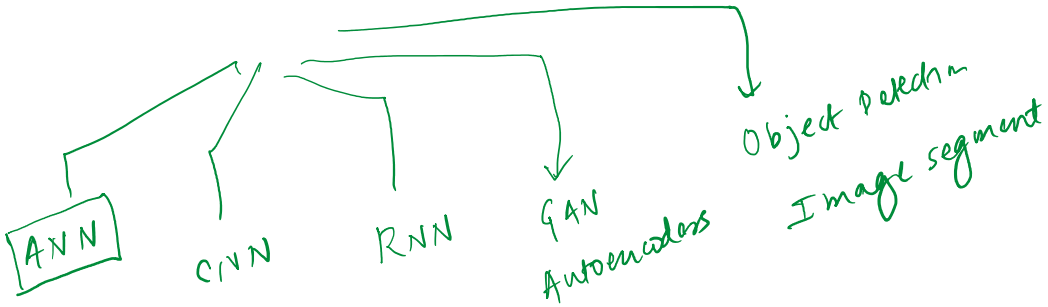
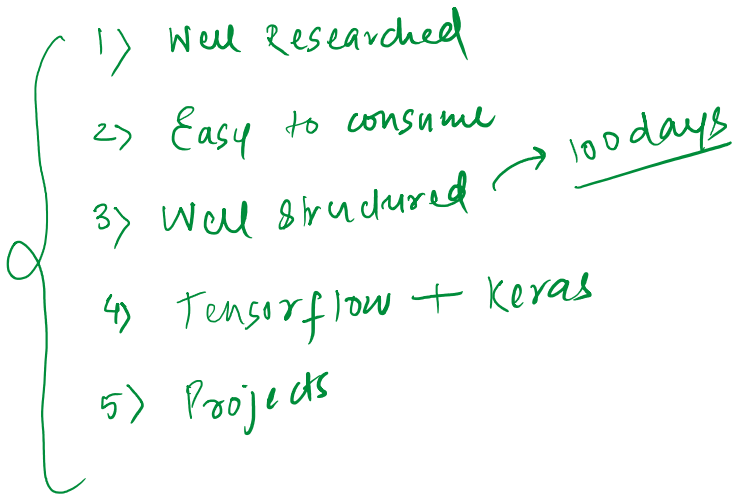
Curriculum

Tuesday, February 15, 2022 3:30 PM



Features

Tuesday, February 15, 2022 3:31 PM



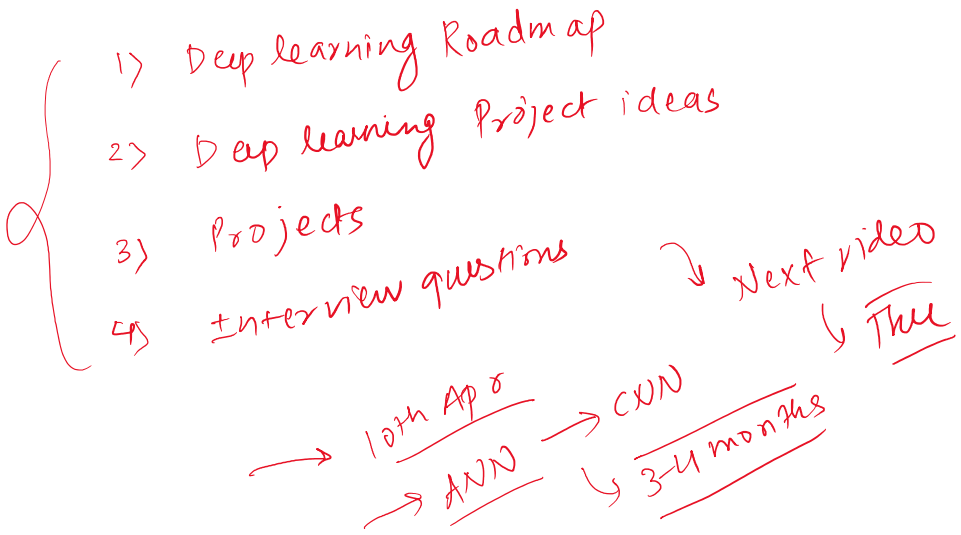
Prerequisites

Tuesday, February 15, 2022 3:31 PM

1) Python →
2) Basics of ML
3) Linear Algebra → 3 Blue 1 Brown / Linear Alg → (5)

Extra Content

Tuesday, February 15, 2022 3:32 PM



What is Deep Learning?

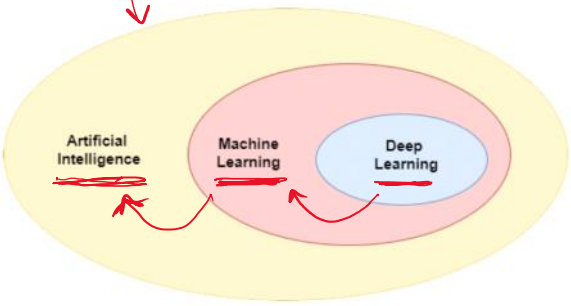
16 February 2022 06:32

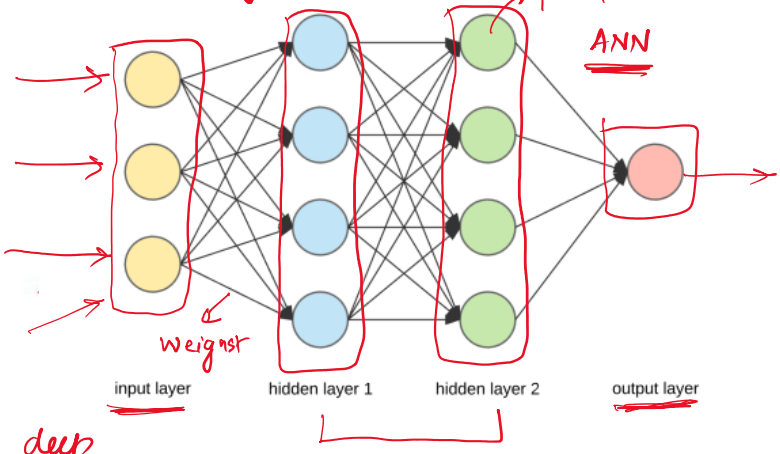
Deep Learning is a subfield of Artificial Intelligence and Machine Learning that is inspired by the structure of a human brain.
Deep learning algorithms attempt to draw similar conclusions as humans would by continually analyzing data with a given logical structure called Neural Network.

learn from data

input | output

statistical





deep

ANN →

CNN → convolutional NN ✓ image

RNN → Recurrent NN → speech / text

GAN → generate (text) images

why dl getting so famous?

1) Applicability →

2) Performance → state-of-the-art → human experts

Applications

Go → Alphago → AI

5 → 4

self driving

drugs

→ chemistry

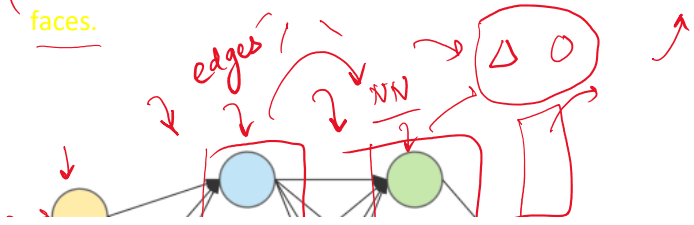
1) Representation

Deep learning is part of a broader family of machine learning methods based on artificial neural networks with representation learning.

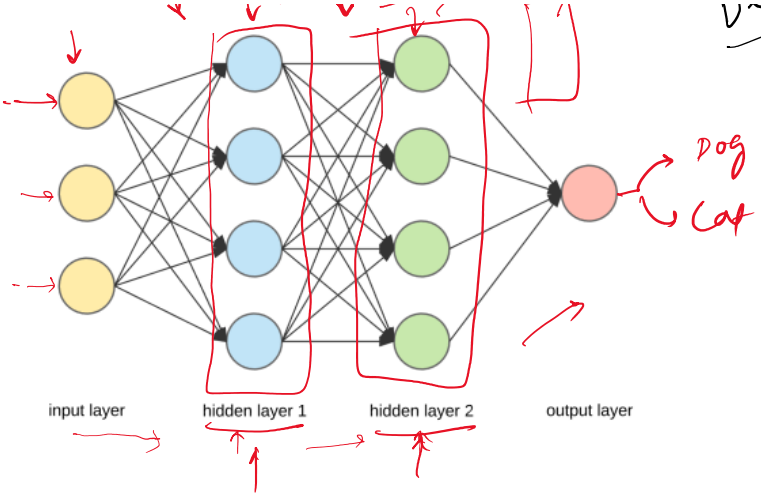
Deep Learning Algorithms uses multiple layers to progressively extract higher-level features from the raw input. For example, in image processing, lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces.

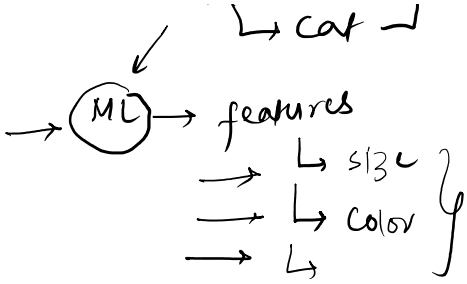
feature extraction engineering

features



Deep learning → Dog / cat → classifier → Dog / cat


input layer
hidden layer 1
hidden layer 2
output layer
Dog
Cat


ML
features
size
color

Deep Learning VS Machine Learning

16 February 2022 06:33

1. Data Dependency
2. Hardware Dependency
3. Training Time
4. Feature Selection
5. Interpretability

costly DL

Data ↑ hungry

Data ↑ performance ↑

CPU → run slow

matrix multiplication → GPU → powerful

Representation learning → features extract

complex

training time - high → weeks

ML → low minutes - hrs

less data

ML wins

Prediction

DL → fast

ML

KNN

DL → Algorithm → feature

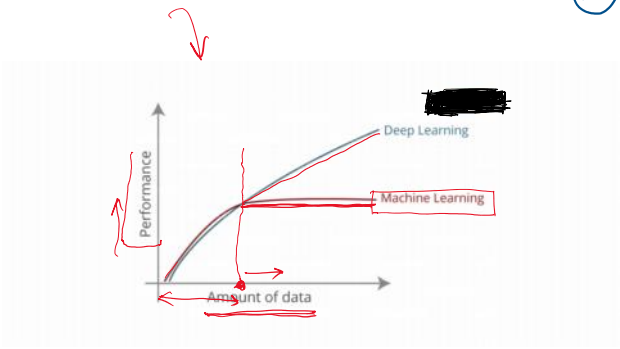
Resume based

→ predict → Y/N

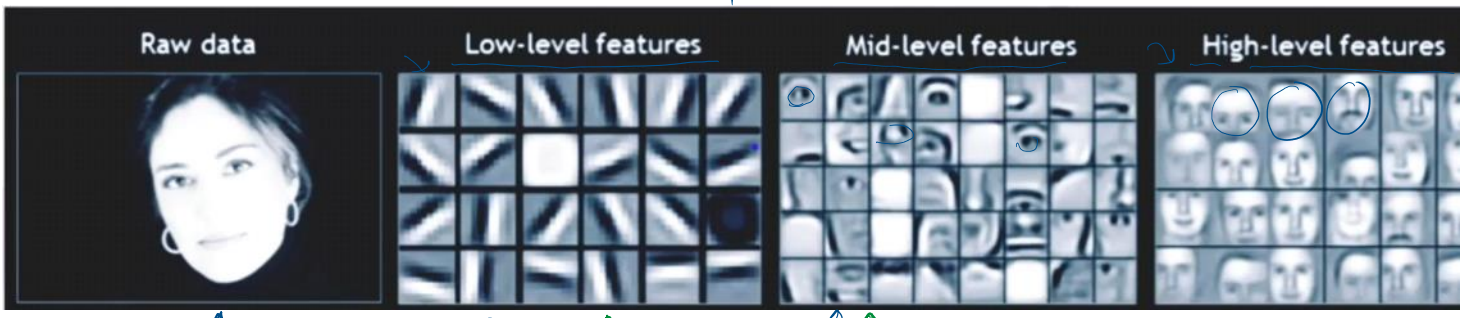
→ features

domain expert → 12th marks, 10th mars

teachers → No. of ach, No. of course, quality of college



Deep learning



feature → interpre

Deep learning

comment → ban → user

Dog

Dog

cat

Black box

logistic

cgpa | iq | placement

w_1 w_2 (N)

DT

explainability

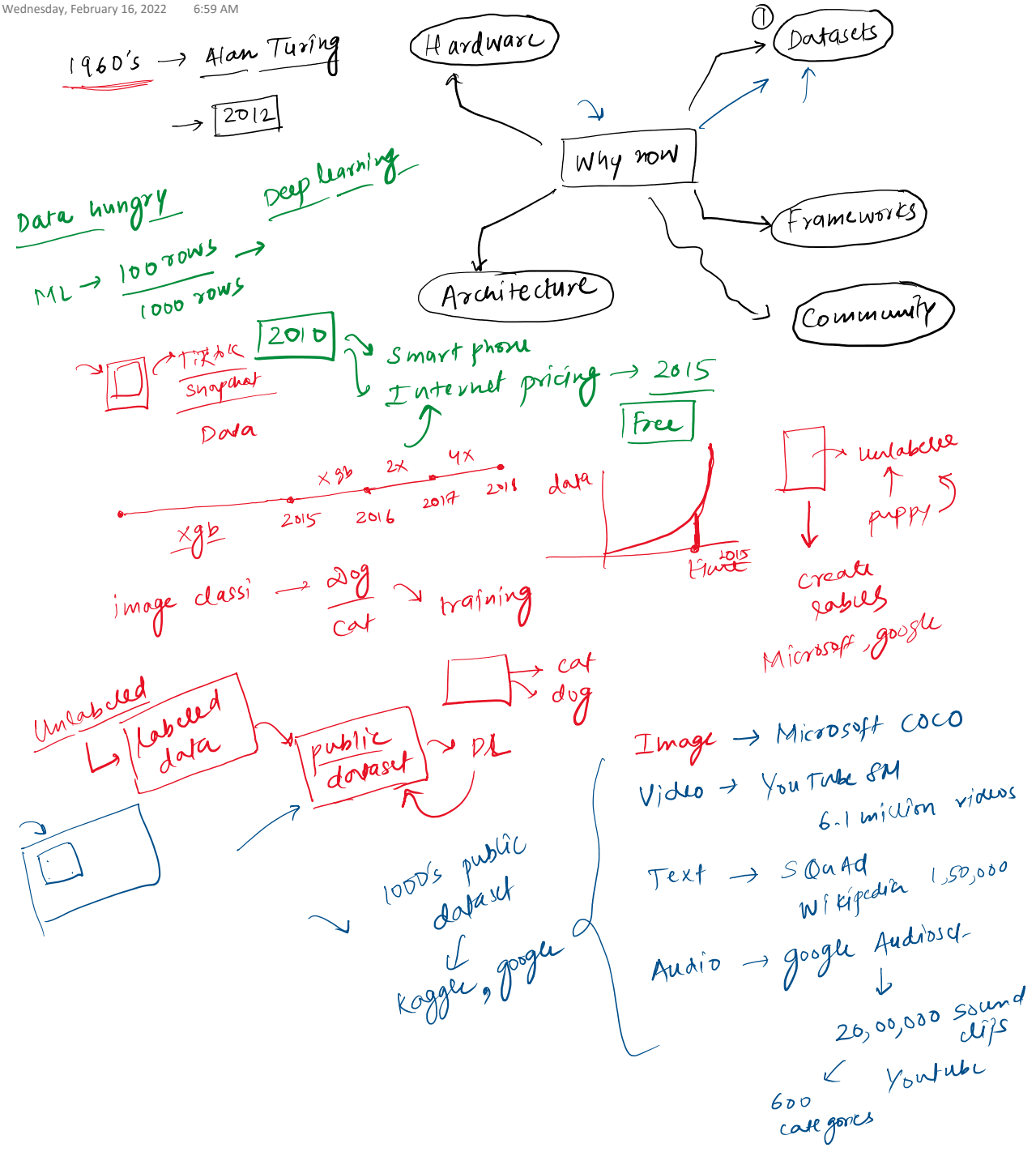
flow chart

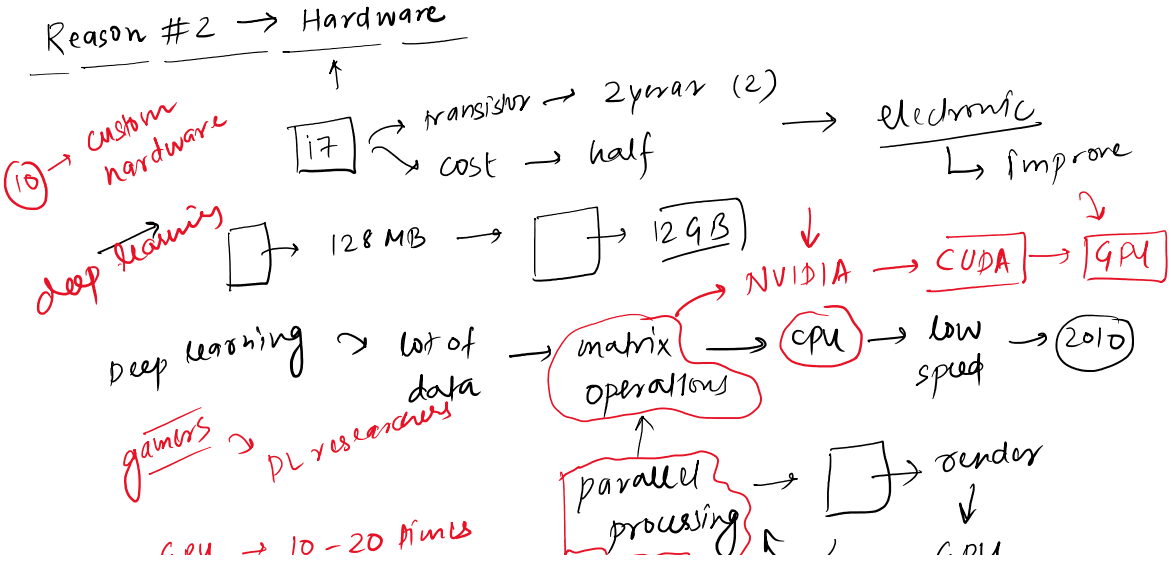
High ↑

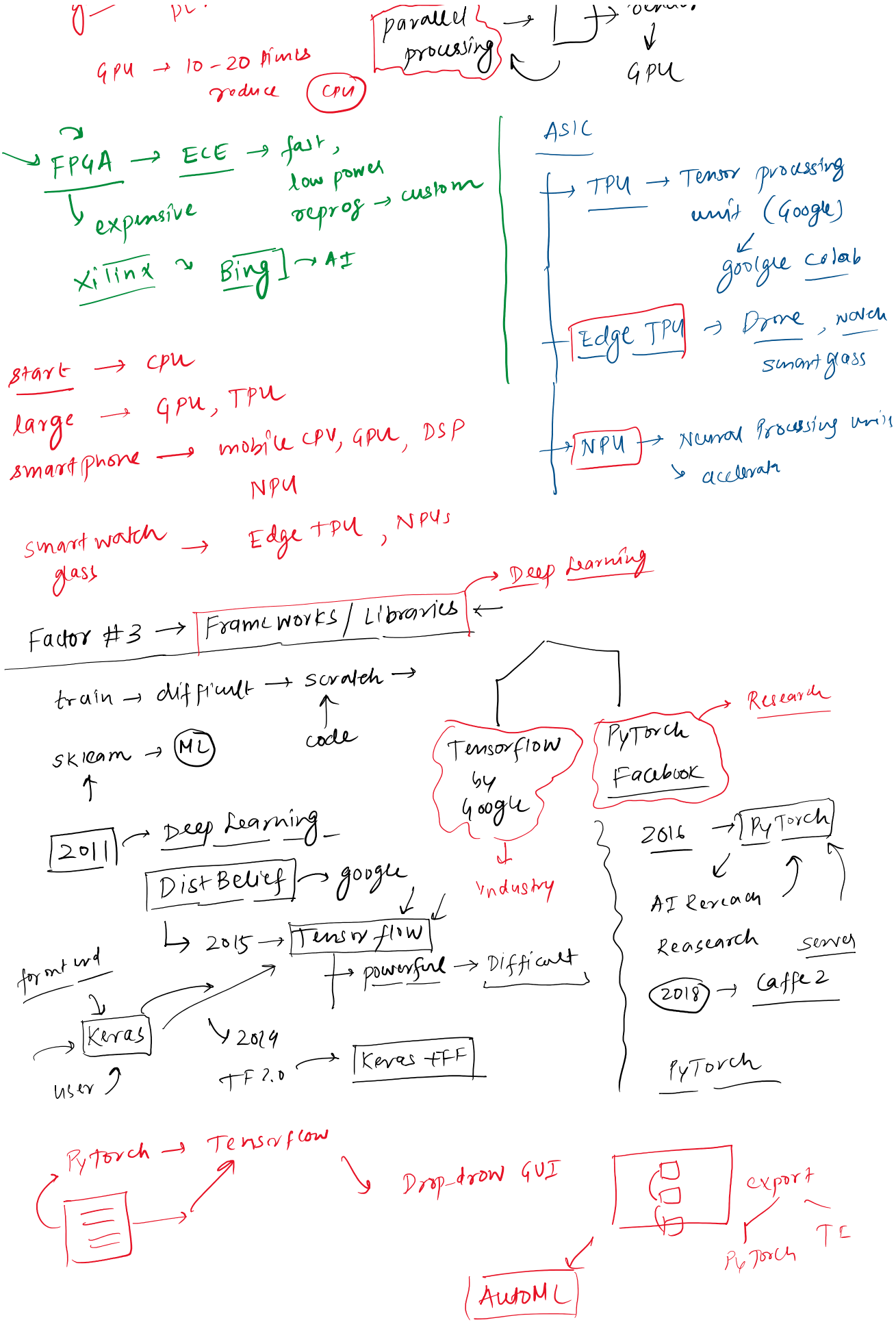
Machine learning →

Why now?

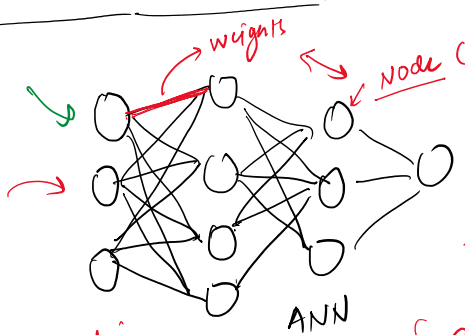
Wednesday, February 16, 2022 6:59 AM






GPU → 10-20 times reduce CPU
parallel processing
GPU
FPGA → ECE → fast, low power reprog → custom
expensive
Xilinx ↘ Bing → AI
ASIC
TPU → Tensor processing unit (Google)
google colab
Edge TPU → Drone, watch smart glass
NPU → Neural Processing units → accelerate
start → CPU
large → GPU, TPU
smartphone → mobile CPU, GPU, DSP NPU
smart watch glass → Edge TPU, NPUs
Factor #3 → Frameworks / Libraries
Deep Learning
train → difficult → scratch → code
sklearn → ML
2011 → Deep Learning
DistBelief → google
2015 → Tensorflow
powerful → Difficult
front end
Keras
user
2019
TF 2.0 → Keras TFF
Tensorflow by Google
Industry
PyTorch Facebook
Research
2016 → PyTorch
AI Research
Research
server
2018 → Caffe 2
PyTorch
Pytorch → Tensorflow
Drop-down GUI
export
PyTorch
TF
AutoML
Factor #4 → Deep Learning Architectures

Factor #4 → Deep Learning Architectures



CNN RNN

DNN archi

Stat-of-the-art best accuracy

Experiment
- time
- effort
- money

Transfer learning

ANN → existing archite

NN → Archi
- fixes down
- Dataset → train → ready to use

image classification → ResNET	Object detect → YOLO
Text classifi → BERT	speech gen → WaveNET
Image segment → UNet	
image tran → Pix2Pix	

#5 → People / community

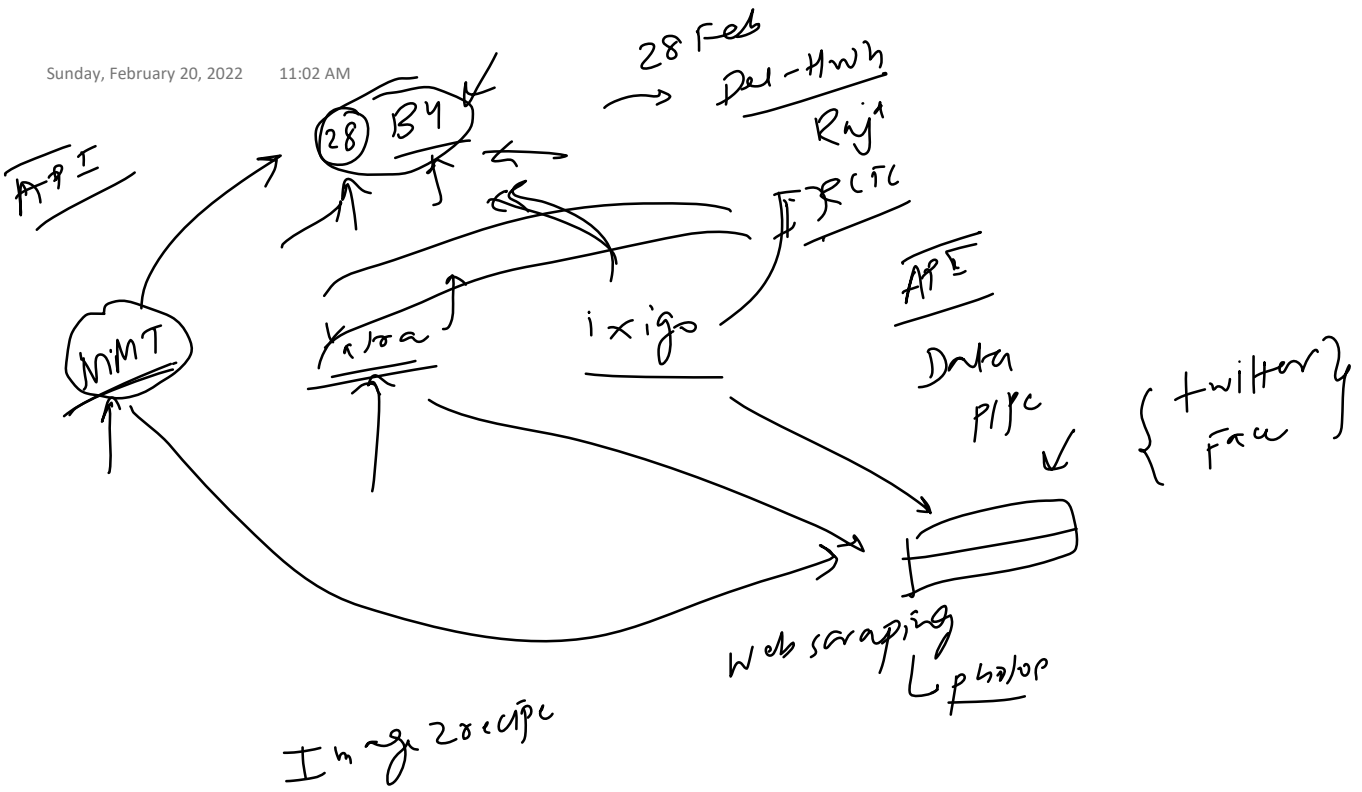
↳ Deep learning → 1960 → 2011 → PL →

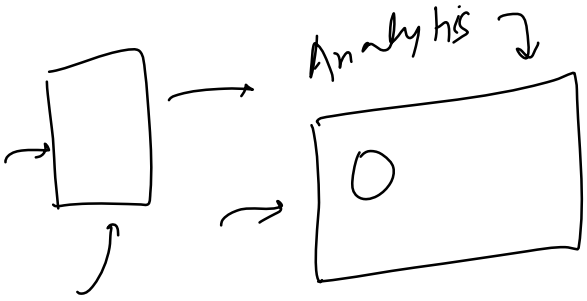
Research
- ↳ DL engine
- ↳ Teach → student → Kaggle

