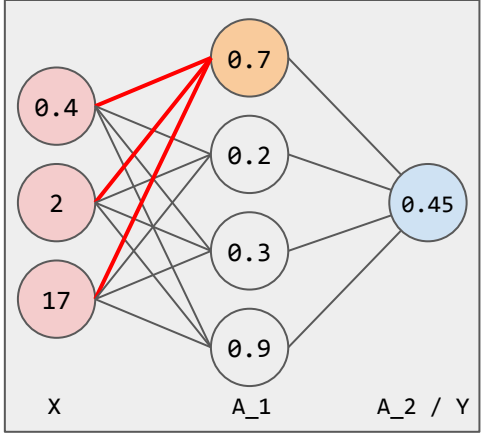
Matrix vector multiplication

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} ax + by + cz \\ dx + ey + fz \\ gx + hy + iz \end{bmatrix}$$

3x3 3x1 = 3x1



Vectorizing within one activation



$$z^{[l]} = \left(w_1^{[l]} a_1^{[l-1]} + \ldots + w_n^{[l]} a_n^{[l-1]} + b^{[l]} \right)$$

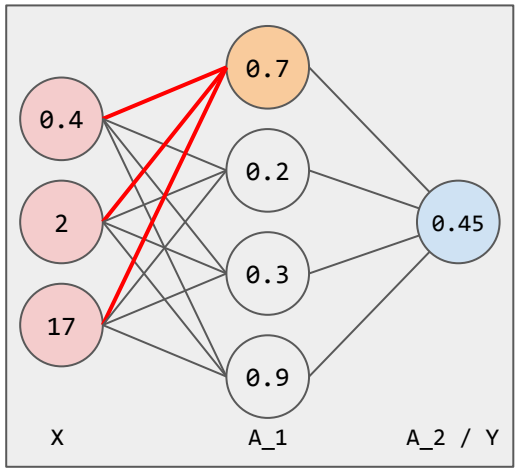
$$= \begin{bmatrix} w_1^{[l]} \\ \vdots \\ w_n^{[l]} \end{bmatrix}^T \begin{bmatrix} a_1^{[l-1]} \\ \vdots \\ a_n^{[l-1]} \end{bmatrix} + b^{[l]} = w^{[l]T} a^{[l-1]} + b^{[l]}$$

$$a^{[l]} = g^{[l]}(z^{[l]}) = g^{[l]}(w^{[l]T} a^{[l-1]} + b^{[l]})$$

Vectorizing within one activation (example)

$$z^{[l]} = \left(w_1^{[l]}a_1^{[l-1]} + \ldots + w_n^{[l]}a_n^{[l-1]} + b^{[l]}\right) = w^{[l]T}a^{[l-1]} + b^{[l]}$$

$$a^{[l]} = g^{[l]}(z^{[l]}) = g^{[l]}(w^{[l]T}a^{[l-1]} + b^{[l]})$$

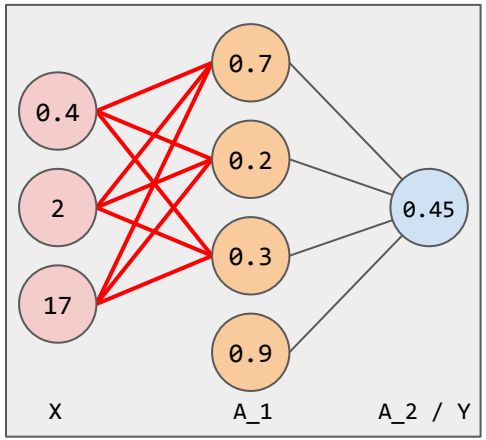


$$z_1^{[1]} = w_1^{[1]}x_1 + w_1^{[1]}x_2 + w_3^{[1]}x_3 + b$$

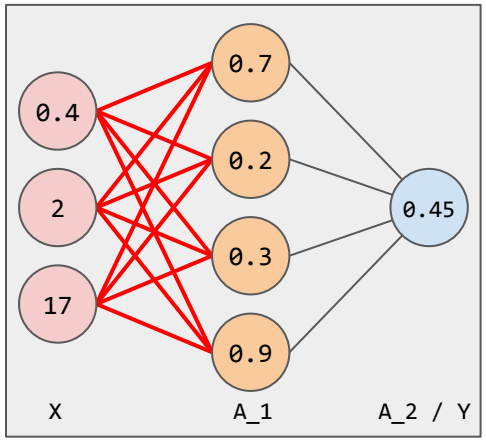
$$= \underbrace{0.5 * 0.4 + 0.1 \times 2 + 0.0058 \times 17}_{\begin{bmatrix} 0.5 \\ 0.1 \\ 0.0058 \end{bmatrix}^T \begin{bmatrix} 0.4 \\ 2 \\ 17 \end{bmatrix}} + 0.2 = 0.7$$

$$a_1^{[1]} = g(0.7) = \text{ReLU}(0.7) = 0.7$$

Vectorizing across all activations

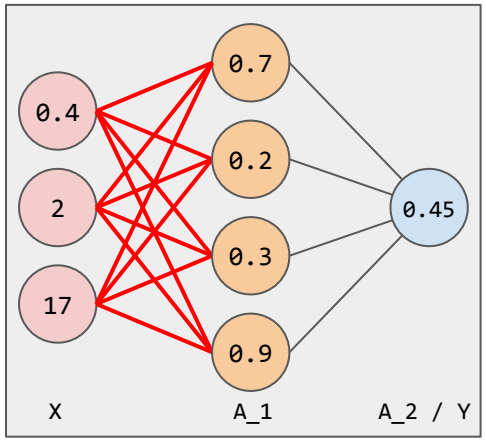


Vectorizing across all activations



$$z_1^{[1]} = w_1^{[1]T} x + b_1^{[1]}, \quad a_1^{[1]} = g^{[1]}(z_1^{[1]})$$
$$z_2^{[1]} = w_2^{[1]T} x + b_2^{[1]}, \quad a_2^{[1]} = g^{[1]}(z_2^{[1]})$$
$$z_3^{[1]} = w_3^{[1]T} x + b_3^{[1]}, \quad a_3^{[1]} = g^{[1]}(z_3^{[1]})$$
$$z_4^{[1]} = w_4^{[1]T} x + b_4^{[1]}, \quad a_4^{[1]} = g^{[1]}(z_3^{[1]})$$

