

Week 4

Deep neural networks

Neural networks are of two types - Shallow and deep

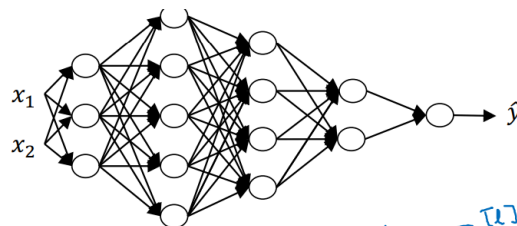
Shallow are the ones with one layer and deep have 5 or more layer
the shallow one can be said to be a Logistic neural network

If \hat{y} for some nn is $a[L]$, i.e., L no of layers present in the nn, then
 w, b, g, z will have same super script 'L', instead of layer no.

$n[0]$ (superscript = 0) can be given as n_x (subscript = x) and equals no
of inputs to the NN

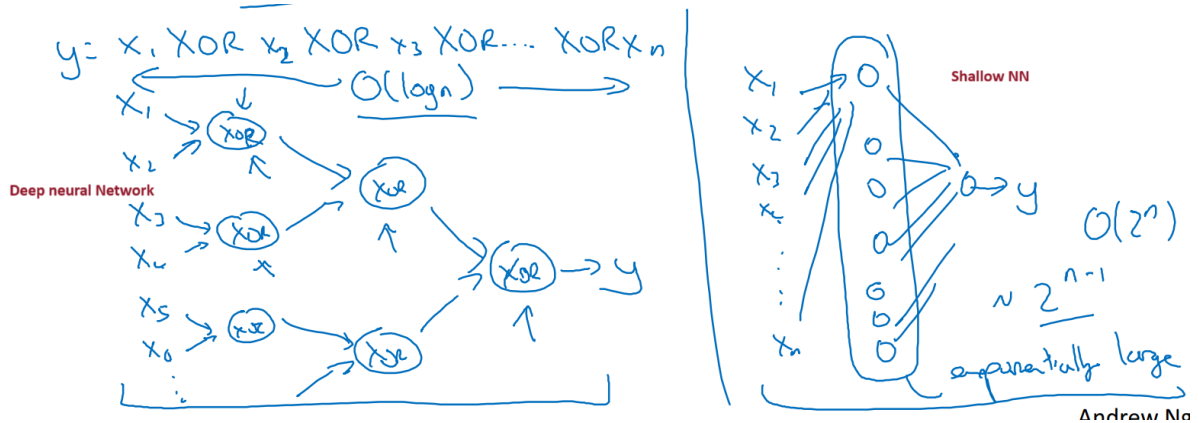
Dimensions

- $Z^{[l]}$: $n^{[l]}$ by 1
- $W^{[l]}$: $n^{[l]}$ by $n^{[l-1]}$
- X : $n^{[l-1]}$ by 1
- $B^{[l]}$: $n^{[l]}$ by 1
- $DW^{[l]}$: $n^{[l]}$ by $n^{[l-1]}$
- $DB^{[l]}$: $n^{[l]}$ by 1
- $A^{[l]}$: $n^{[l]}$ by 1
- $DZ^{[l]}$: $n^{[l]}$ by 1
- $DA^{[l]}$: $n^{[l]}$ by 1



$$\begin{aligned} z^{[l]} &= W^{[l]} \cdot x + b^{[l]} \\ &\quad \begin{matrix} (n^{[l]}, 1) & (n^{[l]}, n^{[l-1]}) & (n^{[l]}, 1) & (n^{[l]}, 1) \end{matrix} \end{aligned}$$
$$\begin{aligned} \begin{bmatrix} z^{[l,0]} & z^{[l,1]} & \dots & z^{[l,m]} \end{bmatrix} \\ \rightarrow z^{[l]} &= W^{[l]} \cdot X + b^{[l]} \\ &\quad \begin{matrix} (n^{[l]}, m) & (n^{[l]}, n^{[l-1]}) & (n^{[l]}, m) & (n^{[l]}, 1) \\ & \uparrow & & \uparrow \\ & & (n^{[l-1]}, m) & \end{matrix} \end{aligned}$$
$$\begin{aligned} z^{[l]}, a^{[l]} &: (n^{[l]}, 1) \\ z^{[l]}, A^{[l]} &: (n^{[l]}, m) \\ l=0 \quad A^{[0]} &= X = (n^{[0]}, m) \\ dz^{[l]}, dA^{[l]} &: (n^{[l]}, m) \end{aligned}$$

