Lecture slides for this course
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Deep Learning

Chapter 2 Building Neural Network from Scratch

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Chapter 2: Building Neural Network from Scratch

1. Shallow neural network
2. Deep neural network
3. Building neural network: step-by-step (modulation)
4. Regularization
5. Dropout
6. Batch Normalization
7. Optimizers
8. Hyper-parameters
9. Practice

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Previous Lecture Overview

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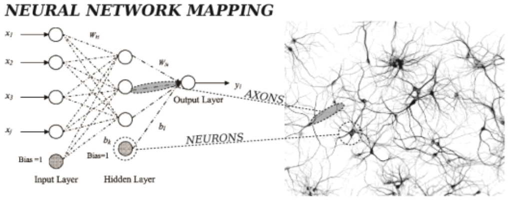
Biologically inspired (akin to the neurons in a brain)

NEURAL NETWORK MAPPING



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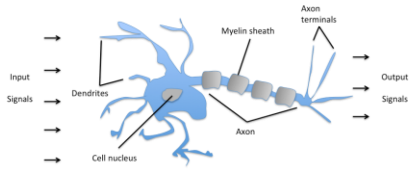
Previous Lecture Overview

Artificial Neurons and the McCulloch-Pitts Model (1943)



Schematic of a biological neuron.

W. S. McCulloch and W. Pitts. A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics, 5(4):115–133, 1943.

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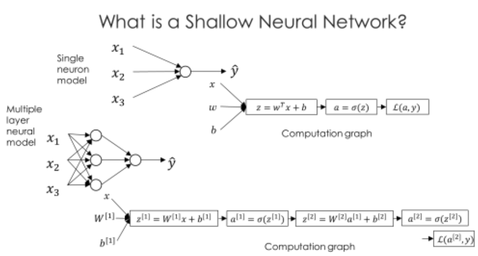
Previous Lecture Overview



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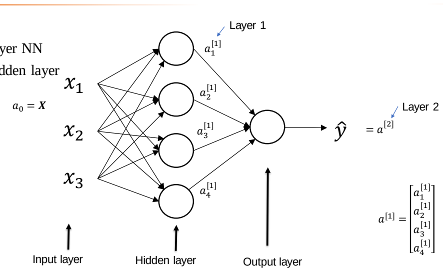
Previous Lecture Overview

One hidden layer Neural Network

- 2-layer NN
- 1 hidden layer



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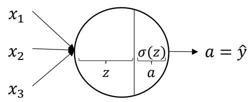
Previous Lecture Overview

Computing NN's Output



$z = w^T x + b$

$a = \sigma(z)$

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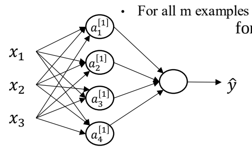
Previous Lecture Overview

Vectorizing across multiple examples



- For all m examples …

for i = 1 to m:

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

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

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

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

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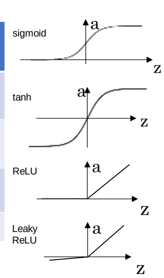
Activation functions

Activation Function	Formula (g(z))	Derivative (g'(z))
sigmoid	$a = \frac{1}{1+e^{-z}}$	$a(1-a)$
tanh	$a = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	$1 - a^2$
ReLU	$\max(0, z)$	0 if $z < 0$ 1 if $z \geq 0$
Leaky ReLU	$\max(0.01z, z)$	0.01 if $z < 0$ 1 if $z \geq 0$



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Previous Lecture Overview

Vectorizing across multiple examples

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

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

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

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

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

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

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

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

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

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

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

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Previous Lecture Overview

Gradient descent for one hidden layer

x, $W^{[1]}$, $b^{[1]}$ → $z^{[1]} = W^{[1]}x + b^{[1]}$ → $a^{[1]} = \sigma(z^{[1]})$

$dz^{[1]} = W^{[2]T}dz^{[2]} * g^{[1]\prime}(z^{[1]})$

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

$W^{[2]}$, $b^{[2]}$ → $z^{[2]} = W^{[2]}x + b^{[2]}$ → $a^{[2]} = \sigma(z^{[2]})$ → $\mathcal{L}(a^{[2]}, y)$