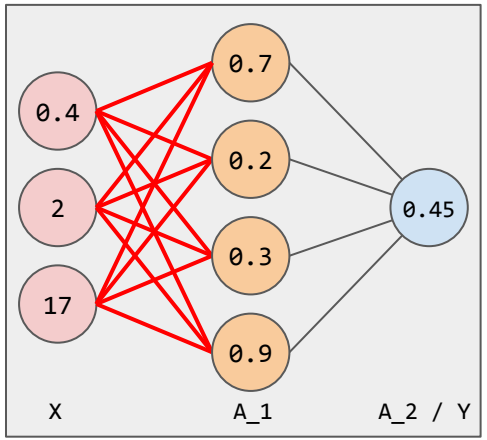
Vectorizing across all activations



$$
\begin{aligned}
z_1^{[1]} &= w_1^{[1]T} x + b_1^{[1]}, & a_1^{[1]} &= g^{[1]}(z_1^{[1]}) \\
z_2^{[1]} &= w_2^{[1]T} x + b_2^{[1]}, & a_2^{[1]} &= g^{[1]}(z_2^{[1]}) \\
z_3^{[1]} &= w_3^{[1]T} x + b_3^{[1]}, & a_3^{[1]} &= g^{[1]}(z_3^{[1]}) \\
z_4^{[1]} &= w_4^{[1]T} x + b_4^{[1]}, & a_4^{[1]} &= g^{[1]}(z_3^{[1]})
\end{aligned}
$$

$$
z^{[1]} = \begin{bmatrix} w_1^{[1]T} \\ w_2^{[1]T} \\ w_3^{[1]T} \\ w_4^{[1]T} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1^{[1]} \\ b_2^{[1]} \\ b_3^{[1]} \\ b_4^{[1]} \end{bmatrix} = \begin{bmatrix} w_1^{[1]T} x + b_1^{[1]} \\ w_2^{[1]T} x + b_2^{[1]} \\ w_3^{[1]T} x + b_3^{[1]} \\ w_4^{[1]T} x + b_4^{[1]} \end{bmatrix} = \begin{bmatrix} z_1^{[1]} \\ z_2^{[1]} \\ z_3^{[1]} \\ z_3^{[1]} \end{bmatrix}
$$

Vectorizing across all activations



$$z^{[1]} = \begin{bmatrix} w_1^{[1]T} \\ w_2^{[1]T} \\ w_3^{[1]T} \\ w_4^{[1]T} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1^{[1]} \\ b_2^{[1]} \\ b_3^{[1]} \\ b_4^{[1]} \end{bmatrix} = \begin{bmatrix} w_1^{[1]T} x + b_1^{[1]} \\ w_2^{[1]T} x + b_2^{[1]} \\ w_3^{[1]T} x + b_3^{[1]} \\ w_4^{[1]T} x + b_4^{[1]} \end{bmatrix} = \begin{bmatrix} z_1^{[1]} \\ z_2^{[1]} \\ z_3^{[1]} \\ z_3^{[1]} \end{bmatrix}$$

$$z^{[l](i)} = W^{[l]} a^{[l-1](i)} + b^{[l]}, \quad a^{[l](i)} = g^{[l]}(z^{[l](i)})$$

```
for i = 1 to m:
```

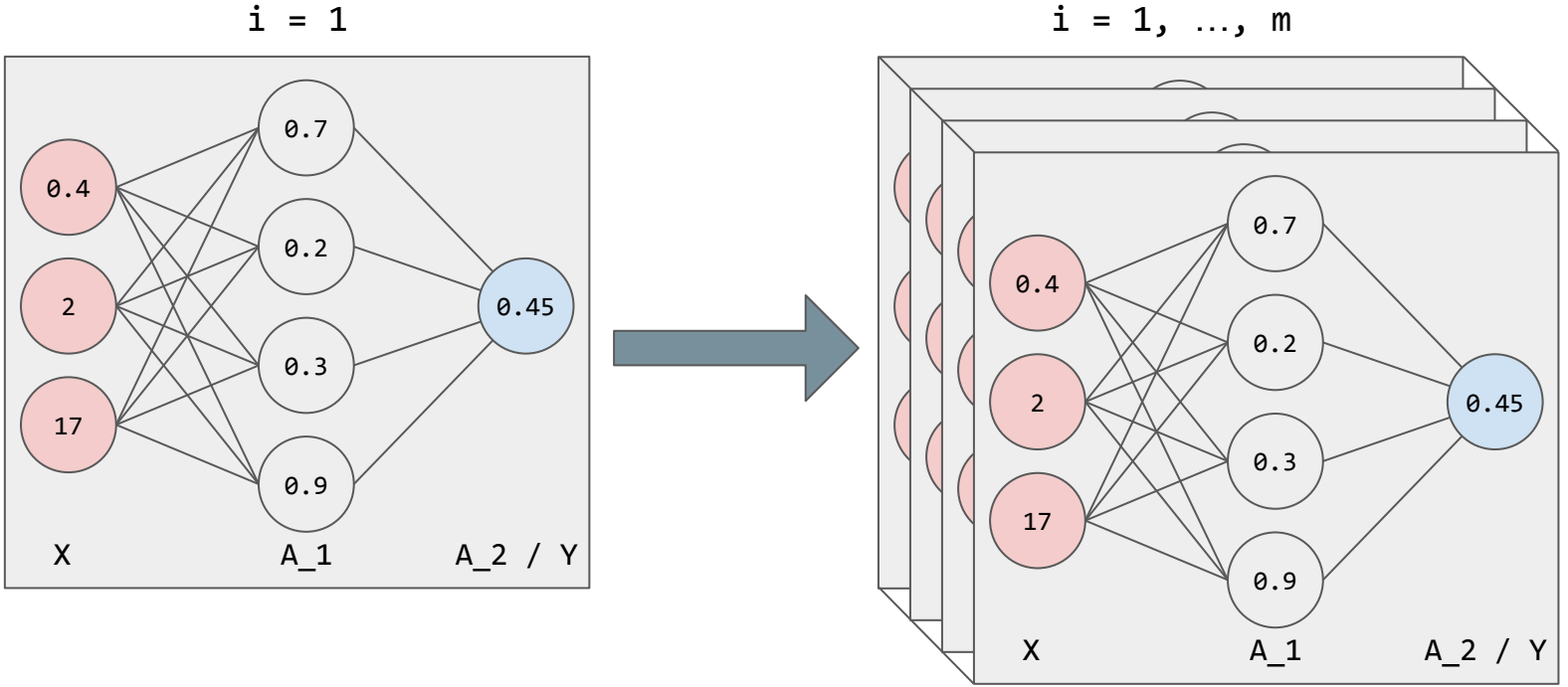
$$z^{[1](i)} = W^{[1]} x^{(i)} + b^{[1]}$$

