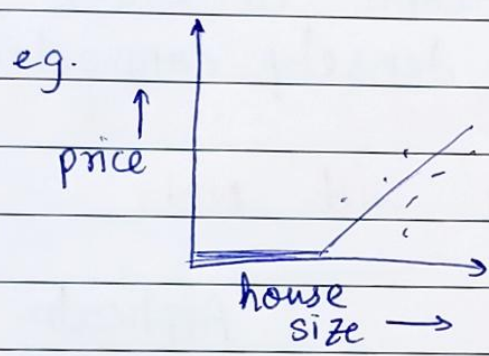
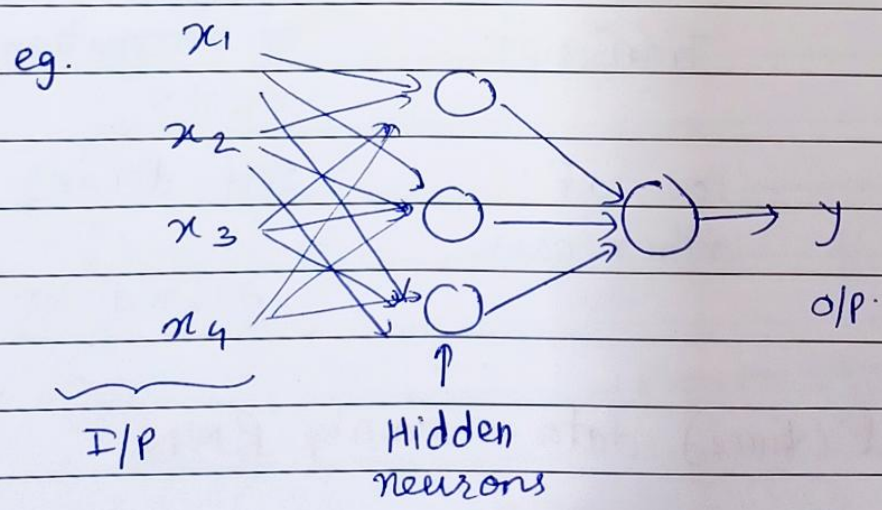
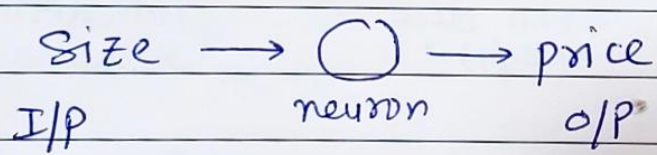


# NEURAL NETWORKS & DEEP LEARNING (C-1)

## # Neural Network



ReLU function.  
Rectified Linear  
Unit  
 $\max(-, 0)$



→ (Koala example)

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N.N. has ability to decide by itself what I/P features each of the hidden neuron wants/requires to do its computation.

Every I/P feature conn. to every middle neurons  $\Rightarrow$  densely connected.

# Supervised Learning with NN.

I/P	O/P	Applicatn.
Ad, User Info.	Will click (0/1)?	Advertising $\hookrightarrow$ Standard NN
Image	object	Tagging $\hookrightarrow$ CNN
Audio	Transcript	sp. recognition $\hookrightarrow$ RNN
Img, Radar	Pos. of other cars	Self-driving $\hookrightarrow$ Custom/ Hybrid NN

Temporal (time) data  $\rightarrow$  mainly RNN.



↑ Data & ↑ Scale (i.e. more layers of NN)

⇓  
↑ Performance

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Structured Data

⇒ eg.      Size      #bedrooms      Price  
                 |                   |                   |  
                 |                   |                   |

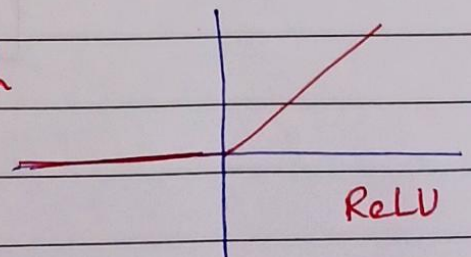
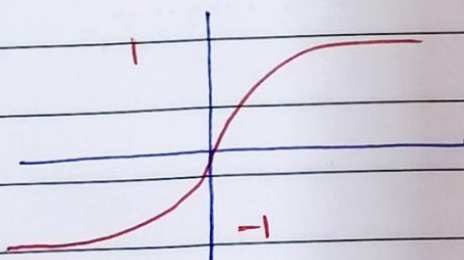
Unstructured Data

⇒ Audio, Image, Text

# Basics - Activation Functions.



⇒ eg. People above 28y.  
will buy & below  
won't.  
But X.