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

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

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

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Previous Lecture Overview

Vectorizing Gradient Descent

$dz^{[2]} = a^{[2]} - y$	$dZ^{[2]} = A^{[2]} - Y$
$dW^{[2]} = dz^{[2]}a^{[1]^T}$	$dW^{[2]} = \frac{1}{m}dZ^{[2]}A^{[1]^T}$
$db^{[2]} = dz^{[2]}$	$db^{[2]} = \frac{1}{m}np.sum(dZ^{[2]}, axis = 1, keepdims = True)$
$dz^{[1]} = W^{[2]T}dz^{[2]} * g^{[1]\prime}(z^{[1]})$	$dZ^{[1]} = W^{[2]T}dZ^{[2]} * g^{[1]\prime}(Z^{[1]})$
$dW^{[1]} = dz^{[1]}x^T$	$dW^{[1]} = \frac{1}{m}dZ^{[1]}X^T$
$db^{[1]} = dz^{[1]}$	$db^{[1]} = \frac{1}{m}np.sum(dZ^{[1]}, axis = 1, keepdims = True)$

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

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2. Deep neural network

Deep Learning???

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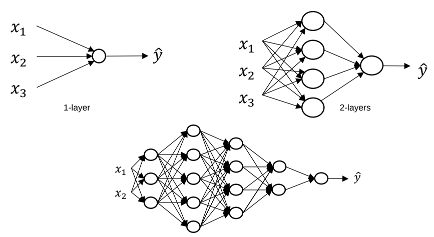
2. Deep neural network

Multiple layers



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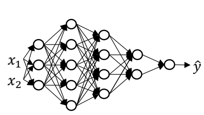
2. Deep neural network

Notations in Deep Neural Networks

- #Layers = L = 5
- $n^{[l]}$ = #units in layer l
  - $n^{[1]} = 3, n^{[2]} = 5, n^{[3]} = 4, n^{[4]} = 2, n^{[5]} = n^{[L]} = 1$
  - $n^{[0]} = n^{[x]} = 2$
- $a^{[l]} = g^{[l]}(z^{[l]})$
- $W^{[l]}$ = weights for computing $z^{[l]}$
- $b^{[l]}$ = bias for computing $z^{[l]}$
- $a^{[0]} = X$ (input)
- $a^{[L]} = \hat{y}$ (prediction output)



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2. Deep neural network

Dimensions of vectorized implementations

- For one single training example:
- $z^{[l]} = W^{[l]} a^{[l-1]} + b^{[l]}$
- $(n^{[l]}, 1) = (n^{[l]}, n^{[l-1]}) \times (n^{[l-1]}, 1) + (n^{[l]}, 1)$

- For a vectorized implementation over m examples
- $Z^{[l]} = W^{[l]} A^{[l-1]} + b^{[l]}$
- $(n^{[l]}, m) = (n^{[l]}, n^{[l-1]}) \times (n^{[l-1]}, m) + (n^{[l]}, m)$

Matrix	Dimensions
$Z^{[l]}, A^{[l]}, b^{[l]}, dZ^{[l]}, dA^{[l]}, db^{[l]}$	$(n^{[l]}, m)$
$W^{[l]}, dW^{[l]}$	$(n^{[l]}, n^{[l-1]})$

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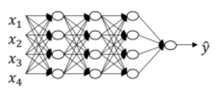
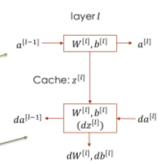
2. Deep neural network

Building Blocks of Deep Neural Networks



- Focus on some layer l, parameters include $W^{[l]}$, $b^{[l]}$
- Forward Propagation
  - Input: $a^{[l-1]}$
  - Output: $a^{[l]}$
  - Method: $z^{[l]} = W^{[l]} a^{[l-1]} + b^{[l]}$, $a^{[l]} = g^{[l]}(z^{[l]})$
  - Cache: $z^{[l]}$
- Backward Propagation
  - Input: $da^{[l]}$, $z^{[l]}$ (from cache)
  - Output: $da^{[l-1]}$, $dW^{[l]}, db^{[l]}$