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

$$z^{[2](i)} = W^{[2]} a^{[1](i)} + b^{[2]}$$

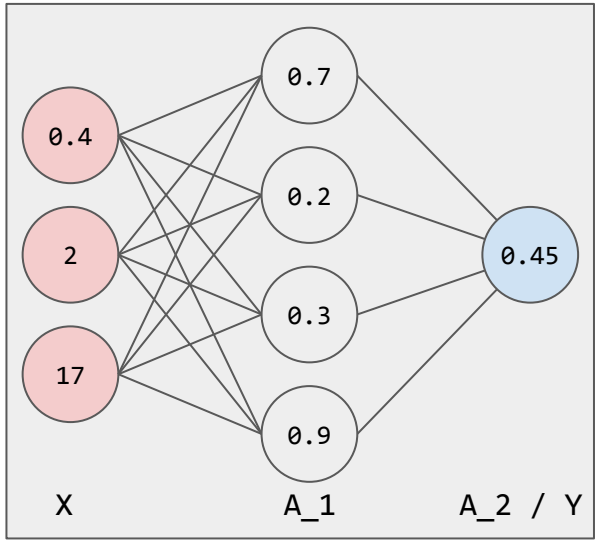
$$a^{[2](i)} = \sigma(z^{[2](i)})$$

Vectorizing across multiple examples



Vectorizing across multiple examples

Algorithm: forward propagate through each example




```
for i = 1 to m:
```

$$z^{[1](i)} = W^{[1]}x^{(i)} + b^{[1]}$$

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

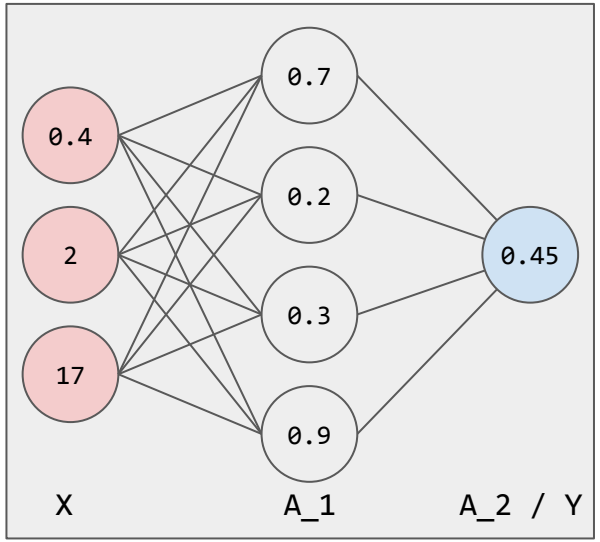
$$z^{[2](i)} = W^{[2]}a^{[1](i)} + b^{[2]}$$

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

$$J(\hat{y}, y) = \sum_{i=1}^{m} L(\hat{y}^{(i)}, y^{(i)})$$

Vectorizing across multiple examples

Algorithm: forward propagate through each example



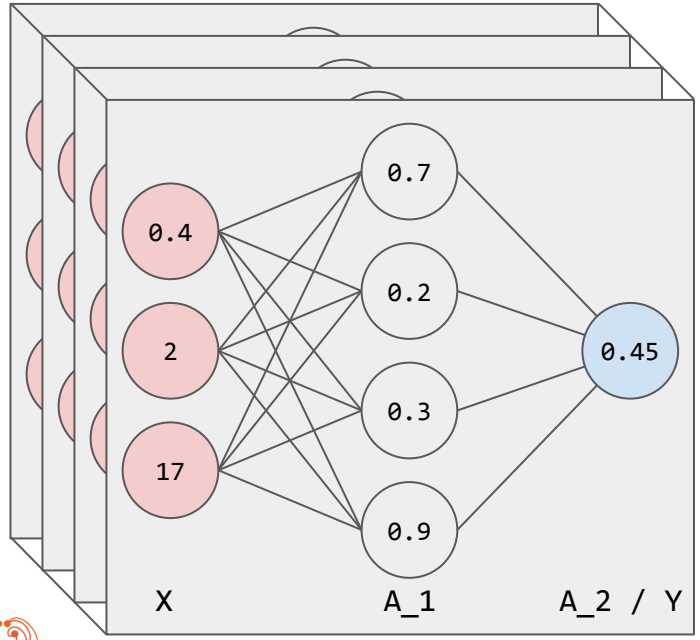
$$z^{[l](i)} = W^{[l]} a^{[l-1](i)} + b^{[l]}, \quad a^{[l](i)} = g^{[l]}(z^{[l](i)})$$

$$\underbrace{\begin{bmatrix} \\ \\ \\ \end{bmatrix}}_{z^{[l]}} = \underbrace{\begin{bmatrix} & & \\ & & \\ & & \\ & & \end{bmatrix}}_{W^{[l]}} \times \underbrace{\begin{bmatrix} \\ \\ \end{bmatrix}}_{a^{[l-1]}} + \underbrace{\begin{bmatrix} \\ \\ \\ \\ \end{bmatrix}}_{b^{[l]}}$$

