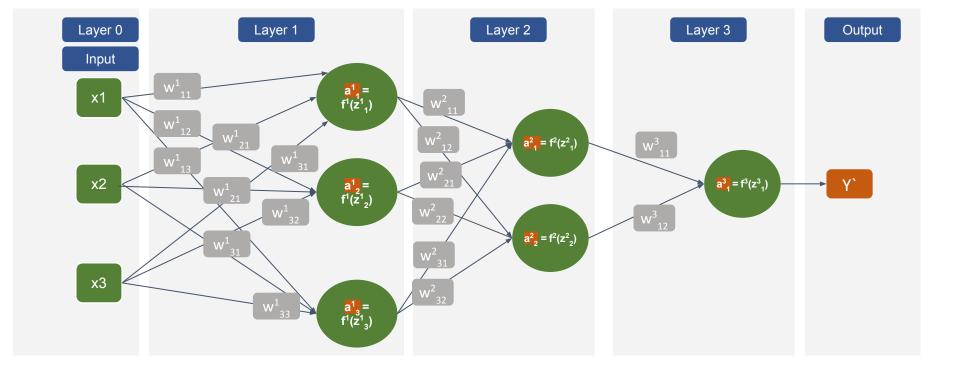
Deep Learning



Layers
$$L = 3$$

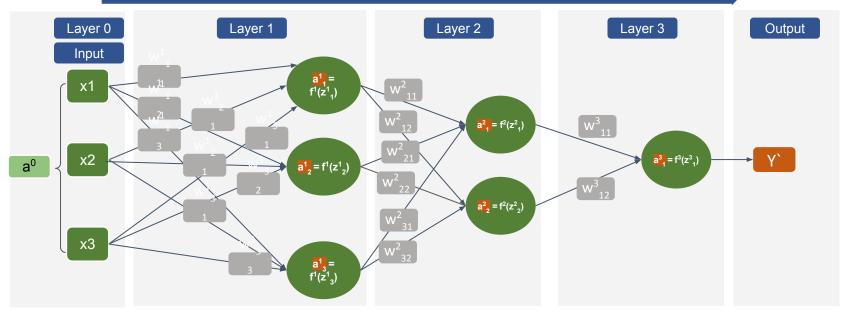
$$n^{[L]}$$
 = # units in layer L $n^{[1]}$ = 3 , $n^{[2]}$ = 2 , $n^{[3]}$ = 1

$$a^{[L]}$$
 = # activations in layer L = $f^{[L]}(z^{[L]})$

$$w^{[L]}$$
 = weights for layer L







Layers L = 3

n^[L] = # units in layer L

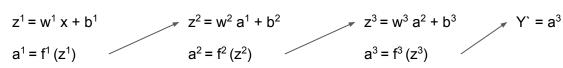
 $a^{[L]}$ = # activations in layer L = $f^{[L]}$

 $(z^{[L]})$

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

w^[L] = weights for layer L

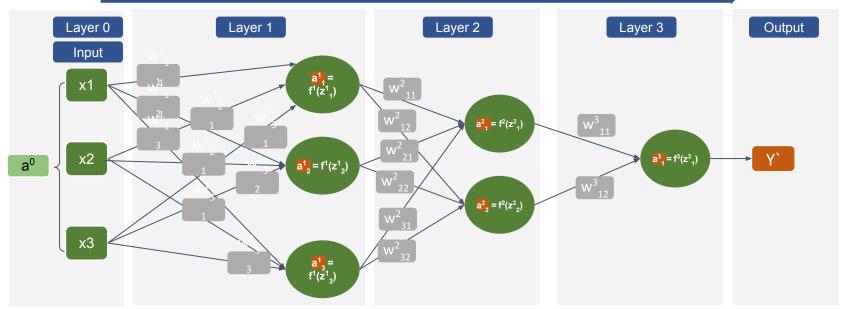
 $b^{[L]}$ = biases for layer L



$$z^{[L]} = w^{[L]} a^{[L-1]} + b^{[L]}$$

$$\mathbf{a}^{[\mathsf{L}]} = \mathbf{f}^{[\mathsf{L}]} \left(\mathbf{z}^{[\mathsf{L}]} \right)$$





Layers
$$L = 3$$

 $n^{[L]}$ = # units in layer L

 $a^{[L]}$ = # activations in layer L = $f^{[L]}$ ($z^{[L]}$)

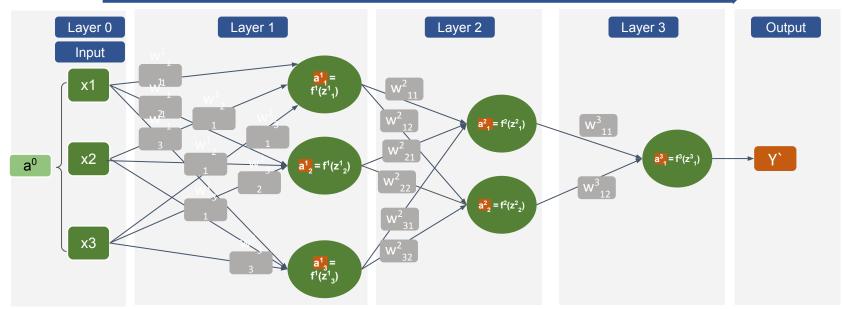
 $n^{[1]} = 3$, $n^{[2]} = 2$, $n^{[3]} = 1$

w^[L] = weights for layer L

b^[L] = biases for layer L

$$z^1 = w^1 x + b^1$$

$$z_{1}^{1}$$
 w_{11}^{1} w_{21}^{1} w_{31}^{1} a_{1}^{0} b^{1}
 z_{2}^{1} = w_{12}^{1} w_{22}^{1} w_{32}^{1} x a_{2}^{0} + b^{1}
 x_{33}^{1} w_{13}^{1} w_{23}^{1} w_{33}^{1} x a_{3}^{0} x