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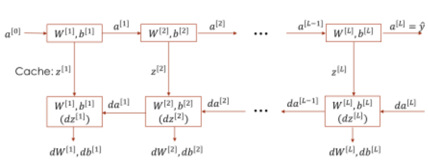
2. Deep neural network

Forward and backward functions



$$W^{[l]} = W^{[l]} - \alpha dW^{[l]}$$
$$b^{[l]} = b^{[l]} - \alpha db^{[l]}$$

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2. Deep neural network

Forward Propagation for DNN

- Input: $a^{[l-1]}$
- Forward Propagation:
  - For single example:
    $$z^{[l]} = W^{[l]}a^{[l-1]} + b^{[l]}, \quad a^{[l]} = g^{[l]}(z^{[l]})$$
  - Vectorized version:
    $$Z^{[l]} = W^{[l]}A^{[l-1]} + b^{[l]}, \quad A^{[l]} = g^{[l]}(Z^{[l]})$$
- Output: $a^{[l]}$
- Cache: $z^{[l]}, W^{[l]}, b^{[l]}$

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2. Deep neural network

Backward Propagation for DNN

- Inputs: $da^{[l]}, z^{[l]}, W^{[l]}, b^{[l]}$ (last 3 from cache)
- Outputs: $da^{[l-1]}, dW^{[l]}, db^{[l]}$
- Backward Propagation:
- For **single example**
  $$dz^{[l]} = da^{[l]} * g^{[l]\prime}(z^{[l]})$$
  $$dW^{[l]} = dz^{[l]}.a^{[l-1]}$$
  $$db^{[l]} = dz^{[l]}$$
  $$da^{[l-1]} = W^{[l]T}dz^{[l]}$$
  $$dz^{[l]} = W^{[l+1]T}dz^{[l+1]} * g^{[l]\prime}(z^{[l]})$$

Vectorized implementation

$$dZ^{[l]} = dA^{[l]} * g^{[l]\prime}(Z^{[l]})$$
$$dW^{[l]} = \frac{1}{m}dZ^{[l]}.A^{[l-1]T}$$
$$db^{[l]} = \frac{1}{m}np.sum(dZ^{[l]}, axis = 1, keepdims = True)$$
$$dA^{[l-1]} = W^{[l]T}dZ^{[l]}$$

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2. Deep neural network

Parameters vs. Hyperparameters

- Parameters: $W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}, \ldots$
- Hyperparameters
  - Learning rate: α
  - Number of iterations
  - Number of hidden layers or L
  - Number of hidden units in each layer: $n^{[1]}, n^{[2]}, \ldots$
  - Choice of activation function: sigmoid, ReLU, tanh, etc.
  - Momentum, mini-batch size, regularization parameters, … (in the next Chapter)

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2. Deep neural network

Summary of Forward/Backward Computations

$$Z^{[1]} = W^{[1]}X + b^{[1]}$$
$$A^{[1]} = g^{[1]}(Z^{[1]})$$
$$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$$
$$A^{[2]} = g^{[2]}(Z^{[2]})$$
$$\vdots$$
$$A^{[L]} = g^{[L]}\left(Z^{[L]}\right) = \hat{Y}$$

Forward Propagation

$$dZ^{[L]} = A^{[L]} - Y$$
$$dW^{[L]} = \frac{1}{m} dZ^{[L]} A^{[L]^T}$$
$$db^{[L]} = \frac{1}{m} np.\text{sum}(\text{d}Z^{[L]}, axis = 1, keepdims = True)$$
$$dZ^{[L-1]} = dW^{[L]^T} dZ^{[L]} g'^{[L]}(Z^{[L-1]})$$
$$\vdots$$
$$dZ^{[1]} = dW^{[L]^T} dZ^{[2]} g'^{[1]}(Z^{[1]})$$
$$dW^{[1]} = \frac{1}{m} dZ^{[1]} A^{[1]^T}$$
$$db^{[1]} = \frac{1}{m} np.\text{sum}(\text{d}Z^{[1]}, axis = 1, keepdims = True)$$

Backward Propagation

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3. Building neural network: step-by-step (modulation)

On Assignments
Coding time !!!

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