Deep learning

$y = f(x) + \varepsilon$

ML

Reg

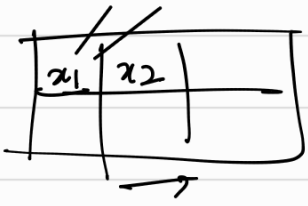
Class.

LR, LR ← Parametric models

DT, RF, Xgboost ← Non-parametric

Process

$y \sim f(x)$

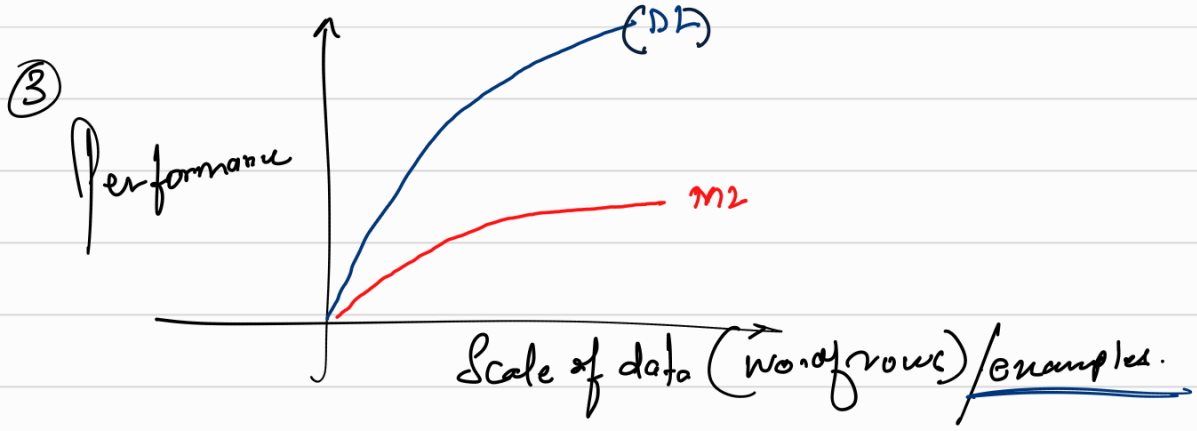


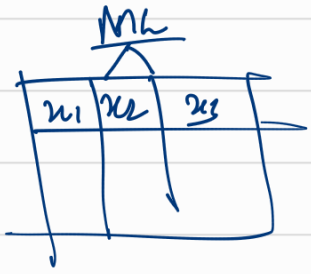
① $x \rightarrow$ (image, video, audio, text, tabular data, graph).

architecture

multimodality

② Tabular data, text, Scan → model → Diagnosis



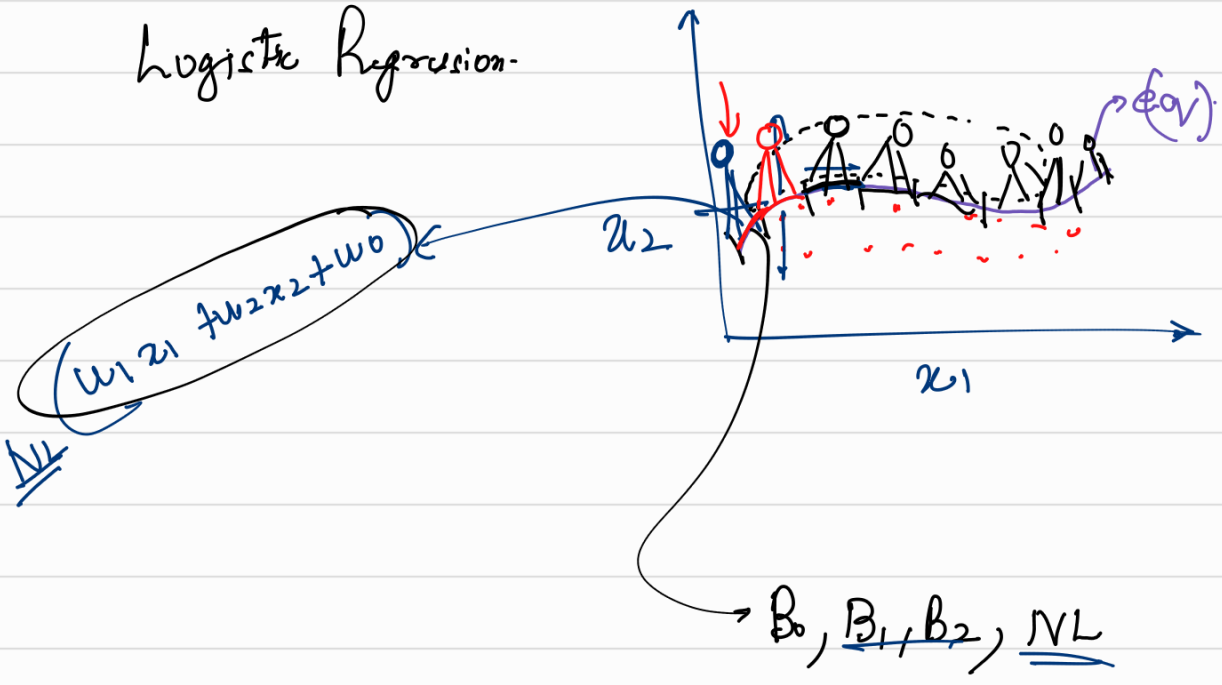


DL → automated feature engineering

DL

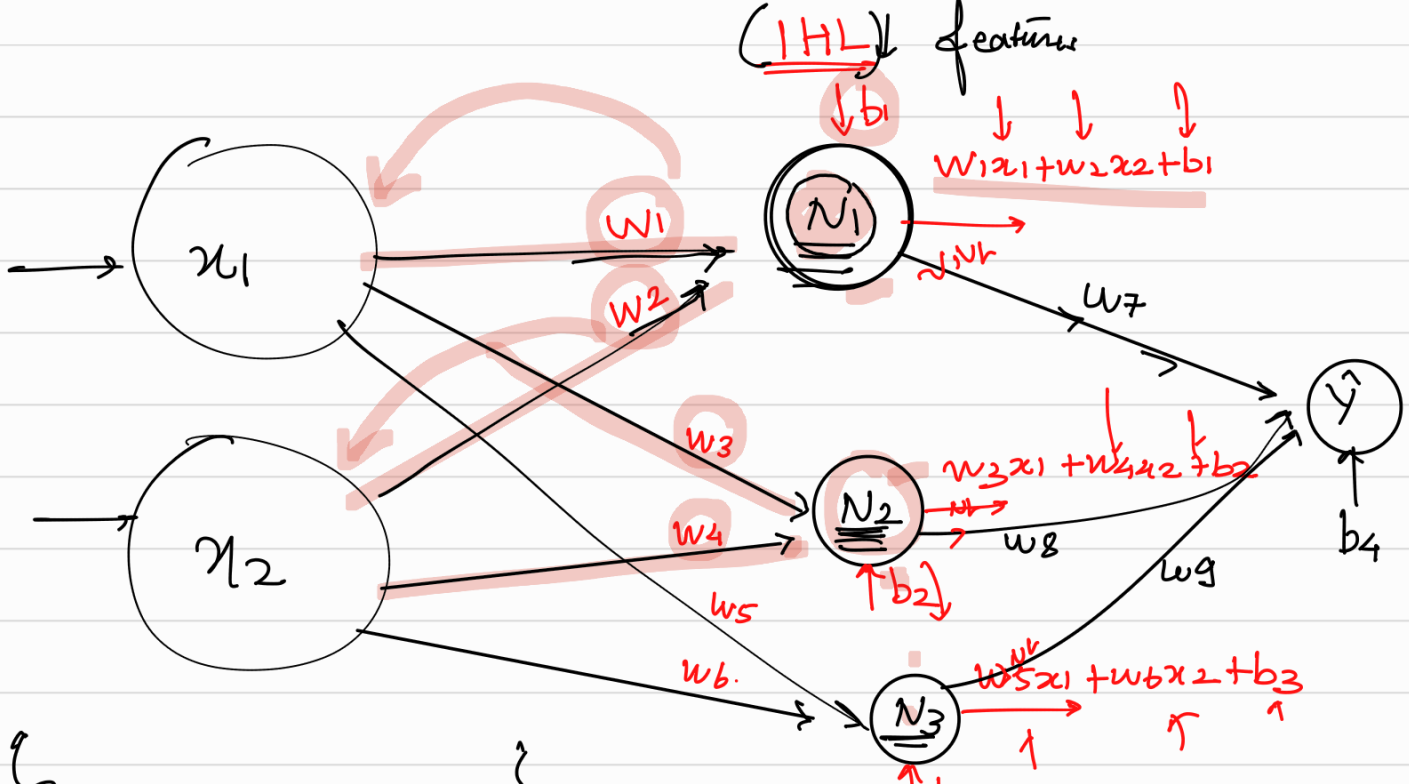
What is a Neuron

Logistic Regression.



B_0, B_1, B_2, NL

x_1	x_2	y



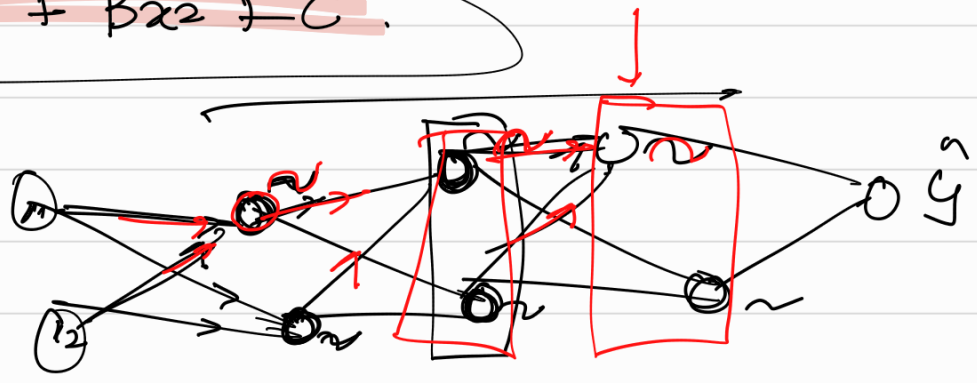
$N_1 = (w_1x_1 + w_2x_2 + b_1)$, $N_2 = (w_3x_1 + w_4x_2 + b_2)$ $N_3 = (w_5x_1 + w_6x_2 + b_3)$

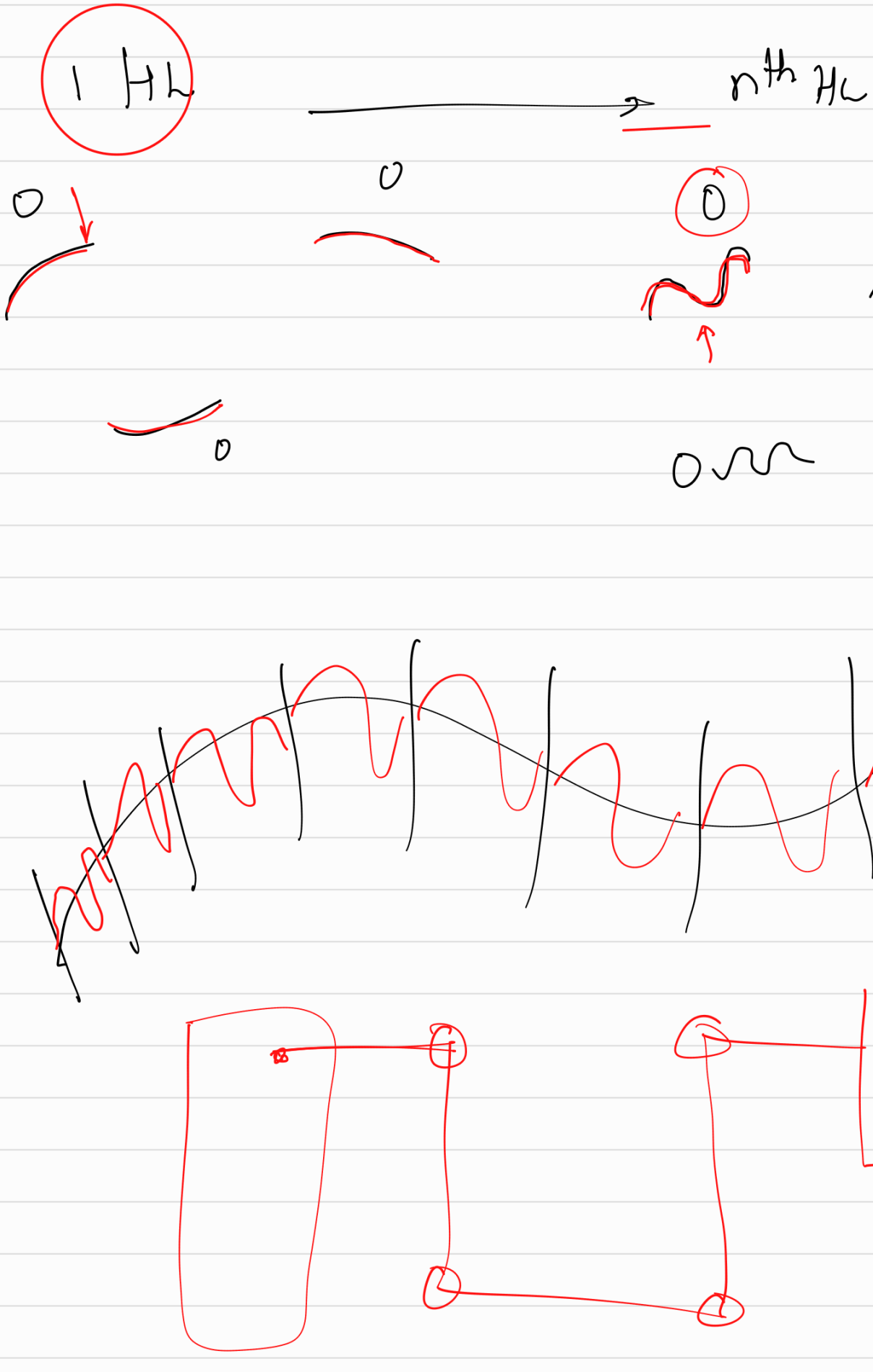
$$\hat{y} = w_7N_1 + w_8N_2 + w_9N_3 + b_4$$

$$\Rightarrow \hat{y} = w_7(w_1x_1 + w_2x_2 + b_1) + w_8(w_3x_1 + w_4x_2 + b_2) + w_9(w_5x_1 + w_6x_2 + b_3) + b_4$$

$$\Rightarrow \hat{y} = x_1(w_7w_1 + w_8w_3 + w_9w_5) + x_2(w_7w_2 + w_8w_4 + w_9w_6) + w_7b_1 + w_8b_2 + w_9b_3 + b_4$$

$$\Rightarrow \hat{y} = Ax_1 + Bx_2 + C$$



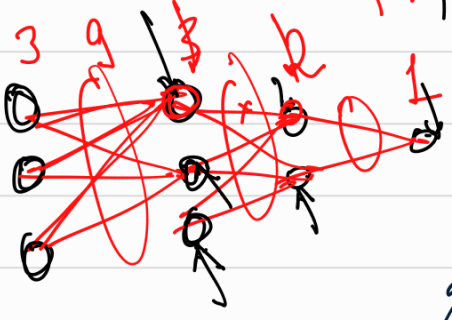

1 HL
nth HL

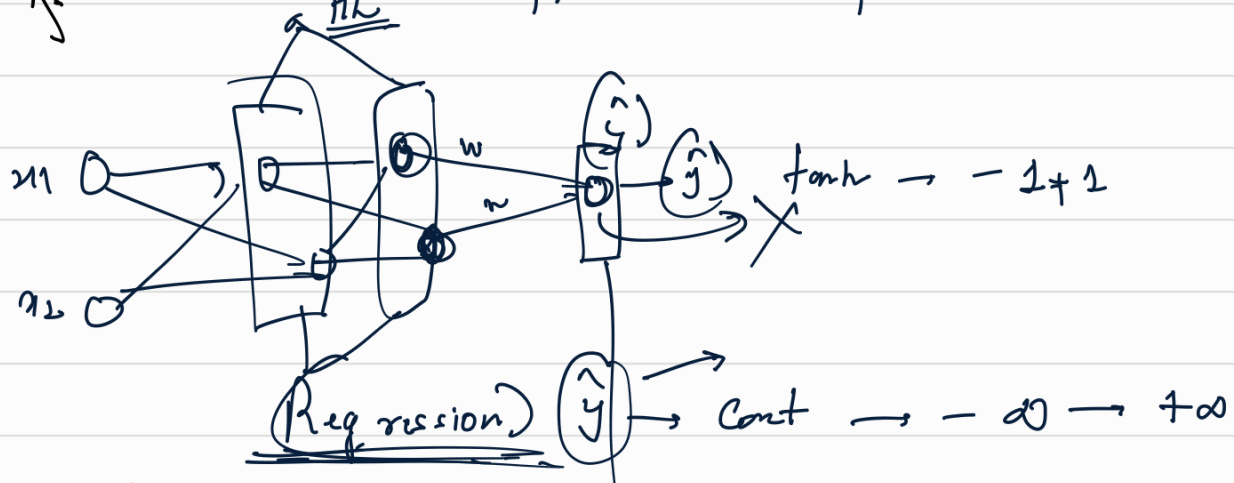
Gradient Descent : minimise the loss by updating the W, B. for all neurons.

Random

1) Define the neural network architecture

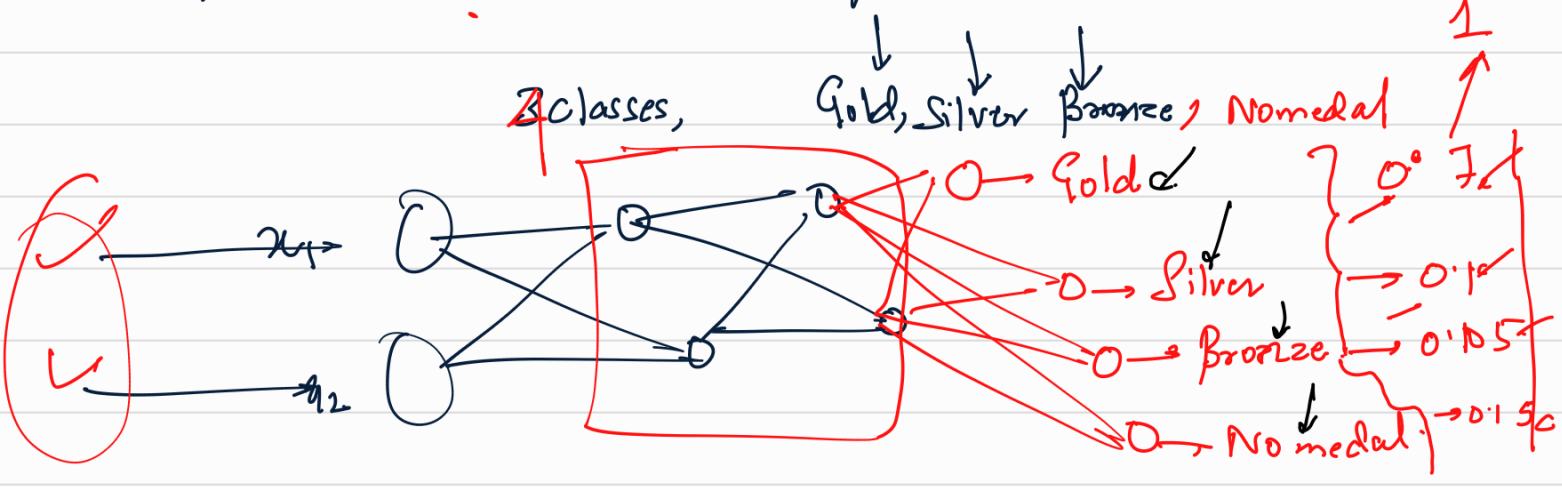
W, b → HLs → Hidden layers
→ Neurons
→ activation function
→ weights and biases → Random
→ optimizer and loss function

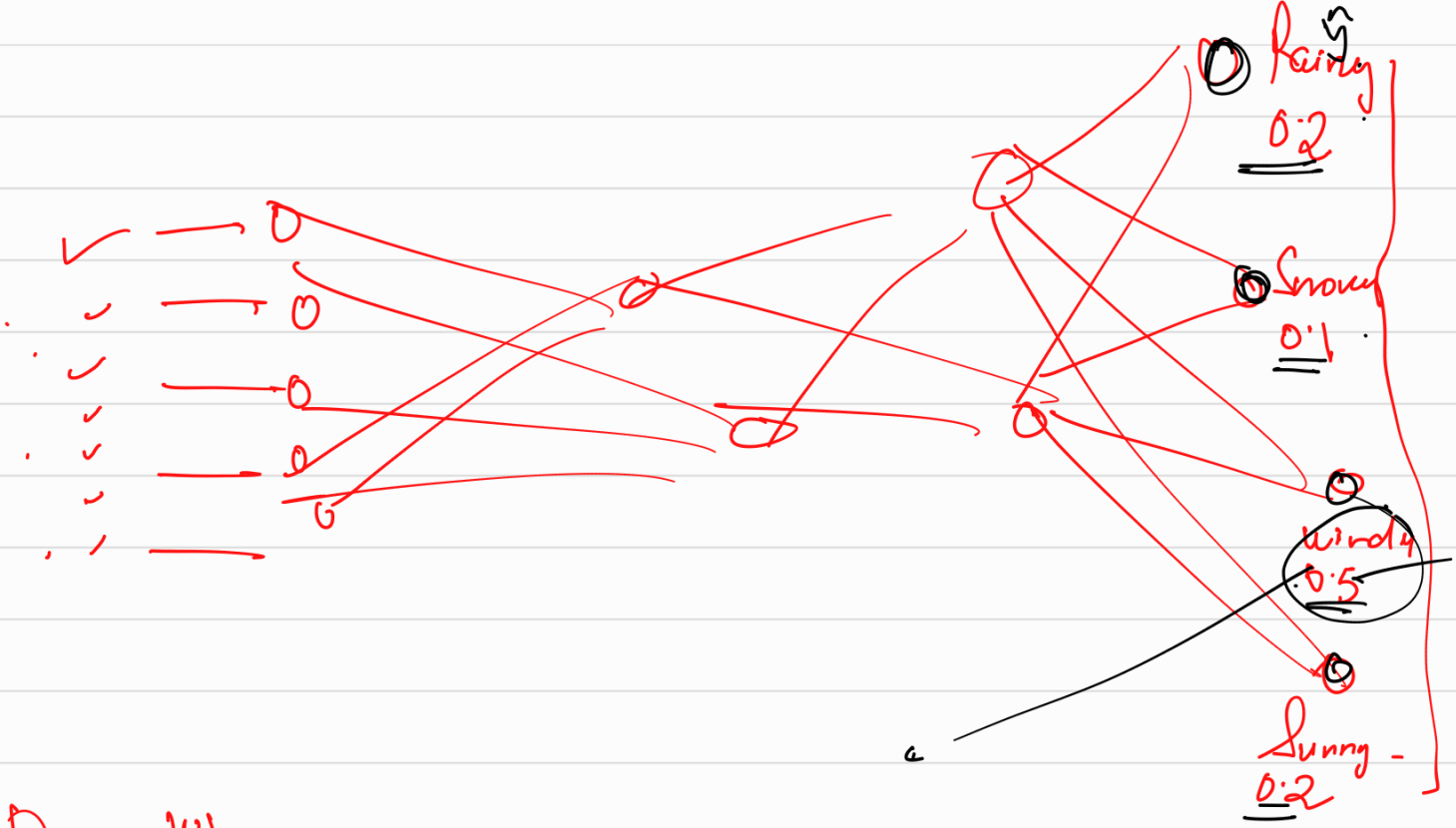




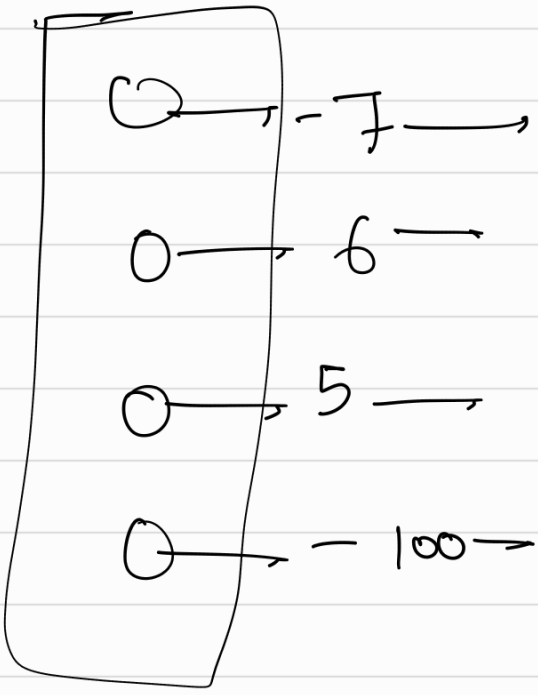
Classification (Binary). → $sig(\hat{y})$ → 0 - 1

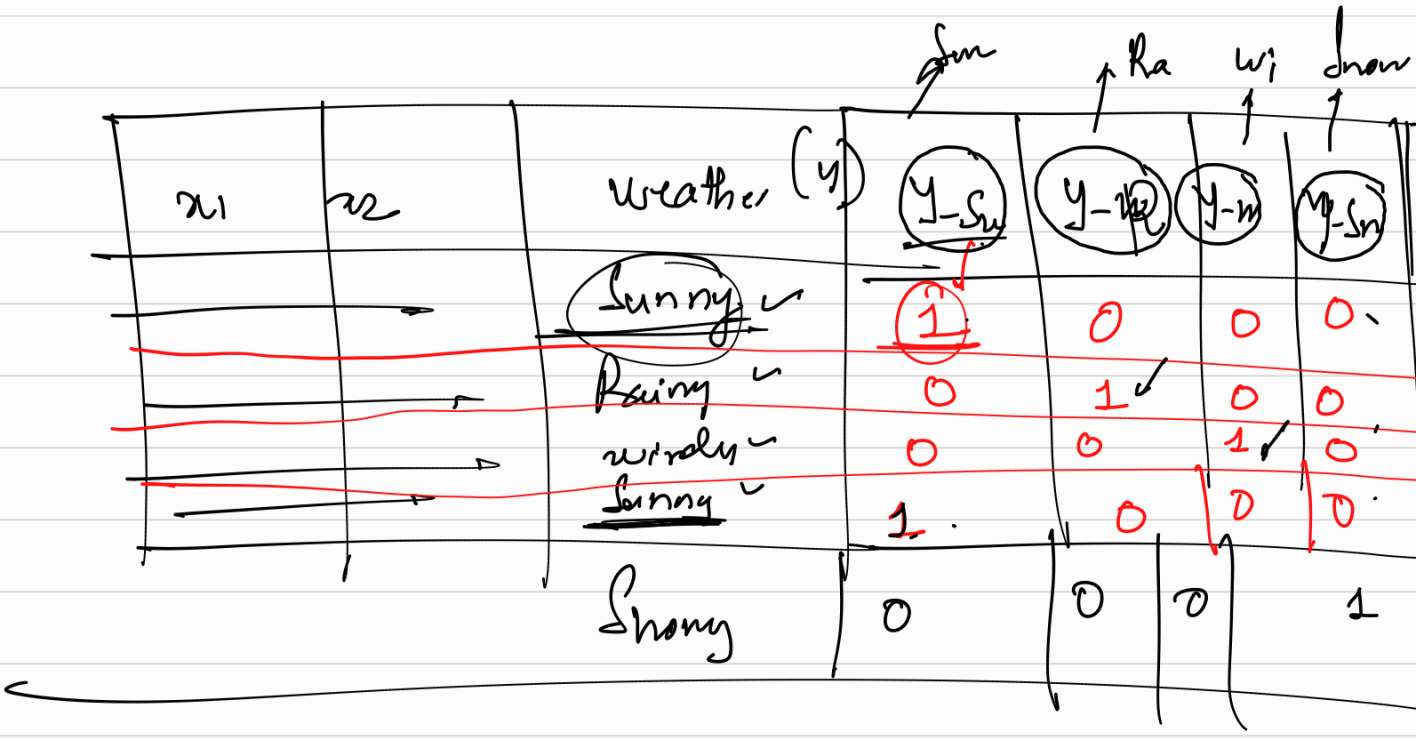
Classification (multiclass). Softmax ($\hat{y}$).

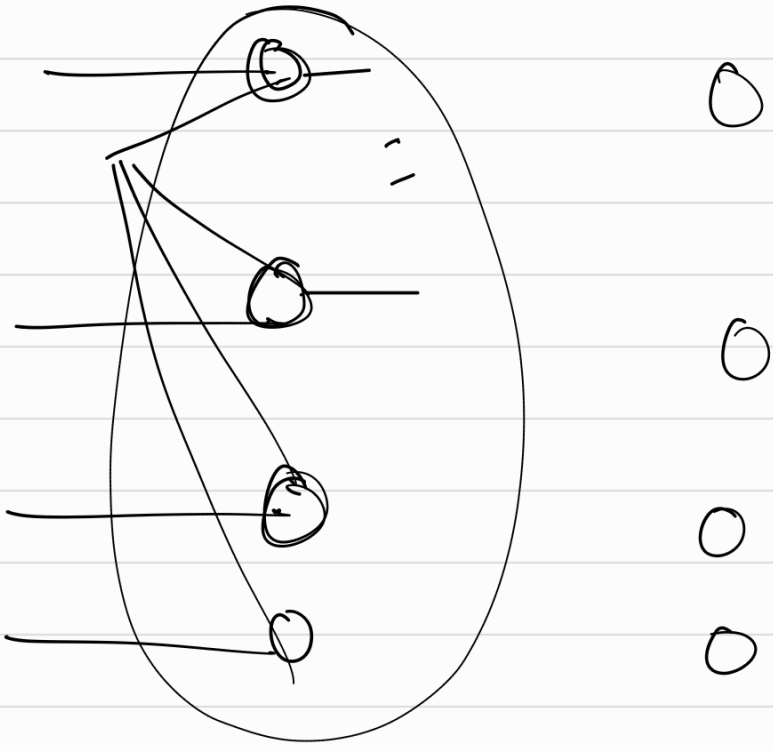


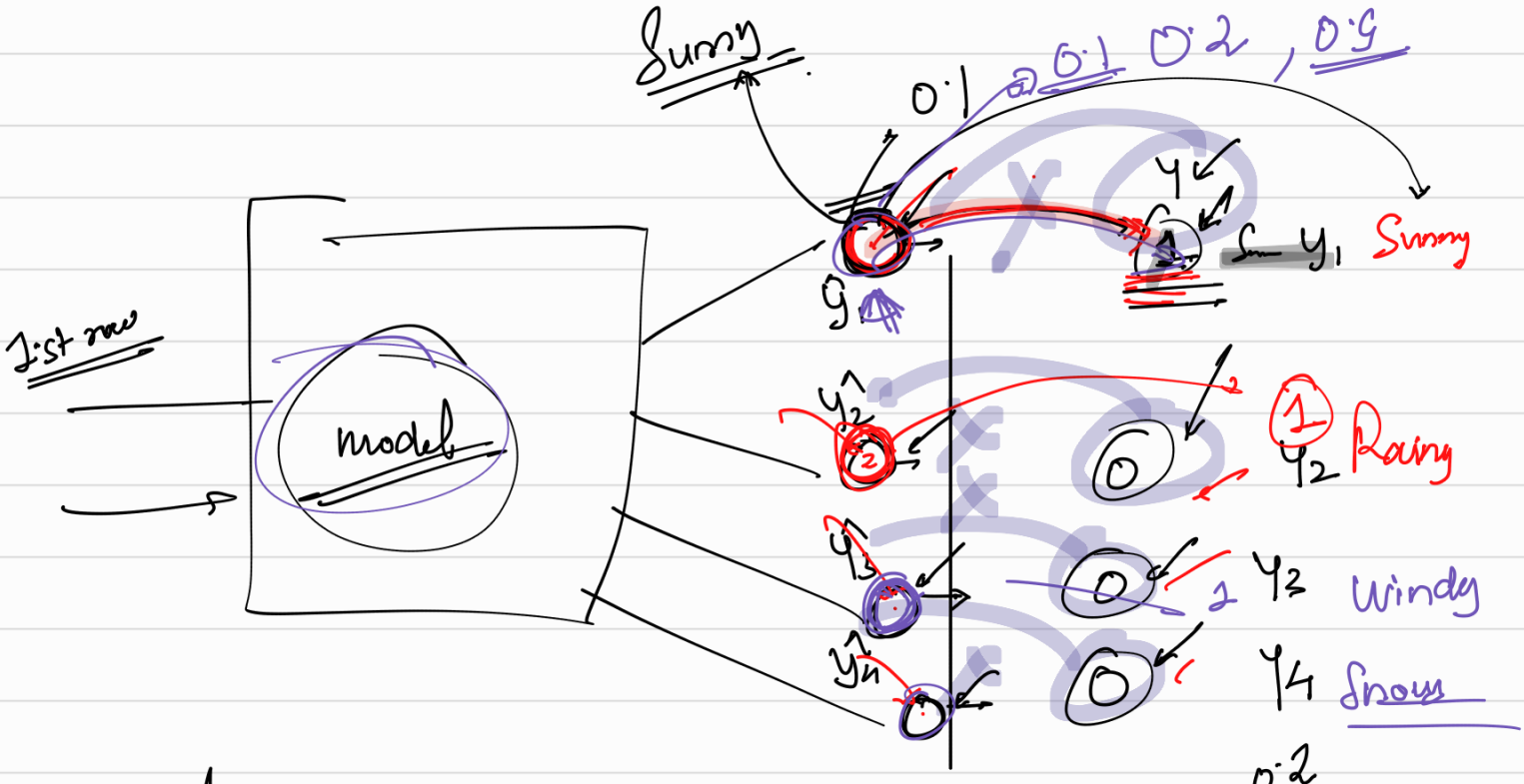

Rainy
0·2
Snowy
0·1
Windy
0·5
Sunny -
0·2


x
w1
x


7
6
5
100


Sun
Ra
Wi
Snow
x1
x2
weather (y)
y-Su
y-Ra
y-Wi
y-Sn
Sunny
Rainy
windy
Sunny
Snowy
1
0
0
0
0
1
0
0
0
1
0
0
1
0
0
0
0
1





Log loss = for all rows of data sum $-\left(y_1 \log(\hat{y}_1) + y_2 \log \hat{y}_2 + y_3 \log \hat{y}_3 + y_4 \log \hat{y}_4\right)$.