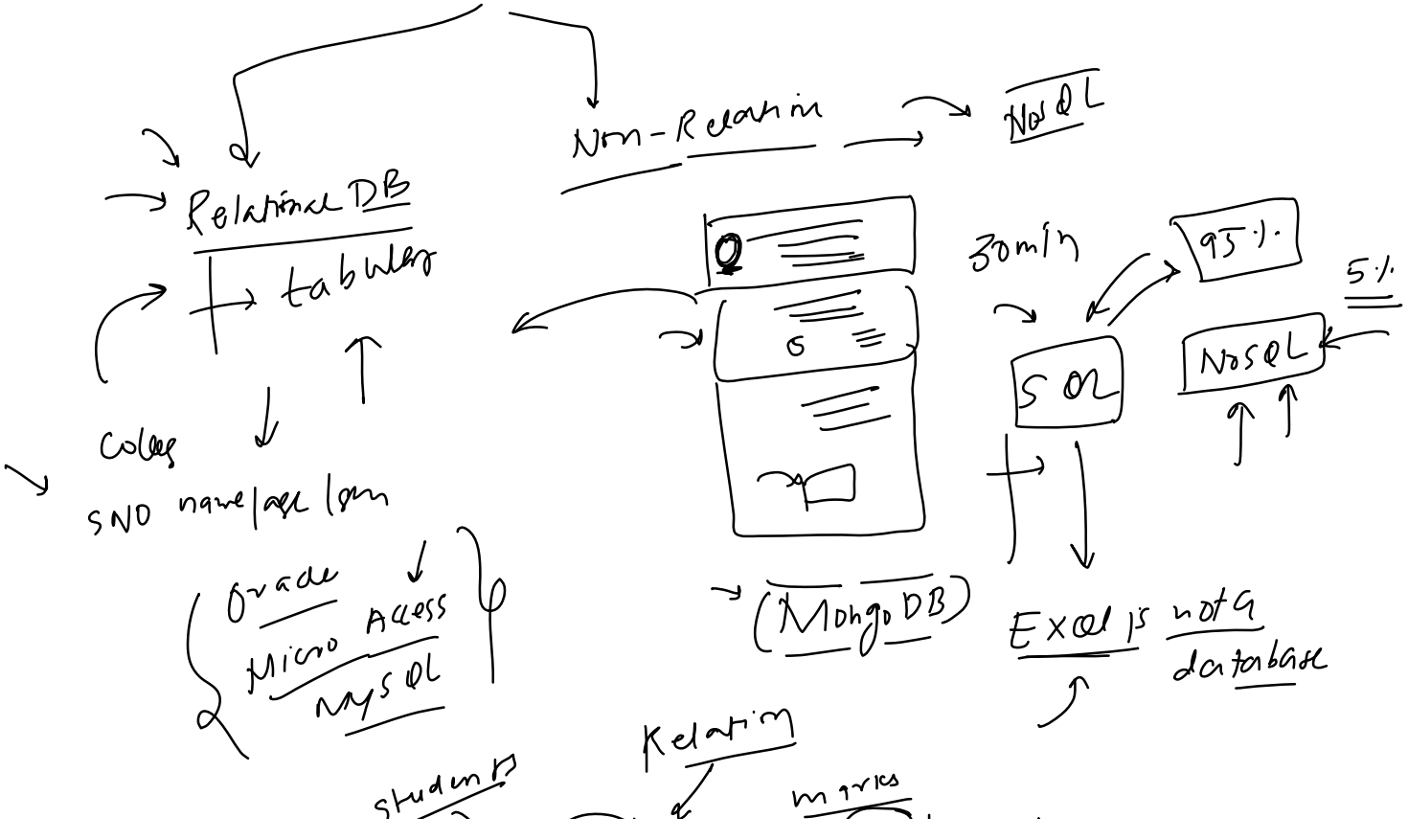
Code Example

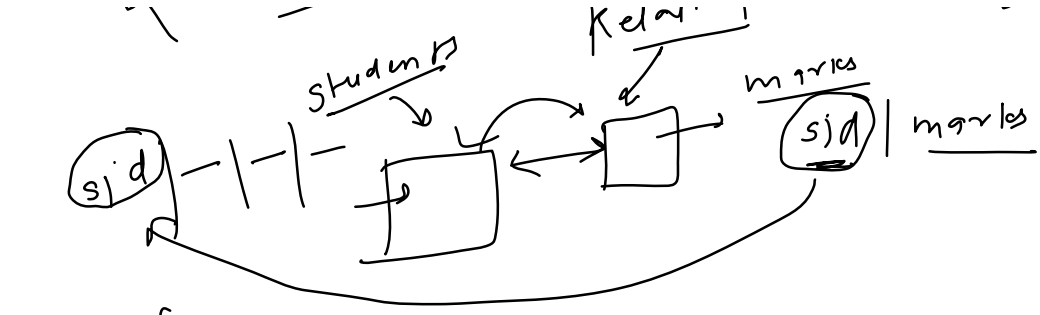
Saturday, February 19, 2022 7:10 AM

Sunday, February 20, 2022 11:02 AM

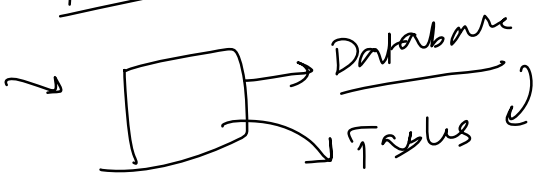


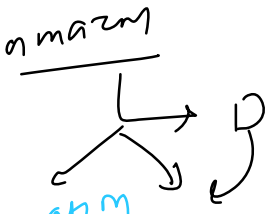






DBMS Oracle





Normalization

student- marks

DB → storage

sid	name	gender	age	course	marks
1	satyam	M	21	Eng	24
1	Satyam	M	21	Maths	32

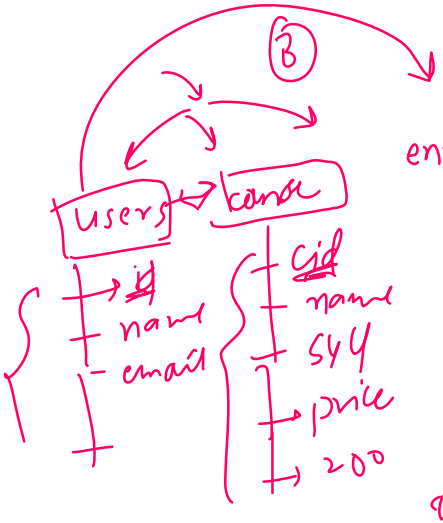
Denorm

OLTP

OLAP

website

a

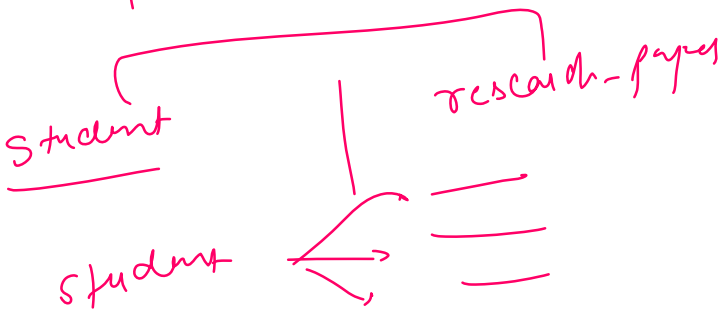


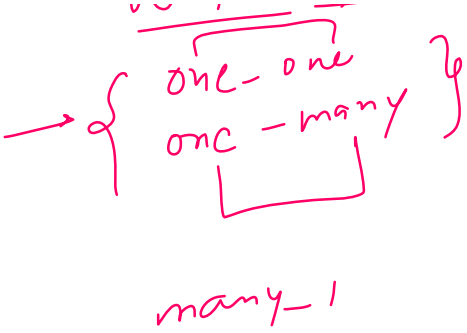
enrollment

id
cid
pay
data

relationship

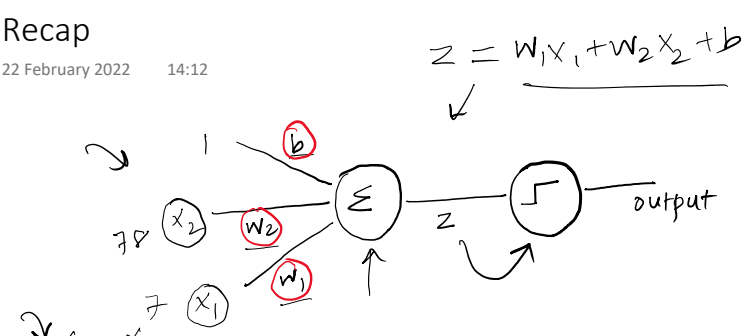
one-one

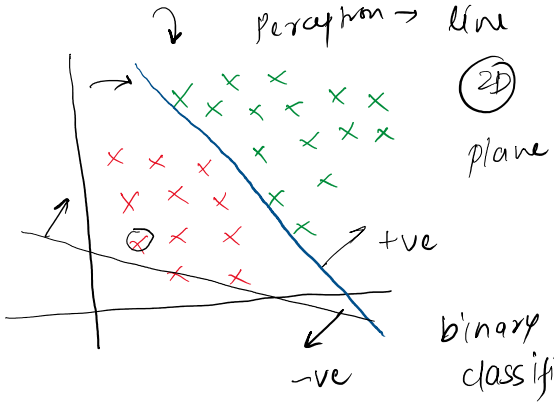



one-one
one-many
many-1

Recap

22 February 2022 14:12





x_1 cgpa	x_2 iq	placed
7	78	1
6	61	0
9	92	1

1) mathematical model → neuron

$z \geq 0 \rightarrow 1$

$z < 0 \rightarrow 0$

Prediction

→ Training

1000 random

Perceptron Rule

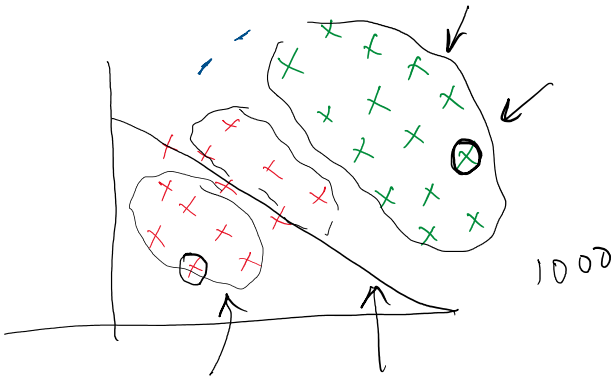
$Ax + By + C = 0$

$A \rightarrow w_1$

$B \rightarrow w_2$ $C \rightarrow b$

Problem with Perceptron Trick

22 February 2022 16:10



line → $w_1 w_2 b$

randomly per

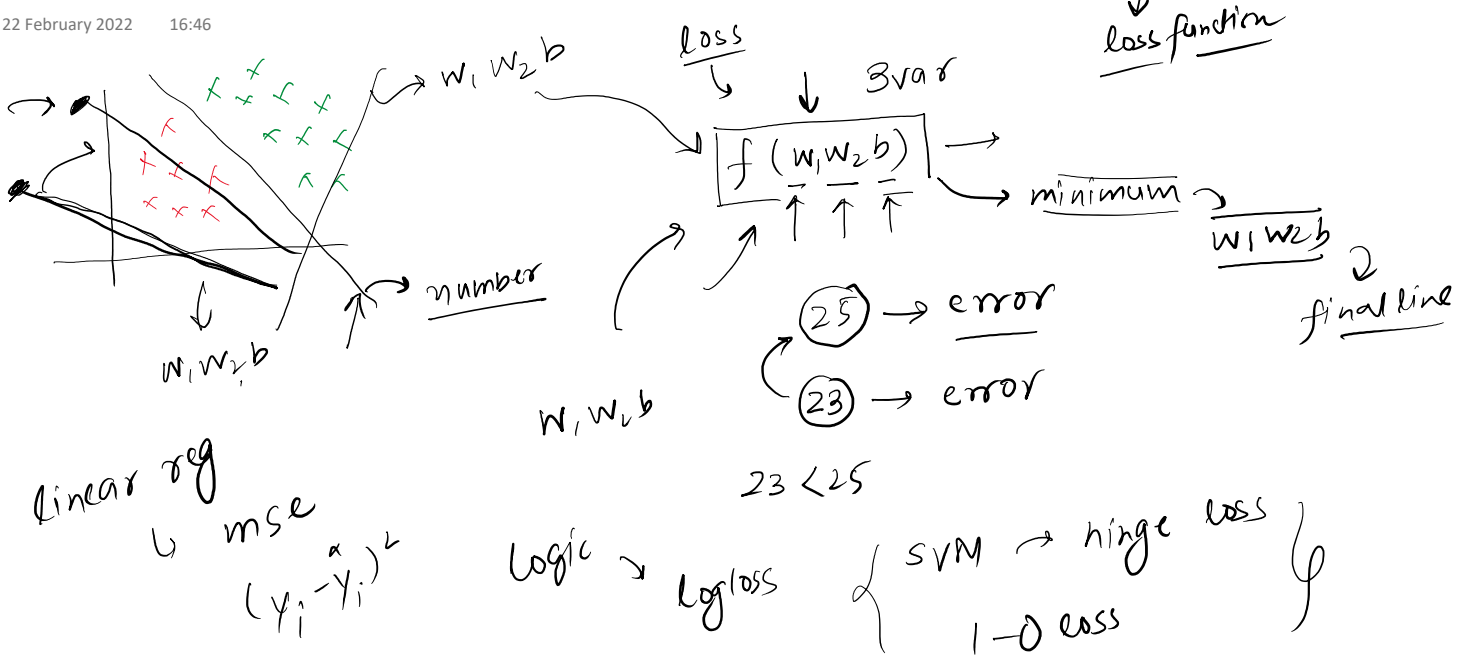
converge

quantify

$w_1 w_2 b$ → loss functions

Loss Function

22 February 2022 16:46

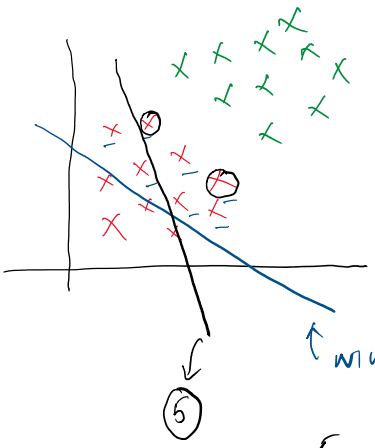


Perceptron Loss Function

22 February 2022 17:47

$f(w_1, w_2, b)$ → number → error

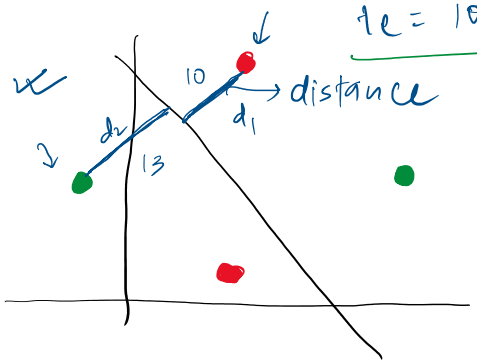
misclassified points



$w_1 w_2 b$ → 7

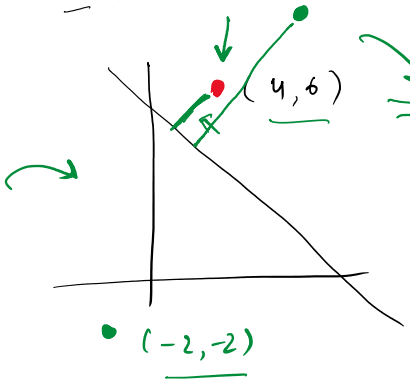
5

$1+1+1+1+1 = 5$



$le = 10 + 13$

compute ↑ distance



$= 2(4) + 3(6) + 4 = 30$

↑ dot product

30+6

$2(-2) + 3(-2) + 4 = |-6| = 6$

Sklearn

$$L(w_1, w_2, b) = \frac{1}{n}\sum_{i=1}^{n} L(y_i, f(x_i)) + \alpha R(w_1, w_2)$$

Regularization

cgpa | placement

↓ y_i

$$L(y_i, f(x_i)) = \max(0, -y_i f(x_i))$$

$$f(x_i) = w_1 x_1 + w_2 x_2 + b$$

$z =$

hinge

$$L = \frac{1}{n}\sum_{i=1}^{n} \max(0, -y_i f(x_i))$$

$L(w_1, w_2, b)$

n: # rows in data

$w_1 w_2 b$

$$L = \underset{w_1, w_2, b}{\operatorname{argmin}} \frac{1}{n}\sum_{i=1}^{n} \max(0, -y_i f(x_i))$$

minimum

gradient descent

$L =$ argmin $\sum_{i=1}^{n}$

w_1, w_2, b

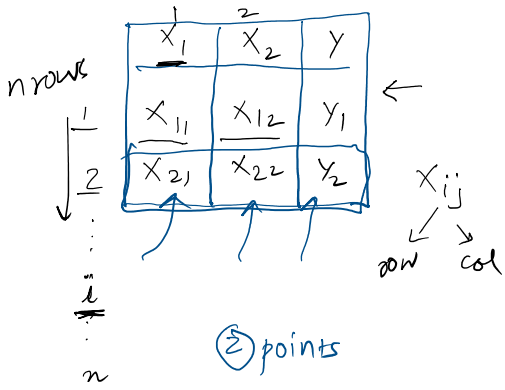
gradient descent

Explanation of Loss Function

23 February 2022 08:07

$$L = \frac{1}{n}\sum_{i=1}^{n} \max(0, -y_i f(x_i)) \qquad w_1, w_2, b$$

where $f(x_i) = w_1 x_{i1} + w_2 x_{i2} + b$



$\max(0, -y_i f(x_i)) = \max(0, x)$ → $= x$ if $x \geq 0$; $= 0$ if $x < 0$

$f(x_2) = w_1 x_{21} + w_2 x_{22} + b$

$-y_i f(x_i) \geq 0$

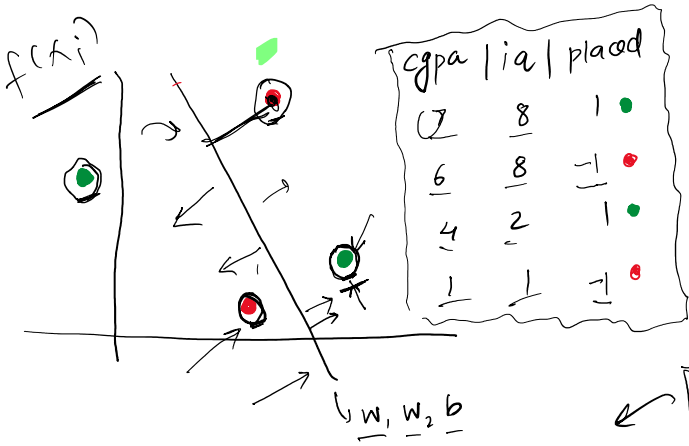
$< 0 \quad = 0$

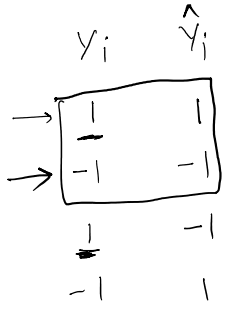
$y_i f(x_i)$

$L = \frac{1}{2}\left[\max(0, -y_1 f(x_1)) + \max(0, -y_2 f(x_2))\right]$ — 2 points, n points

$= 0$ — distance

$\max(0, -y_i f(x_i))$





$w_1 x_1 + w_2 x_2 + b \geq 0$

$\max(0, -ve) = 0$

1 $f(x_i) = +ve$

+ve +ve $= -ve$

$\max(0, -ve) = 0$

y_i $f(x_i) = +ve$

-1

-ve -ve $= -ve$

y_i $f(x_i)$

+ve -ve $= -ve = +ve$

+1

$\max(0, +ve) = +ve$

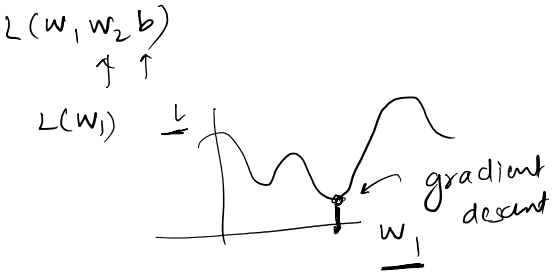
y_i $f(x_i)$

-ve +ve → $-ve \cdot -1 = +ve$

Gradient Descent

23 February 2022 08:50

$$L = \underset{w_1 w_2 b}{\operatorname{argmin}} \left[\frac{1}{n} \sum_{j=1}^{n} \max(0, -y_i f(x_i)) \right]$$



where $f(x_i) = w_1 x_{i1} + w_2 x_{i2} + b$

100/1000

$\eta = 0.01$

$(w_1, w_2, b) = 1$

for i in epochs:

$$w_1 = w_1 + \eta \frac{\partial L}{\partial w_1}$$

$$w_2 = w_2 + \eta \frac{\partial L}{\partial w_2}$$

$$b = b + \eta \frac{\partial L}{\partial b}$$

$$\left[\frac{\partial L}{\partial w_1}, \frac{\partial L}{\partial w_2}, \frac{\partial L}{\partial b} \right]$$

Loss Function Differentiation

23 February 2022 12:57

$$L = \frac{1}{n}\sum_{i=1}^{n} \max(0, -y_i f(x_i))$$

where $f(x_i) = w_1 x_{i1} + w_2 x_{i2} + b$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial f(x_i)} \times \frac{\partial f(x_i)}{\partial w_1}$$

cgpa is placed → x_{i1}

$$\frac{\partial L}{\partial f(x_i)} = \begin{cases} 0 & \text{if } y_i f(x_i) \geq 0 \\ -y_i & \text{if } y_i f(x_i) < 0 \end{cases} \qquad \frac{\partial f(x_i)}{\partial w_1} = x_{i1}$$

$$\frac{\partial L}{\partial w_1} = \begin{cases} 0 & \text{if } y_i f(x_i) \geq 0 \\ -y_i x_{i1} & \text{if } y_i f(x_i) < 0 \end{cases}$$

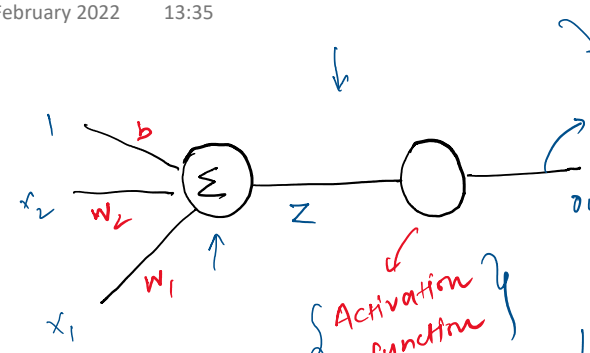
$$\frac{\partial L}{\partial w_2} = \begin{cases} 0 & \text{if } y_i f(x_i) \geq 0 \\ -y_i x_{i2} & \text{if } y_i f(x_i) < 0 \end{cases}$$

→ code using gradient descent

$$\frac{\partial L}{\partial b} = \begin{cases} 0 & \text{if } y_i f(x_i) \geq 0 \\ -y_i & \text{if } y_i f(x_i) < 0 \end{cases}$$

More Loss Functions

23 February 2022 13:35



mathematical model

flexible by design

SGD

loss function → binary cross entropy

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

1, -1 prob

$z = w_1x_1 + w_2x_2 + b$

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

SGD → output prob.

Perceptron == Logistic Regression

Activation: sigmoid

Loss func

multiclass (3)

Activation → softmax

$f = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$

Loss function → categorical cross entropy

$L = \sum_{j=1}^{M} y_j \log(\hat{y}_j)$

Softmax regression

$f = \frac{e^{z_1}}{e^{z_1} + e^{z_2} + e^{z_3}}$

Regression

$z \geq 0 \quad 1$

$z < 0 \quad -1$

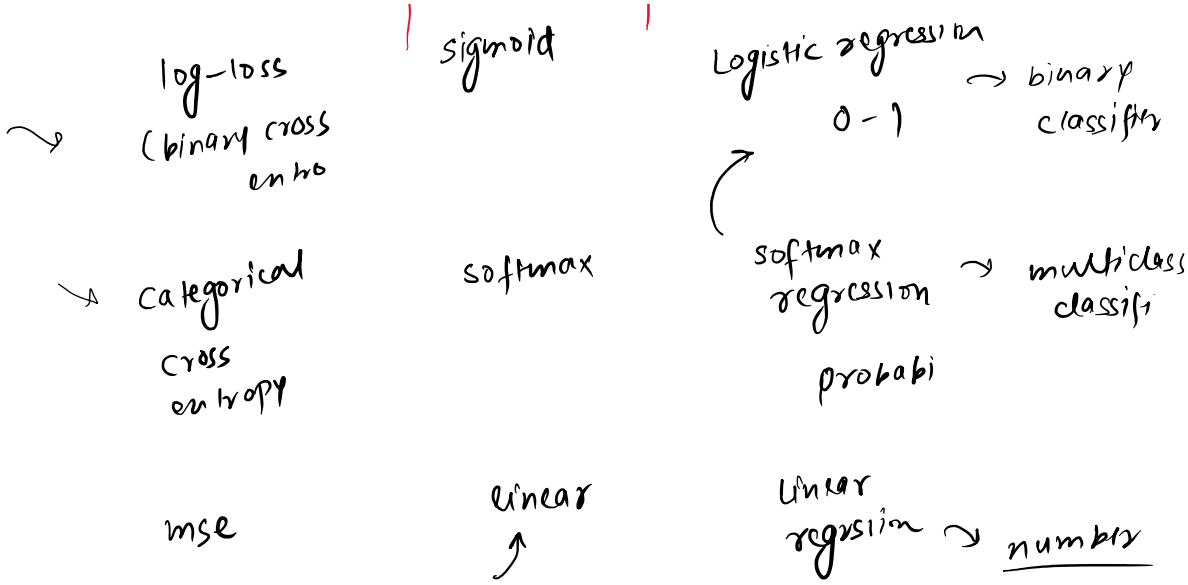
$z \rightarrow z$

Activation → linear

Loss function → mse → linear regression

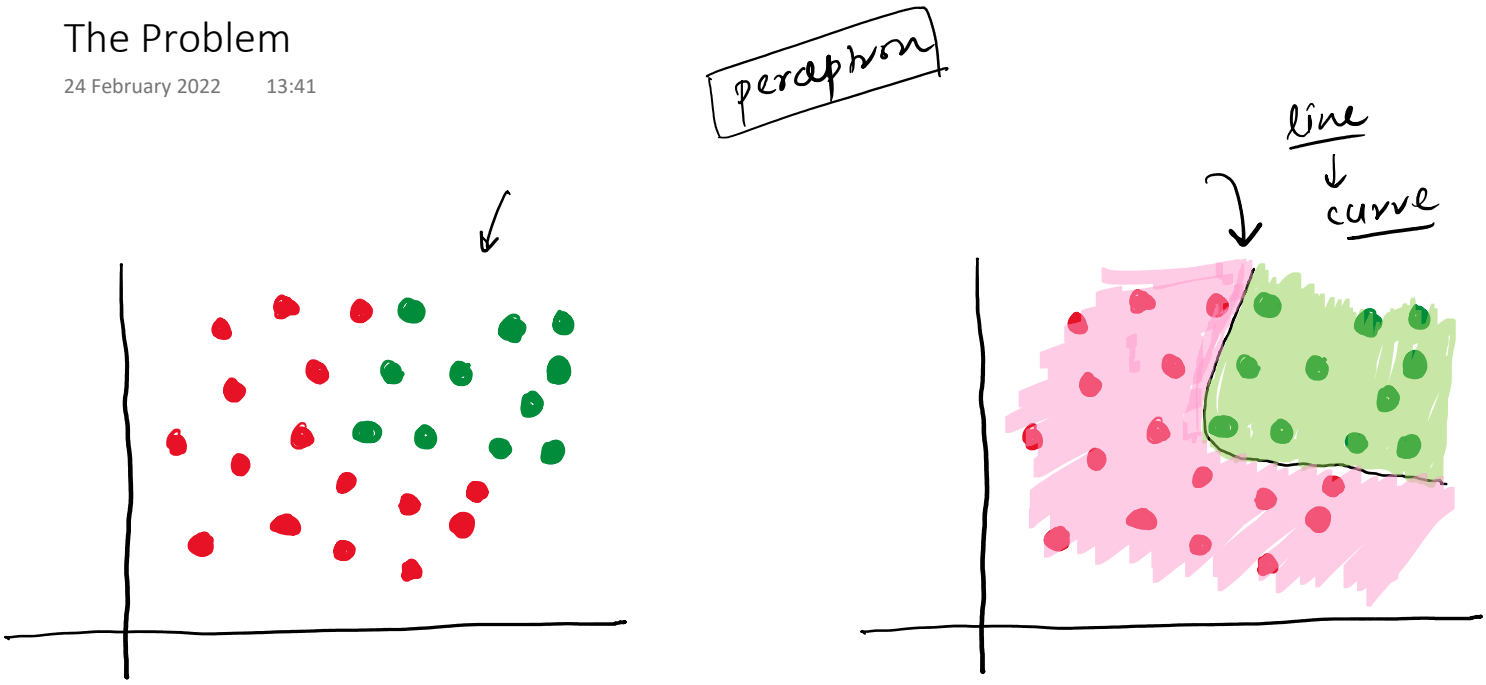
$(y_i - \hat{y}_i)^2$

Loss function	Activation	output
Hinge loss	Step	Perceptron → binary classifier (-1, 1)
log-loss	sigmoid	Logistic regression → binary


log-loss
(binary cross entro
sigmoid
Logistic regression
0-1
binary classifier
softmax regression
multiclass classifi
probabi
Categorical cross entropy
softmax
mse
linear
linear regresiin
numbr

