

# Neural Networks

# Matrix Multiplication

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 10 & 11 \\ 20 & 21 \\ 30 & 31 \end{bmatrix}$$
$$= \begin{bmatrix} 1 \times 10 + 2 \times 20 + 3 \times 30 & 1 \times 11 + 2 \times 21 + 3 \times 31 \\ 4 \times 10 + 5 \times 20 + 6 \times 30 & 4 \times 11 + 5 \times 21 + 6 \times 31 \end{bmatrix}$$
$$= \begin{bmatrix} 10 + 40 + 90 & 11 + 42 + 93 \\ 40 + 100 + 180 & 44 + 105 + 186 \end{bmatrix} = \begin{bmatrix} 140 & 146 \\ 320 & 335 \end{bmatrix}$$

# Matrix dimensions

$$\begin{matrix} \left[ \right] \\ X \times M \end{matrix} \times \begin{matrix} \left[ \right] \\ M \times Y \end{matrix} = \begin{matrix} \left[ \right] \\ X \times Y \end{matrix}$$

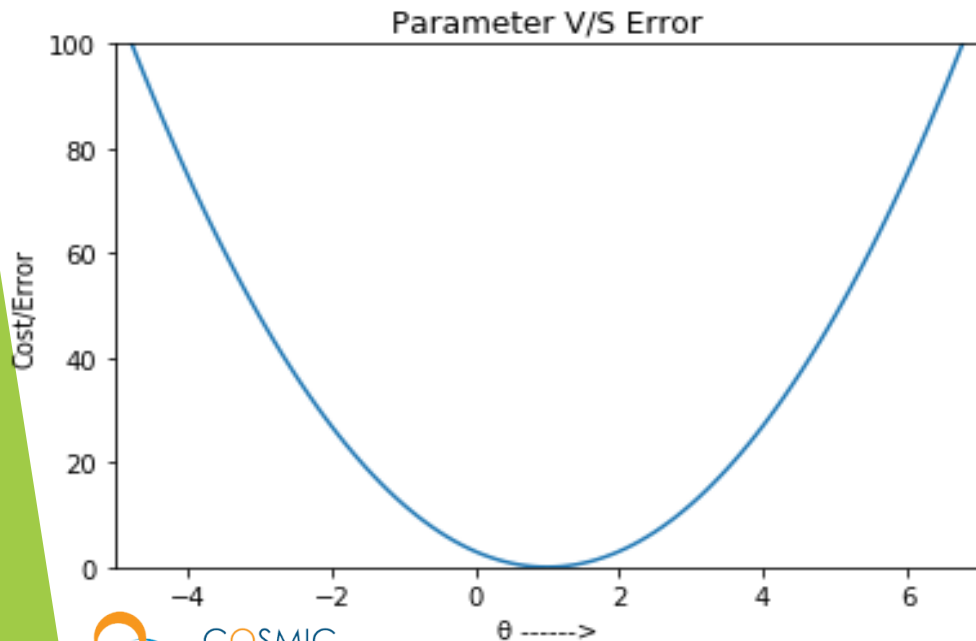