0.2, 0.8

$$- \left(\log 0.2\right)$$

$$= 0.69$$

$$- \left(\log 0.8\right)$$

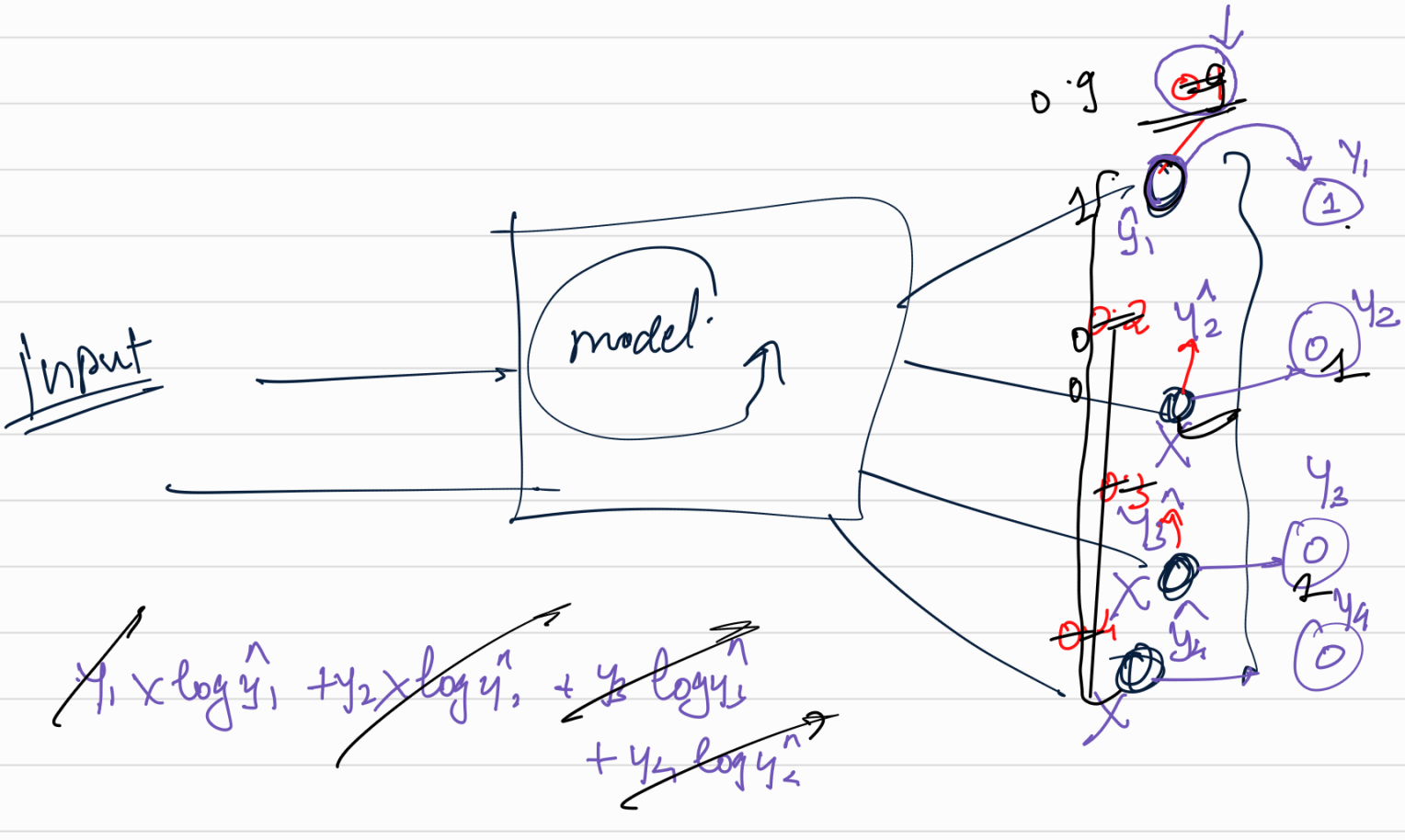
$$= 0.09$$

$$- \log(0.95) = 0.02$$

$$\log 1 = 0$$

$$y_1 \log \hat{y}_1 + y_2 \log \hat{y}_2 + y_3 \log \hat{y}_3 + y_4 \log \hat{y}_4$$

$$\log(0.1) = 1$$



$y_1 \times \log \hat{y}_1 + y_2 \times \log \hat{y}_2 + y_3 \log \hat{y}_3 + y_4 \log \hat{y}_4$

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

$\log 1 = 0$

①

$-[\log(0.1)] = 1$

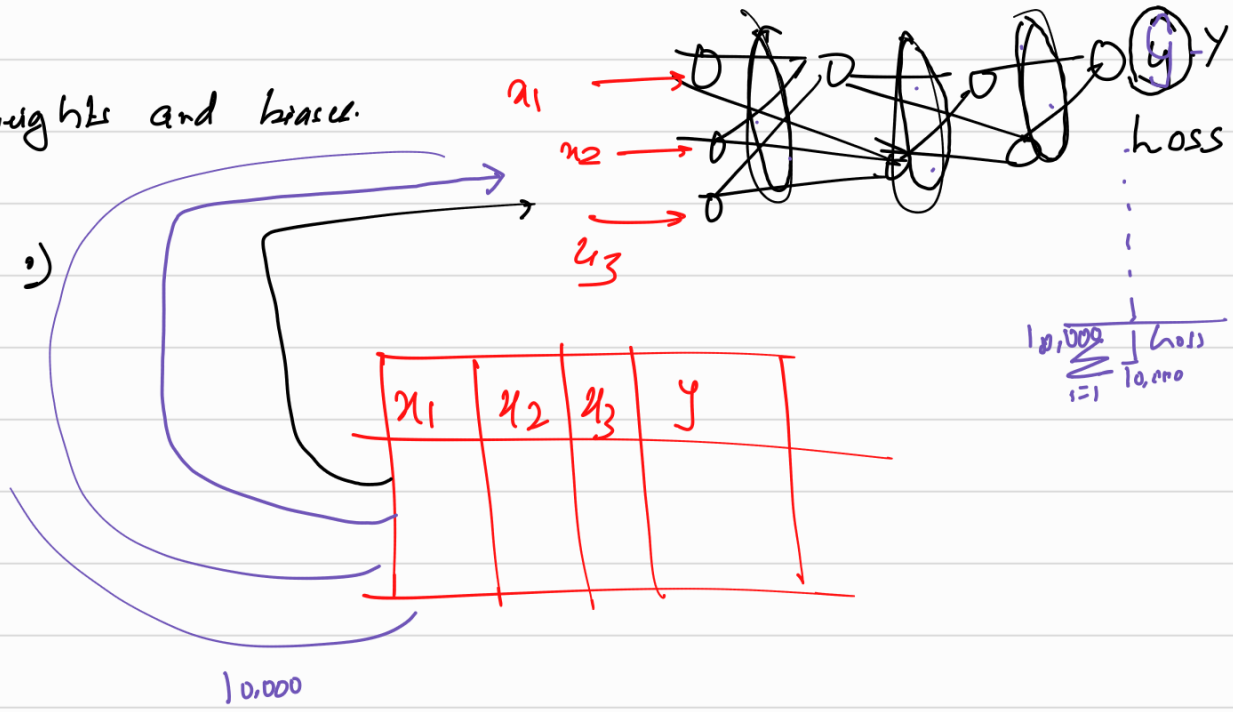
vs

$-\log(0.9) = 0.045$

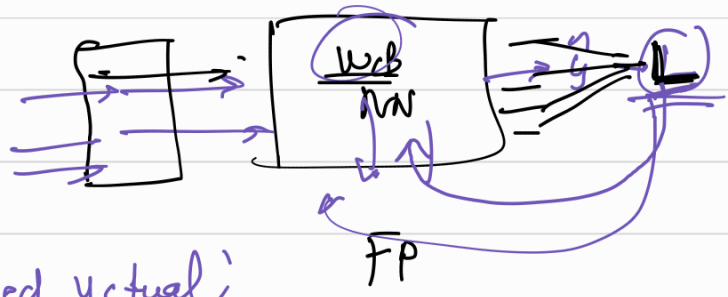
$$\begin{matrix}0\\0\\0\end{matrix} \quad \begin{matrix}0\\0\\0\end{matrix} \rightarrow \text{Softmax o/p}$$

log Loss

Random weights and biases.



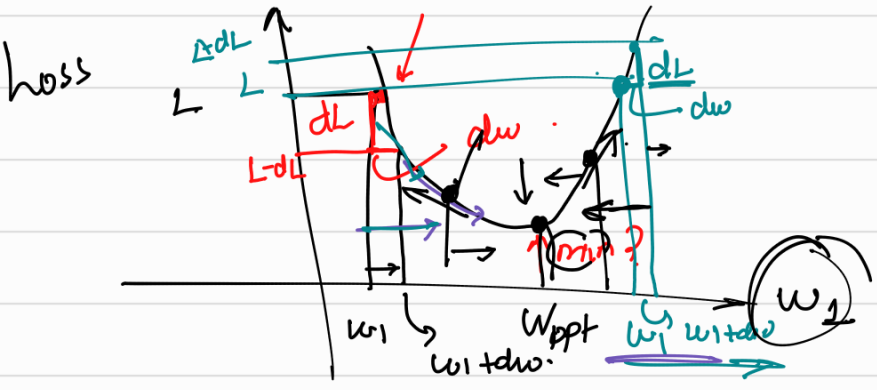
To minimise the loss



$L = f(y_{pred}, y_{actual})$

$L = f((w, B, x), y_{actual})$

$L = f(w, B)$.



$\frac{dL}{dw} = -ve.$

which side we know +ve move

$\frac{dL}{dw} = +ve$

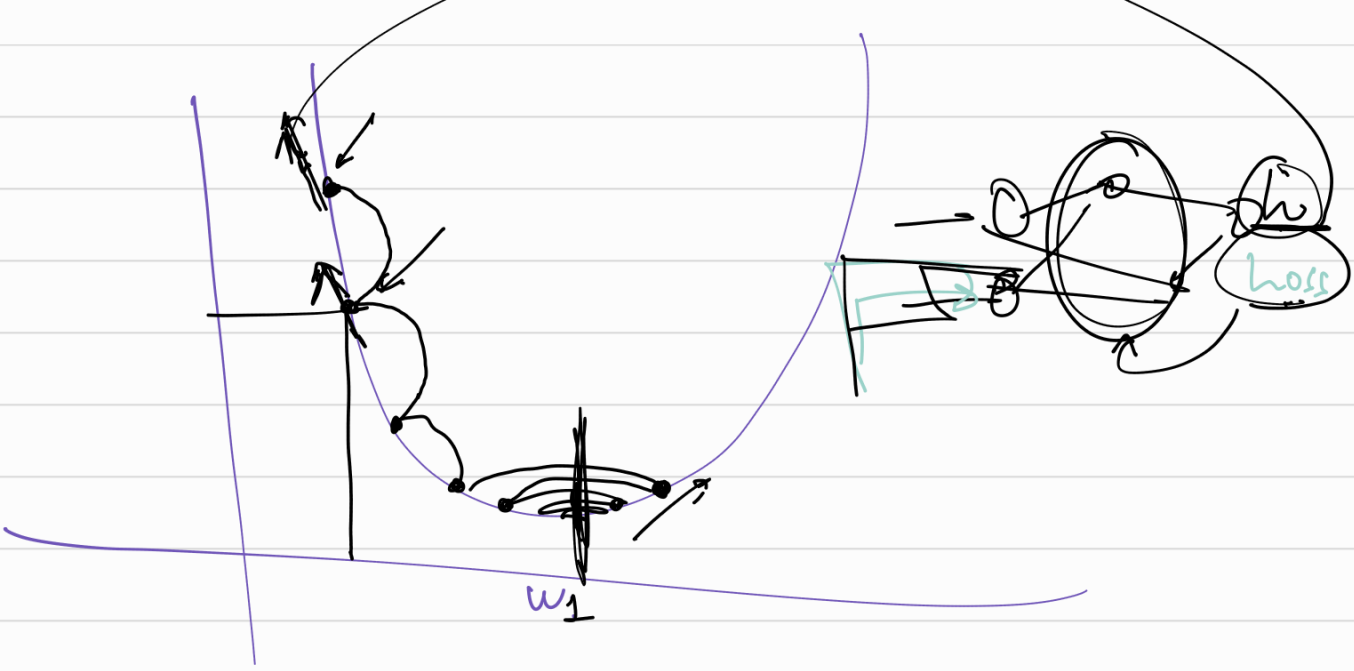
$w = -ve.$

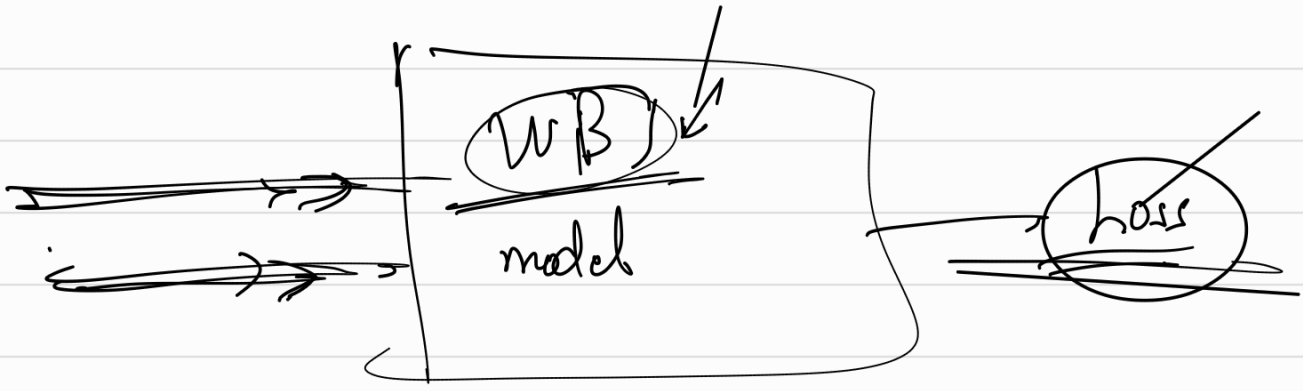
$$w_1(new) = w_1(old) - \alpha\left(\frac{dL}{dw_1}\right)$$

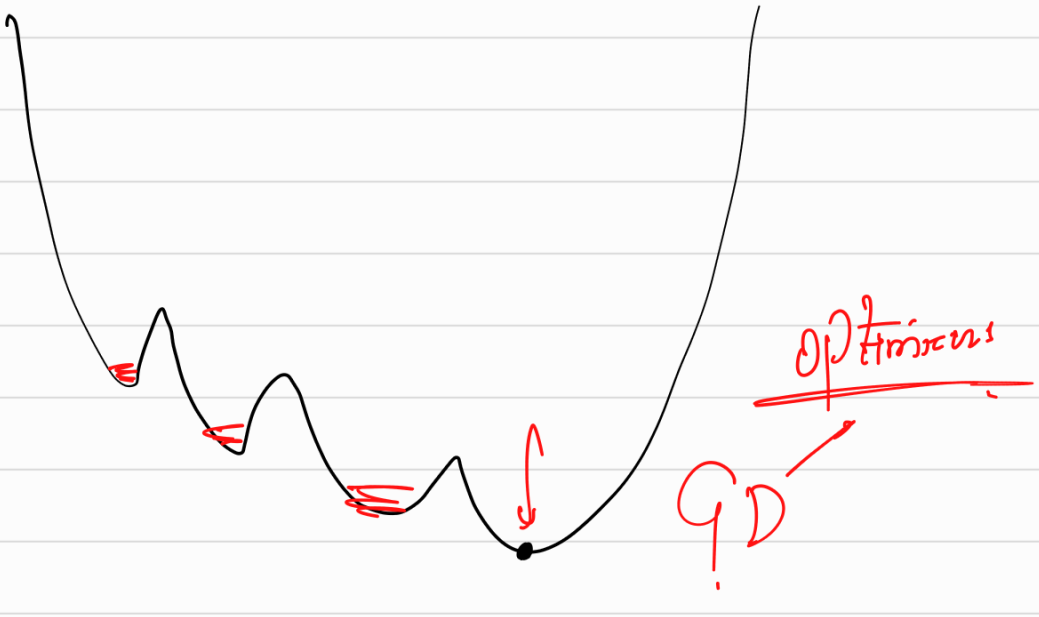
Hyp

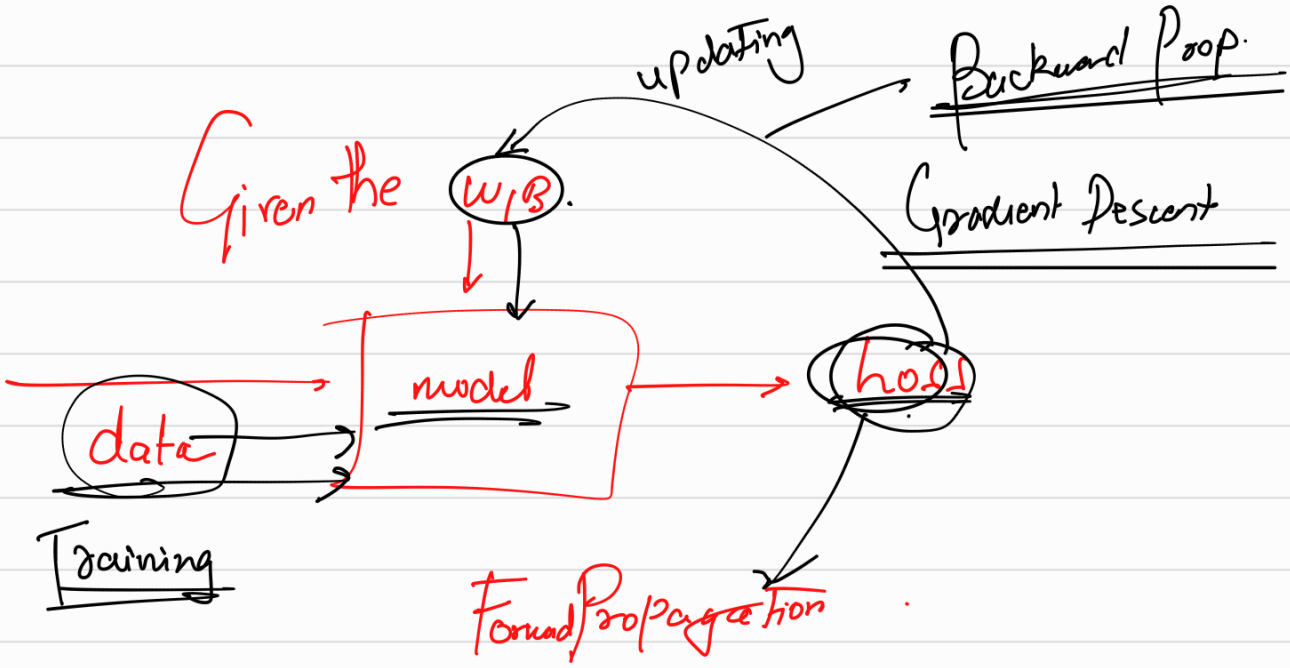
Partial

applicable for all weights and biases.


loss
w_1


WB
model
loss


optimizers
GD



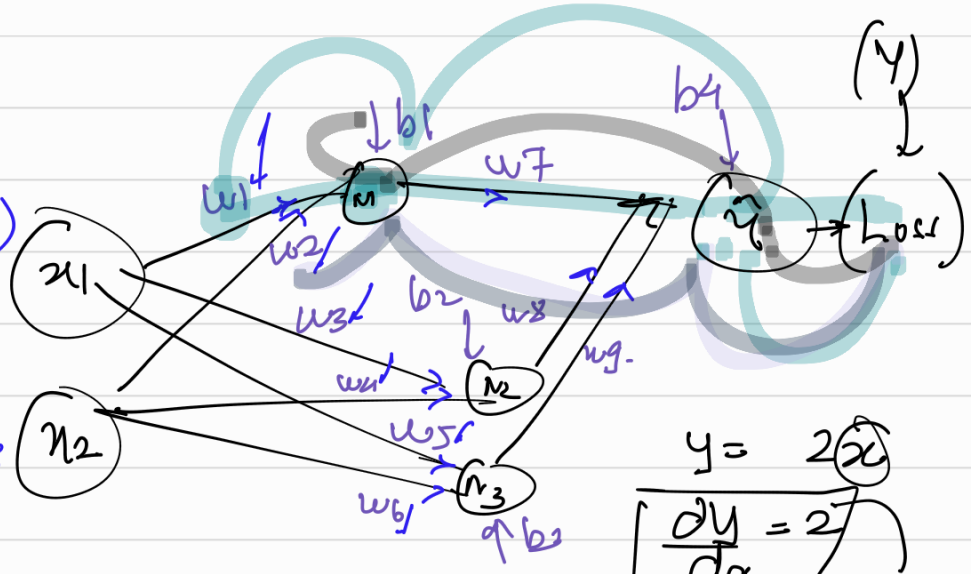
(1FP + 1BP) → epoch

(1FP, 1BP) → 1 epoch.

188 epoch

188 (1FP + 1BP)

lecture-3



$N_1 = w_1 x_1 + w_2 x_2 + b_1$ (1)

$N_2 = w_3 x_1 + w_4 x_2 + b_2$

$N_3 = w_5 x_1 + w_6 x_2 + b_3$

$\hat{y} = w_7 N_1 + w_8 N_2 + w_9 N_3 + b_4$

$y = 2x$

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

$\hat{y} = w_7 N_1$

$\frac{d\hat{y}}{dw_7} = N_1$

$\frac{\partial(L)}{\partial \hat{y}} = \sum_{i=1}^{n} \frac{1}{n} (y_i - \hat{y}_i)^2 \rightarrow$ MSE

$\frac{\partial L}{\partial w_7} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial w_7} \Rightarrow \sum_{i=1}^{n} \frac{1}{n} \times 2 \times (y_i - \hat{y}_i) \times -1 \times N_1$

$\frac{\partial h}{\partial w_9}$, $\frac{\partial h}{\partial w_1}$ 6mins

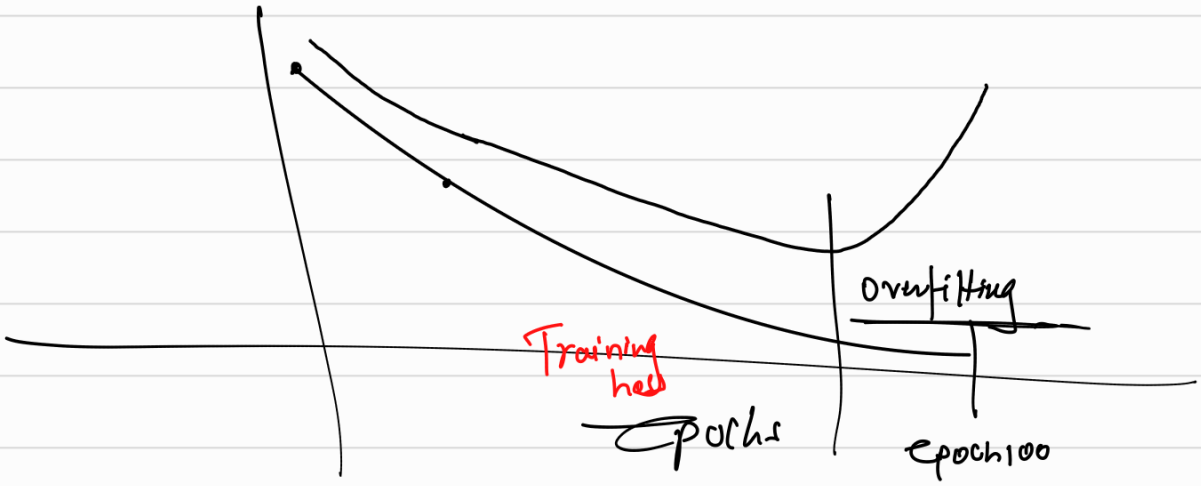
$\frac{\partial L}{\partial w_9} = \left(\frac{\partial h}{\partial \hat{y}}\right) \times \frac{d\hat{y}}{dw_9} \rightarrow N3$

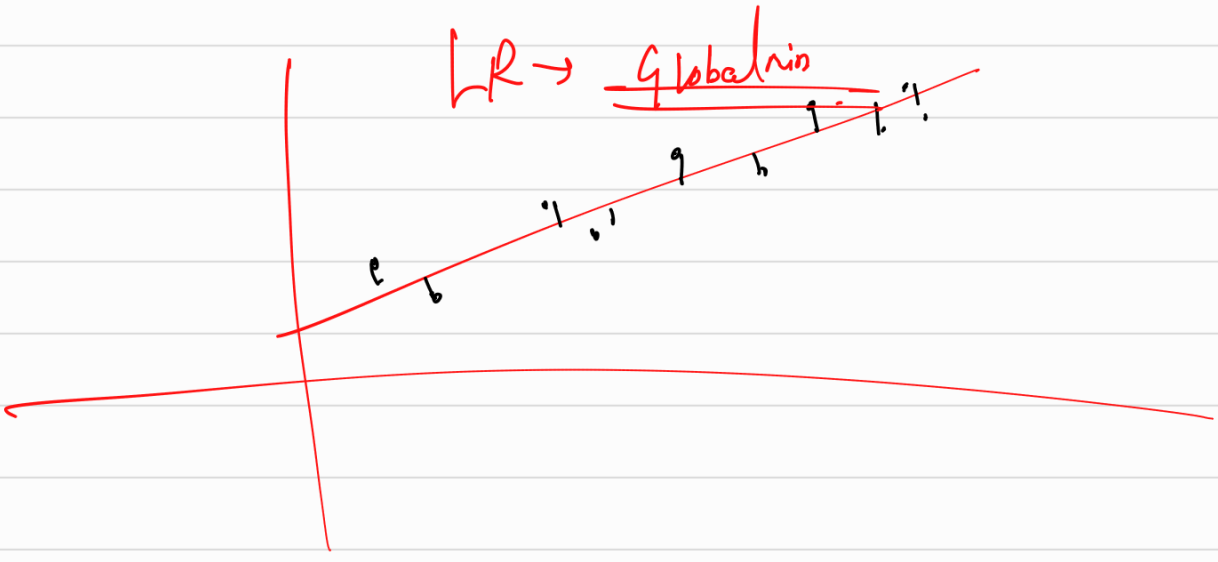
$\frac{\partial h}{\partial w_1} = \frac{\partial h}{\partial \hat{y}} \times \frac{d\hat{y}}{dN_1} \times \frac{dN_1}{dw_1}$

$\hat{y} = w_7 N_1 + w_8 N_2 + w_9 N_3 + b_4$ (0, 0, 0)

$\frac{d\hat{y}}{dw_7} = \frac{\partial (w_7 N_1)}{dw_7} = N_1$

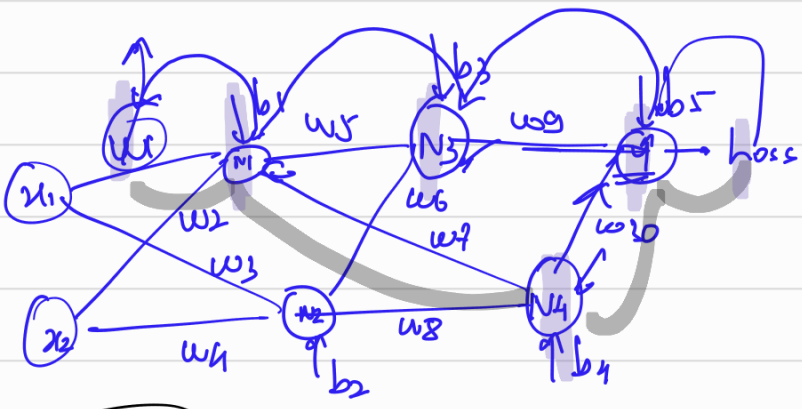
$\frac{d(x \times 2)}{dx} = 2.$


Overfitting
Training
halt
Epochs
epoch100


LR → Globalmin

Activation functions

$w_1 x_1 + w_2 x_2 + b_1$



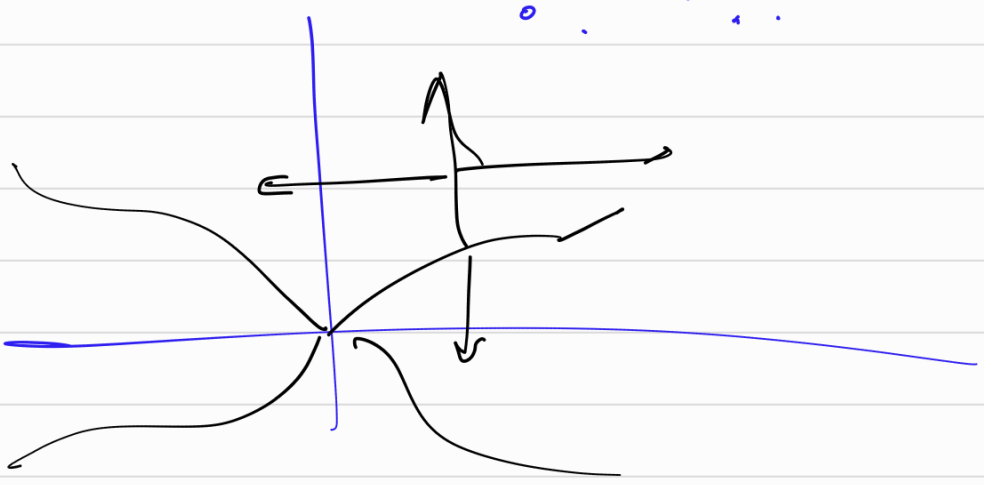
$\frac{\partial L}{\partial w_1}$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial N_3} \times \frac{\partial N_3}{\partial N_1} \times \frac{\partial N_1}{\partial w_1} + \left(\frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial N_4} \times \frac{\partial N_4}{\partial N_1} \times \frac{\partial N_1}{\partial w_1} \right).$$

$\frac{\partial L}{\partial w} = 100000$ Terms $= N(HL) + 2$

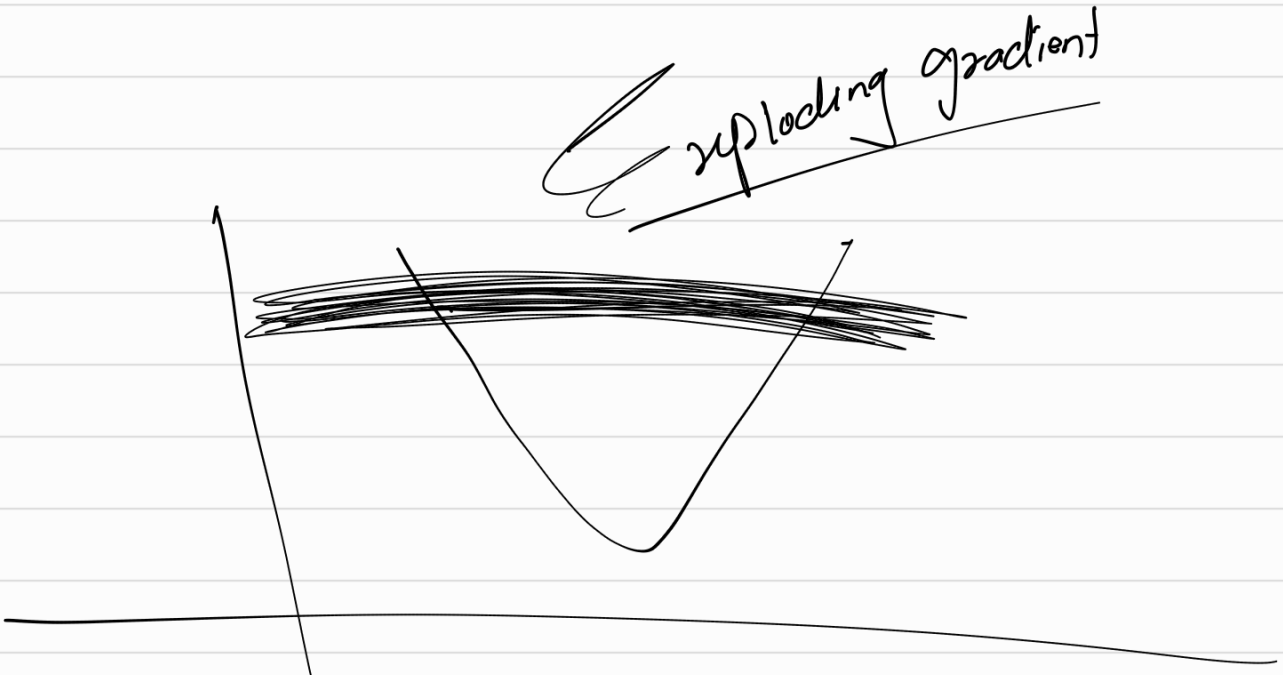
$\frac{\partial L}{\partial w_1} = 0.000002$