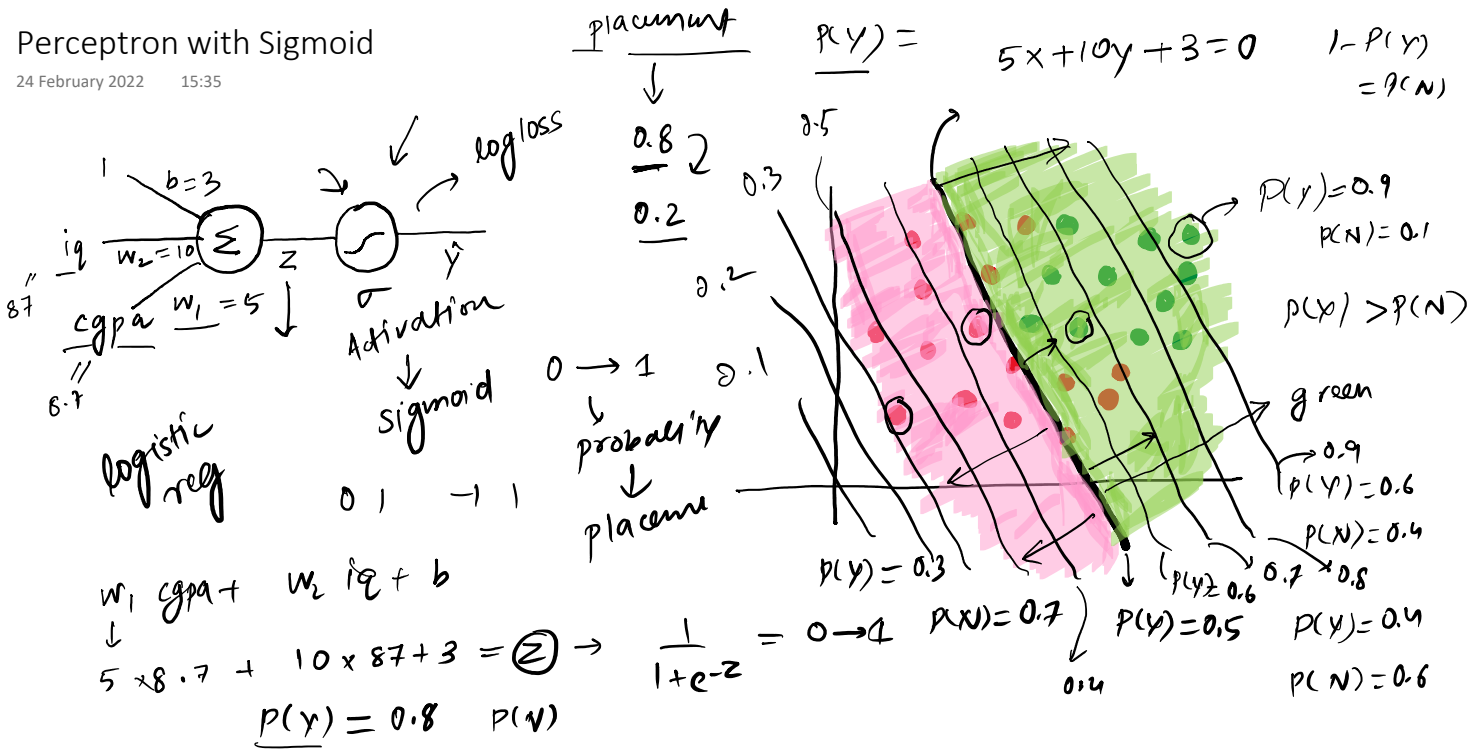
The Problem

24 February 2022 13:41



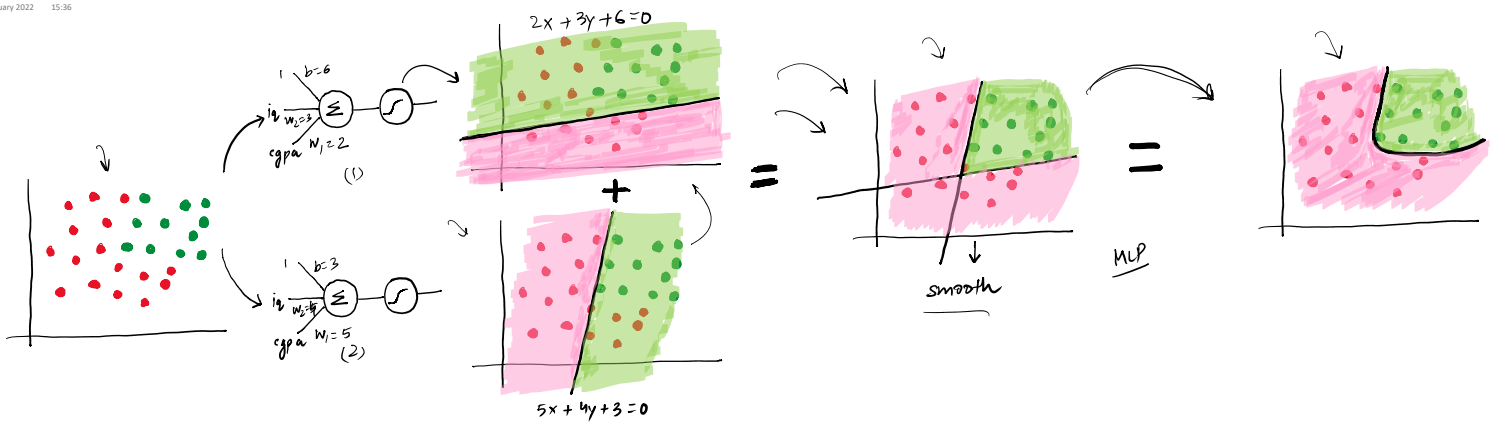
Perceptron with Sigmoid

24 February 2022 15:35



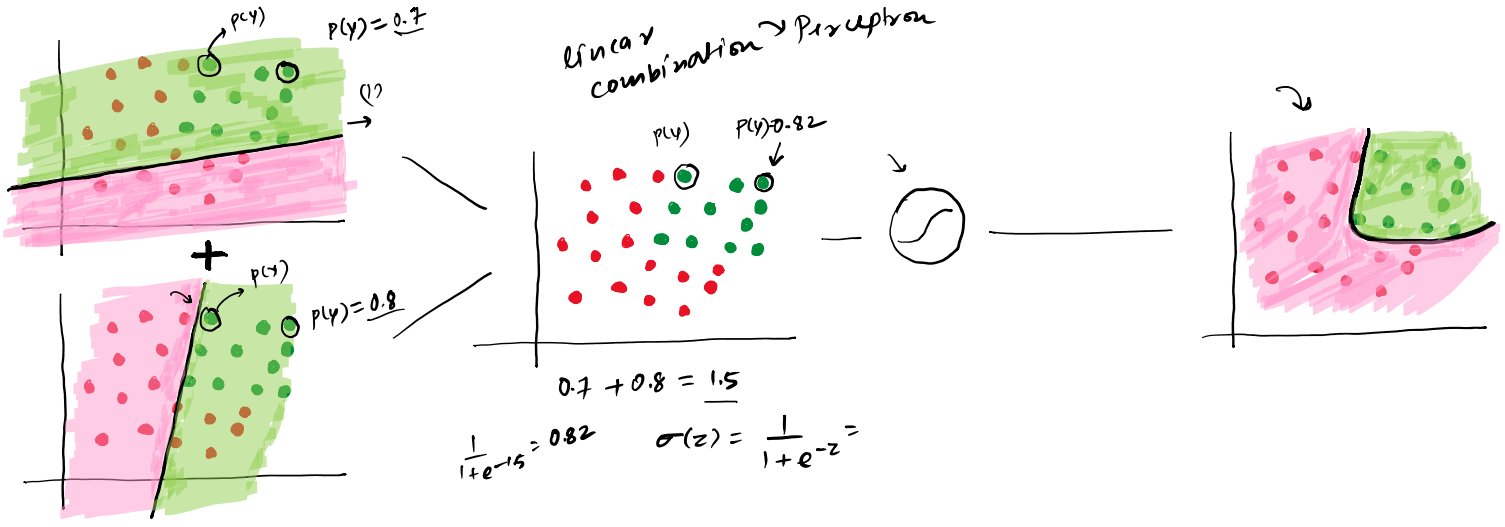
Abstract Solution

24 February 2022 15:36



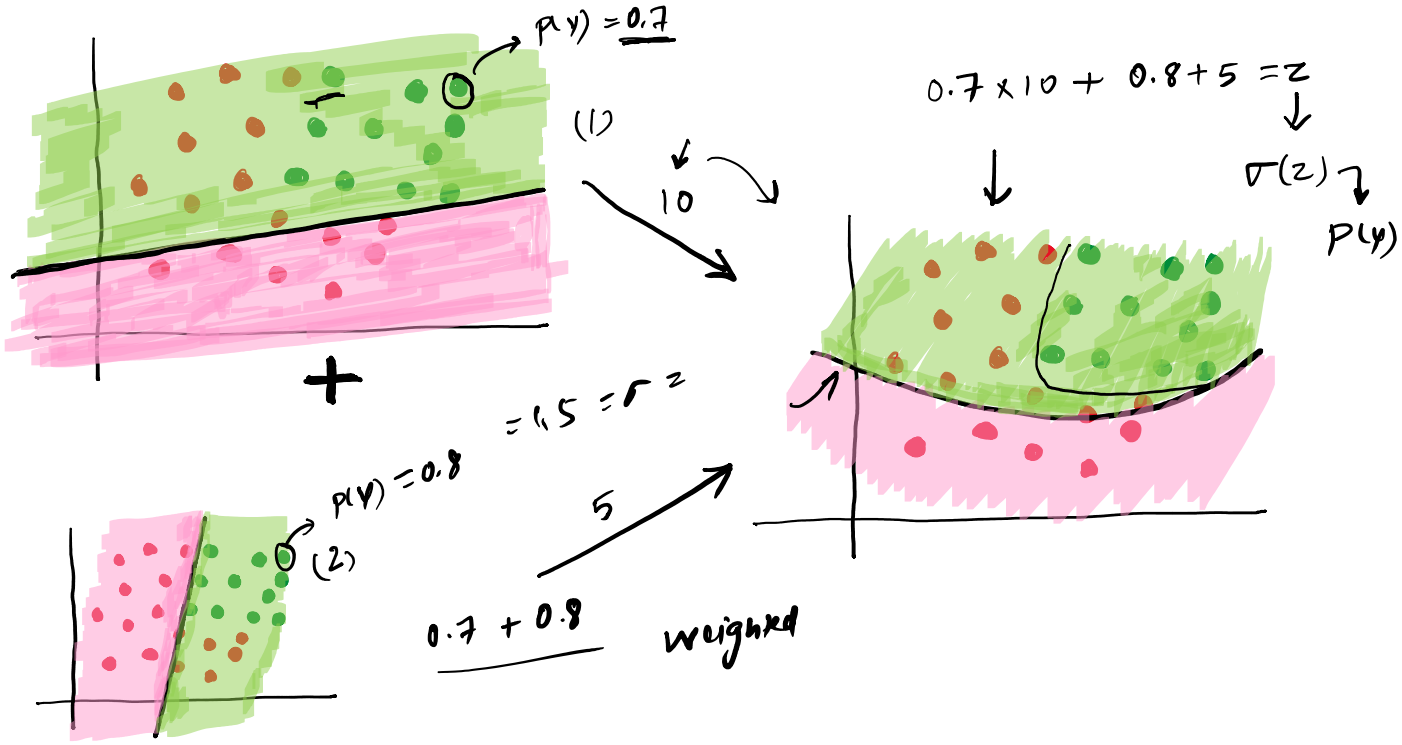
Mathematical Reasoning

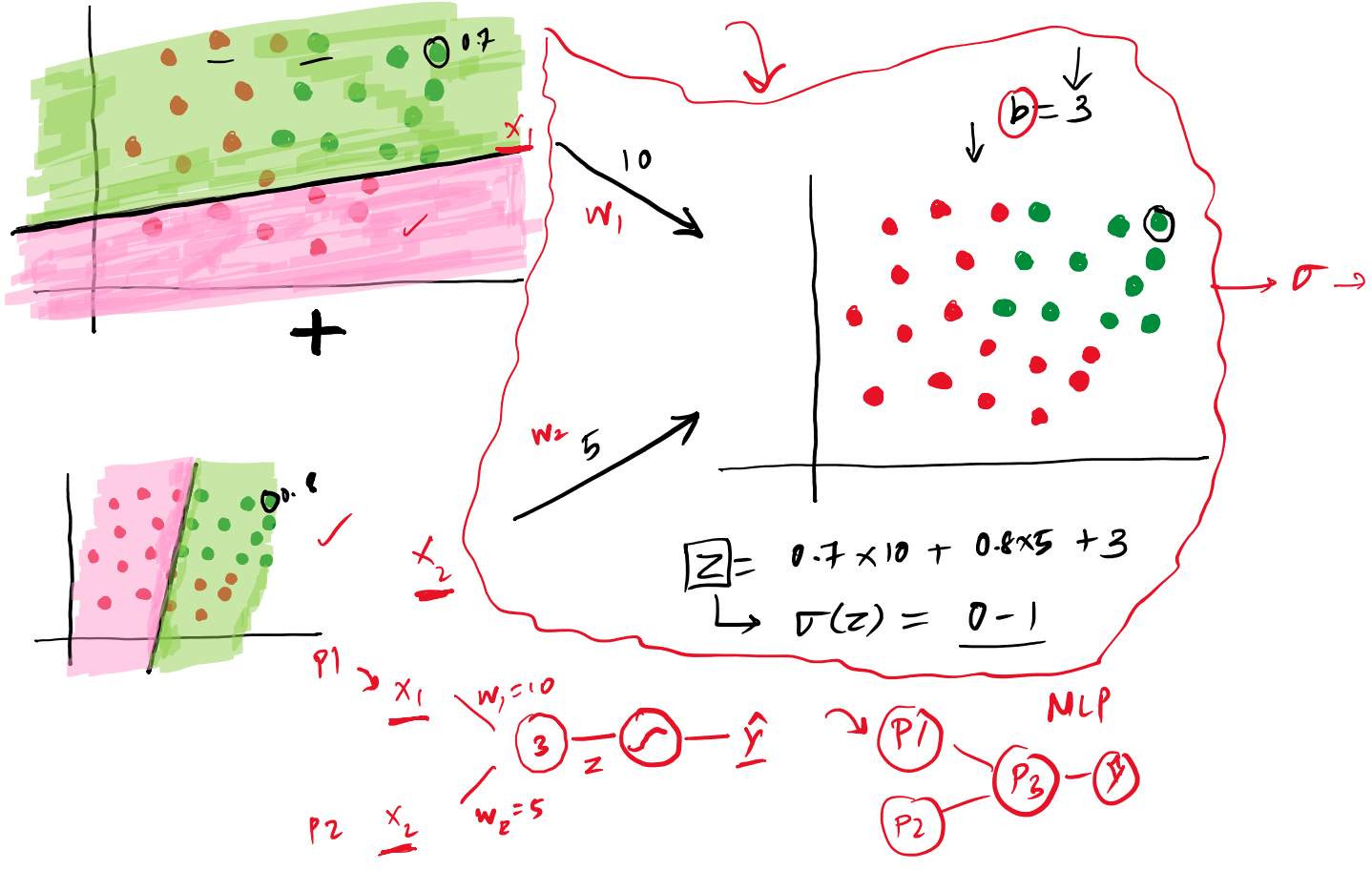
24 February 2022 15:36



Adding Weights

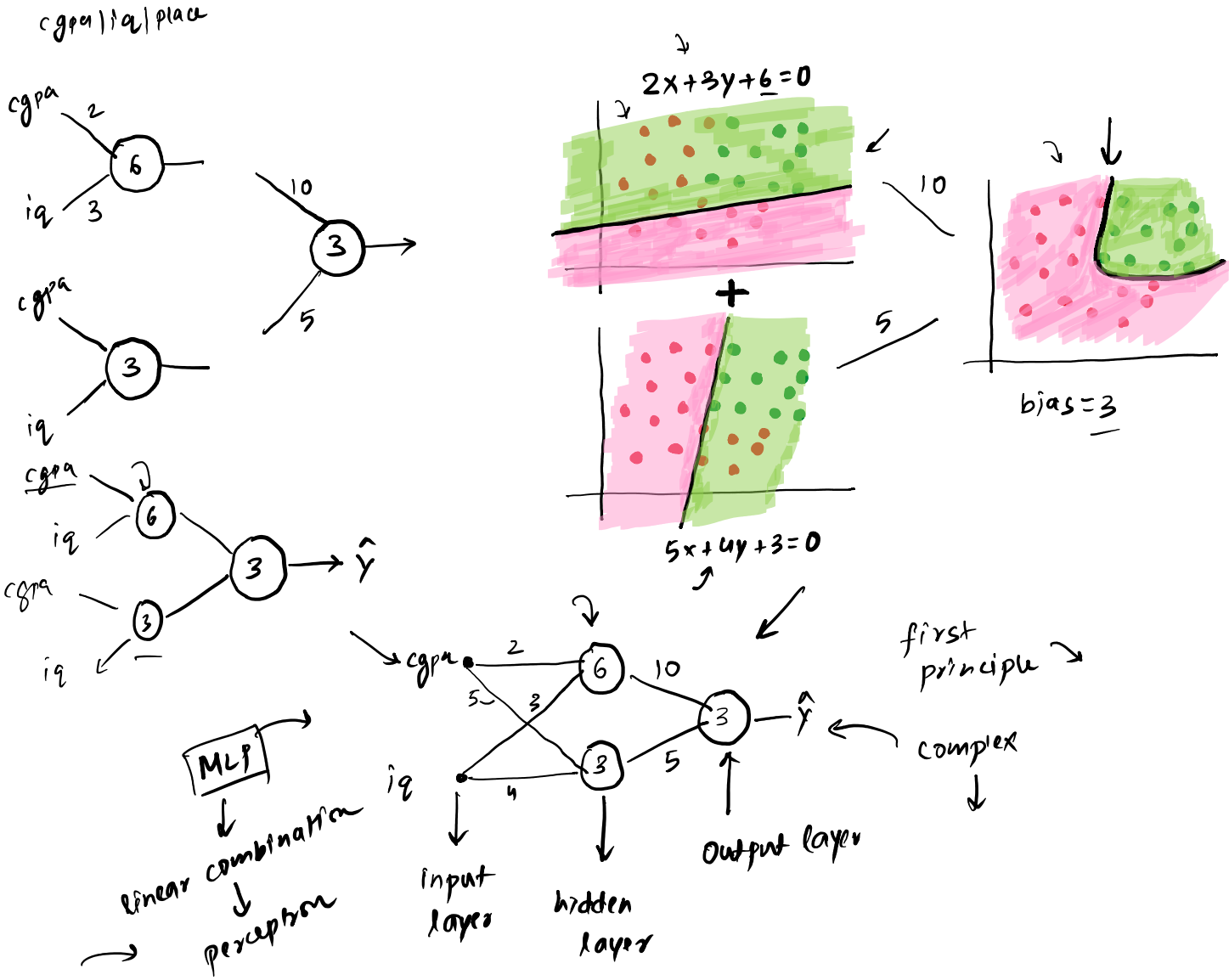
24 February 2022 15:37





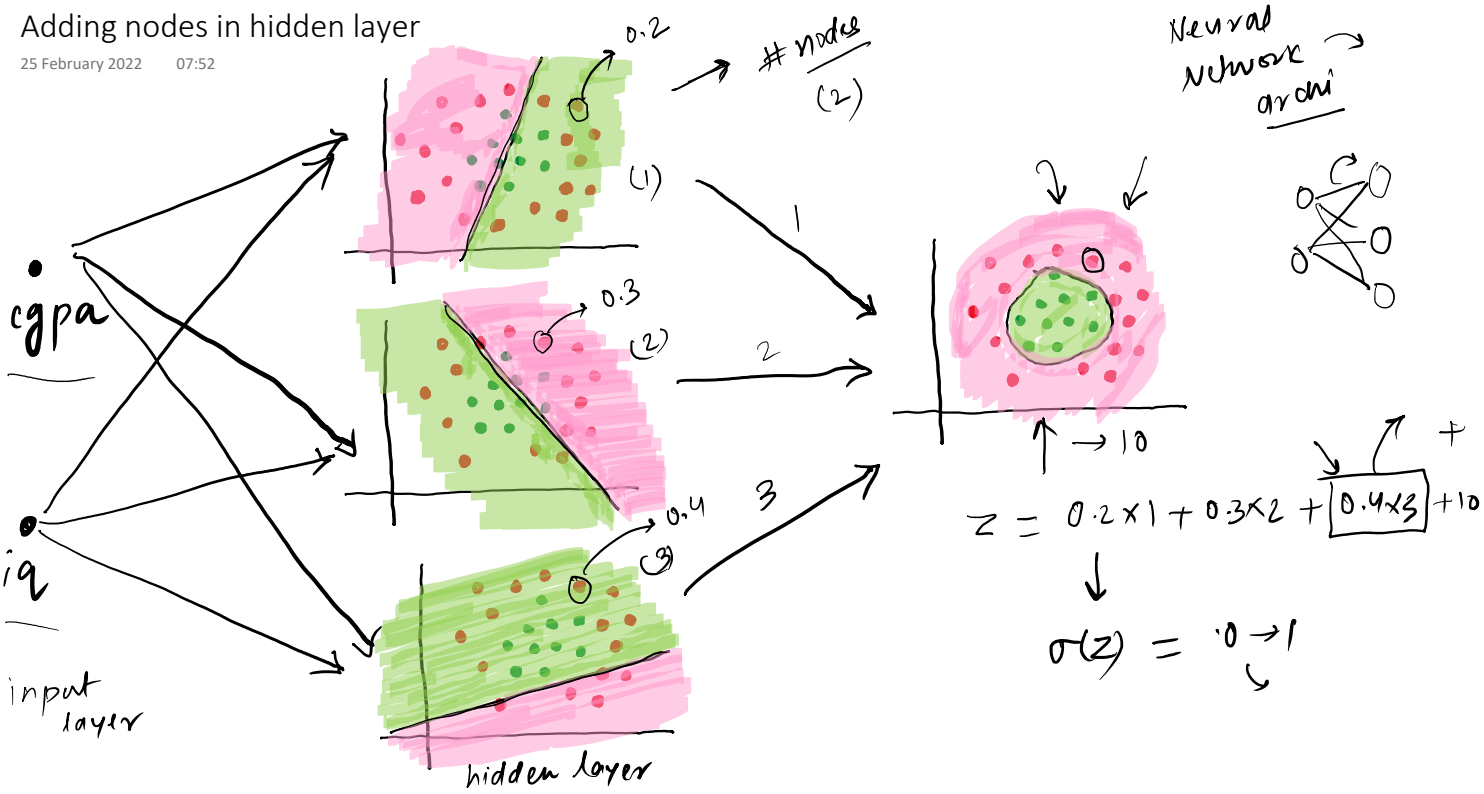
The Idea of MLP

24 February 2022 15:37



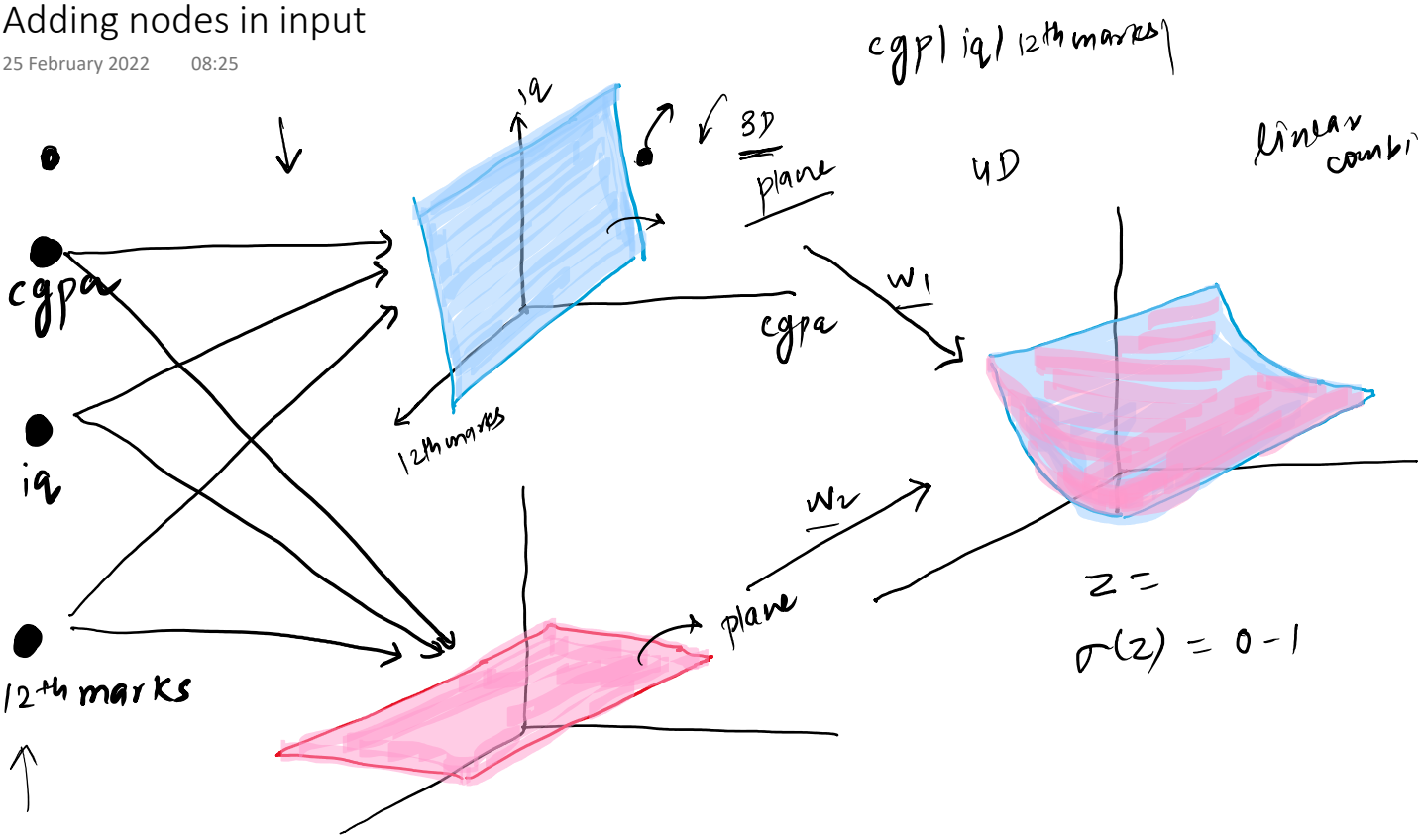
Adding nodes in hidden layer

25 February 2022 07:52



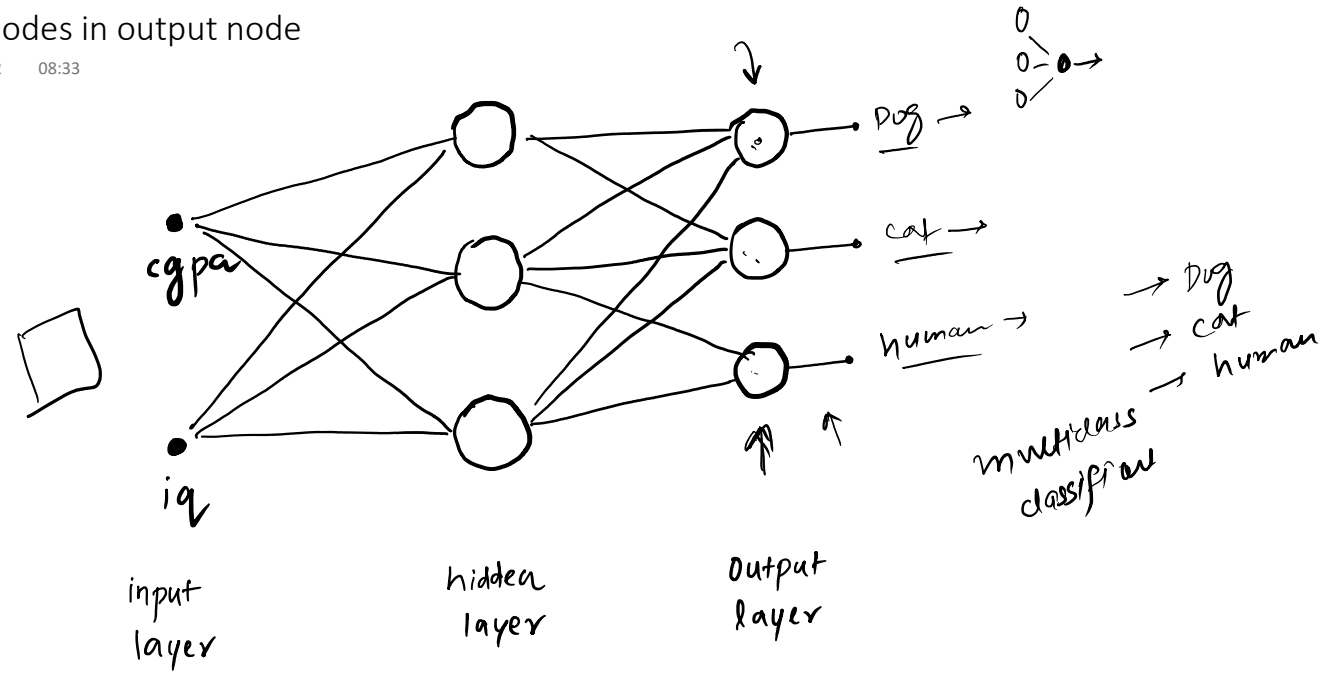
Adding nodes in input

25 February 2022 08:25



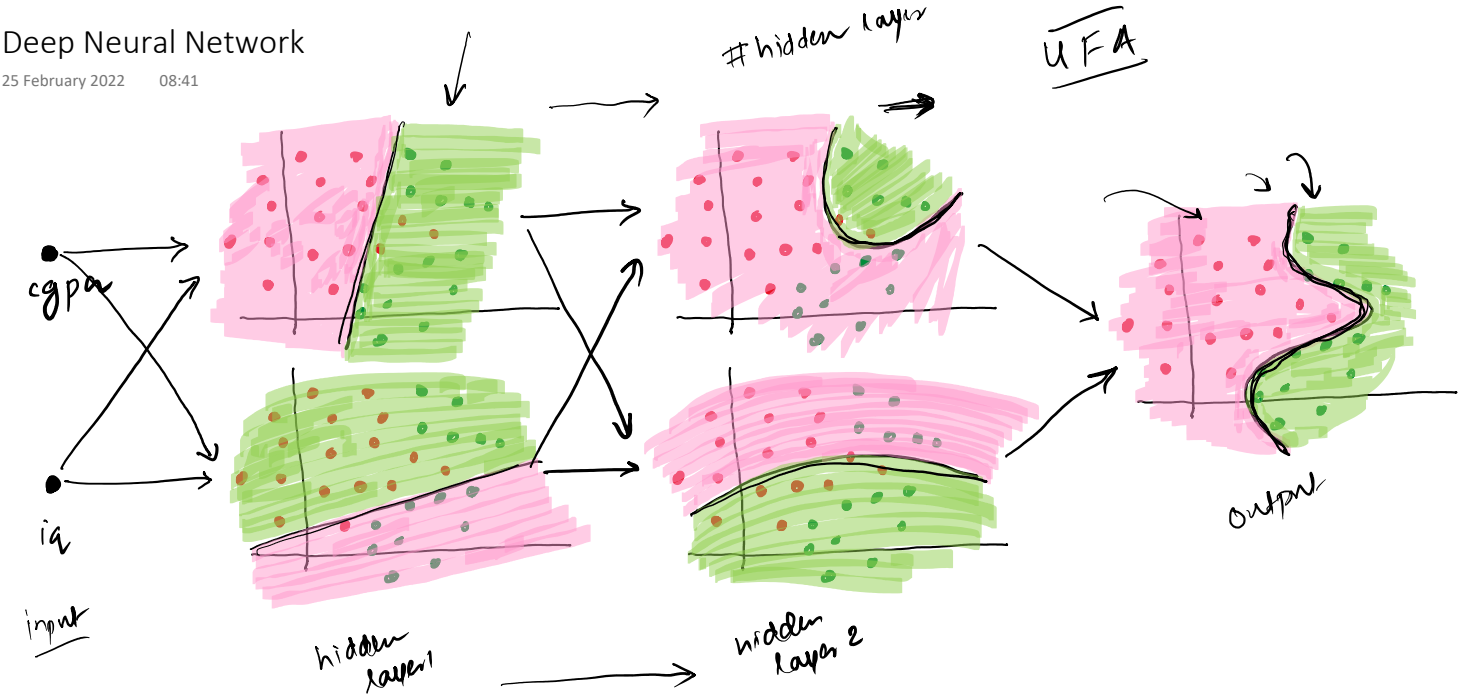
Adding nodes in output node

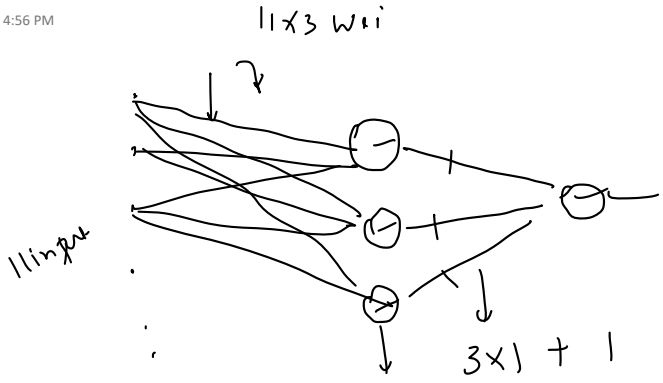
25 February 2022 08:33

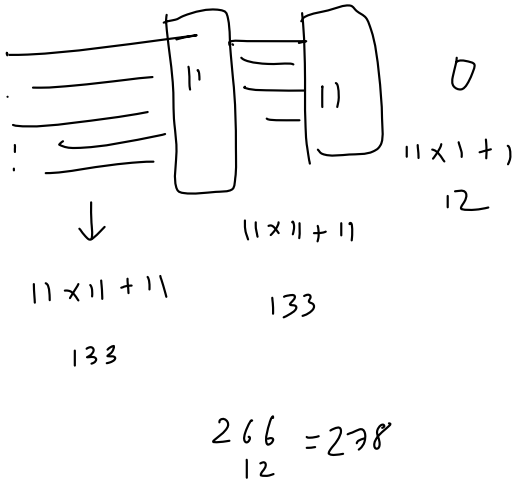


Deep Neural Network

25 February 2022 08:41

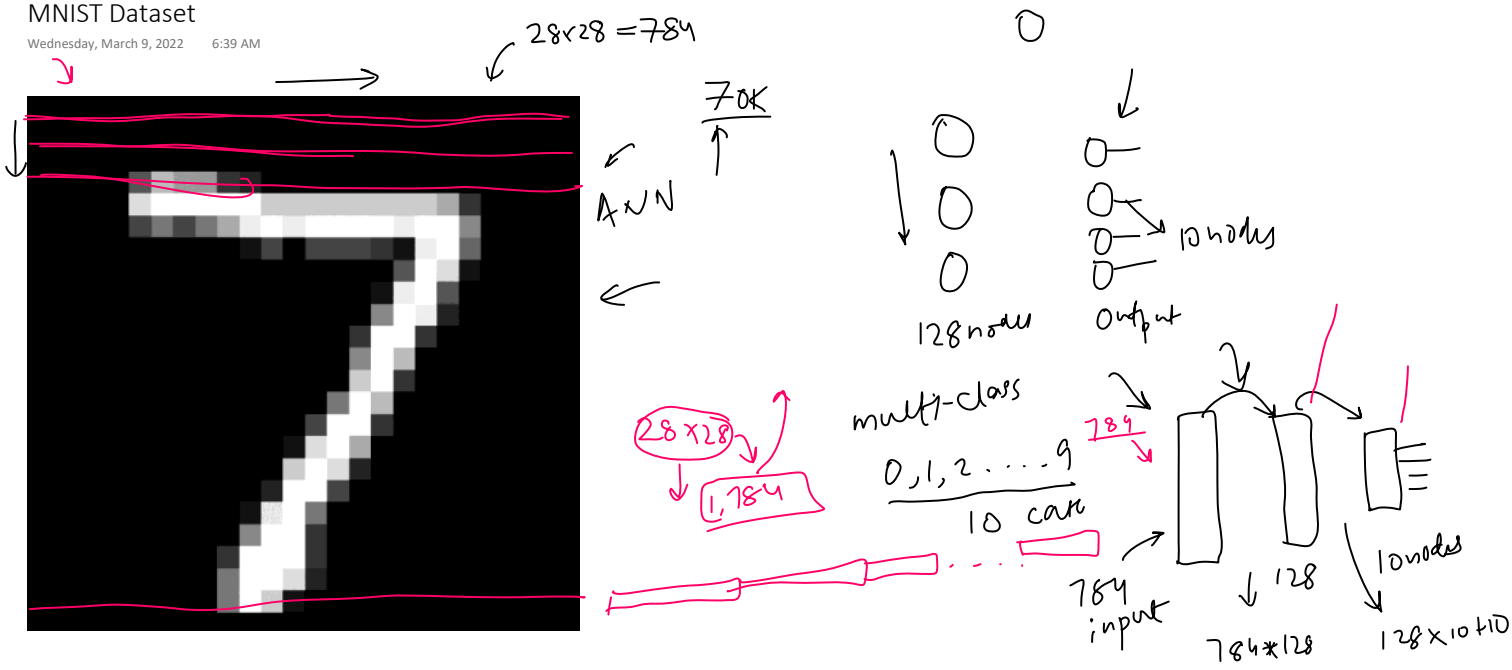


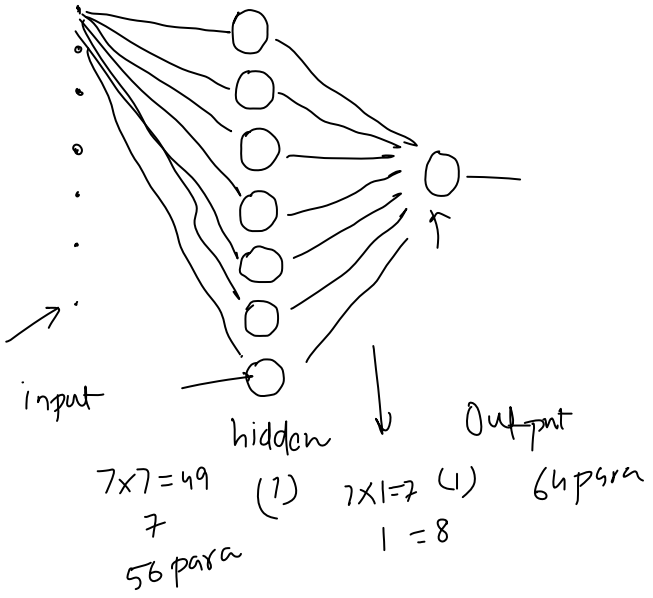

11x3 wei
11 inputs
3x1 + 1
11x3 +3
36
4 = 40


11
11
0
11x1 +1
12
11x11 + 11
133
11x11 + 11
133
266 = 278
12

MNIST Dataset

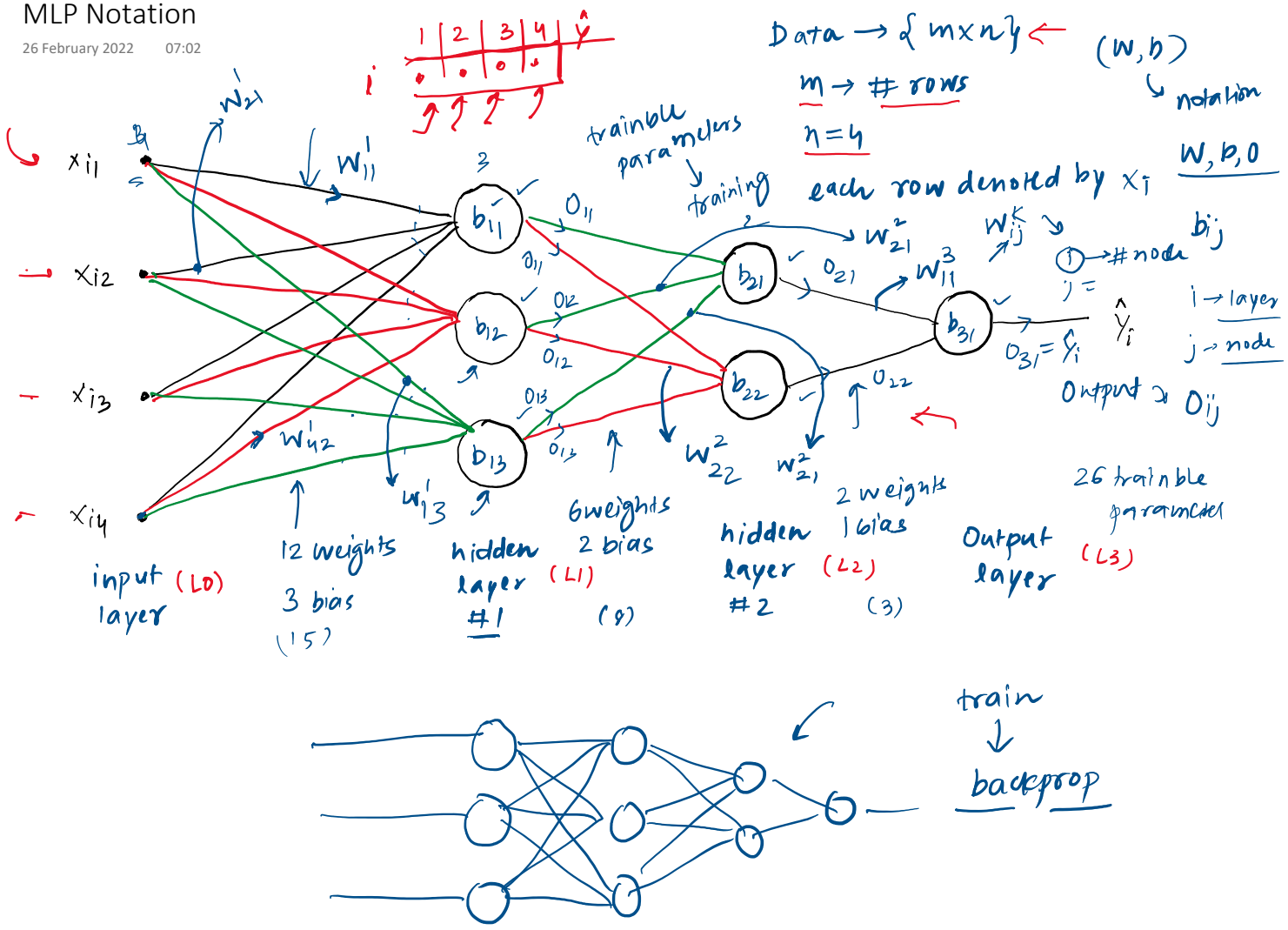
Wednesday, March 9, 2022 6:39 AM





MLP Notation

26 February 2022 07:02



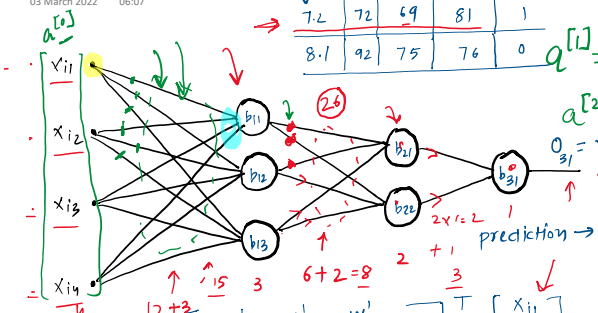
train → backprop

Forward Propogation

03 March 2022 06:07

cgpa	iq	10th m	12th m	placed
7.2	72	69	81	1
8.1	92	75	76	0

$\hat{y}$ → # of trainable parameters



$a^{[1]} = \sigma(a^{[0]} w^{[1]} + b^{[1]})$

$a^{[2]} = \sigma(a^{[1]} w^{[2]} + b^{[2]})$

$a^{[3]} = \sigma(a^{[2]} w^{[3]} + b^{[3]})$

prediction → $\sigma(w^T x + b)$ →

$\sigma(\sigma((\sigma(a^{[0]} w^{[1]} + b^{[1]})) w^{[2]} + b^{[2]}) w^{[3]} + b^{[3]})$

$a^{[1]}$ $a^{[2]}$

$a^{[3]} = \hat{y}$

Layer #1

$$\begin{bmatrix} w'_{11} & w'_{12} & w'_{13} \\ w'_{21} & w'_{22} & w'_{23} \\ w'_{31} & w'_{32} & w'_{33} \\ w'_{41} & w'_{42} & w'_{43} \end{bmatrix}^T \begin{bmatrix} x_{i1} \\ x_{i2} \\ x_{i3} \\ x_{i4} \end{bmatrix} + \begin{bmatrix} b_{11} \\ b_{12} \\ b_{13} \end{bmatrix}$$

4x3 → 3x4 (T) 3x1 4x1 3x1 → 3x1

$$= \begin{bmatrix} w'_{11} x_{i1} + w'_{21} x_{i2} + w'_{31} x_{i3} + w'_{41} x_{i4} \\ w'_{12} x_{i1} + w'_{22} x_{i2} + w'_{32} x_{i3} + w'_{42} x_{i4} \\ w'_{13} x_{i1} + w'_{23} x_{i2} + w'_{33} x_{i3} + w'_{43} x_{i4} \end{bmatrix} \begin{bmatrix} b_{11} \\ b_{12} \\ b_{13} \end{bmatrix}$$

3x1

$$= \sigma\left(\begin{bmatrix} w'_{11} x_{i1} + w'_{21} x_{i2} + w'_{31} x_{i3} + w'_{41} x_{i4} + b_{11} \\ w'_{12} x_{i1} + w'_{22} x_{i2} + w'_{32} x_{i3} + w'_{42} x_{i4} + b_{12} \\ w'_{13} x_{i1} + w'_{23} x_{i2} + w'_{33} x_{i3} + w'_{43} x_{i4} + b_{13} \end{bmatrix} \right)$$

$$= \begin{bmatrix} O_{11} \\ O_{12} \\ O_{13} \end{bmatrix} \rightarrow a^{[1]}$$

Layer #2

$$\begin{bmatrix} w^2_{11} & w^2_{12} \\ w^2_{21} & w^2_{22} \\ w^2_{31} & w^2_{32} \end{bmatrix}^T \begin{bmatrix} O_{11} \\ O_{12} \\ O_{13} \end{bmatrix} + \begin{bmatrix} b_{21} \\ b_{22} \end{bmatrix} \rightarrow$$

3x2 → 2x3 (T) 3x1 2x1

$$= \sigma\left(\begin{bmatrix} w^2_{11} O_{11} + w^2_{21} O_{12} + w^2_{31} O_{13} + b_{21} \\ w^2_{12} O_{11} + w^2_{22} O_{12} + w^2_{32} O_{13} + b_{22} \end{bmatrix} \right) = \begin{bmatrix} O_{21} \\ O_{22} \end{bmatrix} \leftarrow a^{[2]}$$

Layer #3

$$\rightarrow \begin{bmatrix} w^3_{11} \\ w^3_{21} \end{bmatrix}^T \begin{bmatrix} O_{21} \\ O_{22} \end{bmatrix} + \begin{bmatrix} b_{31} \end{bmatrix}$$

1x1

2x1 → 1x2 (T) 2x1

1x1

$$= \sigma\left(\begin{bmatrix} w^3_{11} O_{21} + w^3_{21} O_{22} + b_{31} \end{bmatrix} \right) = \hat{y}_i = [O_{31}] \quad a^{[3]}$$

What is Loss Function?

