Neural Network and Deep Learning

B.Tech. Data Science, NMIMS

By,

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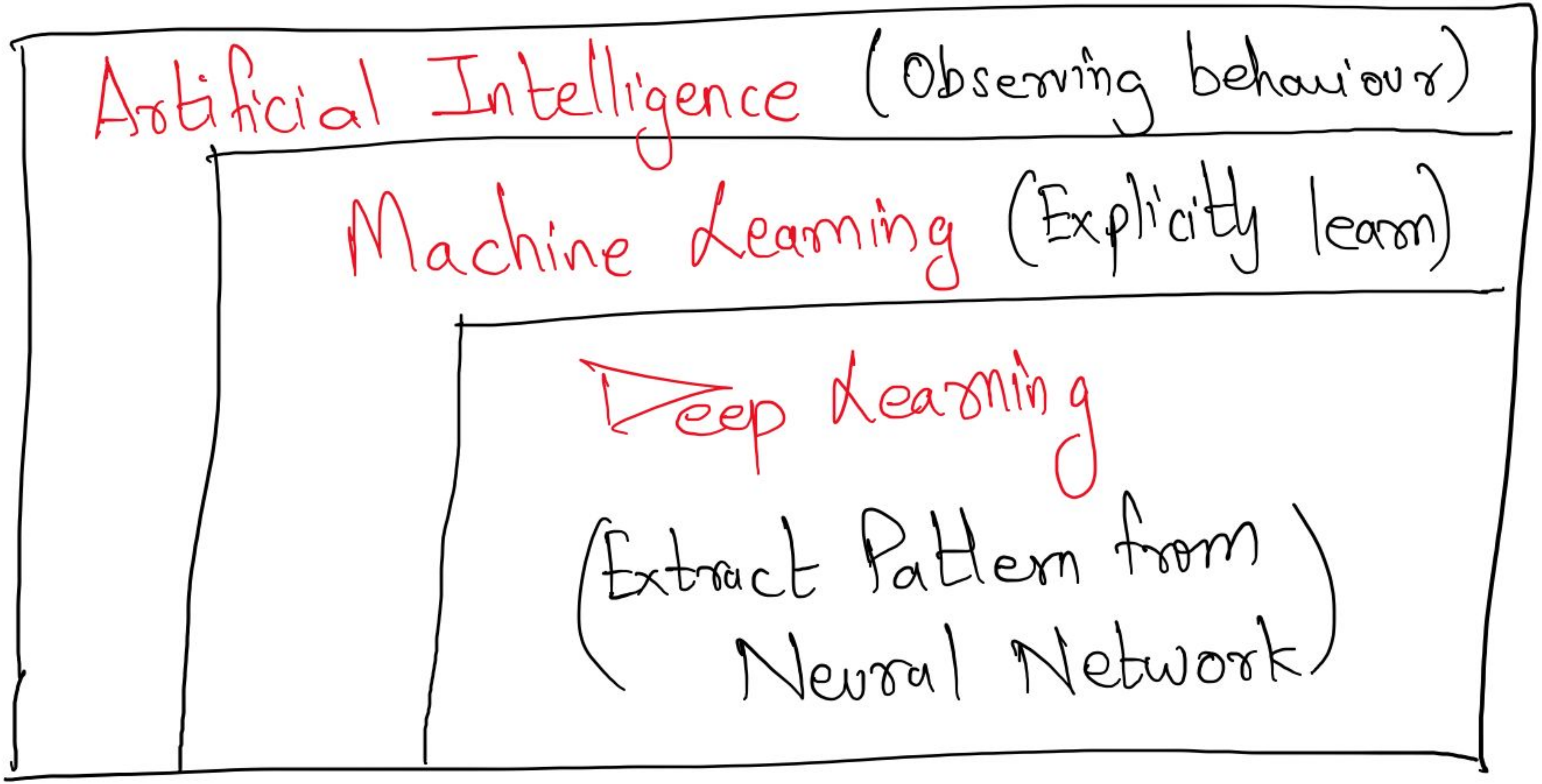