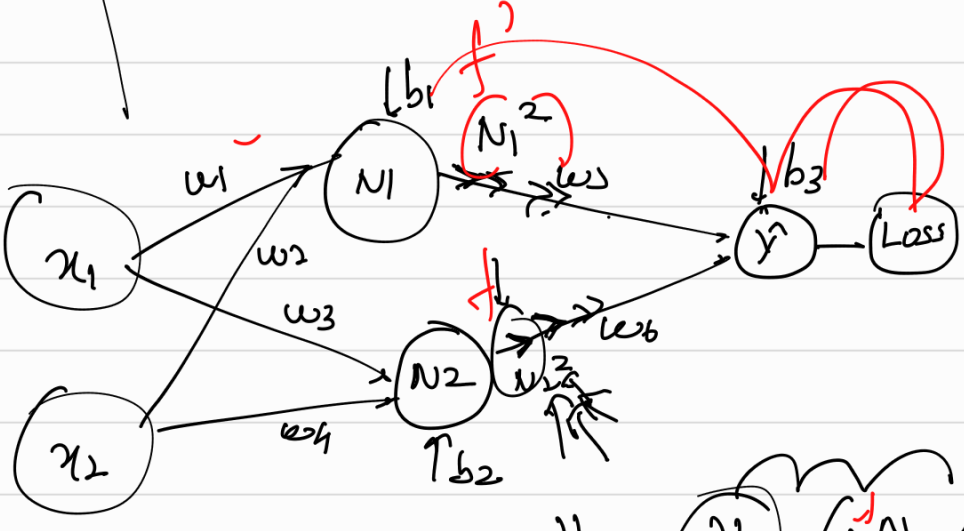
$w_1 -$



$(0.99)^{365} \approx$ 0

$(1.01)^{365} =$ 37.78





$$N_1 = w_1 x_1 + w_2 x_2 + b_1$$

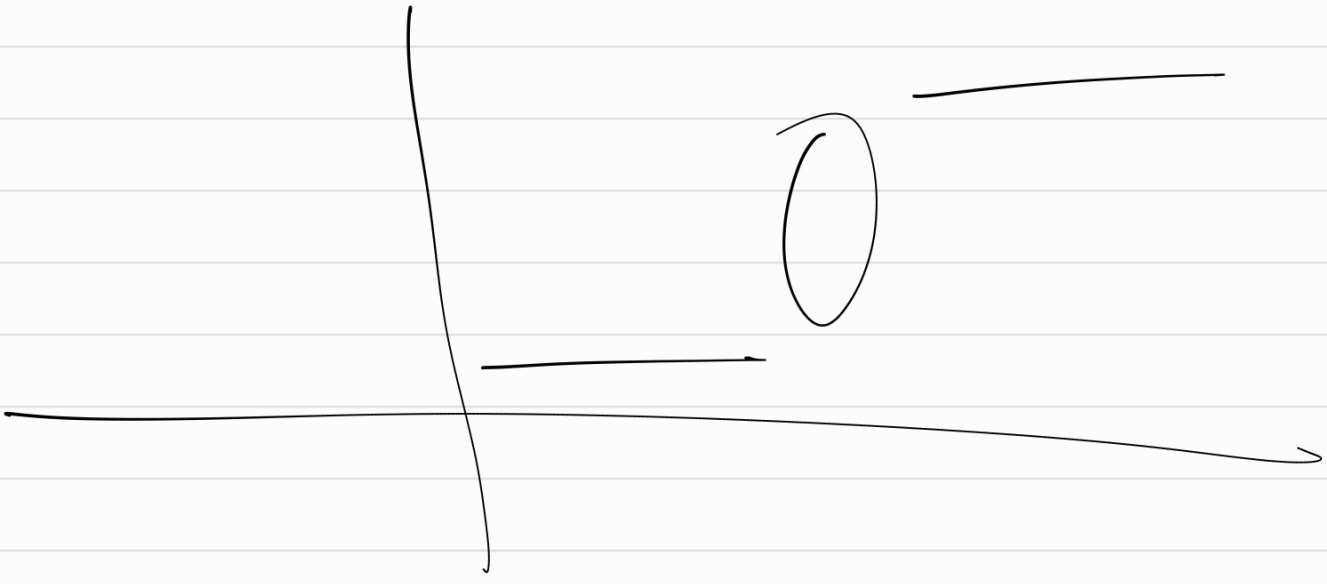
$$N_2 = w_3 x_1 + w_4 x_2 + b_2$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial N_1} \times \frac{\partial N_1}{\partial w_1}$$

$$\hat{y} = w_5 (N_1)^2 + w_6 N_2^2 + b_3$$

$$\frac{\partial \hat{y}}{\partial n_1} = w_5 \times 2 \times N_1$$

Activation functions → Should be cont & diff

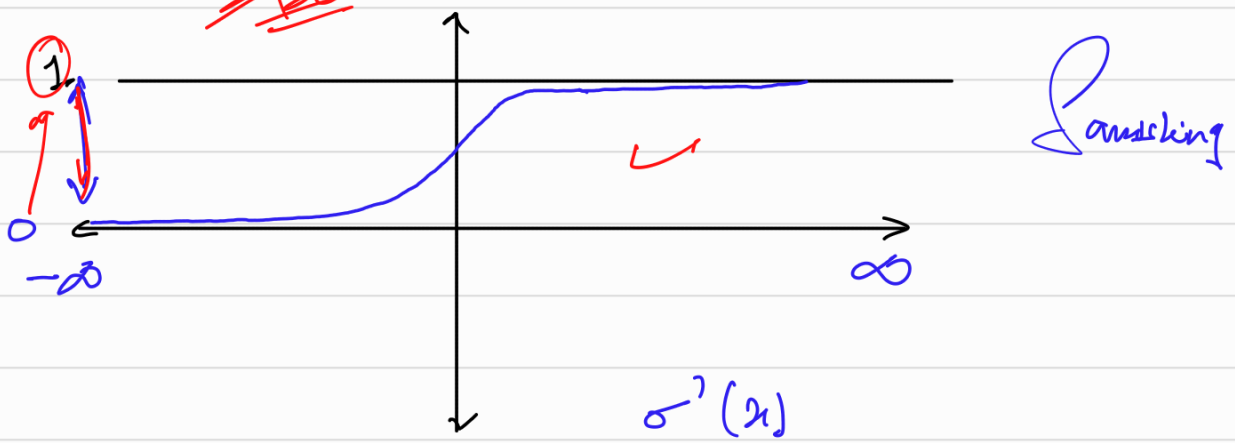


Activation functions are functions which should be continuous & diff that can be applied at the output of any hidden layers to create non-linear feature or at the o/p to create bounded outputs → Probs

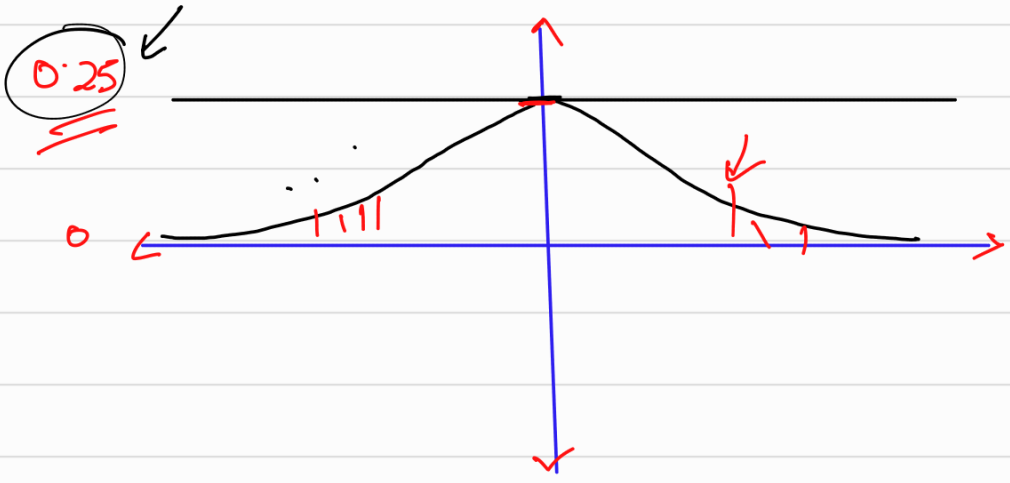
o/p → output layer

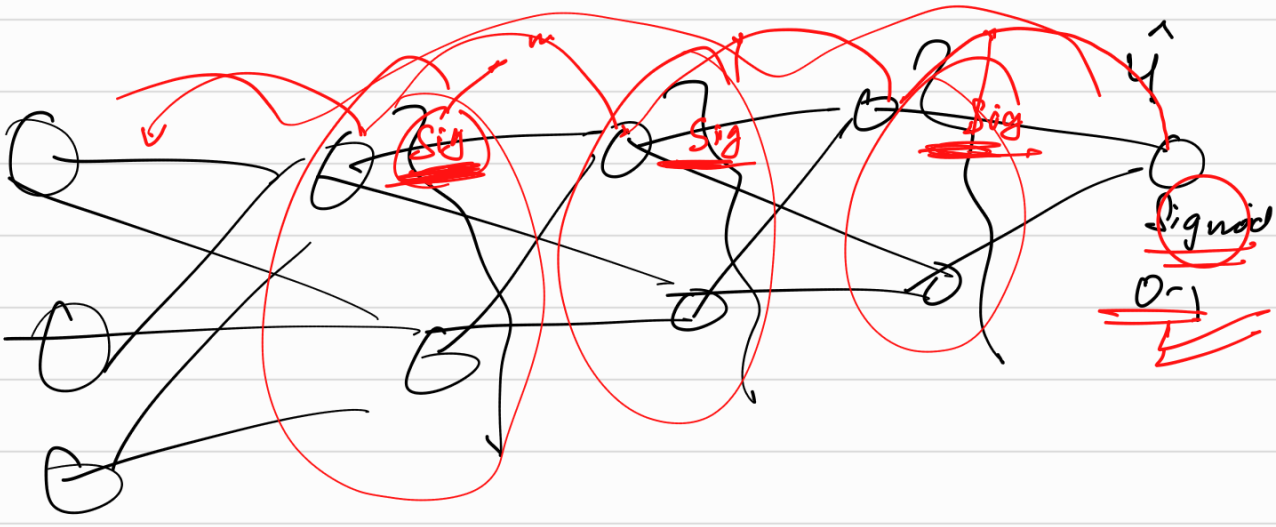
→ Sigmoid $\sigma(x) = \frac{1}{1+e^{-x}}$ $-\infty < x < \infty$

HLX 0/L Probs $0 < \sigma(x) < 1$



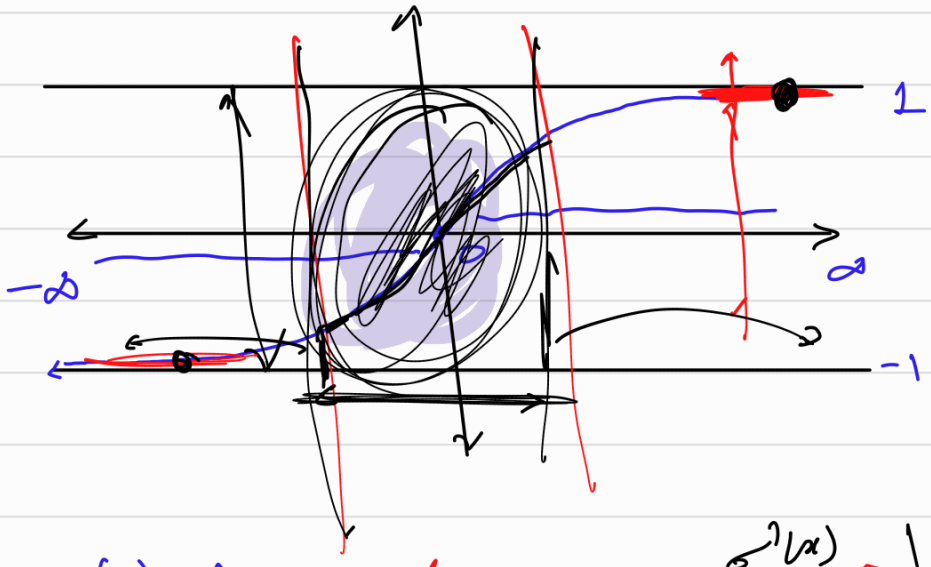
$\sigma'(x)$

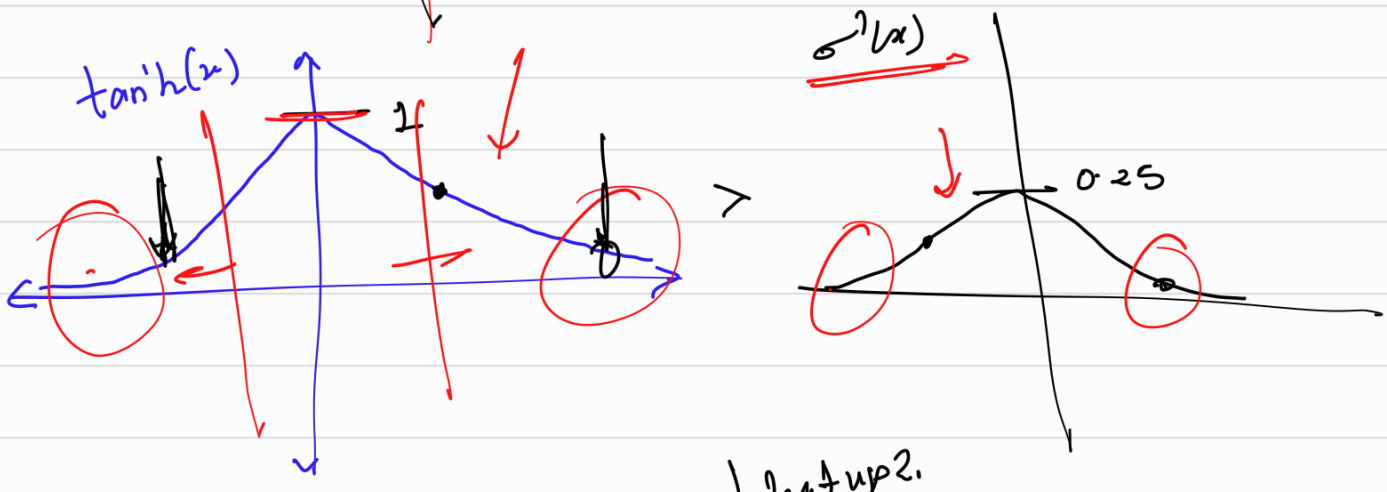


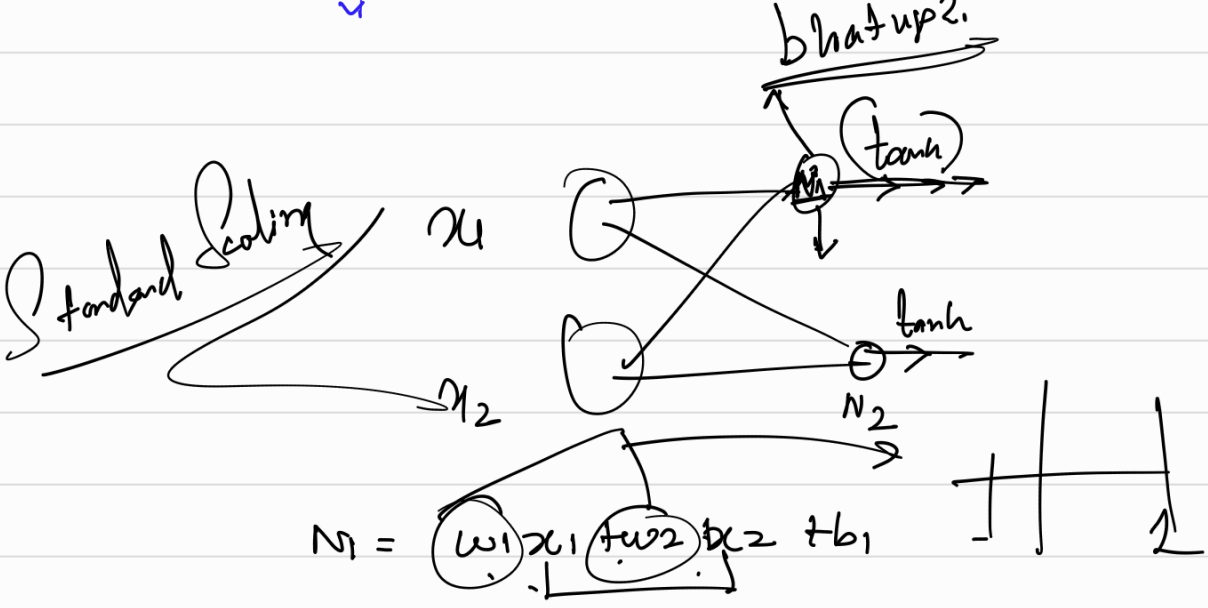


tanh → hyperbolic tangent.

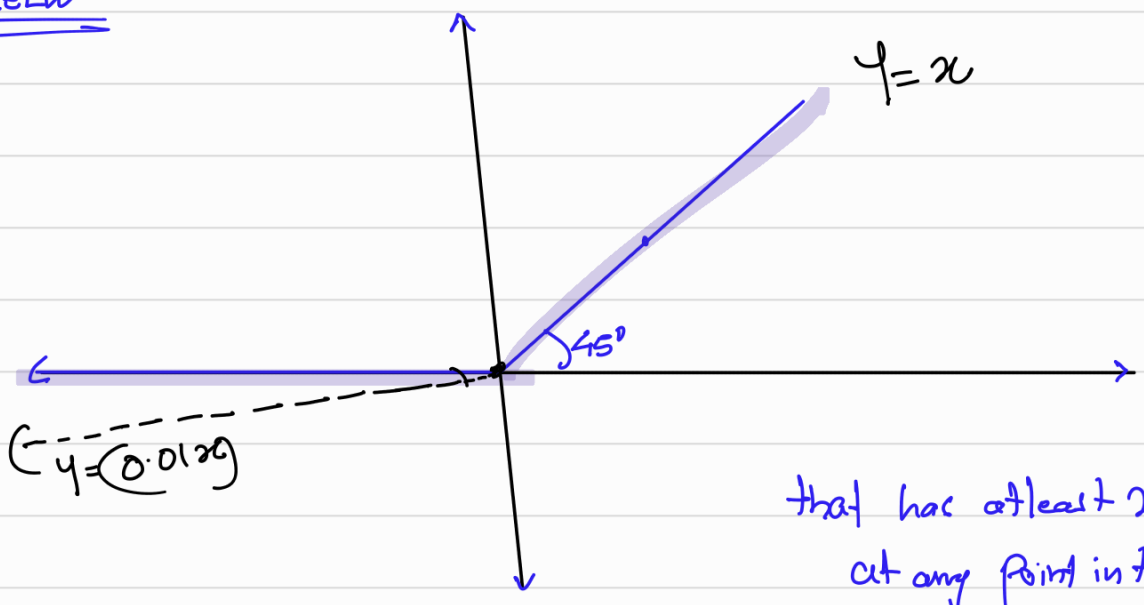
$$\tanh = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$







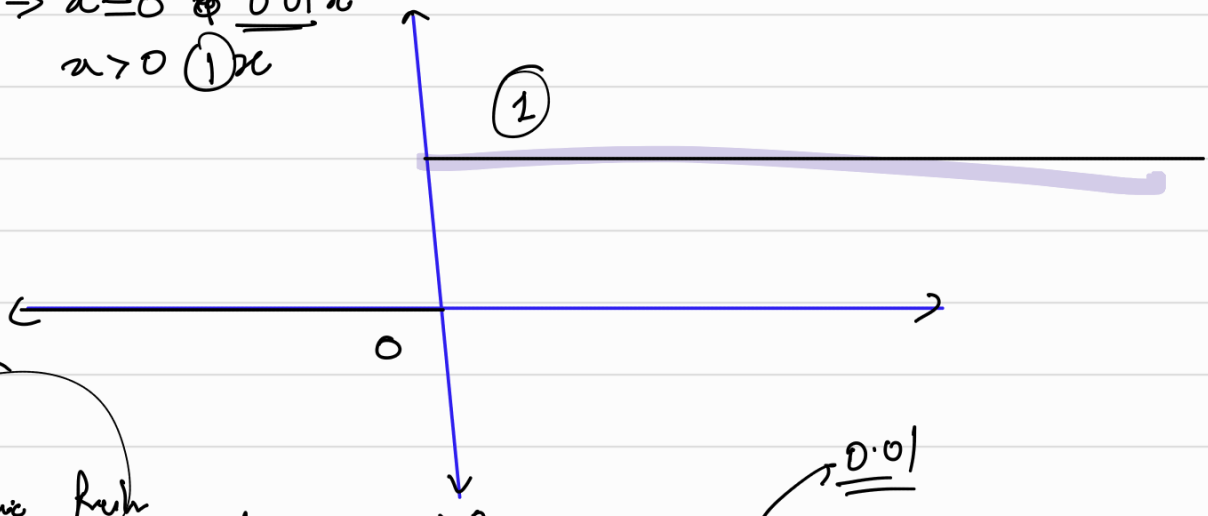
ReLu



that has atleast 2 slopes at any point in the x space.

$ReLu(x) = \begin{cases} x \le 0 & 0 \\ x > 0 & x. \end{cases}$

Leaky ReL(x) $\Rightarrow \begin{cases} x \le 0 & 0.01x \\ x > 0 & (1)x \end{cases}$



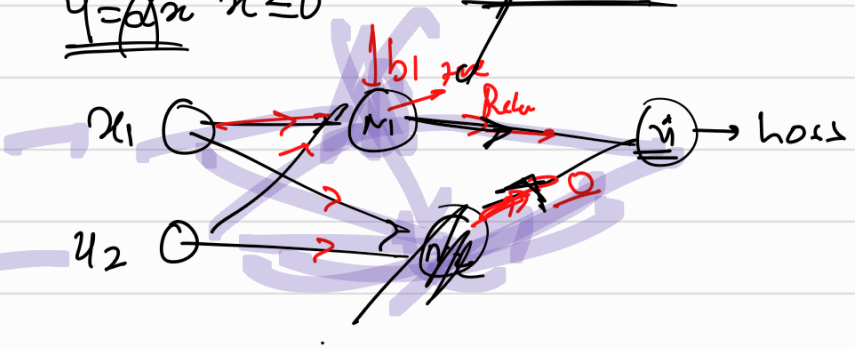
Parametric ReLu

$y = x \quad x > 0$

$y = \alpha x \quad x \le 0$

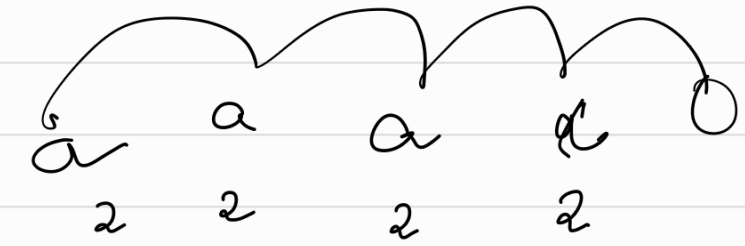
$0 < \alpha < 1$

0.01



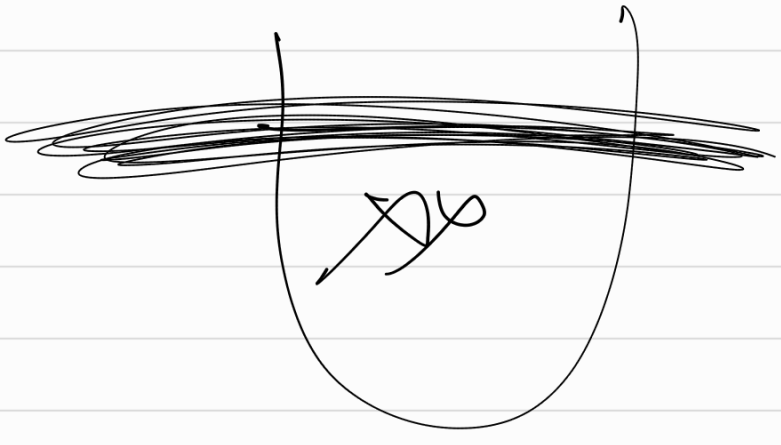
Deep Neural network

$(2)^{0+10+50} = 32$

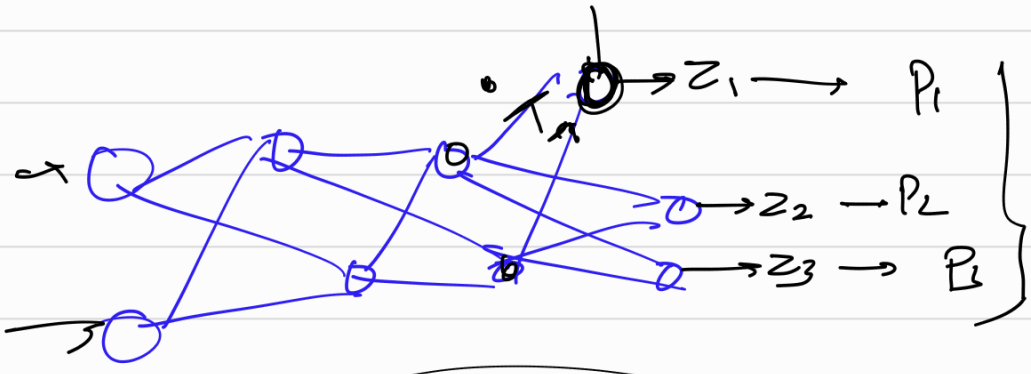


$(2)^3$ $(2)^{100}$

$$\frac{dw}{dw_1} = w_1 - \alpha(\quad)$$

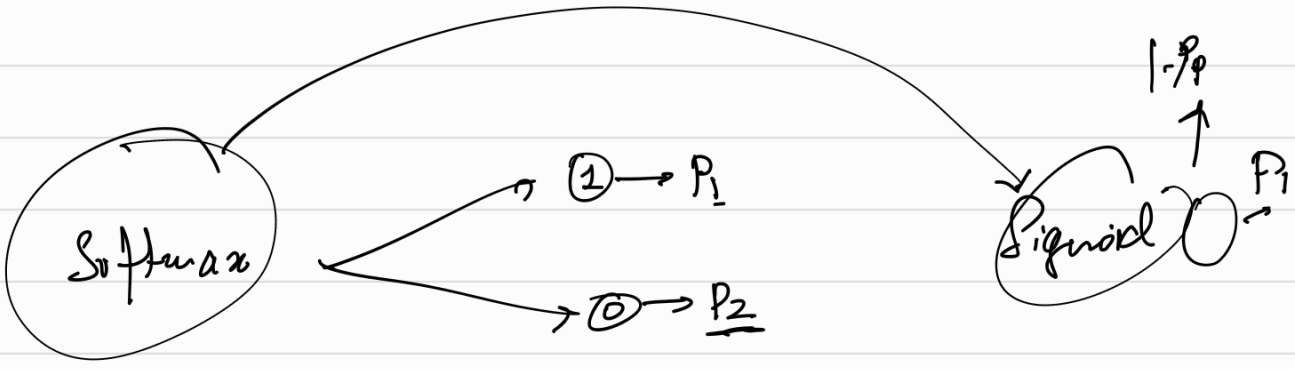


Softmax : needs to be applied at the o/p of a multiclass problem



$p_1 + p_2 + p_3 = 1$

$$p_1 = \frac{e^{z_1}}{e^{z_1} + e^{z_2} + e^{z_3}} \qquad p_2 = \frac{e^{z_2}}{e^{z_1} + e^{z_2} + e^{z_3}} \qquad p_3 = \frac{e^{z_3}}{e^{z_1} + e^{z_2} + e^{z_3}}$$



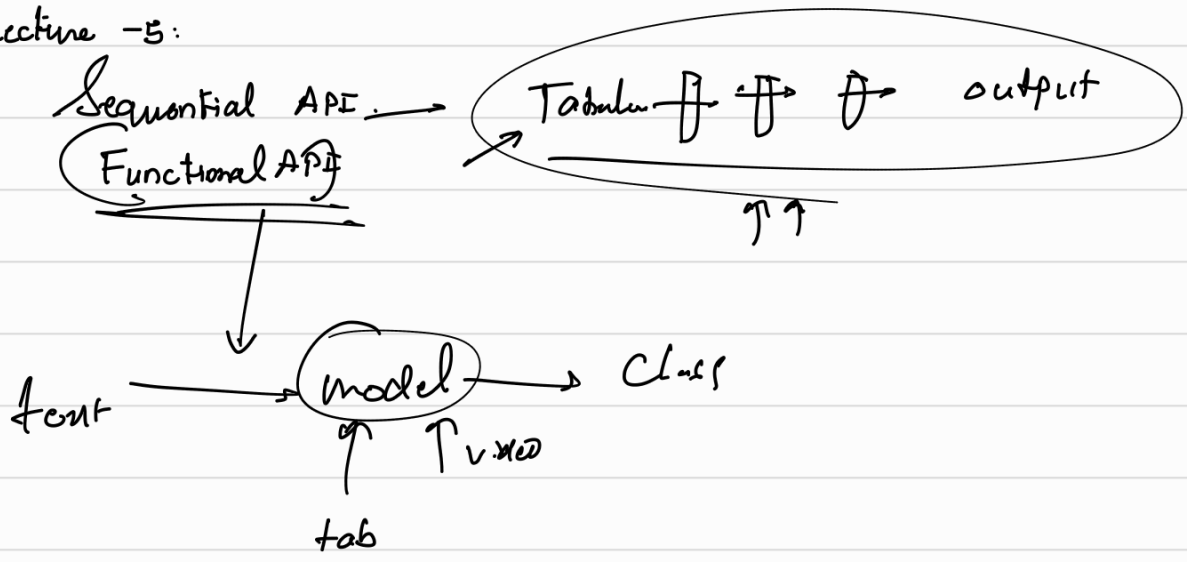
$p_1 + p_2 = 1$

$p_1 = 1 - p_2$

$p_2 = 1 - p_1$

Break

Lecture -5:



Sparse.

$y \rightarrow$ LE (0, 1, 2)

$(y = 1)$

$\hat{y} = [0.1 \quad 0.3 \quad 0.6]$

0 1 2

$-\log(\hat{y}[y])$

$-\log 0.3$

$y \rightarrow$ OHE.

$y \rightarrow [0,1,0]$.

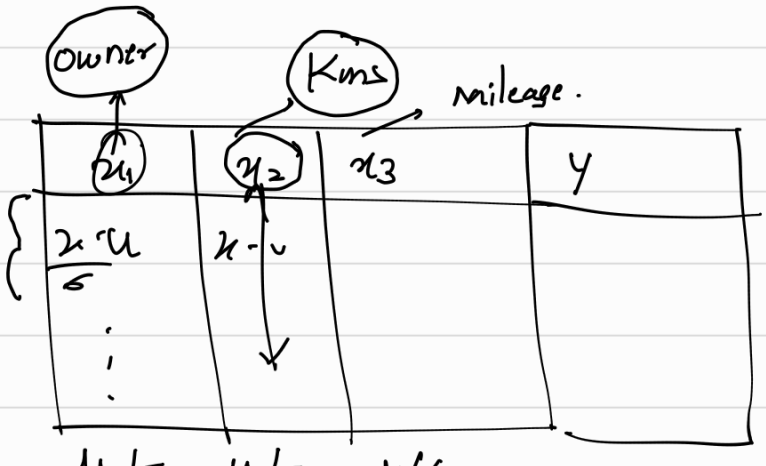
cce.

$\hat{y} = [0.1 \quad 0.3 \quad 0.6]$.

$y = [0 \quad 1 \quad 0]$.

