

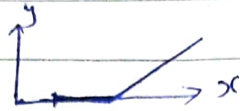
Neural Network and

Deep Learning

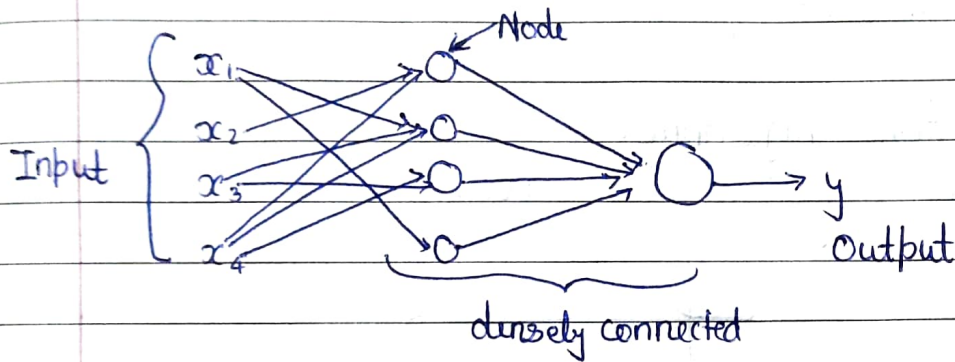
~~ReLU function~~

ReLU function

Rectified Linear Unit



Neuron is a single function. A group of neurons form a network.



Supervised learning

	Input (x)	Output (y)	Application
Ex.	Ad, user info	click on ad? (0/1)	Online advertising
	English	Other lang	Machine translating
CNN	Image	Object (1, ..., 1000)	Photo tagging

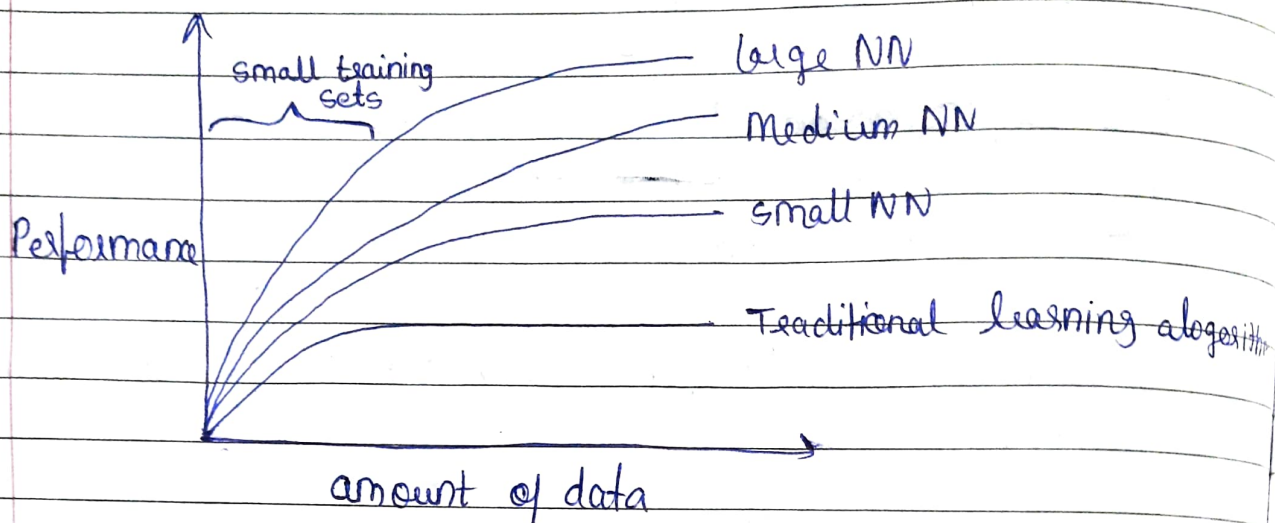
You should figure out what is X and what is Y .

Recurrent NN — One dimensional structured data.

