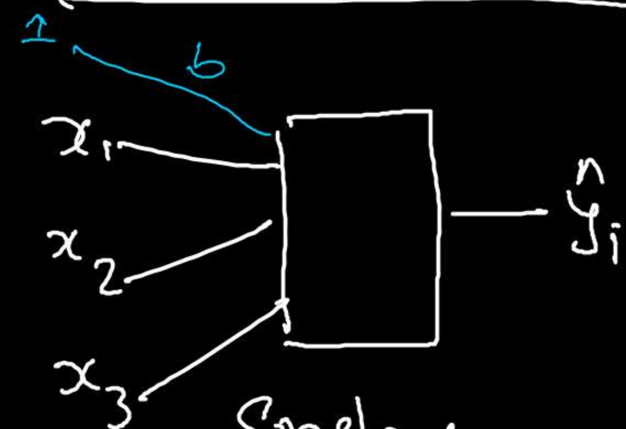
Deep Neural Netw

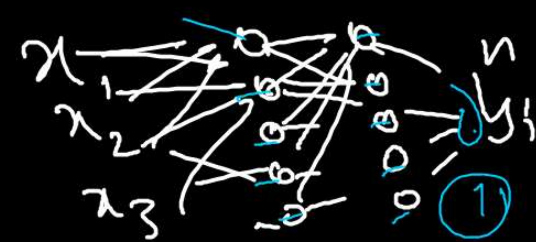
Agenda :-

1. Notation
2. Backpropogation method
3. Data Normalization
4. early stopping
5. case study
6. Dropout

Multi Layer perceptron

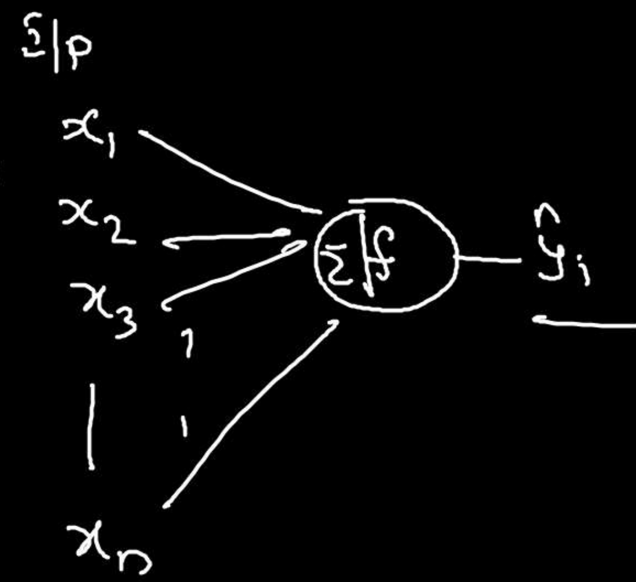


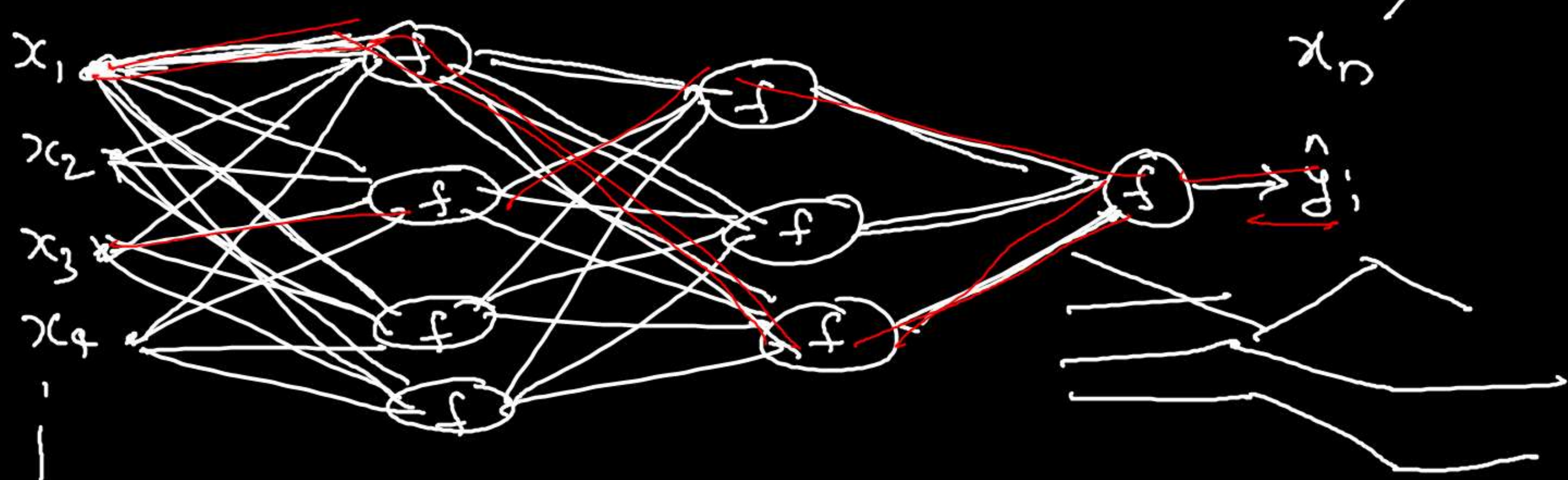
Single Layer



Multilayer Perceptron

Perceptron — Single Neuron →





Q:- Why should we care about MLP? — Intern —

① Biological Inspiration

Neuroscience — human, rats, ants, monkeys etc.

— Neural Structure Network —

② Mathematical Arguments :-

regression :- $\{x_i, y_i\}$, $\boxed{x_i \in \mathbb{R}^n, y \in \mathbb{R}}$ ← Real Num

eg :- $\boxed{2 * \sin(x^2) + \text{sqrt}(x * 5)}$

LR :-

$y = m_1x_1 + c + m_2x_2 + m_3x$

plot $(2 * \sin(x^2) + \sqrt{5x})$

$y = f(x)$

x_1	y
1	1
2	4
3	9

square(x)

$y = f(x)$

NN

Let,

f_1 = add()