# So far,

$$h_{\theta}(x) = \Theta_0 + \Theta_1 x_1 + \Theta_2 x_2$$

Parameters were initialized randomly

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (\hat{y}_i - y_i)^2$$

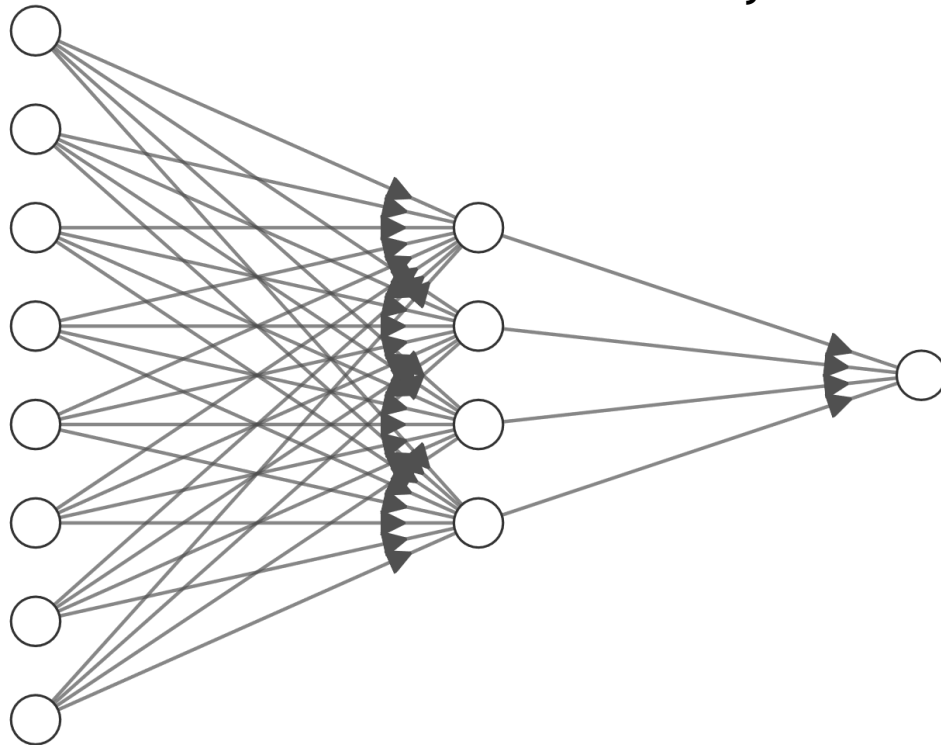
Compute loss based on all the examples  
For that particular weight



Find Derivative of loss w.r.t parameter  
Update the parameters

# Neural Networks

Hidden layers = 1



Input Layer  $\in \mathbb{R}^8$

Hidden Layer  $\in \mathbb{R}^4$

Output Layer  $\in \mathbb{R}^1$

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

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

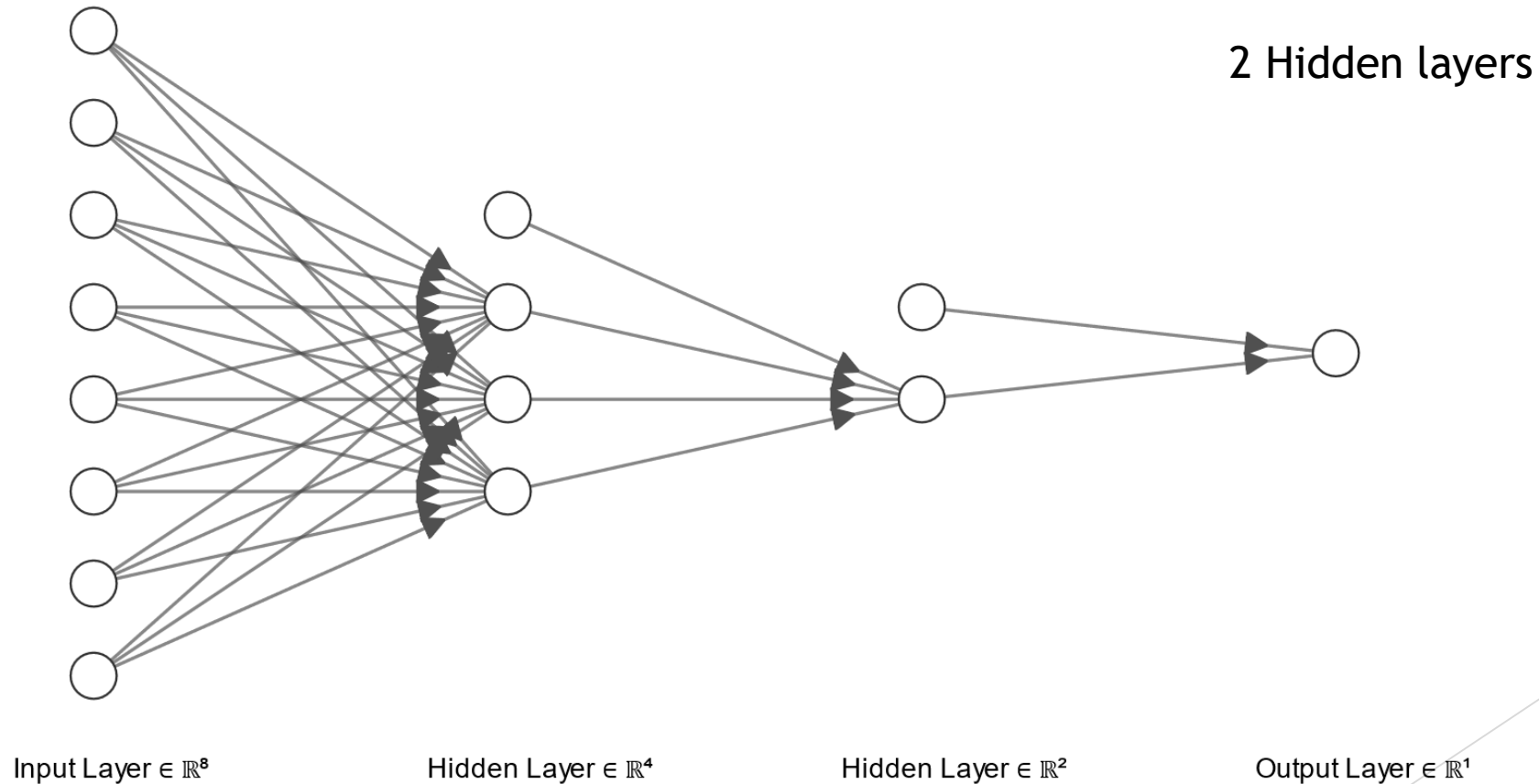
$$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$$

