DEEP LEARNING

We need to provide a good amount of data to create a model (ML model)
ex : identifying a dog - length of legs, nose size, etc

We need to populate all Features and create the model. Even after this, there is a chance for failure

→ Rule based system : (Around 1970)

Rules + Data] → MODEL $\xrightarrow{\text{gives}}$ output.

→ ML system : (1970 - 2010)

Input data + Output date] → MODEL $\xrightarrow{\text{creates}}$ Rules

Need to provide structured / tabular data (rows & columns)

→ DL Model :

- No need to provide structured data
- Finds out features on itself
- It is a ML model which works on unstructured data and derives the features on itself.

Image → Finds basic primitive features → uses these features to form more complex features

→ | / ^ → ○ □ △ → ... → Final dog picture

$\underbrace{\hspace{6cm}}_{\text{many layers are present}}$ - SEQUENTIAL LAYER ARCHITECTURE

(Good inputs, Good outputs)

We need to provide the data as accurately as possible - otherwise system gives bad outputs (GIGO - Garbage In Garbage Out

Learning happens in a sequential manner.

Every layer is responsible for different type of features. More layers means more deeper architecture.

DL model learns the representations from raw data.

- Supervised Learning : labelled data.

- Unsupervised Learning (clustered approach) : Unlabelled
Find similarity in data and cluster it

- DL model : Supervised learning
- DL is mostly used in unstructured data
- It does not have much applications in structured data (not required).
- DL is mostly designed for unstructured data. Incase of structured data, the features are already present - does not make sense to use DL. DL model can be used, but not required - other simpler models can be used

Low level Features →	Mid level Features →	High level Features
(Edges, dark spots)	(Eyes, ears, nose).	(Facial structure)
Conv Layer 1	Conv. Layer 2	Conv. Layer 3

Mostly in DL, the first few layers (lowe level features) are the same. As we go deeper the features will be different.

More layers / deeper architecture → Better accuracy

→ Difference b/w DL and ML:

① Data dependency : DL requires more data.

② Hardware dependency : requires speacialised hardwares like GPUs.

③ Training Time : higher for DL.

④ Feature selection : Features are automatically extracted by layers.

⑤ Interpretability : Very less or not present in DL model.

TENSOR FLOW

Sklearn helps use numpy functions more efficiently

numpy → Sklearn → used in CPUs.

numpy → TensorFlow → used in GPUs.

The background of Sklearn and TensorFlow is numpy functions (arrays).
TensorFlow functions are supported by both CPUs and GPUs. Sklearn supports only CPUs.

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Keras - can run on top of TensorFlow.

TensorFlow consists of tensors (similar to arrays)

Constant :(cannot be changed) and variable tensors

Arithmetic operations : Tensors

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} + 20$$

gets converted to

$$\begin{bmatrix} 20 & 20 & 20 \\ 20 & 20 & 20 \end{bmatrix}$$

$(2, 3, 2) + (2, 3)$

Need to change dimension of $(2, 3)$

(can be added on either side)

$$\begin{cases} (1, 2, 3) \\ \text{or} \\ (2, 3, 1) \end{cases}$$

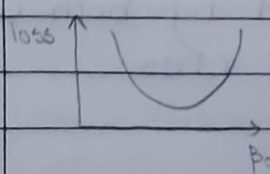
Simple Linear Regression

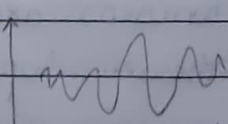
$$y = \beta_1 x + \beta_0$$

$\beta_0, \beta_1 \rightarrow$ weights

Loss Function : $mse = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$

Loss Functions helps get best fit line - From parabola of curve





For diff values of β_0, β_1 compute β_{new}
at that β_{new}, check loss.