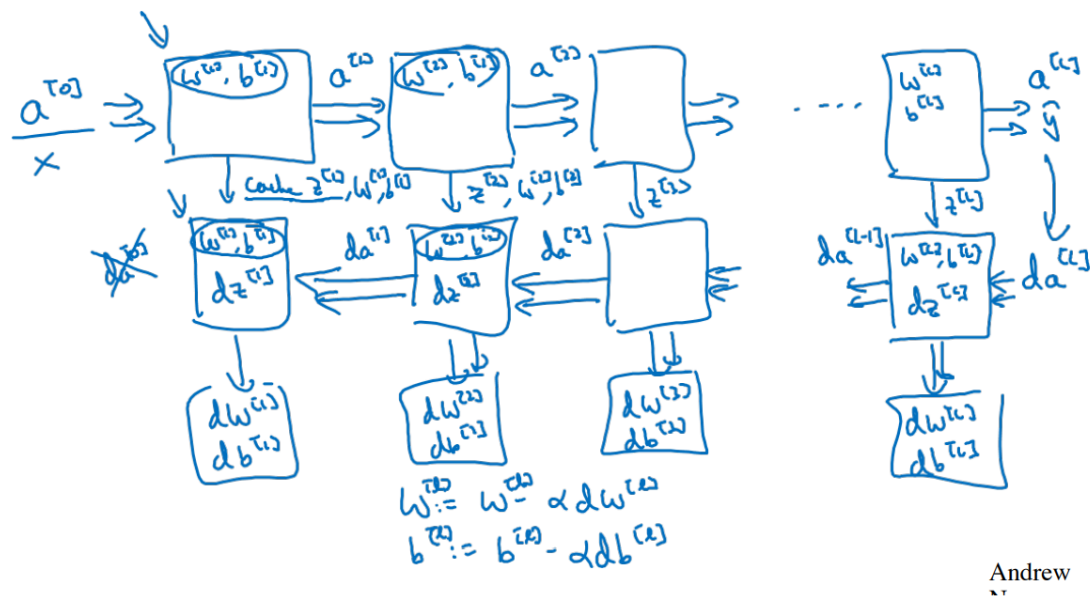
The image below is on the circuit theory and DL



This fig shows that the deep neural network is preferable than shallow as the $O(n)$ is less for deep

The below image represents how forward and backward propagation occurs.

Forward and backward functions



Z, w, b is the cache i.e., stored temporarily to be used in back function/propagation for dZ, dw, db .

As seen the parameters are calculated from previous functions[for eg. w_2 from w_1 in forward function] and the cache is collected in forward function

Once, \hat{y} is calculated, $da[L]$ is calculated by differentiating it.

Go thru the above chart once

$da[0]$ is computed at the end of backward function but isn't needed

Forward Propagation:

Input - $a^{(l-1)}$, and output - a^l , $cache(z^l)$

- Forward function: $a^l = g(z^l)$, where $z^l = w^l * a^{(l-1)} + b^l$
- Vectorized implementation: $a^l = g(z^l) = g(w^l * a^{(l-1)} + b^l)$

Backward Propagation:

Input - da^l and output - dw^l , db^l , $da^{(l-1)}$

- Derivative of z^l : $dz^l = da^l * g'(z^l)$
- Derivative of w^l : $dw^l = dz^l * a^{(l-1)T}$
- Derivative of b^l : $db^l = dz^l$
- Derivative of $a^{(l-1)}$: $da^{(l-1)} = w^{lT} * dz^l$

Vectorized Backward Propagation:

- Derivative of z^l : $dz^l = da^l * g'(z^l)$
- Derivative of w^l : $dw^l = (1/m) * dz^l * a^{(l-1)T}$
- Derivative of b^l : $db^l = (1/m) * np.sum(dz^l, axis=1, keepdims=True)$
- Derivative of $a^{(l-1)}$: $da^{(l-1)} = w^{lT} * dz^l$

Hyperparameters: control the parameters

- Learning rate (α)
- Number of iterations
- Number of hidden layers (capital L)
- Number of hidden units
- Choice of activation function (RELU, tangent, sigmoid)

Parameters:

- Model parameters (W and B)

Applied deep learning is a very empirical process [trial n erro]

As the cycle goes of idea->code->experiment->idea...