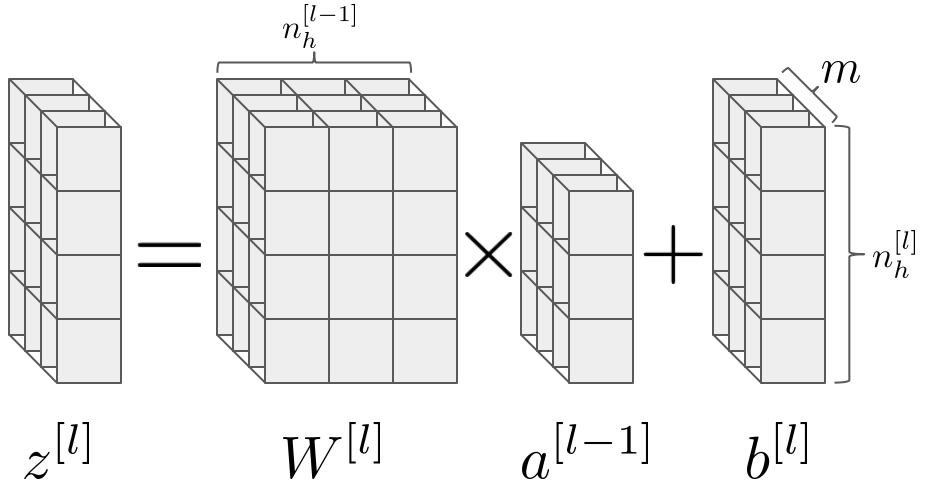
$n_h^{[l-1]}$ (above $W^{[l]}$), $n_h^{[l]}$ (beside $b^{[l]}$)

Vectorizing across multiple examples

Vectorized algorithm: forward propagate through multiple examples in parallel



$$z^{[l]} = W^{[l]} a^{[l-1]} + b^{[l]}, \quad a^{[l]} = g^{[l]}(z^{[l]})$$



Vectorizing Gradient Descent

Going from: Iteratively changing each weight by the derivative of the cost function

To: In parallel, simultaneously changing each weight by the derivative of the cost function

Vectorizing Gradient Descent

Going from: Iteratively changing each weight by the derivative of the cost function

To: In parallel, simultaneously changing each weight by the derivative of the cost function

Previously, $\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$

Now, W is the weight matrix for layer l

$$W^{[l]} := W^{[l]} - \alpha \frac{\partial}{\partial W^{[l]}} J(\theta)$$

Note similarly we do this for the bias vector as well

Derivatives for a simple Neural Network

$$dZ^{[2]} = A^{[2]} - Y$$

$$dW^{[2]} = \frac{1}{m} dZ^{[2]} A^{[1]^T}$$

$$db^{[2]} = \frac{1}{m} np.sum(dZ^{[2]}, axis = 1, keepdims = True)$$

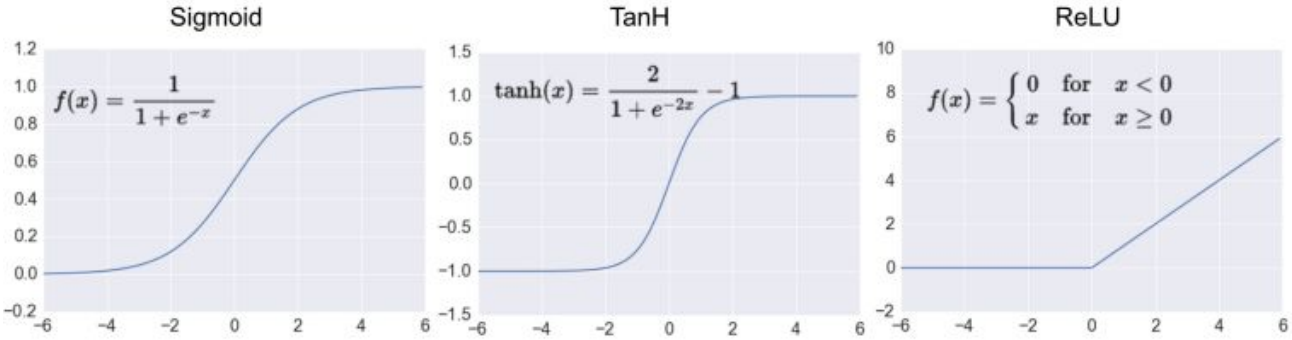
$$dZ^{[1]} = W^{[2]^T} dZ^{[2]} * g^{[1]'}(\mathrm{Z}^{[1]})$$

$$dW^{[1]} = \frac{1}{m} dZ^{[1]} X^T$$

$$db^{[1]} = \frac{1}{m} np.sum(dZ^{[1]}, axis = 1, keepdims = True)$$

Derivatives for activation functions

$$g'(x) = \begin{cases} \dfrac{d}{dx}\sigma(x) = \sigma(x)(1-\sigma(x)) \\ \dfrac{d}{dx}\tanh(x) = 1 - \tanh^2(x) \\ \dfrac{d}{dx}\mathrm{ReLU}(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x > 0 \end{cases} \end{cases}$$



Upcoming Events

- Society and MI Discussion
  - Tue, February 5, 7pm – 8pm
- First Paper Discussion
  - Tue, February 19, TBD
- Google Brain Talk by Sammy Bengio
  - Mon, February 4, 10:30-12pm
  - Photonics Building: 8 St. Mary's Street, 9th Floor, Colloquium Room
  - Link to description