Layers
$$L = 3$$

$$n^{[L]}$$
 = # units in layer L

$$a^{[L]}$$
 = # activations in layer L = $f^{[L]}$

 $(Z^{[L]})$

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

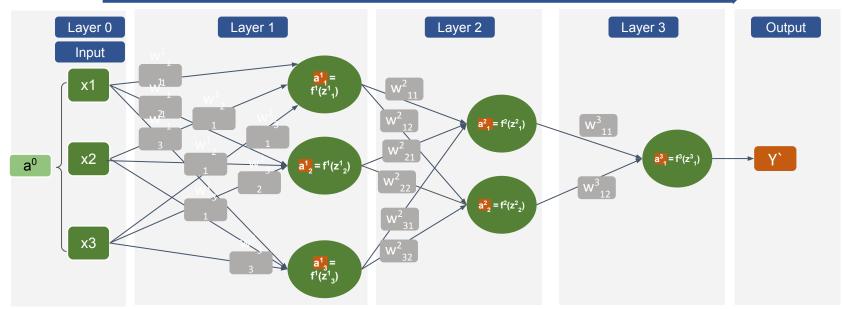
$$z^{1} = w^{1} x + b^{1} \qquad z^{1} = w^{1} a^{0} + b^{1}$$

$$z^{1}_{1} \qquad w^{1}_{11} \qquad w^{1}_{21} \qquad w^{1}_{31}$$

$$z^{1}_{2} = \qquad w^{1}_{12} \qquad w^{1}_{22} \qquad w^{1}_{32} \qquad x \qquad a^{0}_{1} \qquad b^{1}_{1}$$

$$z^{1}_{3} \qquad w^{1}_{13} \qquad w^{1}_{23} \qquad w^{1}_{33} \qquad x \qquad a^{0}_{3} \qquad b^{1}_{3}$$

$$z^{1}_{1} = w^{1}_{11} a^{0}_{1} + w^{1}_{21} a^{0}_{2} + w^{1}_{31} a^{0}_{3} + b^{1}_{1}$$



Layers
$$L = 3$$

$$n^{[L]}$$
 = # units in layer L

$$a^{[L]}$$
 = # activations in layer L = $f^{[L]}$

$$(z^{[L]})$$

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

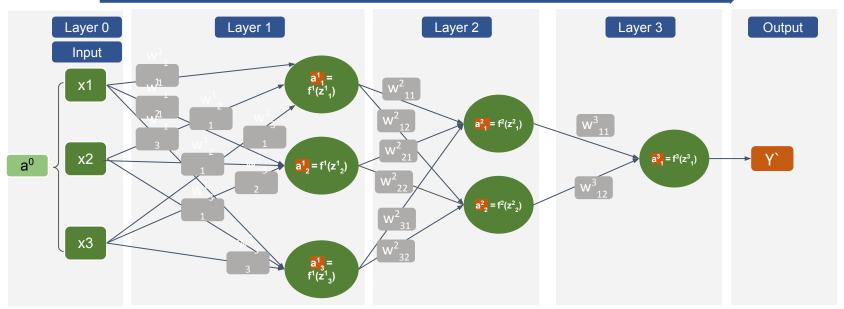
$$z^{1} = w^{1} x + b^{1} z^{1} = w^{1} a^{0} + b^{1}$$

$$z^{1}_{1} w^{1}_{11} w^{1}_{21} w^{1}_{31}$$

$$z^{1}_{2} = w^{1}_{12} w^{1}_{22} w^{1}_{32} x$$

$$z^{1}_{3} w^{1}_{13} w^{1}_{23} w^{1}_{33} x$$

$$z^{1}_{2} = w^{1}_{12} a^{0}_{1} + w^{1}_{22} a^{0}_{2} + w^{1}_{32} a^{0}_{3} + b^{1}_{2}$$



Layers
$$L = 3$$

$$n^{[L]}$$
 = # units in layer L

$$a^{[L]}$$
 = # activations in layer L = $f^{[L]}$

 $(Z^{[L]})$

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

$$z^{1} = w^{1} x + b^{1} z^{1} = w^{1} a^{0} + b^{1}$$

$$z^{1}_{1} w^{1}_{11} w^{1}_{21} w^{1}_{31}$$

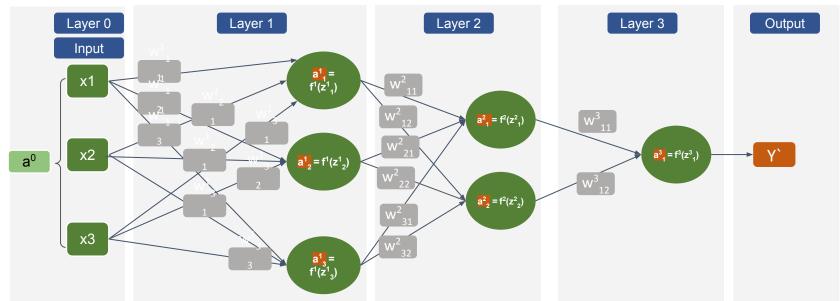
$$z^{1}_{2} = w^{1}_{12} w^{1}_{22} w^{1}_{32} x$$

$$w^{1}_{13} w^{1}_{23} w^{1}_{33}$$

$$x^{1}_{23} b^{1}_{3}$$

$$Z_{3}^{1} = w_{13}^{1} a_{1}^{0} + w_{23}^{1} a_{2}^{0} + w_{33}^{1} a_{3}^{0} + b_{3}^{1}$$





