29/11/20
Target

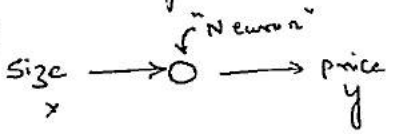
Deep learning . AI

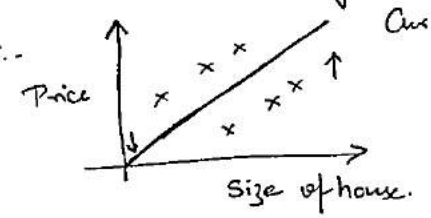
Coursera Specialization

* Courses:-
  1. Neural Networks and Deep Learning
  2. Im
  3.
  4.
  5.

* Course 1 : Neural Networks & Deep Learning.

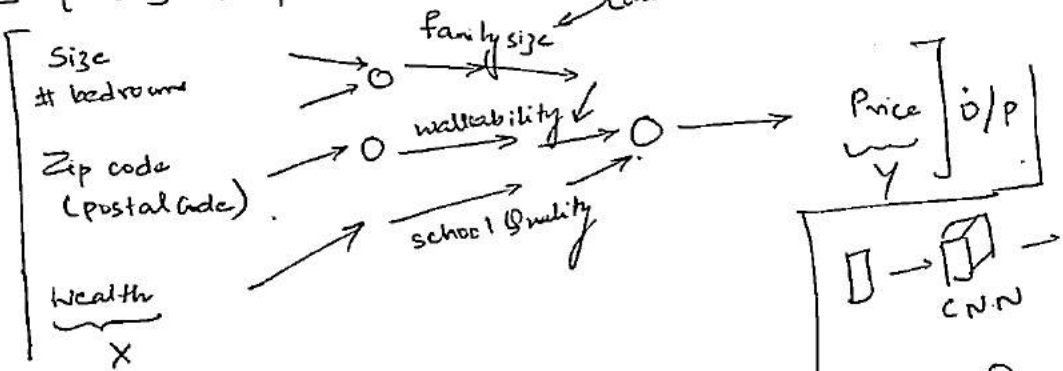
∴ Housing price prediction :-

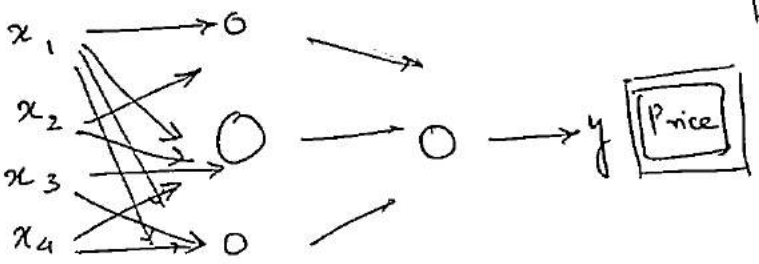




Curve fit linear regression.

[ReLU] : Rectified Linear unit.

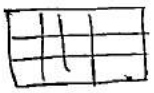




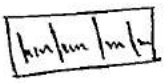
II Supervised learning :

I/p (x)	O/p (y)	Application	
Home feat..	Price	Real Estate	Standard NN
Ad, User info	Click	Onl Adv	
Image	Obj (...)	Photo tagging	CNN (Convoluted)
Audio	Text transcript	Speech Recognition	Audi RNN (Recurred)
		Mtc-translation	
Image/Ra-	---	Autonomous Driving	Custom/Hybrid

Supervised learning:

Structured data : 

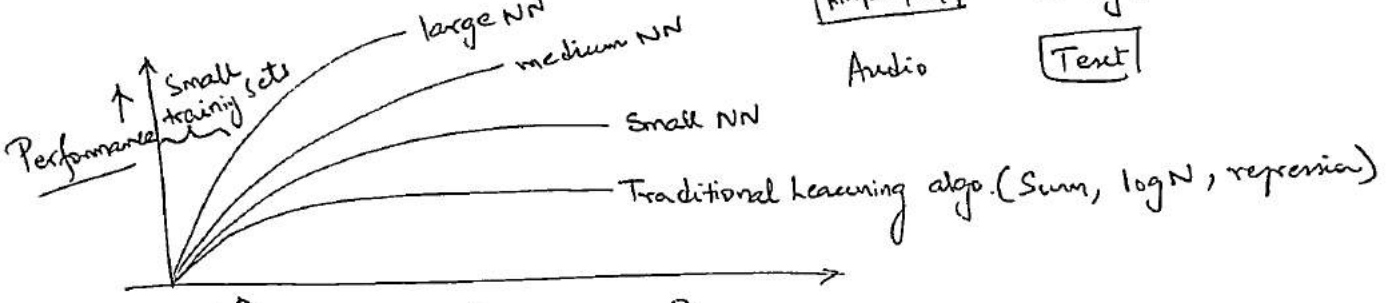
Unstructured Data



Image

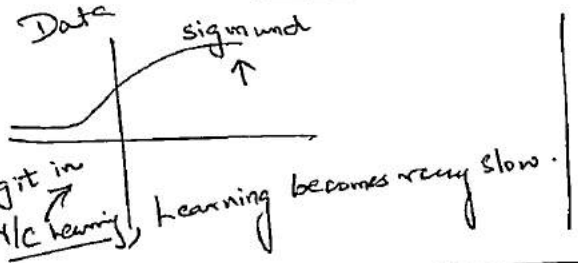
Audio

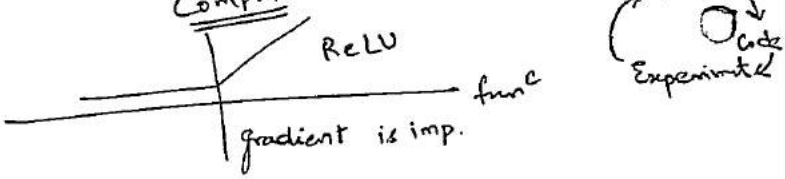
Text



Digitization of Data (Collecting More & More Data).

Performance increases with large NN. > medium > Small NN.



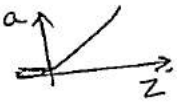


INTRODUCTION TO NEURAL NETWORKS.

1. Neural Networks & Deep Learning.

Week 1 : Intro.
Week 2 : Basics of NN programing
Week 3 : One hidden layer NN
Week 4 : Deep Neural Networks.

Quiz:

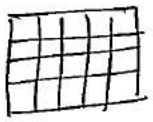
1. 'AI' is the new electricity :- Similar to electricity starting about 100 yrs ago, AI is transforming multiple industries.
2. Deep learning requires multiple iterations; train models, experience is 2nd
3. 

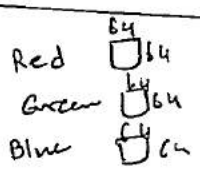
Increasing the size of NN, training set doesnot hurt algorithm performa & it may help significantly.

* Binary Classification :-

FPP / BPP : Forward / Backward propagation

Pixels 64x64.





$x = \begin{bmatrix} \vdots \end{bmatrix} = 64 \times 64 \times 3 = 12288$ $\quad \boxed{n = n_x = 12288}$

$(x, y) \quad x \in \mathbb{R}^{n_x}, \quad y \in \{0, 1\}$ m training examples : $\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots (x^{(m)}, y^{(m)})\}$

$X = \begin{bmatrix} | & | & | & & | \\ x^{(1)} & x^{(2)} & x^{(3)} & \cdots & x^{(m)} \\ | & | & | & & | \end{bmatrix} \updownarrow n_x \qquad \begin{bmatrix} - & x^{(1)T} & - \\ & \vdots & \end{bmatrix}.$

$\leftarrow m \rightarrow$

$x \in \mathbb{R}^{n_x \times m}$ $\quad X.shape = (n_x, m)$; $\quad Y = [\, y^{(1)} \; y^{(2)} \; \dots \; y^{(m)} \,]$.

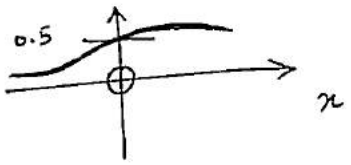
$y \in \mathbb{R}^{1 \times m}$

$y.shape = (1, m)$

Logistic Regression

Given X, want $\hat{y} = P(y=1|x)$ $\quad x \in \mathbb{R}^{n_x}$ (x dim vector). ; Par. $\boxed{w} \in \mathbb{R}^{n_x}$ $\quad \boxed{b} \in \mathbb{R}$.

Output $\boxed{\hat{y} = w^T x + b}$ $\quad 0 \le \hat{y} \le 1$



Sigmund func.: $\hat{y} = \sigma(\underbrace{w^T x + b}_{z})$

$\boxed{\sigma(z) = \frac{1}{1+e^{-z}}}$ $\quad$ if z large $\sigma(z) \approx \frac{1}{1+0} = 1$.

if z large negative num, $\sigma(z) = \frac{1}{1+e^{-z}} \approx$

$\approx \frac{1}{1+\text{Big num}} \approx 0$.

alternative notation :-

$x_0 = 1$, $\quad x \in \mathbb{R}^{n_x+1}$, $\quad \hat{y} = \sigma(\theta^T x)$.

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_{R_x} \end{bmatrix} \begin{matrix} \} b \leftarrow \\ \\ \\ \} w \leftarrow \end{matrix}$$

Summary Parameters : $w \in \mathbb{R}^{n_x}$, $b \in \mathbb{R}$; $\hat{y} = w^T x + b$; $\hat{y} = \sigma(w^T x + b)$

$\hat{y} = \sigma(\theta^T x)$; $\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_R \end{bmatrix} \begin{matrix} \} b \leftarrow \\ \} w \leftarrow \end{matrix}$

Logistic Regression Cost function

$\hat{y} = \sigma(w^T x + b)$ where $\sigma(z) = \frac{1}{1+e^{-z}}$. $\quad z^{(i)} = w^T x^{(i)} + b$ $\quad x^{(i)}$ $y^{(i)}$ $z^{(i)}$.

Given $\{(x^{(1)}, y^{(1)}), \dots, (x^{(m)}, y^{(m)})\}$, want $\hat{y}^{(i)} \approx y^{(i)}$.

* loss (error) func: $\boxed{\mathcal{L}(\hat{y}, y) = \frac{1}{2}(\hat{y} - y)^2}$ (efficiency of Alg.)

how good $\boxed{\hat{y}}$ is ?? given by

* $\boxed{\mathcal{L}(\hat{y}, y) = -\left(y \log \hat{y} + (1-y) \log(1-\hat{y})\right)}$

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

if $y=0$: $\mathcal{L}(\hat{y}, y) = -\log(1-\hat{y})$

* Cost function $J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) = -\frac{1}{n}\sum_{i=1}^{n} \ldots$

$$= -\frac{1}{n}\sum_{i=1}^{n}\left[y^{(i)}\log\hat{y}^{(i)} + (1-y^{(i)})\log(1-\hat{y}^{(i)})\right].$$

Summary:

∴ w, b minimize cost func^c;
Loss func^c for efficiency of Algorithm

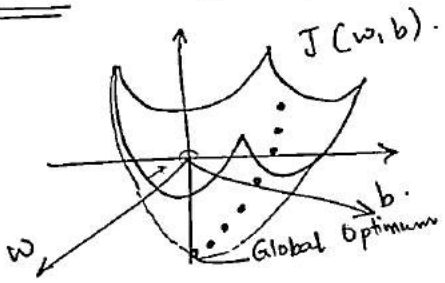
Logistic Regression

Note: The loss func^c computes the error for a single training example, the cost func^c is the average of the loss func^{es} of the entire training set.

