

# Artificial Intelligence and Machine Learning

**Neural Networks** 

#### Lecture Outline

LADY Margaret Hall
UNIVERSITY OF OXFORD

- Logistic Regression Review
- Neural Networks
  - Forward pass
  - Backward pass

#### Review: Logistic Regression





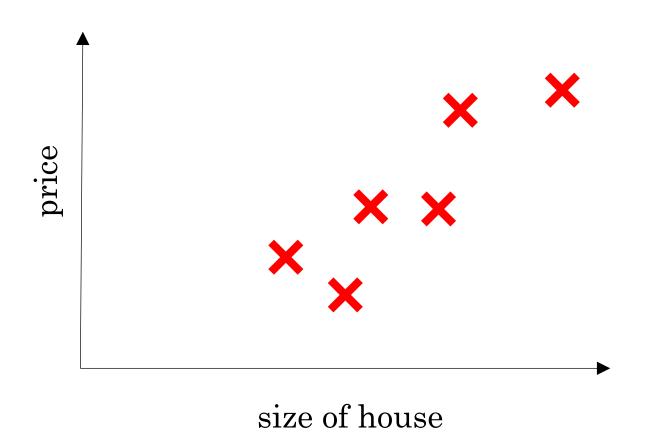


# Introduction to Deep Learning

# What is a Neural Network?



#### Housing Price Prediction

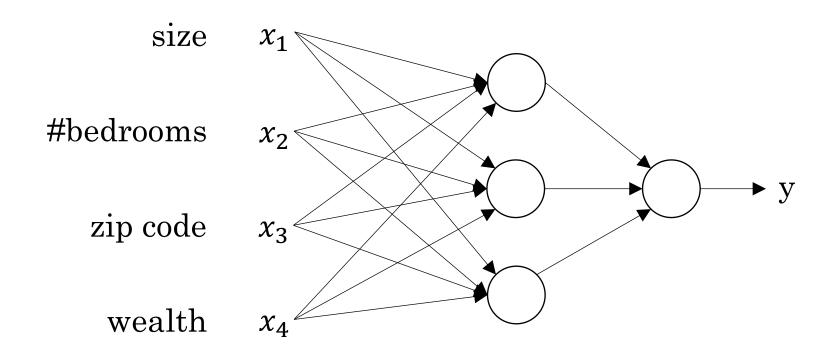
















# Introduction to Deep Learning

Supervised Learning with Neural Networks



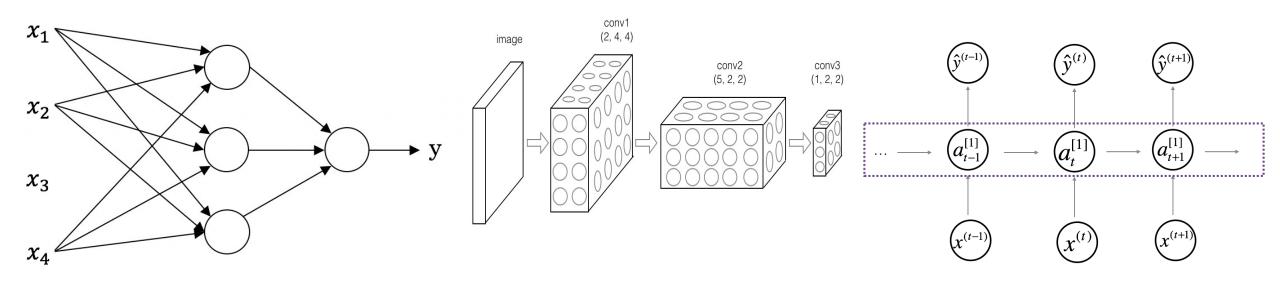


#### Supervised Learning

Input(x)	Output (y)	Application
Home features	Price	Real Estate
Ad, user info	Click on ad? (0/1)	Online Advertising
Image	Object (1,,1000)	Photo tagging
Audio	Text transcript	Speech recognition
English	Chinese	Machine translation
Image, Radar info	Position of other cars	Autonomous driving