Layers L = 3
$$n^{[L]} = # \text{ units } i$$

n[L] = # units in layer L

 $a^{[L]}$ = # activations in layer L = $f^{[L]}(z^{[L]})$

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

w[L] = weights for layer L

b[L] = biases for layer L

$$z^{1} = w^{1} x + b^{1} \qquad z^{1} = w^{1} a^{0} + b^{1}$$

$$z^{1}_{1} \qquad w^{1}_{11} \quad w^{1}_{21} \quad w^{1}_{31}$$

$$z^{1}_{2} = w^{1}_{12} \quad w^{1}_{22} \quad w^{1}_{32} \quad x$$

$$x^{1}_{3} \qquad w^{1}_{13} \quad w^{1}_{23} \quad w^{1}_{33}$$

$$x^{1}_{3} \qquad b^{1}_{1} \qquad a^{0}_{2} \qquad b^{1}_{2} \qquad a^{0}_{3}$$

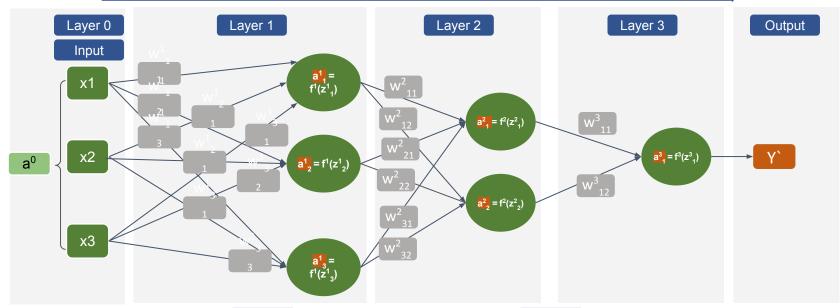
$$\begin{bmatrix}
 z_{1} \\
 z_{2} \\
 z_{3} \\
 z_{3}
 \end{bmatrix}$$

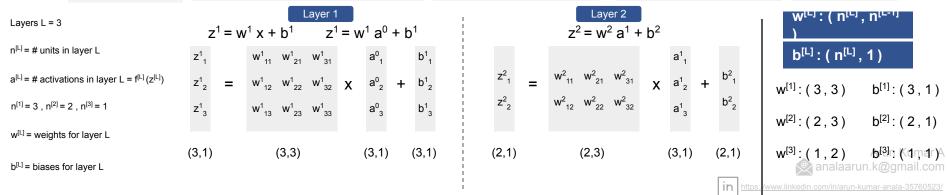
$$z^{2} = w^{2} a^{1} + b^{2}$$

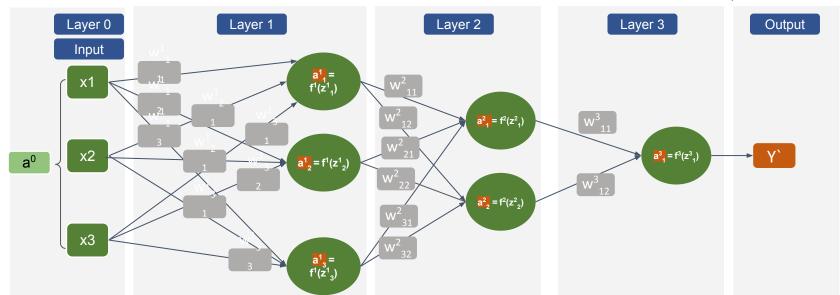
$$z^{2}_{1} = \begin{bmatrix} w^{2}_{11} & w^{2}_{21} & w^{2}_{31} \\ w^{2}_{12} & w^{2}_{22} & w^{2}_{32} \end{bmatrix} \times \begin{bmatrix} a^{1}_{1} \\ a^{1}_{2} \\ a^{1}_{3} \end{bmatrix} + \begin{bmatrix} b^{2}_{1} \\ b^{2}_{2} \end{bmatrix}$$

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

$$z_{1}^{2} = w_{11}^{2} a_{1}^{1} + w_{21}^{2} a_{2}^{1} + w_{31}^{2} a_{3}^{1} + b_{1}^{2}$$
 Arun Kumar A $z_{2}^{2} = w_{12}^{2} a_{1}^{1} + w_{122}^{2} a_{12}^{1} + w_{32}^{2} a_{331}^{1} + b_{24/arun-kumar-anala-35760523/2}^{2}$







Layers L = 3

n^[L] = # units in layer L

 $a^{[L]}$ = # activations in layer L = $f^{[L]}(z^{[L]})$

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

w^[L] = weights for layer L

 $b^{[L]}$ = biases for layer L

 $z^{[L]} = w^{[L]} a^{[L-1]} + b^{[L]}$

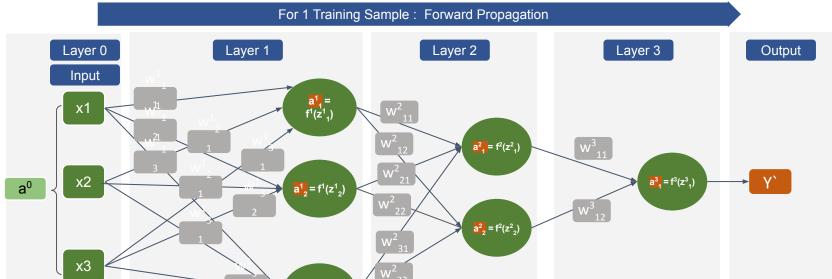
 $\mathbf{a}^{[\mathsf{L}]} = \mathbf{f}^{[\mathsf{L}]} \left(\mathbf{z}^{[\mathsf{L}]} \right)$