Artificial Intelligence (Observing behaviour)
Machine Learning (Explicitly learn)
Deep Learning
(Extract Pattern from Neural Network)

Why Deep Learning

- → Time Consuming and brittle in Unstructured data
- → Hard engineered features are not scalable
- → Ways to learn underlying features for unstructured data

Evolution of Deep Learning

1952 Gradient Descent

1958 Perceptron

⋮

1986 Backpropagation

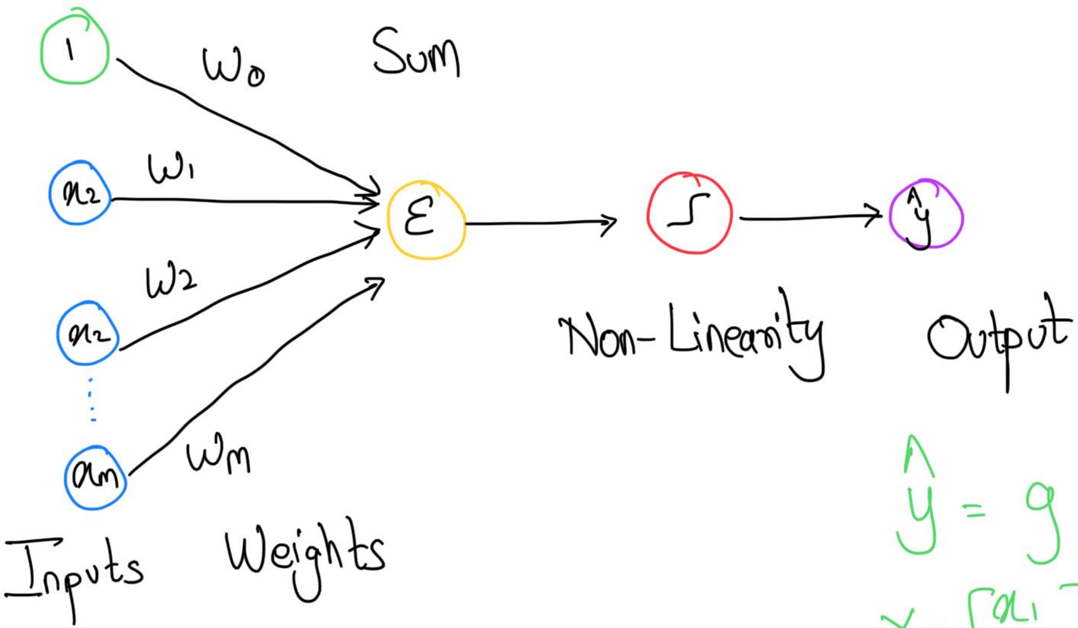
1995 Deep Convolution NN

⋮

Why now?

1) Big Data
2) Hardware (GPUs, TPUs)
3) Software (Pytorch, Tensorflow)

Perceptron

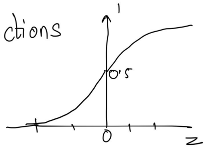


$$\hat{y} = g\left(w_0 + \sum_{i=1}^{m} x_i w_i\right)$$

$g(z) = \sigma(z)$

Activation Functions

$$\frac{1}{1+e^{-z}}$$



Simplify to Matrix

$$\hat{y} = g\left(w_0 + X^T W\right)$$

$$X = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} \quad W = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix}$$

Hyperbolic Tangent (tanh)