∴ $J(w,b) = \frac{1}{m}\sum_{i=1}^{m}\mathcal{L}(\hat{y}^{(i)}, y^{(i)}) = -\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}\log\hat{y}^{(i)} + (1-y^{(i)})\log(1-\hat{y}^{(i)})\right)$. ○

Gradient Descent: (train / learn w, b on training set).

until now:



Cost func^c: $J(w,b)$

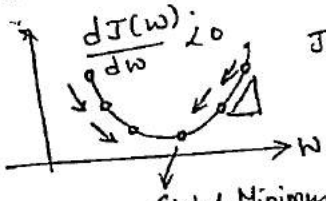
Recap: $\hat{y} = \sigma(w^T x + b)$, $\sigma(z) = \frac{1}{1+e^{-z}}$.

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

$$= -\frac{1}{m}\sum_{i=1}^{m} y^{(i)}\log\hat{y}^{(i)} + (1-y^{(i)})\log(1-\hat{y}^{(i)}).$$

∴ Want to find w, b that minimize $J(w,b)$??? *** ○

Convex ↑↑ Non Convex.



Slope: dw

$w := w - \alpha \frac{dJ(w)}{dw}$

learning rate; update on w: "dw".

$w := w - \alpha\, dw$ Gradient Descent Update.

∂ = partial der

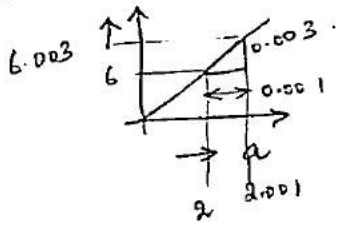
$$w := w - \alpha\frac{dJ(w,b)}{dw}, \quad \frac{dJ(w,b)}{dw} \to \frac{\partial J(w,b)}{\partial w}\, dw$$

$$b := b - \alpha\frac{dJ(w,b)}{db}, \quad \frac{dJ(w,b)}{db} \to \frac{\partial J(w,b)}{\partial b}\, db.$$

$J(w,b)$ Update Rule for Gradient Descent

∴ A Convex func^c has single local optima

Derivatives :-



$f(a) = 3a$

$a = 2, f(a) = 6$

$a = 2.001, f(a) = 6.003$

Slope derivative of $f(a)$ at $a = 2$ is 3.

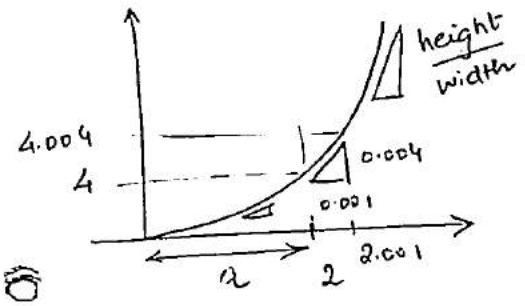
$a = 5.001 \quad f(a) = 15.003$

Slope at $a = 5$ is also 3

$$\frac{df(a)}{da} = 3 = \frac{d}{da} f(a).$$

---

* Examples : Intuition about derivatives :



$f(a) = a^2 \quad a = 2 \quad f(a) = 4$

$a = 2.001 \quad f(a) \approx 4.004 = 4.004001$

Slope (derivative) of $f(a)$ at $a = 2$ is 4.

$\frac{d}{da} f(a) = 4$, when $a = 2$

$\because$ if $a = 5 \quad f(a) = 5$

$a = 5.001 \quad f(a) = 25.010.$

$\frac{d}{da}(f(a)) = 10$ when $a = 5$.

$$\frac{d}{da} f(a) = \frac{d}{da} a^2 = 2a.$$

as $a \uparrow \quad \frac{d}{da} f(a) = \uparrow\uparrow\uparrow$

$f(a) = a^2 \quad \frac{d}{da} f(a) = 2a$

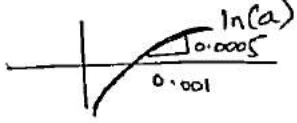
$a = 2 \quad f(a) = 4$

$a = 2.001 \quad f(a) \approx 4.004$

$f(a) = a^3 \quad \frac{d}{da} f(a) = 3a^2; 3 \times 2^2 \quad a = 2 \quad f(a) = 8$

$3 \times 2.001^2 \quad a = 2.001 \quad f(a) \simeq 8.012.$

$f(a) = \log_e(a)$
$\ln(a)$



$\frac{d}{da} f(a) = \frac{1}{a} \quad a = 2 \quad f(a) = 0.69315$

$a = 2.001 \quad f(a) = 0.69365$

$\frac{d}{da} f(a) = \frac{1}{2}$ (0.0005 / 0.0005)

Derivative is slope of a line;

* Slope is constant for linear lines whereas varies for exponential, logarithm.

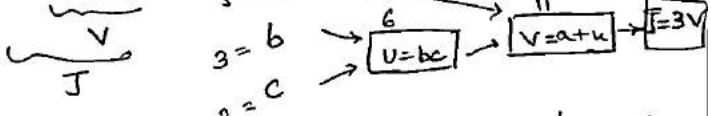
Computation graph :- FPP/BPP.

$J(a,b,c) = 3(a + \underbrace{bc}_{u})$

V

J

$\because u = bc$



Note: One step of backward propagation on a computation graph yields derivative of final output variable.

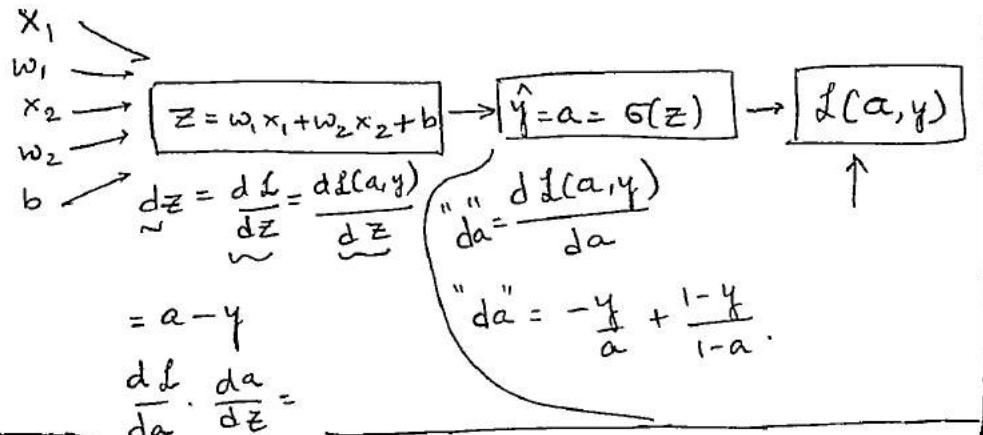
Derivatives with a computation graph: -

Logistic regression recap.

$$z = w^T x + b$$

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

Loss fun^n: $\mathcal{L}(a, y) = -(y \log(a) + (1-y) \log(1-a))$.



$\frac{d\mathcal{L}}{dw_1}$ "dw_1"

$= x_1 \, dz$

$dw_2 = x_2 \cdot dz$

$db = dz$

$w_1 := w_1 - \alpha \, dw_1$

$w_2 = w_2 - \alpha \, dw_2$

$b := b - \alpha \, db$.

* Gradient Descent on 'm' Examples:

training example $(x^{(i)}, y^{(i)})$.

$dw_1^{(i)}, dw_2^{(i)}, db^{(i)}$.

Cost fun^n: $J(w,b) = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(a^{(i)}, y)$.

$a^{(i)} = \hat{y}^{(i)} = \sigma(z^{(i)}) = \sigma(w^T x^{(i)} + b)$

$\frac{\partial}{\partial w_1} J(w,b) = \frac{1}{m} \sum_{i=1}^{m} \underbrace{\frac{\partial}{\partial w_1} \mathcal{L}(a^{(i)}, y^{(i)})}_{dw_1^{(i)} - (x^{(i)}, y^{(i)})}$

Lets say

$J = 0, dw_1 = 0, dw_2 = 0,$

$db = 0$.

For $i = 1$ to m

$z^{(i)} = w^T x^{(i)} + b$; $a^{(i)} = \sigma(z^{(i)})$; $J += -[y^{(i)} \log a^{(i)} + (1-y^{(i)}) \log (1-a^{(i)})]$

$dz^{(i)} = a^{(i)} - y^{(i)}$; $dw_1 += x_1^{(i)} dz^{(i)}$; $dw_2 += x_2^{(i)} dz^{(i)}$; $db += dz^{(i)}$

$n = 2$; $J /= m$; $dw_1 /= m$; $dw_2 /= m$; $db /= m$.

* $dw_1 = \frac{\partial J}{\partial w_1}$; $w_1 := w_1 - \alpha \, dw_1$; $w_2 := w_2 - \alpha \, dw_2$; $b := b - \alpha \, db$.

2 for loops: $i = 1$ to m; $dw_1, dw_2 \ldots$ features.

Vectorization °. to avoid for loops.

Time 12:00

* Derivation of DL/dz 8, 6, 10, 7, 9, 11, 6, 3, 7,

$$\frac{dL}{dz} = a - y$$

Deeplearning. AI.

Basics of Neural Network Programming

* Vectorization :-

$z = w^T x + b$.

if vectorize your code a Deep learning runs much faster

Normal	Vectorize
	a = np.random.rand(1000000)
	b = "
tic = time.time()	tic = time.time()
for i in range(1000000): c += a[i] * b[i]	c = np.dot(a,b)
toc = time.time()	toc = time.time()
481.311020 39 ms	1.5051 ms.

300 times faster than normal

GPU (Graphical P.U. has many cores & used for parallel computing (Simult. many things) CPU (few cores & less parallelization)

GPU vs CPU

GPU, CPU } SIMD - single instruction multiple data. [Note : if you use In-Built func, it enables python to efficient Parallelism]

* Examples :-

AVOID Explicit "FOR" Loops.