$-[0 \times \log 0.1 + 1 \times \log 0.3 + 0 \times \log 0.6]$

$= -\log 0.3$



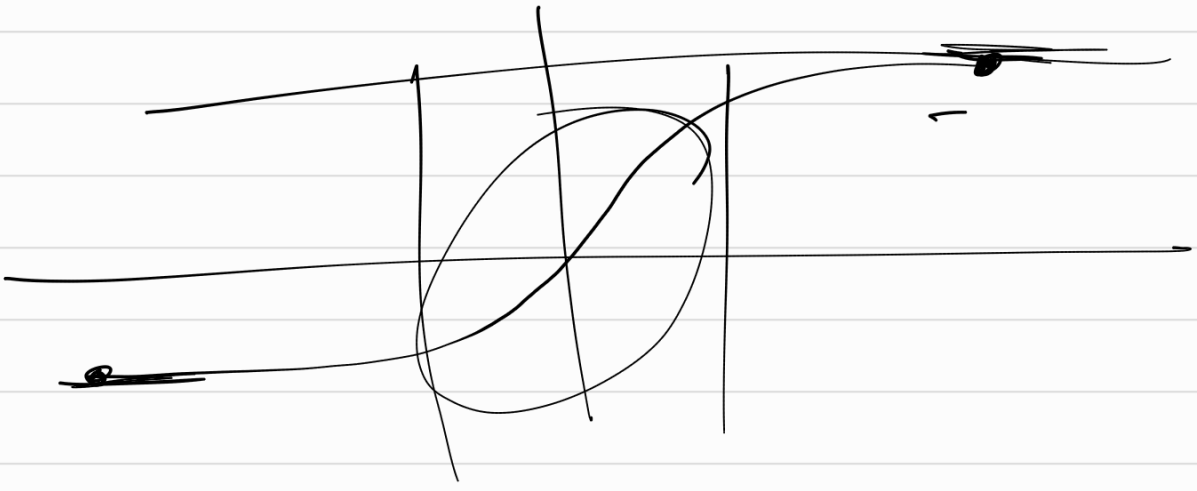
$w_1 \times (\text{owner}) + w_2 \times (\text{kms}) + w_3 \times \text{mileage}$

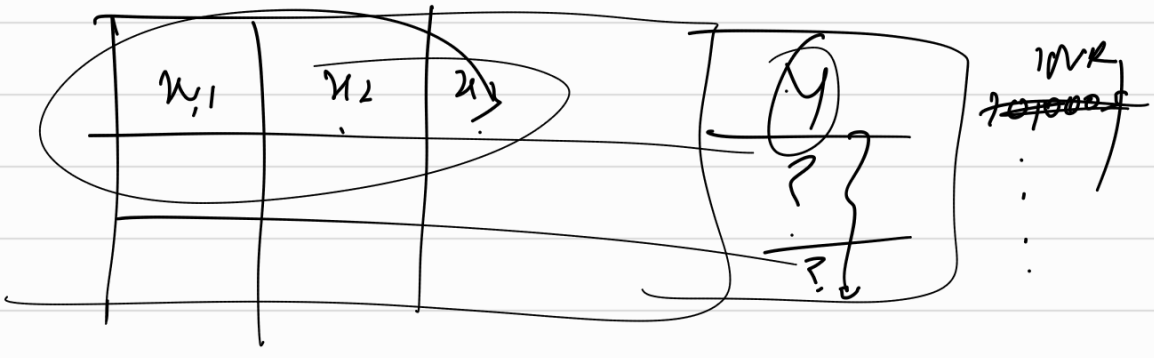
(1) Honda City

50,000 ↑

(2) ~~2nd~~ Honda city

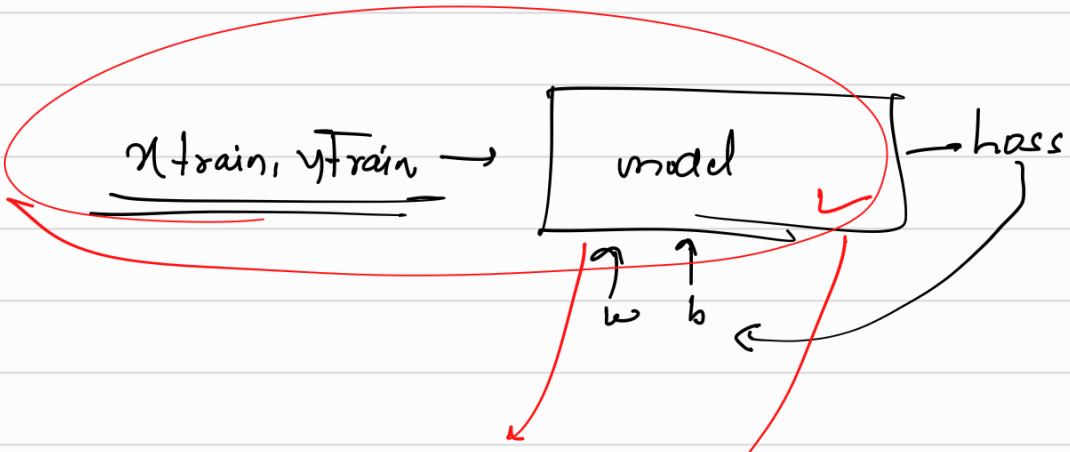
40,000

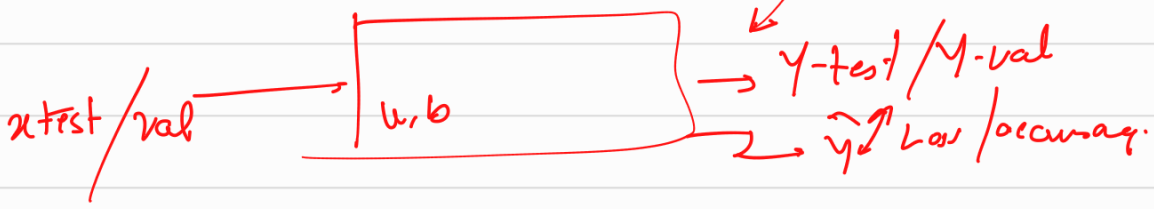


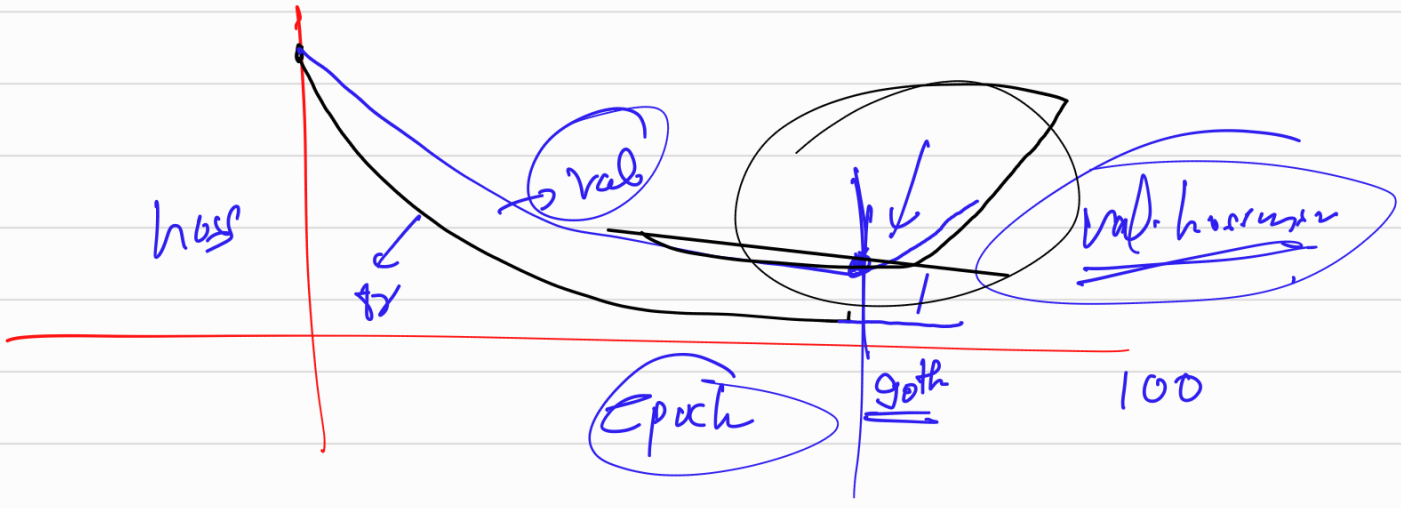


3.-3

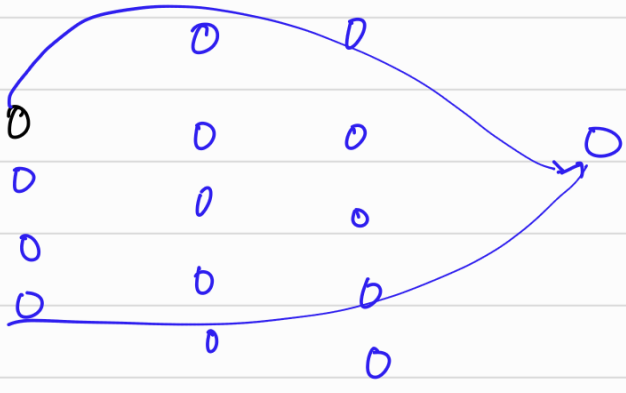
$(w_1 \sim -1, 1)$

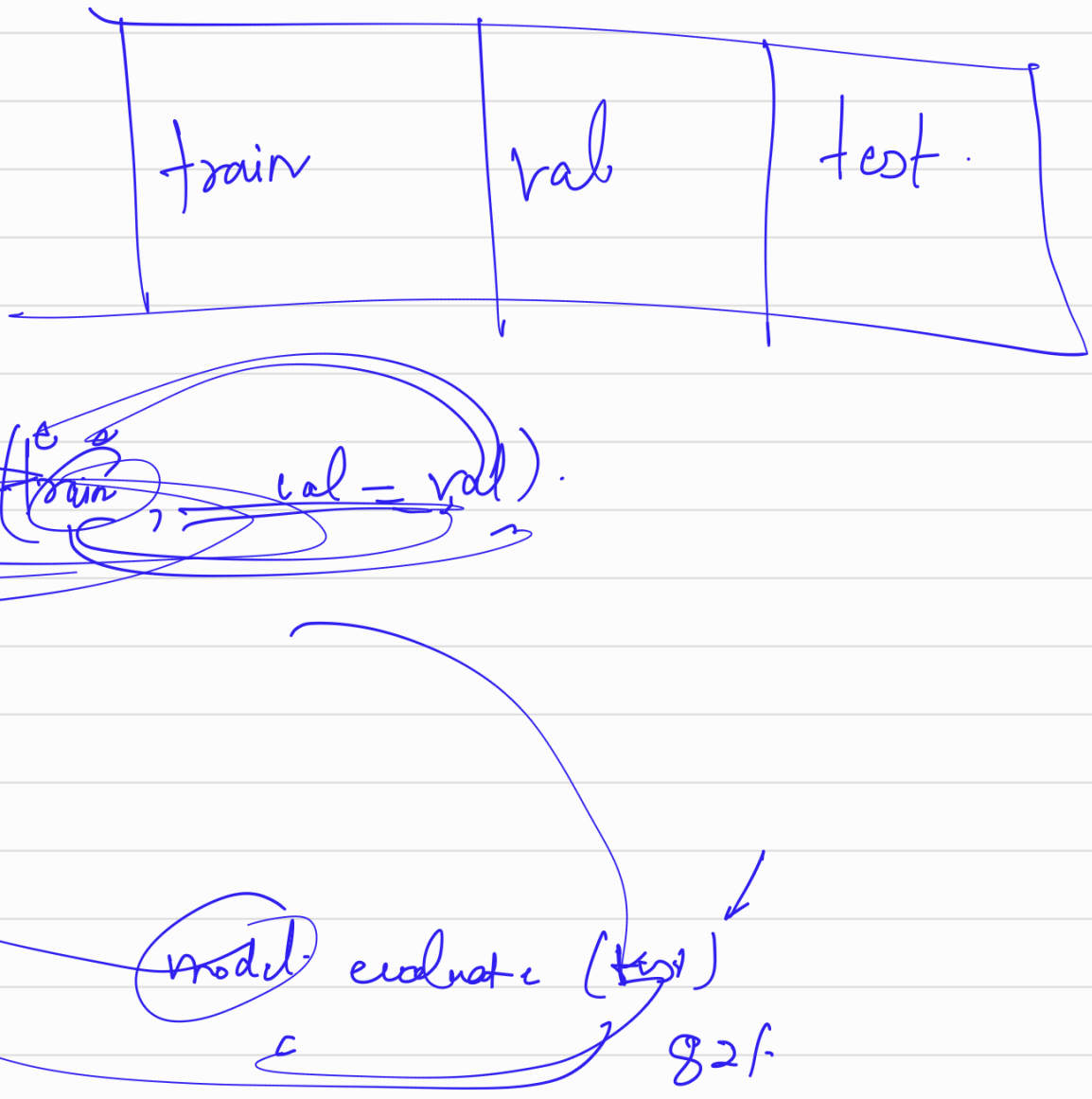

Xtrain, ytrain
model
loss
w
b


xtest/val
w, b
y-test/y-val
ŷ
Loss/accuracy


loss
val
val. loss
Epoch
90th
100

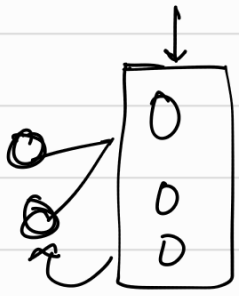
Callbacks



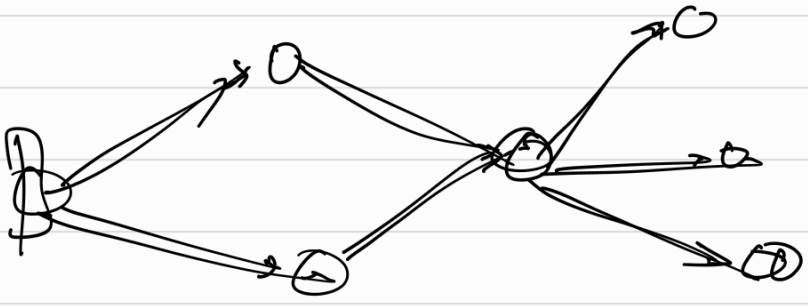

train
val
test.
model.fit(train, val).
model.evaluate(test)
82%

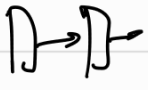
Functional API:

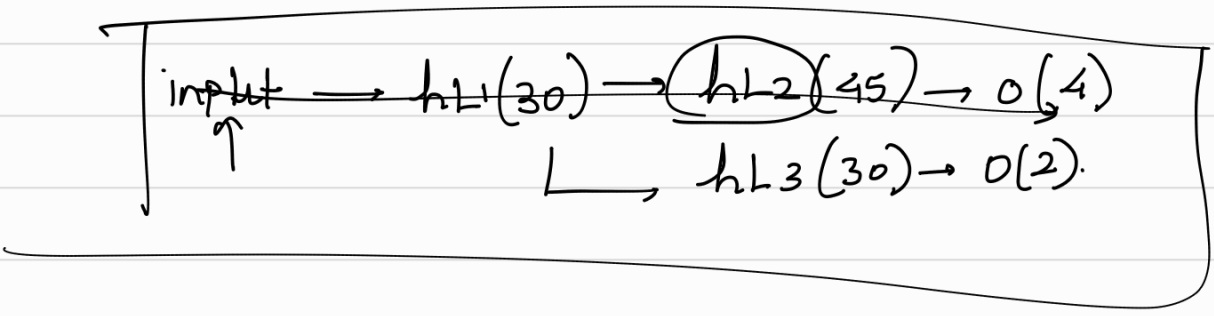
Graph Structure

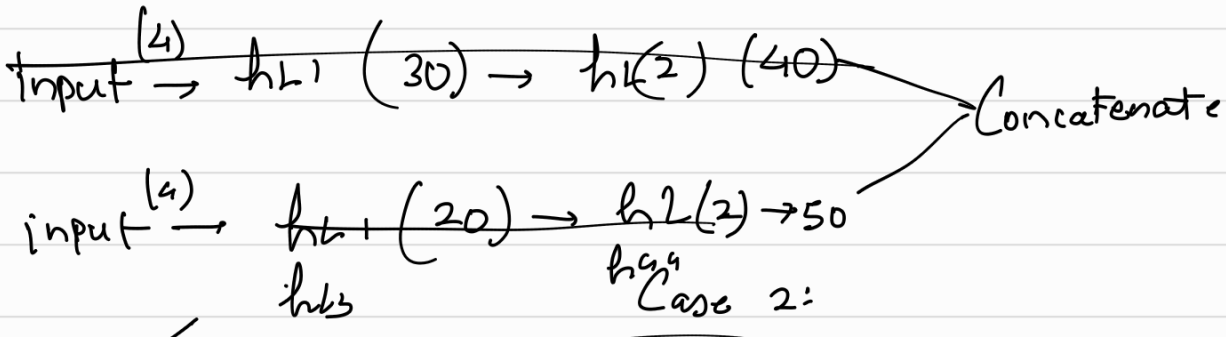


any layer (✓)









Case 1:

inputs = Input (4,)

hL1 = Dense (30) (inputs)

hL2 = Dense (45, activation = 'relu') (hL1)

O1 = Dense (4) (hL2).

hL3 = Dense (30) (hL1)

O2 = Dense (2) (hL3).

Case 2:

inp1 = Input (4,)

inp2 = Input (4,).

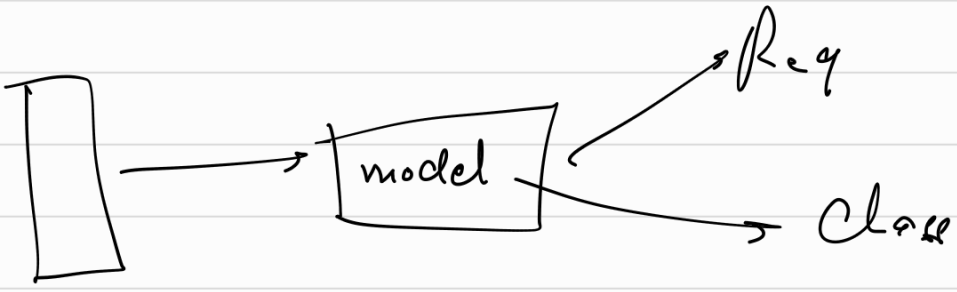
hL1 = Dense (30) (inp1).

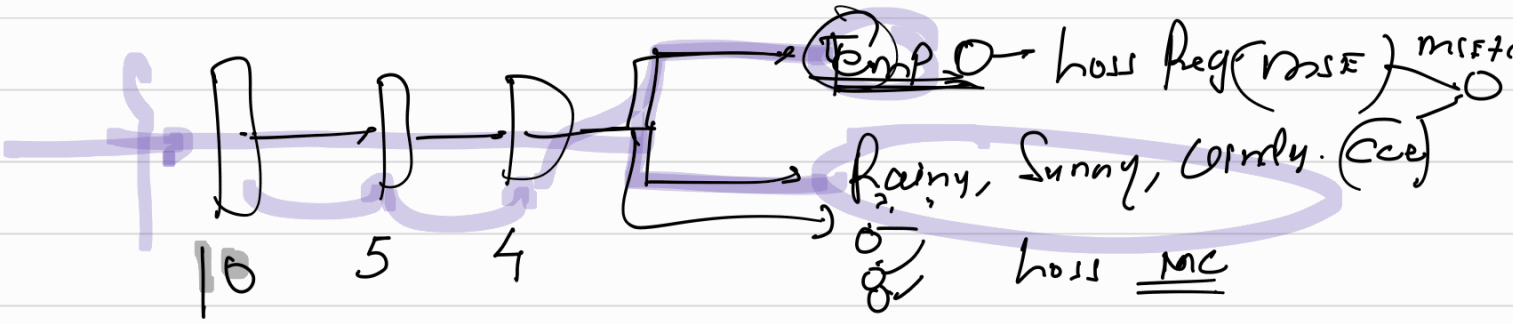
hL2 = Dense (40) (hL1).

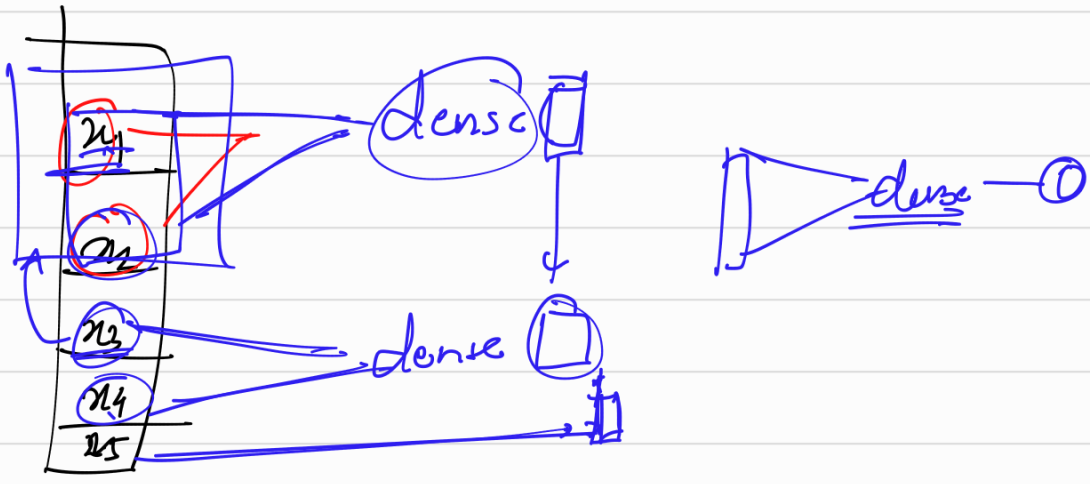
hL3 = Dense (20) (inp2).

hL4 = Dense (50) (hL3)

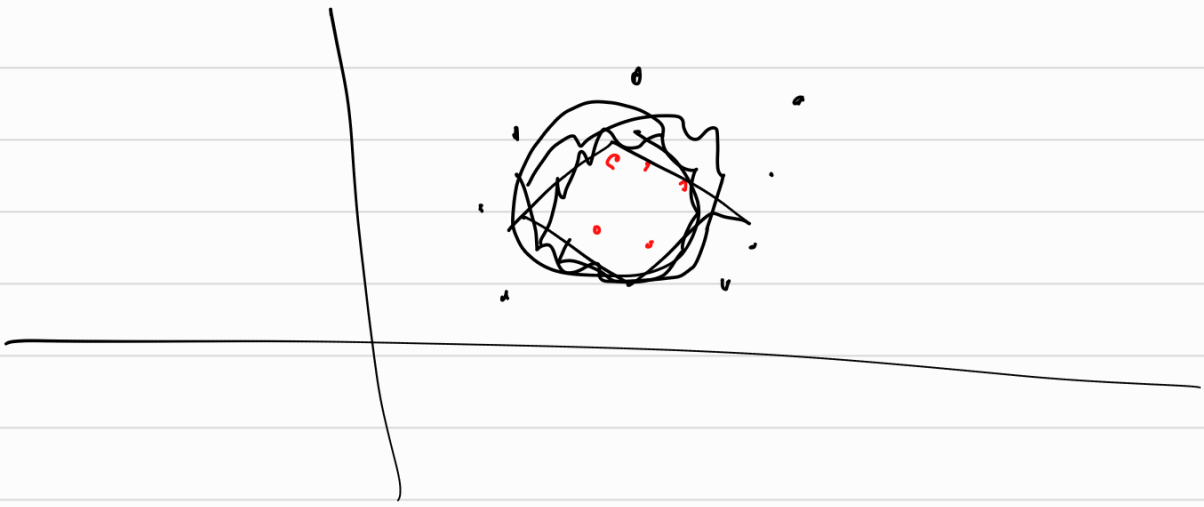
O = Concatenate ( ) ([hL2, hL4])

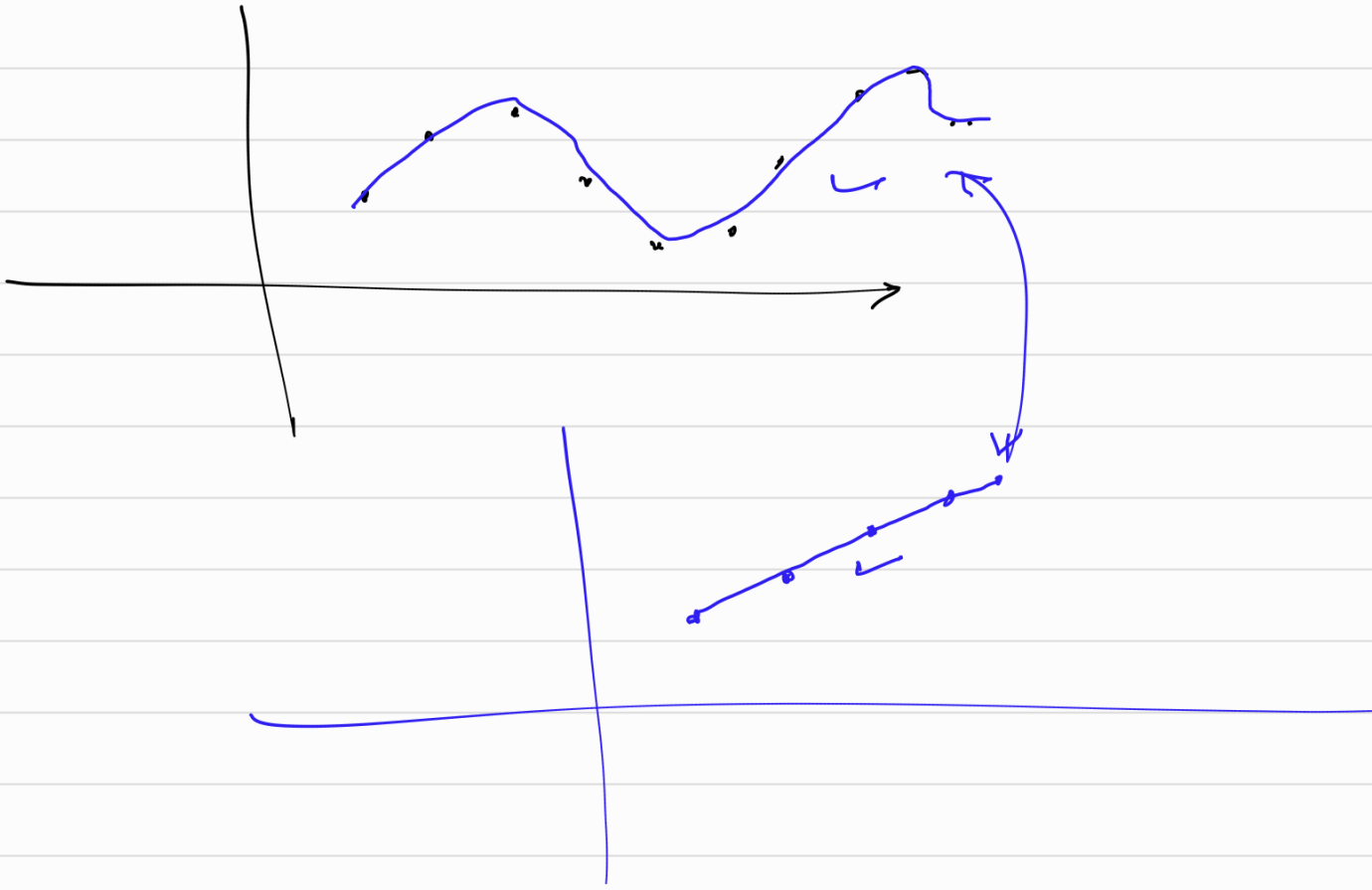


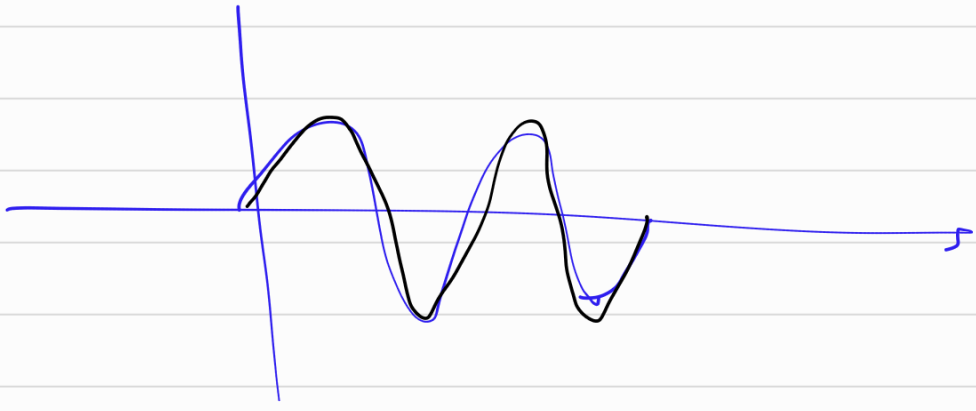

Temp
loss Reg(MSE)
MSE/cc
Rainy, Sunny, Windy. (CCE)
loss MC
10
5
4


dense
dense
dense

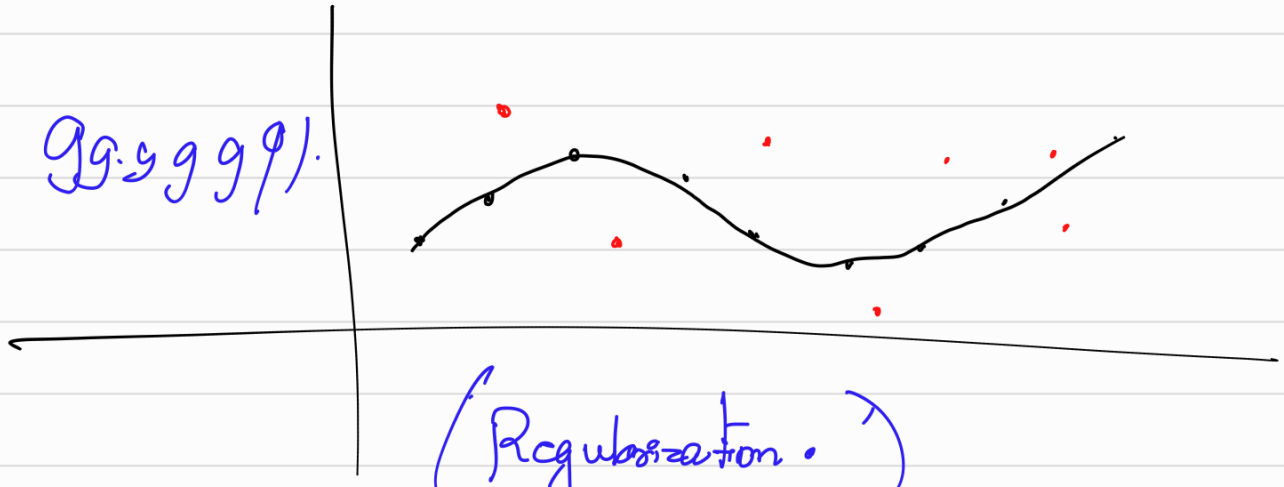

Optimizers
loss
w_1







99.9999%.



(Regularization.)

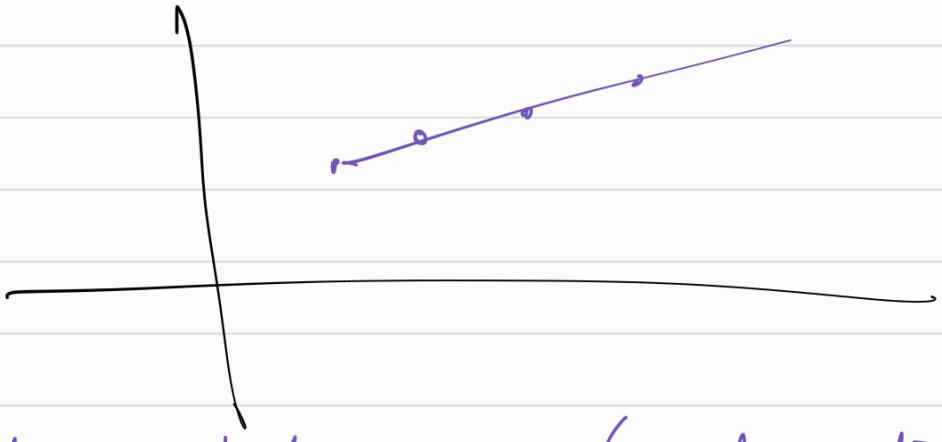
- Regularization
  - Dropout.
  - optimizers.
  - Callbacks
  - Batch Normalization
  - weight initialization

→ Hyperparameter Tuning.

Regularization:

↓↓

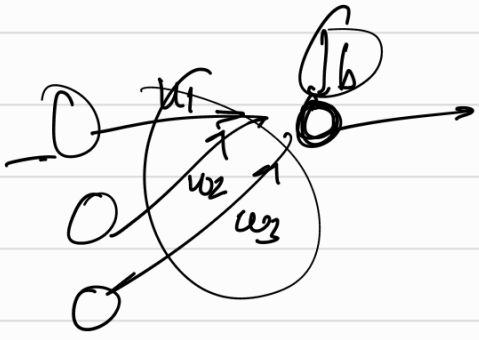
(Ridge and Lasso.) ?



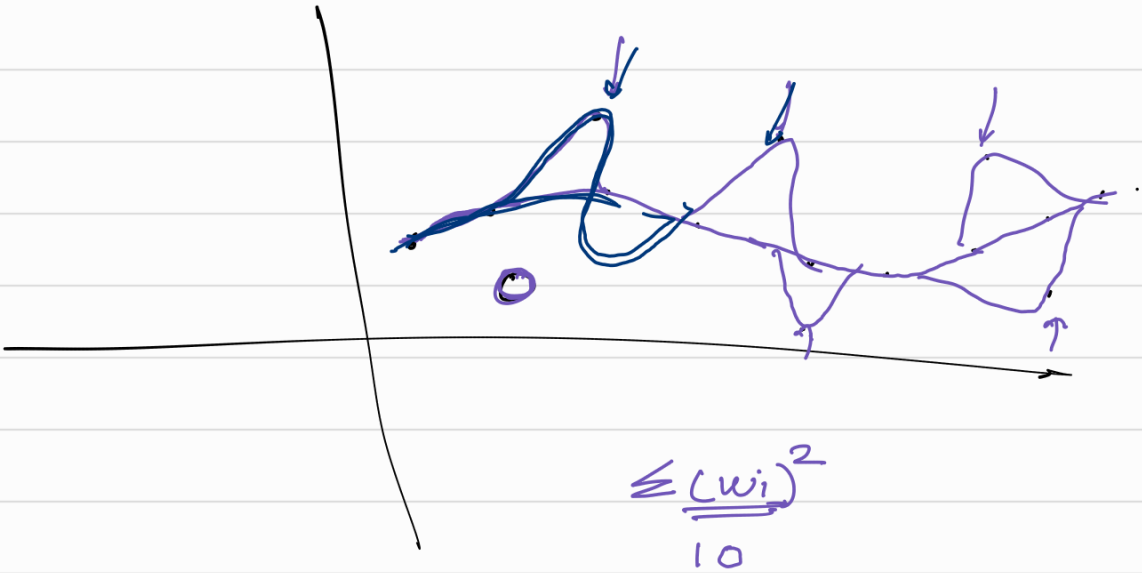
Overfit → has high variance (model is extremely sensitive to changes in x dist).