The Algorithm

How to implement and train a neural network

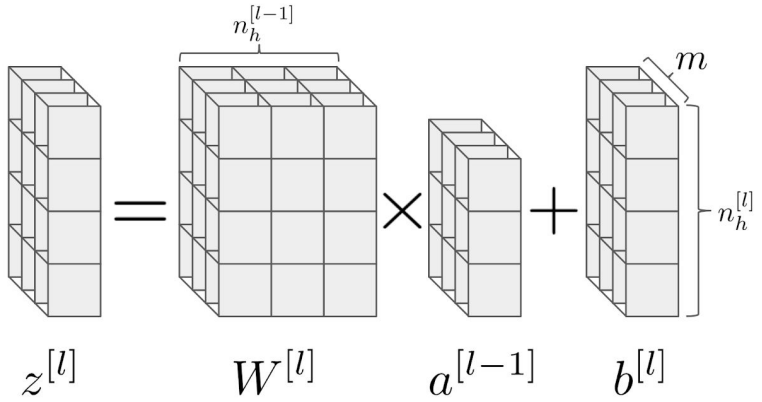
Google Colaboratory

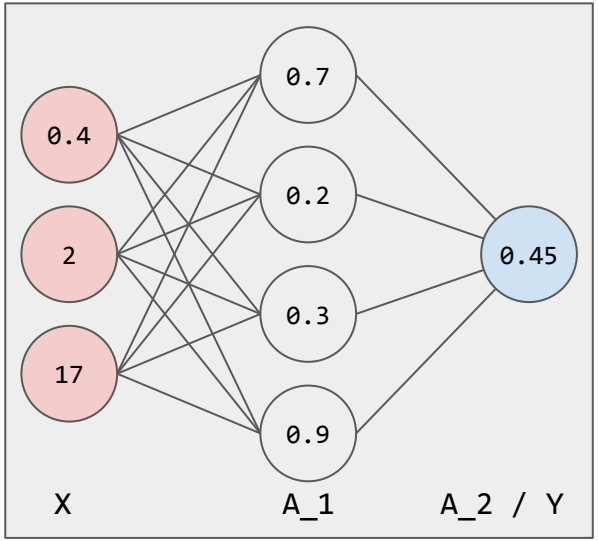
Worksheet: bit.ly/2S5Tg7N

Answer key: bit.ly/2RxPIG3

The Algorithm

```
def initialize_parameters(n_x, n_h, n_y):
    W1 = np.random.randn(n_h, n_x) * 0.01
    b1 = np.zeros(shape=(n_h, 1))
    W2 = np.random.randn(n_y, n_h) * 0.01
    b2 = np.zeros(shape=(n_y, 1))

    parameters = {"W1": W1, "b1": b1, "W2": W2, "b2": b2}

    return parameters
```

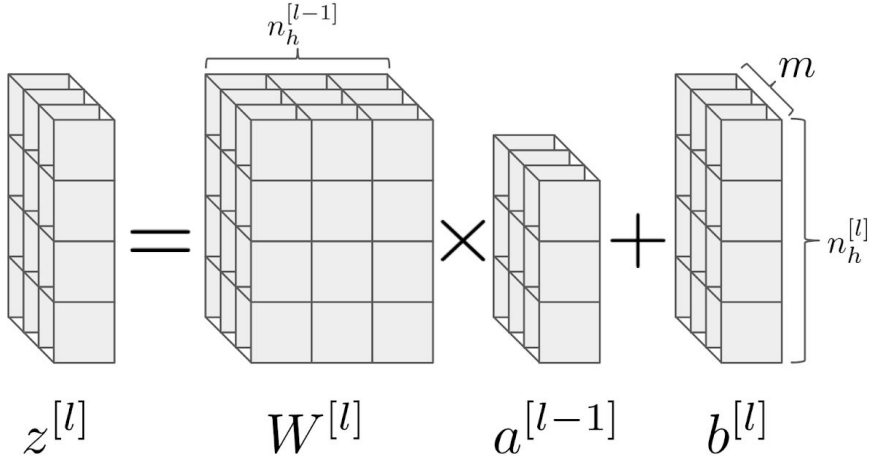




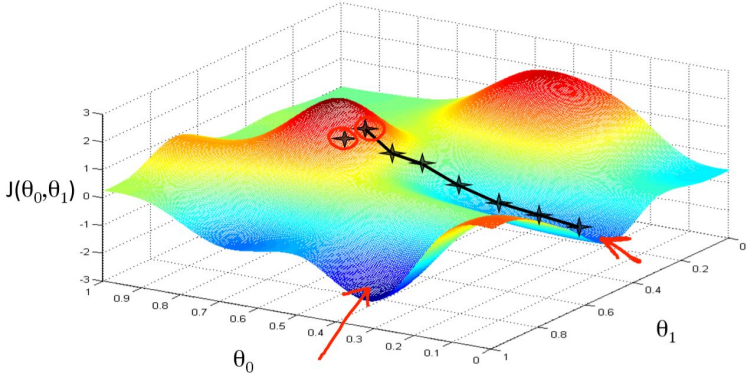

```
# n_x: 3 activations(features) at layer 0
# n_h: 4 activations(hidden) at layer 1
# n_y: 1 activations(output) at layer 2
```

The Algorithm

```
def forward_propagation(X, parameters):
    W1 = parameters['W1']
    b1 = parameters['b1']
    W2 = parameters['W2']
    b2 = parameters['b2']

    Z1 = np.dot(W1, X) + b1
    A1 = np.tanh(Z1)
    Z2 = np.dot(W2, A1) + b2
    A2 = sigmoid(Z2)

    cache = {"Z1": Z1, "A1": A1, "Z2": Z2, "A2": A2}

    return A2, cache
```



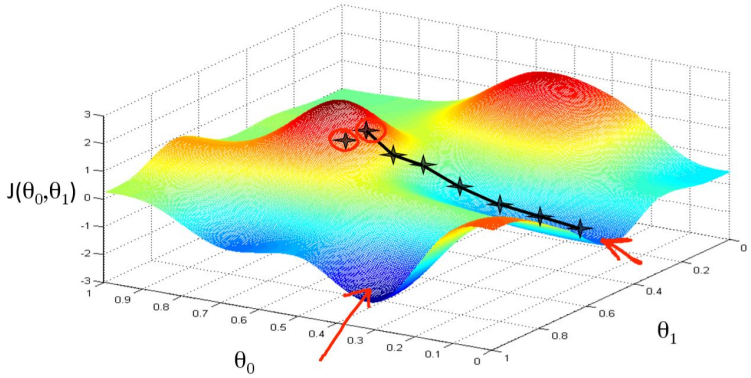
The Algorithm




```
def compute_cost(A2, Y, parameters):
    m = Y.shape[1] # number of examples

    W1 = parameters['W1']
    W2 = parameters['W2']

    logprobs = np.multiply(np.log(A2), Y) + np.multiply((1 - Y), np.log(1 - A2))
    cost = - np.sum(logprobs) / m

    cost = np.squeeze(cost)

    return cost
```