Standard NN

**Convolutional NN** 

Recurrent NN



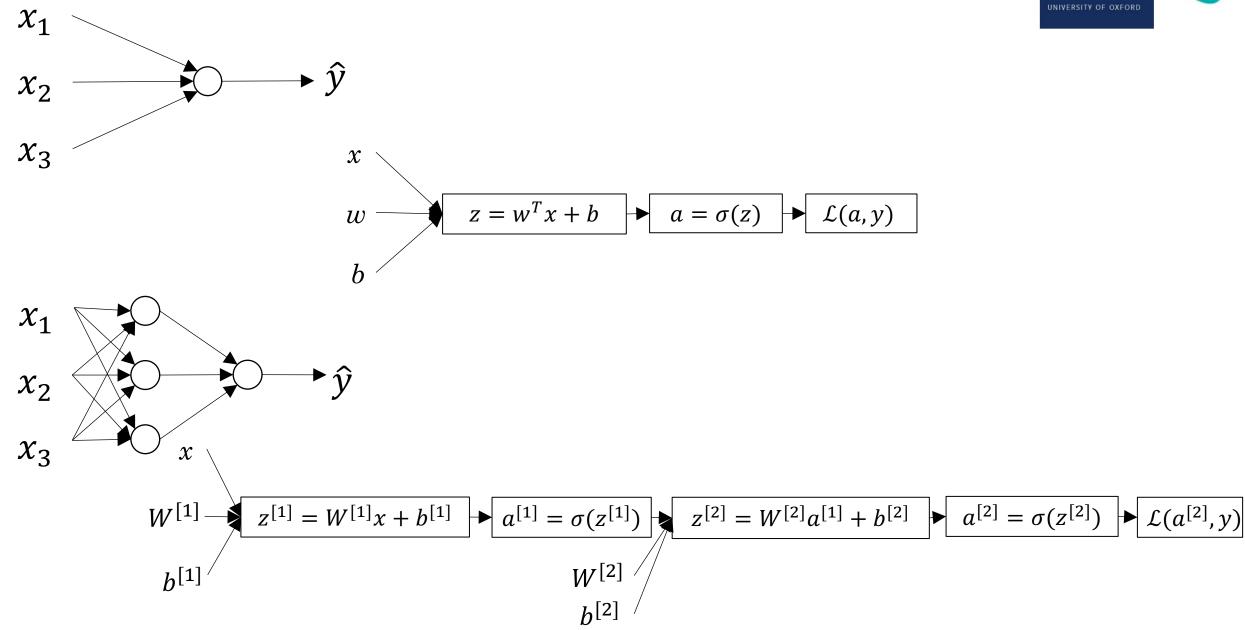


### One hidden layer Neural Network

# Neural Networks Overview

#### What is a Neural Network?



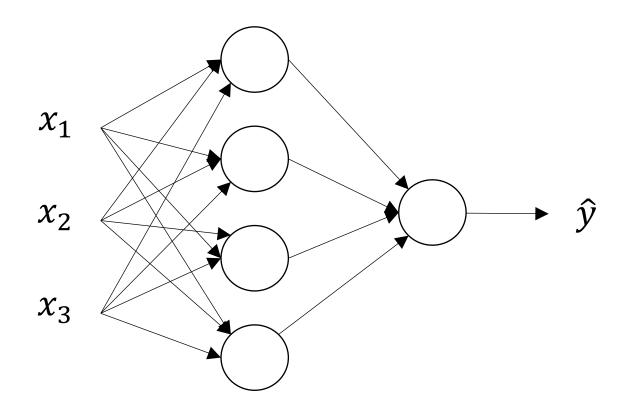






## One hidden layer Neural Network





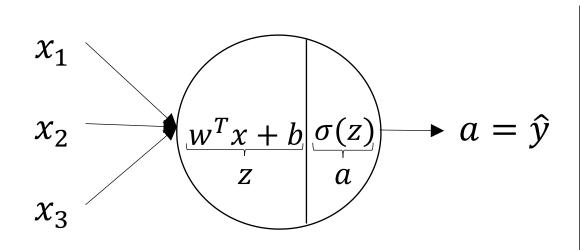


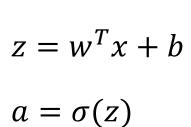


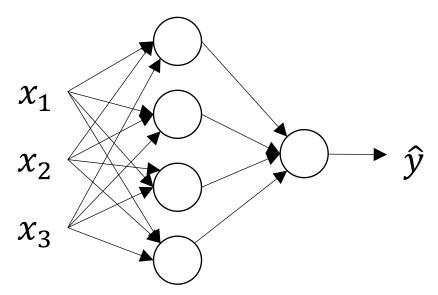
## One hidden layer Neural Network

Computing a Neural Network's Output

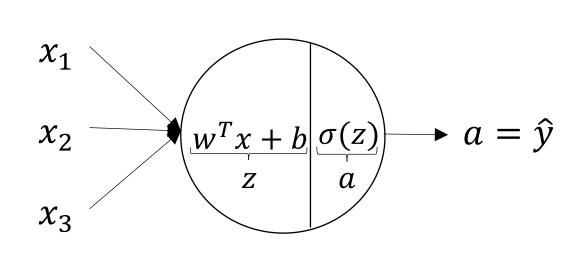