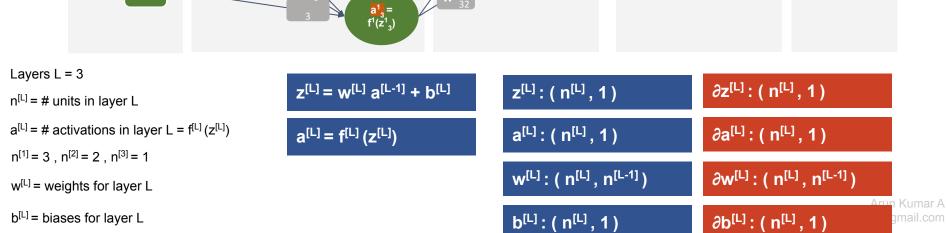
w^[L]: (n^[L], n^[L-1])

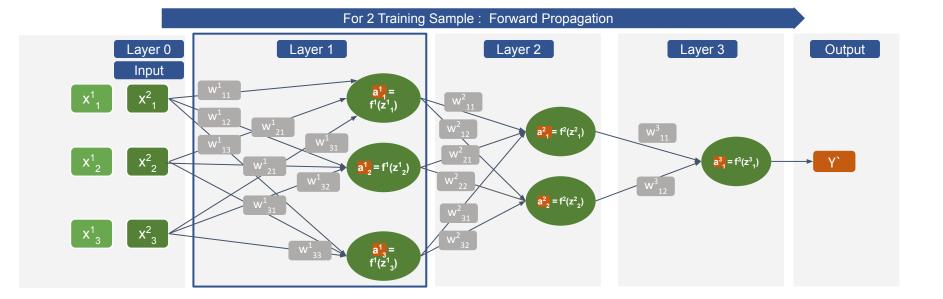
b^[L]: (n^[L], 1)