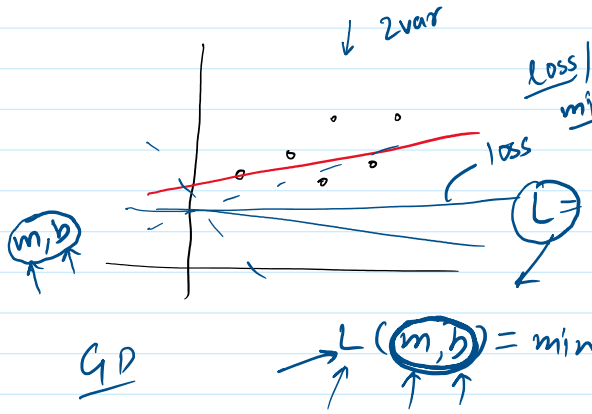
23 March 2022 07:15

high → poor

small → great

Loss function is a method of evaluating how well your algorithm is modelling your dataset.

$f(x) = x^2 + 2$



L (parameters)

Loss function eye of ML algorithm

Why is Loss function important?

[You can't improve what you can't measure.]

Peter Drucker

Loss Function in Deep Learning?

multiple epochs

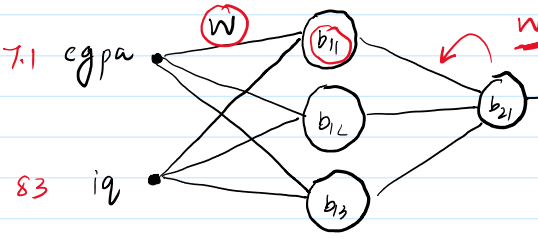
Backprop

random w, b → gradient descent

w, b

cgpa | iq | package(lpa)

7.1	83	3.2
8.5	91	4.5
6.3	102	6.1
5.1	87	2.7

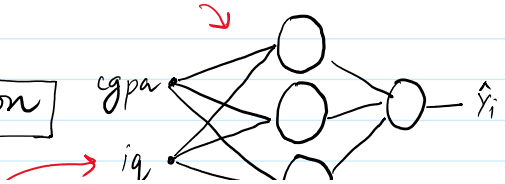


Keras

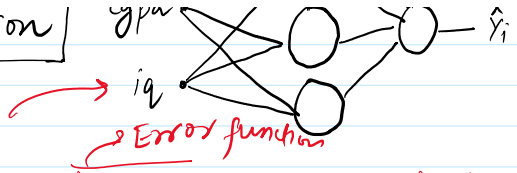
Loss functions in DL

- Object detection
  - focal loss
- Regression
  - mse
  - mae
  - huber loss
- Classification
  - binary cross entropy
  - categorical cross entro
  - hinge loss
- Autoencoders
  - KL divergence
- GAN
  - discriminator loss
  - min max gan loss
- Embedding
  - Triplet loss

Loss Function Vs Cost Function



Loss Function Vs Cost Function



Error function

Loss function → single training eg.

$y_i = 6.3 \quad \hat{y}_i = 6.1$

$(y_i - \hat{y}_i)^2$

$(6.3 - 6.1)^2 =$

batch Cost function

$\frac{1}{4}[(6.1-6.3)^2 + (4.1-4)^2 + (3.5-3.7)^2 + (7.2-7)^2] = CF$

$\frac{1}{n}\sum (y_i - \hat{y}_i)^2$

(5) lpa $\sqrt{5}$ lpa $(lpa)^2$

cgpa	iq	package (y_i)	Prediction ($\hat{y}_i$)	error $(y_i - \hat{y}_i)^2$
6.3	100	6.3	6.1	0.2 → 0.1
7.1	91	4.1	4	−0.2 → 0.2
8.5	83	3.5	3.7	
9.2	102	7.2	7	
8.1	100	50	8	overall error

1. Mean Squared Error (MSE)

Squared loss L2 Loss

$(y_i - \hat{y}_i)^2$

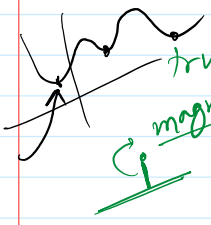
(true − predict)^2

$(6.3 - 6.1)^2 =$ —

$(y_i - \hat{y}_i)^2$

Advan / DisAdv

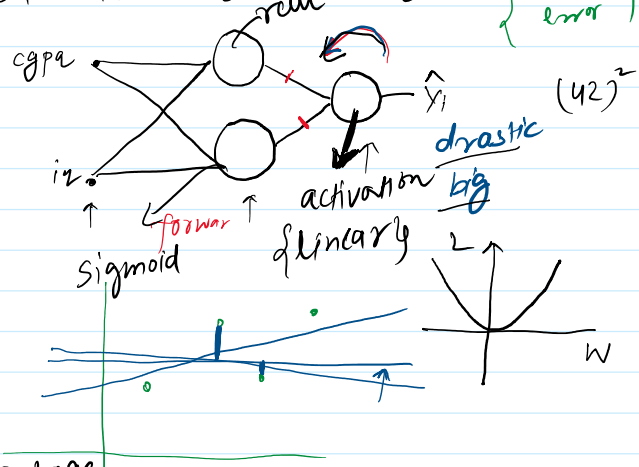
mae → $(y_i - \hat{y}_i)^2$ ← quadratic $\wedge 2$ punish



$(y_i - \hat{y}_i)^2$

(W, b) → (L) min

1 unit → 1 unit
2 unit → 4 unit
4 unit → 16 unit



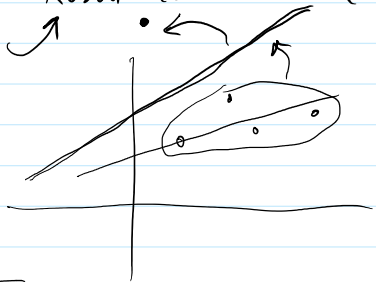
Advantages

1) Easy to interpret
2) Differentiable (GD)
3) 1 local minima

Disadvantage

1) Error unit (squared) → diff
2) Robut to Outliers (Not)

$CF = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$



mse

2. Mean Absolute Error (MAE) → L1 loss

2 lpa

cgpa | iq | package lpa | $|(y_i - \hat{y}_i)|$ → lpa

$L = |y_i - \hat{y}_i|$ 2 | abs

$C = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$ | true − predict |

punish

$C = \frac{1}{n}\sum_{i=1}^{n} |y_i - y_i|$ | true - predict |

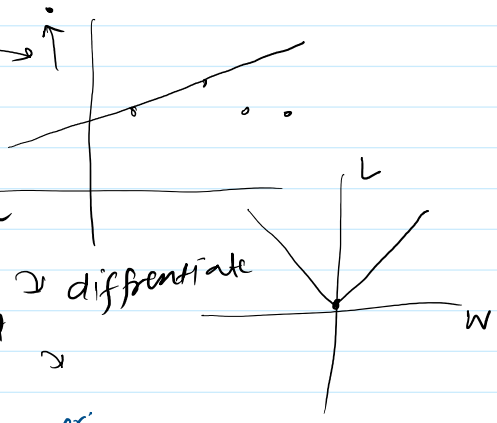
punish

Advantages

1) Intuitive and easy
2) Unit → same - y
3) Robust to outliers

Disadvantage

1) Not differentiable
   - GD ✗ differentiate
   - Subgradient ✓



mae huber mse

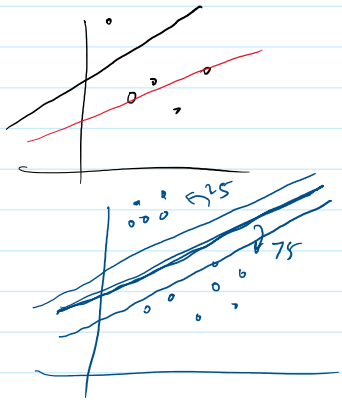
3. Huber Loss ✓

$$L = \begin{cases} \frac{1}{2}(y-\hat{y})^2 & \text{for } |y-\hat{y}| \le \delta \\ \delta|y-\hat{y}| - \frac{1}{2}\delta^2 & \text{otherwise} \end{cases}$$

mse — mae

hyper

mse — outliers ✓
mae — normal point ✓



4. Binary Cross Entropy

→ classification ✓
→ Two classes ✓

log loss

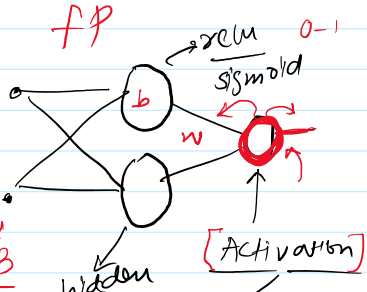
100 days

cgpa	iq	placement
8	80	1
7	70	0
6	60	0

1 0 GD fp

0.73
0.25
0.13

0.12



{sigmoid}

Loss function = $-y\log(\hat{y}) - (1-y)\log(1-\hat{y})$

Keras

y → actual value / target
ŷ → NN prediction

$-(1-0)\log(1-0.25)$
$-1\log(0.75)$
0.12 — 0.12

$-1\log(0.73)$
$-1 \times -0.13 = 0.13$

Cost function $= -\frac{1}{n}\left[\sum_{i=1}^{n} y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)\right]$

maximum likli

Logistic Reg

Advantage

* Differentiable

Disadvan

→ multi local minima
→ Intuitive

5. Categorical Cross Entropy [used in Softmax Regression]

→ [Multi-class classification] ✓

OHE

cgpa	iq	placed?	Yes	No	Maybe
		1			

5. Categorical Cross Entropy [used in softmax Regression]

→ [Multi-class] classification

1 point

$$L = -\sum_{j=1}^{K} y_j \log(\hat{y}_j)$$

cgpa	iq	placed?
8	80	Yes 1
6	60	No 2
7	70	Maybe 3

Yes	No	Maybe	
1	0	0	Yes
0	1	0	No
0	0	1	Maybe

where K is # classes in the data

1 point

$$L = -(y_1 \log(\hat{y}_1) + y_2 \log(\hat{y}_2) + y_3 \log(\hat{y}_3))$$

[0.2 0.3 0.5]

[1 0 0]

$L = -1 \times \log(0.2)$

$$\frac{e^{z_3}}{e^{z_1}+e^{z_2}+e^{z_3}}$$

$$\frac{e^{z_2}}{e^{z_1}+e^{z_2}+e^{z_3}}$$

$$\frac{e^{z_1}}{e^{z_1}+e^{z_2}+e^{z_3}}$$

$f(z) =$

softmax

GD

WB

8, 6, 60, 80

z_1 0.2 0-1 → Yes 0.3

z_2 0.3 0-1 → No 0.6

0.5 0-1 → Maybe 0.1

forward prop

Activation

neurons

class ← categories

[0.3 0.6 0.1]

[0 1 0]

$-1 \times \log(0.6) =$

Sparse categorical Cross Entropy

	cgpa	iq	placed	OHE
1/2/3	7	70	Yes	1
	8	80	No	2
	6	60	Maybe	3

[0.1 0.4 0.5]

L → $-1 \times \log(0.1)$

[0.1 0.4 0.6]

$-1 \times \log(0.4)$

[0.6 0.2 0.2]

$-1 \times \log(0.2)$

{SCE / CCE} Loss function

SCE → fast

fast

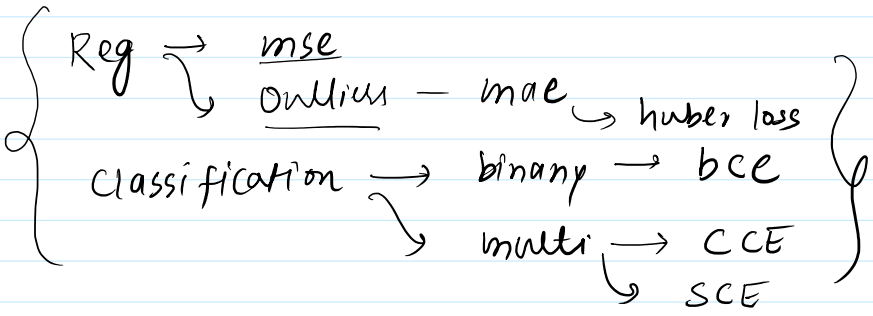
OHE — fast

SCE

$$L = -\sum_{j=1}^{K} y_j \log(\hat{y}_j)$$

Cost function

$$C = -\frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{K} y_{ij} \log(\hat{y}_{ij})$$


Reg
mse
outliers
mae
huber loss
classification
binary
bce
multi
CCE
SCE

23 March 2022 07:31

Backpropogation

30 March 2022 13:18

Pre requisite

→ Gradient Descent (v) →
→ Forward Propogation (v) →

Backprop → Algo → train nn (How)

training

cgpa	iq	lpa
8	80	8
7	70	7

weights, bias → correct value

$\sigma(z)$

$O_{21} = w^2_{11} O_{11} + w^2_{21} O_{12} + b_{21}$

predict (W, b)

6 + 3 → 9 trainable

Backprop

4 students

iq	cgpa	lpa	error so
80	8	3	225
60	9	5	
70	5	8	
120	7	11	

activation = linear

L min → $\hat{y} \to O_{21}$

$\hat{y} = O_{21}$ (W, b) Random val

$w \to 1, b \to 0$

18 lpa

$L = (y - \hat{y})^2$

$(3-18)^2 = 225$ error

Steps

0) Init w, b
1) You select a point (row) ↳ student
2) Predict (lpa) → forward poop [Dot product]
3) Choose a loss function (mse)
4) Weights and bias update
↳ Gradient Descent

Hierarchy: Backprop

$$w_{new} = w_{old} - \eta \frac{\partial L}{\partial w_{old}}$$

$\eta = 0.1$

$$w^2_{11\,new} = w^2_{11\,old} - \eta \frac{\partial L}{\partial w^2_{11}}$$

$\frac{\partial L}{\partial w^2_{11}}$ derivative

$$b_{new} = b_{old} - \eta \frac{\partial L}{\partial b_{old}}$$

$$w^2_{21\,new} = w^2_{21\,old} - \eta \frac{\partial L}{\partial w^2_{21}}$$

$$b_{21\,new} = b_{21\,old} - \eta \frac{\partial L}{\partial b_{21}}$$

derivative of loss wrt weight

$\frac{\partial L}{\partial w^2_{11}}$ partial derivative

derivative

$\frac{\partial L}{\partial w^2_{11}}, \frac{\partial L}{\partial w^2_{21}}, \frac{\partial L}{\partial b_{21}}$ | $\frac{\partial L}{\partial w^1_{11}}, \frac{\partial L}{\partial w^1_{21}}, \frac{\partial L}{\partial b_{11}}$ | $\frac{\partial L}{\partial w^1_{12}}, \frac{\partial L}{\partial w^1_{22}}, \frac{\partial L}{\partial b_{12}}$

$$\frac{\partial L}{\partial w^2_{11}} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial w^2_{11}}$$ → chain rule of differn

$$\frac{\partial L}{\partial \hat{y}} = \frac{\partial}{\partial \hat{y}} (y - \hat{y})^2 = -2(y - \hat{y})$$

$$\frac{\partial \hat{y}}{\partial w^2_{11}} = \frac{\partial}{\partial w^2_{11}} [O_{11} w^2_{11} + O_{12} w^2_{21} + b_{21}]$$

$$= O_{11}$$

$$\frac{\partial L}{\partial w^2_{11}} = -2(y - \hat{y}) O_{11}$$

$$\frac{\partial L}{\partial w^2_{21}} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial w^2_{21}}$$

$$\frac{\partial \hat{y}}{\partial w^2_{21}} = \frac{\partial}{\partial w^2_{21}} [O_{11} w^2_{11} + O_{12} w^2_{21} + b_{21}]$$

$$= O_{12}$$

$$\frac{\partial L}{\partial w^2_{21}} = -2(y - \hat{y}) O_{12}$$

$\hat{y} \to b$

$$\frac{\partial \hat{y}}{\partial b_{21}} = 1$$

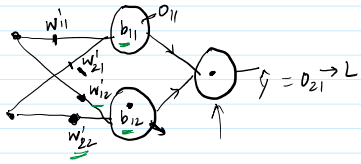
$$\frac{\partial L}{\partial w_{21}^2} = -2(y-\hat{y})\,o_{12}$$ 2

$$\frac{\partial L}{\partial b_{21}} = -2(y-\hat{y})$$ 3

$\hat{y} \to b$ (L)

$$\frac{\partial \hat{y}}{\partial b_{21}} = 1$$

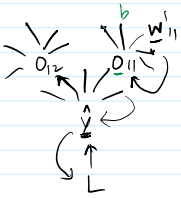
$$\frac{\partial L}{\partial b_{21}} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial b_{21}}$$



$$\frac{\partial L}{\partial w_{11}^1} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_{11}} \frac{\partial o_{11}}{\partial w_{11}^1} \to -2(y-\hat{y})\, w_{11}^2\, x_{i1}$$ 4

$$\frac{\partial L}{\partial w_{21}^1} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_{11}} \frac{\partial o_{11}}{\partial w_{21}^1} \to -2(y-\hat{y})\, w_{11}^2\, x_{i2}$$ 5

$$\frac{\partial L}{\partial b_{11}} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_{11}} \frac{\partial o_{11}}{\partial b_{11}} \to -2(y-\hat{y})\, w_{11}^2$$ 6



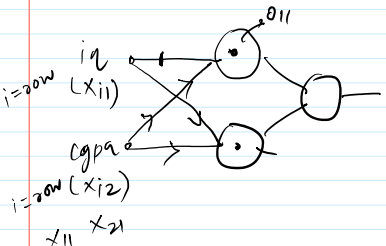
$$\frac{\partial L}{\partial w_{12}^1} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_{12}} \frac{\partial o_{12}}{\partial w_{12}^1} \to -2(y-\hat{y})\, w_{21}^2\, x_{i1}$$ 7

$$\frac{\partial L}{\partial w_{22}^1} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_{12}} \frac{\partial o_{12}}{\partial w_{22}^1} \to -2(y-\hat{y})\, w_{21}^2\, x_{i2}$$ 8

$$\frac{\partial L}{\partial b_{12}} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial o_{12}} \frac{\partial o_{12}}{\partial b_{12}} \to -2(y-\hat{y})\, w_{21}^2$$ 9

w_{11}^2

$\frac{\partial \hat{y}}{\partial o_{12}} = w_{21}^2$



$$\frac{\partial o_{11}}{\partial w_{11}^1} = \frac{\partial}{\partial w_{11}^1}\left[iq\, w_{11}^1 + cgpa\, w_{21}^1 + b_{11} \right] = (iq) = x_{i1}$$

$$\frac{\partial o_{11}}{\partial w_{21}^1} = x_{i2}$$

$$\frac{\partial o_{11}}{\partial b_{11}} = 1$$

$$\frac{\partial o_{12}}{\partial w_{12}^1} = \frac{\partial}{\partial w_{12}^1}\left[iq\, w_{12}^1 + cgpa\, w_{22}^1 + b_{12} \right] = iq\,(x_{i1})$$

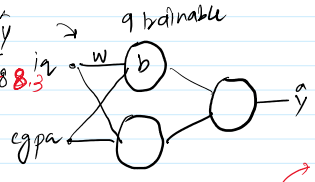
$$\frac{\partial o_{12}}{\partial w_{22}^1} = x_{i2}$$

$$\frac{\partial o_{12}}{\partial b_{12}} = 1$$

epochs

multiple changes

	cgpa	iq	lpa	$\hat{y}$
usw	8	80	8	8.3
	6	60	6	
	7	70	7	
	9	90		



Steps (once again)

0) weights/bias → init (random: w=1, b=0)

Loop-100/100 (converge)

1) for i in range(4):

1a) 1 student → forward prop → lpa → 12 min

1b) Loss calculate (mse) →

1c) Adjust all weights and biases ↻.

4D → 9 times

$$w_{new} = w_{old} - \eta \frac{\partial L}{\partial w_{old}}$$

The How

Backpropagation Algorithm

epochs = 5

for i in range(epochs):

    for j in range(X.shape[0]):

$$\frac{\partial L}{\partial w_{11}^2} = -2(y-\hat{y})\, o_{11}$$

$$\frac{\partial L}{\partial w_{21}^2} = -2(y-\hat{y})\, o_{12}$$

Ready

```
for i in range(epochs):
    for j in range(X.shape[0]):
        → Select 1 row (random)
        → Predict (using Forward prop)
        → Calculate loss (using loss function → mse)
        ↑
        → Update weights and bias using GD
              w_n = w_o - η · ∂L/∂w
    → Calculate avg loss for the epoch
      Loss
```

$$\frac{\partial L}{\partial w^2_{21}} = -2(y-\hat{y})o_{12}$$

$$\frac{\partial L}{\partial b_{21}} = -2(y-\hat{y})$$

$$\frac{\partial L}{\partial w^1_{11}} = -2(y-\hat{y})w^2_{11}x_{i1}$$

$$\frac{\partial L}{\partial w^1_{21}} = -2(y-\hat{y})w^2_{11}x_{i2}$$

$$\frac{\partial L}{\partial b_{11}} = -2(y-\hat{y})w^2_{11}$$

$$\frac{\partial L}{\partial w^1_{12}} = -2(y-\hat{y})w^2_{21}x_{i1}$$

$$\frac{\partial L}{\partial w^1_{22}} = -2(y-\hat{y})w^2_{21}x_{i2}$$

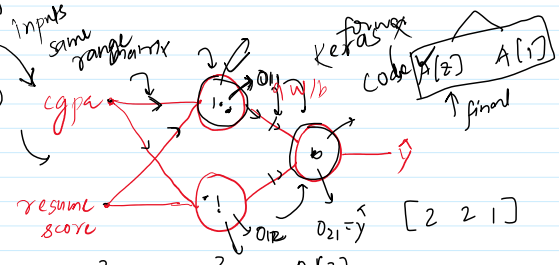
$$\frac{\partial L}{\partial b_{12}} = -2(y-\hat{y})w^2_{21}$$

Regression Problem — 80-120

cgpa (x_{i1})	resume score (x_{i2})	package (lpa)
8	8	4
7	9	5
6	10	6
5	12	7

4 students

NN inputs same range matrix

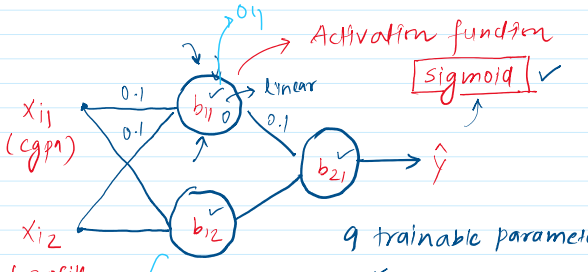


Keras forward code: A[1] = f(z) A[2] ← final

code: A[0] → [8 8]

Classification Example

cgpa	profile score	placement
8	8	1
7	9	1
6	10	0
5	5	0



$z = 0.1 \times 8 + 0.1 \times 8 + 0$

$f(z) = O_{11}$

Backpropagation Algorithm

```
epochs = 5
for i in range(epochs):  (rows)
    for j in range(X.shape[0]):
        → Select 1 row (random)  → 1by1
        → Predict (using Forward prop)  → predict
        → Calculate loss (using loss function → bce)  → code convert
        ↑
        → Update weights and bias using GD
```

Backpropagation Algorithm

cross entropy

epochs = 5 ✓

for i in range(epochs): (rows)

  for j in range(X.shape[0]):

  → Select 1 row (random) → 1by1

  → Predict (using Forward prop) → predict

  → Calculate loss (using loss function → bce) → {code convert}

  → Update weights and bias using GD

$$w_n = w_0 - \eta \frac{\partial L}{\partial w}$$

q w, b update

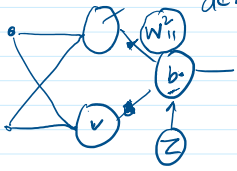
  → Calculate avg loss for the epoch

Lavg

$z = w_{11}^2 o_{11} + w_{21}^2 o_{12} + b_{21}$

$\hat{y} = \sigma(z)$

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



$\hat{y} \to L$ der wrt L

$z_{final} = w_{11}^2 o_{11} + w_{21}^2 o_{12} + b_{21}$

$z_{final} \to \hat{y} \to L$

$w_{11}^2 \times w_{21}^2$

$$\frac{\partial L}{\partial w_{11}^2} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z} \times \frac{\partial z}{\partial w_{11}^2} = -(y-\hat{y})\, o_{11} \quad (3)$$

$$\frac{\partial L}{\partial w_{21}^2} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z} \times \frac{\partial z}{\partial w_{21}^2} = -(y-\hat{y})\, o_{12}$$

$$\frac{\partial L}{\partial b_{21}} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z} \times \frac{\partial z}{\partial b_{21}} = -(y-\hat{y})$$

$$\frac{\partial L}{\partial \hat{y}} = \frac{\partial}{\partial \hat{y}}\left[-y \log(\hat{y}) - (1-y)\log(1-\hat{y})\right]$$

$$= -\frac{y}{\hat{y}} + \frac{(1-y)}{(1-\hat{y})} = \frac{-y(1-\hat{y}) + \hat{y}(1-y)}{\hat{y}(1-\hat{y})} = \frac{-y + y\hat{y} + \hat{y} - y\hat{y}}{\hat{y}(1-\hat{y})}$$

$$= \frac{-(y-\hat{y})}{\hat{y}(1-\hat{y})}$$

$\hat{y} = \sigma(z)$

$\frac{\partial}{\partial z}\sigma(z) = \sigma(z)[1-\sigma(z)]$

$\sigma(z) = \hat{y}$

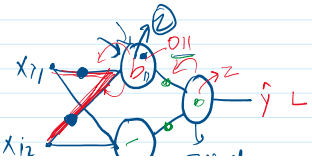
$$\frac{\partial \hat{y}}{\partial z} = \frac{\partial}{\partial z}(\sigma(z)) = \sigma(z)[1-\sigma(z)] = \hat{y}(1-\hat{y})$$

$$\frac{\partial L}{\partial \hat{y}} = \frac{-(y-\hat{y})}{\hat{y}(1-\hat{y})} \qquad \frac{\partial \hat{y}}{\partial z} = \hat{y}(1-\hat{y}) \Rightarrow \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z} = \frac{-(y-\hat{y})}{\hat{y}(1-\hat{y})} \times \hat{y}(1-\hat{y})$$

$\to -(y-\hat{y})$

$z_p = w_{11}' x_{11} + w_{21}' x_{12} + b_{11}$

$\frac{\partial z_p}{\partial w_{11}'}$

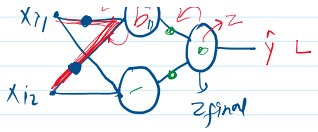


$\frac{\partial L}{\partial w_{11}'}, \frac{\partial L}{\partial w_{21}'}, \frac{\partial L}{\partial b_{11}}$

$\to -(y-\hat{y})$

$z_f = w_{11}^2 o_{11} + w_{21}^2 o_{12} + b_{21}\, o_{11}(1-o_{11})$

$o_{11} = \sigma(z_{prev})$



$\frac{\partial L}{\partial w^1_{11}}$, $\frac{\partial L}{\partial w^1_{21}}$, $\frac{\partial L}{\partial b_{11}}$

$z_f = w^2_{11} o_{11} + w^2_{21} o_{12} + b_{21}$ $o_{11}(1-o_{11})$

$o_{11} = \sigma(z_{prev})$

$= \sigma(z_{prev})[1-\sigma(z_{prev})]$

$L \to \hat{y} \to z_f \to o_{11} \to z_{prev} \to w^1_{11}$

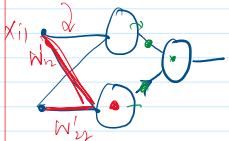
$$\frac{\partial L}{\partial w^1_{11}} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z_f} \times \frac{\partial z_f}{\partial o_{11}} \times \frac{\partial o_{11}}{\partial z_{prev}} \times \frac{\partial z_{prev}}{\partial w^1_{11}}$$

$-(y-\hat{y})$; $\frac{\partial z_f}{\partial o_{11}} \to w^2_{11}$; $\frac{\partial o_{11}}{\partial z_{prev}} \to o_{11}(1-o_{11})$; $\frac{\partial z_{prev}}{\partial w^1_{11}} \to x_{i1}$

$$\boxed{\frac{\partial L}{\partial w^1_{11}} = -(y-\hat{y}) w^2_{11} o_{11}(1-o_{11}) x_{i1}} \quad (3)$$

$$\boxed{\frac{\partial L}{\partial w^1_{21}} = -(y-\hat{y}) w^2_{11} o_{11}(1-o_{11}) x_{i2}}$$

$$\boxed{\frac{\partial L}{\partial b_{11}} = -(y-\hat{y}) w^2_{11} o_{11}(1-o_{11})}$$



$\frac{\partial L}{\partial w^1_{12}}$, $\frac{\partial L}{\partial w^1_{22}}$, $\frac{\partial L}{\partial b_{12}}$

$\frac{\partial z_f}{\partial o_{12}} = w^2_{11} o_{11} + w^2_{21} o_{12} + b_{21}$

$L \to \hat{y} \to z_f \to o_{12} \to z_p \to w^1_{12}$

$$\frac{\partial L}{\partial w^1_{12}} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z_f} \times \frac{\partial z_f}{\partial o_{12}} \times \frac{\partial o_{12}}{\partial z_p} \times \frac{\partial z_p}{\partial w^1_{12}}$$

$\frac{\partial z_f}{\partial o_{12}} \to w^2_{21}$; $\frac{\partial o_{12}}{\partial z_p} \to o_{12}(1-o_{12})$; $\frac{\partial z_p}{\partial w^1_{12}} \to x_{i1}$

$$\boxed{\frac{\partial L}{\partial w^1_{12}} = -(y-\hat{y}) w^2_{21} o_{12}(1-o_{12}) x_{i1}} \quad (3)$$

$$\boxed{\frac{\partial L}{\partial w^1_{22}} = -(y-\hat{y}) w^2_{21} o_{12}(1-o_{12}) x_{i2}}$$

$$\boxed{\frac{\partial L}{\partial b_{12}} = -(y-\hat{y}) w^2_{21} o_{12}(1-o_2)}$$

Backpropagation → The Why?