$u = Av$; $u_i = \sum_j A_{ij} v_j$

Normal

```
u = np.zeros(n,1).
for i ...
    for j ...
        u[i] += A[i][j] * v[i]
```

Vectorize

```
u = np.dot(A,v)
```

* Vectors & Matrix valued functions

Apply the exponential operation on every element of a matrix/vector.

$$v = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix} \rightarrow u = \begin{bmatrix} e^{v_1} \\ e^{v_2} \\ \vdots \\ e^{v_n} \end{bmatrix}$$

Normal

```
u = np.zeros((n,1))
for i in range(n):
    u[i] = math.exp(v[i])
```

```
import numpy as np.
u = np.exp(v).
np.log(v) ; np.abs(v), np.maximum(v,0)
v**2 , 1/v.
```

∴ dw = np.zeros((n_x, 1)) (dimensional vector).

dw += x^(i) dz^(i).

dw /= m

dw = dw/m

for m training examples **Vectorizing Logistic Regression**

$\rightarrow z^{(1)} = w^T x^{(1)} + b \qquad z^{(2)} = w^T x^{(2)} + b \qquad z^{(3)} = w^T x^{(3)} + b$

$a^{(1)} = \sigma(z^{(1)}) \qquad a^{(2)} = \sigma(z^{(2)}) \qquad a^{(3)} = \sigma(z^{(3)})$

$\because X = \begin{bmatrix} | & | & & | \\ x^{(1)} & x^{(2)} & \cdots & x^{(m)} \\ | & | & & | \end{bmatrix}$ n_x, m $\quad \mathbb{R}^{n_x \times m}$

$Z = np.dot(w.T, X) + b$ ("Broadcasting" in Python) $\quad (1,1)$

$A = [a^{(1)} a^{(2)} \cdots a^{(m)}] = \sigma(Z)$ $\quad [b\ b \cdots b]$

VECTORIZING LOGISTIC REGRESSION'S GRADIENT OUTPUT:-

$* \; dz^{(1)} = a^{(1)} - y^{(1)} \qquad dz^{(2)} = a^{(2)} - y^{(2)} \cdots$

$dz = [dz^{(1)}\ dz^{(2)} \cdots dz^{(m)}]$. 1 row, m columns

$A = [a^{(1)} \cdots a^{(m)}]. \quad Y = [y^{(1)} \cdots y^{(m)}]$

$dz = A - Y = [a^{(1)} - y^{(1)} \quad a^{(2)} - y^{(1)} \cdots]$.

$dw = 0$
$dw += x^{(1)} dz^{(1)}$
$dw += x^{(2)} dz^{(2)}$
$\vdots$
$dw /= m$

$db = 0$
$db += dz^{(1)}$
$db += dz^{(2)}$
$db += dz^{(m)}$
$db /= m$

$* \; db = \frac{1}{m} \sum_{i=1}^{m} dz^{(i)}$

$= \frac{1}{m} np.sum(dz)$

$dw = \frac{1}{m} X \, dz^T$

$= \frac{1}{m} \begin{bmatrix} | & & | \\ x^{(1)} & \cdots & x^{(m)} \\ | & & | \end{bmatrix} \begin{bmatrix} dz^{(1)} \\ \vdots \\ dz^{(m)} \end{bmatrix}$

$= \frac{1}{m} [x^{(1)} dz^{(1)} + \cdots + x^{(m)} dz^{(m)}]$

$n_x, 1$

Broadcasting in Python (faster).

$* \; A = np.array([[\cdot,\cdot,\cdot],[\cdots],[\cdots]])$

$cal = A.sum(axis=0)$.

$percentage = 100 * A / cal.reshape(1,4)$.

Matlab/Octave: bsxfun

$= \begin{bmatrix} | & | & | & | \end{bmatrix}$

0 axis ↓

→ axis 1.

$percentage = 100 * A / (cal.\text{reshape}(1,4))$

Ex ① $\begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix} + 100 \begin{bmatrix} 100 \\ 100 \\ 100 \\ 100 \end{bmatrix} = \begin{bmatrix} 101 \\ 102 \\ 103 \\ 104 \end{bmatrix}$. $\quad b$

② $\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} + [100 \quad 200 \quad 300] = \begin{bmatrix} 101 & 202 & 303 \\ 104 & 205 & 306 \end{bmatrix}$.

(m,n) $\quad (1,n)$ but Python realizes it (m,n)

GENERAL PRINCIPLE of B.C

(m,n) $+ - * /$ $(1,n) \rightsquigarrow (m,n)$

$(m,1) \rightsquigarrow (m,n)$

$(m,1)$ $+ - * /$ $\mathbb{R} \rightsquigarrow (m,1)$ (100)

$(1,n)$ $+ - * /$ $\mathbb{R} \rightsquigarrow (1,n)$

A Note on python/numpy vector.

never use data structures

≠ a = np.random.randn(5) ✗ ← print(a.T) a transpose.

(5,) rank 1 array

np.dot(a, a.T) → value → outerproduct of a vector

Use in NN

a = np.random.randn(5,1). → [; ; ; ;]

Note Never use rank 1 array.

Always use, vector

a = np.random.randn(5,1) → a.shape = (5,1) Column vector

a = np.random.randn(1,5) → a.shape = (1,5) row vector

Reshape an array

a = a.reshape((5,1)).

assert(a.shape == (5,1)) ← inexpensive assertion

Tour of J.N.ipy

Explanation of logistic regression Cost func

* y|x y given x. Note: Minimizing the loss corresponds with maximizing $\log P(y|x)$.

Exercises: Week 2

Q1: A neuron computes a linear func ($z = Wx+b$) followed by an activation func

We generally say that the output of a Neuron is a $g(Wx+b)$ where g is the activation func (Sigmoid, tanh, ReLU, ...).

$\hat{y} = \sigma(w^T x + b)$; $\sigma(z) = \frac{1}{1+e^{-z}}$

Q2. Logistic Loss :- $\mathcal{L}^{(i)}(\hat{y}^{(i)}, y^{(i)}) = -(y^{(i)} \log(\hat{y}^{(i)}) + (1-y^{(i)}) \log(1-\hat{y}^{(i)}))$.

Q3 : img = (32,32,3) array ≈ x = img.reshape((32*32*3, 1)). Column vector.

Q4 a = np.random.randn(2,3); b = " (2,1); c = a+b; c.shape = (2,3) [Broadcasting of b to match a].

Q5 a = np.random.randn(4,3) b = " (3,2); c = a*b; "Error" [The '*' operator in Numpy, indicates element-wise multiplication.

It is different from "np.dot()". If you would try "c = np.dot(a,b)" you would get c.shape = (4,2)

Q6. Suppose you have n_x input features per example. $X = [x^{(1)} x^{(2)} \dots x^{(m)}]$.
What is the dimension of X? (n_x, m)

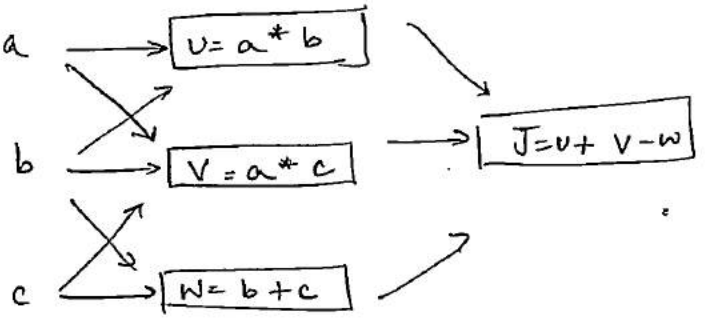
Q7 a = np.random.randn(12288, 150)
b = " (150, 45). $c = np.dot(a,b)$; c.shape = (12288, 45).

Q8. a.shape = (3,4). for 'i' in range(3):
b.shape = (4,1) for j in range(4)
$c[i][j] = a[i][j] + b[j]$.

Vectorize $C = a + b^T$.

Q9. a = np.random.randn(3,3). $c = a * b$
b = np.random.randn(3,1)
This will invoke broadcasting, so b is copied three times to become (3,3) and * is an element-wise product so c.shape will be (3,3).

10)



$\therefore J = (a-1) * (b+c)$.

* Programming exercise. Q. Build a fun^c returns $\text{Sigmoid}(x) = \frac{1}{1+e^{-x}}$ Logistic fun^c

math.exp(x)

Note: We rarely use "math" library in deep learning because the inputs of the fun^c are real numbers. In deep learning we mostly use matrices and vectors.
This is why "numpy" is more useful.
Furthermore, if 'x' is a vector, then Py operation such as $s = x+3$ or $s = \frac{1}{x}$ will output s as a vector of the same size as x.

x = np.array([1,2,3]).

Note: ML/DL Normalize our data because Gradient Descent converges faster after Normalization.

* gradient of Sigmoid fun^c = slope of Sigmoid fun^c. $\frac{x}{\|x\|} \Rightarrow$ np.linalg.norm(a, axis=1, keepdims=True) $\Rightarrow [\sqrt{5}]$

Broadcasting changes matrix dimensions.

np.dot() → matrix-matrix multiplication
np.multiply() → element-wise multiplication

Programming Exercise Part 2

Logistic Regression to identify cats.

Centre & Standardize your Data set in Machine Learning

255 (maximum value of a pixel Channel).

* m_train images labelled as Cat ($y=1$) & non-cat ($y=0$)
* (num_px), (num_px, 3) 3 → 3 channels (RGB).
* Logistic regression is actually a very simple neural network
* $\omega^T x^{(i)} + b \mid \sigma$
* $$J = \frac{1}{m} \sum_{i=1}^{m} L(a^{(i)}, y^{(i)}).$$

The main steps for building a Neural Networks are:

1. Define the model structure (such as number of input features).
2. Initialize the model's parameters.
3. loop:- Calculate current loss (forward propagation).
   :- Calculate current gradient (backward propagation).
   :- Update parameters (gradient descent).

$w = np.zeros((dim, 1))$

You often build 1-3 separately and integrate them into one func^n we call model().

Propagate(): w, b, X, Y.

$$A = \sigma(\omega^T X + b) = (a^{(1)}, a^{(2)} \dots a^{(m-1)}, a^{(m)})$$

$$J = -\frac{1}{m} \sum_{i=1}^{m} y^{(i)} \log(a^{(i)}) + (1-y^{(i)}) \log(1-a^{(i)}).$$

$$\frac{\partial J}{\partial w} = \frac{1}{m} X(A-Y)^T \qquad \frac{\partial J}{\partial b} = \frac{1}{m} \sum_{i=1}^{m} (a^{(i)} - y^{(i)}).$$

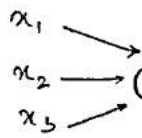
* $\theta = \theta - \alpha d\theta$. α = learning rate