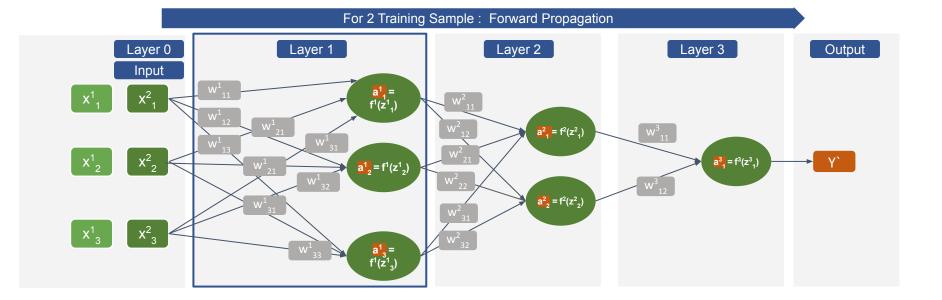


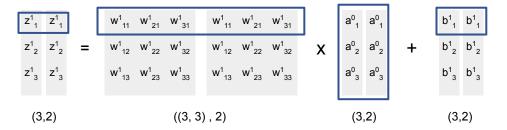


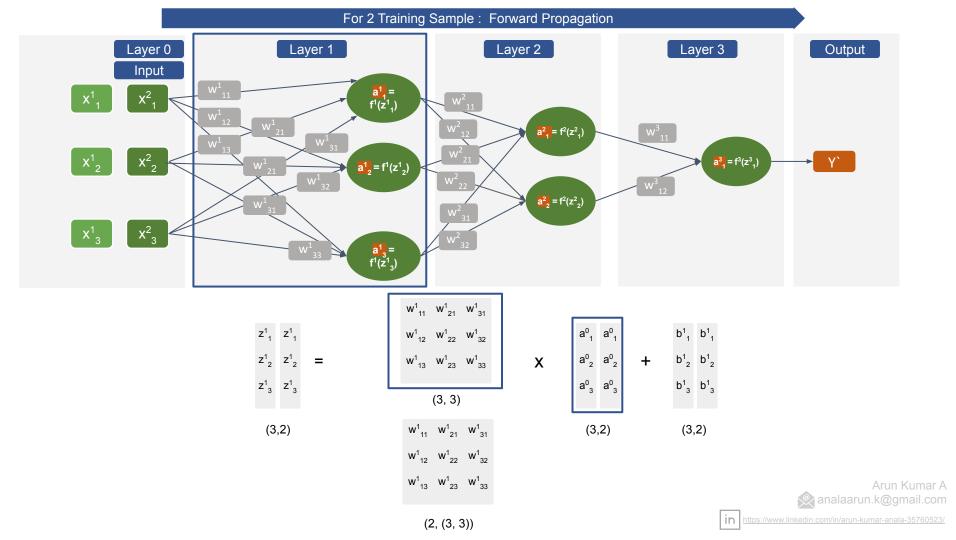


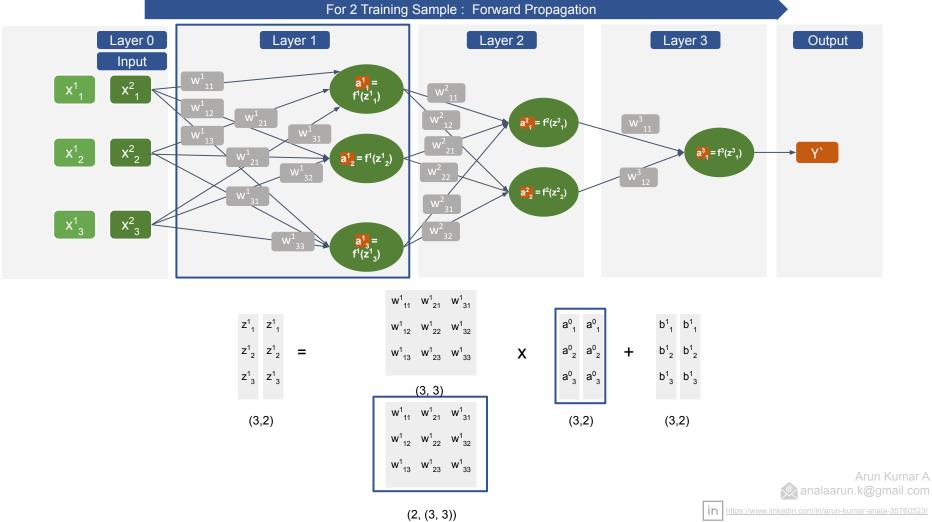


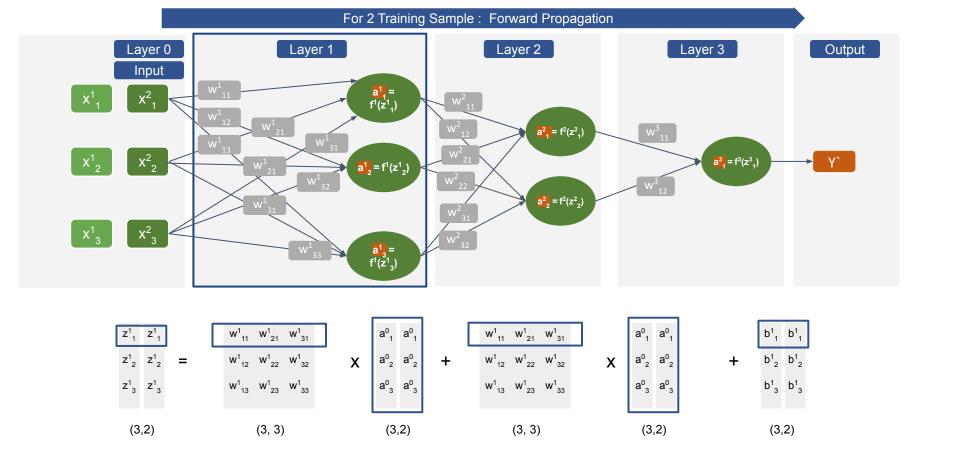


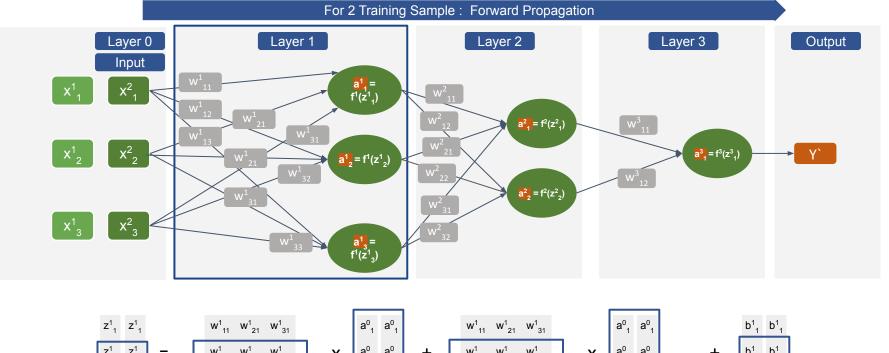


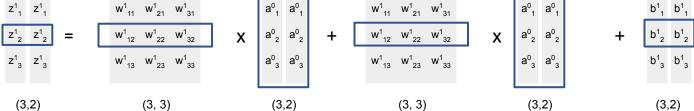


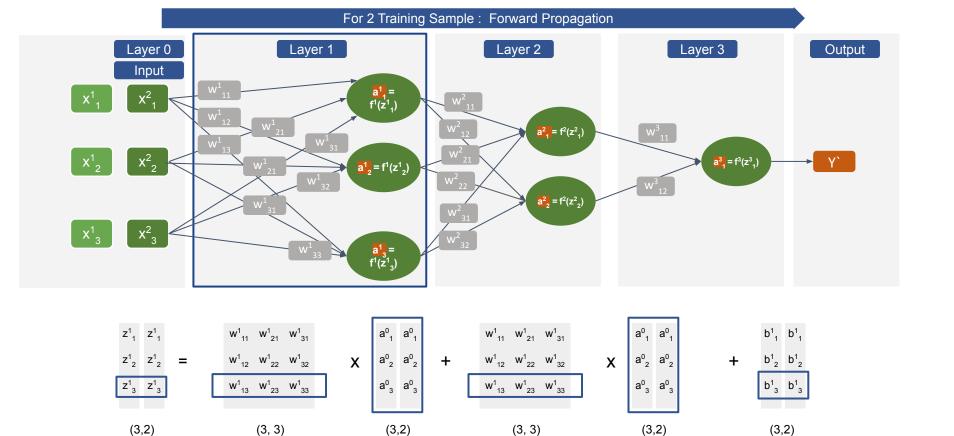


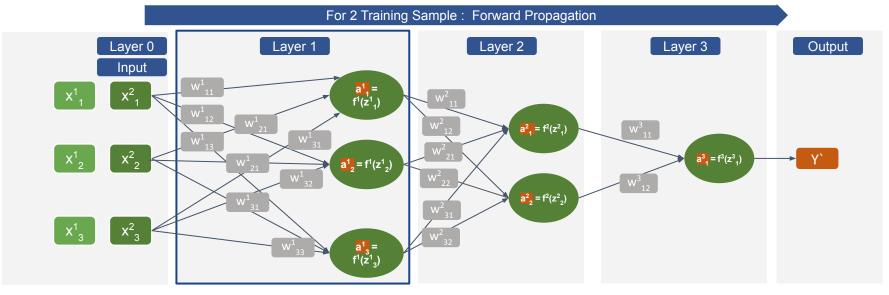


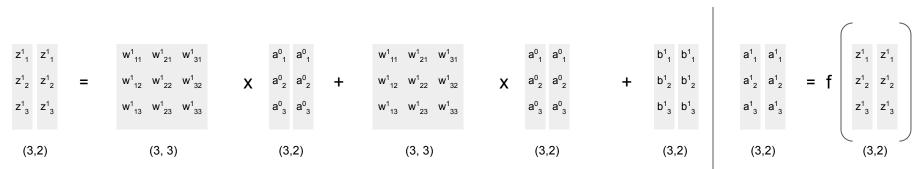