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

$$\begin{bmatrix} \quad \end{bmatrix} \otimes \begin{bmatrix} \quad \\ \quad \\ \quad \\ \quad \end{bmatrix}_{8 \times 1} = \begin{bmatrix} \quad \\ \quad \\ \quad \\ \quad \end{bmatrix}_{4 \times 1}$$

# Fully Connected Network

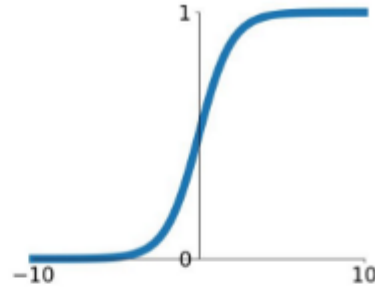
```
model = Sequential()  
model.add(Dense(units=4, activation="relu", input_shape=(8,)))  
model.add(Dense(units=2, activation="relu"))  
model.add(Dense(units=1))
```



# Activation Functions

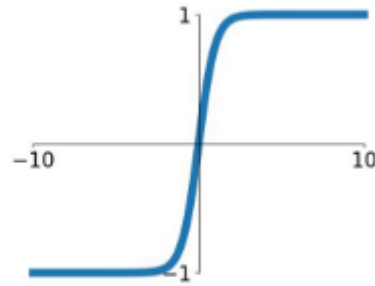
## Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