The intuition behind the algorithm ✓

Backpropagation Algorithm

epochs = 5 ✓ → # epochs × rows

for i in range(epochs):

  for j in range(X.shape[0]):

    → select 1 row (random)

    → Predict (using Forward prop) → $\hat{y}$ y

    → Calculate loss (using loss function → mse) → bce

    → Update weights and bias using GD

      ↳ $w_n = w_0 - \eta \frac{\partial L}{\partial w}$ rule

      magic

  → Calculate avg loss for the epoch

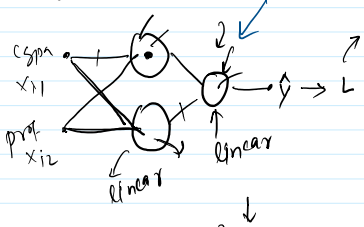
  ↳ avg

→ Loss function is a function of all trainable parameters

data → target

$L = (y - \hat{y})^2$

cgpa | profile | lpa



$L = (y - \hat{y})^2$ → mathematical function

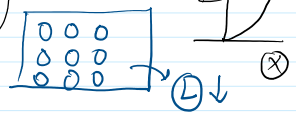
constant

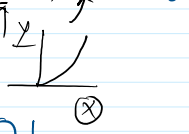
$L(?)$ → $L(\hat{y}) =$

$y = f(x)$ 1 thing

$L(w, b)$ ↓

9 things → w, b





L ↓

$$\hat{y} = w_{11}^2 o_{11} + w_{21}^2 o_{12} + b_{21}$$

$$\hat{y} = w_{11}^2 \left[w_{11}^1 x_{i1} + w_{21}^1 x_{i2} + b_{11} \right] + w_{21}^2 \left[w_{12}^1 x_{i1} + w_{22}^1 x_{i2} + b_{12} \right] + b_{12}$$

→ Concept of Gradient → Gradient Descent

↳ fancy word for derivative

$y = f(x) = x^2 + x$

$\frac{dy}{dx} = \frac{d}{dx}(fx) = \frac{d}{dx}(x^2 + x) = 2x + 1$

derivative

$y \to x \to$ derivative $\frac{d}{dx}$

$z = f(x, y) = x^2 + y^2$

$\frac{\partial z}{\partial x} = 2x$ $\frac{\partial z}{\partial y} = 2y$

gradient $\frac{\partial}{\partial x}$

gradient complex → $\frac{\partial L}{\partial w}, \frac{\partial L}{\partial b}$

↳ 9 params

$L(w_{11}^1, w_{12}^1 \ldots w_{21}^2, b_{21}, b_{11}, b_{12})$

↳ 9D function → 9 diff slopes wrt each dim

3D → $z = x^2 + y^2$ $z = f(x, y)$

→ Concept of Derivative → Derivative at a point

↑ intuition

$\frac{dy}{dx}$ → (y) func x → (x)

rate of change ↑

$\frac{dy}{dx} = 2$ (+ve) ↑ mag, ↳ sign

$\frac{dy}{dx} = -2$ (-ve)

$x \rightarrow$

$y \rightarrow$

derivative

$y = x^2 + 2x$ $\quad x=5$ → derivative

$\frac{dy}{dx} = (2x+1)_{x=5}$

$\left(\frac{dy}{dx}\right)_{x=5} = 11$ → slope

$\frac{\partial L}{\partial w_{11}^1}$

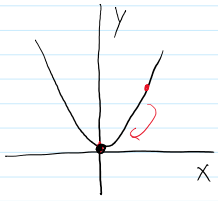
w_{11}^1 — 1 unit

$L \rightarrow ?$ (mag) (sign)

$w_{new} = w_{old} - \eta \frac{\partial L}{\partial w}$

→ the concept of minima

$y = x^2$



$\frac{dy}{dx} = 2x = 0$

$x = 0$

$z = x^2 + y^2$

$(x, y) \rightarrow z$ min

$\frac{\partial z}{\partial x} = 0$ $x \rightarrow$

$\frac{\partial z}{\partial y} = 0$ $y \rightarrow$

$2x = 0 \Rightarrow x = 0$

$2y = 0 \Rightarrow y = 0$

L (q param) → (w, b) → min

L ↓ ↳

$\frac{\partial L}{\partial w_{11}^1} \cdots \frac{\partial b}{\partial b_{12}} = 0$

q dim ↳ minima

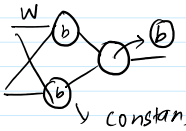
→ Backprop Intuition

$\eta = 1$

$w_{new} = w_{old} - \eta \frac{\partial L}{\partial w}$ ← q step

$w_{new} = w_{old} - \frac{\partial L}{\partial w}$

each parameters



$L = L(w, b)$ ↑ q → 8 ↓ constant

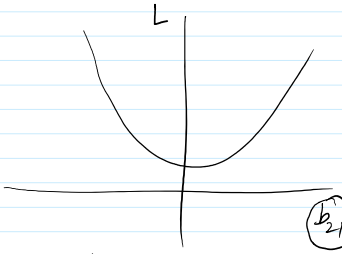
$L = (y - \hat{y})^2$ ↳ $\hat{y} = (b_{21})$

$L(b_{21})$ ↑

$L = b_{21}^2$

$b_{21} = b_{21} - \frac{\partial L}{\partial b_{21}}$ ↘ +ve, -ve

$b_{21} = 5$



$\frac{\partial L}{\partial b_{21}}$ ↘ smart

L derivative wrt b_{21}

↑ ?

↑ 1 unit → L ↓

$\frac{\partial L}{\partial b_{21}} = +ve$ ↘

$b_{21} \downarrow$

$b_{21} \downarrow$

L ↓

$b_{21} \uparrow$ L ↑

$b_{21} \uparrow$

$\frac{\partial L}{\partial b_{21}} = -ve$

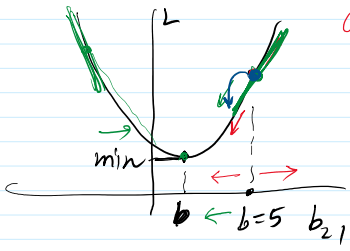
$b_{21} \uparrow$ L ↓

$b_{21} = b_{21} + \frac{\partial L}{\partial b_{21}}$

game ... -ve of the gradient

game derivative (b_{21}) — -ve of the gradient

$$b_{21} = b_{21} - \frac{\partial L}{\partial b_{21}}$$



algo

$b = -5$

$\frac{\partial L}{\partial b}$ = slope

$\frac{\partial L}{\partial b}$ = -ve

-ve

slope (gradient) ↓ -ve

+ve

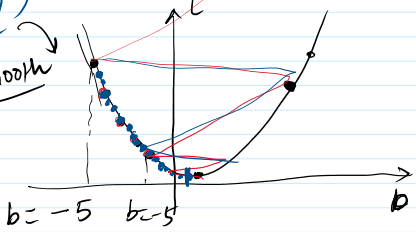
Slope

$$w_n = w_0 - \frac{\partial L}{\partial w} \quad \eta \qquad w_n = w_0 - \eta \frac{\partial L}{\partial w}$$

→ Effect of Learning Rate (η)

$$w_n = w_0 - \eta \frac{\partial L}{\partial w}$$

Smooth



0.1 / 0.01

train

η = parameter ↓ 0.01

$\eta = 1$

$\eta = 0.00001$

$\frac{\partial L}{\partial b} = -50$

$b = -5 - (-50) = 45$

$b = 45$

$\frac{\partial L}{\partial b} = 50$

$b = 45 - 50$

$b = -5 \quad \frac{\partial L}{\partial b} = -50 \quad \eta = 0.01$

$b = -5 + (0.01 \times 50) = 0.5$

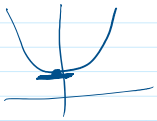
$= -4.5$

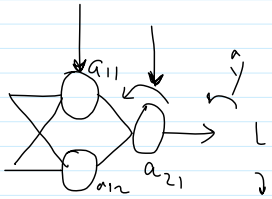
→ What is convergence?

$w_n = w_0 - \eta \frac{\partial L}{\partial w} \simeq 0$

$w_n = w_0$

while → con → for 1000 epoch → 100





$i = 1, 0$

$-(y - \hat{y})$

activation = ②

$\hat{y}(1 - \hat{y})\, o_{11}$

$-(y - \hat{y})\, o_{11}$

$-y \log(a_{21}) - (1-y) \log(1 - a_{21})$

$-\frac{y}{\hat{y}} + \frac{(1-y)}{(1-\hat{y})}$

$\frac{\partial L}{\partial w_{11}^2} = \frac{\partial L}{\partial a_{21}} \times \frac{\partial a_{21}}{\partial w_{11}^2}$

$\frac{\partial L}{\partial} =$

$$\frac{\partial L}{\partial w_{21}^2} =$$

curr_activa = $a[1]$

$$\frac{\partial L}{\partial b_{21}} =$$

$$-\frac{y}{\hat{y}} + \frac{(1-y)}{(1-\hat{y})}$$

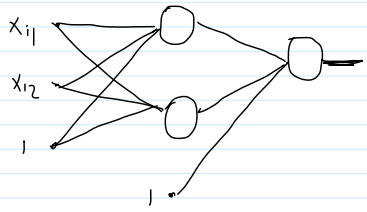
$$\begin{cases} -(y-\hat{y})\ a_{21}(1-a_{21})\ a_{11} \\ -(y-\hat{y})\ a_{21}(1-a_{21})\ a_{12} \\ -(y-\hat{y})\ a_{21}(1-a_{21}) \end{cases}$$

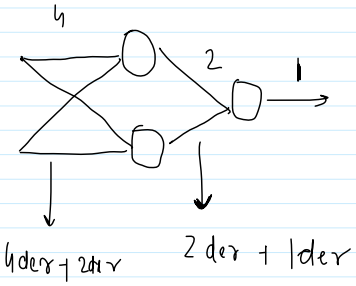
$$\text{delta} = (y-\hat{y})\ a^{[2]}(1-a^{[2]})$$

1×1 — 2×1 — 1×2

$W^{[1]}$ — 1×2

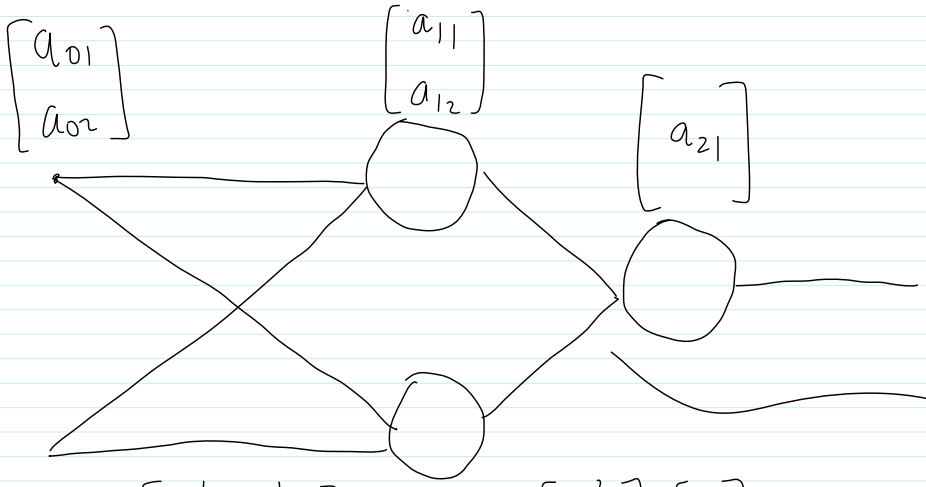
$$-(y-\hat{y})\ a_{21}(1-a_{21}) \times \begin{bmatrix} a_{11} \\ a_{12} \end{bmatrix} \quad a[1]$$





1×1 1×2

1×2 × 2×2



L → a_2 → a_1 →

$$\frac{\partial L}{\partial a_2} \times \frac{\partial a_2}{\partial a_1} \frac{\partial a_1}{\partial w}$$

$$\begin{bmatrix} w_{11}^1 & w_{12}^1 \\ w_{21}^1 & w_{22}^1 \end{bmatrix} \quad \begin{bmatrix} b_{11} \\ b_{12} \end{bmatrix} \quad \begin{bmatrix} w_{11}^2 \\ w_{12}^2 \end{bmatrix} \quad \begin{bmatrix} b_{21} \end{bmatrix}$$

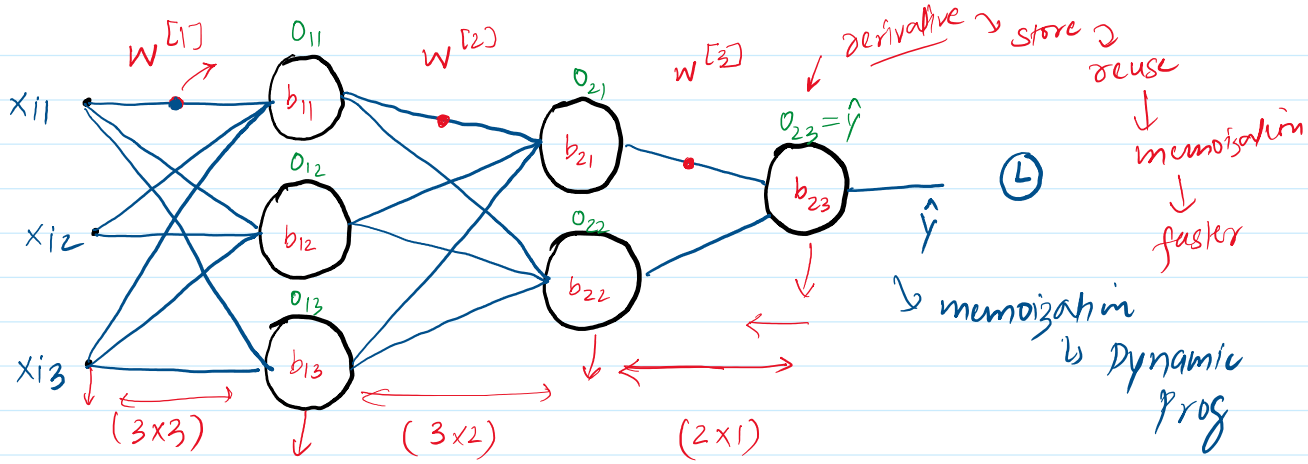
$$\frac{\partial L}{\partial w} = \boxed{\frac{\partial L}{\partial a_2}} \times \boxed{\frac{\partial a_2}{\partial w}}$$

$$\begin{bmatrix} \partial L/\partial w_{11}^1 & \frac{\partial L}{\partial w_{12}^1} \\ \frac{\partial L}{\partial w_{21}^1} & \frac{\partial L}{\partial w_{22}^1} \end{bmatrix} \qquad \begin{bmatrix} \frac{\partial L}{\partial w_{11}^2} \\ \frac{\partial L}{\partial w_{12}^2} \end{bmatrix}$$

MLP Memoization

Thursday, April 7, 2022 7:45 AM

backprop update → w / b) deriv

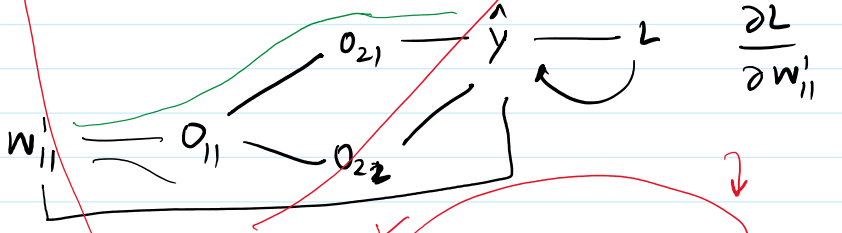


Chain rule

$L \to \hat{y} \to O_{21} \to O_{11} \to w^1_{11}$

$$\frac{\partial L}{\partial w^3_{11}} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial w^3_{11}} \qquad \frac{\partial L}{\partial w^2_{11}} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial O_{21}} \times \frac{\partial O_{21}}{\partial w^2_{11}}$$

$$x \to f(x), g(x) \to h(f(x), g(x)) \qquad \frac{\partial h}{\partial x} = \left[\frac{\partial h}{\partial f(x)} \times \frac{\partial f(x)}{\partial x}\right] + \left[\frac{\partial h}{\partial g(x)} \times \frac{\partial g(x)}{\partial x}\right]$$



$$\frac{\partial L}{\partial w^1_{11}} = \frac{\partial L}{\partial \hat{y}} \left[\frac{\partial \hat{y}}{\partial O_{21}} \times \frac{\partial O_{21}}{\partial O_{11}} \times \frac{\partial O_{11}}{\partial w^1_{11}} + \frac{\partial \hat{y}}{\partial O_{22}} \times \frac{\partial O_{22}}{\partial O_{11}} \times \frac{\partial O_{11}}{\partial w^1_{11}}\right]$$

Backprop → Chain diff (rule) + Memorization

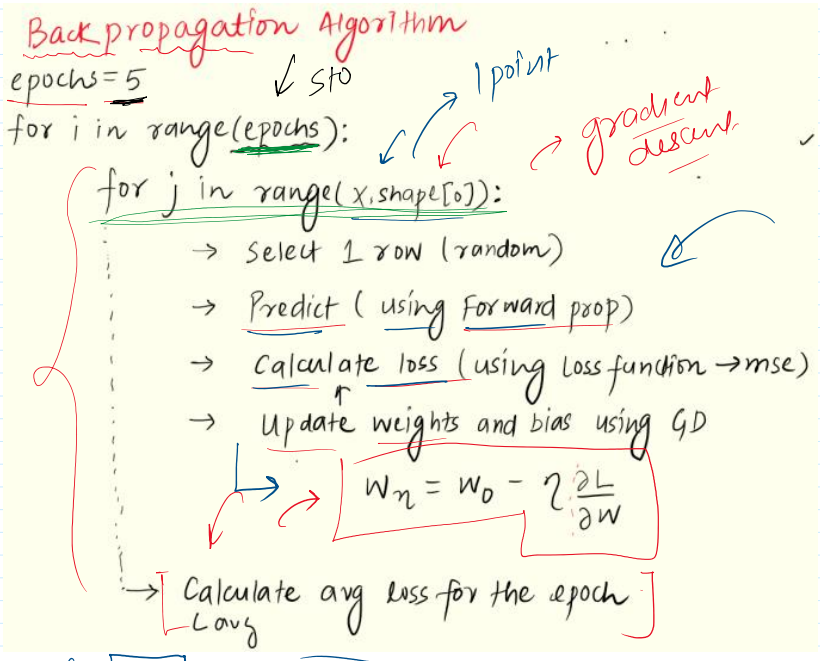
Keras TF — maths — (3)

Gradient Descent

Thursday, April 7, 2022 7:44 AM

Gradient descent is one of the most popular algorithms to perform optimization and by far the most common way to optimize neural networks.

Gradient descent is a way to minimize an objective function J(θ) parameterized by a model's parameters θ∈Rd by updating the parameters in the opposite direction of the gradient of the objective function ∇θJ(θ) w.r.t. to the parameters. The learning rate η determines the size of the steps we take to reach a (local) minimum. In other words, we follow the direction of the slope of the surface created by the objective function downhill until we reach a valley.



50 points
1 epoch
↳ 50 times
w, b update

Batch GD
epoch = 5
↳ 50 points → predict J
dot product
y_hat = np.dot(X, w) + b
↳ 50 predict
y = 50 actual ocw
y y_hat J loss
$J = -\sum_{i=1}^{50}$

Batch / Stochastic / mini batch

There are three variants of gradient descent, which differ in how much data we use to compute the gradient of the objective function. Depending on the amount of data, we make a trade-off between the accuracy of the parameter update and the time it takes to perform an update.

$\frac{\partial L}{\partial w}$ derivative → 3 types
accuracy → time → tradeoff

Batch GD (Vanilla GD)

```
for i in range(nb_epochs):
  params_grad = evaluate_gradient(loss_function, data, params)
  params = params - learning_rate * params_grad
```

entire dataset → update
epochs = # of updates

Stochastic GD

```
for i in range(nb_epochs):
  np.random.shuffle(data)
  for example in data:
    params_grad = evaluate_gradient(loss_function, example, params)
    params = params - learning_rate * params_grad
```

epoch → 10 (50 rows)
for i in range(10): → shuffle
for i in range(X.shape[0])
↳ 1 random point → bias eliminate
↳ y_hat → forward
↳ loss
↳ w, b update → $w_n = w_0 - \eta \frac{\partial L}{\partial w}$
avg loss print → for the epoch

50 × 10 = 500
50 rows
10 × 50 = 500 update

5 epochs
↳ 5 times
w, b update

Batch GD → 1 loop
epoch = 10
for in range(10):
y_hat = np.dot(X, w) + b
50 values
dot → smart replacement → loops
↳ vectorization → faster loop
Y = 50 values

frequency of weight update higher
→ total → 10 times w, b update

50 values dot → smart replacement → loops
↳ vectorization ↘ faster loop
Optimized !

y = 50 values

y_hat, y → loss

↻ w, b update $w_n = w_0 - \eta \frac{\partial L}{\partial w}$

→ loss

Which is faster (given same no. of epochs)

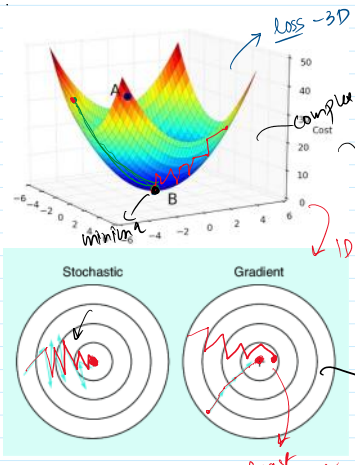
10η D

320 N 1

Which is the faster to converge (given some # epochs)

5

Loss function → 2 Algo



Stochastic → 1 → random → point → updates

Batch → dataset → all point → 1 update

Spikey SGD useful

Yes No

SGD
BGD

SGD help the algo to move out of local minima

Exact solution
Approximate diff
faster ∝ loops
big dataset

Vectorization → np.dot (X, W) + b

X → dataset of 10 crore Ram

Mini Batch Gradient Descent

BGD ↔ SGD Best of both worlds

SGD → BGD

```
for i in range(nb_epochs):
    np.random.shuffle(data)
    for batch in get_batches(data, batch_size=50):
        params_grad = evaluate_gradient(loss_function, batch, params)
        params = params - learning_rate * params_grad
```

320 rows in every epoch
10 batches
batches → 32
10 update

$\frac{n}{x}$ = # of batches

Keras batch-size = x

updates/epoch

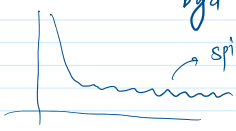
bgd > mbgd > sgd

or

bgd < mbgd < sgd

for i in epochs →
for j in num of batch
1 batch
np.dot
↳ y_pred (vector
↳ loss
↳ update

MBGD



spikey SGD ↘ Vectorization → smaller batch

→ Why batch_size is provided in multiple of(2)?

2, 4, 8, 32, 64, 128, 256

10, 15

RAM effective → binary

RAM → optimization → keras

faster

→ What if batch_size doesn't divide # rows properly

e.g # of rows $n = 400$

batch_size = 150

# of batch = $\frac{400}{150} = 2.66$

3

150, 150, left 100

1 batch 2 batch 3rd batch

Vanishing Gradient Problem

Thursday, April 7, 2022 7:45 AM

In machine learning, the **vanishing gradient problem** is encountered when training artificial neural networks with gradient-based learning methods and backpropagation. In such methods, during each iteration of training each of the neural network's weights receives an update proportional to the partial derivative of the error function with respect to the current weight. The problem is that in some cases, the gradient will be vanishingly small, effectively preventing the weight from changing its value. In the worst case, this may completely stop the neural network from further training. ~~As one example of the problem cause, traditional activation~~

GD

1) $0.1 \times 0.1 \times 0.1 \times 0.1 = 0.0001$ → VGP

2) Deep NN

3) Sigmoid / tanh → Af → 0-1

Backprop

0-0.5

deep

sigmoid

sigmoid derivative

$L \to \hat{y} \to o_{11} \to w'_{11}$

$w_n = w_0 - \eta \frac{\partial L}{\partial w}$ → derivative of L wrt weight

$w_0 = 1$ ↑ small change

$\frac{\partial L}{\partial w'_{11}} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z} \times \frac{\partial z}{\partial o_{11}} \times \frac{\partial o_{11}}{\partial w'_{11}}$

$0 < x < 1$ $0 < x < 1$ 0.1

0.0001

$w_n = 1 - 0.01 \times 0.0001$

$w_n = 0.99999$ → vanishingly small

did not change

{ Sigmoid tanh }

Backprop → model training → x

$\frac{\partial L}{\partial w'_{11}} = 0.000001$

↳ 80's, 90's → main reasons DL failed

0 - 100000

0 - 1

1 - 1

How to recognize?

1) Loss focus → epoch → no changes → VGP

2) weights → graph value

w'_{11}

Keras

{ loss after epoch }

Tensorboard → callbacks

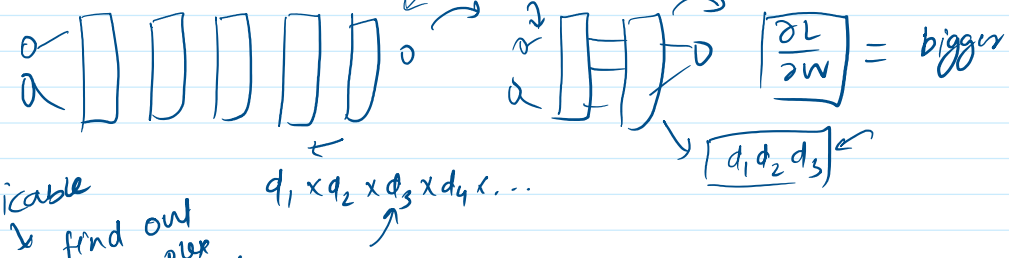
epoch

$w_n = w_0 - \eta \frac{\partial L}{\partial w}$ $\frac{w_0 - w_n}{\eta} =$

$$w_n = w_0 - \eta \left[\frac{\partial L}{\partial w}\right] \rightarrow \qquad \boxed{\frac{w_0 - w_n}{\eta} =}$$

How to handle Vanishing Gradient Problem →

1) Reduce model complexity



Applicable
↳ find out complex patterns

2) Using ReLU Activation functions

max (0, z) → 0, 1

−1000 − 1000 → squish
0 − 1000
0 − 1

z = 1 × 1 × 1 = 1 → vgp

dying relu ↳ derivative $w_n = w_0$

{leaky relu}

3) Proper weight init → Global → xavier

4) Batch norm → layer →

5) Residual Network → CNN → ResNET
↳ building block → ANN

Exploding Gradient Problem → RNN

10, 10, 10, 10 → 10000

big number

$\frac{\partial L}{\partial w_{11}} = d_1 \times d_1 \times \phi_1 \times \phi_3$

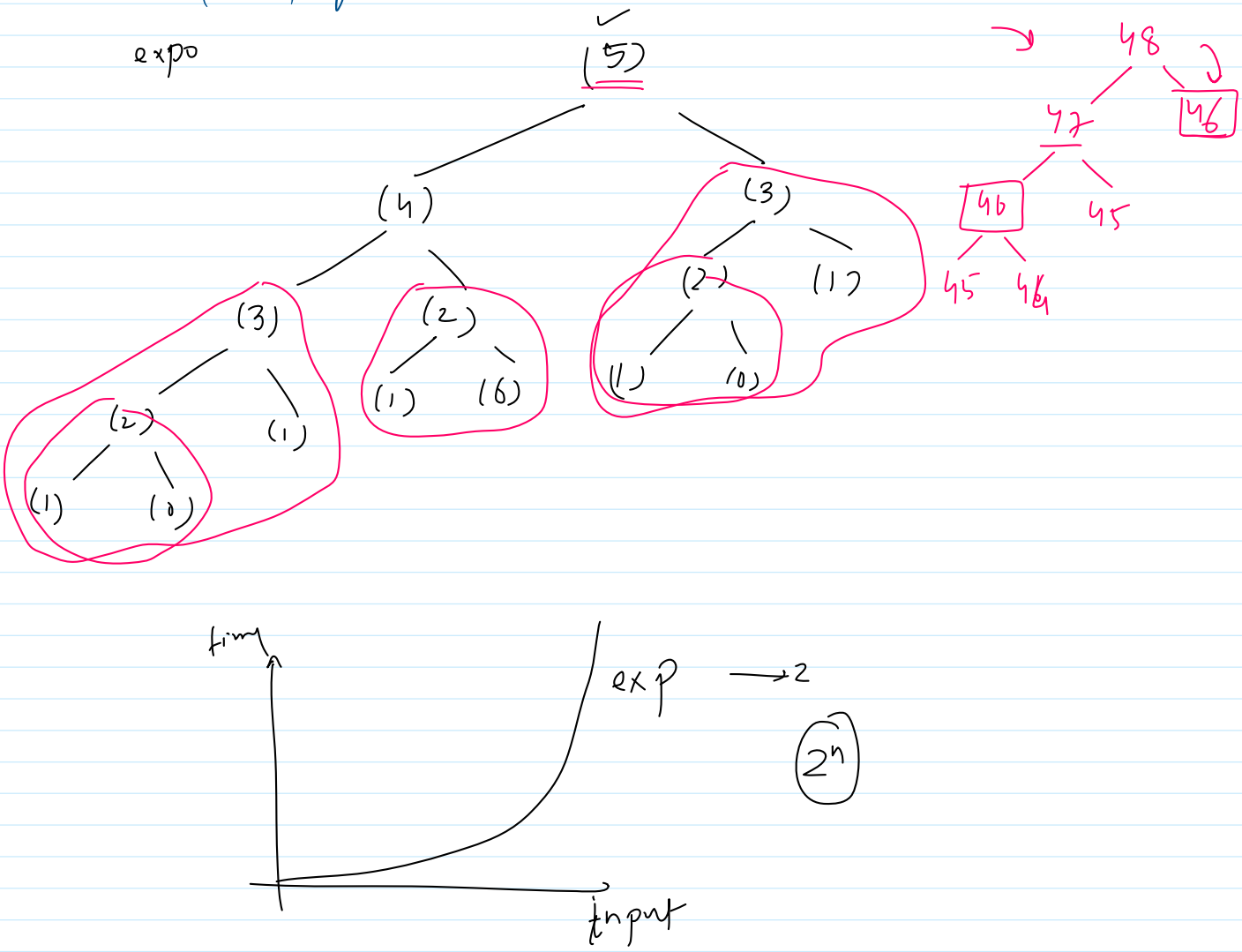
$w_n = w_0 - \eta \frac{\partial L}{\partial w}$ (0.1, 1000)

random

Loss ↓ x 1 − 100 → 99 → 1000 ↘

{Gradient clipping}

expo


expo
(5)
(4)
(3)
(2)
(1)
(3)
(2)
(1)
(0)
(2)
(1)
(6)
48
47
46
46
45
45
46

time
exp → 2
2^n
input

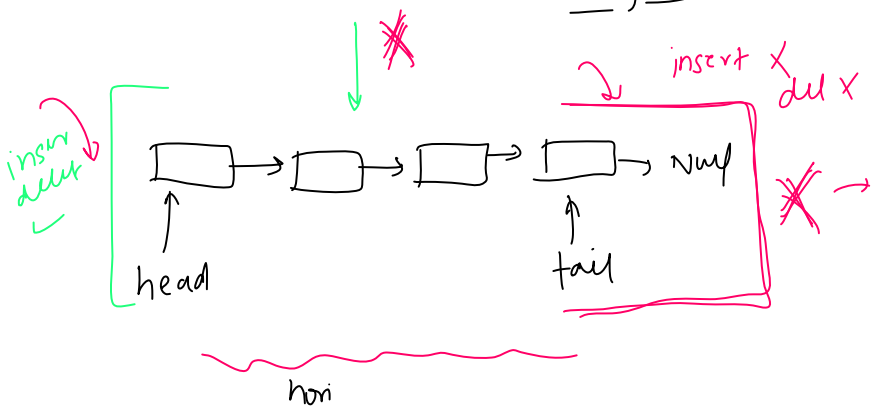
DS Algo → Time complex
→ Arrays → Dynamic Arrays
→ Linked list

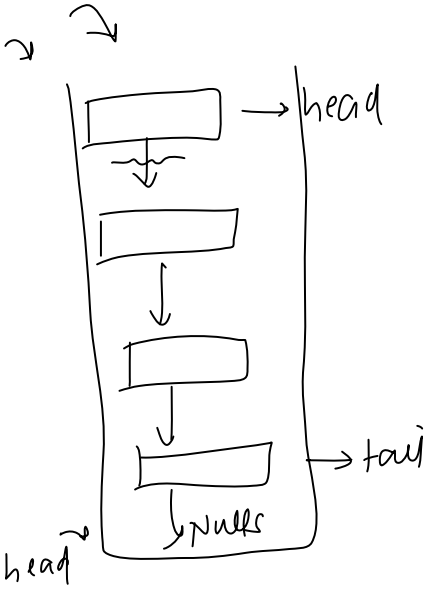
Today → Stacks → LL
→ Arrays

→ 3 → Tuesday
last 3 videos

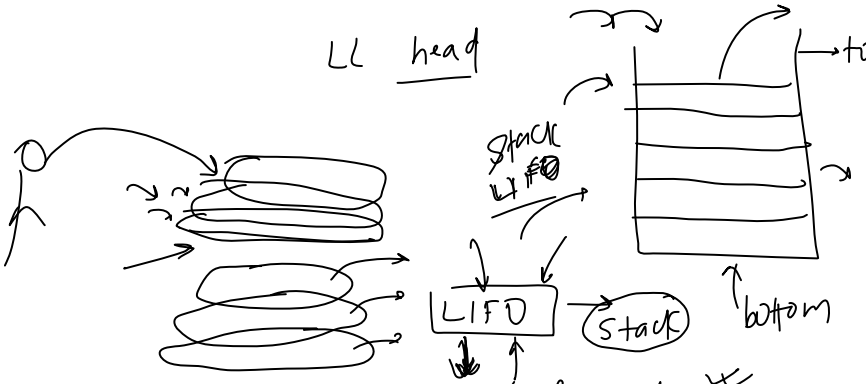
Next → Queues
→ Practice →

→ Stacks → DS
Useful





LL head



ADT → conceptual thing → Normal data type

Last in first out

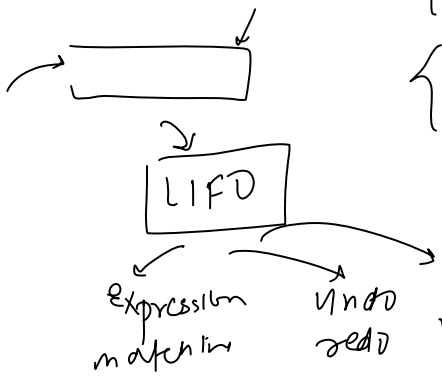
is_empty → empty

push → adding new node from top

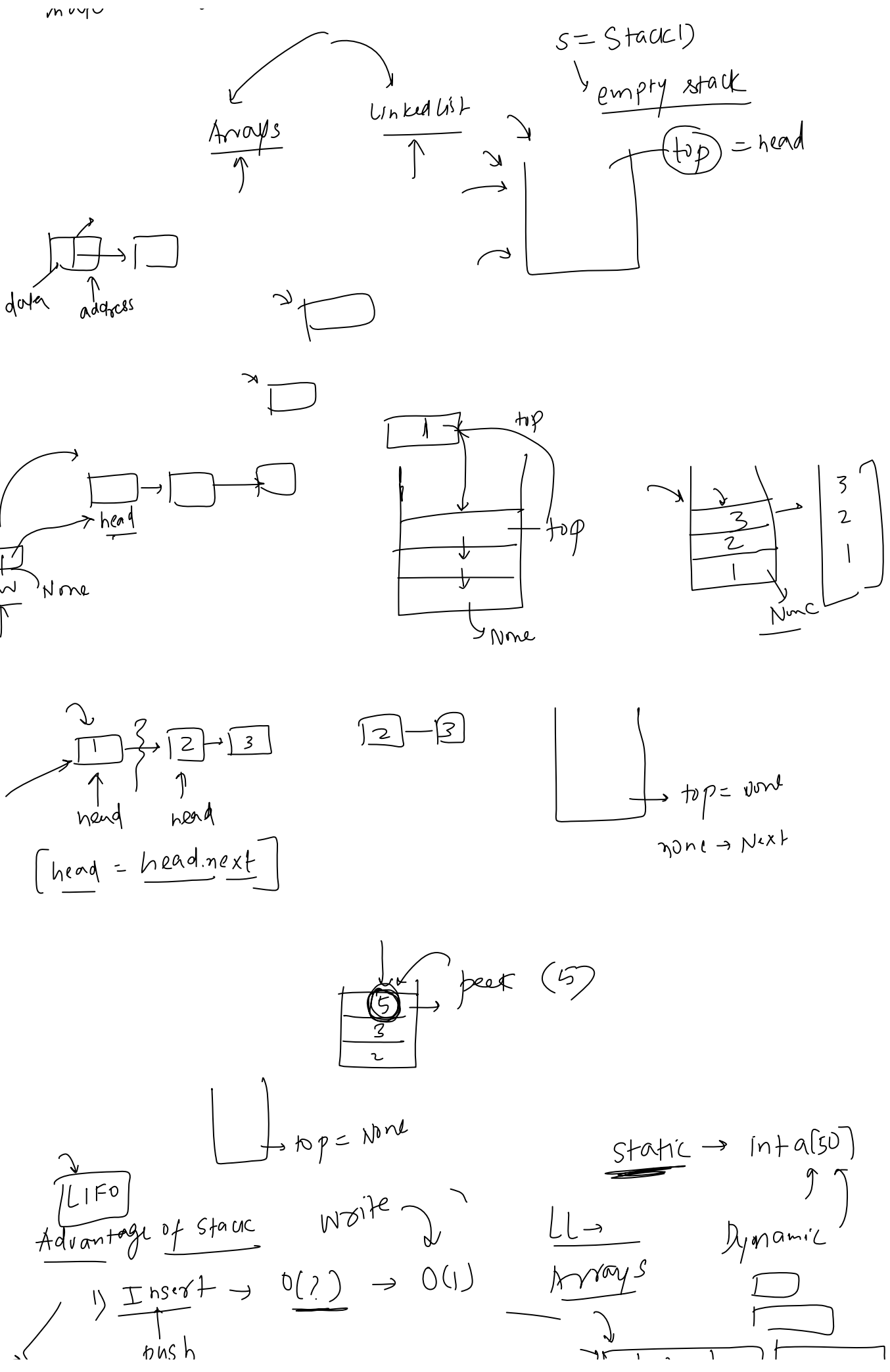
pop → removing from top

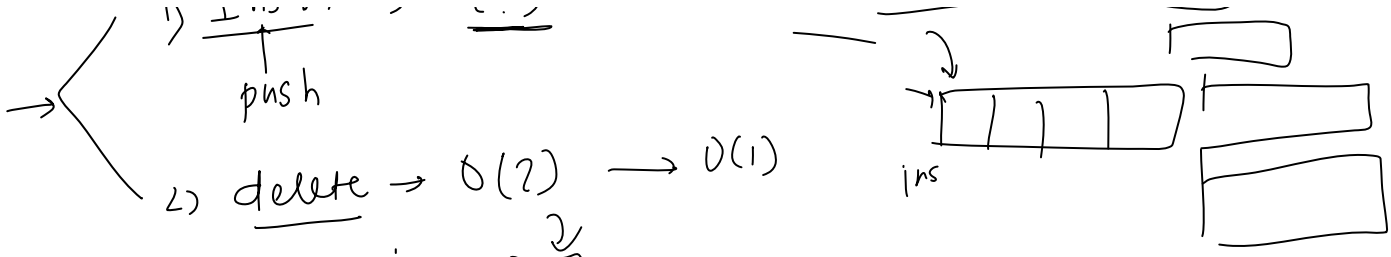
peek → top node → value

size → kitne node



S = Stack()