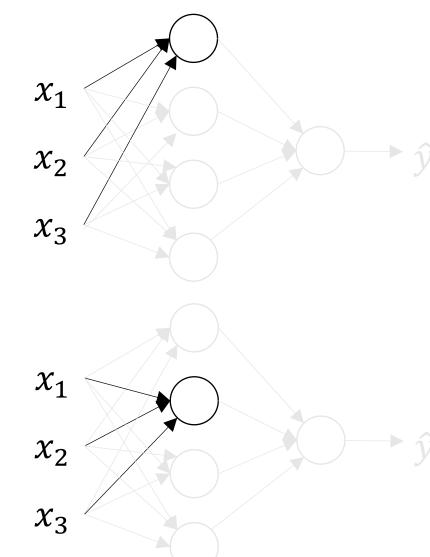




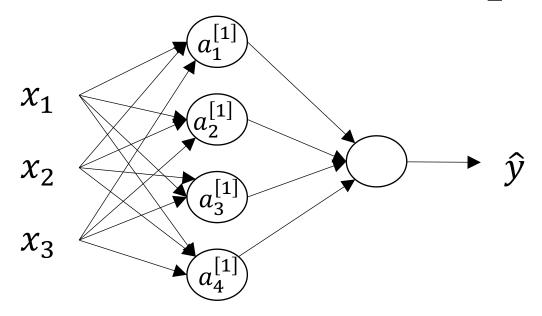




$$z = w^T x + b$$
$$a = \sigma(z)$$







$$z_{1}^{[1]} = w_{1}^{[1]T} x + b_{1}^{[1]}, \ a_{1}^{[1]} = \sigma(z_{1}^{[1]})$$

$$z_{2}^{[1]} = w_{2}^{[1]T} x + b_{2}^{[1]}, \ a_{2}^{[1]} = \sigma(z_{2}^{[1]})$$

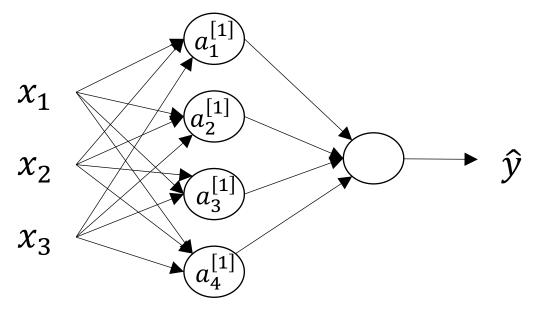
$$z_{3}^{[1]} = w_{3}^{[1]T} x + b_{3}^{[1]}, \ a_{3}^{[1]} = \sigma(z_{3}^{[1]})$$

$$z_{4}^{[1]} = w_{4}^{[1]T} x + b_{4}^{[1]}, \ a_{4}^{[1]} = \sigma(z_{4}^{[1]})$$