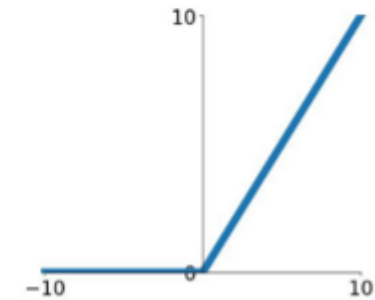
## tanh

$$\tanh(x)$$



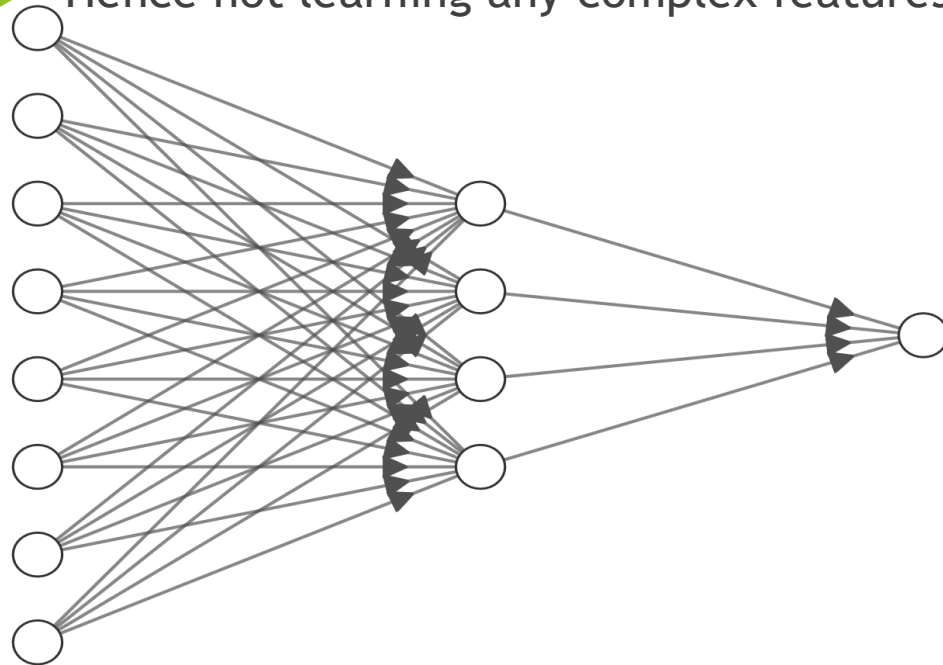
## ReLU

$$\max(0, x)$$



# Why Non linear activation function ?..

- ▶ Equivalent to linear regression (you are just multiplying same thing in different way)
- ▶ Hence not learning any complex features



Input Layer  $\in \mathbb{R}^8$

Hidden Layer  $\in \mathbb{R}^4$

Output Layer  $\in \mathbb{R}^1$

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

$$A^{[1]} = Z^{[1]}$$

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

$$Z^{[2]} = W^{[2]} (W^{[1]}X + b^{[1]}) + b^{[2]}$$

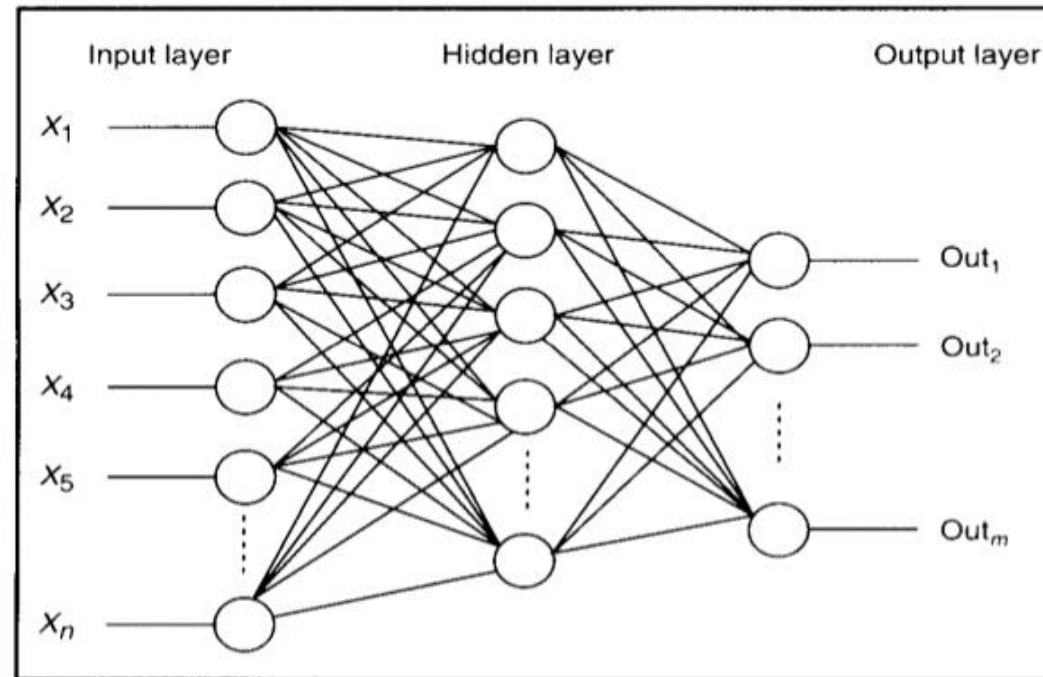
$$Z^{[2]} = W^{[2]} W^{[1]}X + W^{[2]} b^{[1]} + b^{[2]}$$

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

$$A^{[2]} = Z^{[2]}$$



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# Why deep learning frameworks??...