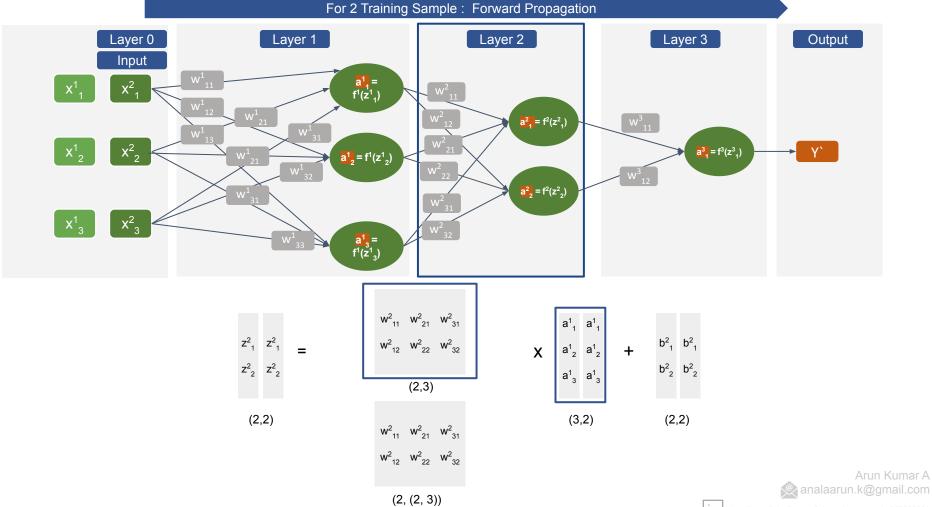


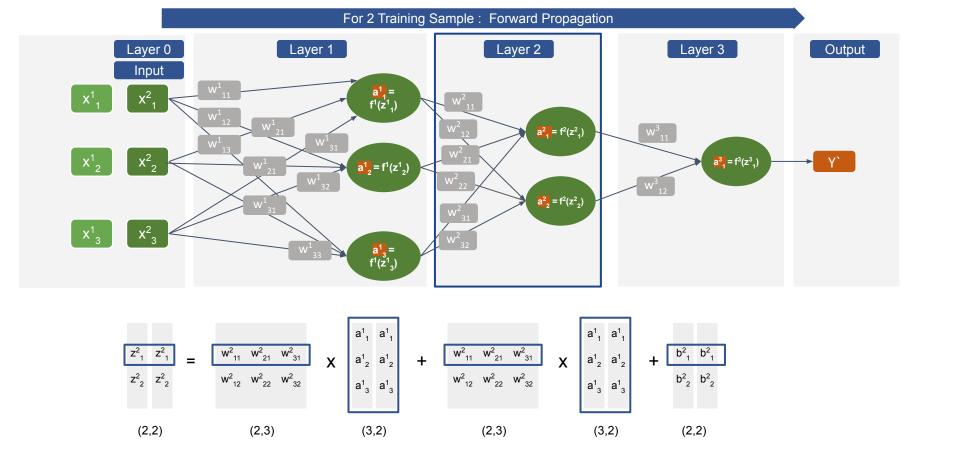


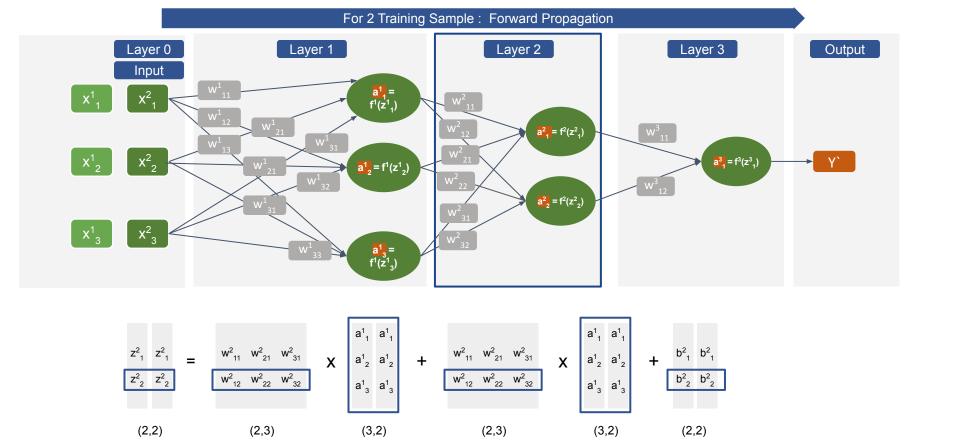


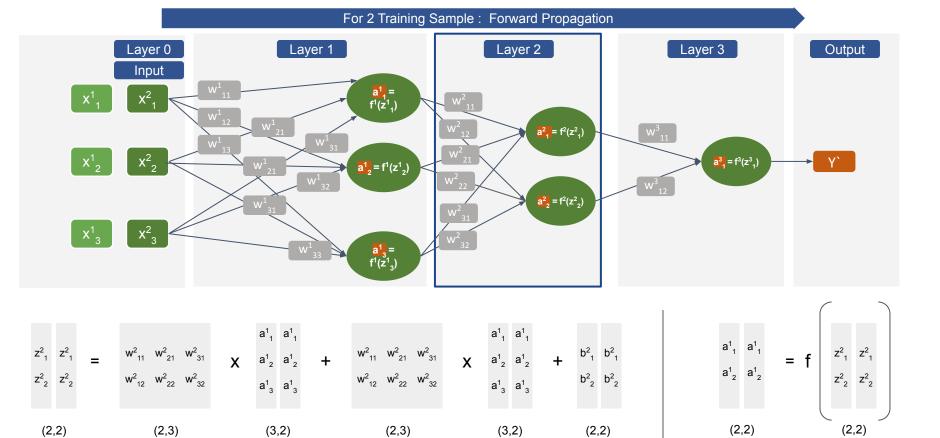
For 2 Training Sample: Forward Propagation Output Layer 0 Layer 1 Layer 2 Layer 3 Input $a_{1}^{1} = f^{1}(z_{1}^{1})$ $a_1^2 = f^2(z_1^2)$ W³₁₁ x_2^2 $a_1^3 = f^3(z_1^3)$ $a_{2}^{1} = f^{1}(z_{2}^{1})$ $a_2^2 = f^2(z_2^2)$ x_{3}^{2} $\frac{a_{3}^{1}}{f^{1}(z_{3}^{1})}$