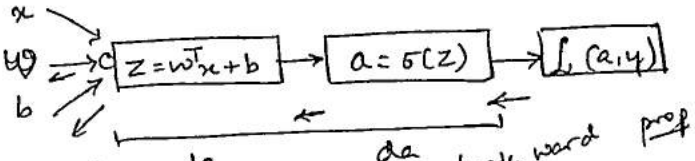
Glimpse

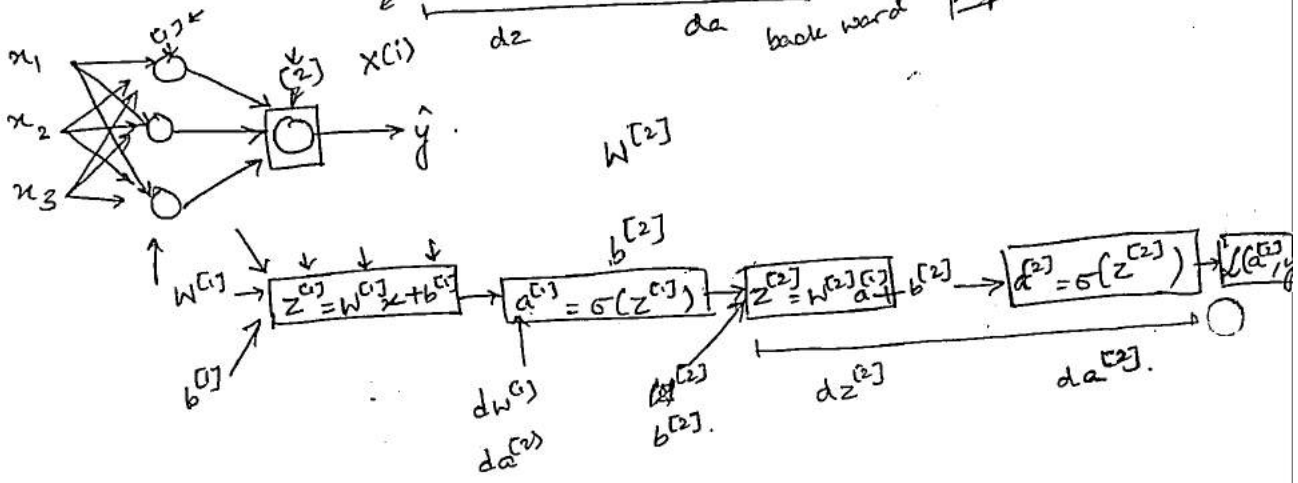
NN & DL

Week 3

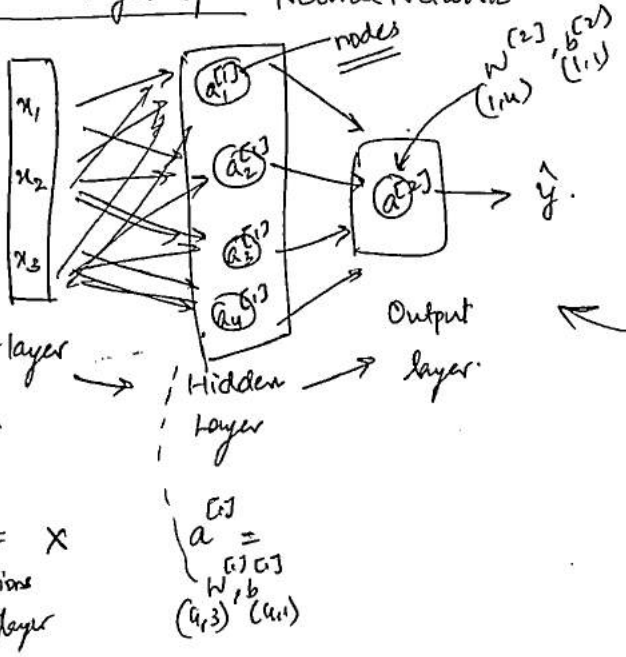
Neural Network Summary :



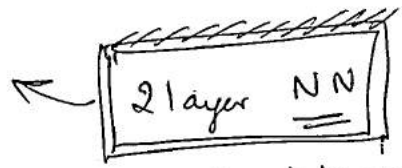




One Hidden Layer of Neural Network



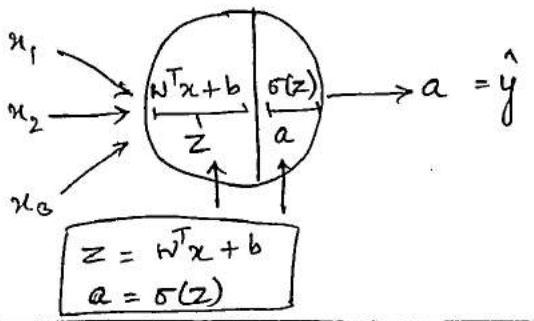
$$a^{[1]} = \begin{bmatrix} a_1^{[1]} \\ a_2^{[1]} \\ \vdots \\ a_4^{[1]} \end{bmatrix}$$

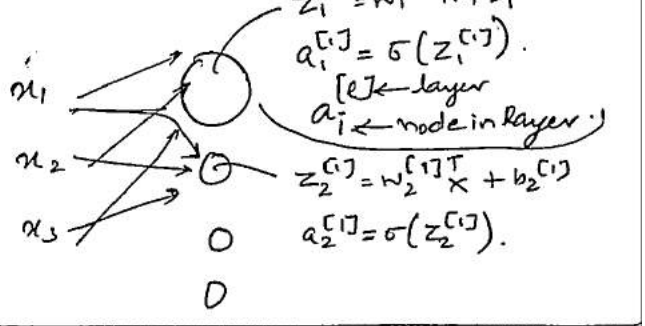


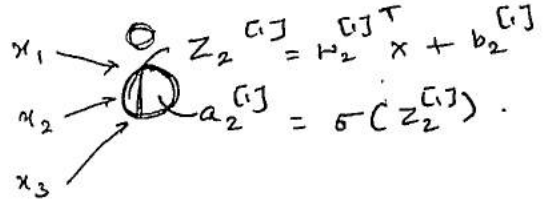
The input layer is not counted as an official layer

Computing a NN output : 2 steps

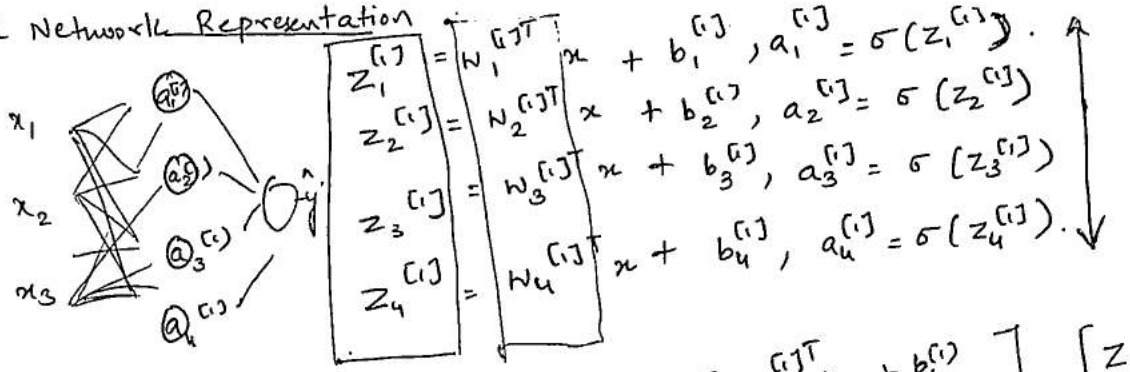
1. Compute z
2. Compute Activation(a) from sig fun of z







* Neural Network Representation



$$z^{[1]} = \begin{bmatrix} — & w_1^{[1]T} & — \\ — & w_2^{[1]T} & — \\ — & w_3^{[1]T} & — \\ — & w_4^{[1]T} & — \end{bmatrix}_{(4,3)} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1^{[1]} \\ b_2^{[1]} \\ b_3^{[1]} \\ b_4^{[1]} \end{bmatrix}_{(4,1)} = \begin{bmatrix} w_1^{[1]T} x + b_1^{[1]} \\ w_2^{[1]T} x + b_2^{[1]} \\ w_3^{[1]T} x + b_3^{[1]} \\ w_4^{[1]T} x + b_4^{[1]} \end{bmatrix} = \begin{bmatrix} z_1^{[1]} \\ z_2^{[1]} \\ z_3^{[1]} \\ z_4^{[1]} \end{bmatrix}$$

$W^{[1]}$ $b^{[1]}$

$$a^{[1]} = \begin{bmatrix} a_1^{[1]} \\ \vdots \\ a_4^{[1]} \end{bmatrix} = \sigma(z^{[1]}).$$

Given input x:

$\rightarrow z^{[1]} = w^{[1]} x + b^{[1]}$
$(4,1) \quad (4,3)(3,1) \quad (4,1)$

$\rightarrow a^{[1]} = \sigma(z^{[1]})$.
$(4,1) \quad (4,1)$.

$\rightarrow z^{[2]} = w^{[2]} a^{[1]} + b^{[2]}$
$(1,1) \quad (1,4)(4,1) \quad (1,1)$

$\rightarrow a^{[2]} = \sigma(z^{[2]})$.
$(1,1) \quad (1,1)$

$z = w^T x + b$.
$\hat{y} = a = \sigma(z)$.

7, 10, 11, 12, 13, 14

Vectorize across multiple examples :-

$x \longrightarrow a^{[2]} = \hat{y}$.

$x^{(1)} \longrightarrow a^{[2](1)} = \hat{y}^{(1)}$.

$x^{(2)} \longrightarrow a^{[2](2)} = \hat{y}^{(2)}$.

$\vdots$

$a^{[2](i)}$ ← example i.
← layer 2.

$$X = \begin{bmatrix} | & | & & | \\ x^{(1)} & x^{(2)} & \cdots & x^{(m)} \\ | & | & & | \end{bmatrix} \quad (n_x, m)$$

$$Z^{[1]} = \begin{bmatrix} | & | & & | \\ z^{[1](1)} & z^{[1](2)} & \cdots & z^{[1](m)} \\ | & | & & | \end{bmatrix}$$

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

training examples

hidden units.

$$\begin{cases} z^{[1]} = W^{[1]} x + b^{[1]} \\ a^{[1]} = \sigma(z^{[1]}) \\ z^{[2]} = W^{[2]} a^{[1]} + b^{[2]} \\ a^{[2]} = \sigma(z^{[2]}) \end{cases}$$

for $i = 1$ to m,

$$\begin{cases} z^{[1](i)} = W^{[1]} x^{(i)} + b^{[1]} \\ a^{[1](i)} = \sigma(z^{[1](i)}) \\ z^{[2](i)} = W^{[2]} a^{[1](i)} + b^{[2]} \\ a^{[2](i)} = \sigma(z^{[2](i)}) \end{cases}$$

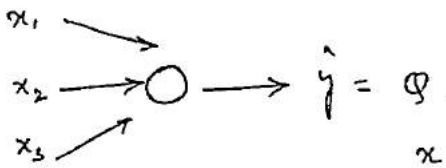
$$z^{[1]} = W^{[1]} X + b^{[1]}$$

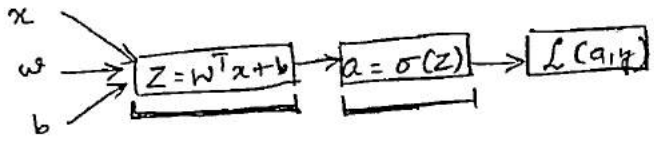
$$A^{[1]} = \sigma(z^{[1]})$$

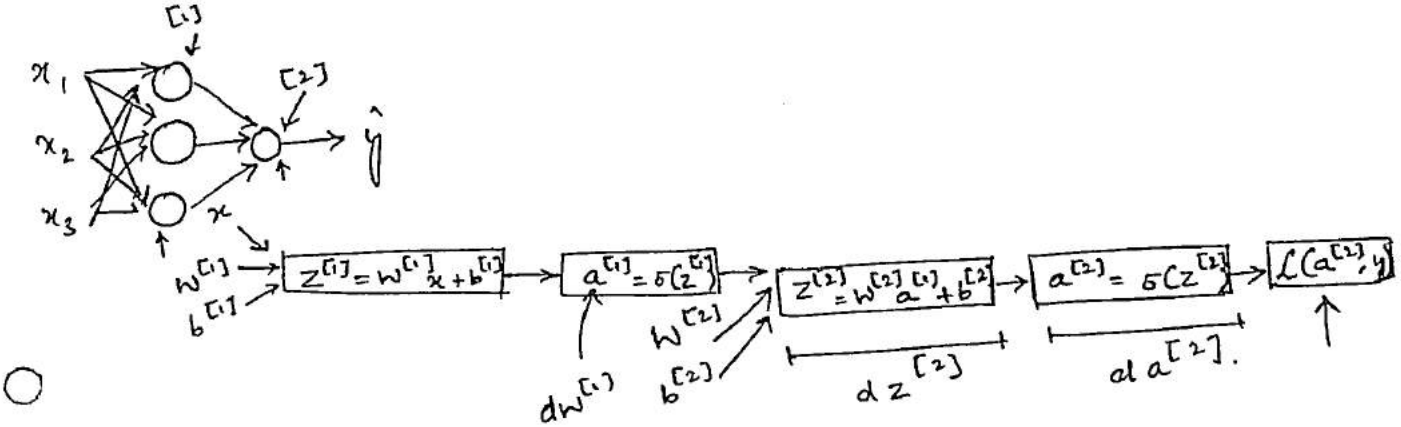
Explanation for Vectorized implementation