Arrays
Linked list
s = Stack()
empty stack
top = head
data
address
head
new
None
top
None
3
2
1
None
head
head
head = head.next
top = None
none → Next
peek (5)
top = None
LIFO
Advantage of stack
1) Insert → O(?) → O(1)
push
write
LL →
Arrays
static → int a[50]
Dynamic



int q[50]

size = 4

top = -1 → 0 → 1 → 2 → 3

1, 2, 3, 4 (5)

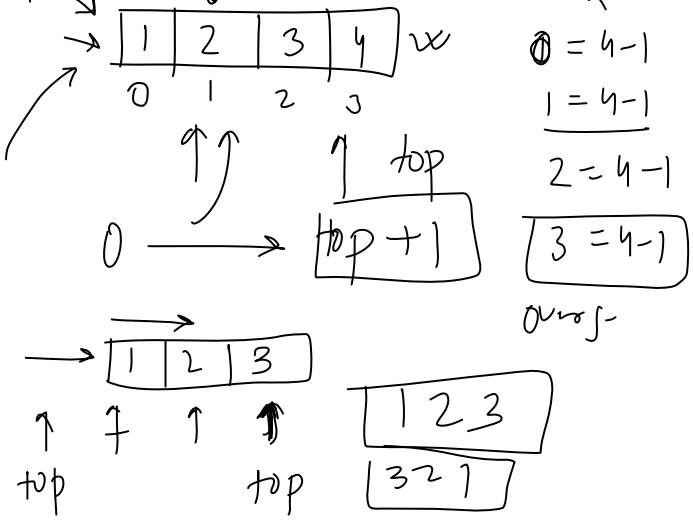
-1 = 4-1 X

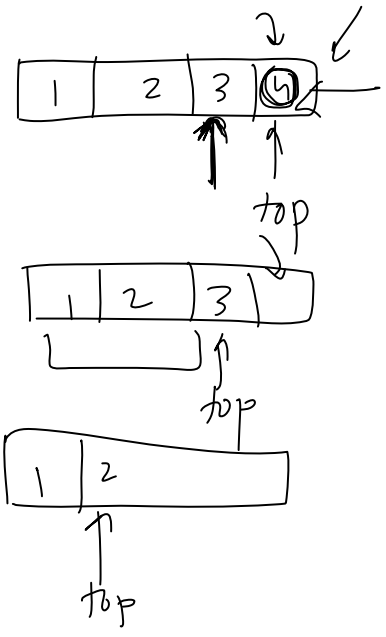
0 = 4-1

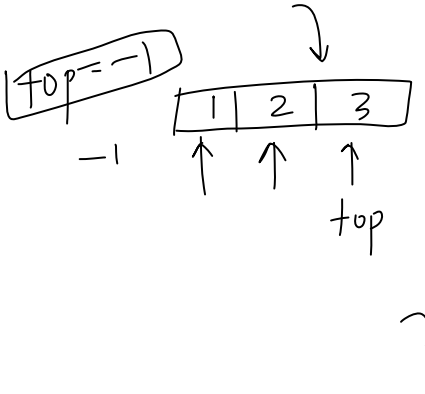
1 = 4-1

2 = 4-1

3 = 4-1 overs-



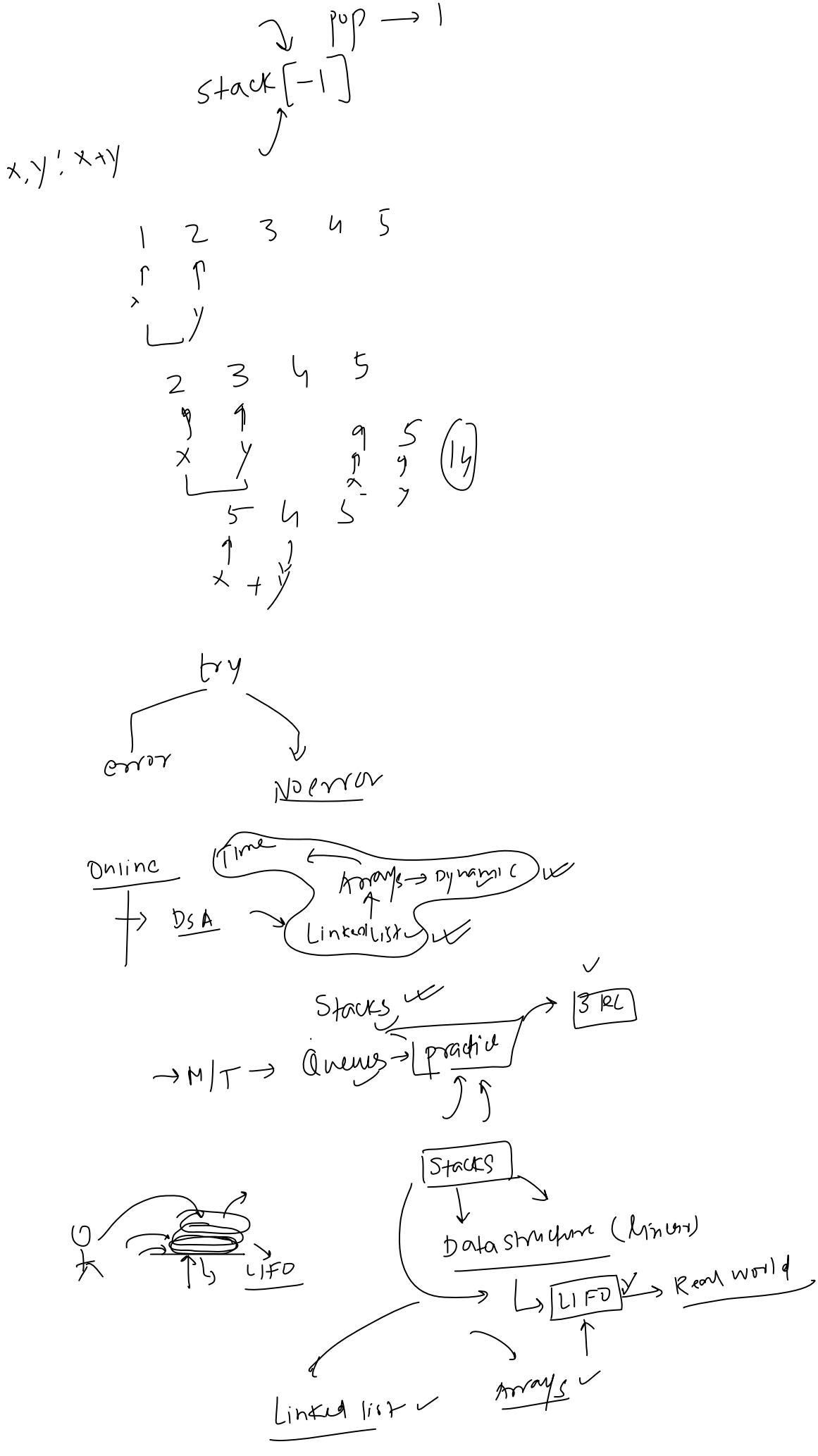


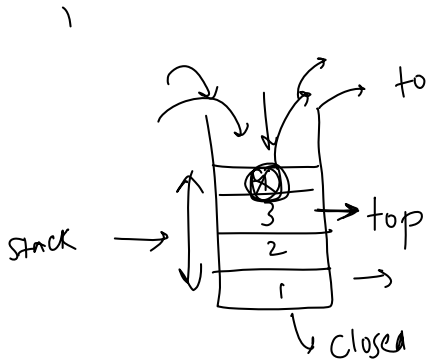


pop → 3

pop → 2

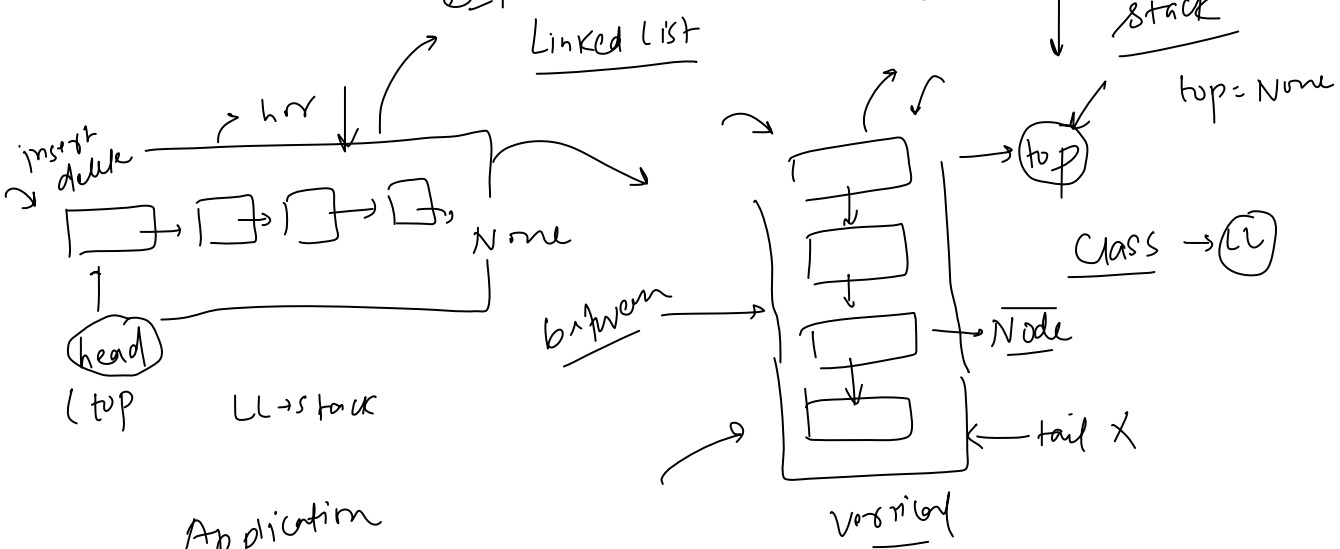
pop → 1


pop → 1
stack[-1]
x, y : x+y
1 2 3 4 5
x y
2 3 4 5
x y
5 4 5
x + y
try
error
No error
Online
DSA
Time
Arrays → Dynamic
LinkedList
Stacks
3 IRL
→ M/T →
Queues
practice
Stacks
LIFO
Data structure (Linear)
LIFO
Real world
Linked list
Arrays



push
pop
peek
is empty
size

Simple

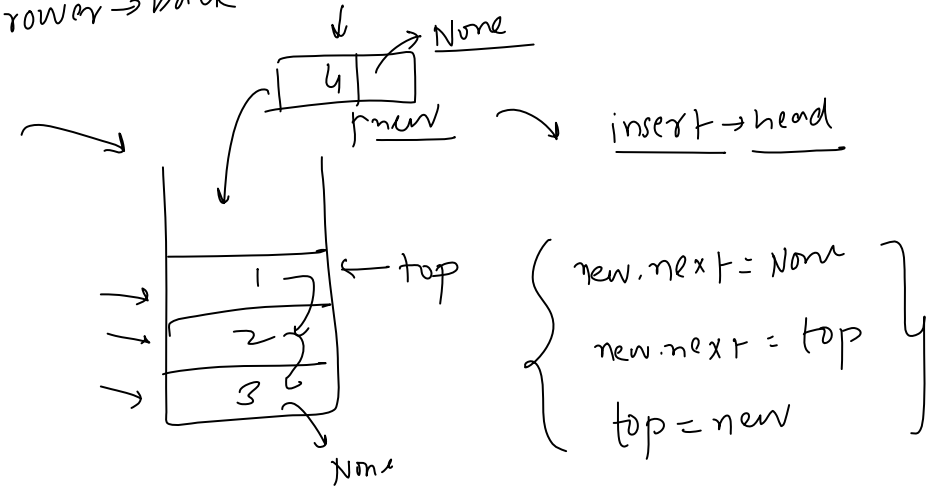


Application

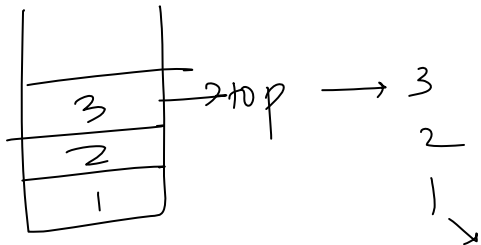
- expression
- undo/redo
- recursion →
- browser → back

LIFO

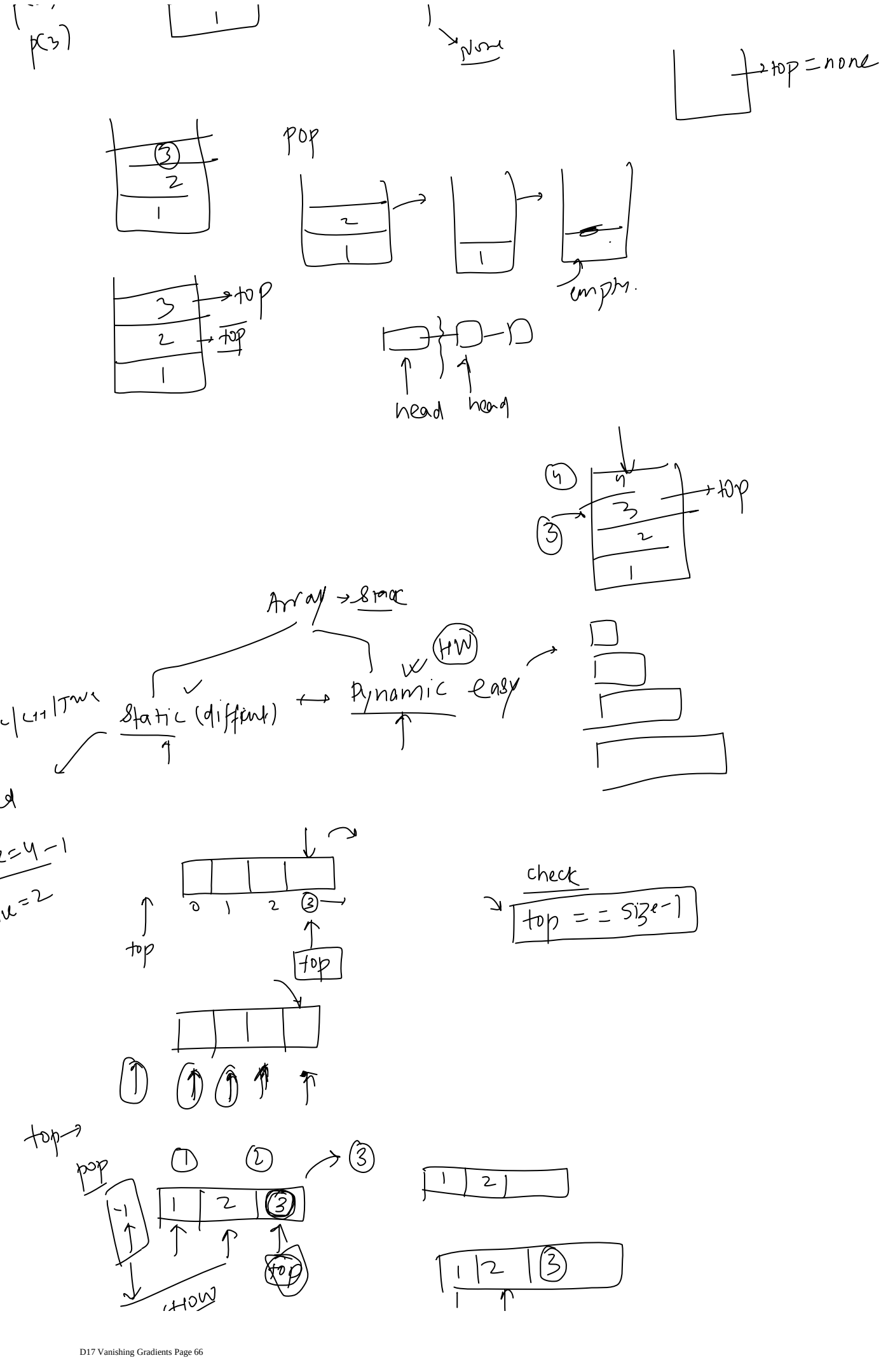
LL

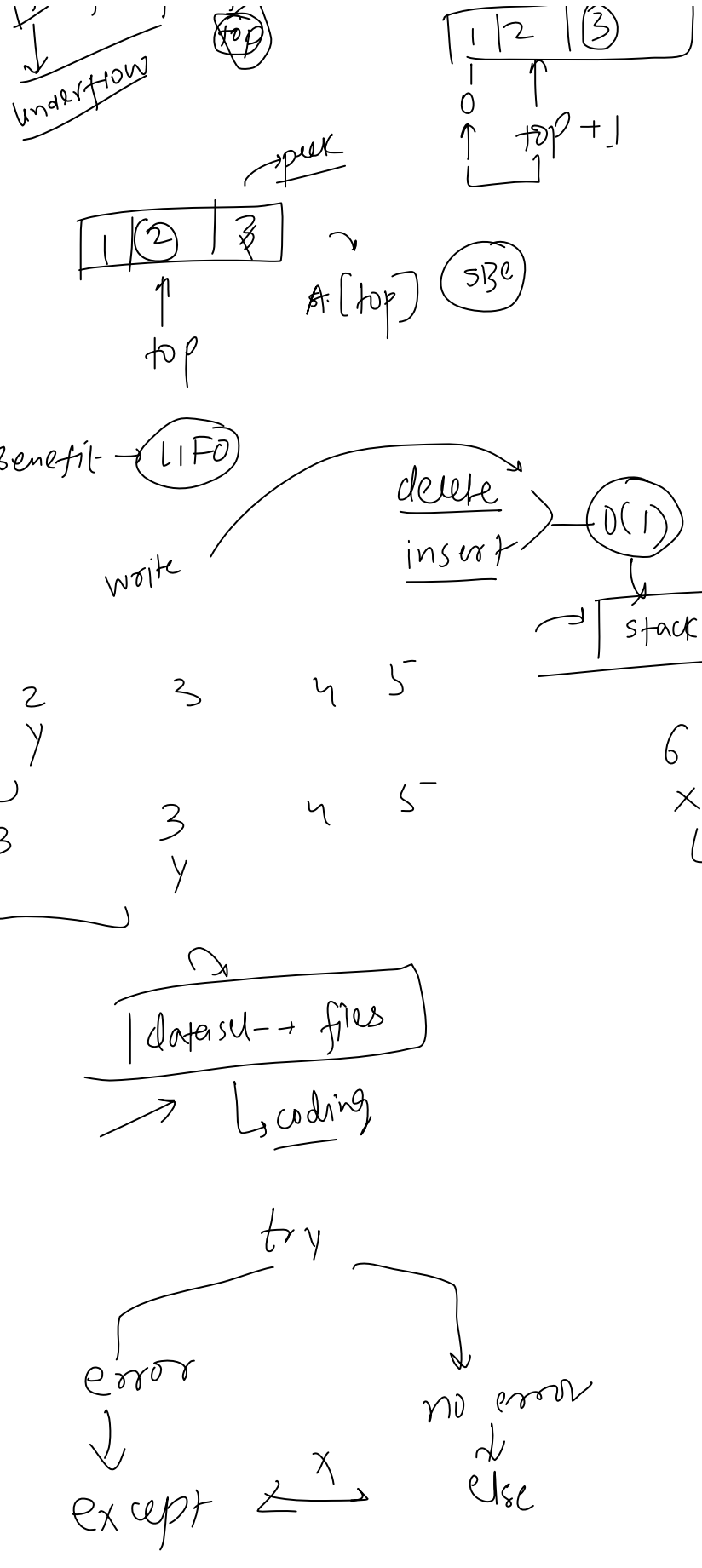


1 2 3



p(1)
p(2)
p(3)


top = none
pop
top
top
head
head
Array → Stack
Static (difficult)
Dynamic easy
HW
fixed
size = 4 - 1
value = 2
top
top
check
top == size-1
top
pop
-1
top
How


top
Underflow
1 2 3
0
top +1
peek
1 2 3
top
A[top]
size
Benefit → LIFO
write
delete
insert
O(1)
stack size
1 2 3 4 5
x y
3 3 4 5
x y
6 4 5
x y
10 15 5
x y
dataset → files
↳ coding
try
error
except
X
no error
else

How to improve a neural network ✓

29 April 2022 13:51

1. Fine tuning NN hyperparameters
2. By solving problems:
   - → Vanishing / Exploding gradient
   - → Not enough data
   - → Slow training
   - → Overfitting

epochs, # hidden layers, # neurons per layer, learning rate → GD, Optimizer → GD, Batch size, Activation function

32 row → 1 update

128 → 64 → 32 hidden

Roadmap → 15 videos

ANN → Keras 90% (92%)

DL?

perceptron

MLP → forward prop → train MLP / ANN → Backprop → GD

update no meaning

minima of weight

weights, gradient

sigmoid 0.00001

Fine tuning Hyperparameters

- No. of hidden layers ✓
- No. of neurons per layer ✓
- learning rate
- Optimizer
- Activation function
- Batch size
- Epochs

1 No. of hidden layers

hidden

Representation

human faces

Transfer learning → CNN

reuse

NN ← line, shapes

1 hidden layer → 512 neurons → complex → lot of neuron

1 h → 512

fewer neurons

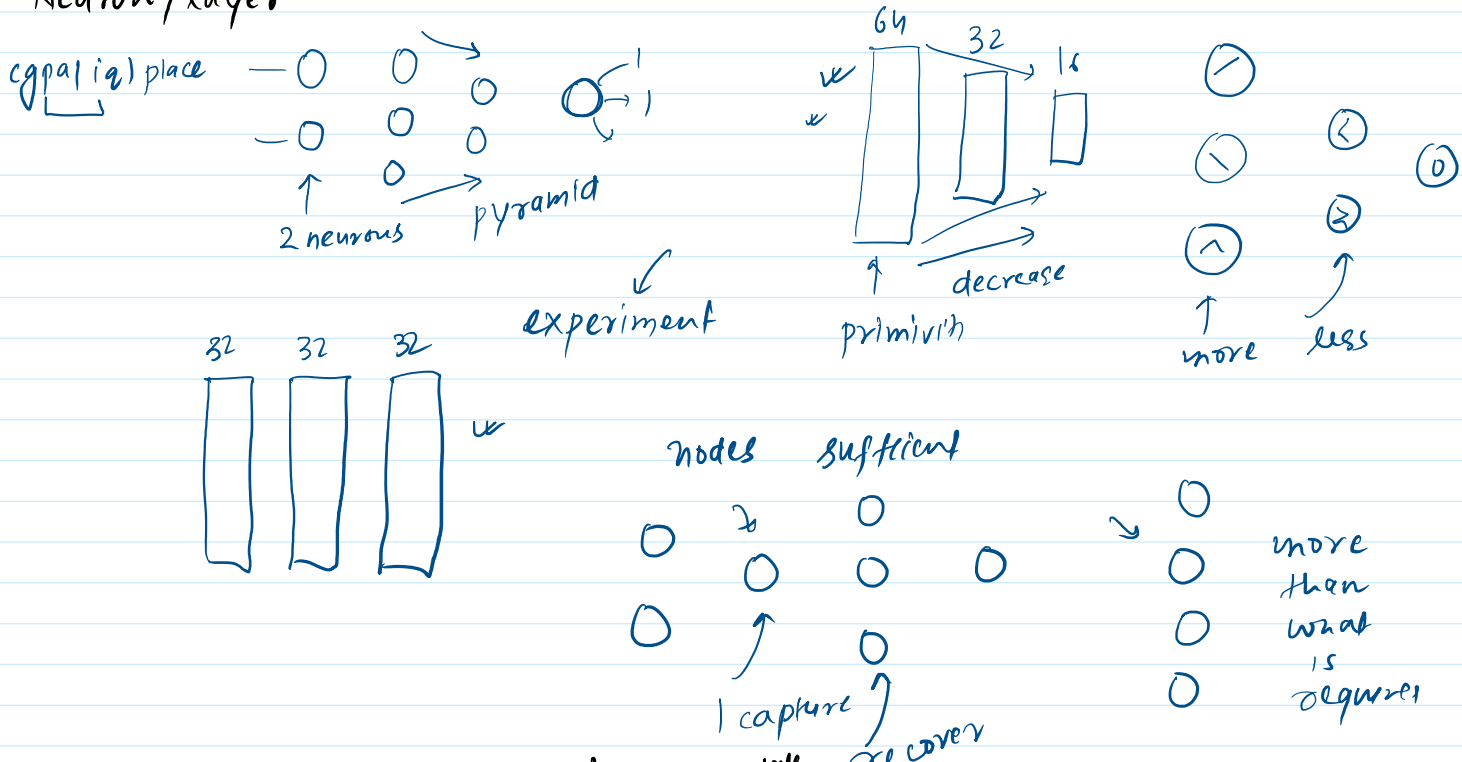
3 / 50 / 300

3 hidden → 32 neuron

deep neural network

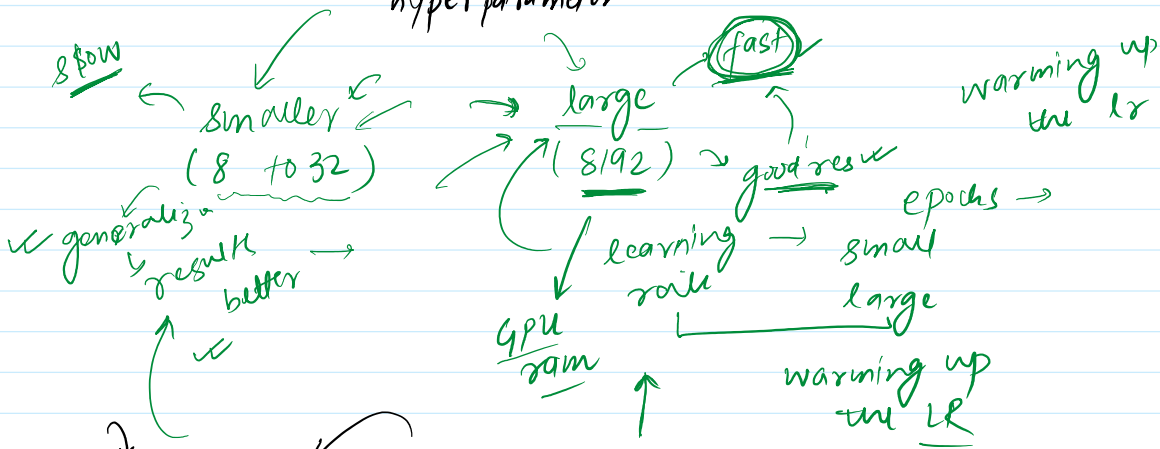
Overfitting

2. Neuron / layer



3. Batch size
- Batch → all row → weight update
- Stochastic → 1 row → weight
- Mini Batch → batch → 32 → row → update

hyper parameter

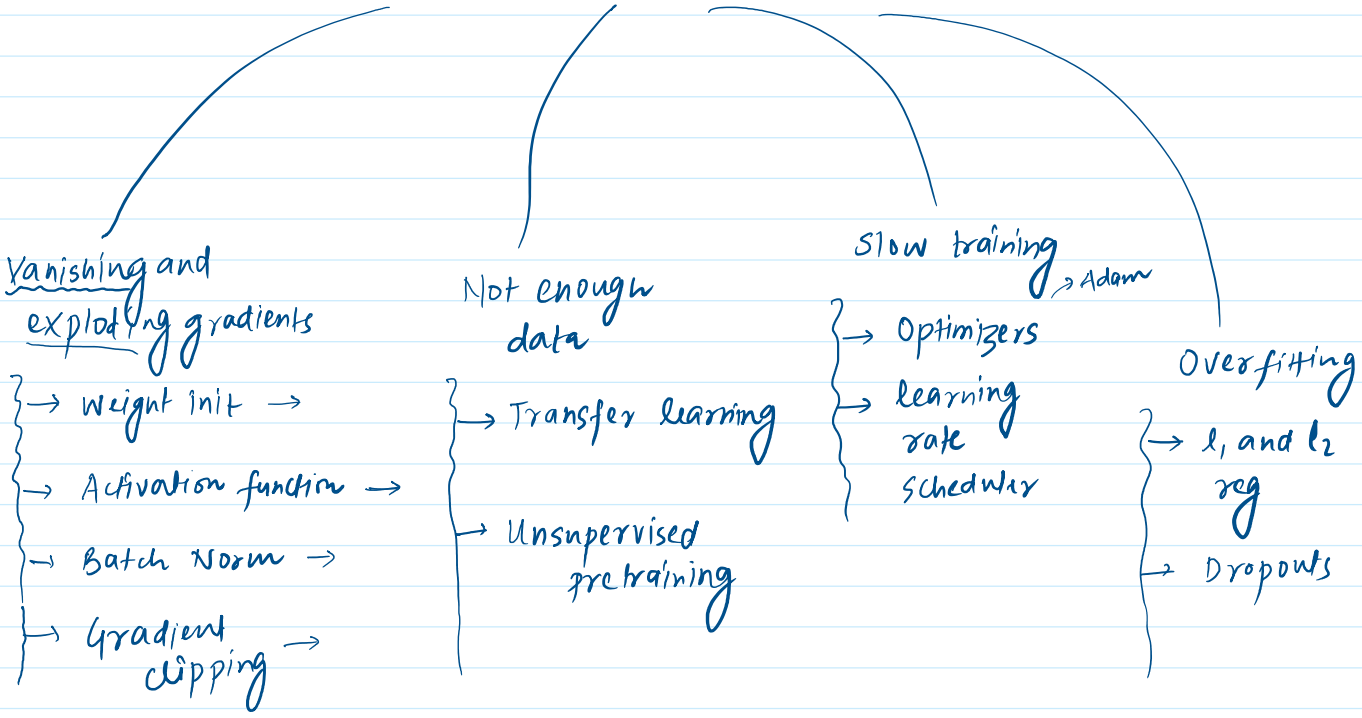


4. Epochs → 100 / 500 / 1000 → early stopping

Keras → callback

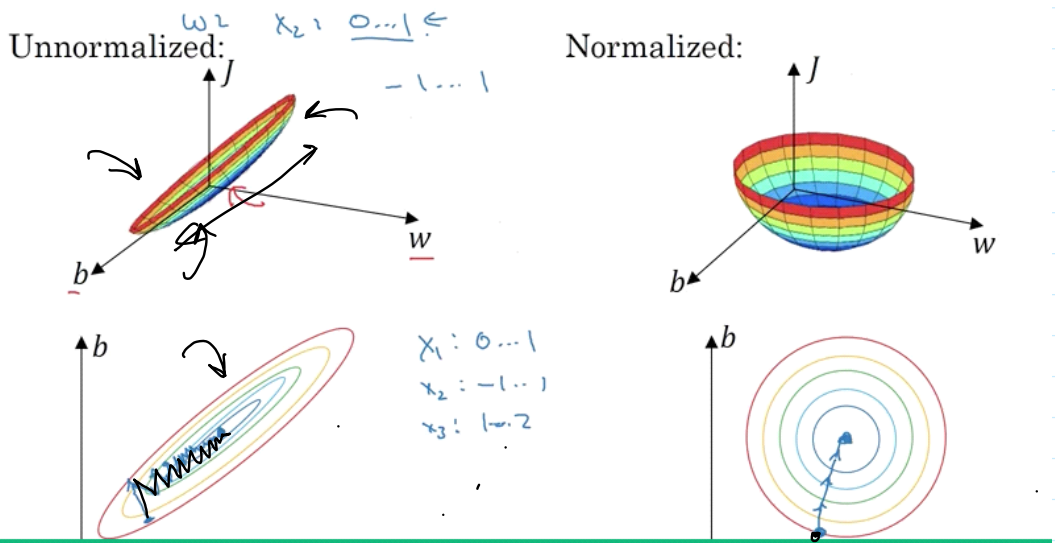
Keras → stable

Problems with Neural Networks


Vanishing and exploding gradients
→ Weight init →
→ Activation function →
→ Batch Norm →
→ Gradient clipping →
Not enough data
→ Transfer learning
→ Unsupervised pretraining
Slow training
→ Adam
→ Optimizers
→ learning rate schedular
Overfitting
→ l_1 and l_2 reg
→ Dropouts