(1) $y = 1000x_1 + 500x_2$ $\quad y = 1000$

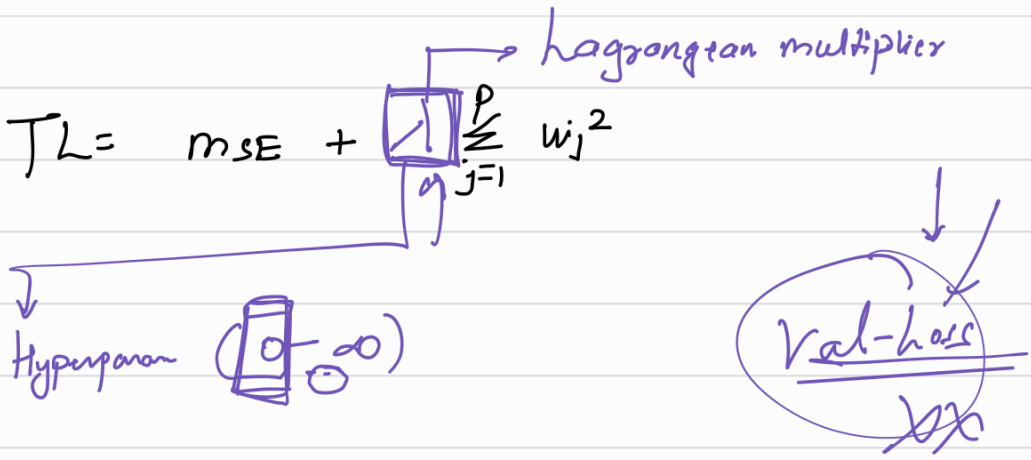
(2) $y = 2x_1 + x_2 \quad = (2)$

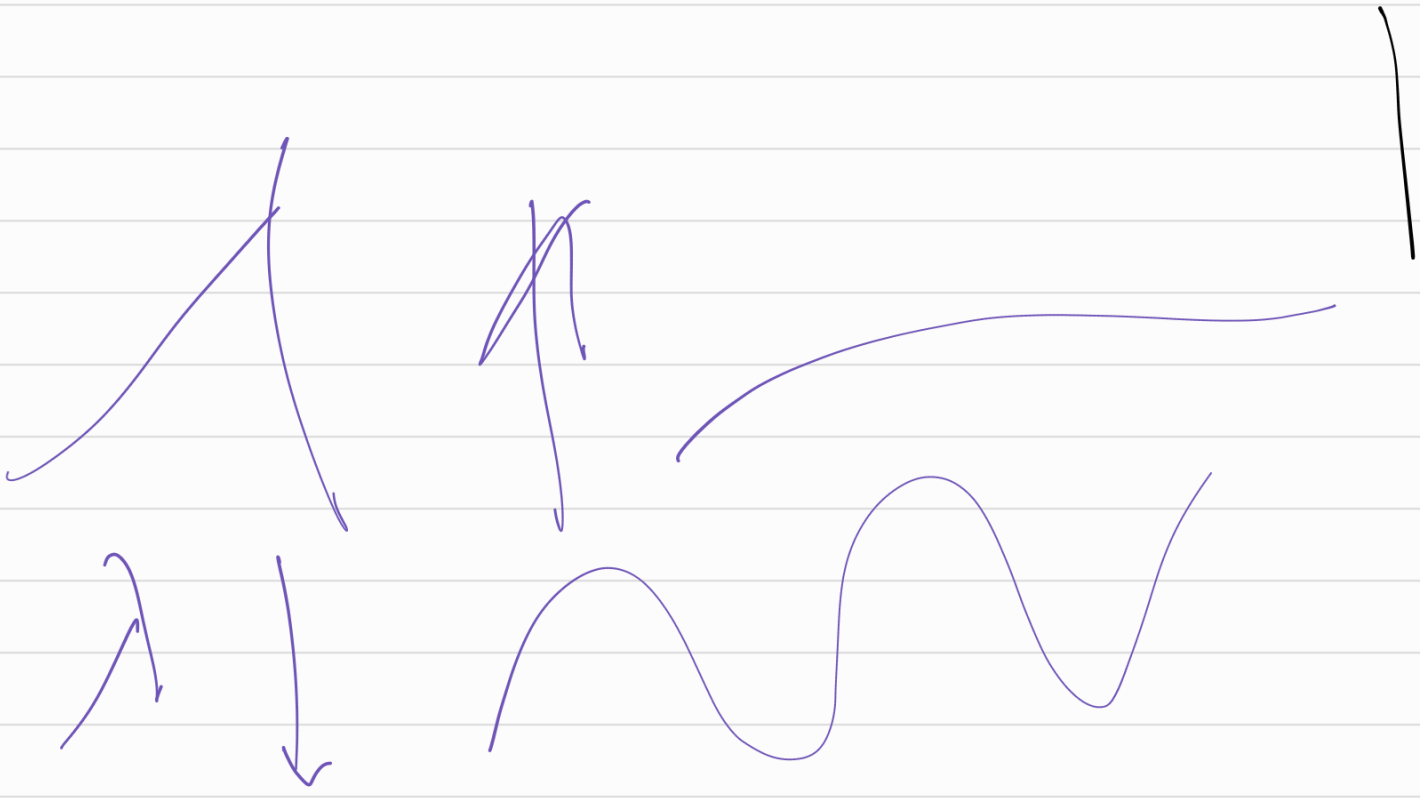


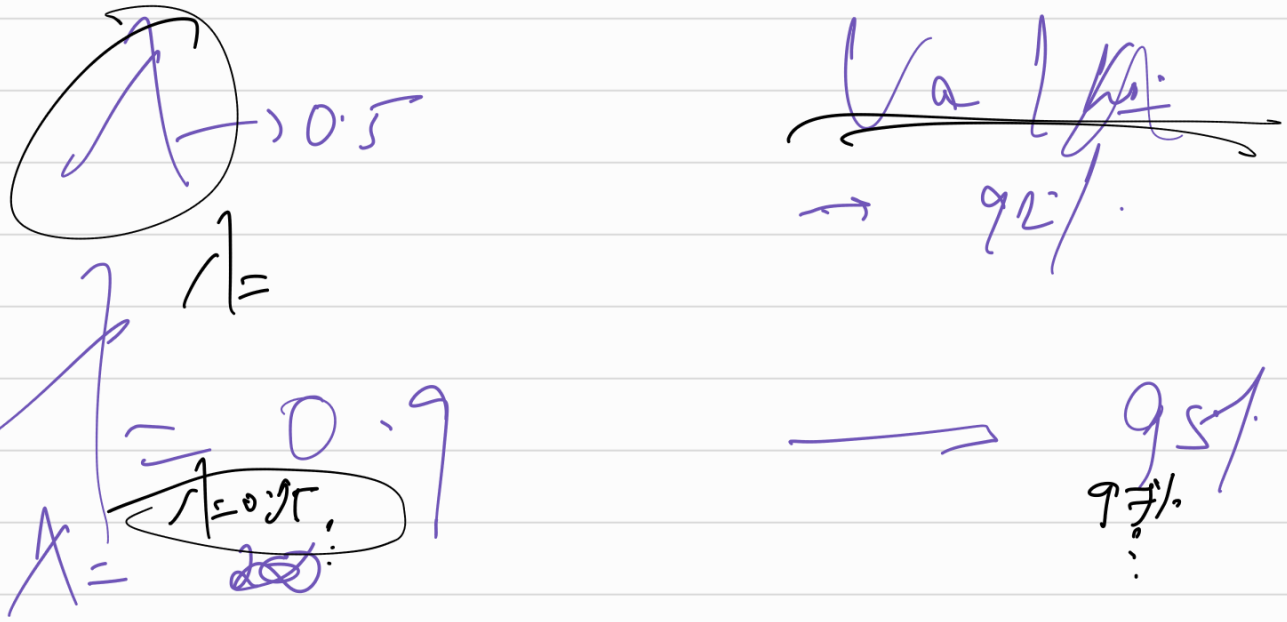
$N_1 = w_1 x_1 + w_2 x_2 + w_3 x_3 + b_1$



TL	MSE	$\sum (w_i)^2$
510 =	500	10
421 =	400	25
375 =	320	55
355 =	260	95
320 =	200	= 120
305 =	150	= 155
345 =	145	= 200


Lagrangian multiplier
$TL = mSE + \frac{\rho}{2} \sum_{j=1} w_j^2$
Hyperparam ($0 \to \infty$)
Val-loss




0.5
Val loss
92%
0.9
95%
97%

Reg.

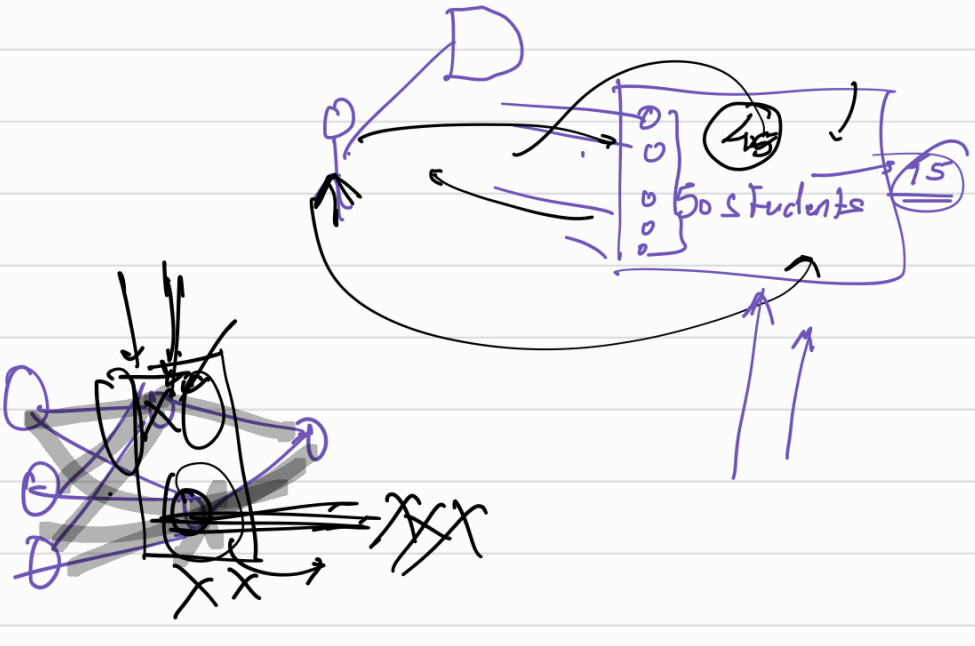
$Th = mse + \lambda \sum w_j^2$ Ridge (L^2).

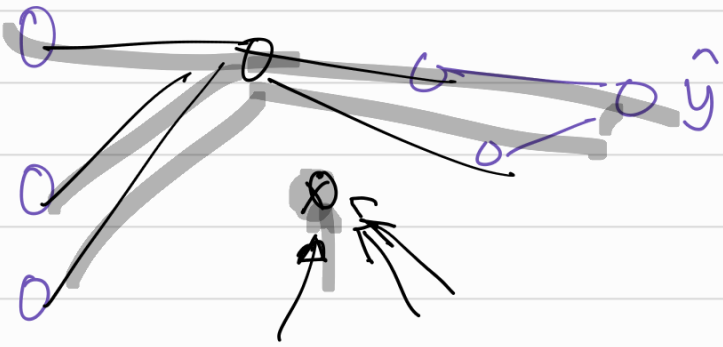
$Th = mse + \lambda \sum |w_j|$ Lasso (L_1).

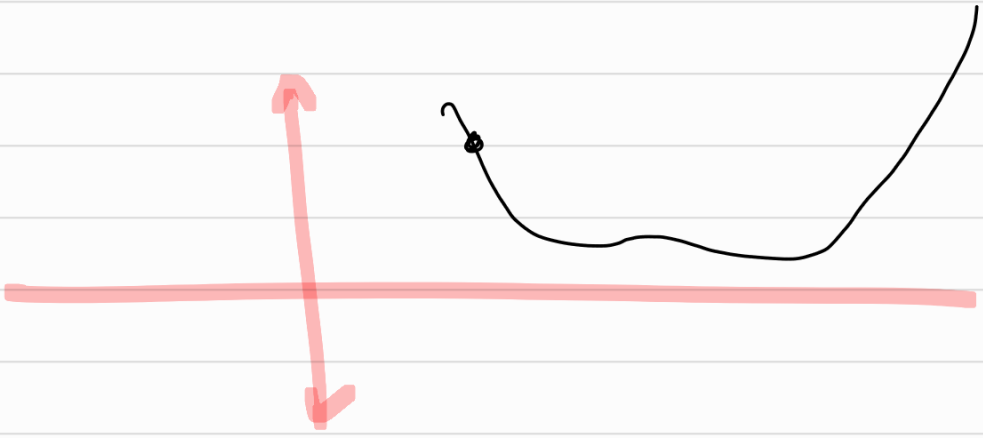
$Th = mse + \lambda_1 (\sum w_j^2) + \lambda_2 \sum |w_j|$ $L_1 L_2$ Elastic Net

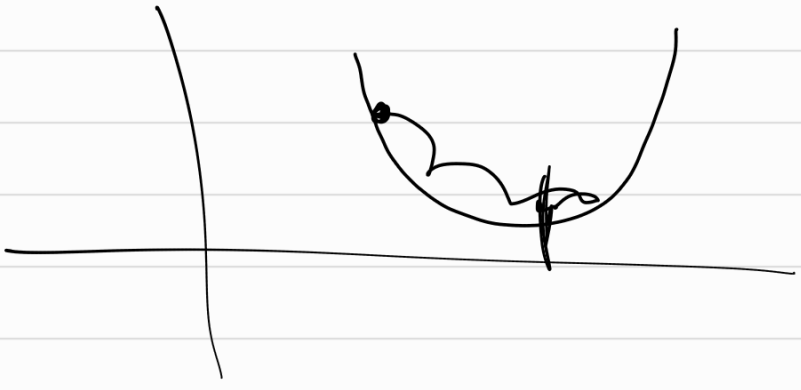
Break!

Dropout:

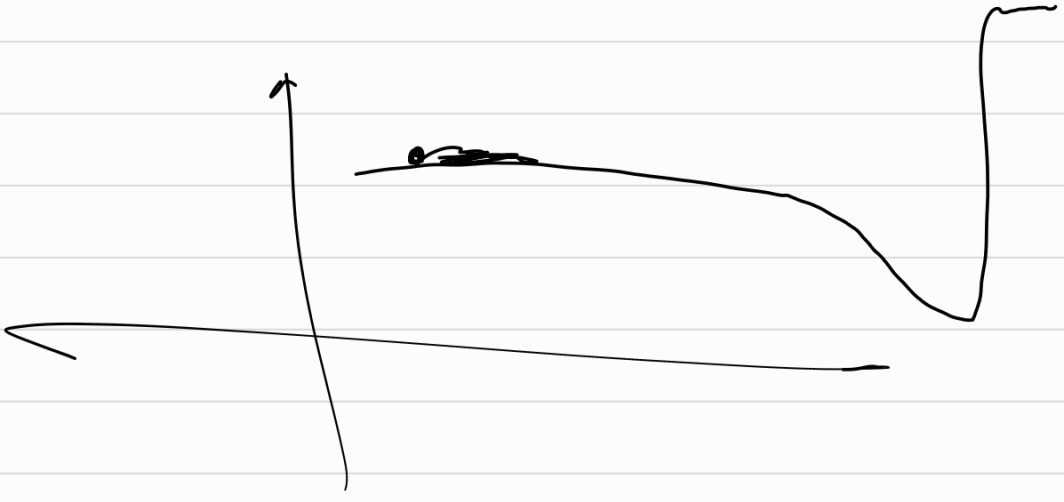




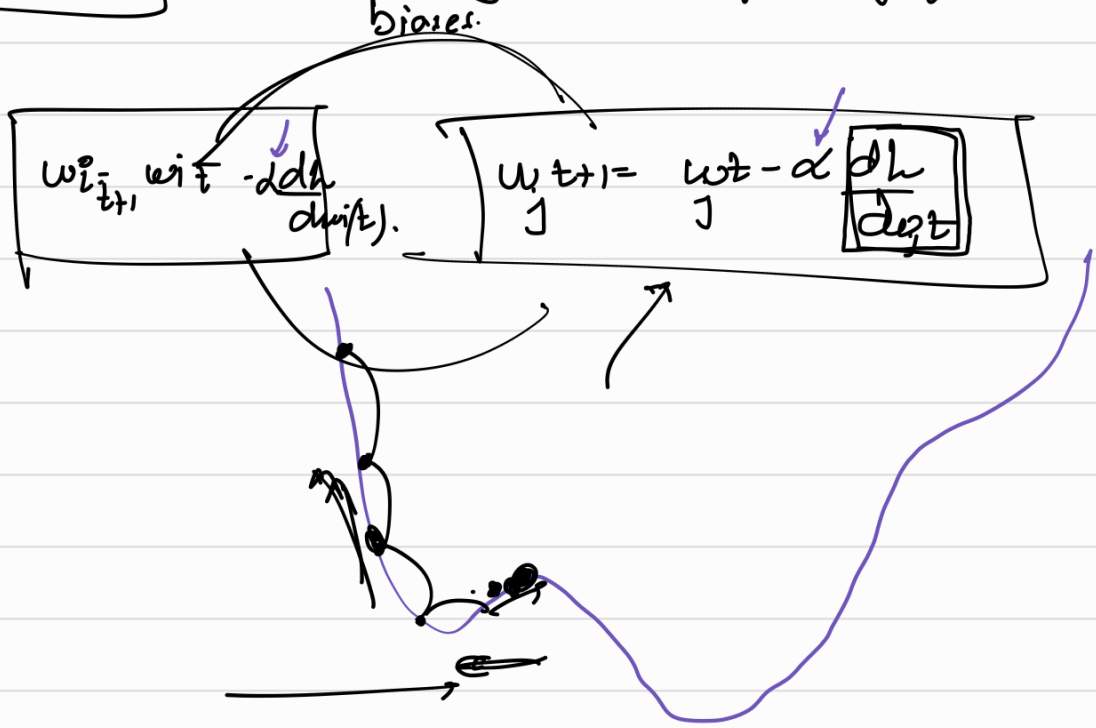


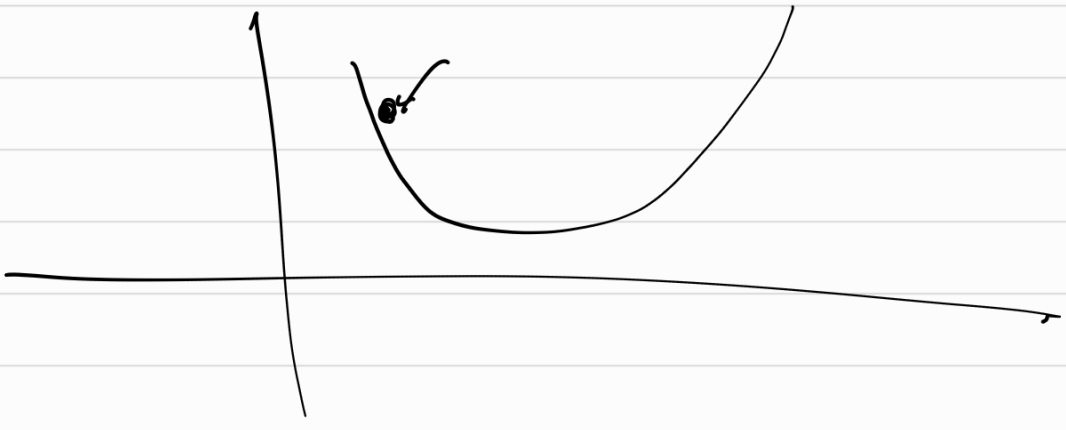


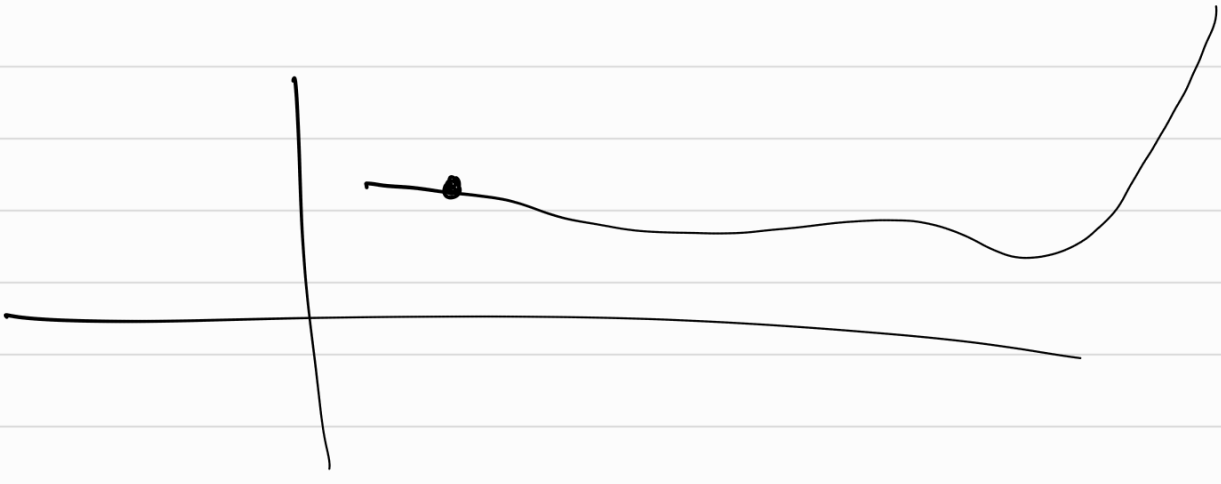
10



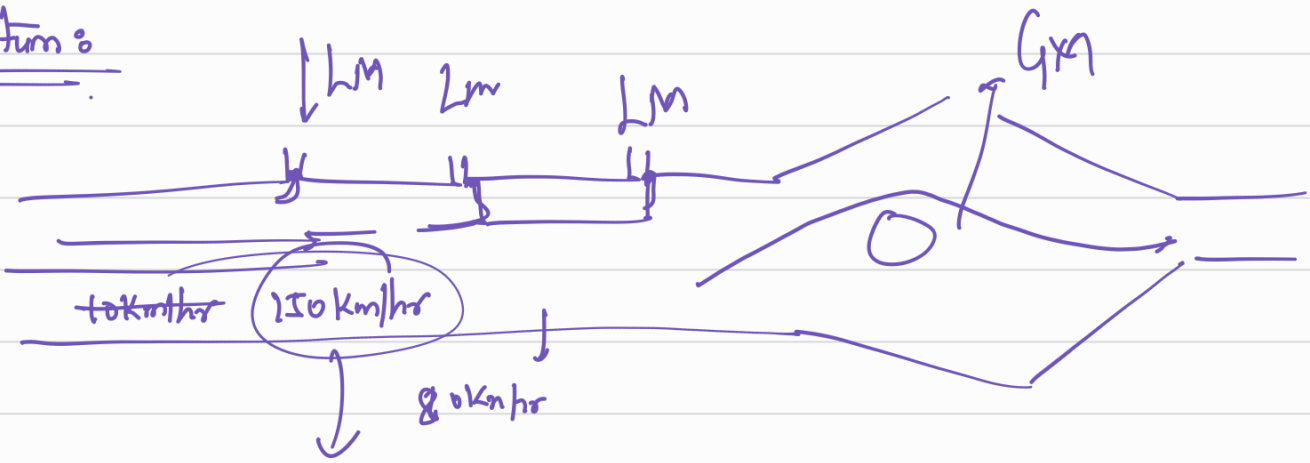
optimizers : minimizing the loss by changing the weights and biases.







Momentum :



momentum

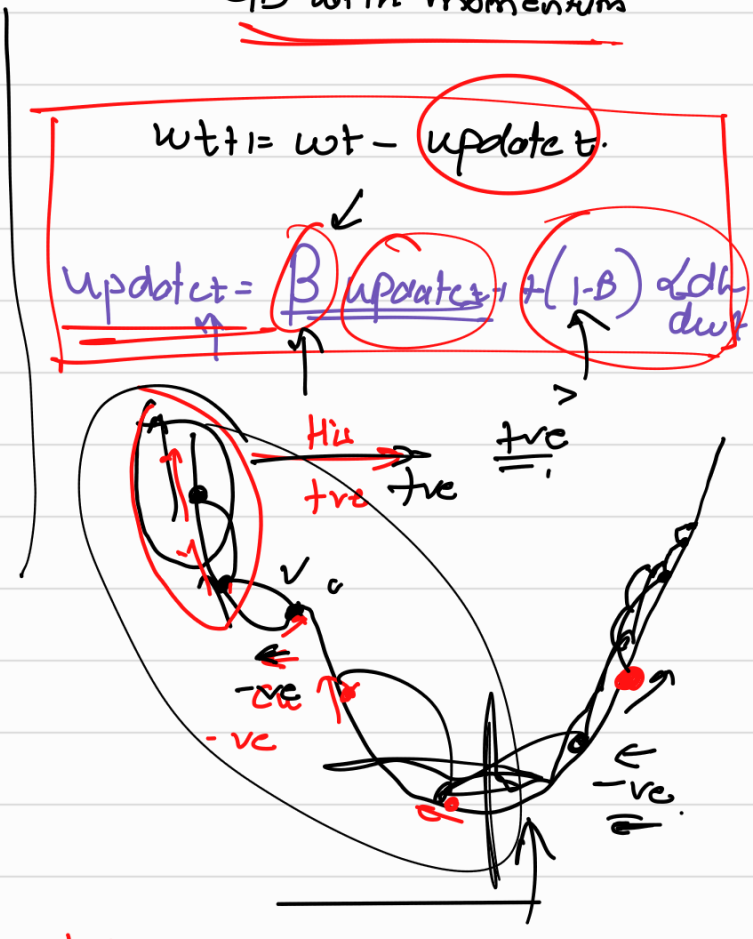
GD

$$w_{t+1} = w_t - \alpha \frac{dh}{dw_t}$$

GD with momentum

$$w_{t+1} = w_t - \text{update}_t$$

$$\text{update}_t = \beta\, \text{update}_{t-1} + (1-\beta)\, \alpha \frac{dh}{dw_t}$$



$t=0 \Rightarrow t=1 \;\; t=2 \;\; t=3$

$$\text{update}_1 = (1-\beta)\, \alpha \frac{dh}{dw_2}$$

$$\text{update}_2 = \beta\, \text{update}_1 + (1-\beta)\, \alpha \frac{dh}{dw_2}$$

$$\text{update}_2 = \beta\,(1-\beta)\, \alpha \frac{dh}{dw_1} + (1-\beta)\, \alpha \frac{dh}{dw_2}$$

$\alpha, \beta < 1$

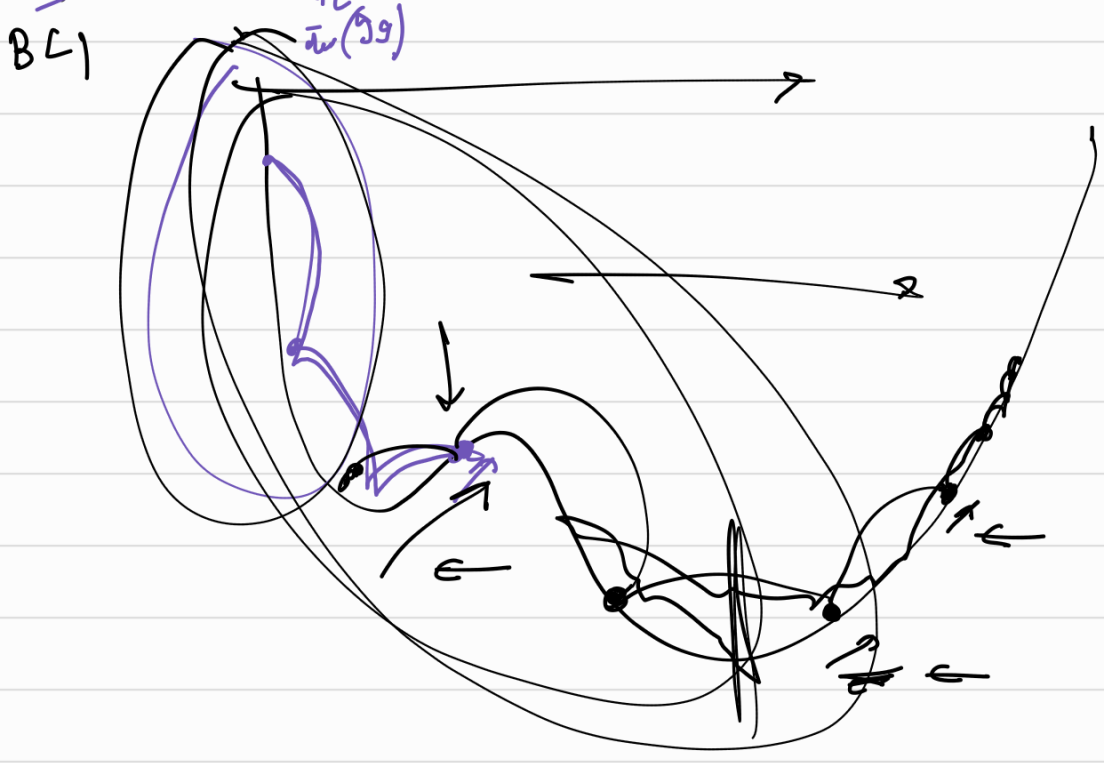
$$update_3 = \beta\, update_2 + (1-\beta)\,\alpha \frac{\partial h}{\partial w_3}$$

$$update_3 = \beta\left(\beta(1-\beta)\alpha\frac{\partial h}{\partial w_1} + (1-\beta)\alpha\frac{\partial h}{\partial w_2}\right) + (1-\beta)\alpha\frac{\partial h}{\partial w_3}$$

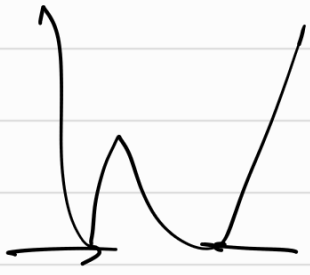
$\beta \to 0$

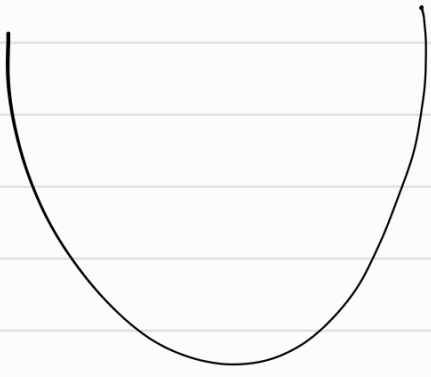
$$update_3 = \beta^2(1-\beta)\alpha\frac{\partial h}{\partial w_1} + \beta(1-\beta)\alpha\frac{\partial h}{\partial w_2} + (1-\beta)\alpha\frac{\partial h}{\partial w_3}$$

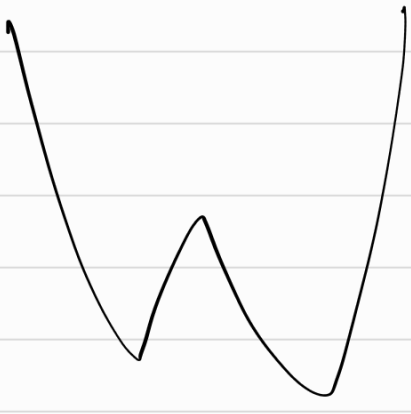
$\beta < 1$

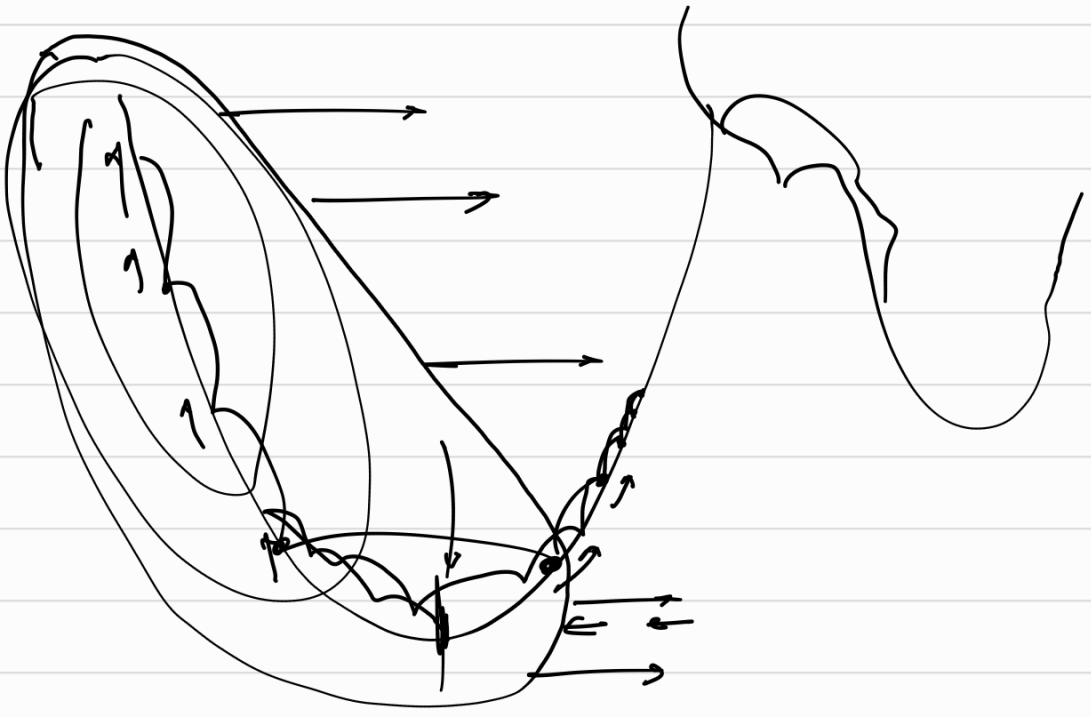


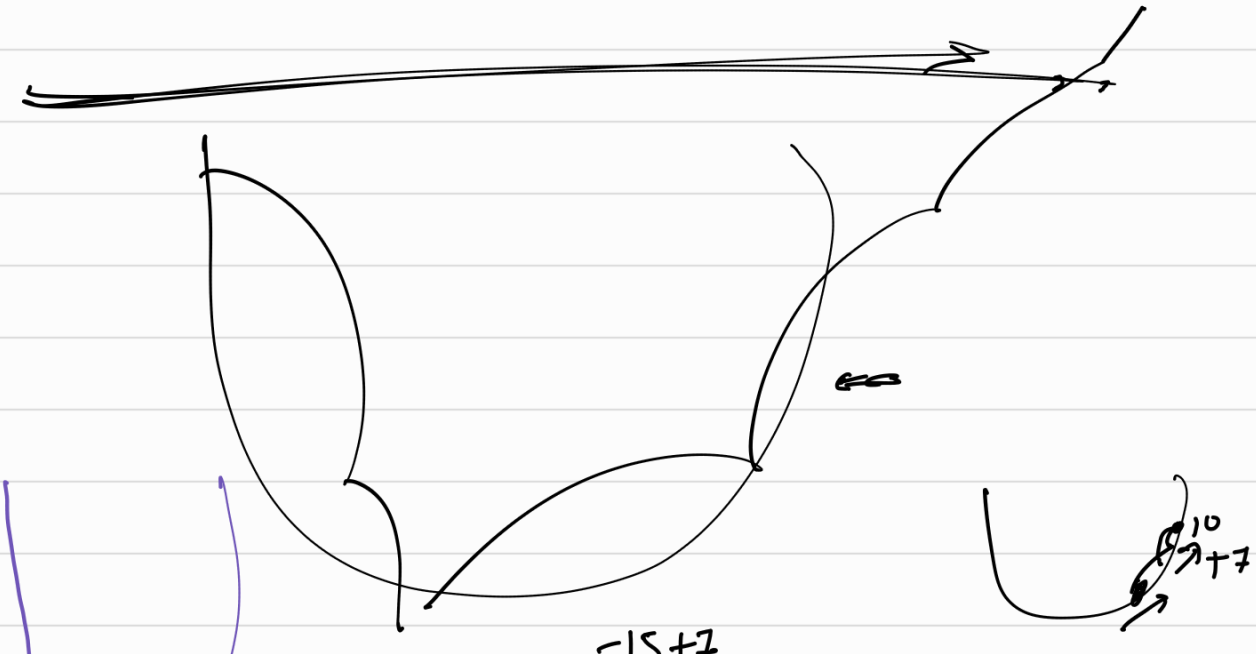
$i = i + 5$











$-15+7$

$-20 \rightarrow -20+5$

$-ve$

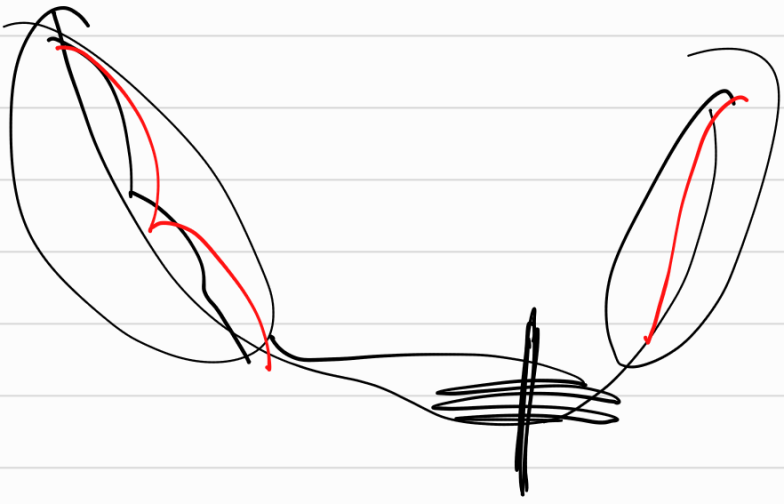
$$\text{update}_t = \text{update}_{t-1} + \alpha \frac{dh}{dwt}$$

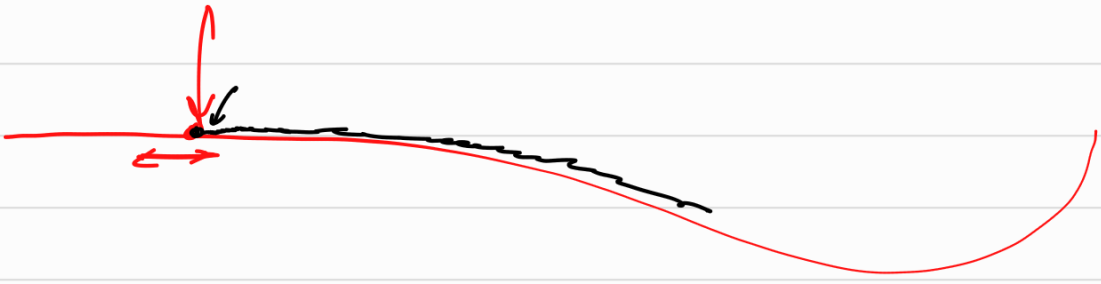
1
2
3

$-8 \quad +10$

$= -15$

6th





Momentum → GD.