$\therefore$ first training example $z^{[1](1)} = W^{[1]} x^{(1)} + b^{[1]}$, $z^{[1](2)} = W^{[1]} x^{(2)} + b^{[1]}$.

$$W^{[1]} = \begin{bmatrix} — \\ — \\ — \end{bmatrix}.$$







Activation (Networks) functions:-

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

$a^{[1]} = \sigma(z^{[1]}) \rightarrow g(z^{[1]})$ — until now Activation func is the sigmoid func

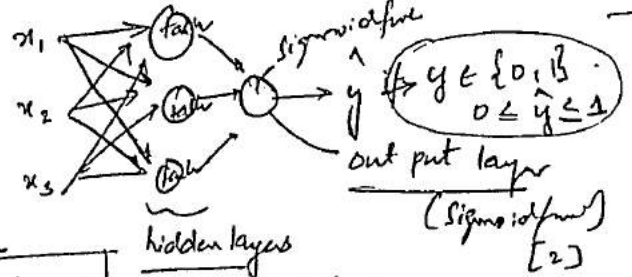
$z^{[2]} = w^{[2]} a^{[1]} + b^{[2]}$.

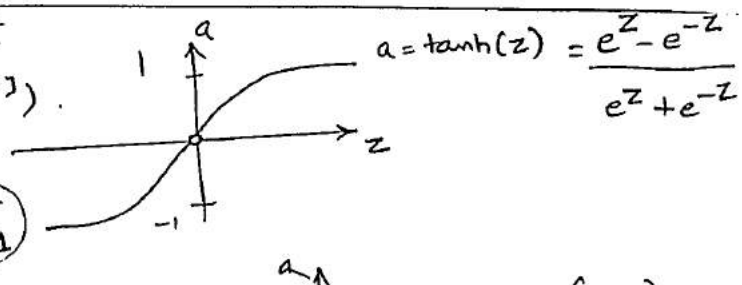
$a^{[2]} = \sigma(z^{[2]}) \rightarrow g(z^{[2]})$ — Nonlinear func (Not sigmoid).

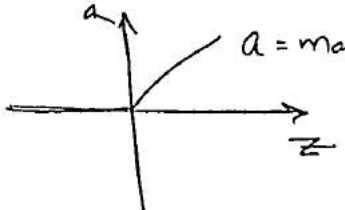
Better: tanh > sigmoid func

Now on Activation func is tanh func

$g(z^{[1]}) = \tanh(z^{[1]})$.



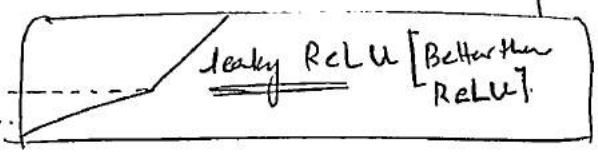




ReLU — Rectified Linear Unit

Default Choice of Activation func for hidden layers if not sure from ... tanh Activation func.

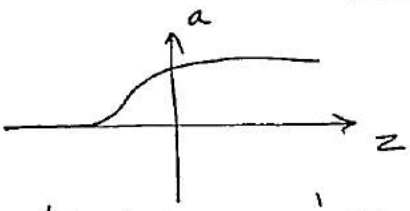
Note:
- hidden layers have data closer to zero mean do, tanh better
- for Output layer (Sigmoid) better.



- NN is much faster when using ReLU Activation func than tanh or sigmoid Activation func

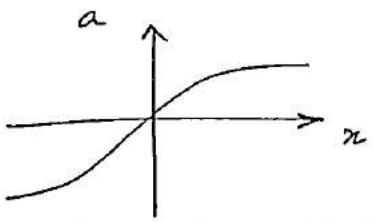
23, 24, 25, 26, 27, 28, 29, 30, 1, 2, 3, 4, 5, 6, 7
15 days.

* Pros & Cons of Activation func.



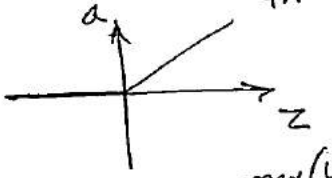
Sigmoid : $a = \frac{1}{1+e^{-z}}$

[Never for hidden layers & always for Output layers].



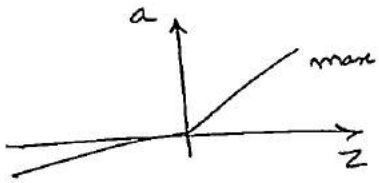
tanh: $a = \frac{e^z - e^{-z}}{e^z + e^{-z}}$

[best for hiddenlayers]



ReLU $a = \max(0, z)$

(Default) for hidden layers.



Leaky ReLU $a = \max(0.01z, z)$

[Sometimes better than ReLU].

* Why do u need a N.L Activation func.? :

$a^{[1]} = z^{[1]} = w^{[1]}x + b^{[1]}$.

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

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

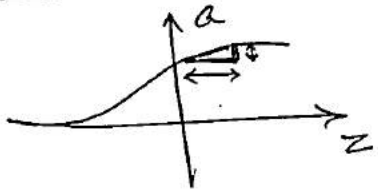
$g(z) = z$

"linear orientation function"

∵ A linear Hidden layer is more or less useless. N.L is better

* Derivatives of Activation Functions

Sigmoid



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

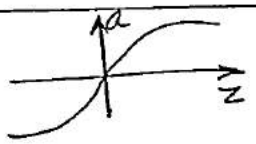
∵ $\frac{d}{dz}(g(z))$ = slope of $g(z)$ at z

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

$= g(z)\,(1 - g(z))$.

$= a\,(1-a)$.

tanh



$g(z) = \tanh(z)$.

$= \frac{e^z - e^{-z}}{e^z + e^{-z}}$

$g'(z) = \frac{d}{dz}(g(z))$

$= 1 - (\tanh(z))^2$

∵

$z = 10 \quad \tanh(z) \simeq 1$

$g'(z) \simeq 0$.

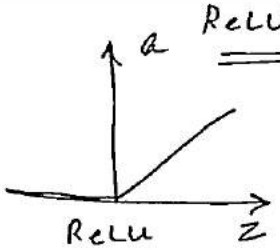
$z = -10 \quad \tanh(z) \simeq -1$

$g'(z) \simeq 0$.

$z = 0 \quad \tanh(z) = 0$

$g'(z) = 1$.

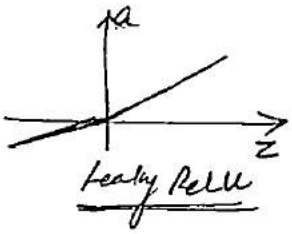
ReLU & Leaky ReLU — (3) —



$g(z) = \max(0, z)$.

$$g'(z) = \begin{cases} 0 & \text{if } z < 0 \\ 1 & \text{if } z \geq 0 \end{cases}$$

$z = 0.000\ldots0$



$g(z) = \max(0.01z, z)$

$$g'(z) = \begin{cases} 0.01 & \text{if } z < 0 \\ 1 & \text{if } z > 0. \end{cases}$$

Gradient Descent for Neural Networks :-

Parameters :- $w^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}$.

$(n^{[1]}, n^{[0]})$ $(n^{[1]}, 1)$ $(n^{[2]}, n^{[1]})$ $(n^{[2]}, 1)$.

Cost fun^{n} : $J(w^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}) = \frac{1}{m} \sum_{i=1}^{n} \mathcal{L}(\hat{y}, y)$.

$\hat{y} \leftarrow a^{[2]}$.

○ Gradient Descent :

Repeat- { Compute predicts $(\hat{y}^{(i)}, i = 1 \ldots, m)$.

$$dw^{[1]} = \frac{\partial J}{\partial w^{[1]}}, \quad db^{[1]} = \frac{\partial J}{\partial b^{[1]}}, \ldots$$

Update rule

$$w^{[1]} := w^{[1]} - \alpha\, dw^{[1]}$$
$$b^{[1]} := b^{[1]} - \alpha\, db^{[1]}$$

Update Rule for Gradient Descent

○ Formulas for computing derivatives :

Forward Propagation :

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

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

$$z^{[2]} = w^{[2]} A^{[1]} + b^{[2]}.$$

$$A^{[2]} = g^{[2]}(z^{[2]}) = \sigma(z^{[2]}).$$

Correct vectorised Implementation of forward propagation for layer 'l'; $1 \leq l \leq L$:

$$z^{[l]} = w^{[l]} A^{[l-1]} + b^{[l]}.$$

$$A^{[l]} = g^{[l]}(z^{[l]})$$

Backward Propagation ○

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

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

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

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

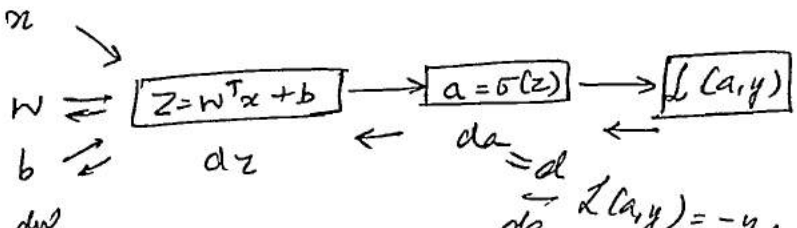
↑ element wise product $(n^{[1]}, m)$

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

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

$(n^{[1]}, 1)$ $(n^{[1]},)$ reshape

Logistic regression



$$= -y\log a - (1-y)\log(1-a)$$

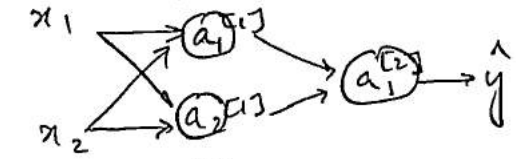
$$= -\frac{y}{a} + \frac{1-y}{1-a}.$$

$dz = da \cdot g'(z)$

$g(z) = \sigma(z)$

Random Initialization :-

* What happens if you initialize weights to zero?