## Neural Network Representation learning







#### Given input x:

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

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

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

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





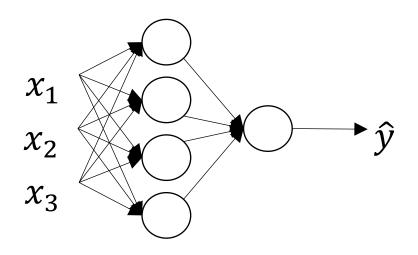
## One hidden layer Neural Network

Vectorizing across multiple examples

#### Vectorizing across multiple examples







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

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

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

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

#### Vectorizing across multiple examples





```
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)})
```





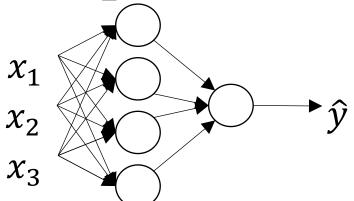
## One hidden layer Neural Network

Explanation for vectorized implementation

# Justification for vectorized implementation



# Recap of vectorizing across multiple examples across multiple examples



$$X = \begin{bmatrix} & & & & & & \\ & & & & & \\ & \chi^{(1)} & \chi^{(2)} & \dots & \chi^{(m)} \\ & & & & & & \end{bmatrix}$$

$$A^{[1]} = \begin{vmatrix} a^{[1](1)} & a^{[1](2)} & a^{[1](m)} \\ a^{[1](1)} & a^{[1](2)} & a^{[1](m)} \end{vmatrix}$$

for i = 1 to m 
$$z^{[1](i)} = W^{[1]}x^{(i)} + b^{[1]}$$
 
$$a^{[1](i)} = \sigma(z^{[1](i)})$$
 
$$z^{[2](i)} = W^{[2]}a^{[1](i)} + b^{[2]}$$
 
$$a^{[2](i)} = \sigma(z^{[2](i)})$$

$$Z^{[1]} = W^{[1]}X + b^{[1]}$$

$$A^{[1]} = \sigma(Z^{[1]})$$

$$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$$

$$A^{[2]} = \sigma(Z^{[2]})$$



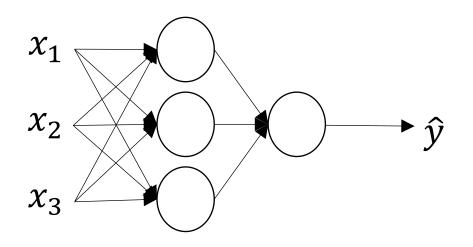


## One hidden layer Neural Network

#### Activation functions

#### Activation functions





#### Given x:

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

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

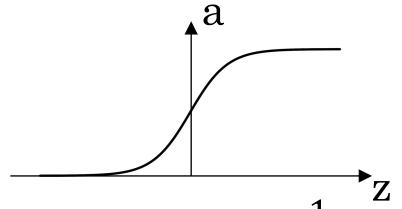
$$z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$$

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

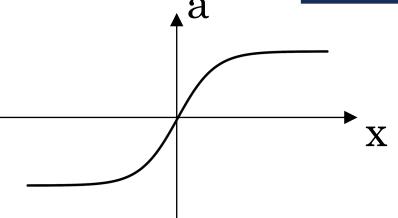
#### Pros and cons of activation functions

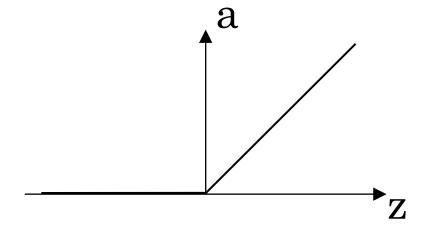


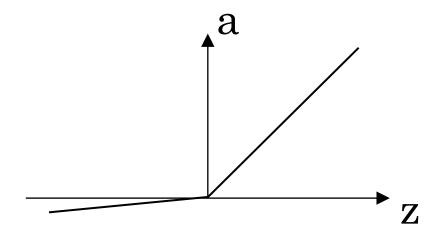




sigmoid: 
$$a = \frac{1}{1 + e^{-z}}$$









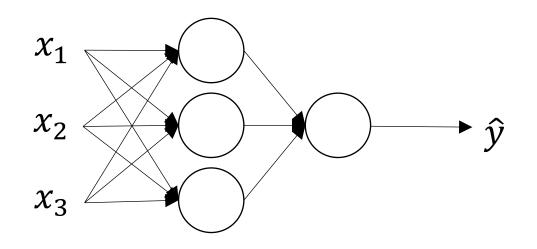


## One hidden layer Neural Network

Why do you need non-linear activation functions?