- ▶ Easy to code
- ▶ Coding reduces hence easy to debug
- ▶ Functions are pre-built and are optimized

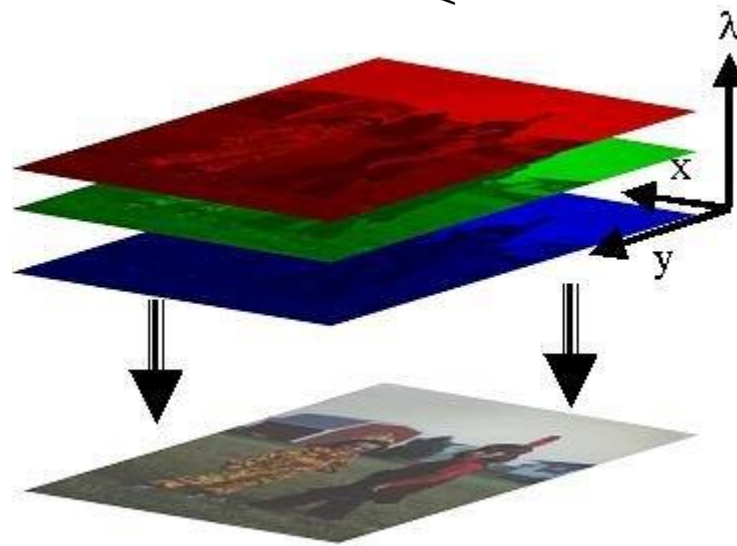
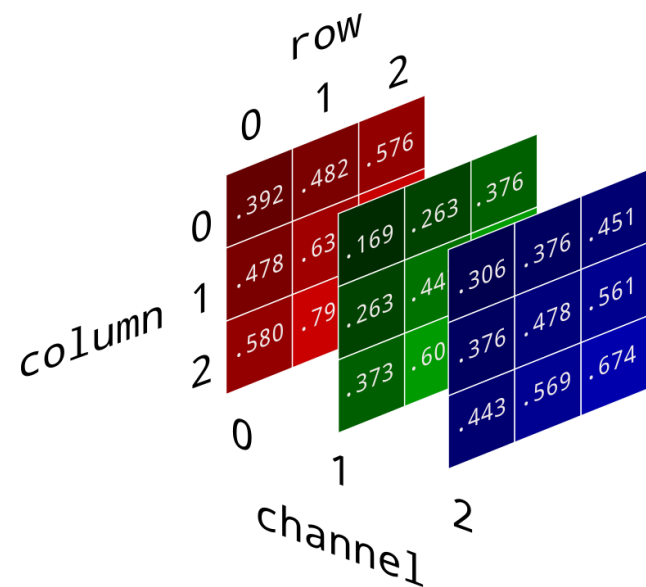
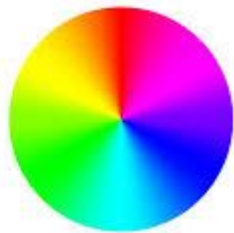
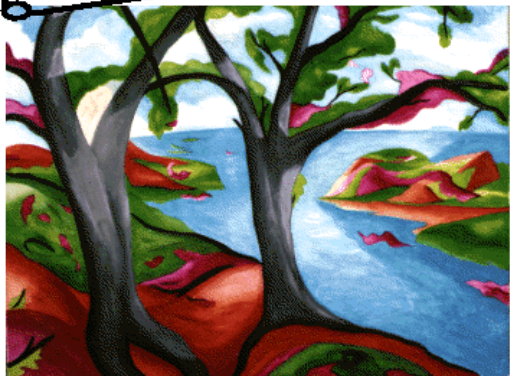
E.g: Simple 3x3 matrix multiplication in pytorch is 50,000 times faster than pure python code

# Tensorflow

- ▶ It is being developed and maintained by Google
- ▶ TensorFlow is a free and open-source
- ▶ It's **written** in a combination of highly-optimized C++ and CUDA (Nvidia's **language** for programming GPUs)
- ▶ A library for defining computation graph and a runtime to execute such graph in different hardware