$n^{[0]} = 2$ $\quad n^{[1]} = 2.$

$$W^{[1]} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \qquad b^{[1]} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Weights. Bias

$a_1^{[1]} = a_2^{[1]}$ $\qquad dz_1^{[1]} = dz_2^{[1]}.$

Symmetric:-

$$dW = \begin{bmatrix} u & v \\ u & v \end{bmatrix} \qquad \boxed{W^{[1]} = W^{[2]} - \alpha dW.} \qquad W^{[1]} = \begin{bmatrix} \cdots \\ \cdots \end{bmatrix}.$$

all the values of 'W'

∴ If you initialize with zero, W1 after every iteration, will have the first row equal to the second row. ∵ They all are computing the same thing

∴ Initialize Randomly :-

$W^{[1]} = np.random.randn((2,2)) * 0.01$ ← if it is too large then ?!

Initialize to very small random values.

$b^{[1]} = np.zero((2,1))$. ∵ W is random, so no longer there is a problem of symmetry breaking.

$W^{[2]} = \ldots$

$b^{[2]} = 0.$

1. Initialize parameters
2. predict w/ forward prop.
3. Gradient Descent w/ Backward prop

if it is very large, 'W' will be large, correspondingly $Z^{[1]} = W^{[1]} x + b^{[1]}$

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

'Z' will be very large, or very small

the slope of the gradient will be very small so Gradient Descent will be very small & so learning slow

Week 3

Lab Planar_Data_Classification_with_one hidden_layer_v6c.

np.random.seed(1).

2-class dataset.

Mathematically,

For one example,

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

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

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

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

$y^{(i)}_{prediction} = \begin{cases} 1 & \text{if } a^{[2](i)} > 0.5 \\ 0 & \text{otherwise} \end{cases}$

$$J = -\frac{1}{m} \sum_{i=0}^{m} \left(y^{(i)} \log(a^{[2](i)}) + (1-y^{(i)}) \log(1-a^{[2](i)}) \right).$$

General Met^{d} to build NN

1. Define NN structure (# of inp units, # of hidden units, etc...)
2. Initialize the Model parameters
3. Loop:
   - Implement forward propagation
   - compute loss
   - Implement backward prop. to get the gradients
   - Update parameters. (Gradient descent)

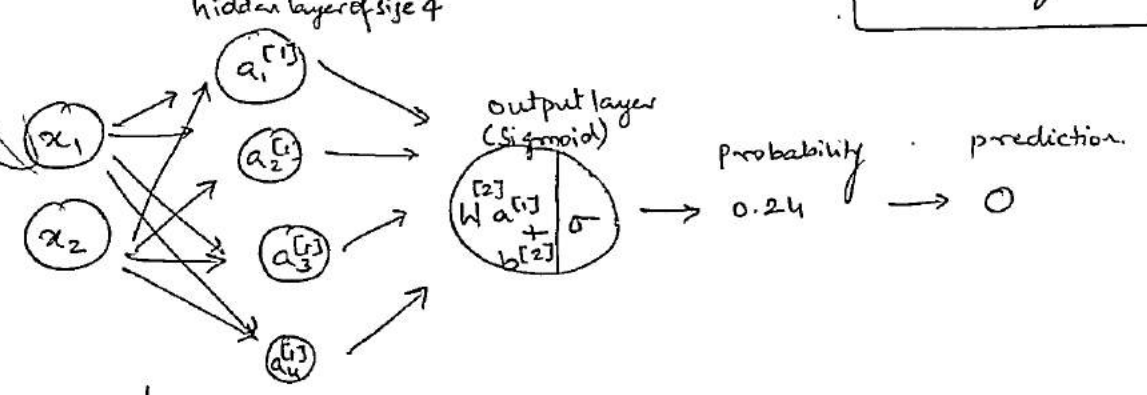
Define NN structure:

Define 3 variables:

- n_x: the size of the input layer
- n_h: the size of the hidden layer (set this to 4)
- n_y: the size of the output layer.

Q: Use shapes of X & Y to find n_x and n_y

Also, hard code the hidden layer size to be 4.



sigmoid()

np.tanh()

$$J = -\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}\log\left(a^{[2](i)}\right)+(1-y^{(i)})\log\left(1-a^{[2](i)}\right)\right)$$

∴ Implement compute_cost() to compute the value of the cost J

$$-\sum_{i=0}^{m} y^{(i)}\log\left(a^{[2](i)}\right):$$

```
logprobs = np.multiply(np.log(A2), Y)
cost = -np.sum(logprobs)
```

Hardest Part in Deep Learning is Backward Propagation

Summary of Gradient Descent:-

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

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

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

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

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

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

- Functions Used
  - X, Y
  - * layer_sizes(X, Y)
  - * initialize_parameters(n_x, n_h, n_y)
  - * forward_propagation(X, parameters)
  - * compute_cost(A2, Y, parameters)
  - * backward_propagation(parameters, cache, X, Y)
  - * update_parameters(parameters, grads, learning_rate = 1.2)

Summary

Forward propagation

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

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

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

$$A^{[2]} = g^{[2]}(Z^{[2]}).$$

$$\vdots$$

$$A^{[L]} = g^{[L]}(Z^{[L]}) = \hat{y}$$

○

Backward Propagation

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

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

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

$$dZ^{[L-1]} = W^{[L]T} \cdot dZ^{[L]} * g'^{[L-1]}(Z^{[L-1]})$$

$$\vdots$$

$$dZ^{[1]} = W^{[2]} dZ^{[2]} * g'^{[1]}(Z^{[1]}).$$

$$dW^{[1]} = \frac{1}{m} dZ^{[1]} A^{[0]T}.$$

Note that $A^{[0]T}$ is another way to ... see previous page.

Implementation info

Cost function:

Compute cost func to check if your model is actually learning.-

$$J = -\frac{1}{m} \sum_{i=1}^{m} \left(y^{(i)} \log\left(a^{[L](i)}\right) + (1-y^{(i)}) \log\left(1-a^{[L](i)}\right) \right).$$

⇒ Backward Propagation:-

○ $$dW^{[L]} = \frac{\partial J}{\partial W^{[L]}} = \frac{1}{m} dZ^{[L]} A^{[L-1]T}.$$

$$db^{[L]} = \frac{\partial J}{\partial b^{[L]}} = \frac{1}{m} \sum_{i=1}^{m} dZ^{[L](i)}.$$

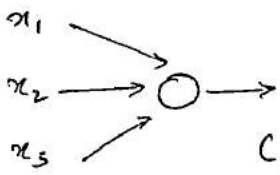
$$dA^{[L-1]} = \frac{\partial L}{\partial A^{[L-1]}} = W^{[L]T} \cdot dZ^{[L]}.$$

Week4

Deep Neural Networks – Deep L-layer Neural Network

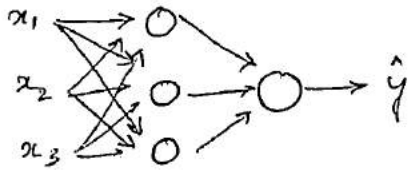
* Deep Neural Network

"1 layer NN"



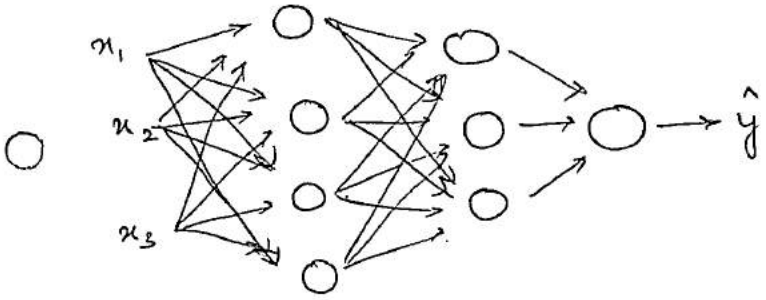
(shallow)

logistic regression "shallow"

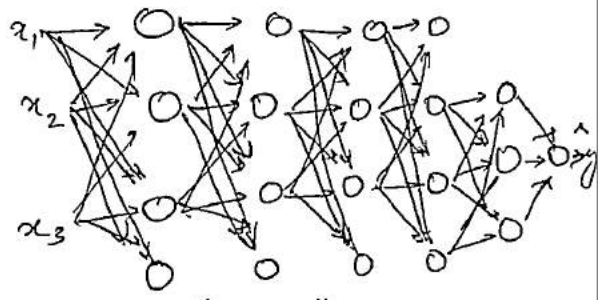


1 hidden layer.

2 Layer NN

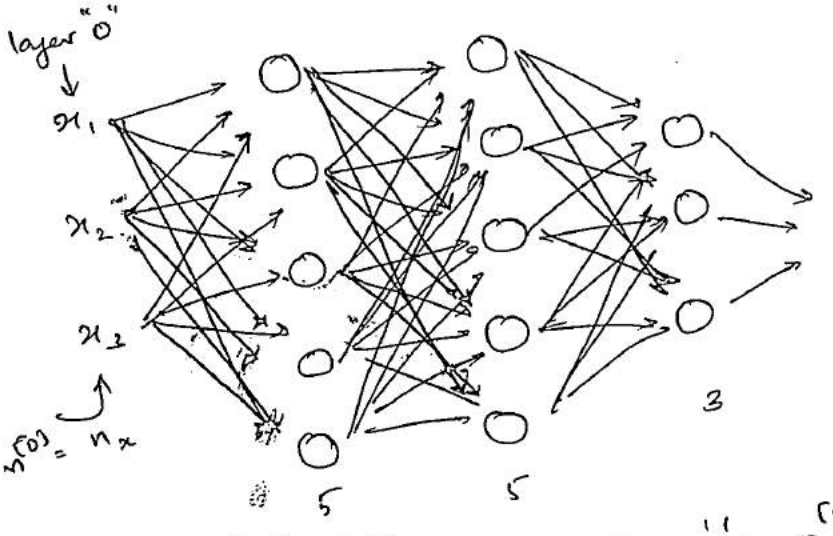


2 hidden layers.



"deep"

5 – hidden layers.



4 layer NN

$L = 4$ (# layers); $n^{[l]}$ = # units in layer 'l'.

$n^{[1]} = 5$, $n^{[2]} = 5$, $n^{[3]} = 3$,

$n^{[4]} = 3$, $n^{[4]} = n^{[L]} = 1$

$n^{[0]} = n_x = 3$.

$a^{[l]}$ = activations in layer 'l'.

$a^{[l]} = g^{[l]}(z^{[l]})$, $W^{[l]}$ = weights for $z^{[l]}$.

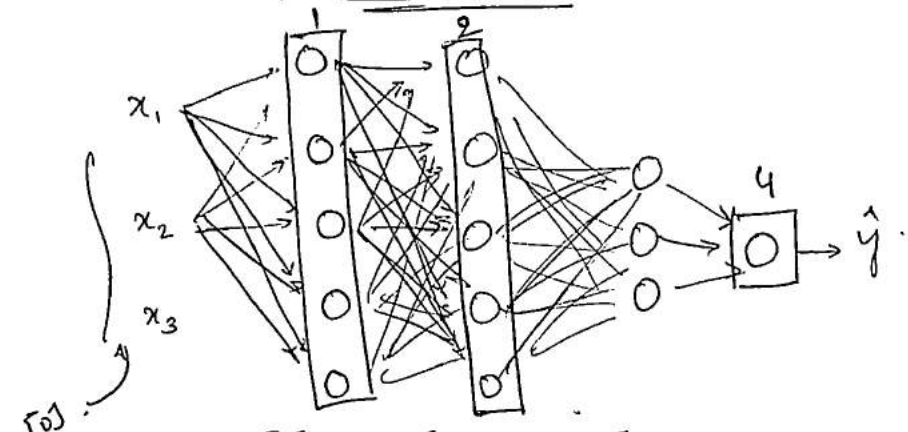
↳ Activation index

$b^{[l]}$ = biases " "

finally, $X = a^{[0]}$

↳ input layer & also activation at index 0.