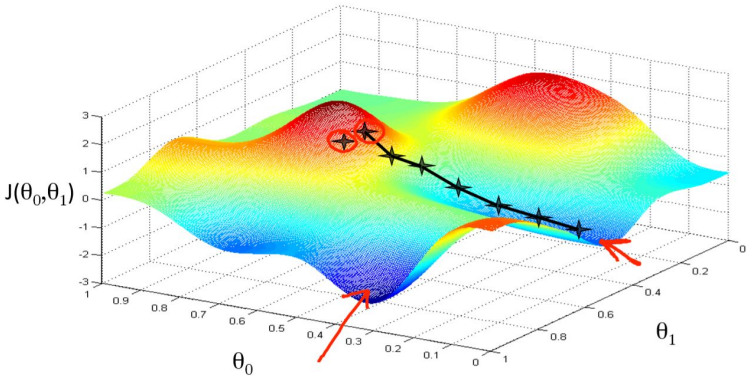
The Algorithm

```
def backward_propagation(parameters, cache, X, Y):
    m = X.shape[1]
    W1 = parameters['W1']
    W2 = parameters['W2']
    A1 = cache['A1']
    A2 = cache['A2']

    dZ2= A2 - Y
    dW2 = (1 / m) * np.dot(dZ2, A1.T)
    db2 = (1 / m) * np.sum(dZ2, axis=1, keepdims=True)
    dZ1 = np.multiply(np.dot(W2.T, dZ2), 1 - np.power(A1, 2))
    dW1 = (1 / m) * np.dot(dZ1, X.T)
    db1 = (1 / m) * np.sum(dZ1, axis=1, keepdims=True)

    grads = {"dW1": dW1, "db1": db1, "dW2": dW2, "db2": db2}
    return grads
```



The Algorithm

```
def update_parameters(parameters, grads, learning_rate=0.001):

    ...

    W1 = W1 - learning_rate * dW1
    b1 = b1 - learning_rate * db1
    W2 = W2 - learning_rate * dW2
    b2 = b2 - learning_rate * db2

    ...

    return parameters
```



The Algorithm

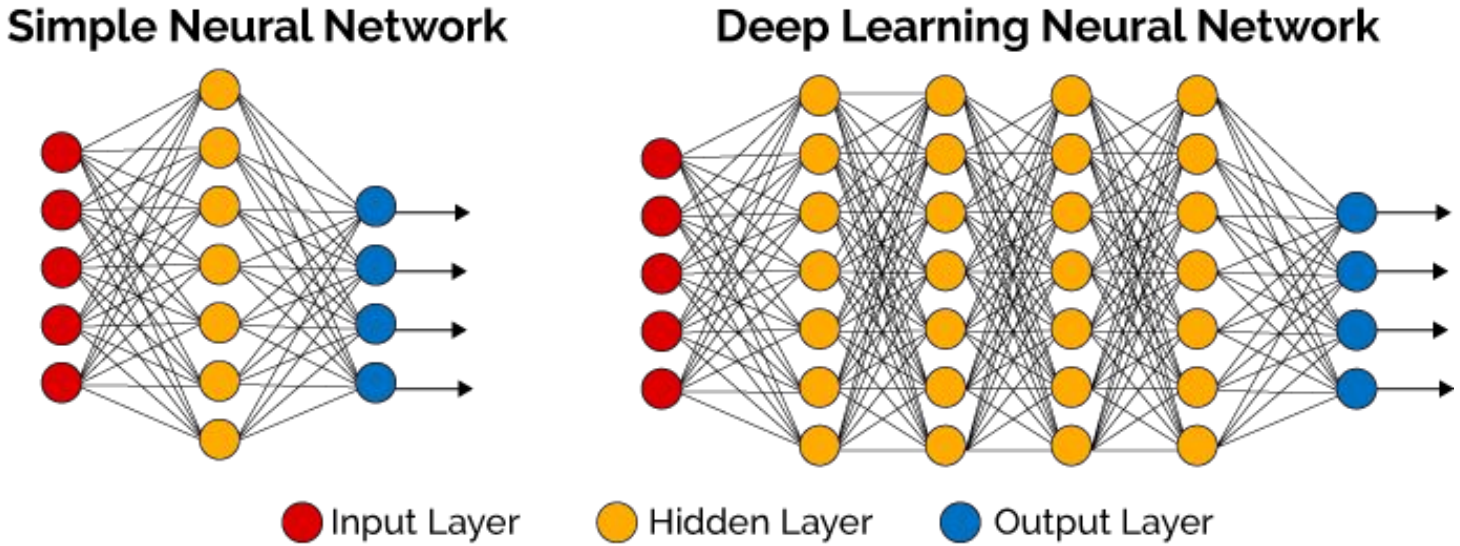
```
def nn_model(X, Y, n_h, num_iterations=10000):
    n_x = layer_sizes(X, Y)[0]
    n_y = layer_sizes(X, Y)[2]

    parameters = initialize_parameters(n_x, n_h, n_y)

    for i in range(0, num_iterations): # Training Loop
        A2, cache = forward_propagation(X, parameters)
        cost = compute_cost(A2, Y, parameters)
        grads = backward_propagation(parameters, cache, X, Y)
        parameters = update_parameters(parameters, grads)

    return parameters
```

Deep Neural Networks

The general case

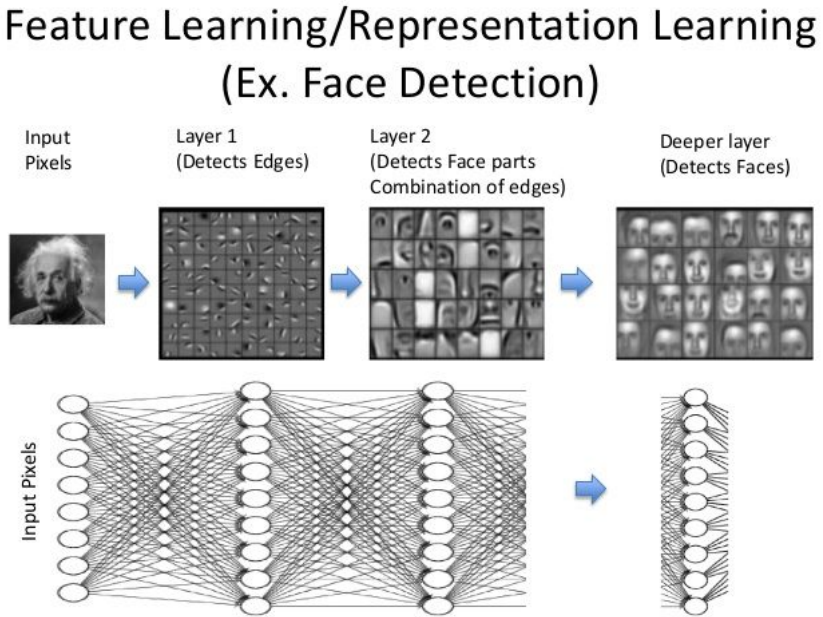
Deep Neural Networks

1. **Just a neural network with more layers**
2. **The number of layers is notated as L**