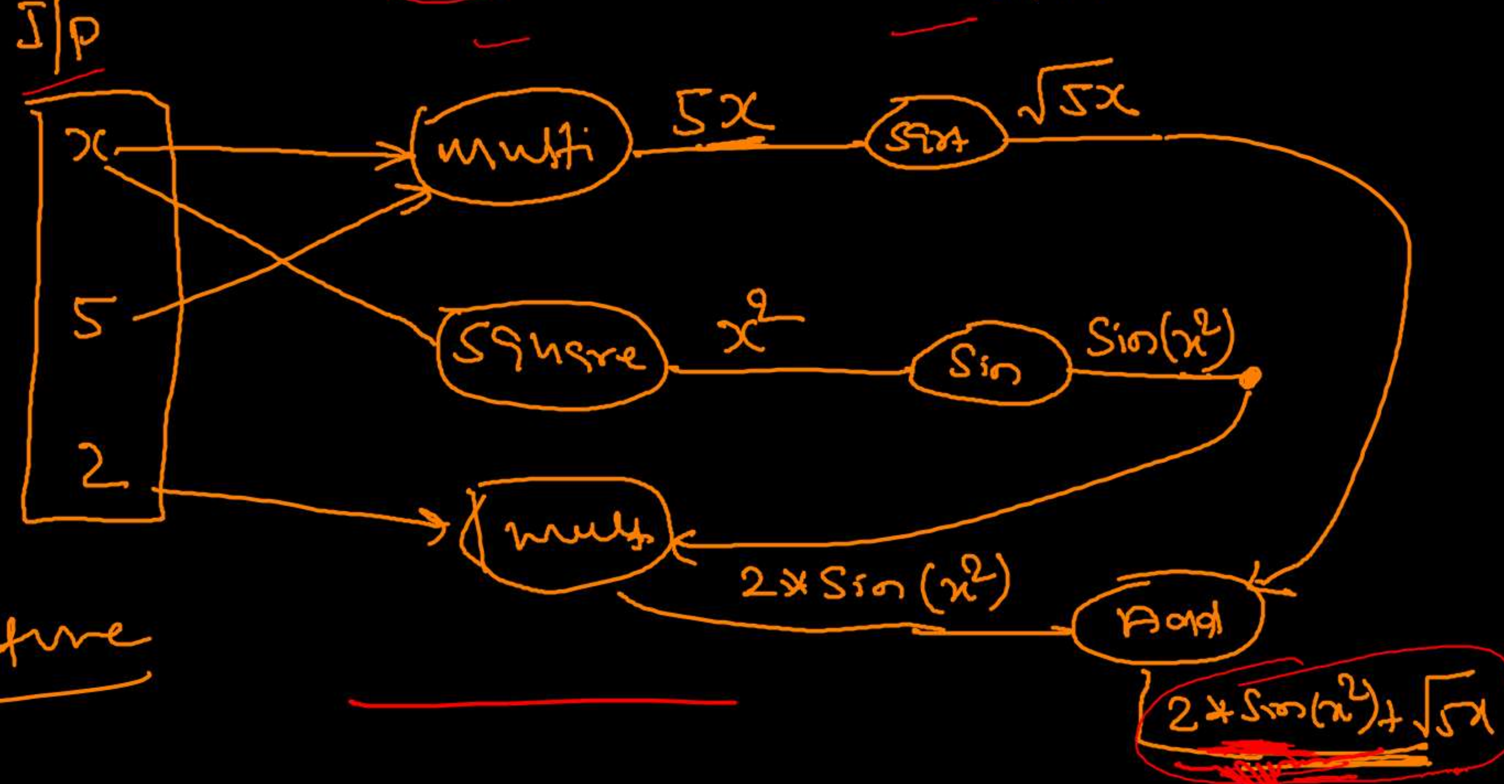
f_2 = square()

f_3 = sqrt()

f_4 = sin()

f_5 = multi()