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

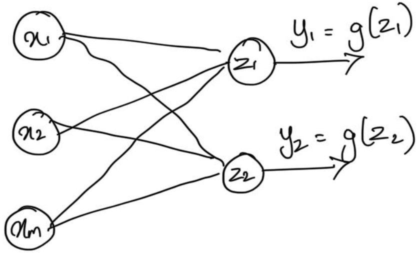
$$g'(z) = 1 - g(z)^2$$

Rectified Linear Unit (ReLU)

$$g(z) = \max(0, z)$$

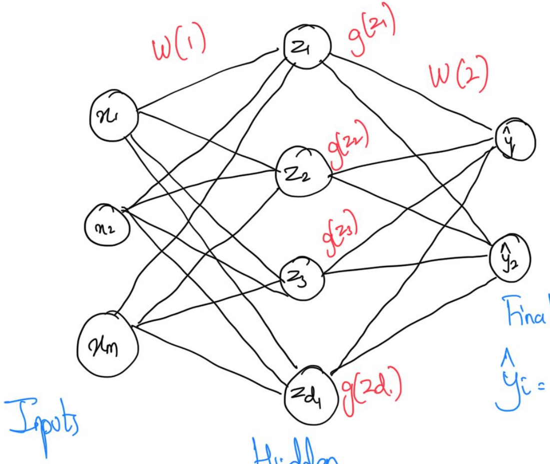
$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