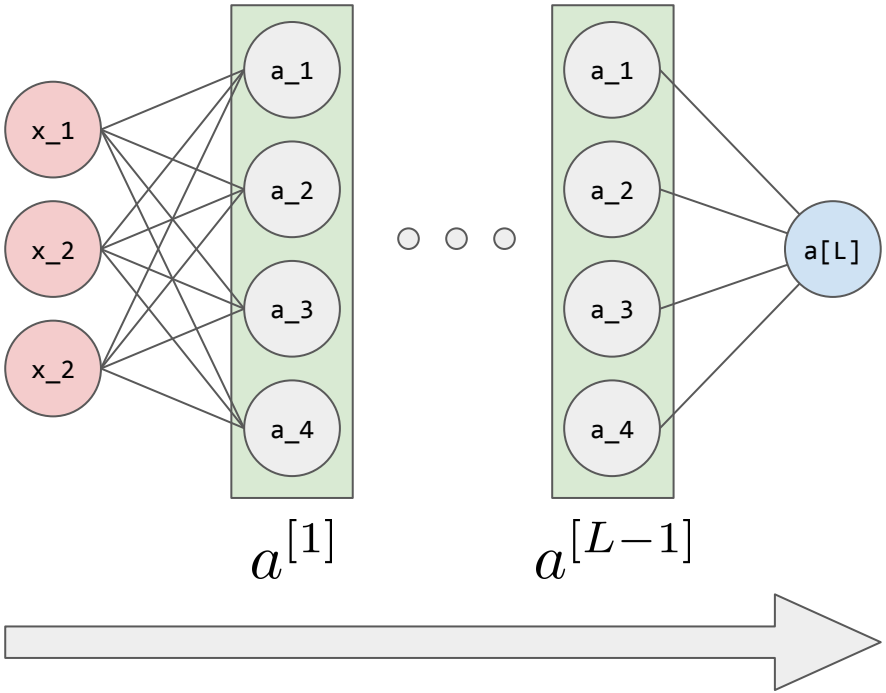


Why do we need more layers?

1. Lower layers learn more basic features of the input (edge detection)
2. Deeper layers build off of previously learned features to conceptualize more complex features (face detection)
3. Adding more layers allows the network to approximate more complex functions

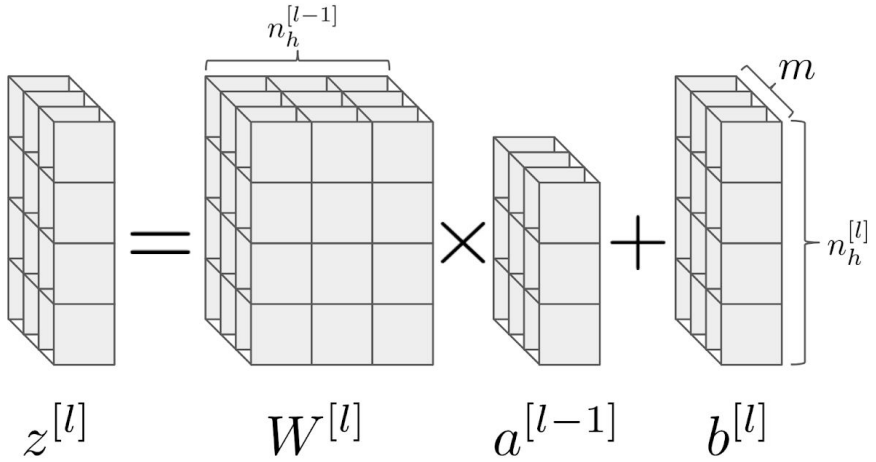


Forward Propagation

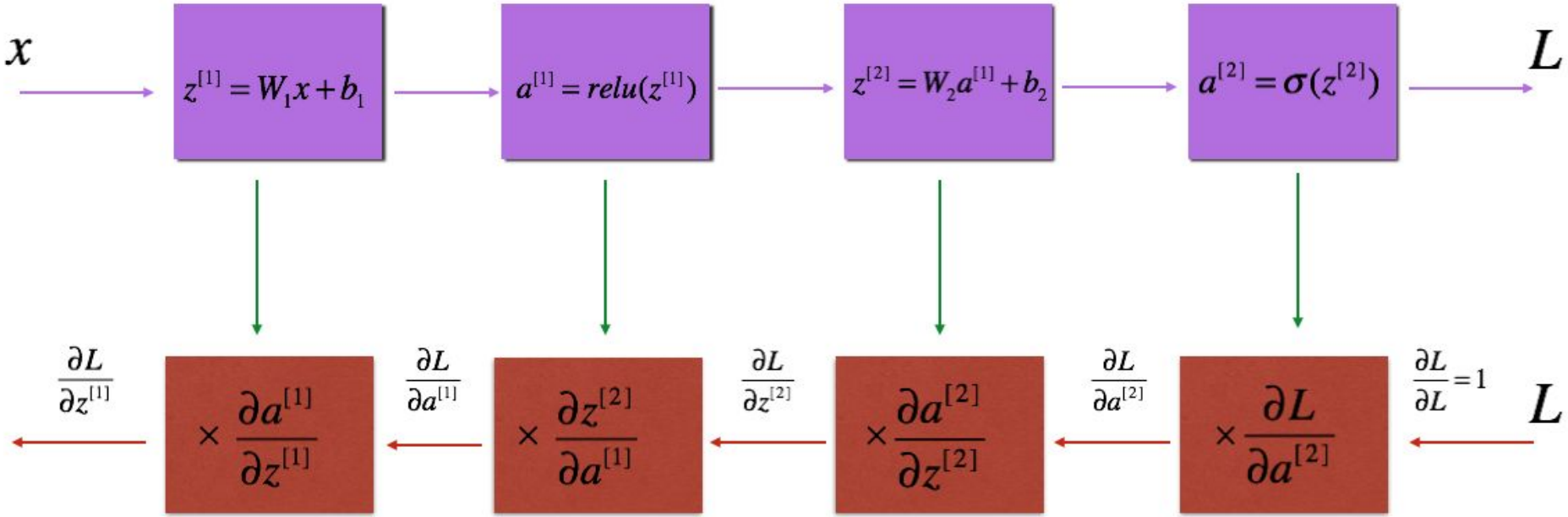


Repeat L-1 times

$$z^{[l]} = W^{[l]} a^{[l-1]} + b^{[l]}, \quad a^{[l]} = g^{[l]}(z^{[l]})$$



Backward Propagation



Backward Propagation

$$dZ^{[L]} = A^{[L]} - Y$$

$$dW^{[L]} = \frac{1}{m} dZ^{[L]} A^{[L-1]T}$$

$$db^{[L]} = \frac{1}{m} \text{np.sum}(dZ^{[L]}, \text{axis} = 1, \text{keepdims} = \text{True})$$