$a_0 = 0$

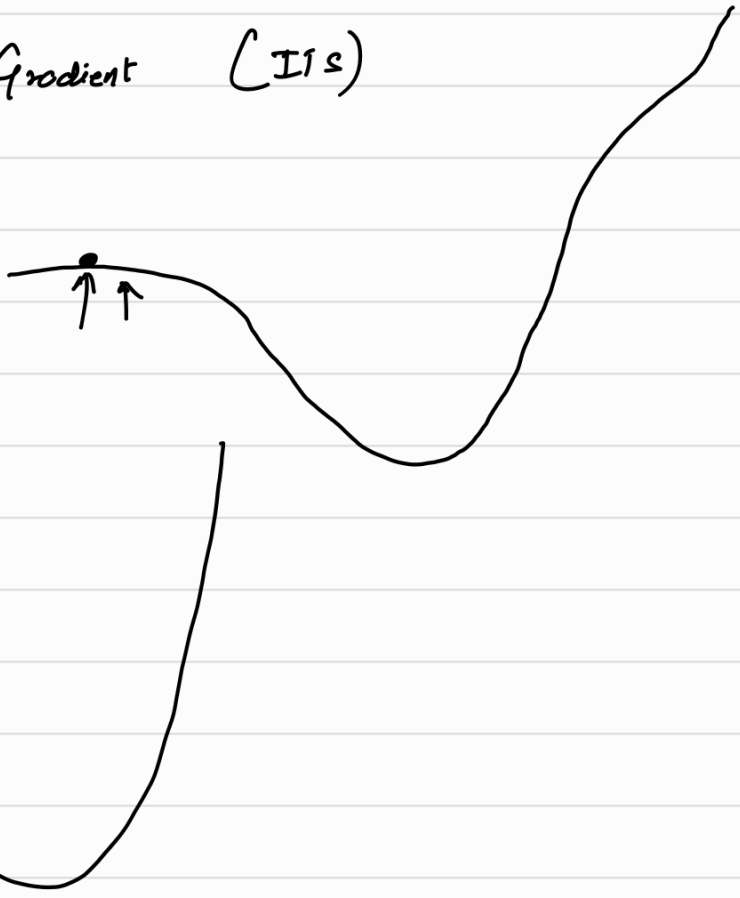
$a_t = a_{t-1} + 5$

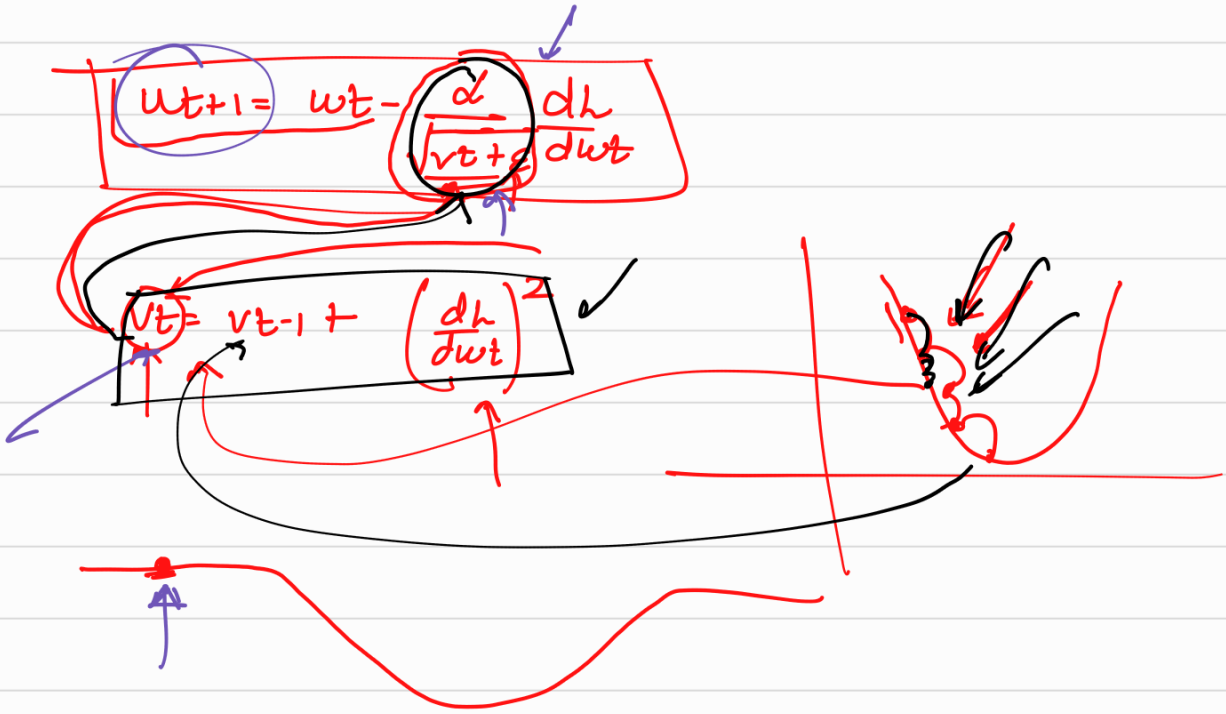
$a_1 = 0 + 5$ $\quad a_2 = a_1 + 5$ $\quad a_3 = a_2 + 5$

$a_1 = 5$ $\quad a_2 = 10$ $\quad a_3 = (a_1 + 5) + 5$

Break!

Adagrad: Adaptive Gradient (IIs)





Rms Prop

$$w_{t+1} = w_t - \frac{\alpha}{\sqrt{v_t + \varepsilon}} \frac{\partial h}{\partial w_t}$$

$$v_t = \beta\, v_{t-1} + (1-\beta) \times \left(\frac{\partial h}{\partial w_t}\right)^2$$

0.99 — 0.01

Adam:

Adaptive moments →

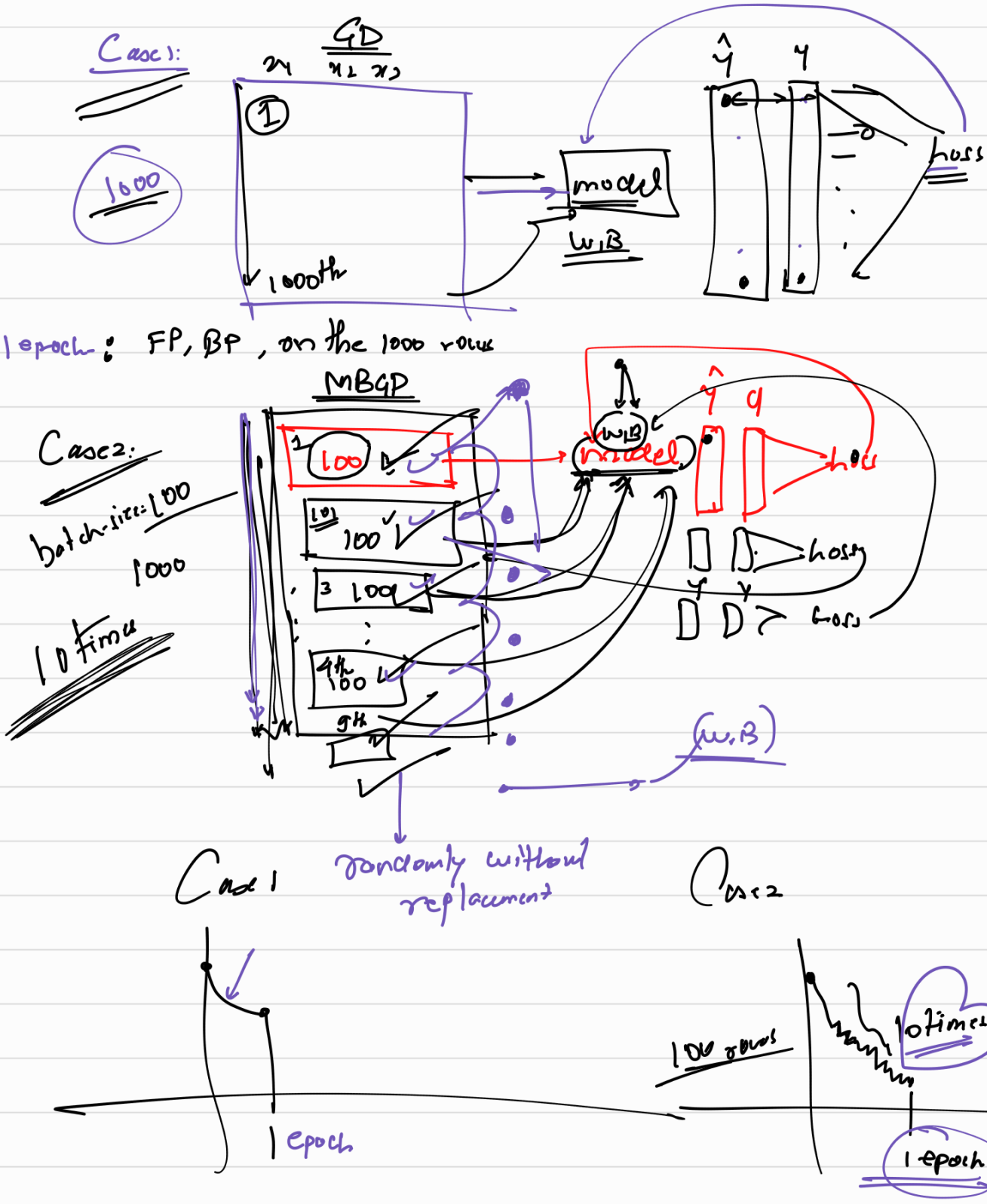
$$m_t = \beta_1 (m_{t-1}) + (1-\beta_1) \frac{\partial h}{\partial w_t}$$

$$v_t = \beta_2 (v_{t-1}) + (1-\beta_2) \times \left(\frac{\partial h}{\partial w_t}\right)^2$$

$$w_{t+1} = w_t - \frac{\alpha}{\sqrt{v_t + \varepsilon}} \times m_t$$

Mini Batch Gradient Decent → Batch Normalization

Callbacks



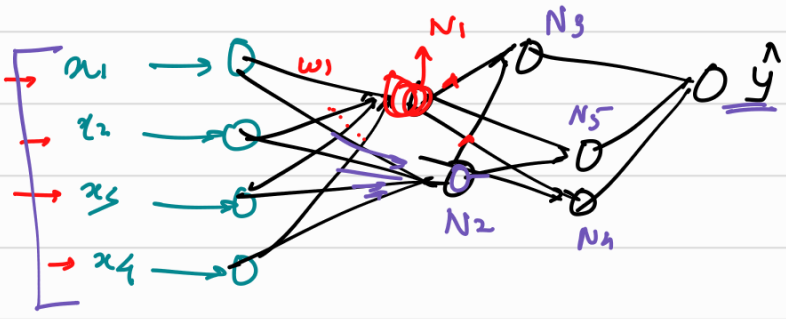
model.fit (10)

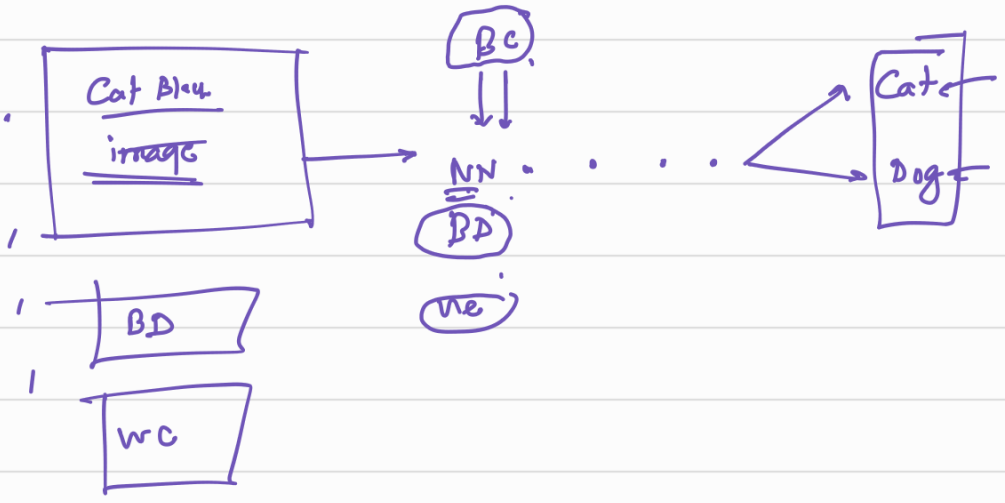
model.fit (20)

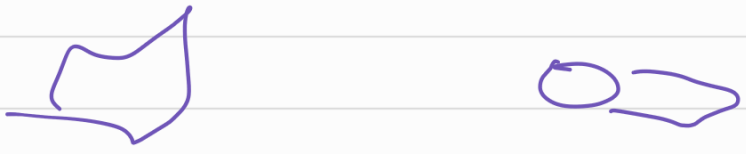
Batch Normalization

Callbacks

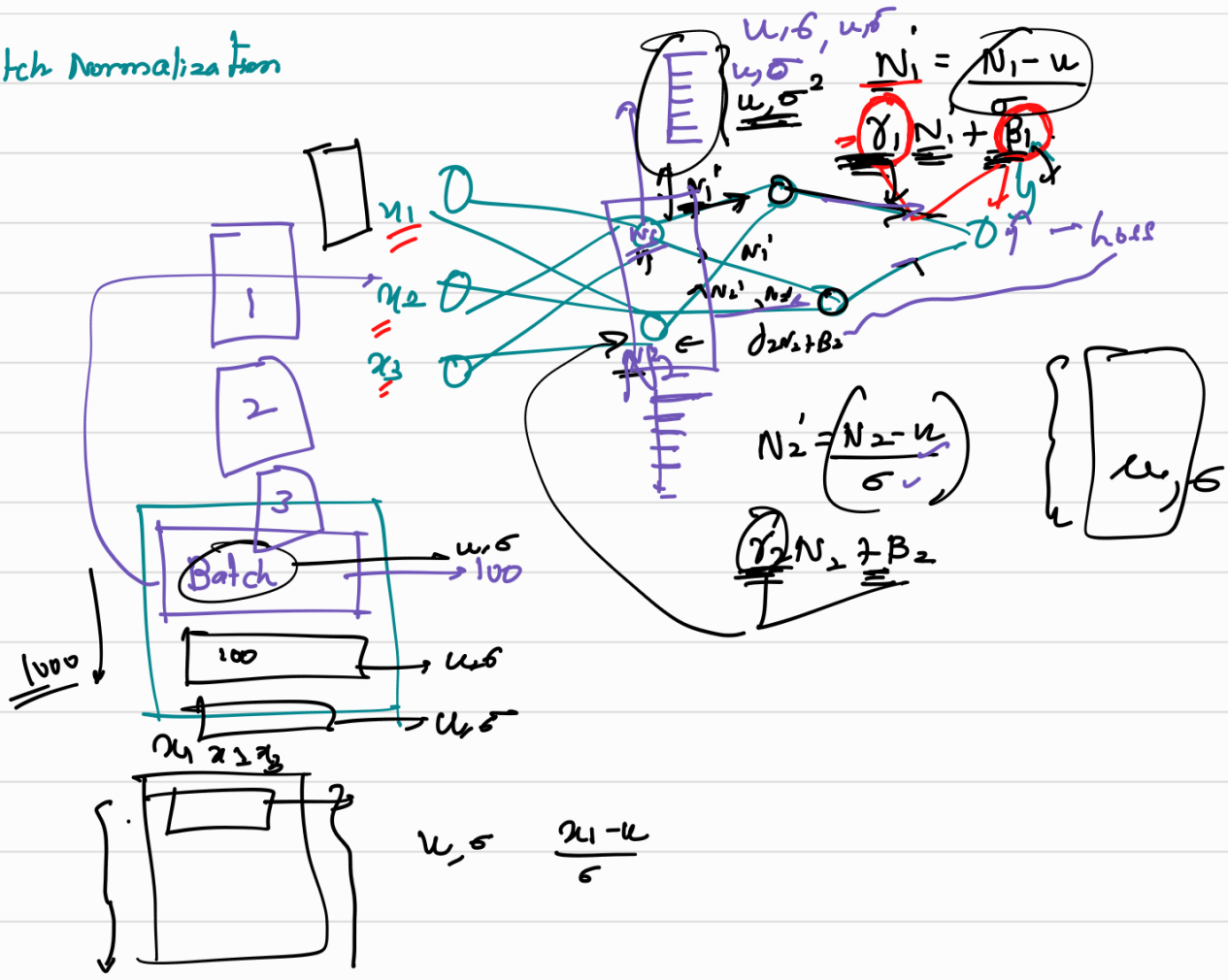
Batch Normalization

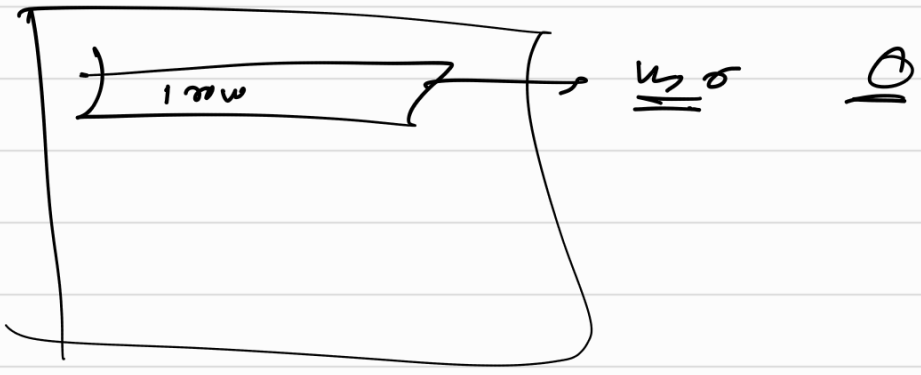


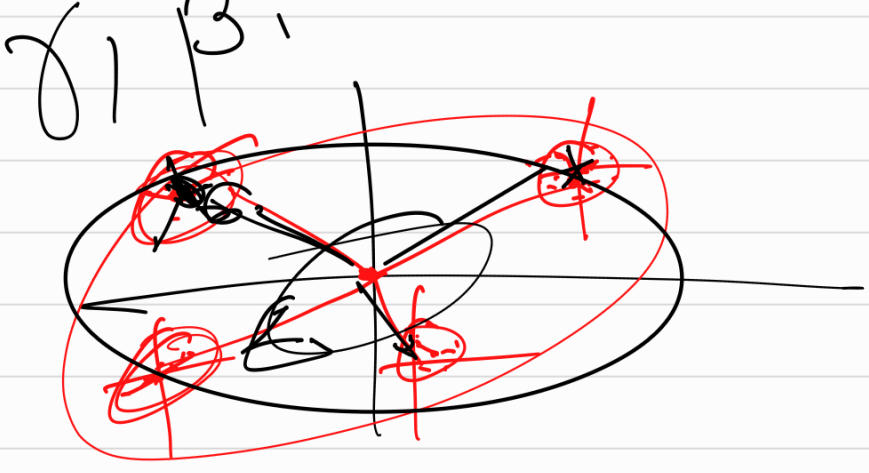


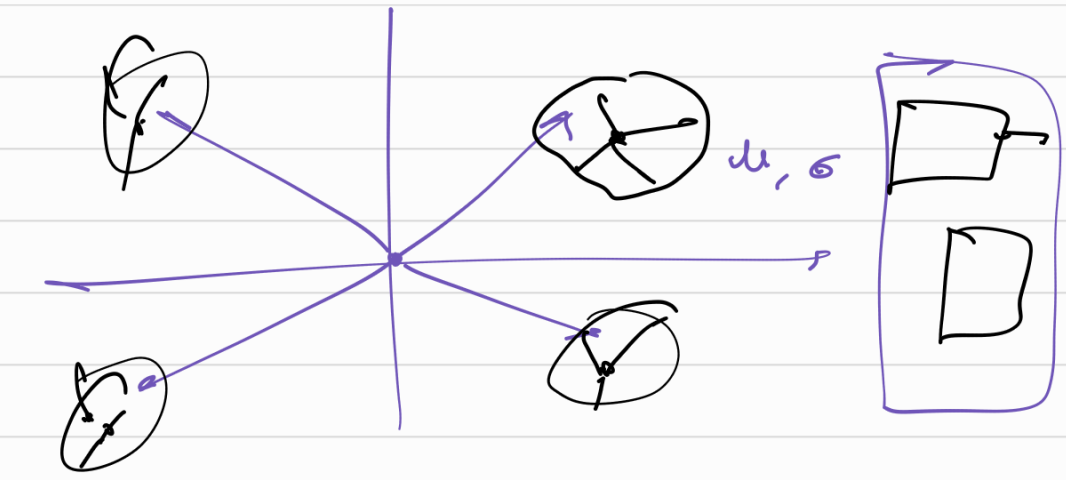


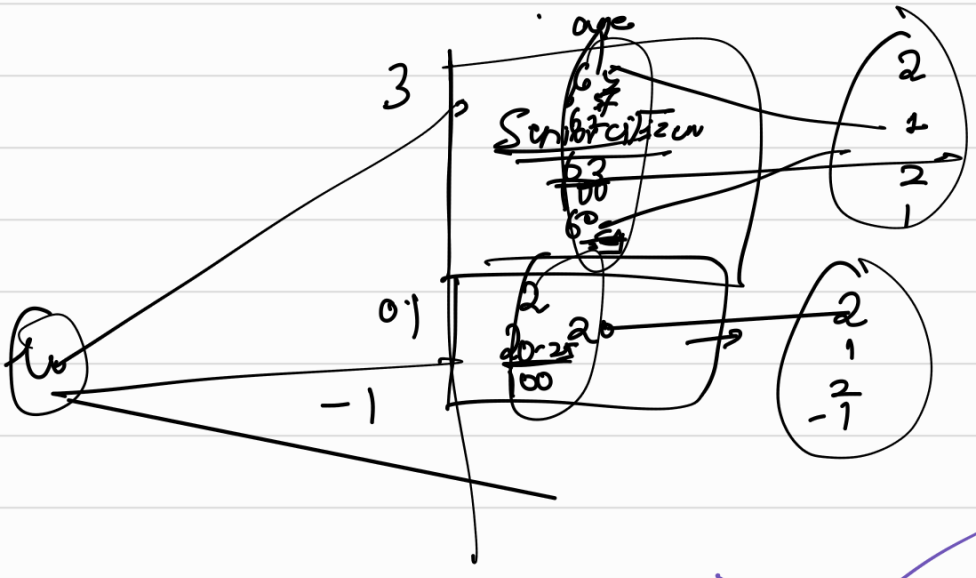
Batch Normalization

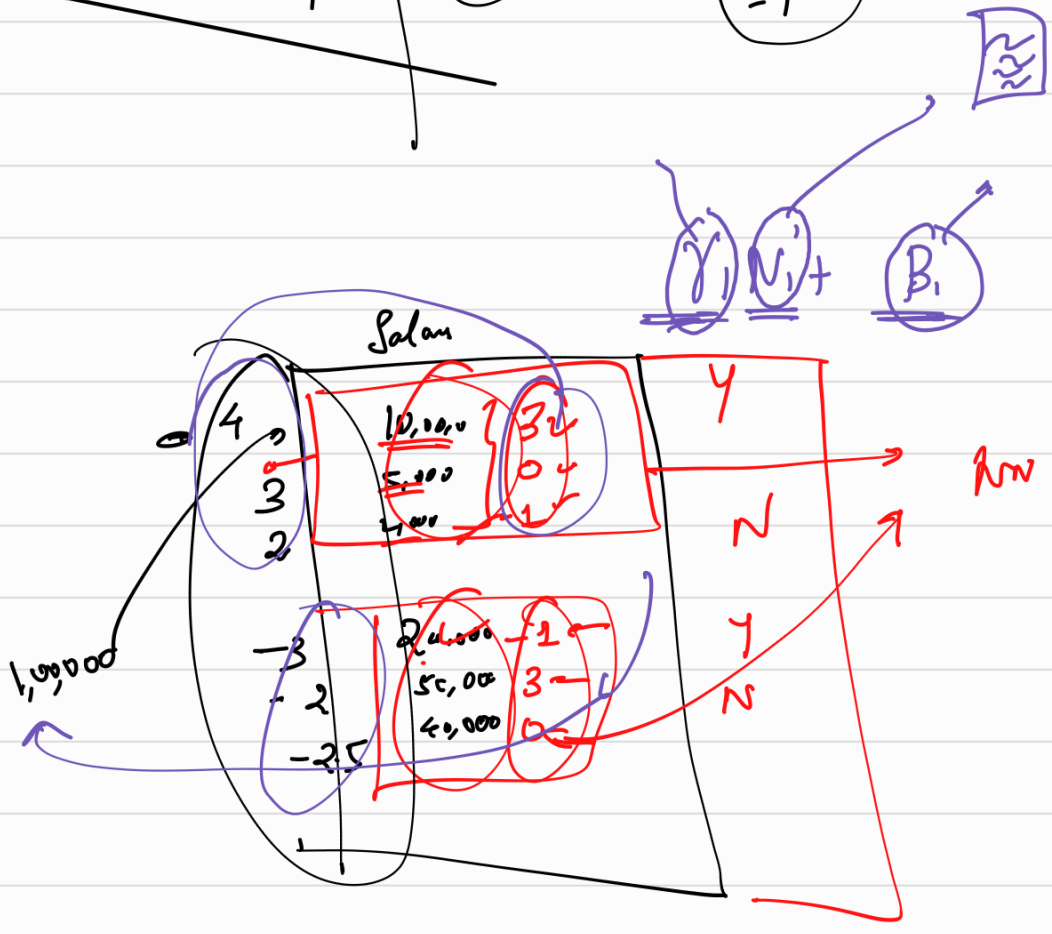


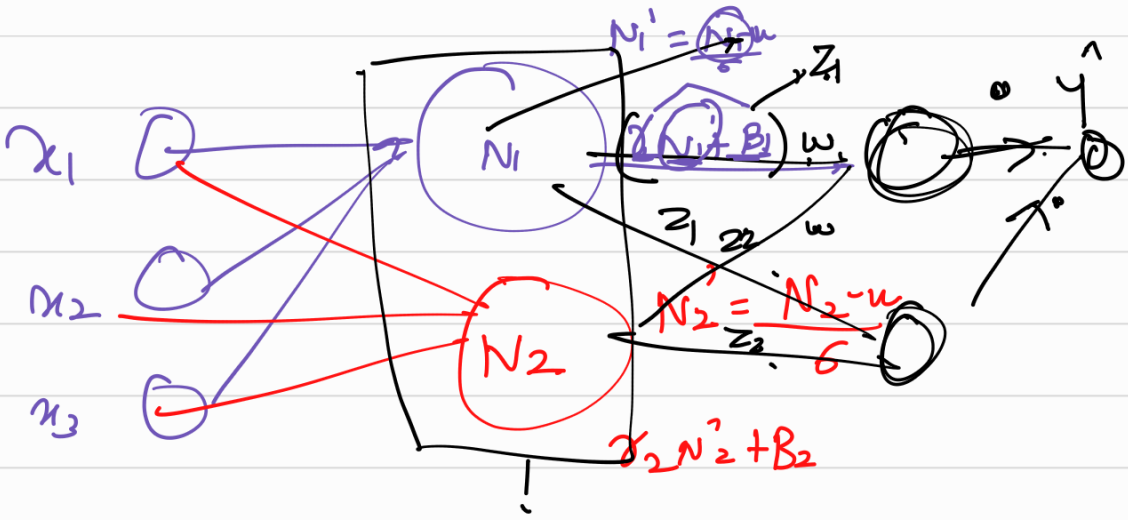




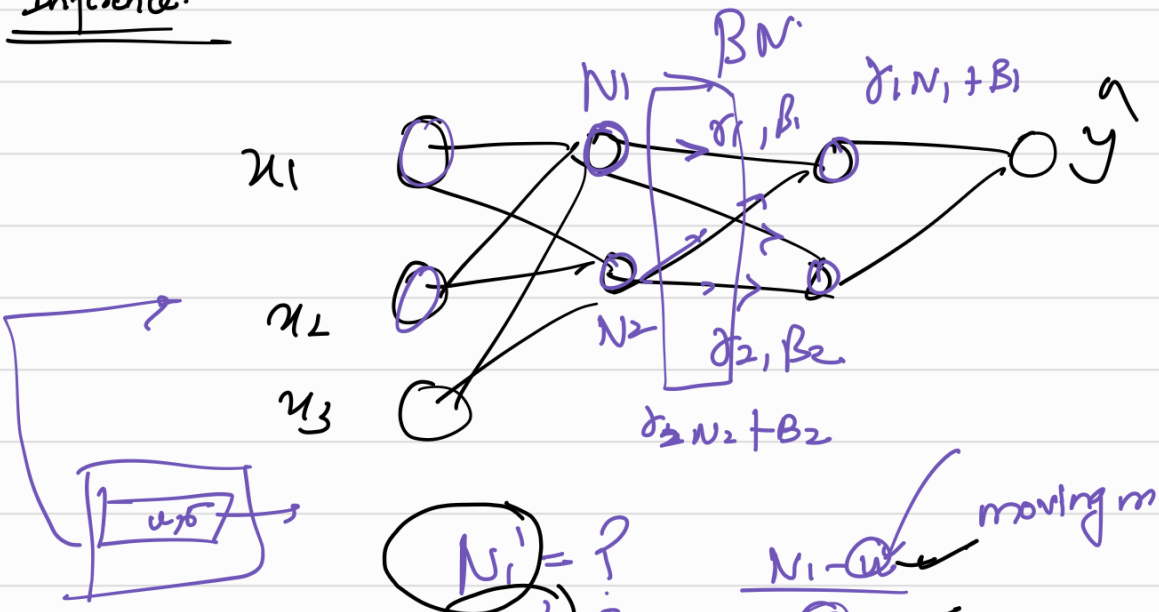

μ, σ

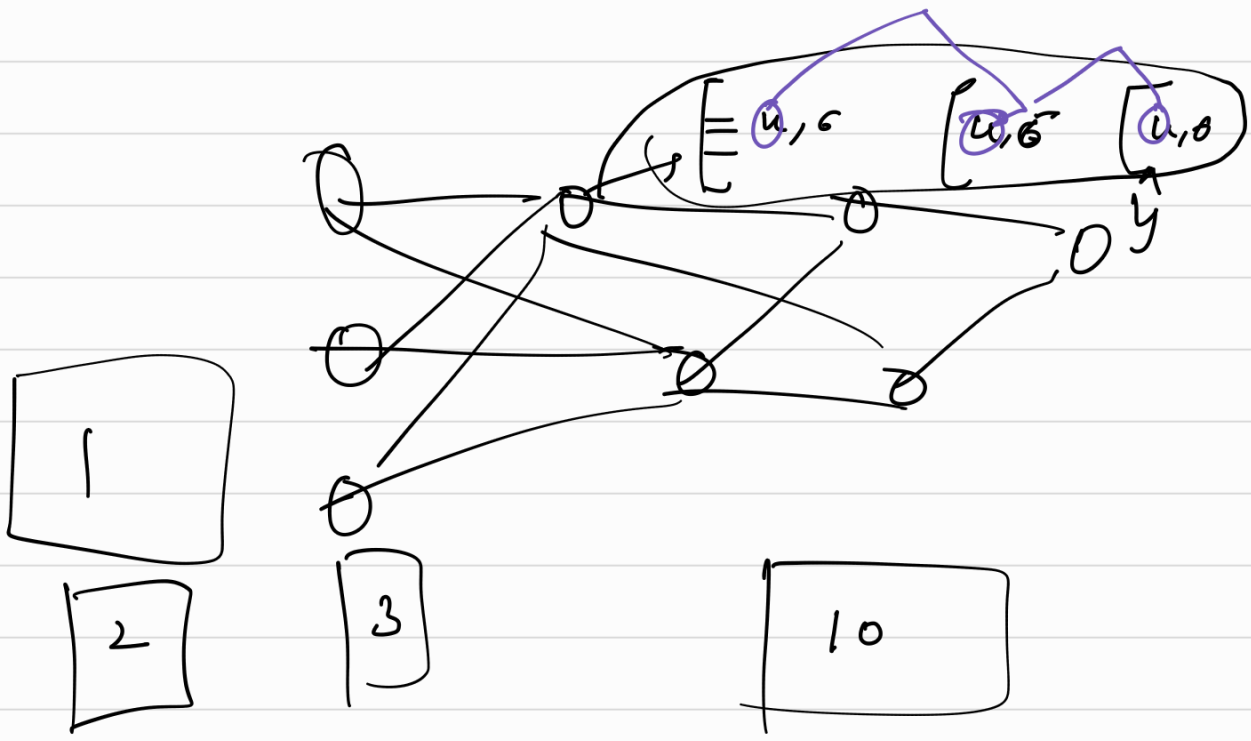

age
Salary
citizen
3
0.1
-1
2
1
2
1
2
1
2
-1


Salary
4
3
2
-3
-2
-2.5
1,00,000
10,000
5,000
4,000
20,000
50,000
40,000
Y
N
Y
N
Any


x_1
x_2
x_3
N_1
N_2
$N_1' = \frac{N_1 - u}{\sigma}$
$N_2' = \frac{N_2 - u}{\sigma}$
$\gamma_2 N_2' + B_2$
z_1
z_2
z_3
ω
y