#### Activation function





#### Given x:

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

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

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

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





## One hidden layer Neural Network

# Gradient descent for neural networks













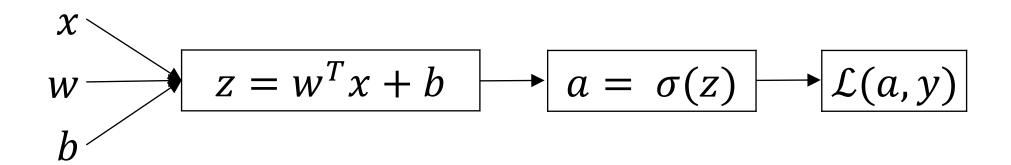
## One hidden layer Neural Network

# Backpropagation intuition



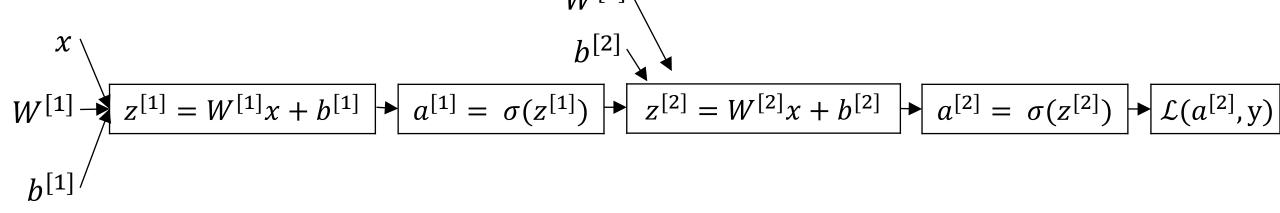


Logistic regression



## Neural network gradients $W^{[2]}$





## Summary of gradient descent



$$dz^{[2]} = a^{[2]} - y$$

$$dW^{[2]} = dz^{[2]}a^{[1]^T}$$

$$db^{[2]} = dz^{[2]}$$

$$dz^{[1]} = W^{[2]T}dz^{[2]} * g^{[1]'}(z^{[1]})$$

$$dW^{[1]} = dz^{[1]}x^T$$

$$db^{[1]} = dz^{[1]}$$

## Summary of gradient descent



$$dz^{[2]} = a^{[2]} - y$$

$$dW^{[2]} = dz^{[2]}a^{[1]^T}$$

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$$dz^{[1]} = W^{[2]T}dz^{[2]} * g^{[1]'}(z^{[1]}) dz^{[1]} = W^{[2]T}dz^{[2]} * g^{[1]'}(z^{[1]})$$