Feature Scaling

05 May 2022 17:37



(age) x_1 → x_2 (salary)

w_1 → w_2

$w_2 = w_2 - \eta \frac{\partial L}{\partial w_2}$

Standard

$\frac{x_j - \mu}{\sigma}$

Normalize

$\frac{x_j - x_{min}}{x_{max} - x_{min}}$

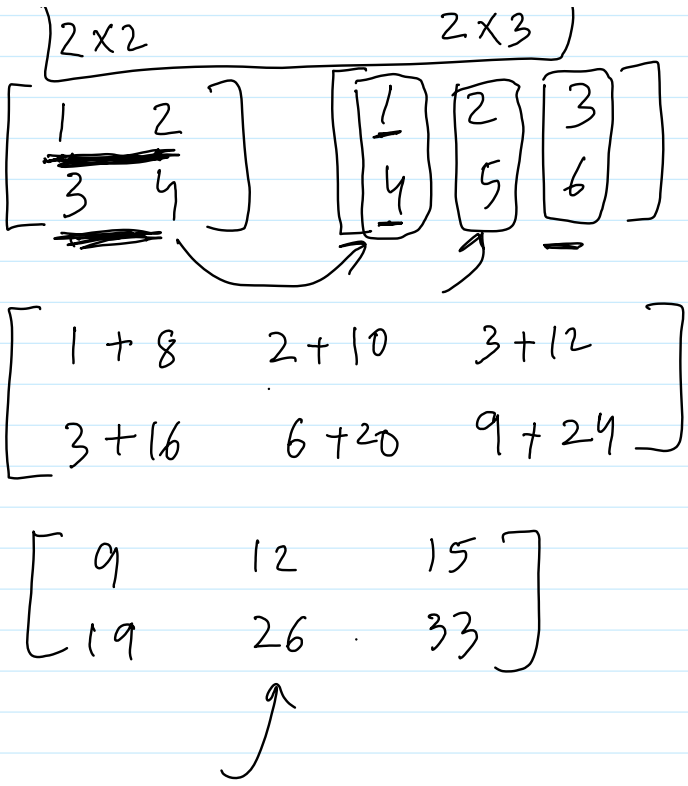
0 to 1

min = 0

max = 1

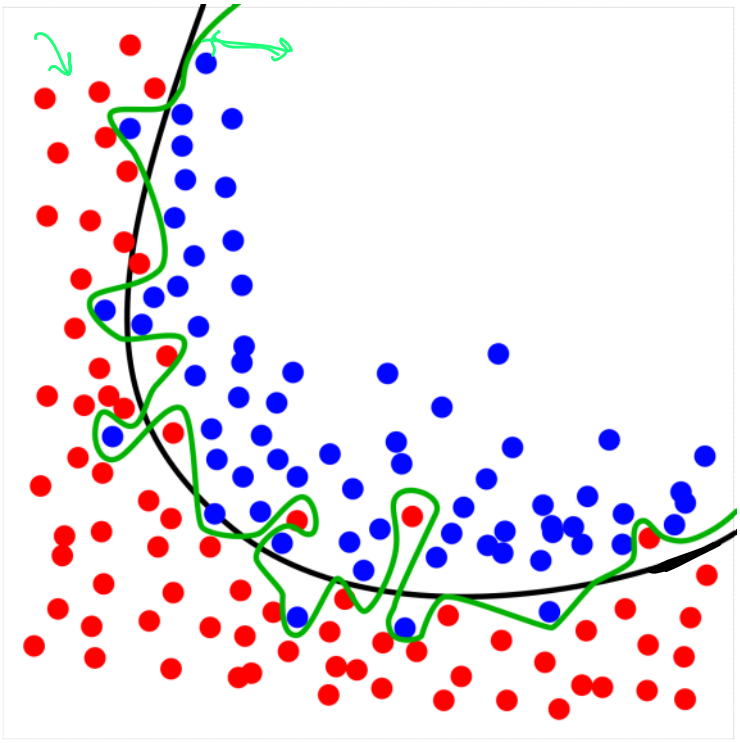
-1 to +1

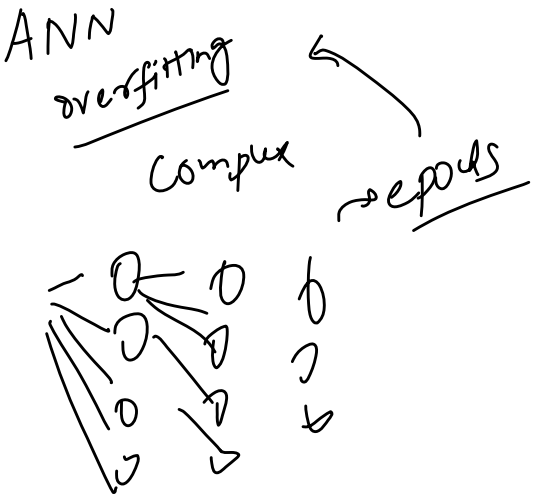
2x2 2x3


2x2
2x3
1 2
3 4
1 2 3
4 5 6
1+8 2+10 3+12
3+16 6+20 9+24
9 12 15
19 26 33

The Problem of Overfitting

12 May 2022 09:32





Possible Solutions

12 May 2022 09:33

1) Add more data

2) Reduce complexity

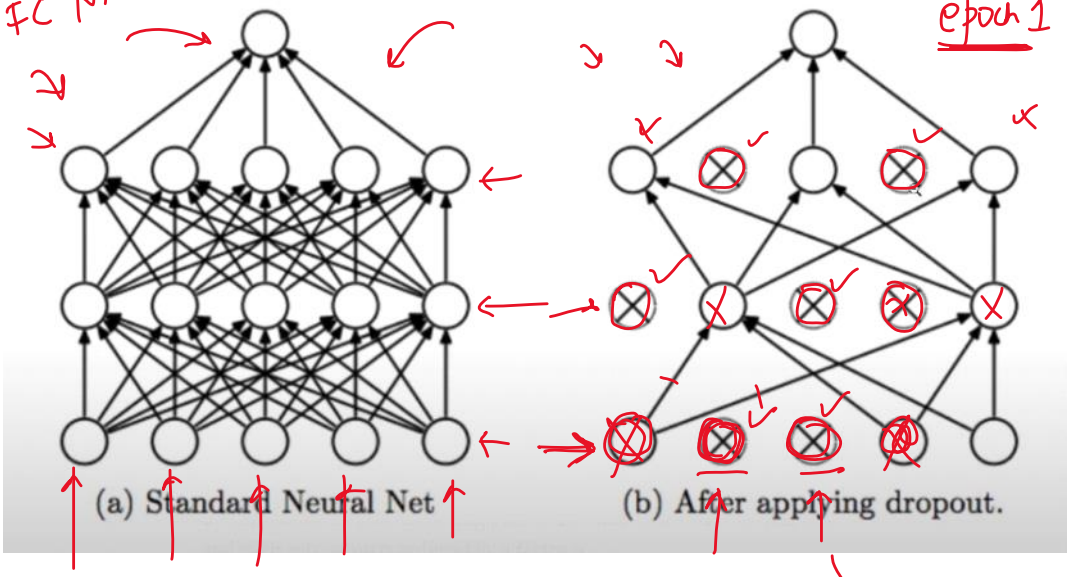
3) Early stopping

4) Regularization → L1, L2

5) Dropout

The concept of Dropouts

12 May 2022 09:33



Dropout

FC NN

epoch 1

$x_1\ x_2\ x_3\ x_4\ x_5\ y$

input nodes

hidden drop

epoch = 10

epoch 2

epoch 3

2·1· → acc

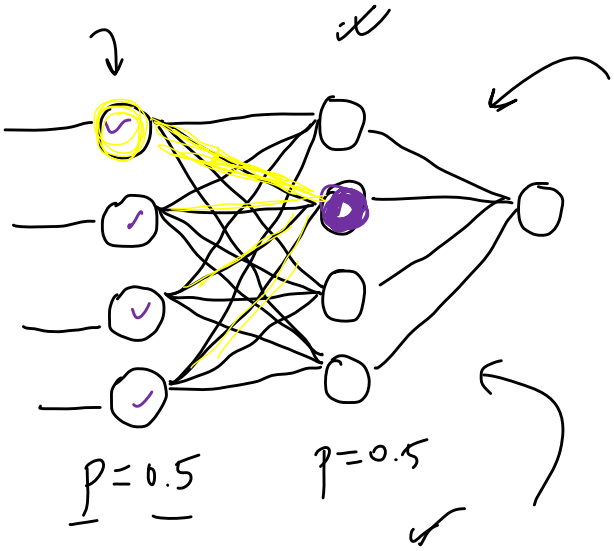
95 → 97

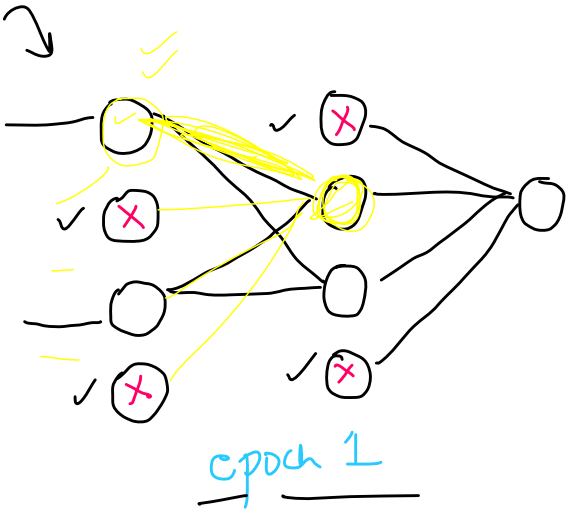
10 epochs

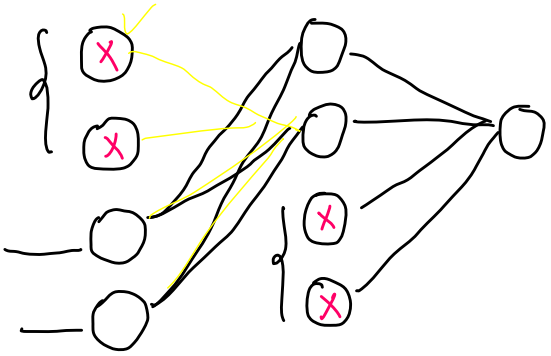
10 diff NNs

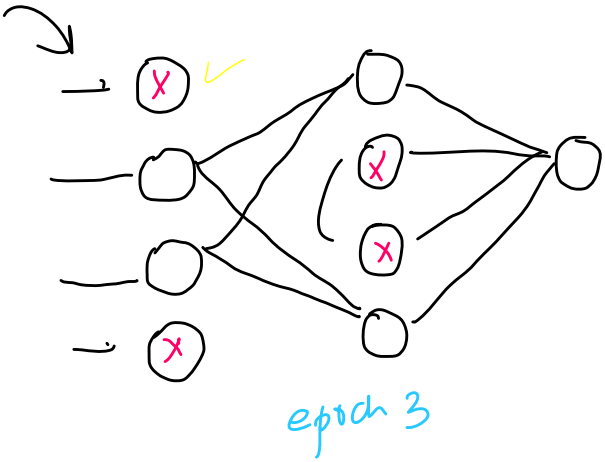
Why this works?

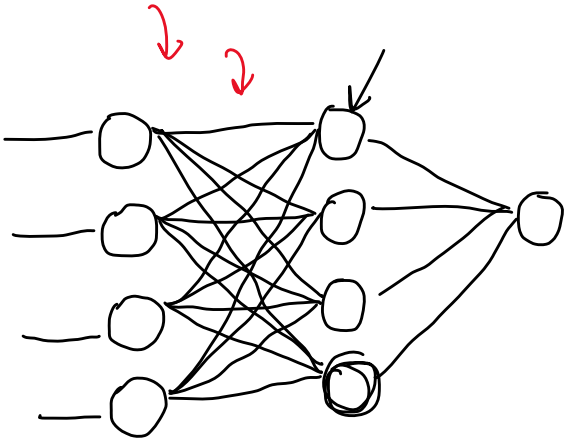
12 May 2022 09:33





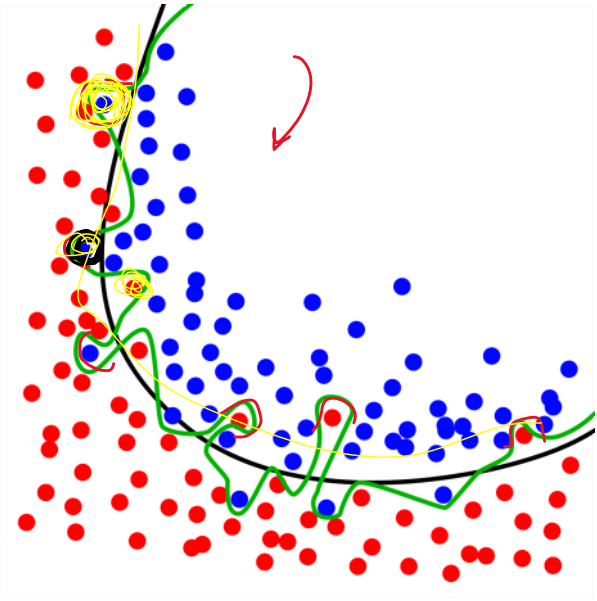






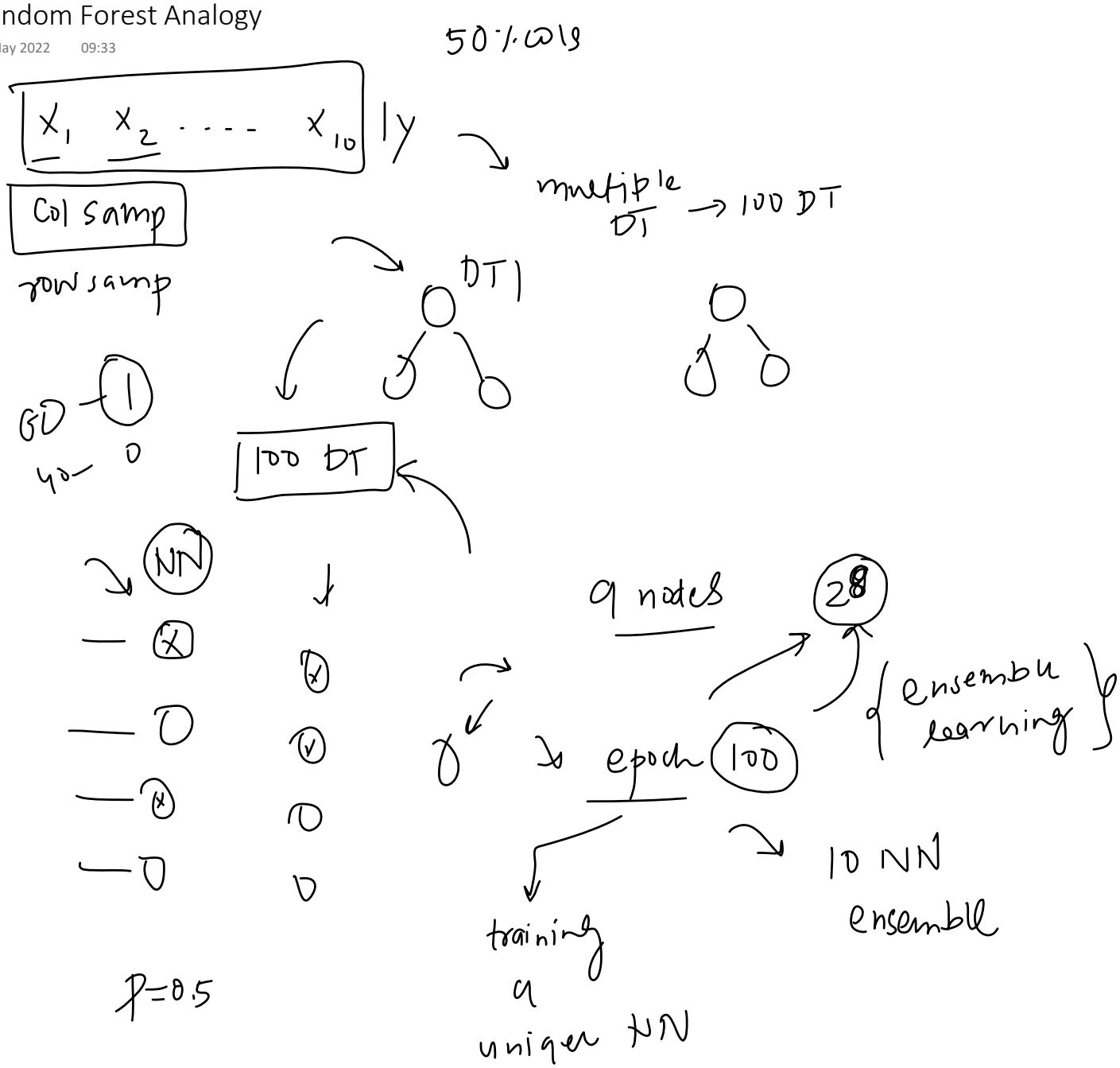
→ Reduce the # nodes

→



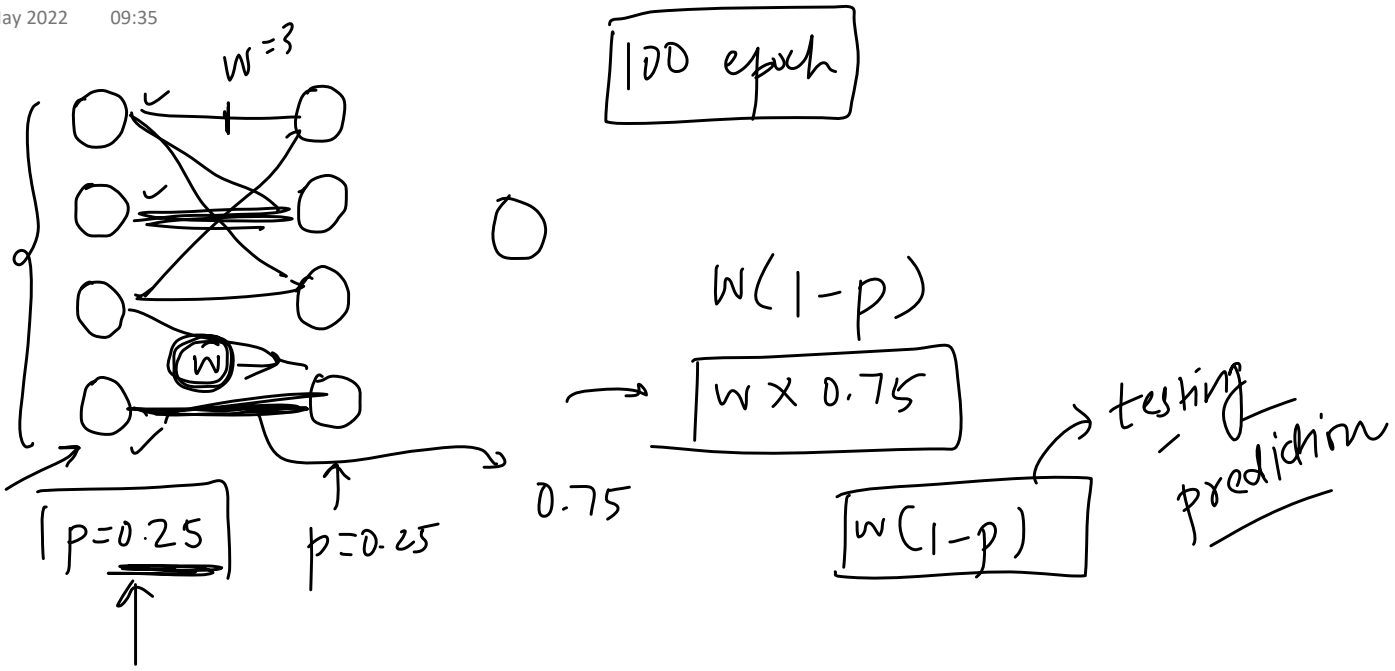
Random Forest Analogy

12 May 2022 09:33



How prediction works?

12 May 2022 09:35



Regression Code Example

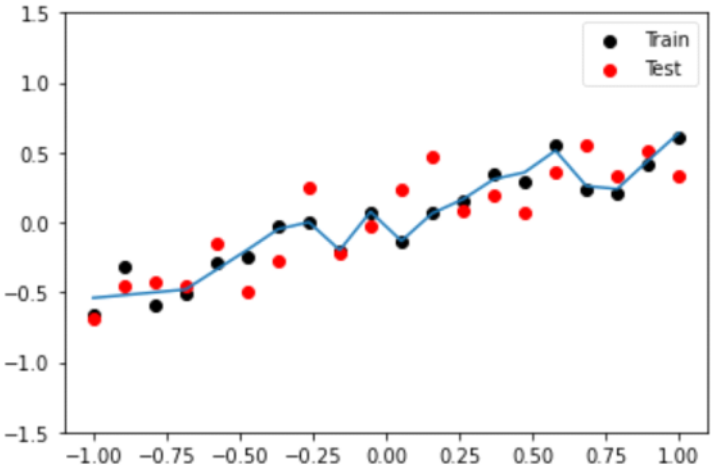
12 May 2022 09:34

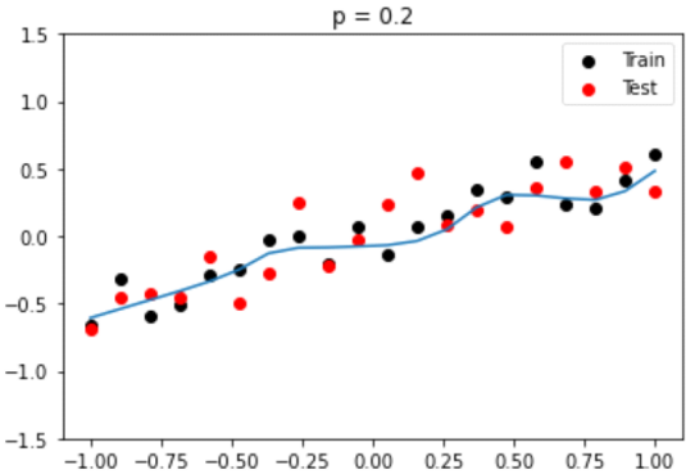
Classification Code Example

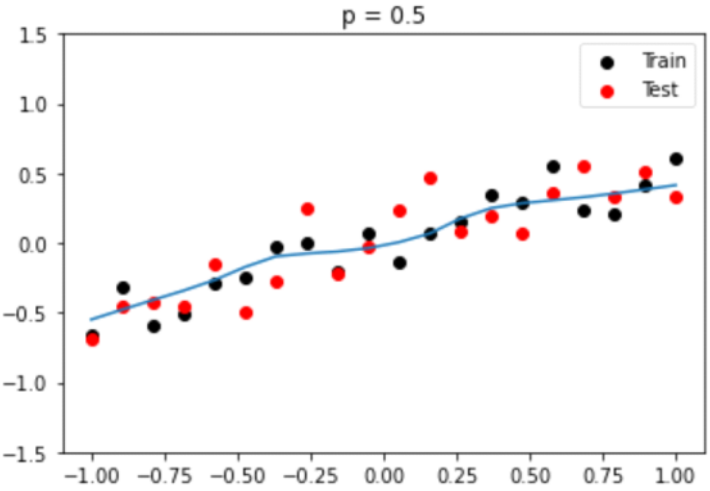
12 May 2022 09:34

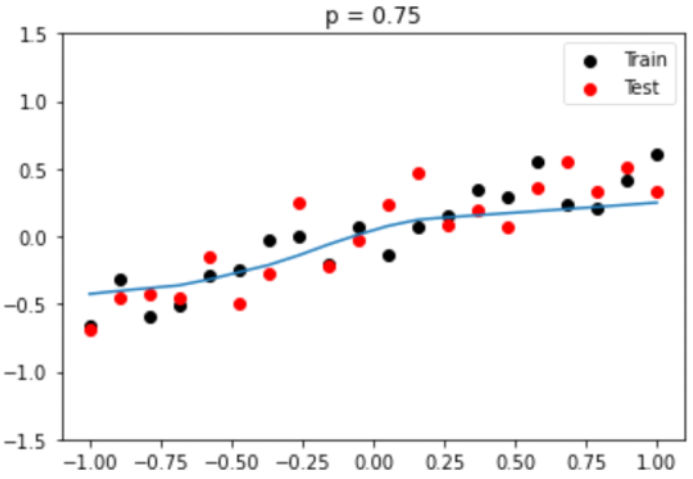
Effect of p

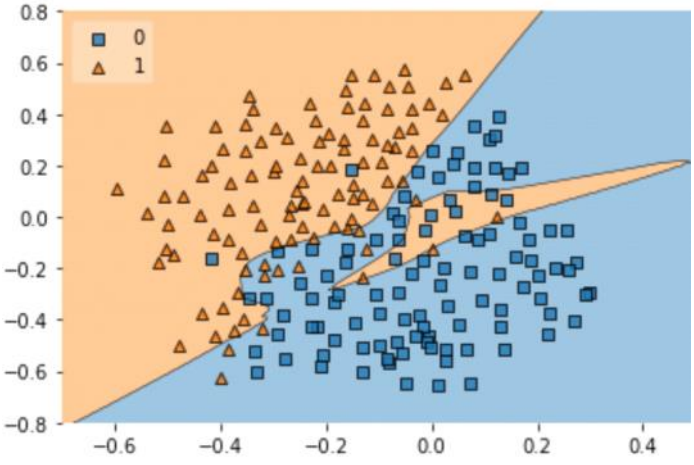
12 May 2022 10:06

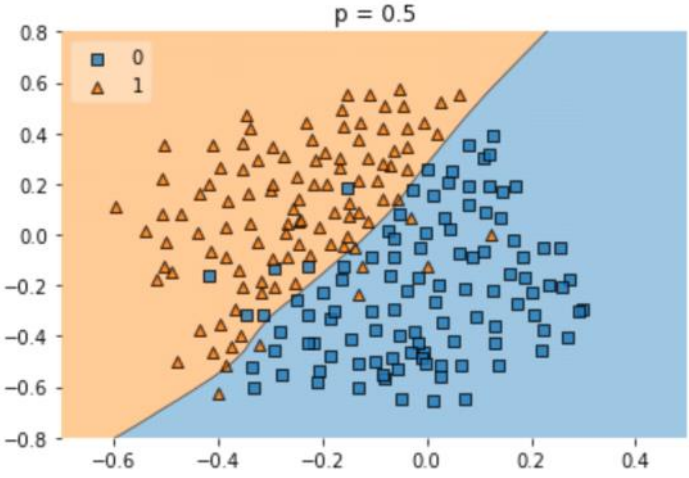










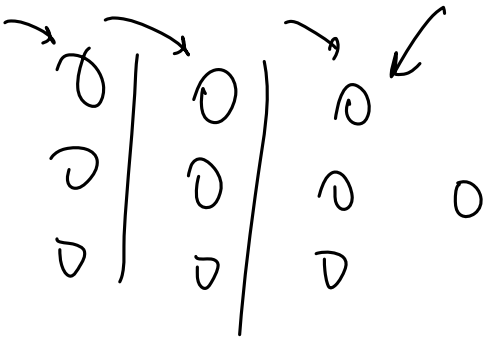


Practical Tips and Tricks

12 May 2022 09:34

1) Overfitting P↑, underfitting P↓

2) Last layer → dropout



3) CNN → 40-50 · (P) → ✓

20-30 RNN 50>

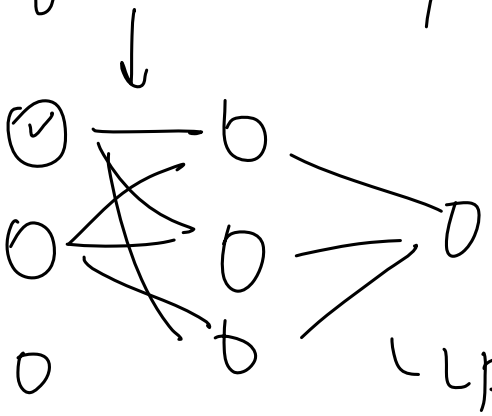
ANN → 10-50

Drawbacks

12 May 2022 09:34

1) convergence → delay

2)



{ loss function } value changes

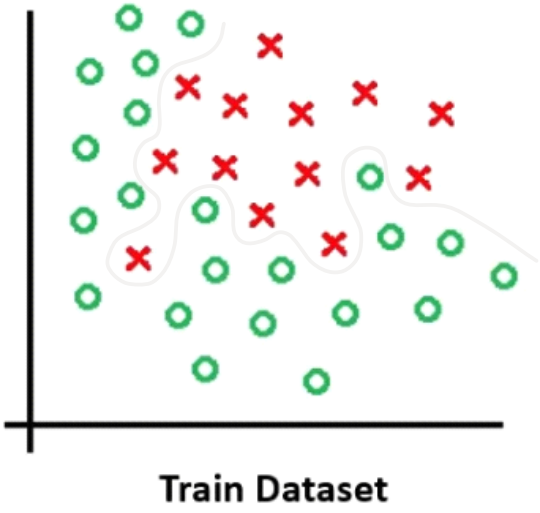
↳ LF – has to change

Resources

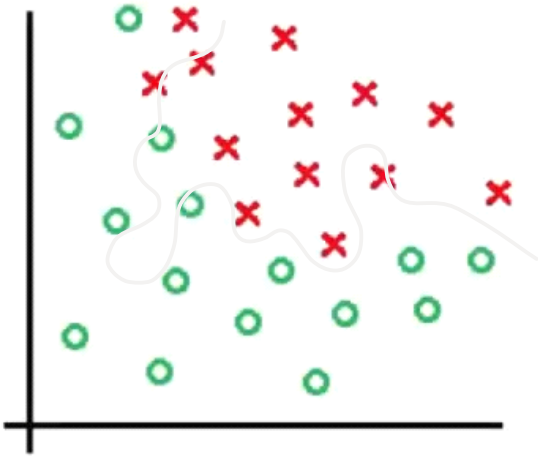
12 May 2022 12:38

Overfitting

20 May 2022 08:14



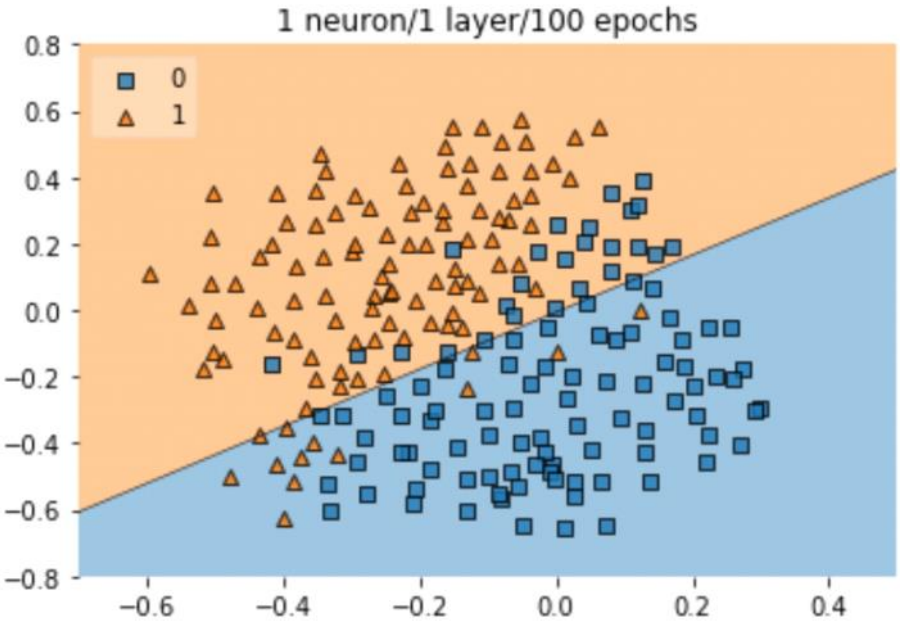
Train Dataset

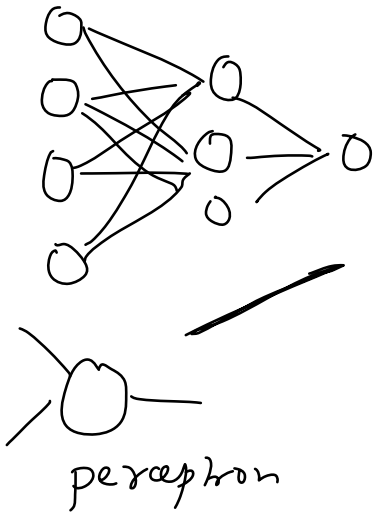


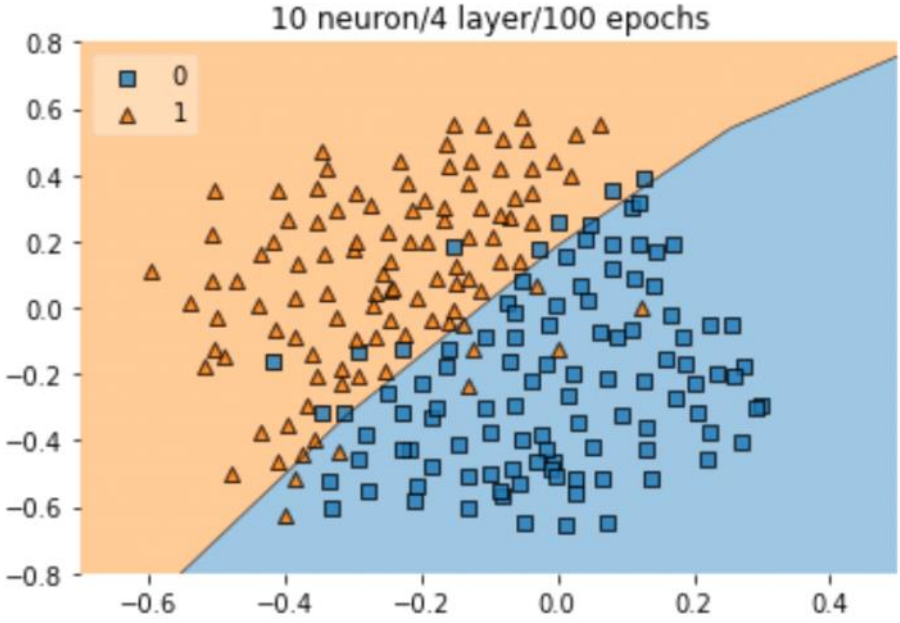
Test Dataset

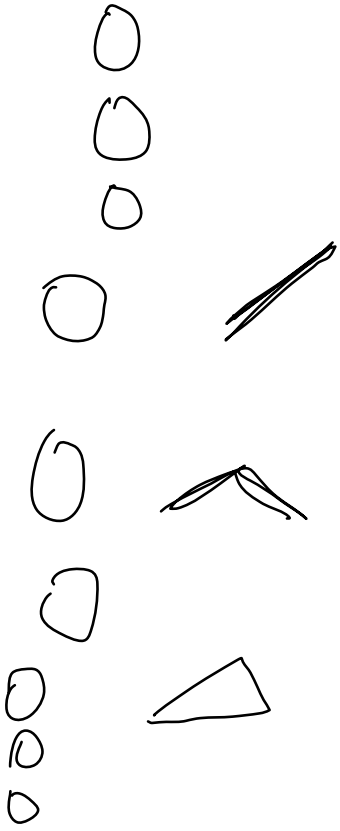
Why Neural Networks Overfit?