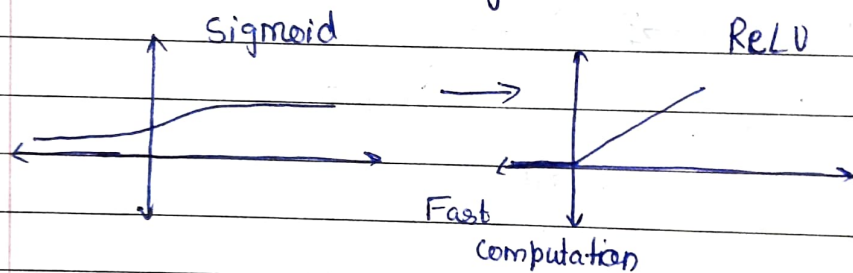
Structured data
Survey data, tabulated
makes sense to computers

Unstructured data
Audio, image, texts
harder to make sense


Why deep learning is getting popular recently?

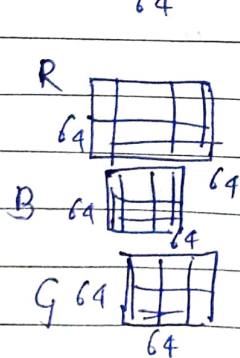


Data, Computation, Algorithms.



Logistic regression is an algorithm for binary classification.

64  \rightarrow 1 (cat) vs 0 (Non-cat)



feature vector

$$X = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}$$

$$64 \times 64 \times 3 = 12288$$

$$N = N_x = 12288$$

dimension

(x, y) $x \in \mathbb{R}^{n_x}$, $y \in \{0, 1\}$
 m training ex: $\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \dots\}$
 {training set}

$$M = M_{\text{train}}$$

$$M = M_{\text{test}}$$

$$X = \begin{bmatrix} | & | & \dots & | \\ x^{(1)} & x^{(2)} & \dots & x^{(m)} \\ | & | & \dots & | \end{bmatrix} \quad \begin{matrix} \uparrow \\ n_x \\ \downarrow \end{matrix}$$

$$X \in \mathbb{R}^{n_x \times m}$$

$$X_{\text{shape}} = (n_x, m)$$

$$Y = [y^{(1)}, y^{(2)}, \dots, y^{(m)}]$$

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

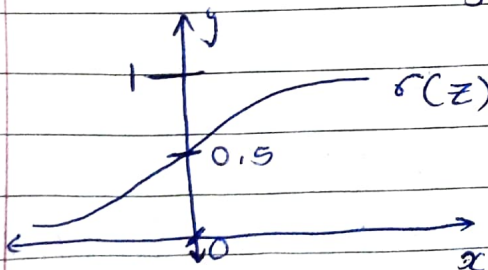
$$Y_{\text{shape}} = (1, m)$$

$$\hat{y} = P(y=1|x) \quad 0 \leq \hat{y} \leq 1$$

estimate / prediction of y

Parameters: $w \in \mathbb{R}^{n_x}$, $b \in \mathbb{R}$ - real number.

$$\text{Output} \Rightarrow \hat{y}^{(i)} = \underbrace{\sigma(w^T x^{(i)} + b)}_{\text{sigmoid } z} = y^{(i)} \quad \text{close to the actual value}$$



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

If z large,

$$\sigma(z) \approx \frac{1}{1+0} = 1$$

If z is small,

$$\sigma(z) \approx 0$$

w & b are separate parameters

Loss function

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

How close \hat{y} is to y

If $y = 1$

$$L(\hat{y}, y) = -(\log \hat{y}) \leftarrow \text{want this to be large}$$

\hat{y} ~~must~~ should be large

If $y = 0$

$$L(\hat{y}, y) = -\log(1-\hat{y}) \leftarrow \text{want } \log(1-\hat{y}) \text{ to be large}$$