$$dW^{[1]} = dz^{[1]}x^T$$

$$db^{[1]} = dz^{[1]}$$

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

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

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

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

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

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





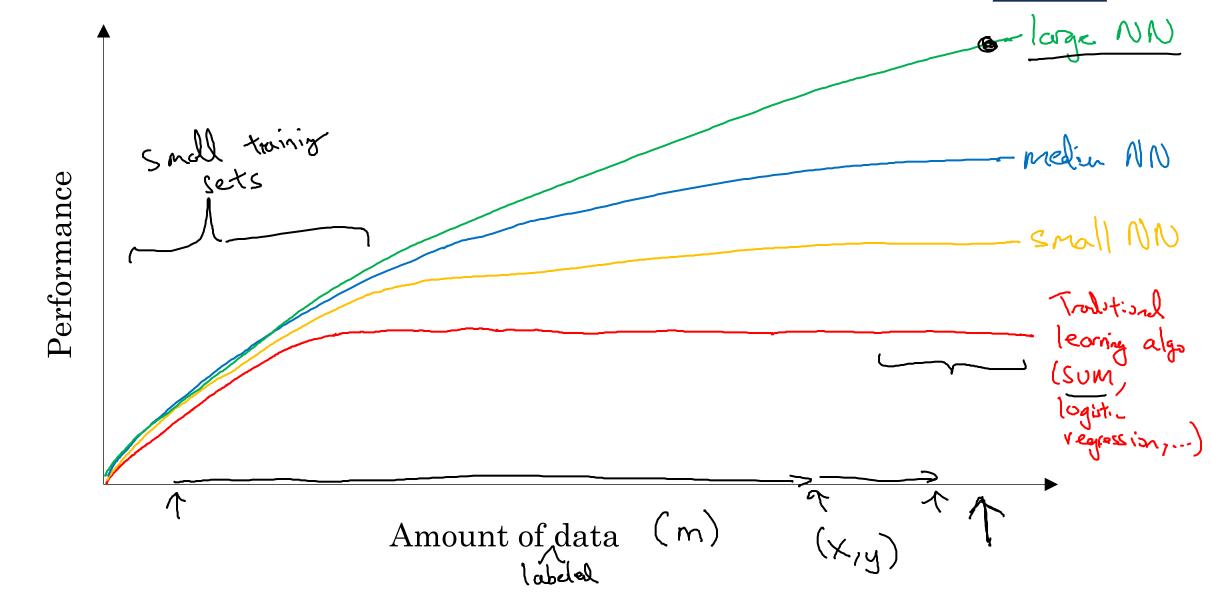
## Introduction to Neural Networks

# Why is Deep Learning taking off?

## Scale drives deep learning progress







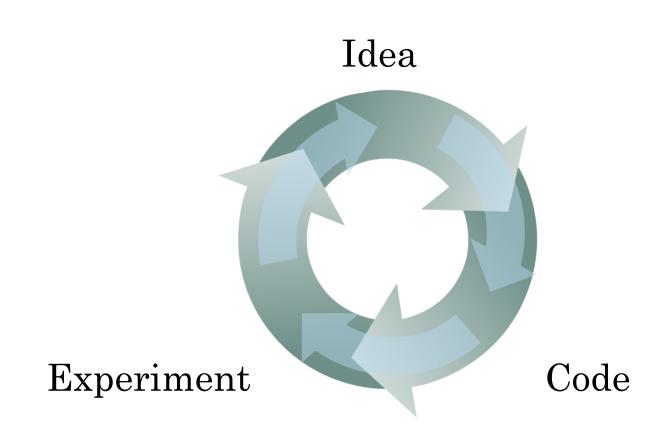
## Scale drives deep learning progress



• Data

Computation

• Algorithms





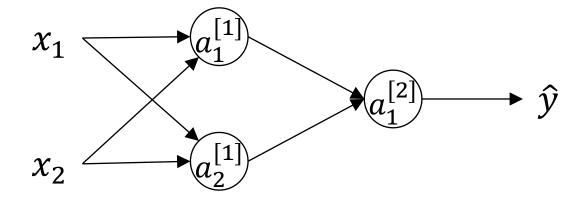


## One hidden layer Neural Network

## Random Initialization

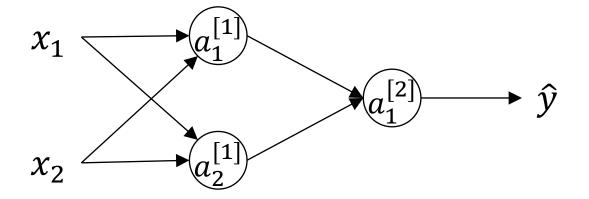
## What happens if you initialize weight Margaret Hall zero?