* Forward propagation in a deep network



General Rule

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

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

General forward propagation Equ^n.

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

effect the activations in layer "1"

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

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

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

activation func^n

$$z^{[4]} = W^{[4]} a^{[3]} + b^{[4]}.$$

$b^{[4]}$: vector bias from [4] layer; $W^{[4]}$: Parameters from [4] layer; $a^{[3]}$: activation from previous layer

$$a^{[4]} = g^{[4]}(z^{[4]}).$$

Estimated Output $\hat{y}$ is computed.

∴ Vectorized -

$$X = A^{[0]}.$$

$$Z^{[1]} = W^{[1]} A^{[0]} + b^{[1]}$$

$$A^{[1]} = g^{[1]}(Z^{[1]}).$$

Seems like for $l = 1, \ldots, 4$

But there is no way to compute for layers Acts 1, 2, 3, ... Perfectly OK for Explicit for loops.

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

$$A^{[2]} = g^{[2]}(Z^{[2]}).$$

stacking columns for m training examples.

$$\begin{bmatrix} z^{[2](1)} & z^{[2](2)} & \cdots & z^{[2](m)} \end{bmatrix} = Z^{[2]}.$$

$$\hat{Y} = g(Z^{[4]}) = A^{[4]}.$$

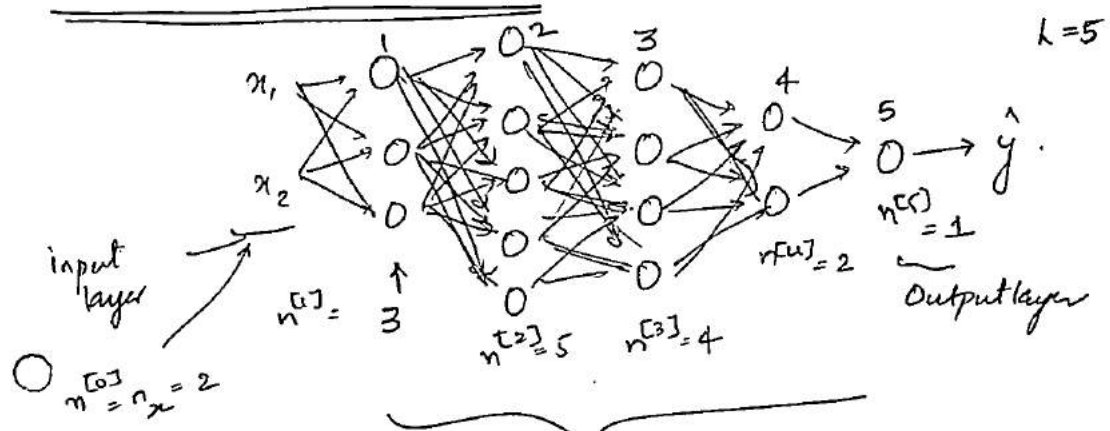
Correction for Video

$a^{[l]} = g^{[l]}(z^{[l]})$. a, z have dimensions $(n^{[l]}, 1)$.

Week 4-3

Getting your matrix dimensions right

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



$z^{[1]} = W^{[1]} \cdot X + b^{[1]}$ (3×1) (3×1).

$(3,1) \leftarrow (3,2)(2,1) + (3,1)$.

$(n^{[1]}, 1) \leftarrow (n^{[1]}, n^{[0]})(n^{[0]}, 1) + (n^{[1]}, 1)$.

$\begin{bmatrix} \cdot \\ \cdot \\ \cdot \end{bmatrix}_{3\times1} = \begin{bmatrix} \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \end{bmatrix}_{3\times2} \begin{bmatrix} \cdot \\ \cdot \end{bmatrix}_{2\times1} +$

from Matrix Multiplication

$W^{[1]} : (n^{[1]}, n^{[0]})$.

$W^{[2]} : (5, 3) : (n^{[2]}, n^{[1]})$

$Z^{[2]} = W^{[2]} \cdot a^{[1]} + b^{[2]}$.

$(5,1) \leftarrow (5,3)\ (3,1) + (5,1)$. $(n^{[2]}, 1)$.

$W^{[3]} : (4,5) \quad (n^{[3]}, n^{[2]})$

$W^{[4]} : (2,4)$, $W^{[5]} : (1,2)$.

$W^{[l]} : (n^{[l]}, n^{[l-1]})$; $b^{[l]} : (n^{[l]}, 1)$ Dimensions of your matrices.

for Back propagation:

same as $dW^{[l]} : (n^{[l]}, n^{[l-1]})$.

$db^{[l]} : (n^{[l]}, 1)$. same as.

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

Vectorized Implementation :-

Normally (Non vectorized)

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

$(n^{[1]}, 1) \quad (n^{[1]}, n^{[0]}) \quad (n^{[0]}, 1) \quad (n^{[1]}, 1)$

for Vectorized (Stacking them).

$$\begin{bmatrix} z^{[1](1)} & z^{[1](2)} & \cdots & z^{[1](m)} \end{bmatrix}$$

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

$(n^{[1]}, m) \quad (n^{[1]}, n^{[0]}) \quad (n^{[0]}, m) \quad (n^{[1]}, 1)$

through Python Broadcasting

$(n^{[1]}, m)$

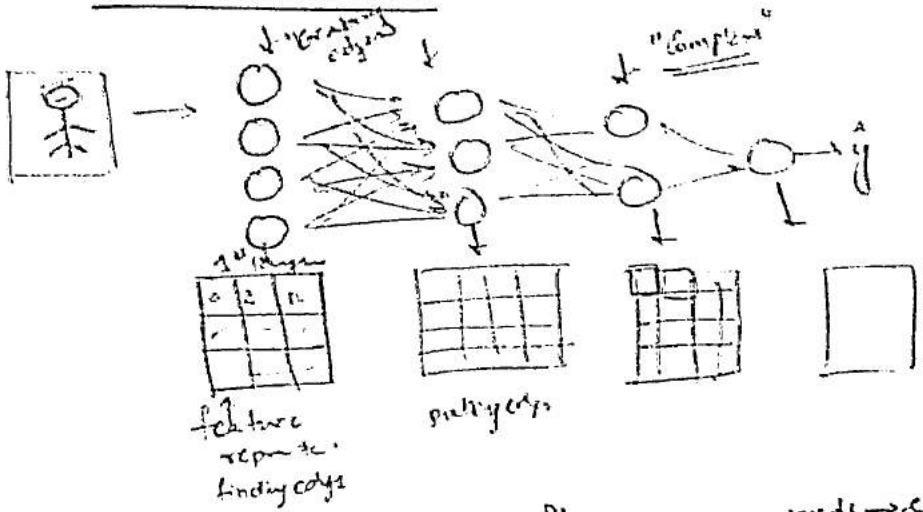
$z^{[l]}, a^{[l]} : (n^{[l]}, 1)$

$Z^{[l]}, A^{[l]} : (n^{[l]}, m)$.

(capital (vectorized)) if $l = 0 \rightarrow A^{[0]} = X = (n^{[0]}, m)$

$dZ^{[l]}, dA^{[l]} : (n^{[l]}, m)$.

Intuition about deep representation



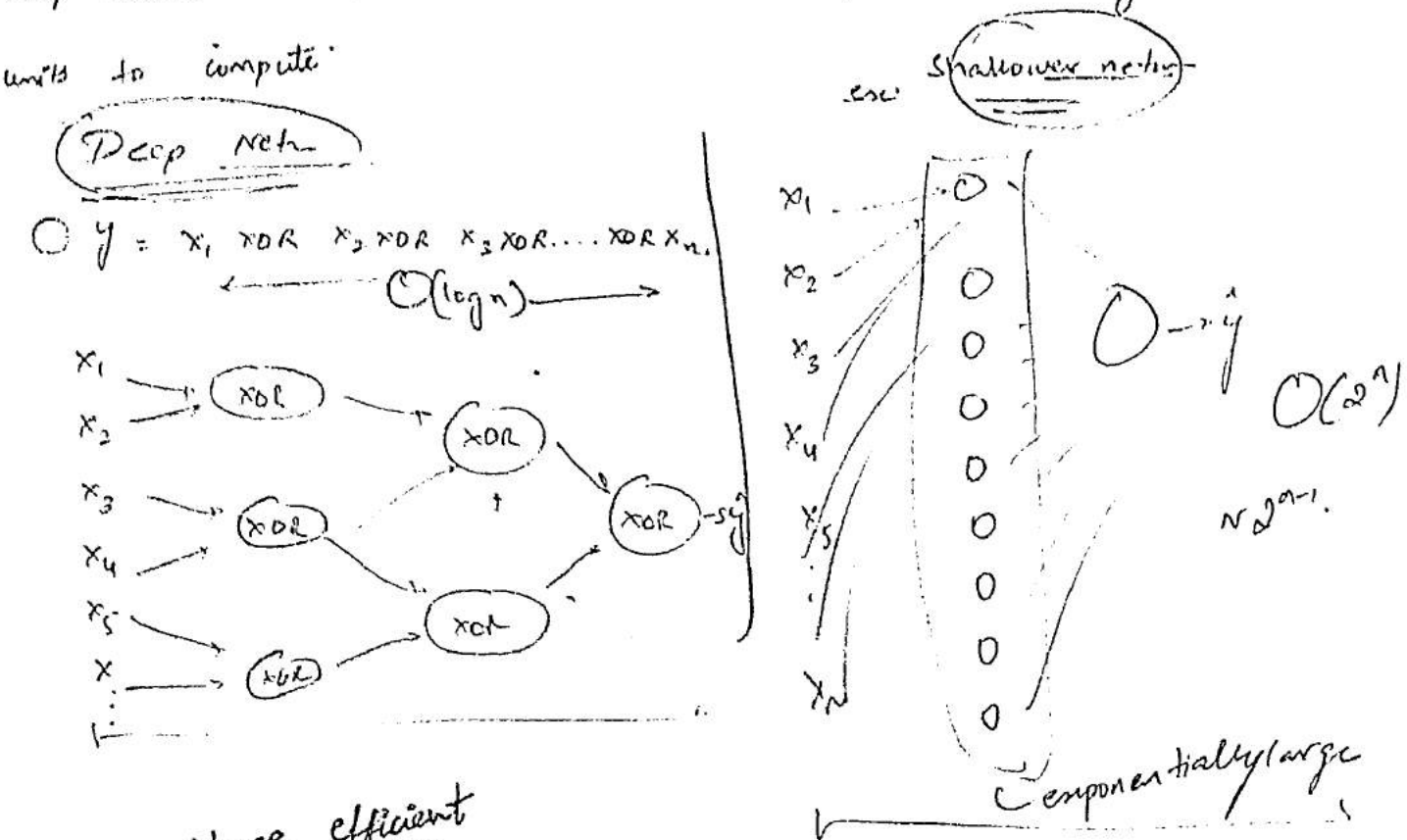
Audio → Low level → Phonemes → words → sentences/phrases

Audio waveform

CAT

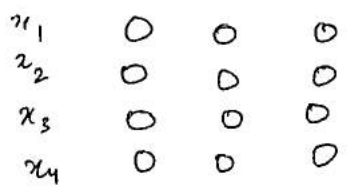
Circuit Theory and Deep learning

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.