Inference:


BN
N_1
N_2
$\gamma_1 N_1 + B_1$
$\gamma_2 N_2 + B_2$
x_1
x_2
x_3
y
u, 0
$N_1' = ?$
$N_2' = ?$
$N_1 - u$
moving mean (-bair)
moving var (bair)

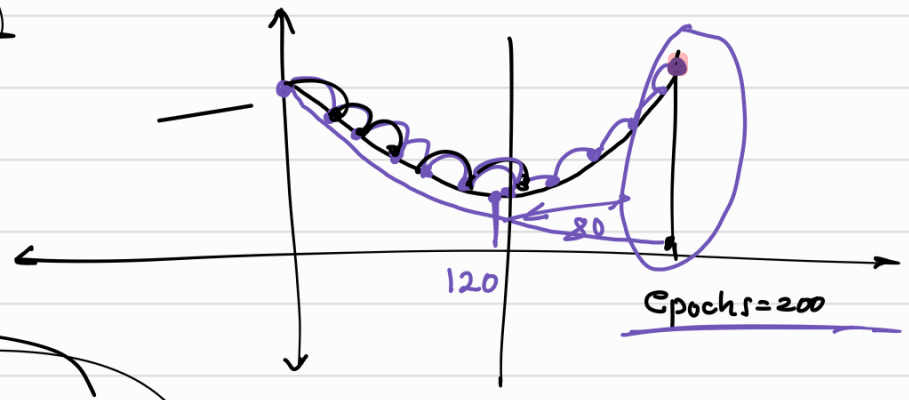

u, 0
u, 0
u, 0
y
1
2
3
10

N1

moving mean → β × moving mean + (1-β) × mean(batch)

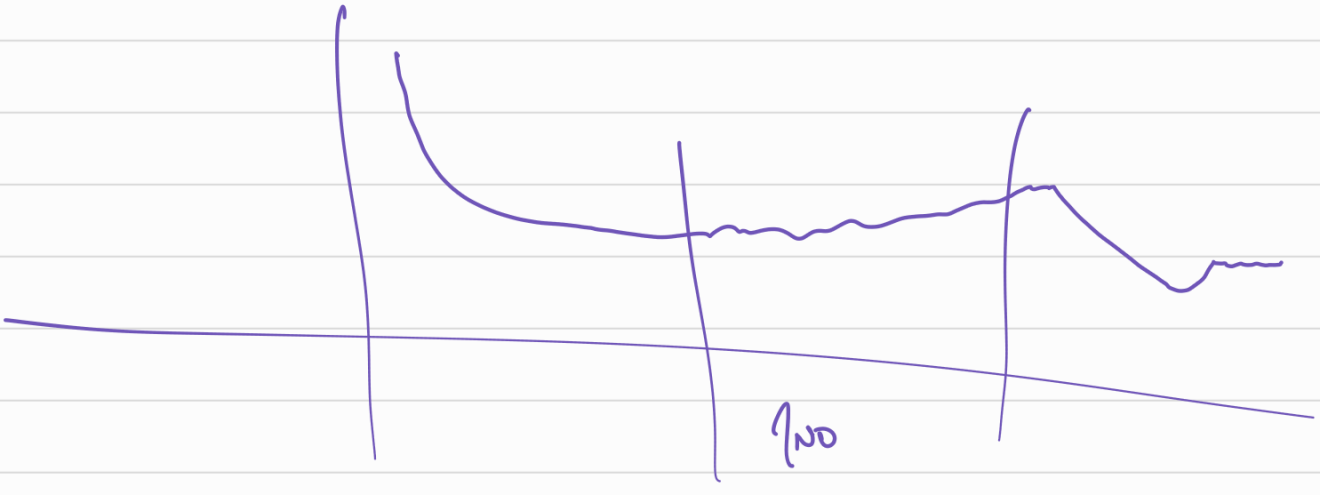
N2 moving var = β × moving var + (1-β) var(batch)

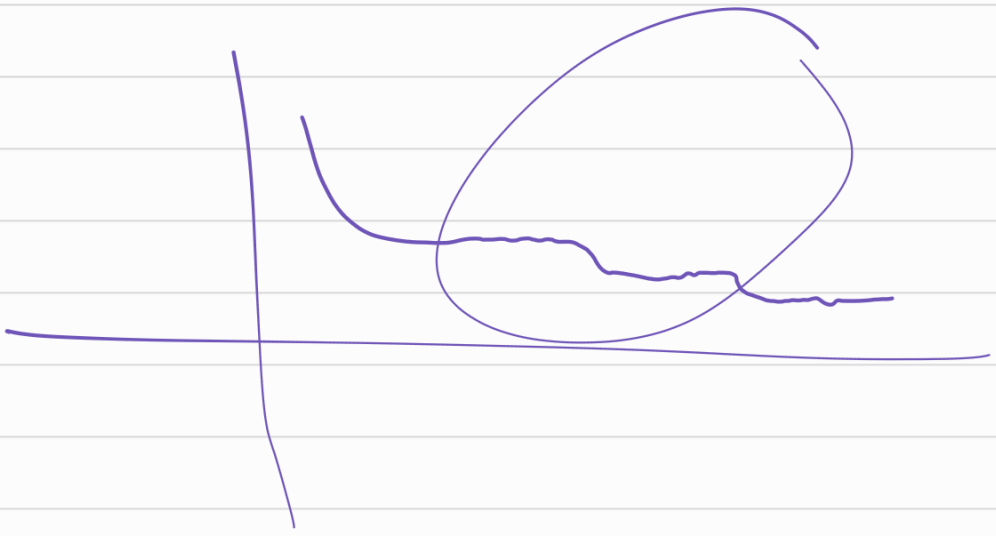
Callbacks



model checkpoint

Early stopping





max_trials = 3

Executions_per_trial = 2

[3, 32, relu, d=T, lr=10^{-2}] → model → fit model. (100)

model → fit (10)

[4, 32, relu, d=N, lr=10^{-4}]

[4, 64, tanh, d=T, lr=10^{-3}]

11:33 PM

Input layer (784)

{Hidden layer (200, 400, activation (tanh, relu).

Hidden layer (100, 200 active tanh, relu).

Batch Norm()

2,4 {[Hidden (50, 100, activation, (tanh, relu), λ = 0.1, 0.5]

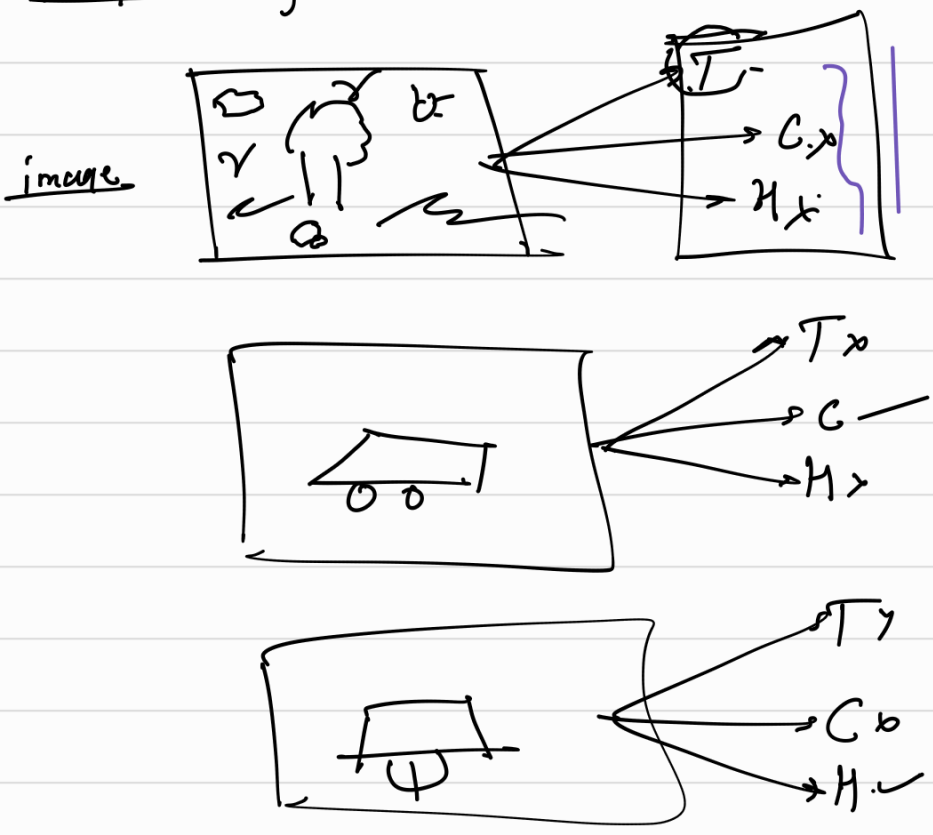
log sampling

Batch Norm().← maybe add / not

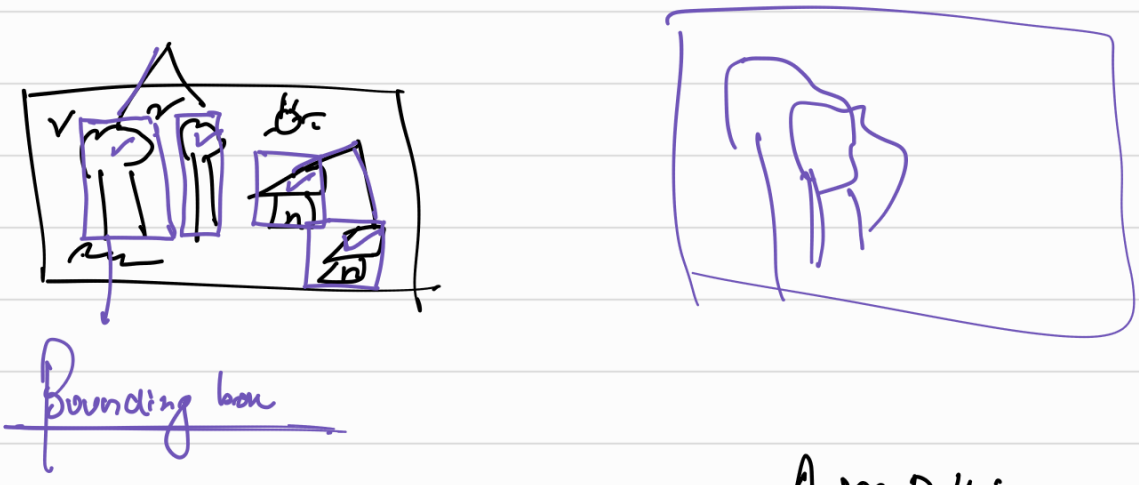
model. layers (Dense (10, softmax).

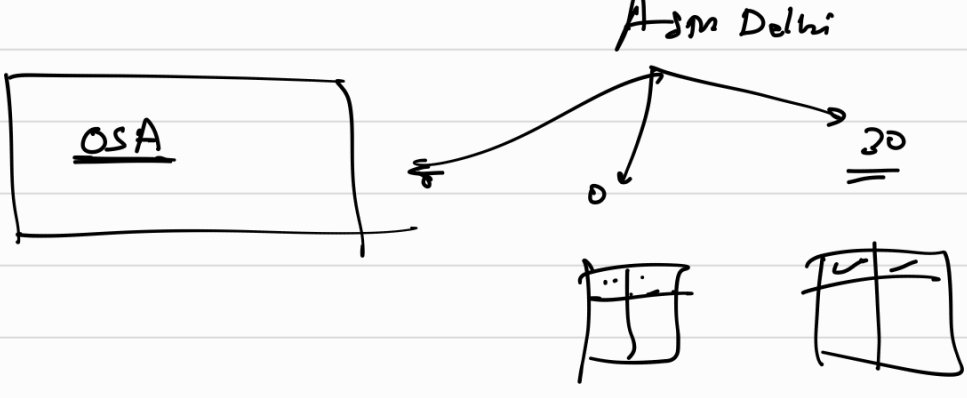
Introduction to Computer Vision

① Image Classification



Object detection & localization





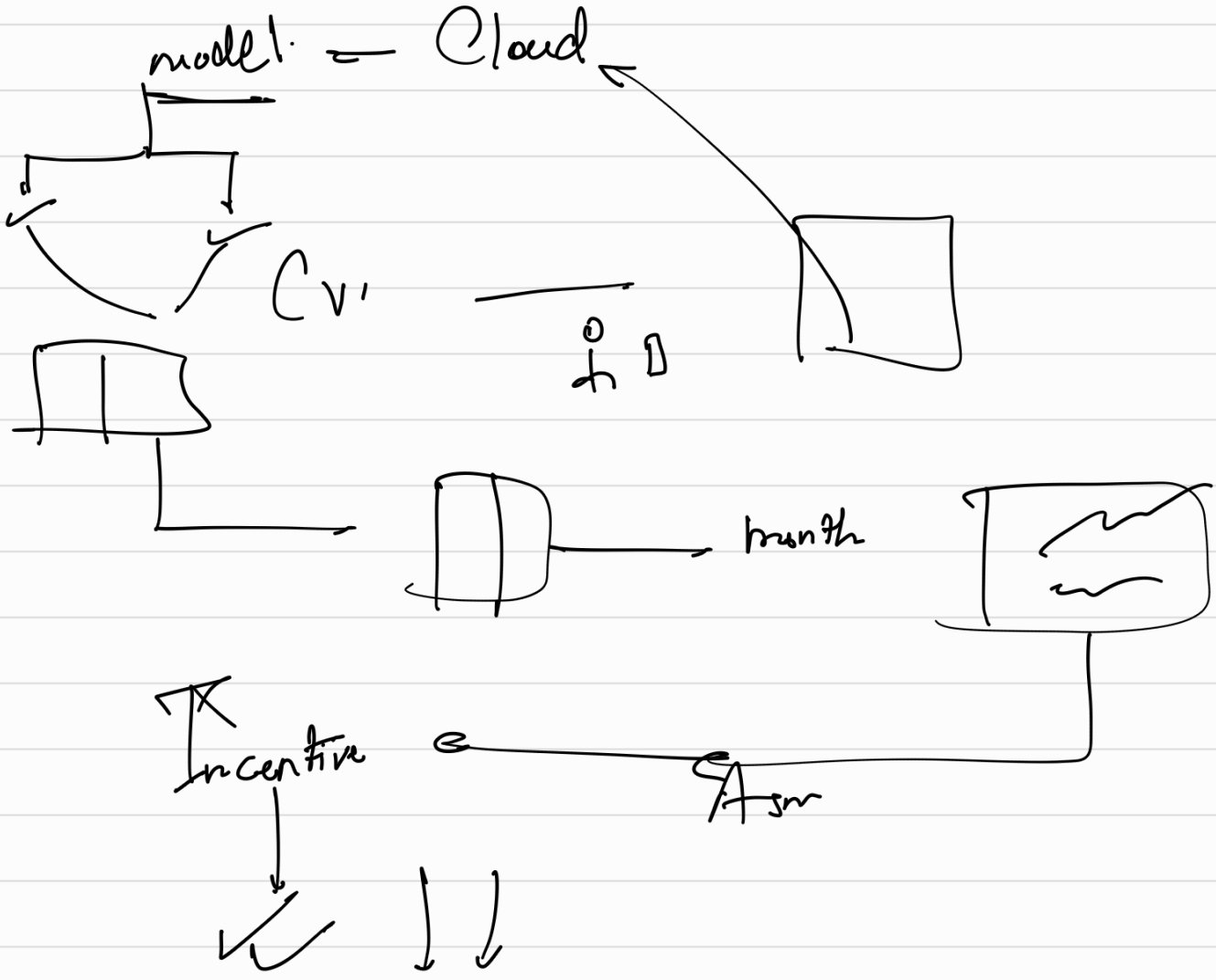
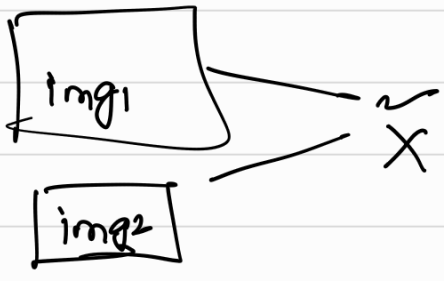


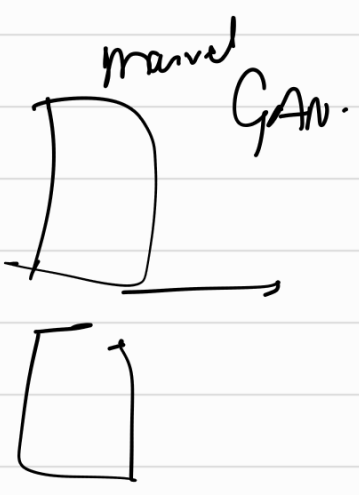
Image Segmentation

④ Siamese networks

FR



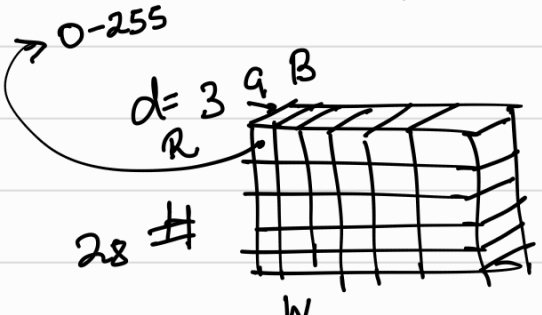
⑤ GAN → Gen Adv Networks.

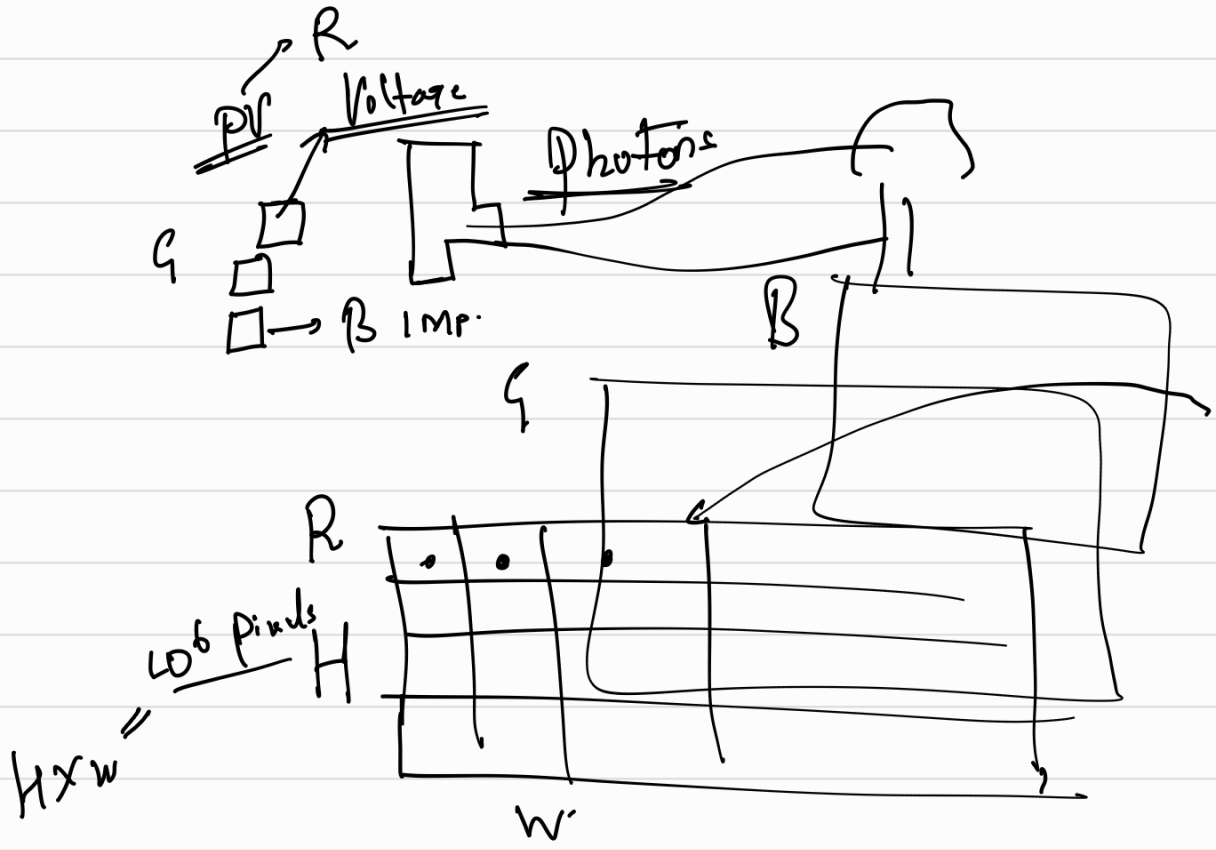


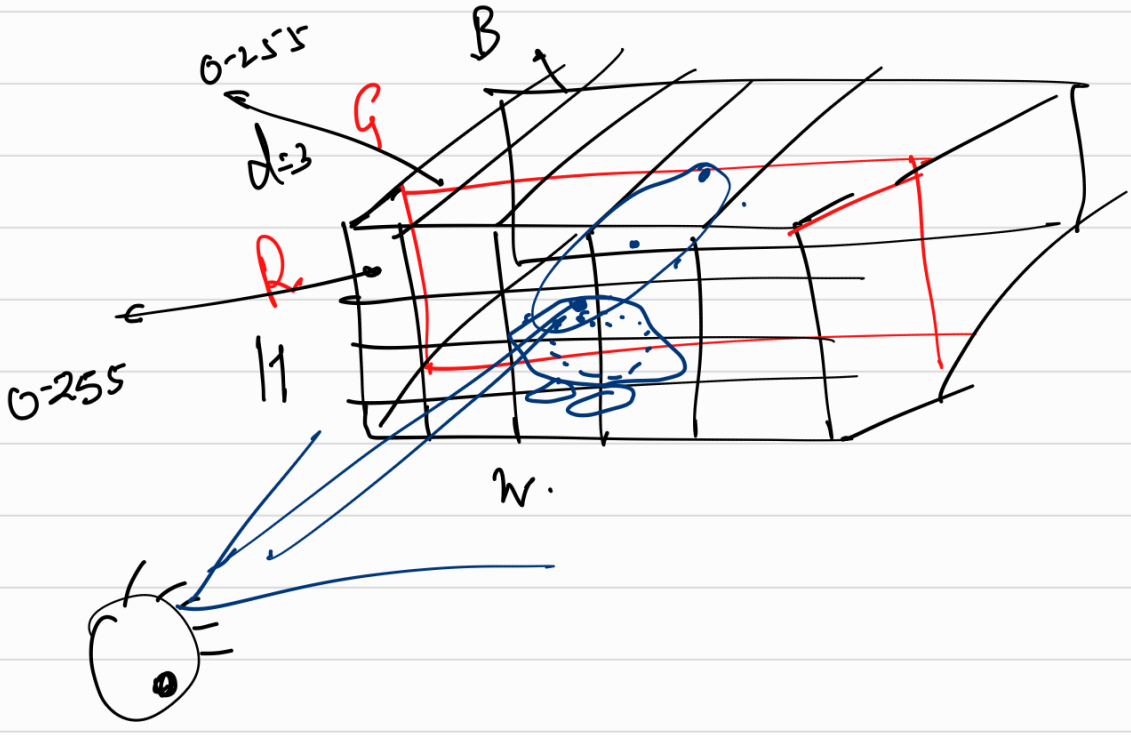
CNN

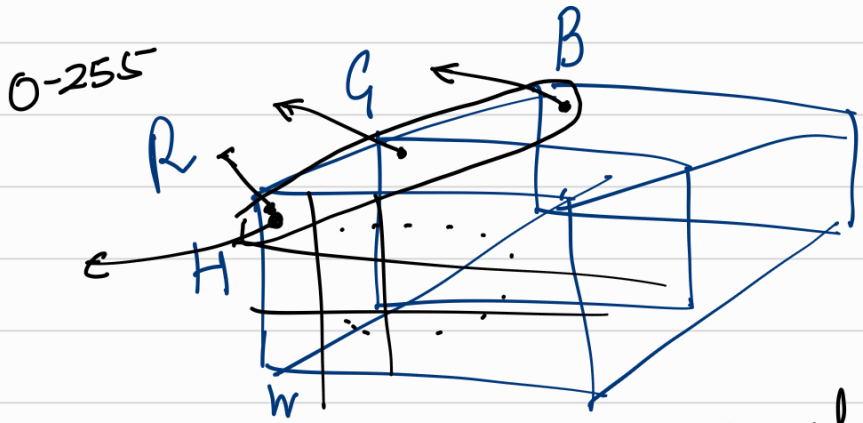
What is an image:

R, G, B

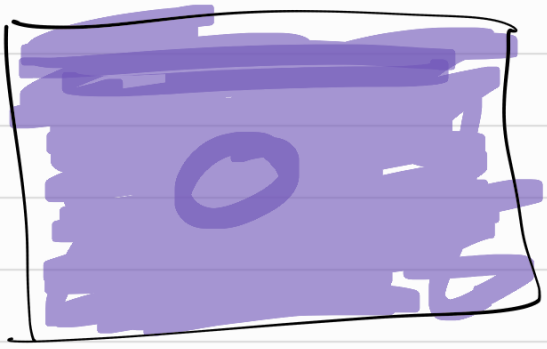


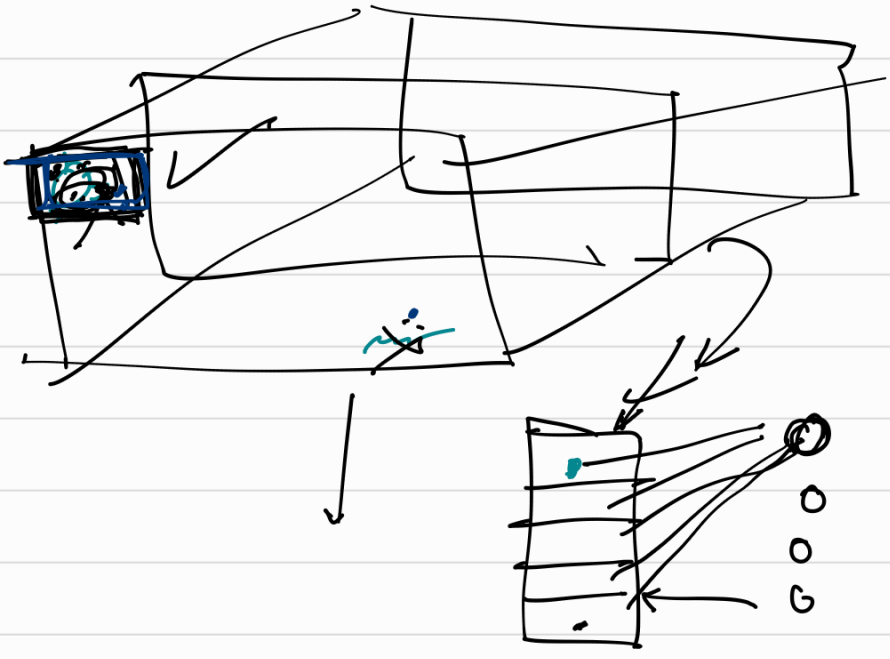

R
PV
Voltage
Photons
G
B Imp.
B
G
R
10^6 Pixels
H
H x W
W.

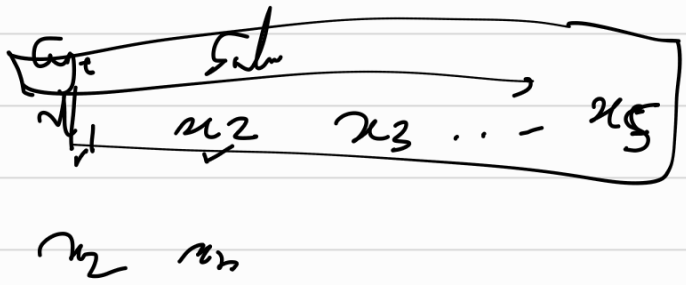

0-255
B
G
d=3
R
0-255
W.