### Random initialization





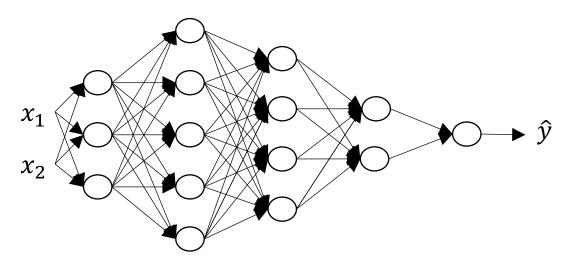




## Deep Neural Networks

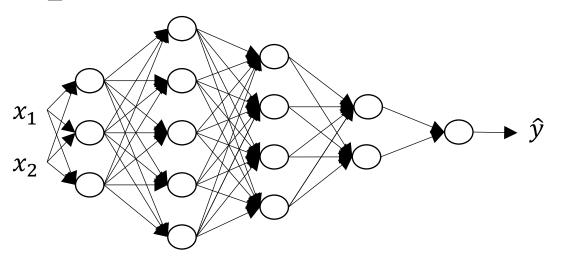
Getting your matrix dimensions right

## Parameters $W^{[l]}$ and $b^{[l]}$





## Vectorized implementation







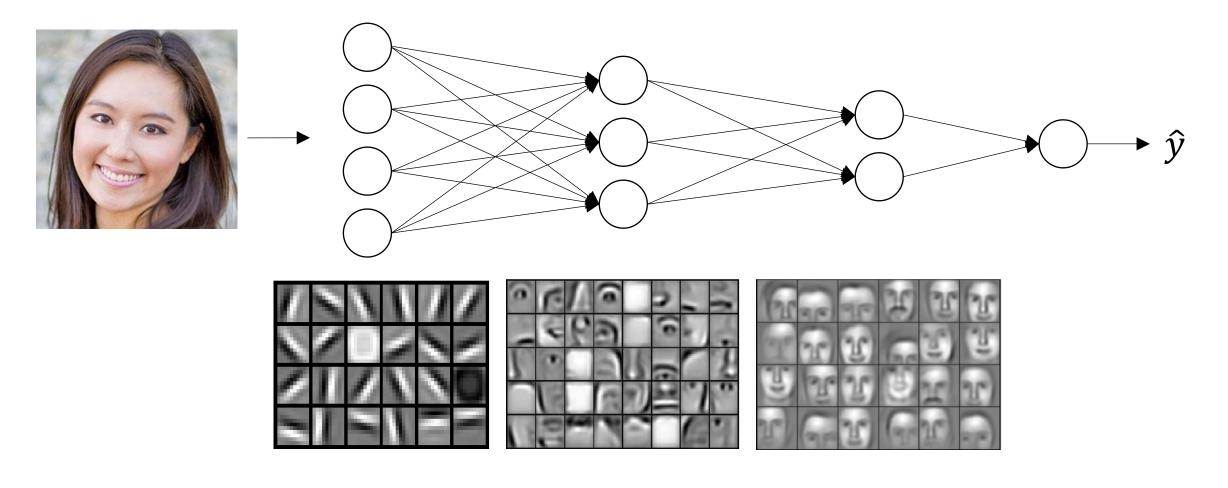


## Deep Neural Networks

Why deep representations?



## Intuition about deep representation





#### Circuit theory and deep learning

Informally: There are functions you can compute with a "small" L-layer deep neural network that shallower networks require exponentially more hidden units to compute.



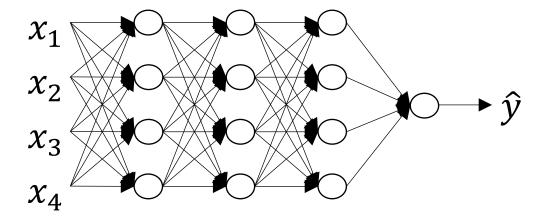


## Deep Neural Networks

Building blocks of deep neural networks

#### Forward and backward functions





#### Forward and backward functions







## Deep Neural Networks

## Forward and backward propagation

#### Forward propagation for layer /



Input  $a^{[l-1]}$ 

Output  $a^{[l]}$ , cache  $(z^{[l]})$ 

#### Backward propagation for layer I



Input  $da^{[l]}$ 

Output  $da^{[l-1]}$ ,  $dW^{[l]}$ ,  $db^{[l]}$ 

## Summary