More efficient

* Building blocks of Deep Neural Networks:



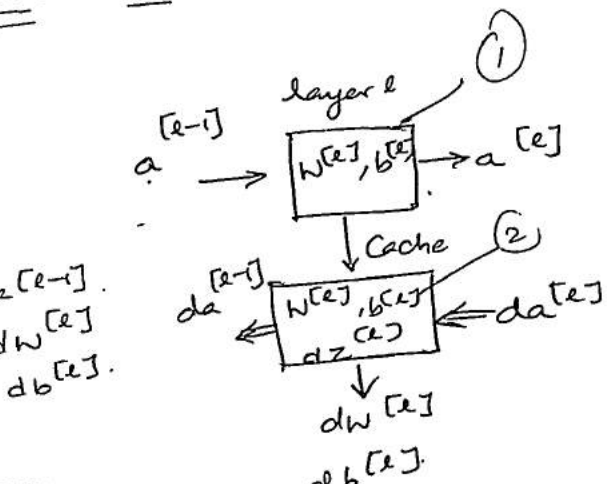
layer l: $W^{[l]}, b^{[l]}$

Forward: Input $a^{[l-1]}$, output $a^{[l]}$.

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

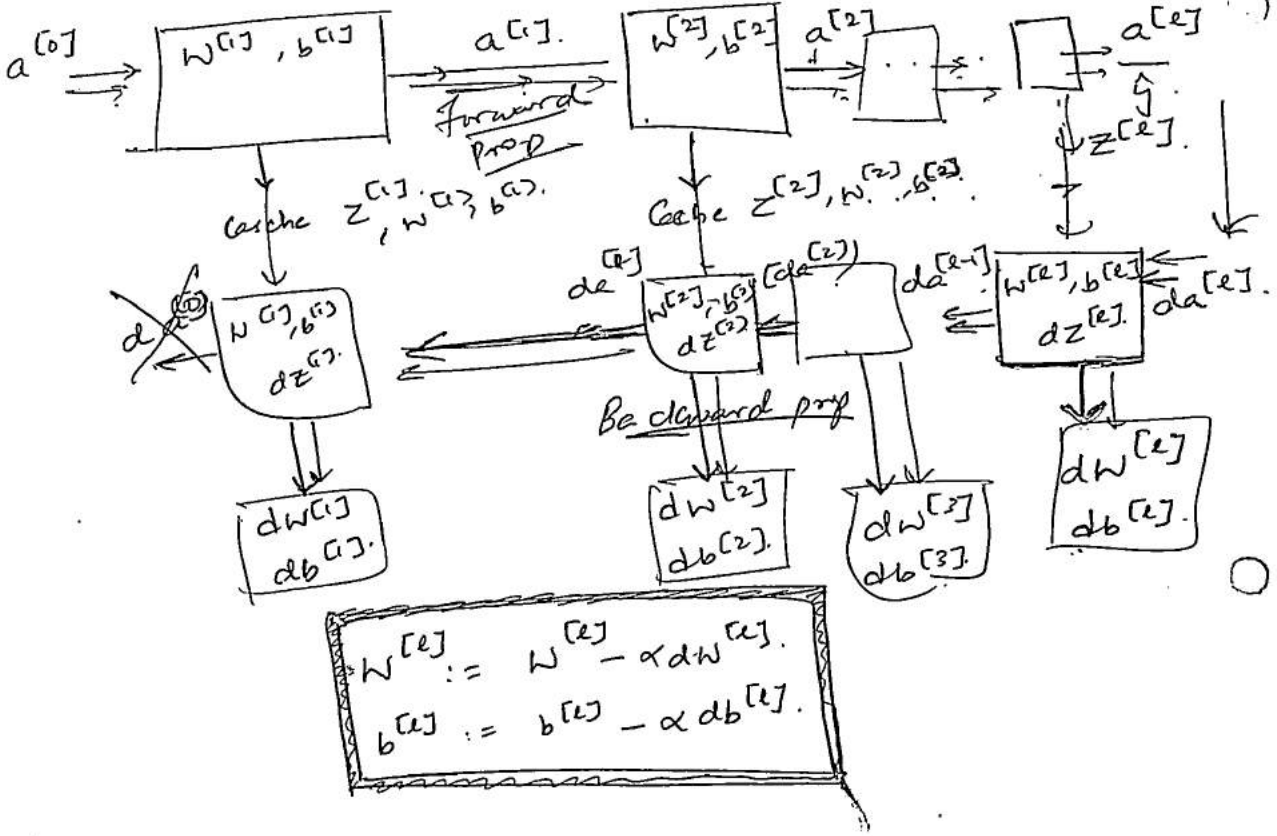
Cache $z^{[l]}$.

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



Backward: Input $da^{[l]}$, output $da^{[l-1]}$, $dW^{[l]}$, $db^{[l]}$

Cache $(z^{[l]})$



$W^{[l]} := W^{[l]} - \alpha\, dW^{[l]}$

$b^{[l]} := b^{[l]} - \alpha\, db^{[l]}$

Corrects Video

$dW^{[l]} = dz^{[l]} * a^{[l-1]T}$

* Forward propagation for layer l

→ Input $a^{[l-1]}$. ← $W^{[l]}, b^{[l]}$.

→ Output $a^{[l]}$, Cache $(z^{[l]})$.

$$z^{[l]} = W^{[l]} \cdot a^{[l-1]} + b^{[l]}$$

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

Vectorized

$$Z^{[l]} = W^{[l]} \cdot A^{[l-1]} + b^{[l]}$$

$$A^{[l]} = g^{[l]}(Z^{[l]})$$

$X = A^{[0]} \rightarrow \square \rightarrow \square \rightarrow \square \rightarrow \cdots$

Backward Propagation for layer l.

○ → Input $da^{[l]}$.

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

(4 eqn's)

$$dz^{[l]} = da^{[l]} * g^{[l]'}(z^{[l]})$$

$$dW^{[l]} = dz^{[l]} * a^{[l-1]T}$$

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

$$da^{[l-1]} = W^{[l]T} \cdot dz^{[l]}$$

Vectorized

$$dZ^{[l]} = dA^{[l]} * g^{[l]'}(Z^{[l]})$$

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

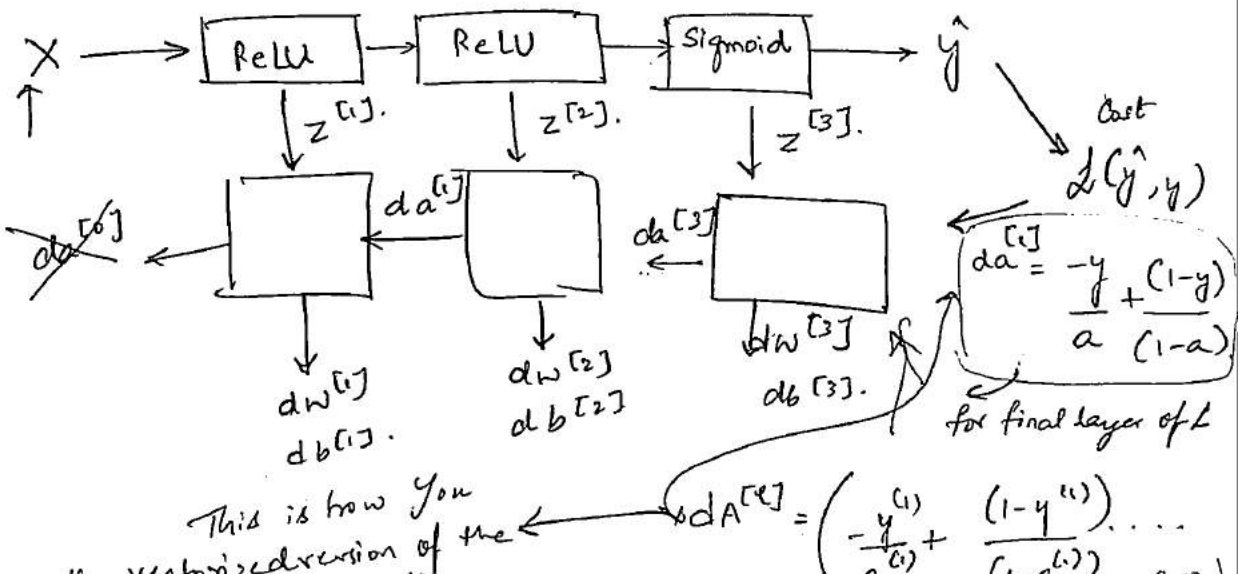
$$db^{[l]} = \frac{1}{m} \text{np.sum}(dZ^{[l]}, \text{axis}=1, \text{keepdims}=\text{True})$$

$$dA^{[l-1]} = W^{[l]T} \cdot dZ^{[l]}$$

$$dz^{[l]} = W^{[l+1]T} \cdot dz^{[l+1]} * g^{[l]'}(z^{[l]})$$ Backpropagation

○

SUMMARY



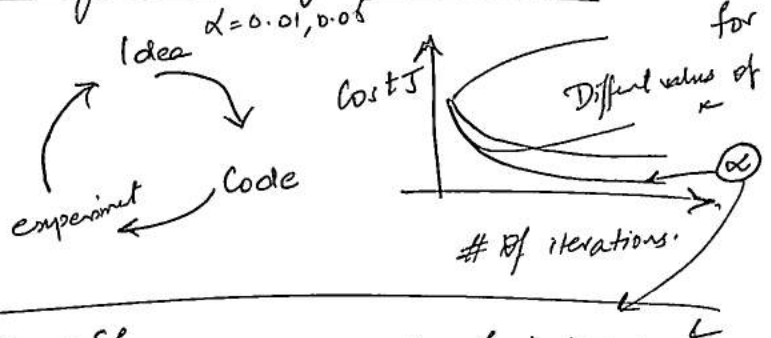
* Parameters Vs Hyperparameters:

Parameters: $W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}, W^{[3]}, b^{[3]} \ldots$

Hyperparameters:
- Learning rate α
- # iterations.
- # hidden layers L
- # hidden units $n^{[1]}, n^{[2]} \ldots$
- Choice of activation function.

Later: Momentum, mini batch size, regularizations....

Note
* Applied deep learning is a very empirical process.



for checking out if the learning rate you think is the best value, try one value of α & see the graph.

The value of α gives me pretty fast learning allows me to converge to a lower cost function.

(1) Try out many different values & check out which is best.

(2)

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

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

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

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

(*) element wise multiplication

$dZ^{[1]} = W^{[2]} dZ^{[2]} * g'^{[1]}(Z^{[1]})$

$dW^{[1]} = \frac{1}{m} dZ^{[1]} A^{[0]T}$

Note that $A^{[0]T}$ is another way to denote the input features, which is also written as X^T. $db^{[1]} = \frac{1}{m} np.sum(dZ^{[1]}, axis=1, keepdims=True)$.