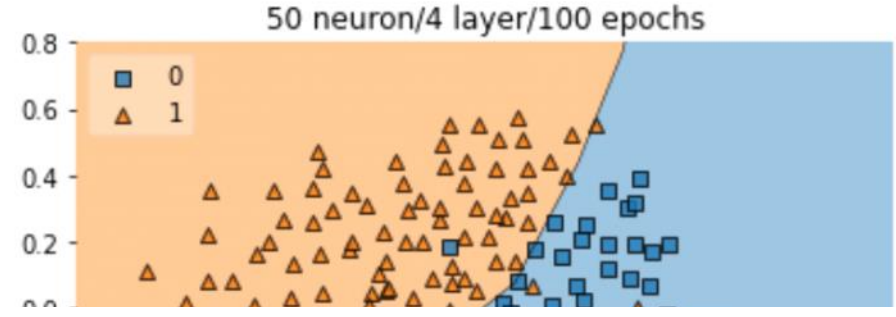
19 May 2022 07:34

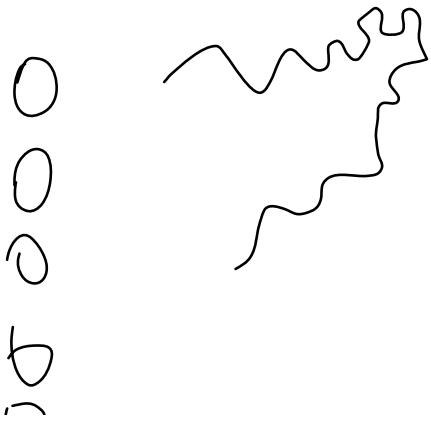


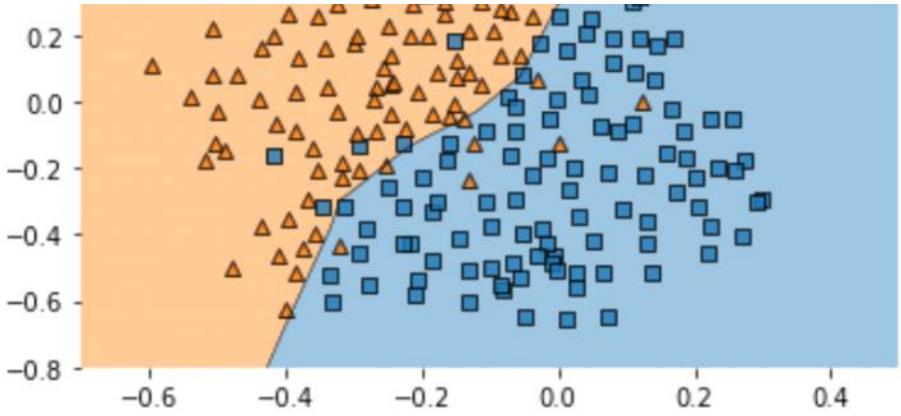


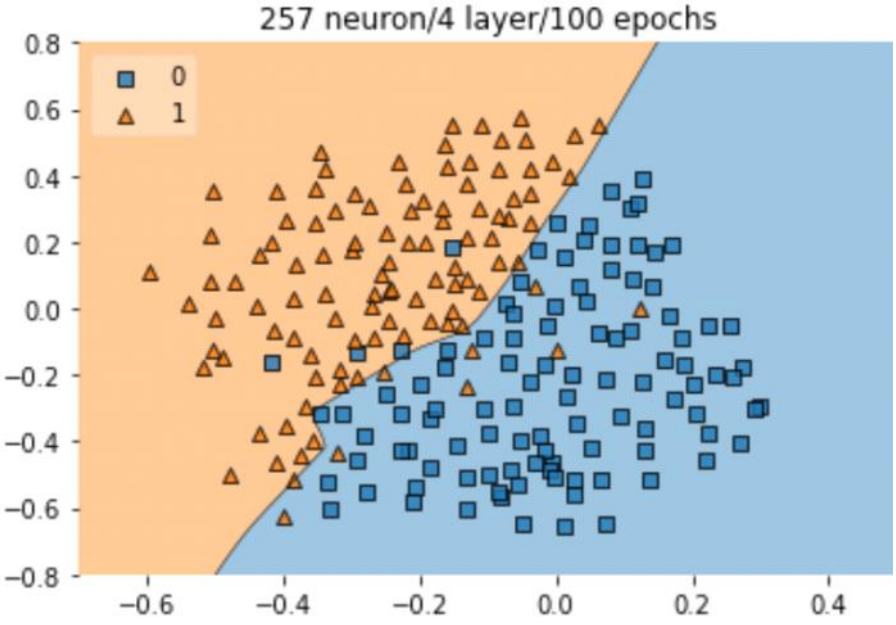


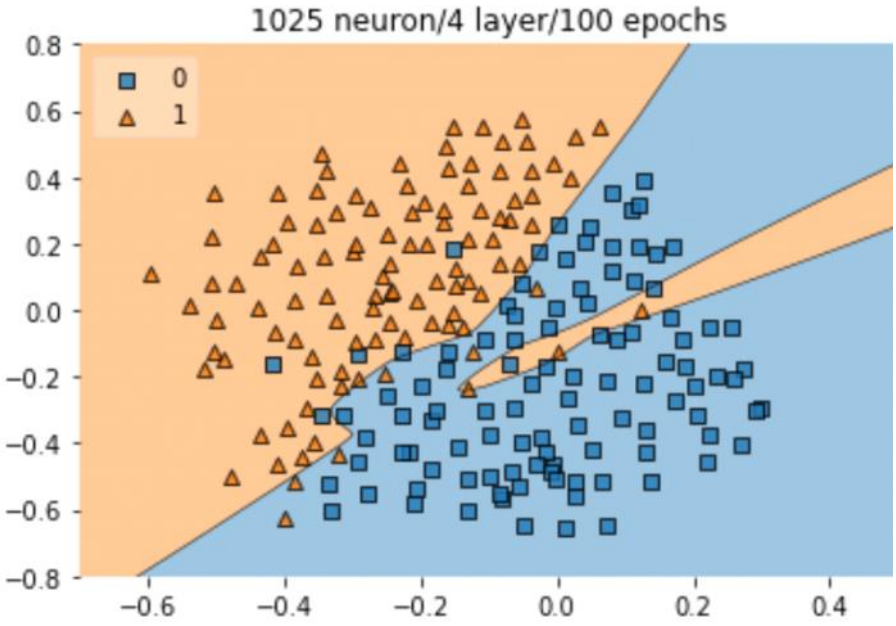


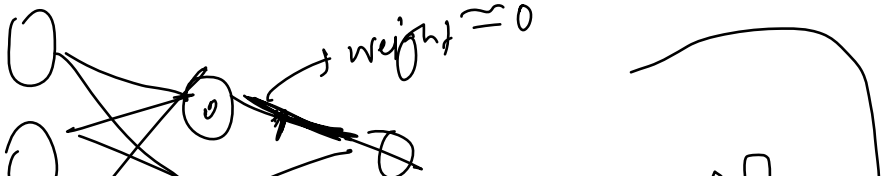


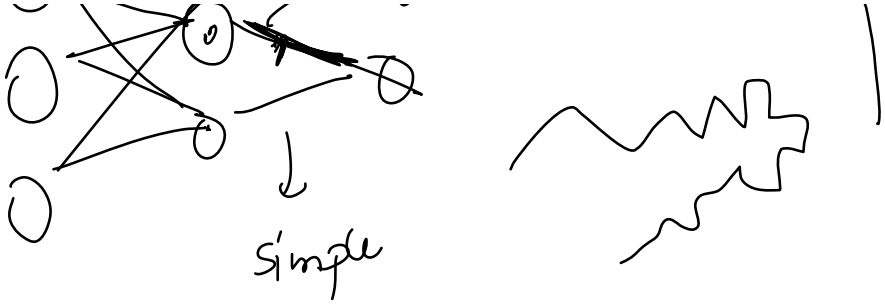





257 neuron/4 layer/100 epochs
0
1

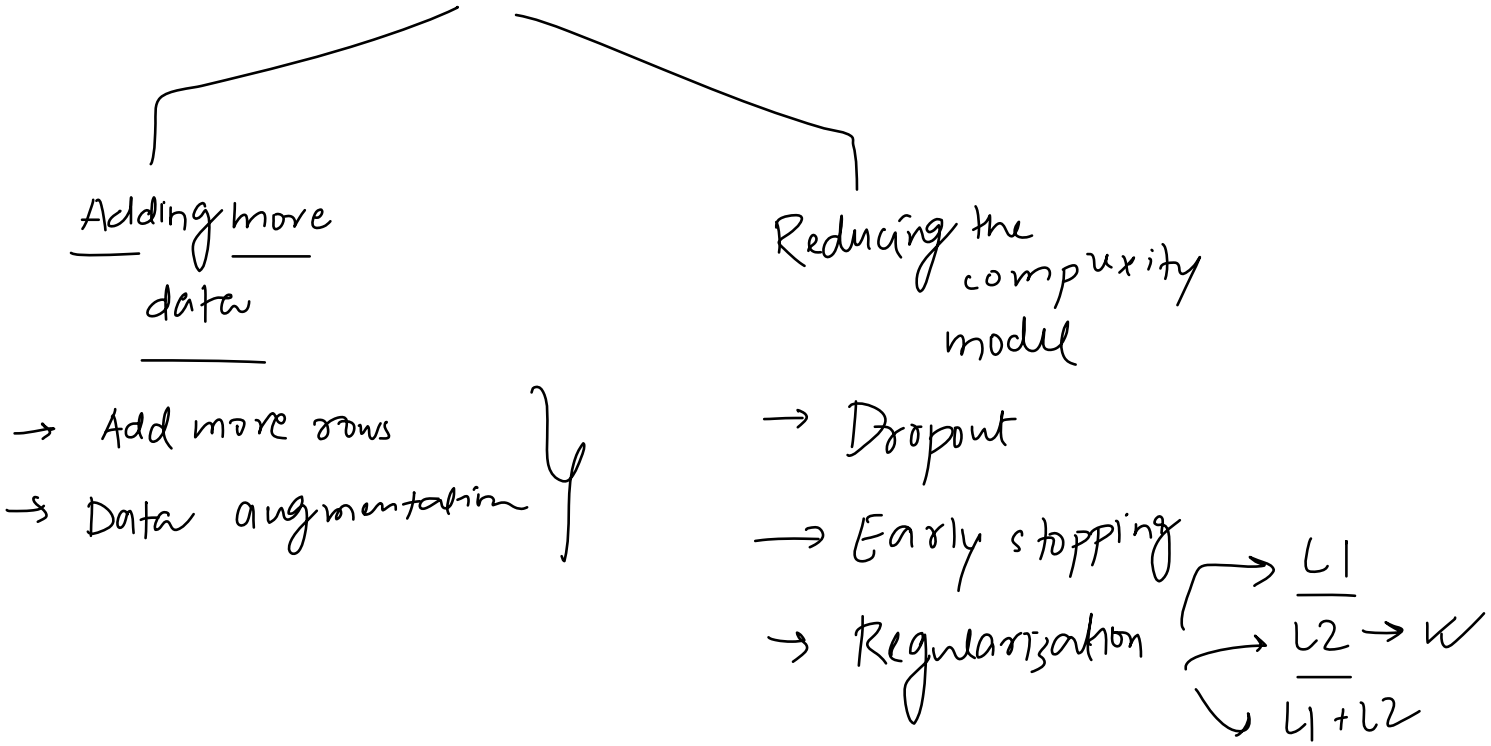

1025 neuron/4 layer/100 epochs
0
1


weight ≈ 0


simple

Ways to solve overfitting

20 May 2022 08:13



Regularization

20 May 2022 08:14

ANN → weights | bias

↳ min Loss function

L = mse

↳ binary

L2

L1

$C = \frac{1}{n}\sum_{i=1}^{n} L(y_i, \hat{y}_i)$ + penalty term

$C = L + \frac{\lambda}{2n}\sum_{i=1}^{k} \|w_i\|^2$ → weightage

$w_1 \rightarrow w_{10}$

$\frac{\lambda}{2n}\left[w_1^2 + w_2^2 + \dots + w_{10}^2\right]$

↑ λ = hyperparameter ↑

$\lambda = 0$

$C = \sum L(y_i, \hat{y}_i) + P$

L2 → L1

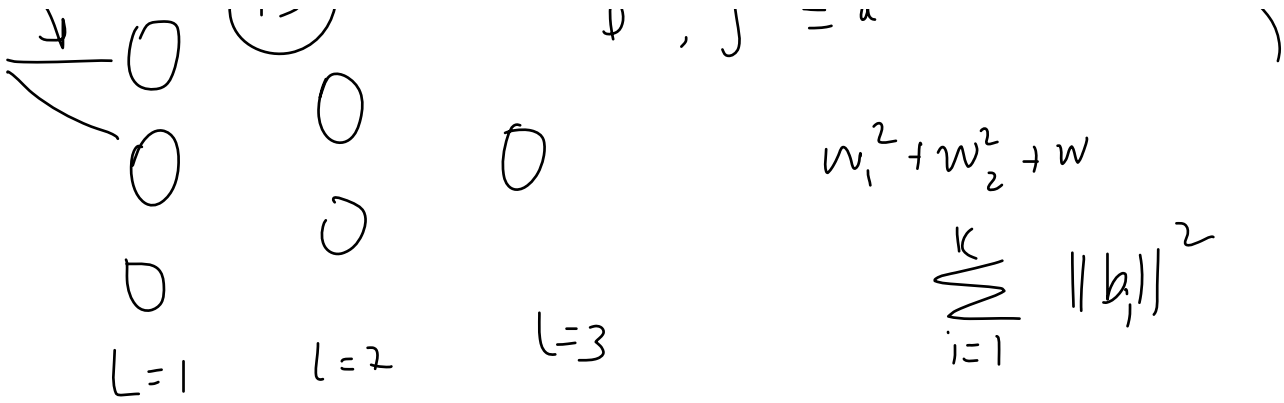
$w \simeq 0$

→ L1 norm

$C = L + \frac{\lambda}{2n}\sum \|w_i\|$

$C = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{l=1}^{L}\sum_{i=1}^{}\sum_{j=1}^{} \|w_{ij}^{l}\|^2$ → $w \simeq 0$

$0, j = d$


L=1
L=2
L=3
$w_1^2 + w_2^2 + w$
$\sum_{i=1}^{K} \|b_i\|^2$
bias X

Intuition behind Regularization

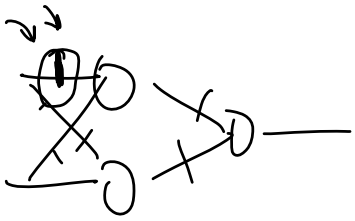
20 May 2022 08:15

$$w_\eta = w_0 - \eta \frac{\partial L}{\partial w_0}$$

$1-\eta\lambda$

positive

L



$$L' = L + \frac{\lambda}{2}\sum \|w_i\|^2$$

$w_2^1 + w_2^2 + w_3 + \dots$

$2w$

$$\frac{\partial L'}{\partial w_0} = \frac{\partial L}{\partial w_0} + \frac{\lambda}{2} 2w_0$$

$$= \frac{\partial L}{\partial w_0} + \lambda w_0$$

$$w_\eta = w_0 - \eta\left(\frac{\partial L}{\partial w_0} + \lambda w_0\right)$$

$$w_\eta = w_0 - \eta\lambda w_0 - \eta\frac{\partial L}{\partial w_0}$$

$$w_\eta = (1-\eta\lambda)w_0 - \eta\frac{\partial L}{\partial w_0}$$

$w_0 << w_0$

L2 reg → weight decay

weight decay w_0

Code Demo

20 May 2022 08:15

Further Resources

20 May 2022 08:15

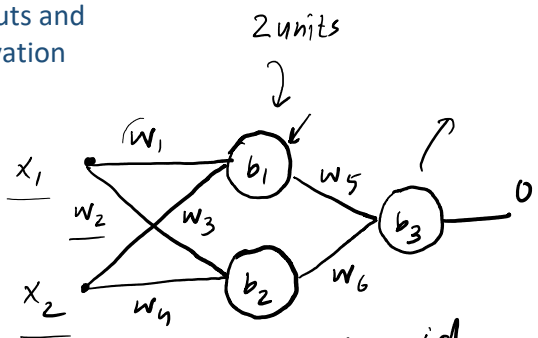
What are Activation Functions?

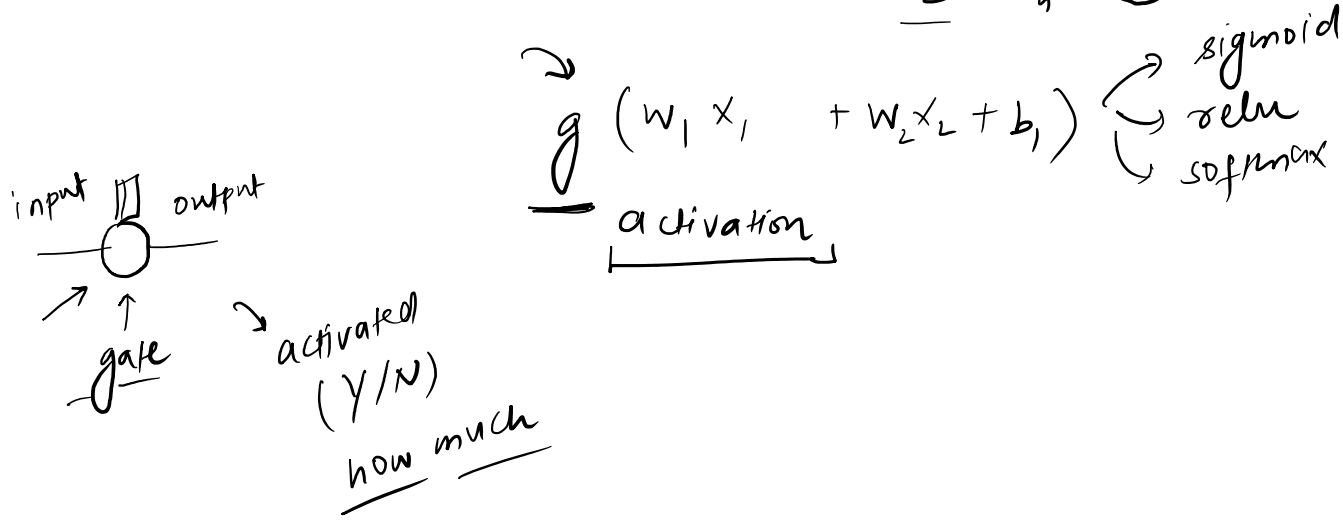
31 May 2022 14:49

In artificial neural networks, each neuron forms a weighted sum of its inputs and passes the resulting scalar value through a function referred to as an activation function or transfer function. If a neuron has n inputs then the output or activation of a neuron is

$$a = g(w_1 x_1 + w_2 x_2 + w_3 x_3 + \ldots w_n x_n + b)$$

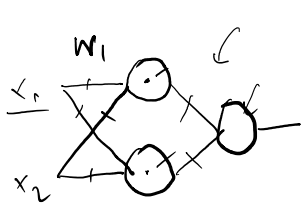
This function g is referred to as the activation function.





Why Activation Functions are needed?

31 May 2022 14:50



forward prop

$$Z_1 = W_1 A_0 + b_1$$

$$A_1 = g(Z_1) = Z_1$$

linear → sigmoid

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

ANN

↓

Non-linear

$$A_2 = g(W_2 A_1 + b_1)$$

Non-linear

output = input

$$= W_2 A_1 + b_2 = W_2 (W_1 A_0 + b_1) + b_2$$

$$= W_2 W_1 A_0 + W_2 b_1 + b_2$$

$$= W' A_0 + b'$$

output

input

$$A_2 = \hat{y} = W' A_0 + b'$$

linear

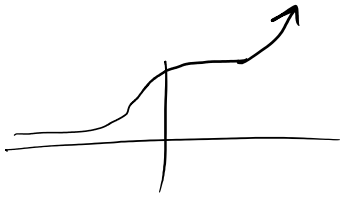
Ideal Activation Function

31 May 2022 14:50

$y = f(x)$ ✓ linear x non-linear

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

1) Non-linear ✓ → Universal Approx Theorem



2) Differentiable ✓ → gradient des → derivatives → relu (0)

3) Computationally inexpensive ✓ → derivative → simples easy fast → training slow

4) Zero centered → zero cent normalized → mean = 0 → normalized data input → later layers → tanh

5) Non-saturating → Sigmoid → [0, 1] → faster → $f(x) = \max(0, x)$

tanh → (-1, 1) Relu

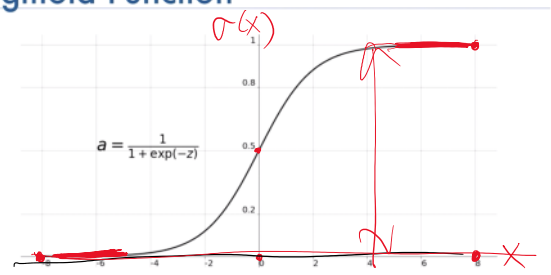
update x [0, 1] → backprop → saturating AF → Vanishing gradient Problem

0.01 → 0.0001 → 0.0001

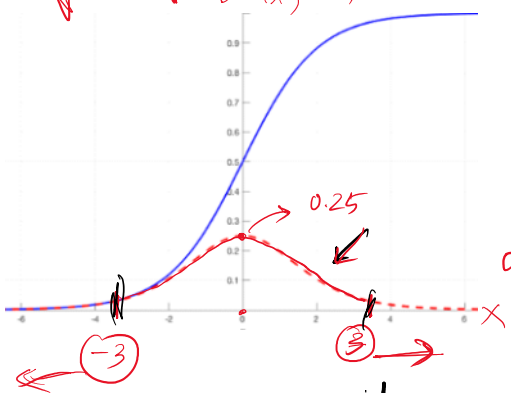
Sigmoid Activation Function

31 May 2022 14:50

Sigmoid Function



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



$w_1x_1 + w_2x_2 + b$

input ↑ → Norm

$x \simeq 0$

$\sigma'(x) \simeq 0$

w_1, w_2, b → weight init

Yes / No

sigmoid → 0-1 — yes / No

Advantages

1) [0,1] → probability → output layer → Binary classification

2) Non-linear → Non-linear data → good option

3) Differentiable → Backprop → $\frac{\partial L}{\partial w}$

Disadvantages

1) Saturating function → $[-\infty, \infty] \rightarrow [0,1]$

↳ Vanishing gradient problem

Hidden layer → sigmoid → training ✗

output → binary classification

Backprop → update

$w_n = w_0 - \eta \frac{\partial L}{\partial w}$

$w_n = w_0$ → training ✗

No update will take place

2) Non Zero centered

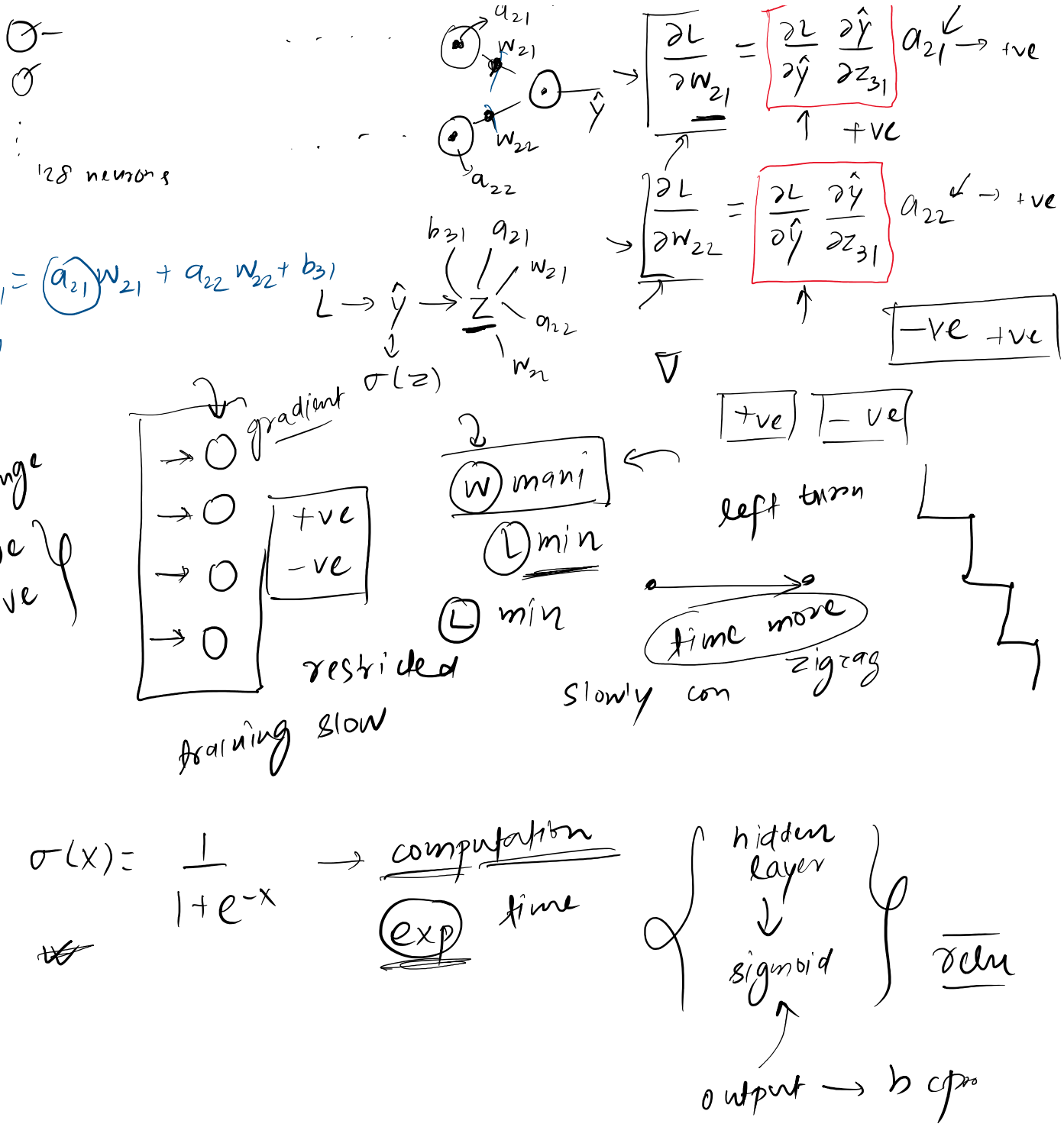
Normalized → mean = 0

+ve / -ve → Training slow

Convergence problem

+ve -ve → 0 → 1

$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial z} a_{21}$ → +ve



3) $\sigma(x) = \frac{1}{1+e^{-x}}$ → computation time

exp

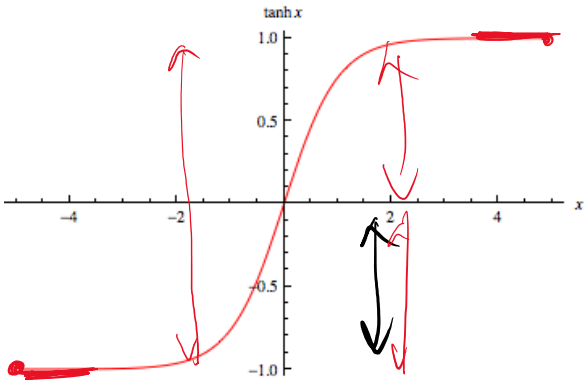
hidden layer → sigmoid → relu

output → b cpu

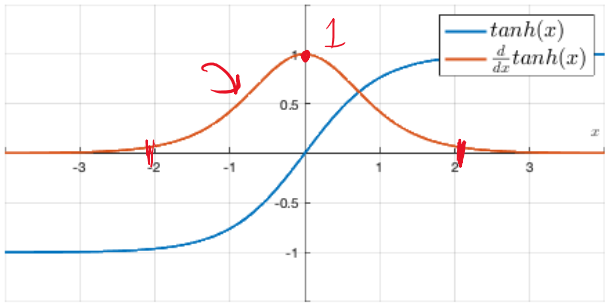
Tanh Activation Function

31 May 2022 14:50

(0,1) (-1,1)



0.25



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

$$f'(x) = (1 - \tanh^2(x))$$

Advantages

1) Non-linear
2) Differentiable
3) zero centered (+ve, -ve) → training faster sigmoid

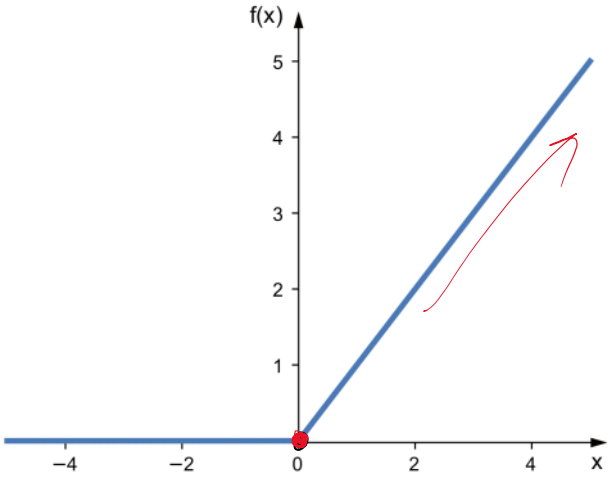
Disadvantage

→ saturating function → vanishing gradient prob

→ Computationally exp exp slow

Relu Activation Function

01 June 2022 16:43



Most activation $f(x) = \max(0, x)$ $f(x) = x$

Advantage

$f(x) = \max(0, x+1) - \max(0, x-1)$

1) Non-linear
2) Not saturated in the +ve region
3) Computationally inexpensive
4) converge → faster → sigmoid, tanh

Disadvantage

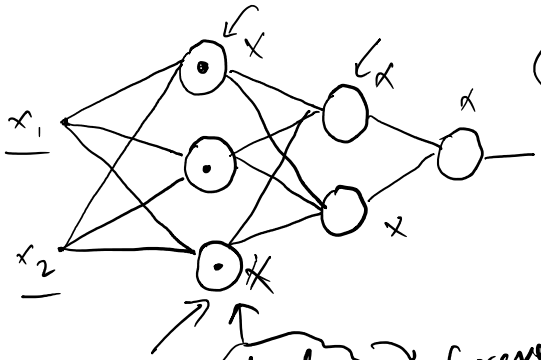
→ Differentiable $x < 0 \rightarrow 0$, $x \geq 0 \rightarrow 1$

→ Non Zero centered → sigmoid → Batch Normalization → normalize →

↳ Dying RELU problem

Dying Relu Problem

08 June 2022 22:53



Relu → Vanishing grad

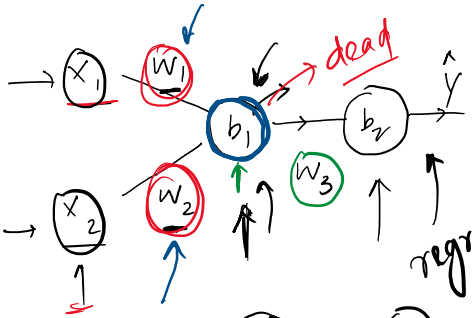
Best choice hidden layers

→ Dying Relu → 50% >

0 → dead neuron → forever dead (0)

100% dead → worst

model → data → low level regrns



$a_1 = \max(0, z_1) = 0$

$z_1 = w_1x_1 + w_2x_2 + b_1 < 0$

$\frac{\partial a_1}{\partial z_1} = 0$

regression

$w_1 = w_1 - \eta \frac{\partial L}{\partial w_1}$ → −ve

$w_2 = w_2 - \eta \frac{\partial L}{\partial w_2}$ → −ve

+ve

$L \to \hat{y} \to w_3, b_2$

$a_1 \to z_1 \to w_1, w_2, x_1, x_2, b_1$

$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial a_1} \frac{\partial a_1}{\partial z_1} \frac{\partial z_1}{\partial w_1}$

$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial a_1} \frac{\partial a_1}{\partial z_1} \frac{\partial z_1}{\partial w_2}$

dying relu

$z_1 = w_1x_1 + w_2x_2 + b_1 < 0$ (−ve)

$b_1 << 0$ (−ve)

dead

1) High learning rate (η)

2) High −ve bias

$b_1 = b_1 - \eta \frac{\partial L}{\partial b_1}$ (−ve)