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

Sigmoid

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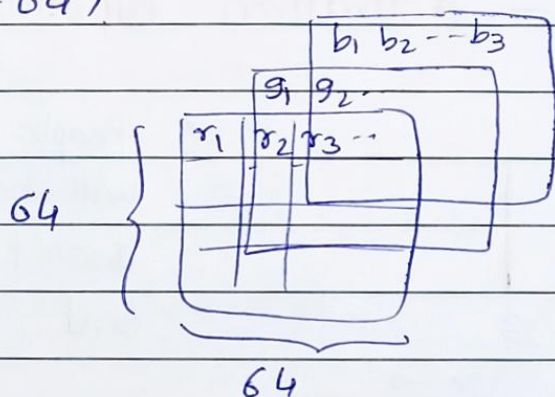
Hidden Layer mostly - ReLU or Leaky ReLU.

O/P  $\rightarrow$  sigmoid mostly.

## # Binary classification

O/P  $\rightarrow$  0 or 1

eg. cat image  $\rightarrow$  cat or non-cat  
(64x64)



Feature vector

$$X = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ g_1 \\ g_2 \\ \vdots \\ b_1 \\ b_2 \\ \vdots \end{bmatrix}$$

$$\Rightarrow n_x = 64 \times 64 \times 3$$

$$= 12288$$

dimension.



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$(x, y) = \text{Training eg.}$

$$x \in \mathbb{R}^{n_x}, \quad y = \{0, 1\}$$

$m \rightarrow \# \text{ training examples.}$

$$\{(x^1, y^1), (x^2, y^2) \dots (x^m, y^m)\}$$

$$X = \underbrace{\begin{bmatrix} | & | & | \\ x^1 & x^2 & \dots & x^m \\ | & | & | \end{bmatrix}}_m \Bigg\} n_x$$

compact notation to store  $m$  training examples.

For  $Y$  also, stack in cols.

$$Y = [y^1, y^2, \dots, y^m]$$

# # Logistic Regression

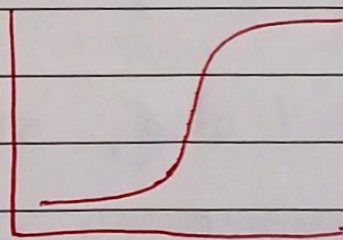
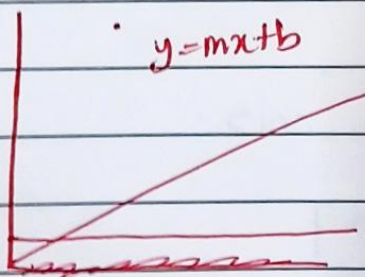
→ Supervised ML Algo. used for binary class. tasks.

Given I/P  $x$ ,  $\hat{y} = P(y=1|x)$   
probability

Params:  $w \in \mathbb{R}^{n_x}$ ,  $b \in \mathbb{R}$

O/P:  $\hat{y} = w^T x + b$   $\rightarrow$  is not bet<sup>n</sup>  $[0, 1]$

$\therefore \hat{y} = \sigma(\underbrace{w^T x + b}_z)$   
 $z \rightarrow$  limits  $\sigma$  to 1



$$y = \frac{1}{1 + e^{-(mx+b)}}$$

no. of weights ( $w$ ) = no. of I/P features.



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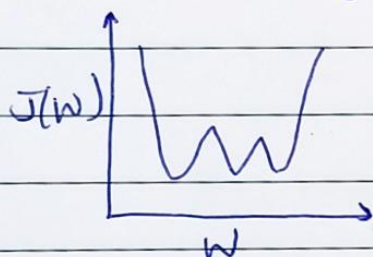
## # Loss Function:

→ Measures how far an estimated value is from its true value.

→ For general Linear Regr.:

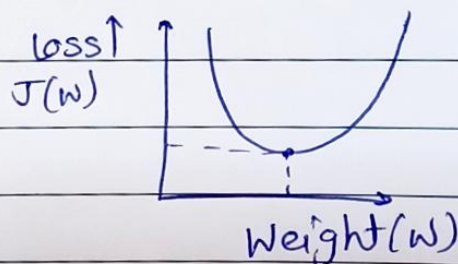
$$\text{Loss} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

→ But for Logistic Regr.  $\nearrow$  ~~don't~~ work.



Curve with multiple local minima

Gradient Descent



optimal Grad. Desc.

Loss fun applied to single training eg.

Cost fn: Cost of parameters.

$$L(\hat{y}, y) = -(y \log \hat{y} + (1-y) \log(1-\hat{y}))$$

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