Multi Output Perceptron



$$z_i = w_{0,i} + \sum_{j=1}^{m} x_j w_{j,i}$$

Single Layer Neural Network



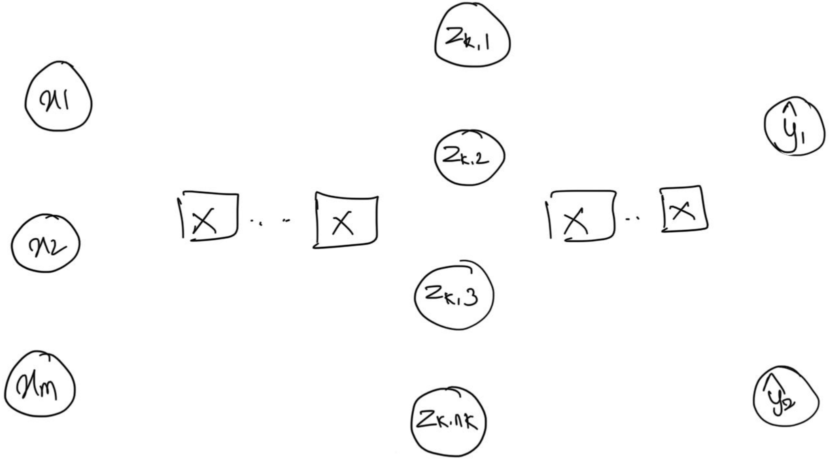
Final Output

$$\hat{y}_i = g\left(w_{0,i} + \sum_{j=1}^{d_1} g(z_j)\, w_{j,i}^{(2)}\right)$$

$$z_i = w_{0,i}^{(1)} + \sum_{j=1}^{m} x_j\, w_{j,i}^{(1)}$$

Deep Neural Network

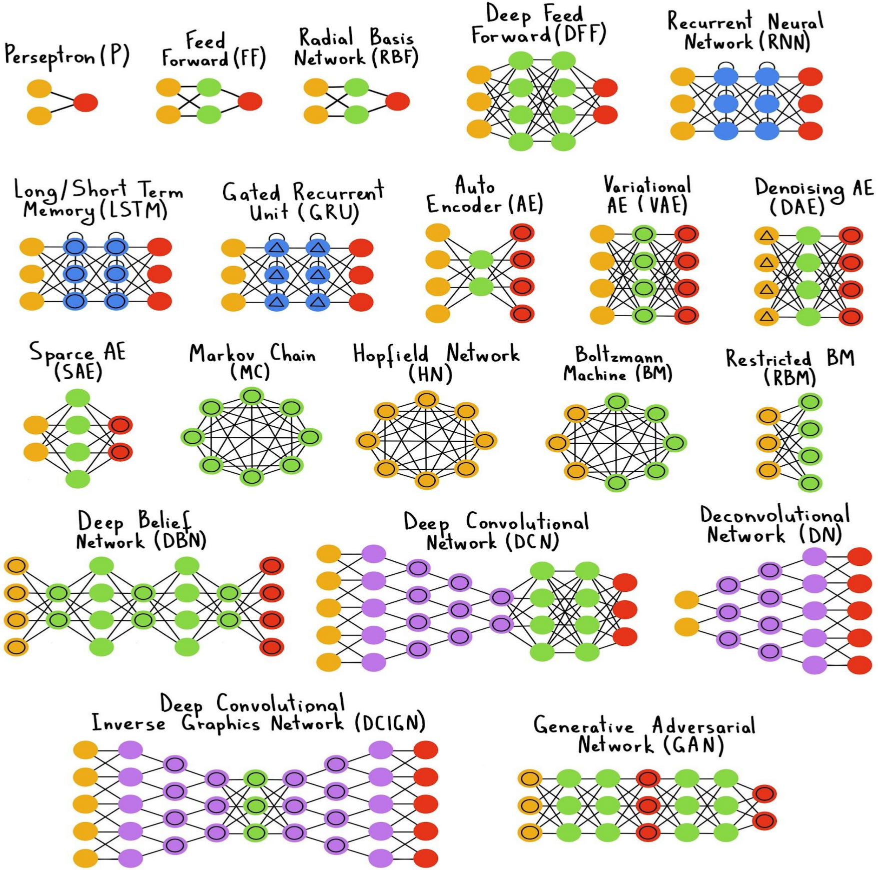
k # hidden layer



$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{n_{k-1}} g(z_{k-1,j})\, w_{j,i}^{(k)}$$

Keep stacking hidden layers

Neural Networks



ABACUS.AI

Quantifying Loss

It measures the cost incurred from incorrect predictions

$$\underbrace{\mathcal{L}\Big(\underbrace{f\big(x^{(i)};\, w\big)}_{\text{Predicted}},\ \underbrace{y^{(i)}}_{\text{Actual}}\Big)}_{J(w) \rightarrow \text{Empirical Loss}}$$

Binary Cross Entropy Loss

$$J(w) = \frac{1}{n}\sum_{i=1}^{n} \underbrace{y^{(i)}}_{\text{Actuals}} \underbrace{\log\big(\hat{y}^{(i)}\big)}_{\text{Predicted}} + \underbrace{\big(1 - y^{(i)}\big)}_{\text{Actuals}} \underbrace{\log\big(1 - \hat{y}^{(i)}\big)}_{\text{Predicted}}$$

Mean Squared Error Loss

$$J(w) = \frac{1}{n}\sum_{i=1}^{n} \big(\underbrace{y^{(i)}}_{\text{Actuals}} - \underbrace{\hat{y}^{(i)}}_{\text{Predicted}}\big)$$

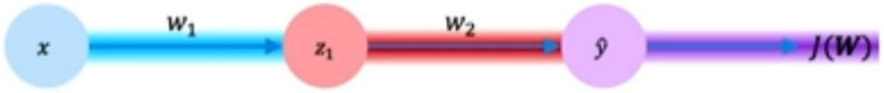
$$W^* = \underset{W}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^{n} \mathcal{L}\left(f\left(x^{(i)}; W\right), y^{(i)}\right)$$

$$W^* = \underset{W}{\operatorname{argmin}}\, J(W)$$

Gradient Descent

Algorithm

1. Initialize weights randomly $\sim\mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(W)}{\partial W}$
4. Update weights, $W \leftarrow W - \eta \frac{\partial J(W)}{\partial W}$
5. Return weights



$$\frac{\partial J(W)}{\partial w_1} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

Repeat this for ***every weight in the network*** *using gradients from later layers*

Optimization

- Learning Rate
- Regularization
- Dropout
- Early Checkpoint