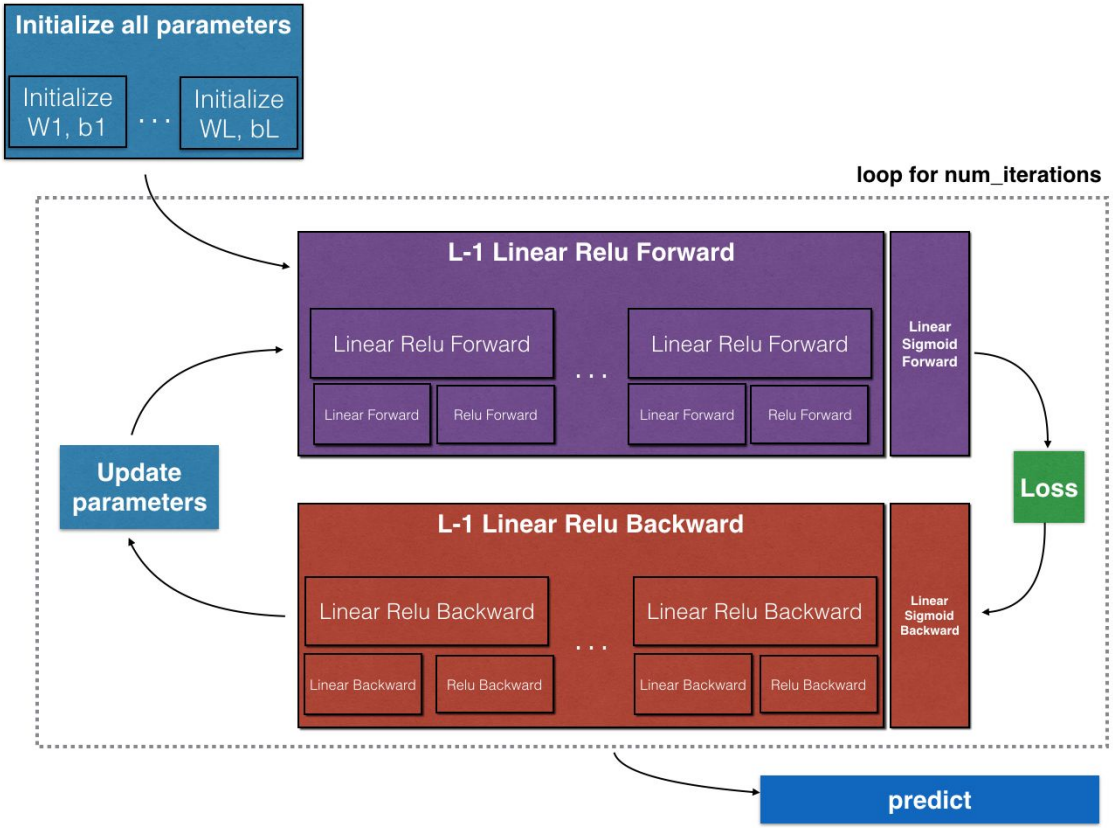
$$dZ^{[l]} = W^{[l+1]T} dZ^{[l+1]} * g^{[l]'}(Z^{[l]})$$

$$dW^{[l]} = \frac{1}{m} dZ^{[l]} A^{[l-1]T}$$

$$db^{[l]} = \frac{1}{m} \text{np.sum}(dZ^{[l]}, \text{axis} = 1, \text{keepdims} = \text{True})$$

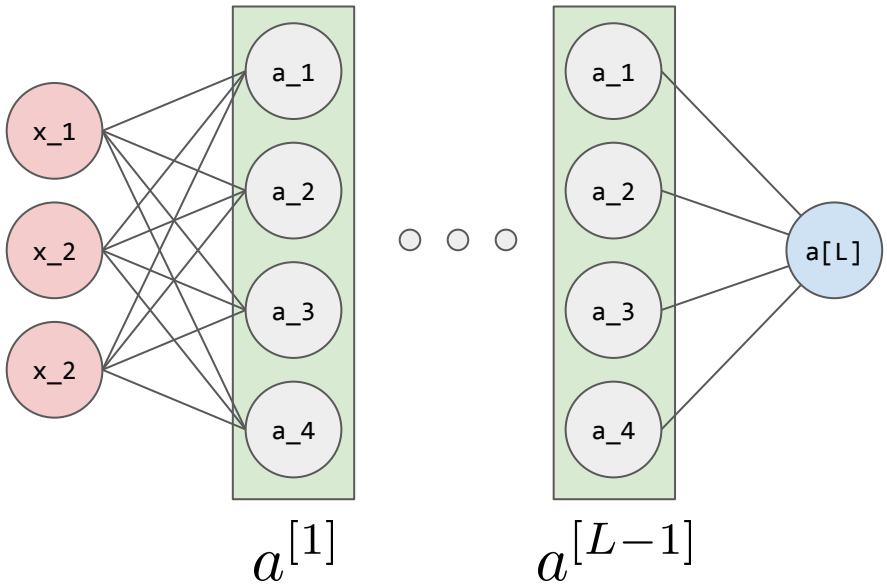
```
for l = L-1 to 1
```

Building blocks of deep neural networks



Summary

1. **Forward propagate**
2. **Compute the cost**
3. **Back propagate**
4. **Update weights**



References and Further Reading

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Thank you for coming!

- Julius