$$Z^{[L]} = (W^{[L]})^T A^{[L-1]} + B^{[L]}$$

$$A^{[L]} = f^{[L]} (Z^{[L]})$$

Z^[L]: (n^[L], m)

$$\partial Z^{[L]}$$
: ($n^{[L]}$, m)

$$\partial A^{[L]}$$
: ($n^{[L]}$, m)

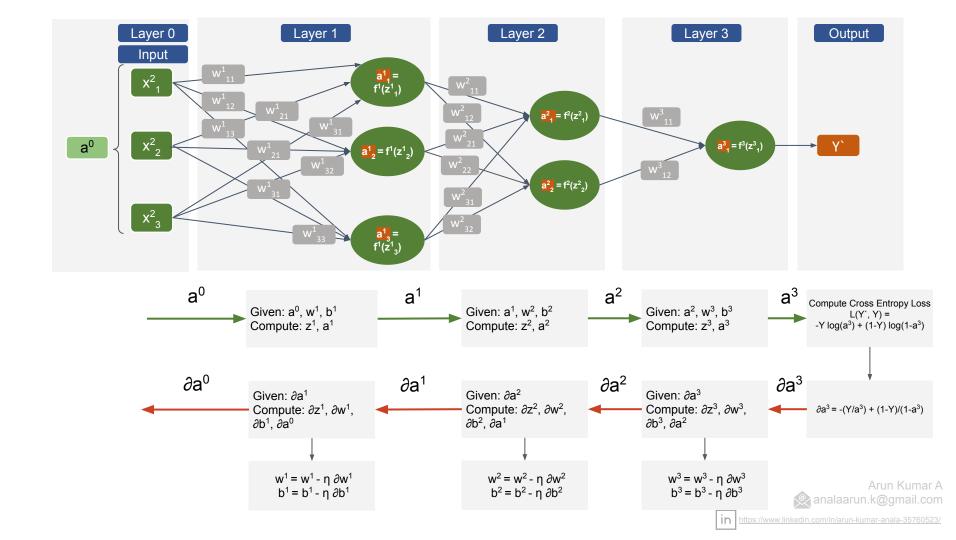
$$W^{[L]}: (n^{[L]}, n^{[L-1]}, m)$$
 $\partial W^{[L]}: (n^{[L]}, m)$
 $\partial B^{[L]}: (n^{[L]}, m)$

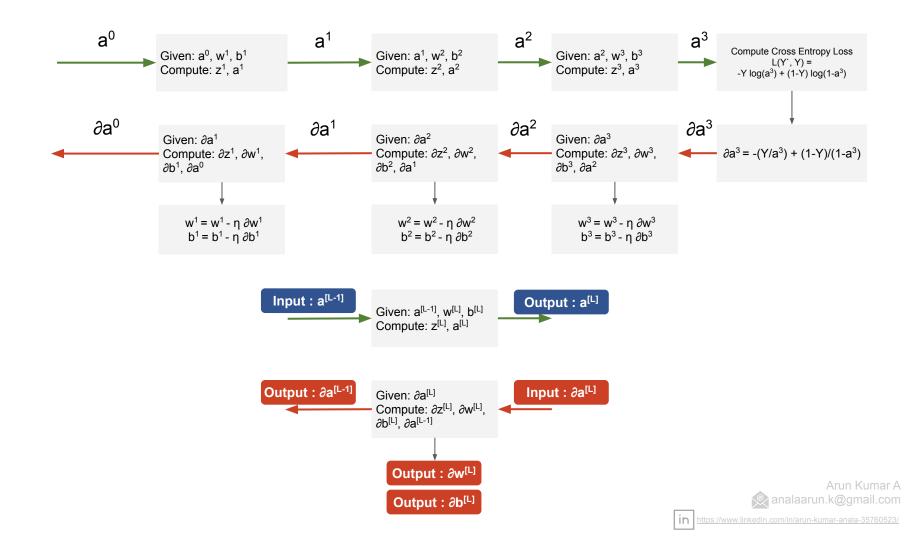
In https://www.linkedin.com

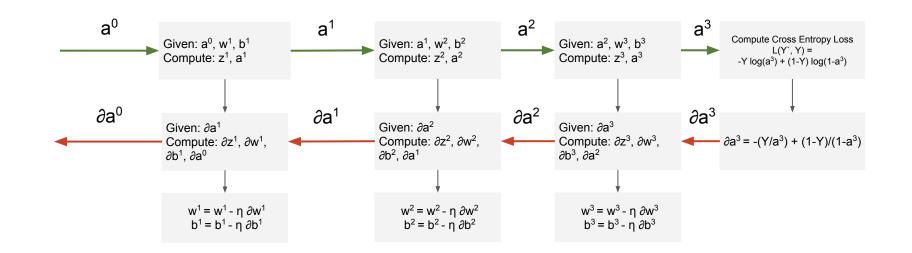
∂B^[L]: (n^[L], m)