$\frac{\partial Loss}{\partial \beta_0, \beta_1}$ where slope = 0 → that is the global minimum point

$$\beta_{0\,new} = \beta_{0\,old} - \eta \frac{\delta Loss}{\delta \beta_{0\,old}}$$

why minus? we need to minimise $\beta_{0\,new}$

① Vanilla gradient descent - batch processing
- slow process
- For ex:

β_0, β_1 Loss
:
:

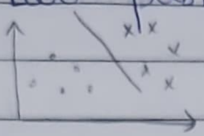
update β_0, β_1 ← Take avg
↓
Calculate loss again - slow process

② Stochastic gradient descent
In 1 epoch: updating 1000 times

There fore we apply vanilla GD in stochastic GD
- mini batch gradient descent (randomly picks batch size)
Perform stochastic - form batches → take avg
↓
Update β_0, β_1

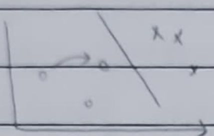
There should not be many batches

Linear Binary Classifier : when you can easily draw a line between two Classes / if you can easily differentiate two classes into two parts



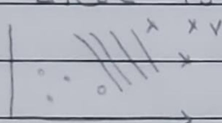
LOGISTIC REGRESSION ⇒

marks	GA	Pass/Fail
20	40	1
20	30	1
10	10	0
10	20	0



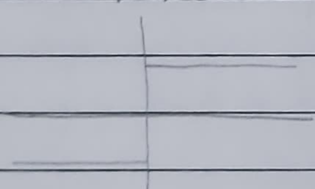
suppose one point is marked incorrectly, it shifts to new position → line also shifts

Suppose there is a huge gap in between

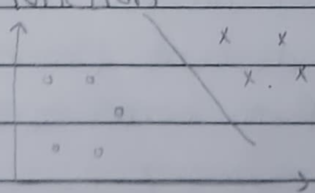


we can draw multiple lines in between
- difficult to determine
→ this is why we need to use optimisation process

we get step Function

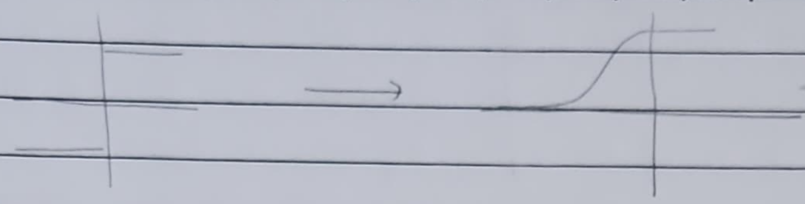


This step function needs to be changed into sigmoid function



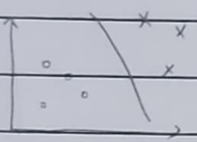
Take a line in between and calculate error
distance b/w point and line
→ depending upon that taken as 0 or 1 class

Likelihood is always taken for class 1
Best line is the one with the best likelihood

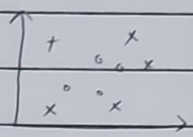


(sigmoid function)

Perceptron with Sigmoid Function = Logistic regression

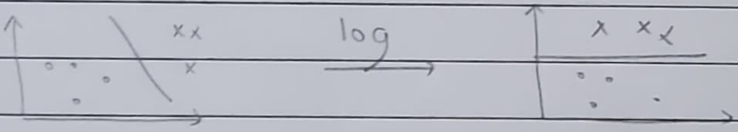


Linear



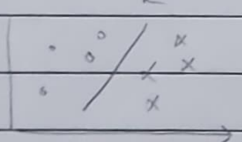
Non linear

Using multiple perceptrons to get the output – Multilayer Perceptron (MLP)

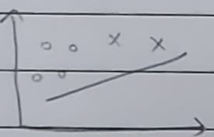


The backstory of Logistic regression – Perceptron

same point



P = 0.8



P = 0.6

$$P = 0.8 + 0.6 = 1.4$$

Cannot be 1.4 as Σ Prob = 1

↓ pass through sigmoid function

o/p