\hat{y} should be small

Cost funcⁿ

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

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

How well the NN is doing on a single training example

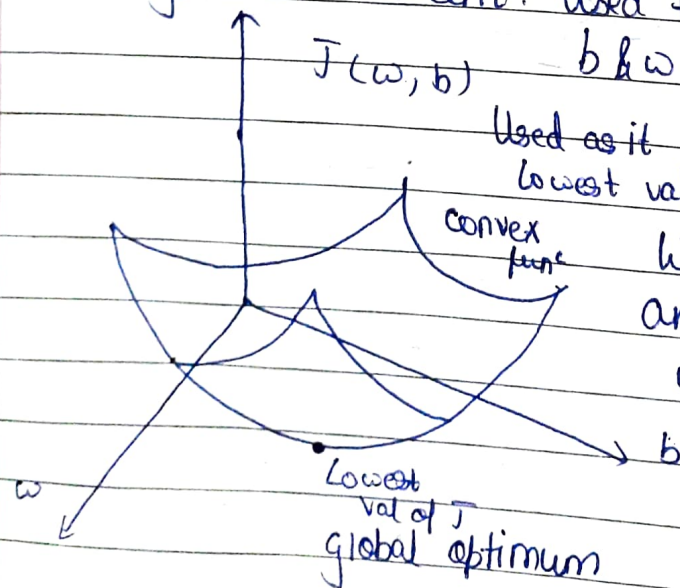
$L(,)$ applied to a single training example.

$J(,)$ - cost of the parameters

How well parameters w & b are doing on the entire training set.

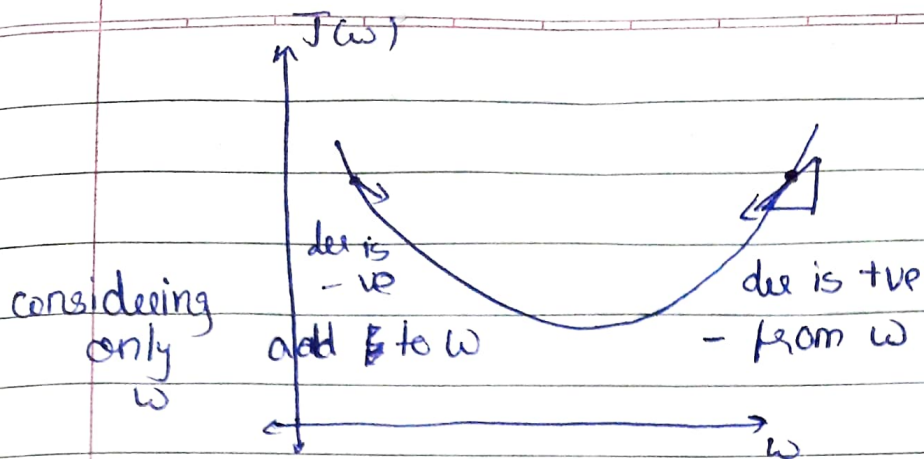
Find w , b and try to minimize J

Gradient descent: Used to choose the val of b & w



Used as it is convex
lowest val of J

We can initialize parameters by any val as func is convex.
We reach the same point



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

learning rate,
how big the next val
will be

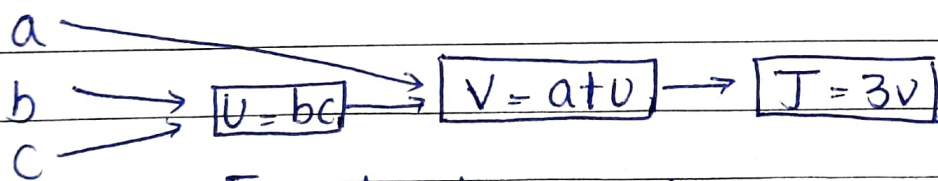
$$b := b - \alpha \frac{\partial J(w, b)}{\partial b}$$

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

Computation Graph

$$Ex - J(a, b, c) = 3(a + bc)$$

$$u = bc, \quad v = a + u, \quad J = 3v$$



Forward path - output

Backward path - Gradients, derivatives

$$\frac{dJ}{dv} = 3$$

$$\frac{dJ}{da} = \frac{dJ}{dv} \cdot \frac{dv}{da}$$