umar A

ail.com







$$a^{[L]} = f^{[L]}(z^{[L]})$$

$$z^{[L]} = w^{[L]} a^{[L-1]} + b^{[L]}$$

$$\partial z^{[L]} = \partial a^{[L]} * f^{[L]}(z^{[L]})$$

$$\partial \mathbf{w}^{[L]} = \partial \mathbf{z}^{[L]} * \mathbf{a}^{[L-1]}$$

$$\partial \mathbf{b}^{[L]} = \partial \mathbf{z}^{[L]}$$

$$\partial a^{[L-1]} = \mathbf{w}^{[L]T} * \partial \mathbf{z}^{[L]}$$

$$\partial z^{[L]} = w^{[L+1]T} * \partial z^{[L+1]} * f^{[L]} `(z^{[L]})$$

$$\partial Z^{[L]} = \partial A^{[L]} * f^{[L]} \cdot (Z^{[L]})$$

$$\partial \mathbf{w}^{[L]} = 1/\mathbf{m} * \partial \mathbf{Z}^{[L]} * \mathbf{A}^{[L-1]T}$$

$$\partial b^{[L]} = 1/m * \Sigma(\partial z^{[L]})$$

$$\partial A^{[L-1]} = W^{[L]T} * \partial Z^{[L]}$$



For 1 Training Sample

Forward Prop	Backward Prop	
Input : a ^[L-1] Output : a ^[L]	Input: $\partial a^{[L]}$ Output: $\partial a^{[L-1]}$	
$z^{[L]} = w^{[L]} a^{[L-1]} + b^{[L]}$	$\partial z^{[L]} = \partial a^{[L]} * f^{[L]} (z^{[L]})$	
$a^{[L]} = f^{[L]}(z^{[L]})$	$\partial \mathbf{w}^{[L]} = \partial \mathbf{z}^{[L]} * \mathbf{a}^{[L-1]}$	
	$\partial b^{[L]} = \partial z^{[L]}$	
	$\partial a^{[L-1]} = \mathbf{w}^{[L]T} * \partial \mathbf{z}^{[L]}$	
z ^[L] : (n ^[L] , 1)	∂z ^[L] : (n ^[L] , 1)	
a ^[L] : (n ^[L] , 1)	∂a ^[L] : (n ^[L] , 1)	
w ^[L] : (n ^[L] , n ^[L-1])	∂w ^[L] : (n ^[L] , n ^[L-1])	
b ^[L] : (n ^[L] , 1)	∂b ^[L] : (n ^[L] , 1)	

For m Training Samples

Also called Vectorized Implementation

Forward Prop Backward Prop

Input: $a^{[L-1]}$ Output: $a^{[L]}$ Output: $\partial A^{[L-1]}$

$$Z^{[L]} = (W^{[L]})^T A^{[L-1]} + B^{[L]}$$
 $\partial Z^{[L]} = \partial A^{[L]} * f^{[L]} (Z^{[L]})$

$$A^{[L]} = f^{[L]} (Z^{[L]})$$

$$\partial w^{[L]} = 1/m * \partial Z^{[L]} * A^{[L-1]T}$$

$$\partial b^{[L]} = 1/m * \Sigma(\partial z^{[L]})$$

$$\partial \mathbf{A}^{[L-1]} = \mathbf{W}^{[L]T} * \partial \mathbf{Z}^{[L]}$$

 $\partial Z^{[L]}$: $(n^{[L]}, m)$

$$A^{[L]}:(n^{[L]},m) \qquad \partial A^{[L]}:(n^{[L]},m)$$

 $Z^{[L]}: (n^{[L]}, m)$

$$\mathsf{A}^{[\mathsf{L}]}:(\mathsf{n}^{[\mathsf{L}]},\mathsf{m})\qquad \quad \partial \mathsf{A}^{[\mathsf{L}]}:(\mathsf{n}^{[\mathsf{L}]},\mathsf{m})$$

$$W^{[L]}: (n^{[L]}, n^{[L-1]}, m)$$
 $\partial W^{[L]}: (n^{[L]}, n^{[L-1]}, m)$

$$B^{[L]}$$
: $(n^{[L]}, m)$ $\partial B^{[L]}$: $(n^{[L]}, m)$

Name	Plot	Equation	Derivative	
Identity		f(x) = x	f'(x) = 1	
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \ge 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$	
Logistic (a.k.a Soft step)		$f(x) = \frac{1}{1 + e^{-x}}$	f'(x) = f(x)(1 - f(x))	
TanH		$f(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$	
ArcTan		$f(x) = \tan^{-1}(x)$	$f'(x) = \frac{1}{x^2 + 1}$	
Rectified Linear Unit (ReLU)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \ge 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \ge 0 \end{cases}$	
Parameteric Rectified Linear Unit (PReLU) ^[2]		$f(x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \ge 0 \end{cases}$	$f'(x) = \begin{cases} \alpha & \text{for } x < 0 \\ 1 & \text{for } x \ge 0 \end{cases}$	
Exponential Linear Unit (ELU) ^[3]		$f(x) = \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \ge 0 \end{cases}$	$f'(x) = \begin{cases} f(x) + \alpha & \text{for } x < 0 \\ 1 & \text{for } x \ge 0 \end{cases}$	
SoftPlus		$f(x) = \log_e(1 + e^x)$	$f'(x) = \frac{1}{1 + e^{-x}}$	Arun Kum alaarun.k@gmail.