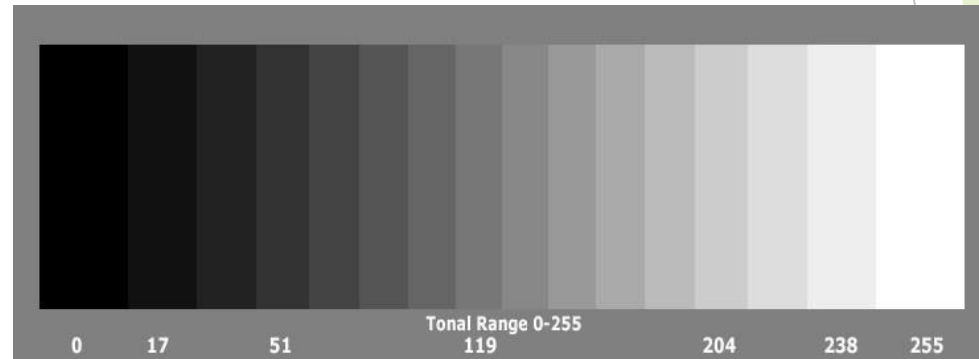
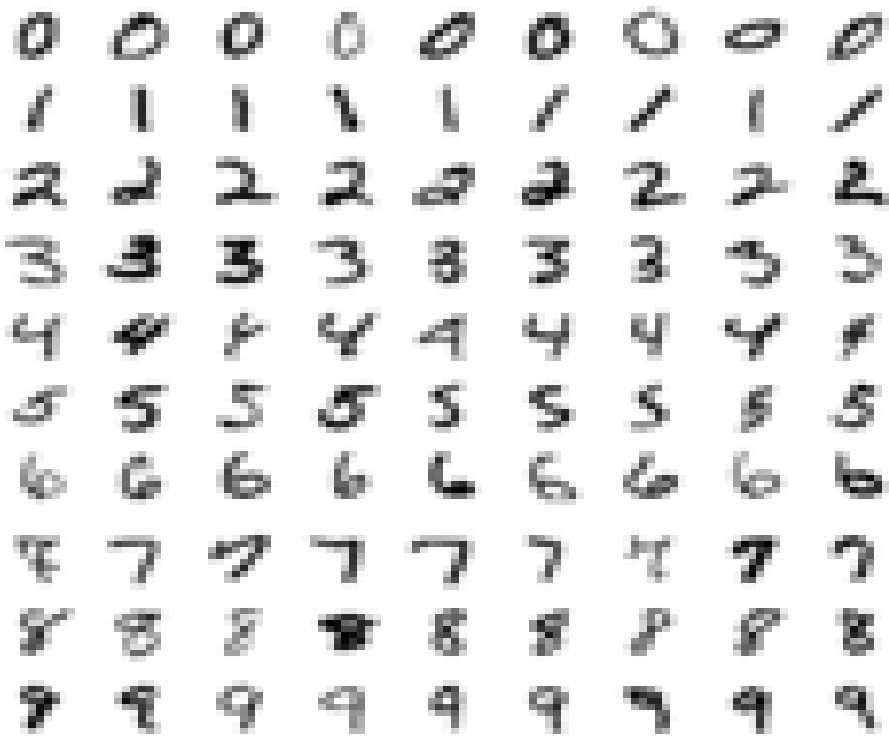
# Representation of Images

	0.2235	0.1294	<b>Blue</b>	0.4196	0.2588	0.2588
	0.5804	0.2902	<b>0.0627</b>	0.2902	0.2902	0.4824
	0.5804	0.0627	0.0627	0.0627	0.2235	0.2588
	0.5176	0.1922	0.0627	<b>Green</b>	0.1922	0.2588
	0.5176	0.1294	<b>0.1608</b>	0.1294	0.2588	0.2588
	0.5176	0.1608	0.0627	0.1608	0.1922	0.2588
	0.5490	0.2235	0.5490	<b>Red</b>	0.7412	0.7765
	0.490	0.3882	<b>0.5176</b>	0.5804	0.5804	0.7765
	0.2588	0.2902	0.2588	0.2235	0.4824	0.2235
	0.2235	0.1608	0.2588	0.2588	0.1608	0.2588
	0.1608	0.2588	0.2588	0.2588	0.2588	0.2588