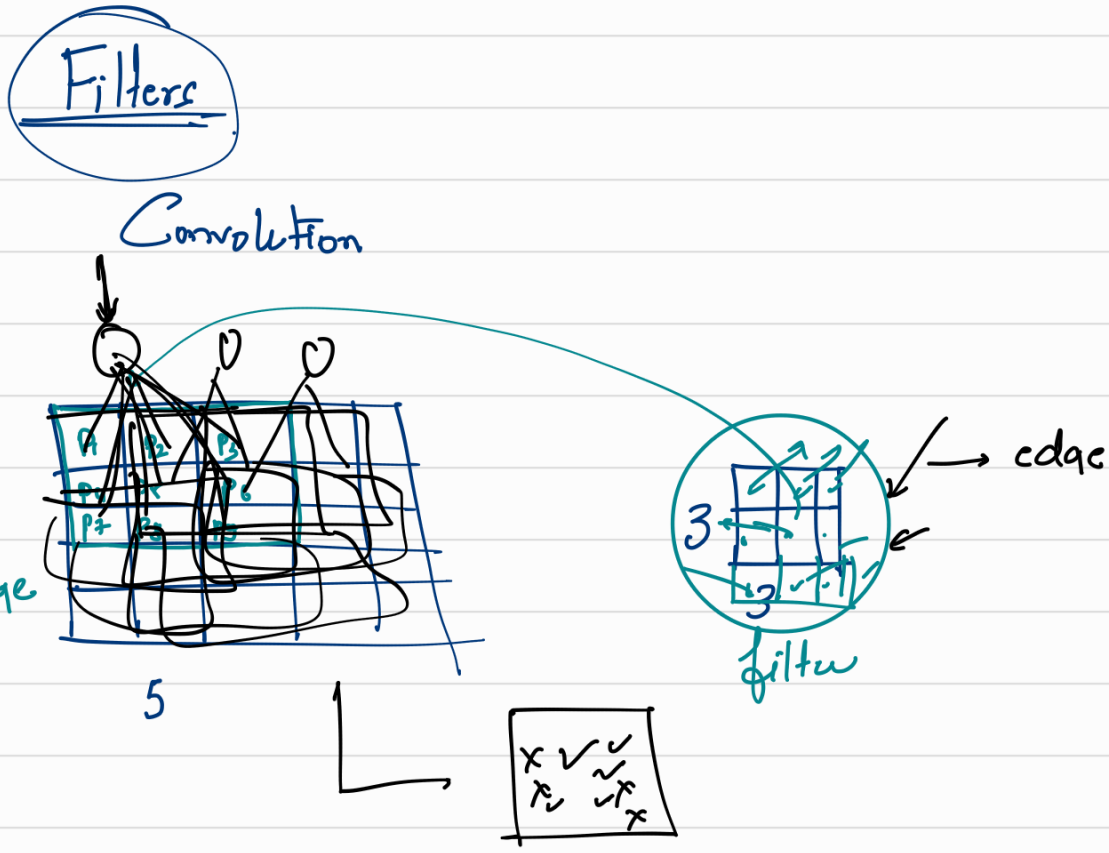


Information — Variation in the pixel intensity

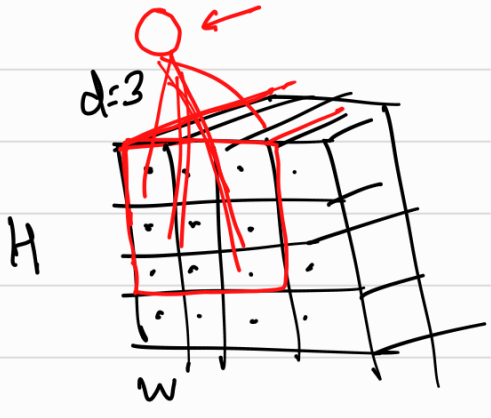




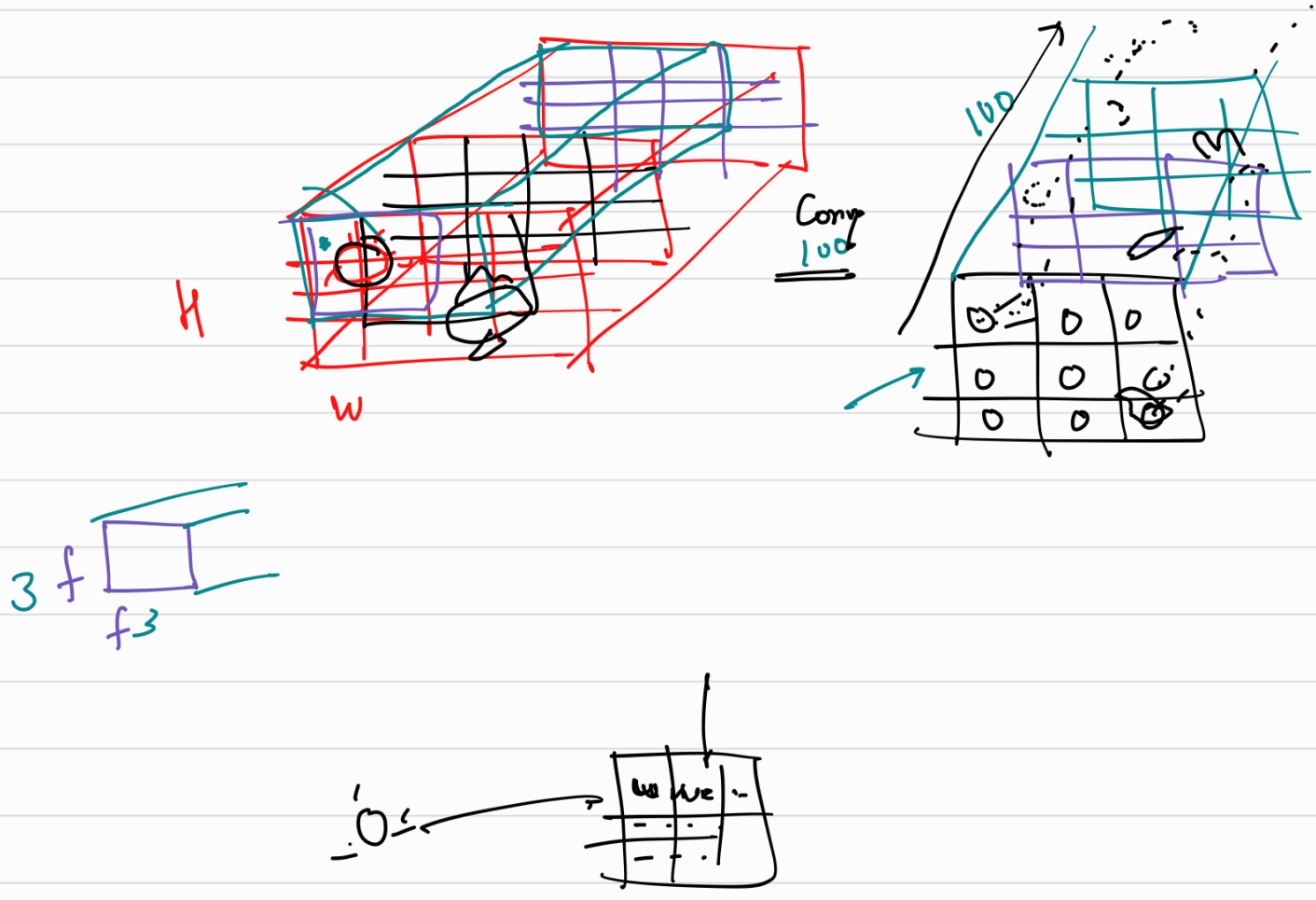




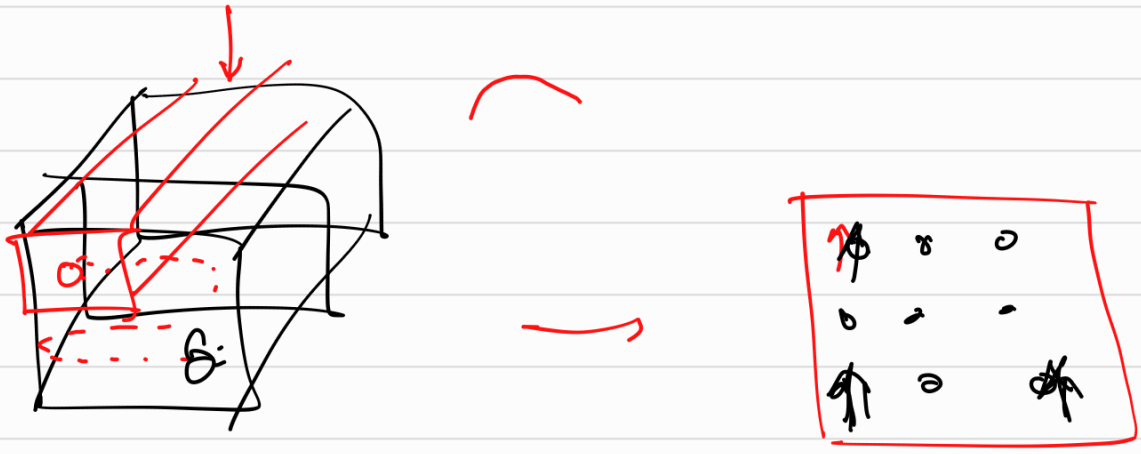
Convolutional Neural Network

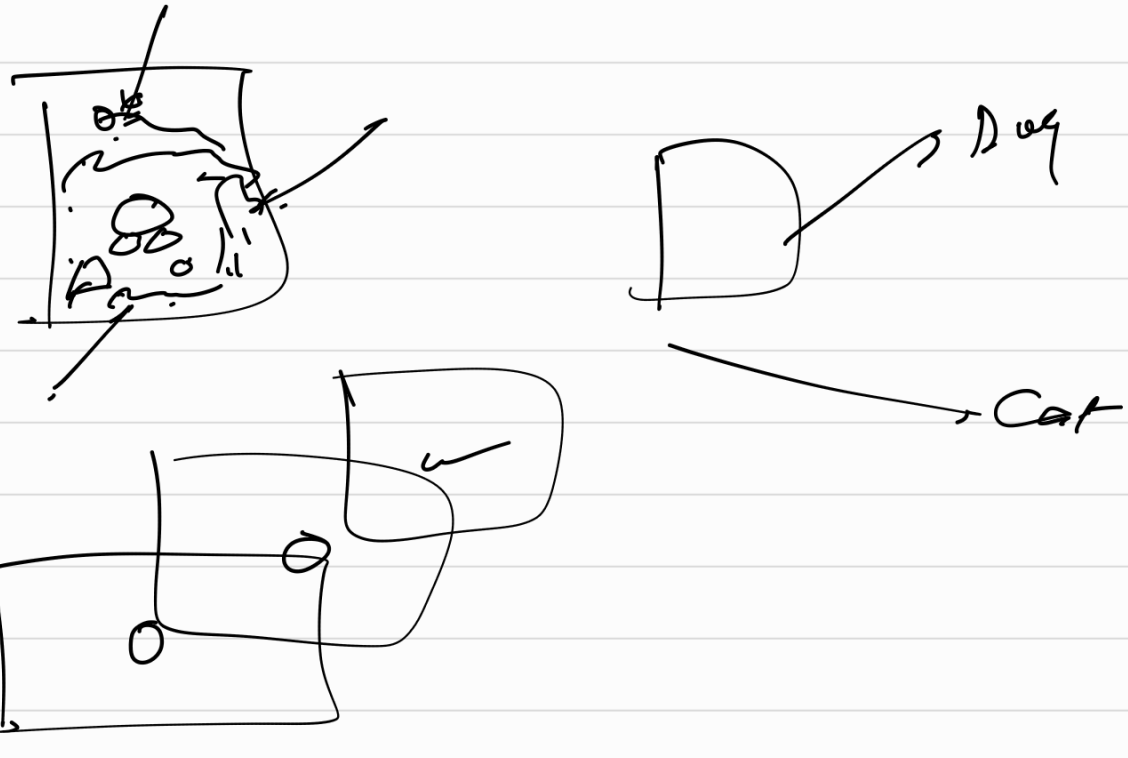


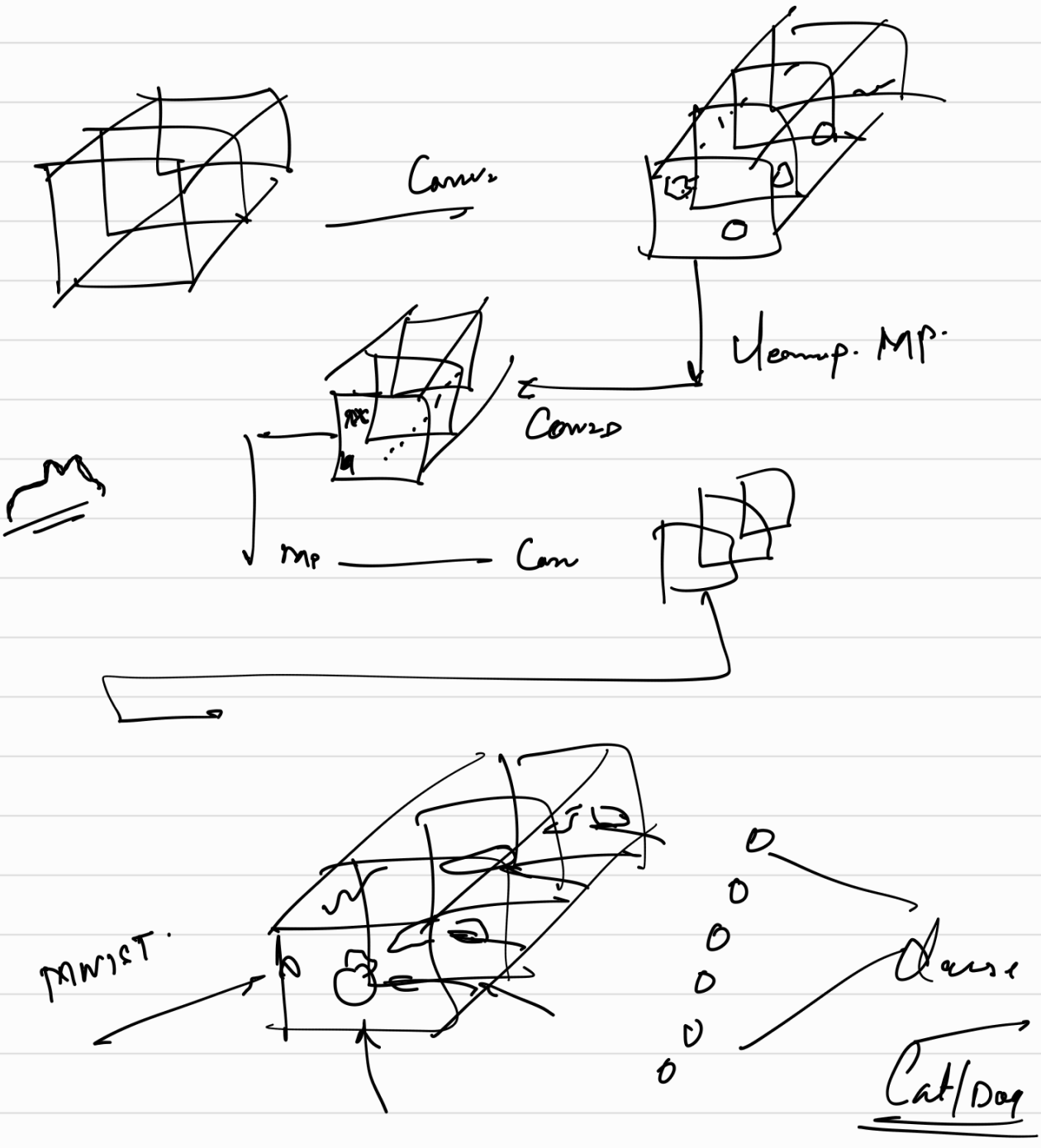
$\tanh(p_1 w_1 + p_2 w_2 + p_3 w_3 \cdots p_{27} w_{27})$

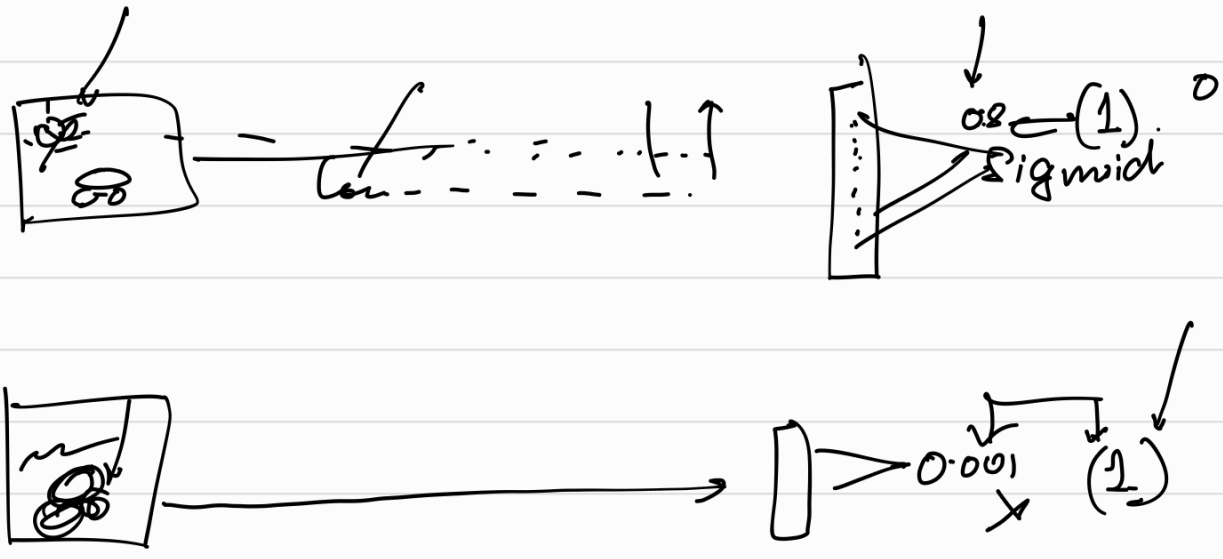


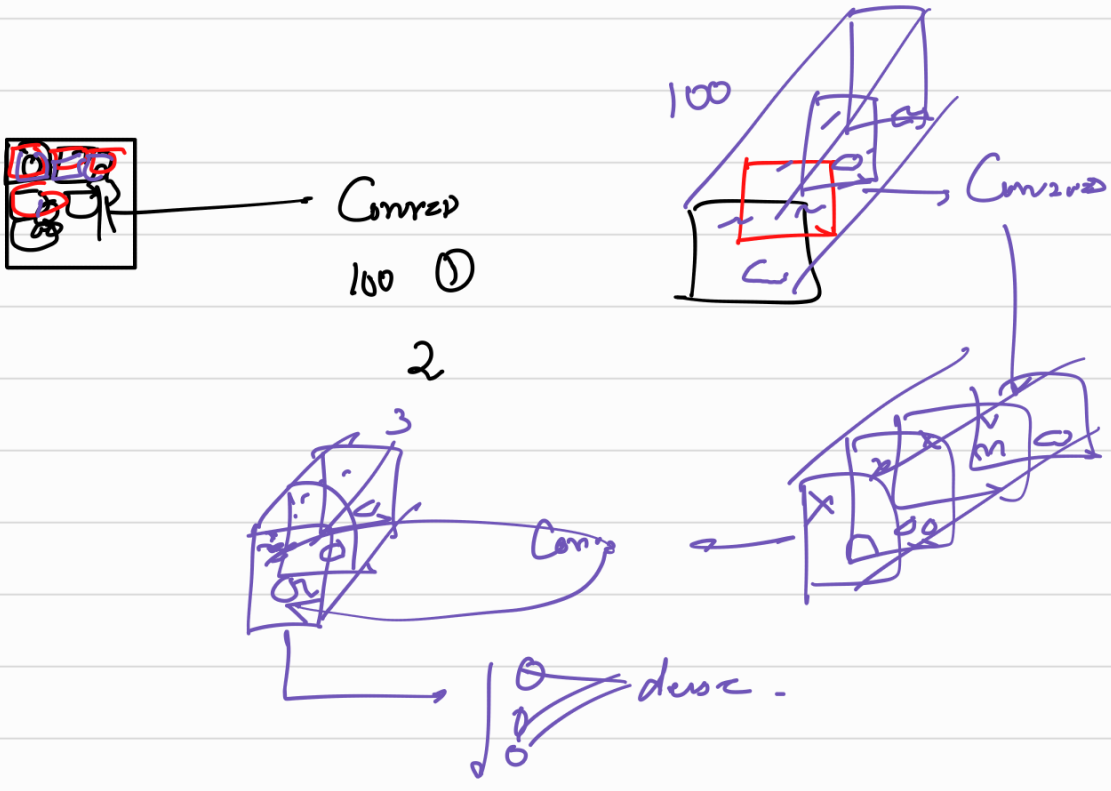
① 9f the filters (100) learnt the weights to extract the dog's features, then the feature maps will be containing majorly the features of the dog and very slight features of other objects like tree / bird/sun.

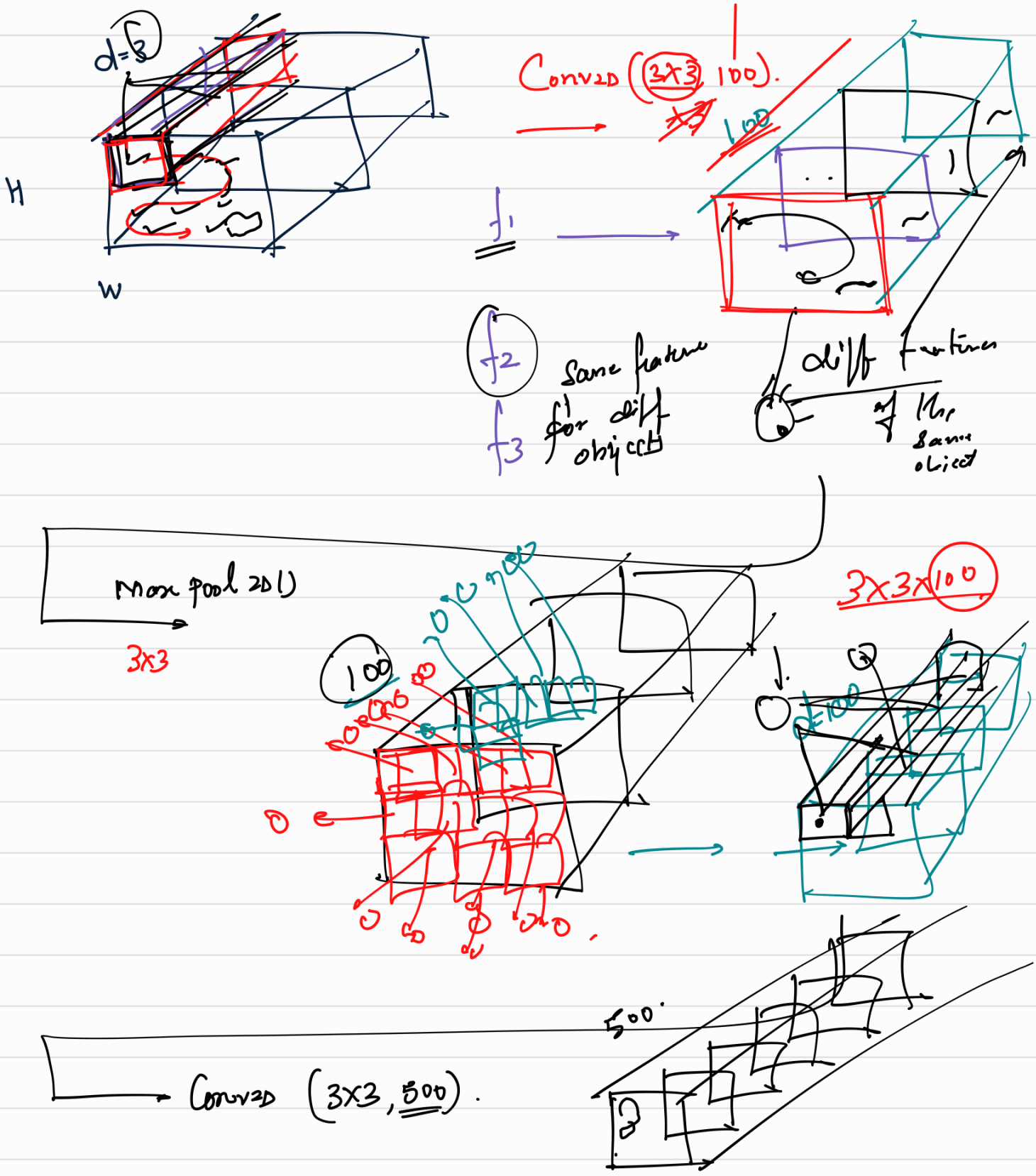


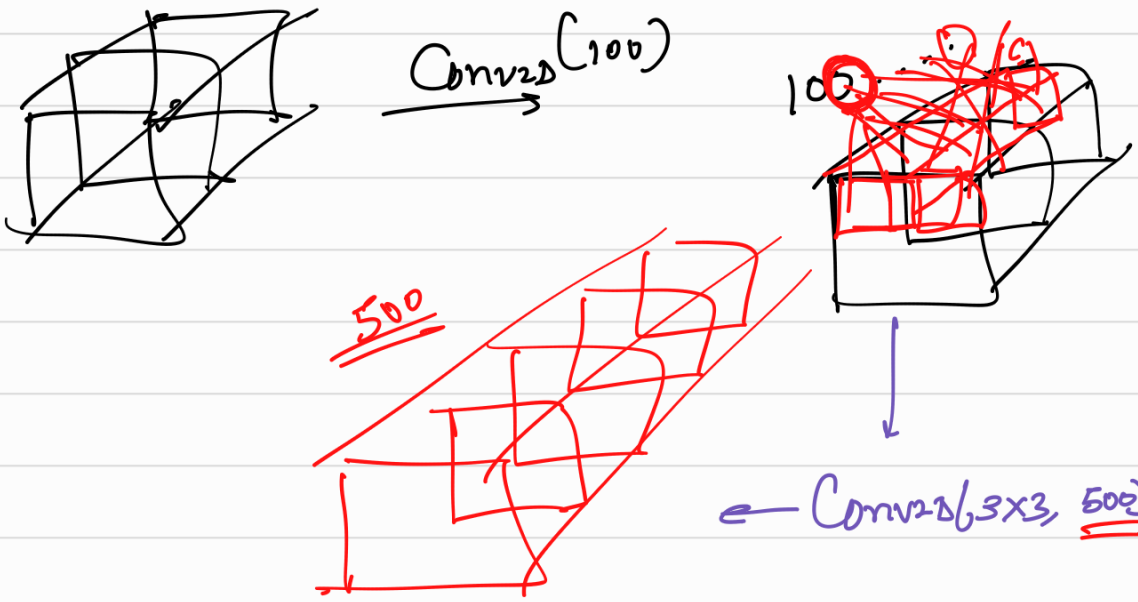

Dog
Cat

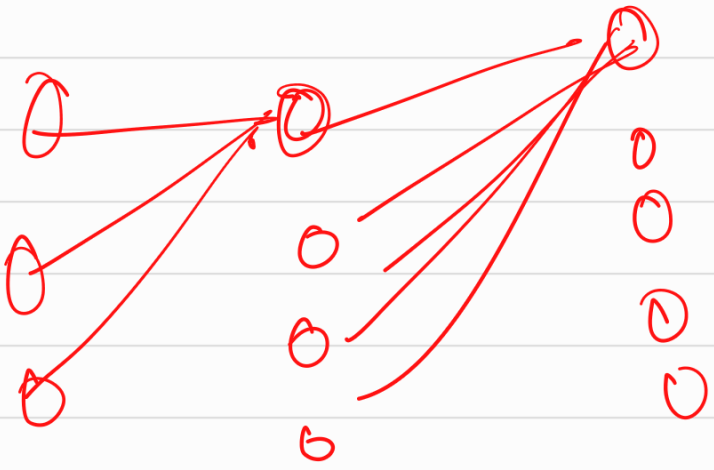

Conv
Glomp. MP.
Conv2D
MP
Conv
Dense
Cat/Dog

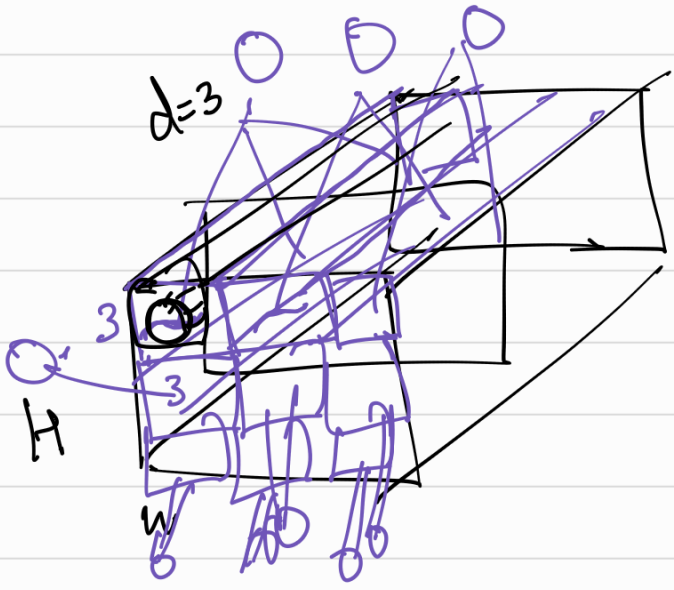

(1)
Sigmoid
0.001
(1)


Conv2D
100
2
100
Conv2D
dense

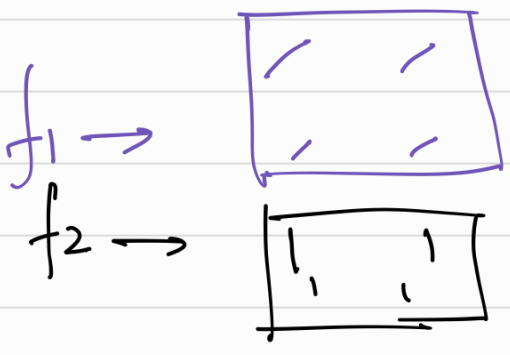

d=3
H
W
Conv2D (3x3, 100).
100
f1
f2
f3
Same feature for diff objects
diff features of the same object
Max pool 2D
3x3
100
3x3x100
500.
Conv2D (3x3, 500).

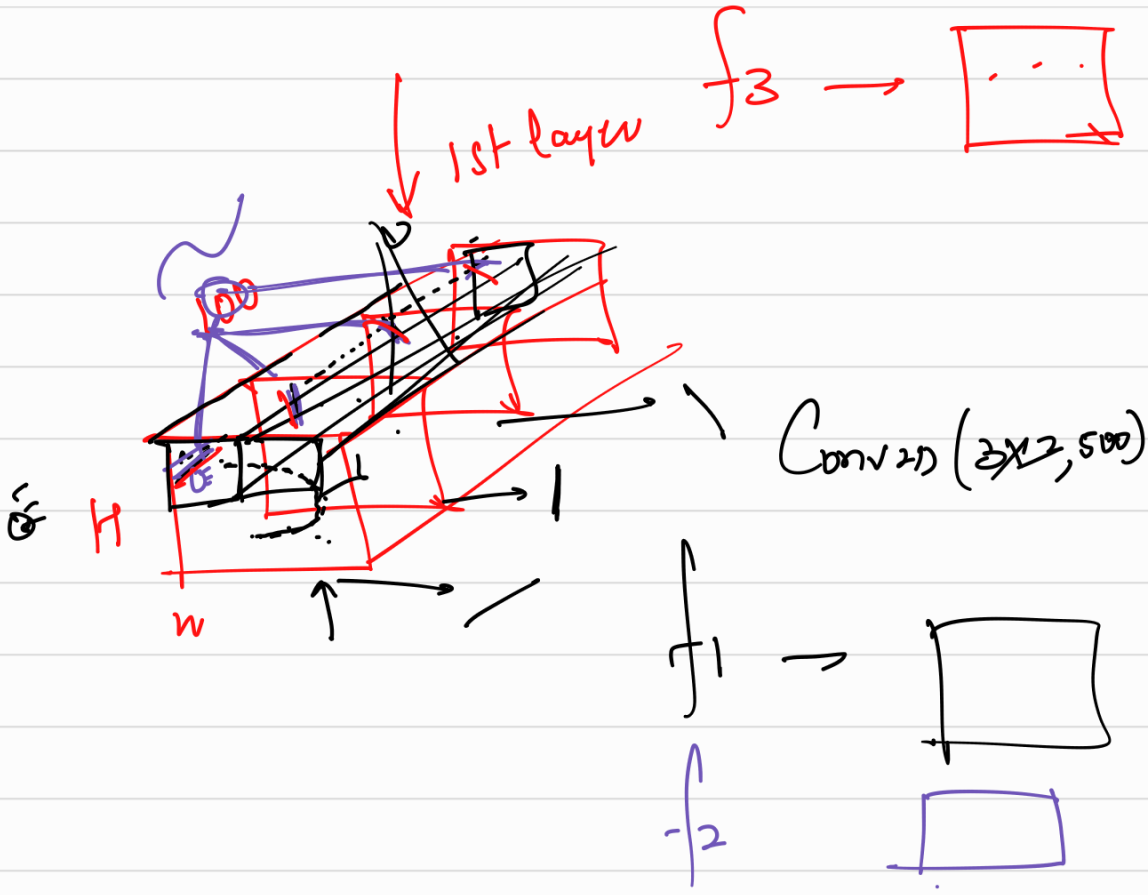


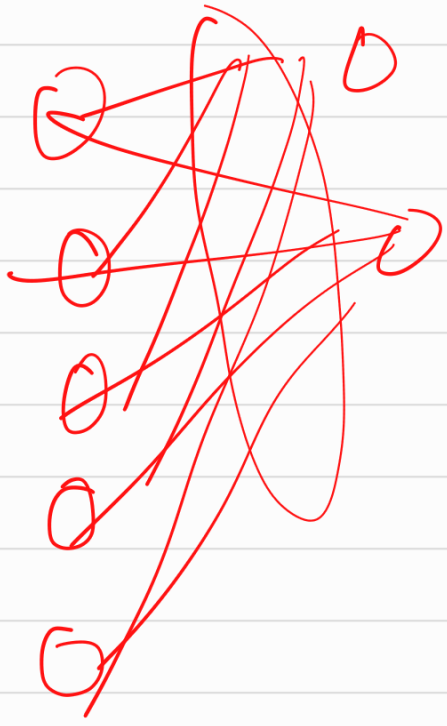


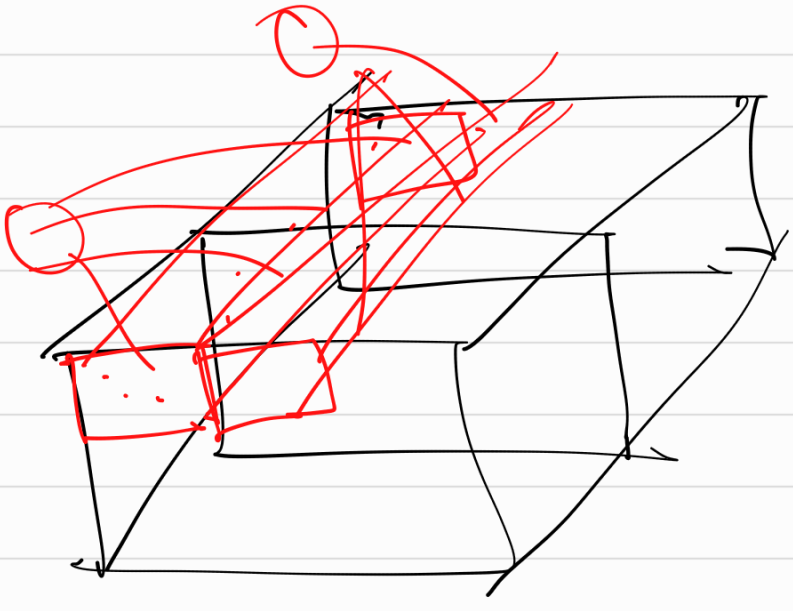


Conv2D
(3x3, 100).




1st layer
f3
500
H
W
Conv2D (3x3, 500)
f1
f2
500
H
W
f3
f500
Conv2D.





model.add (Conv2D(3x3, 100, s=1, p=~~, (input)