# Model for digit recognition

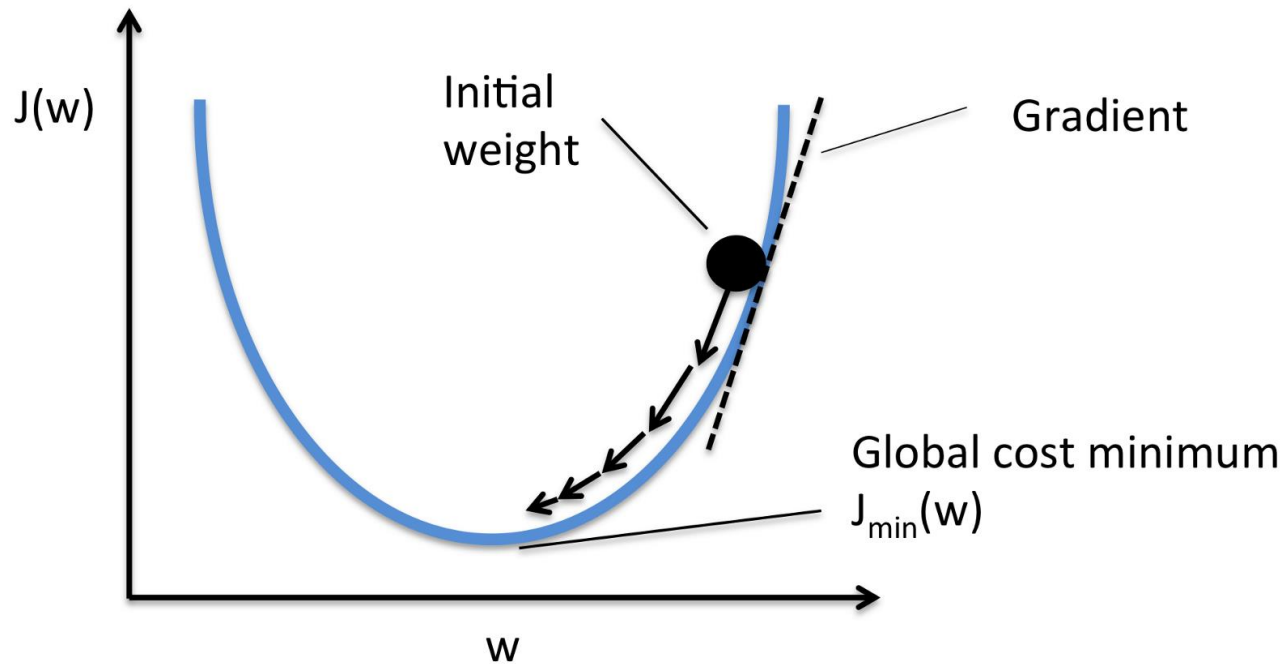
► Data set : MNIST



# Gradient Descent

## Batch Gradient descent

- It considers all the examples in training set to take one step



## Mini batch gradient descent

- It considers batch of examples from training set to take each step

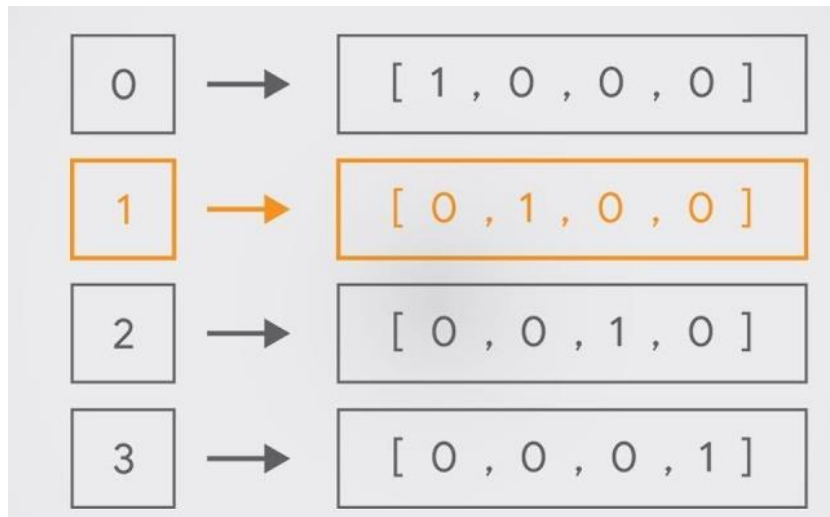
Repeat until convergence {

$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

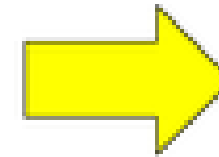
}

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (\hat{y}_i - y_i)^2$$

```
keras.utils.to_categorical(train_y,10)
```



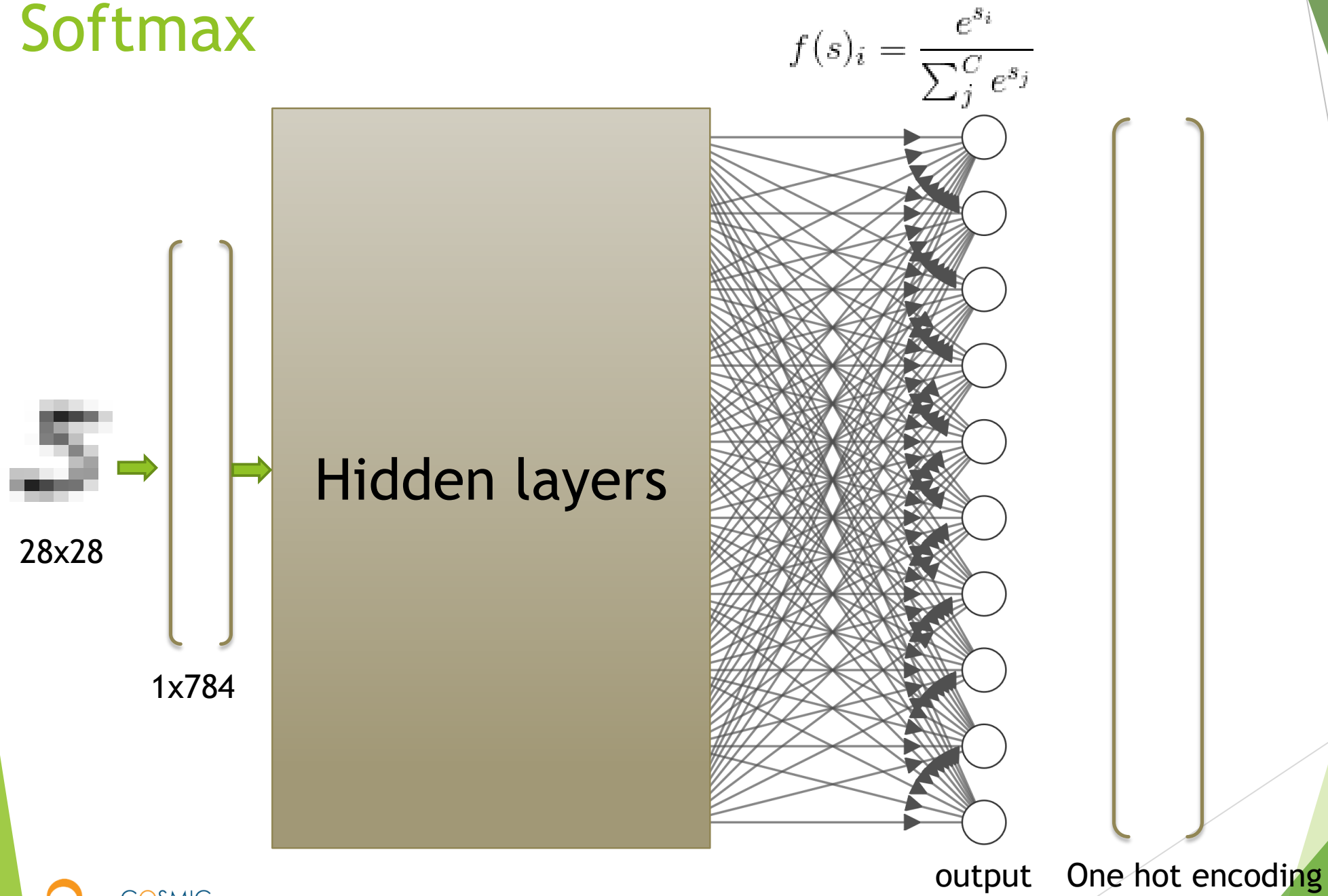
Color
Red
Red
Yellow
Green
Yellow



Red	Yellow	Green
1	0	0
1	0	0
0	1	0
0	0	1

# One Hot encoding

# Softmax





# 5. Loss Function

## Softmax

$$CE = - \sum_i^C t_i \log(f(s)_i)$$

Where  $f(s)_i$  represents SoftMax function and is given by,

$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}}$$

Where C represents total number of class and  $s_j$  are the score inferred by the neural network for each class in C.

$$- \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \times \log \begin{bmatrix} 0.23 \\ 0.04 \\ 0.06 \\ 0.6 \\ 0.07 \end{bmatrix} = 0.22$$

True Values  
(one hot encoded)