MLP- structure



high-school :- Functional composition

$f(g(x)) = f \circ g\,(x)$ $\quad$ $g \circ f(x) \rightarrow g(f(x))$

$f1 = add$

$f2 = square$

$f3 = sqrt$

$f4 = sin$

$f5 = multi$

$$\boxed{f(x) = 2 * \sin(x^2) + sqrt(x * 5)}$$

$\sqrt{x * 5}$

$x * 5 = f5(x, 5)$

$sqrt(x * 5) = f3(f5(x, 5))$

$x^2 = f2(x)$

$\sin(x^2) = f4(f2(x))$

$2 * \sin(x^2) = f5(2, f4(f2(x)))$

$2 * \sin(x^2) + sqrt(x * 5)$

$= f_1(f5(2, f4(f2(x))), f_3(f5(x, 5)))$

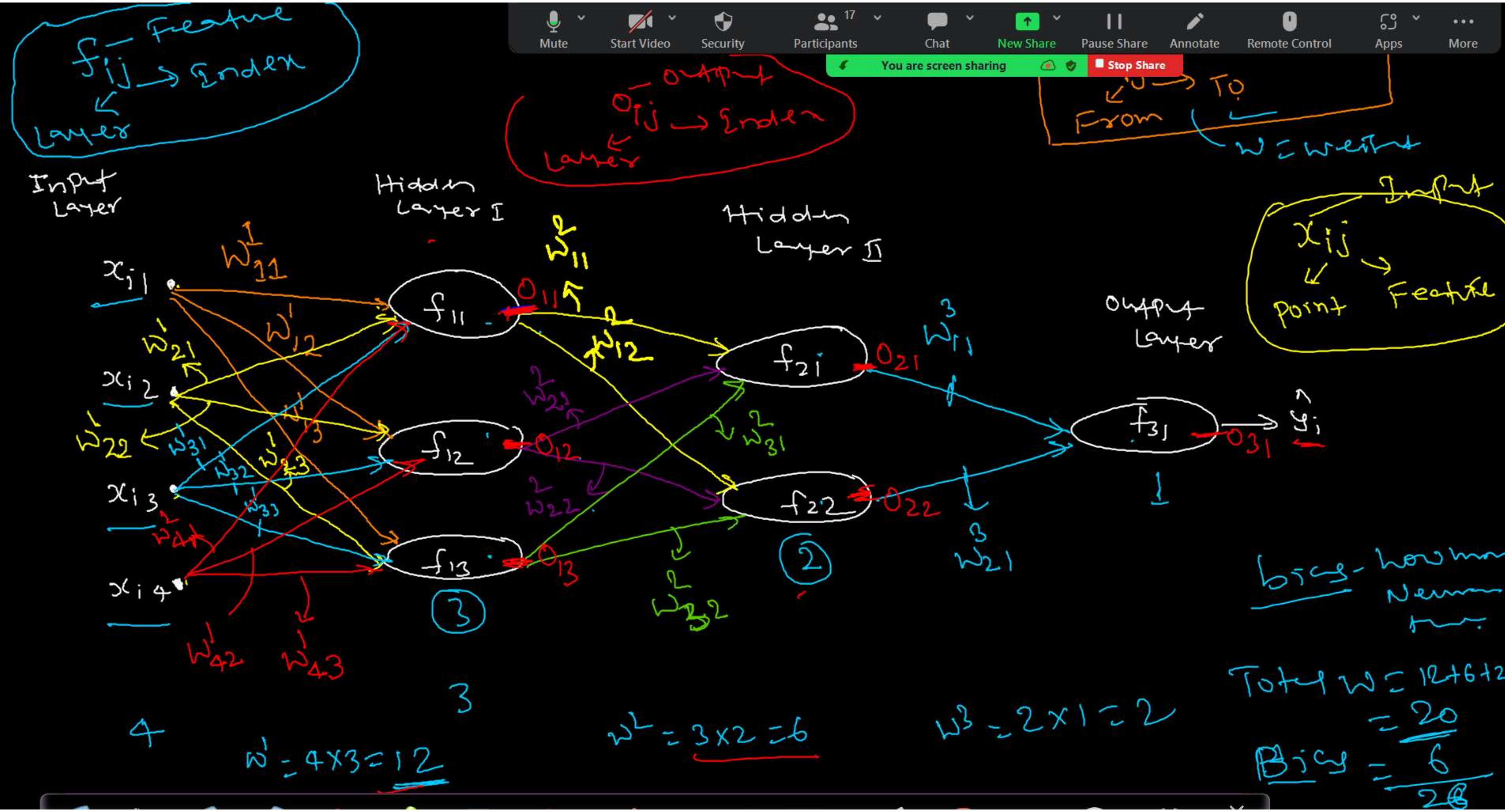
MLP - Graphical way of representation ($f \circ g$, $g \circ f$) - Function Compo

MLP is very powerful structure which can handle linear or non-linear or such by using DNN | MLP Connection

* Notation

$\mathbb{R}$ — Real Num

$D = \{x_i, y_i\}$, $x_i \in \mathbb{R}^4$, $y_i \in \mathbb{R}$ — Regression



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f — Feature
fij → Index
Layer
O — Output
Oij → Index
Layer
To
From
W = weight
Input
xij
point
Feature
Input Layer
Hidden Layer I
Hidden Layer II
Output Layer
xi1
xi2
xi3
xi4
f11
f12
f13
f21
f22
f31
O11
O12
O13
O21
O22
O31
yi
bias - how many Neurons
w' = 4x3 = 12
w² = 3x2 = 6
w³ = 2x1 = 2
Total w = 12+6+2
= 20
Bias = 6
26

$$W_1 = \begin{bmatrix} w^1_{11} & w^1_{12} & w^1_{13} \\ w^1_{21} & w^1_{22} & w^1_{23} \\ w^1_{31} & w^1_{32} & w^1_{33} \\ w^1_{41} & w^1_{42} & w^1_{43} \end{bmatrix}_{4 \times 3}$$

how weight calculate —

— weight

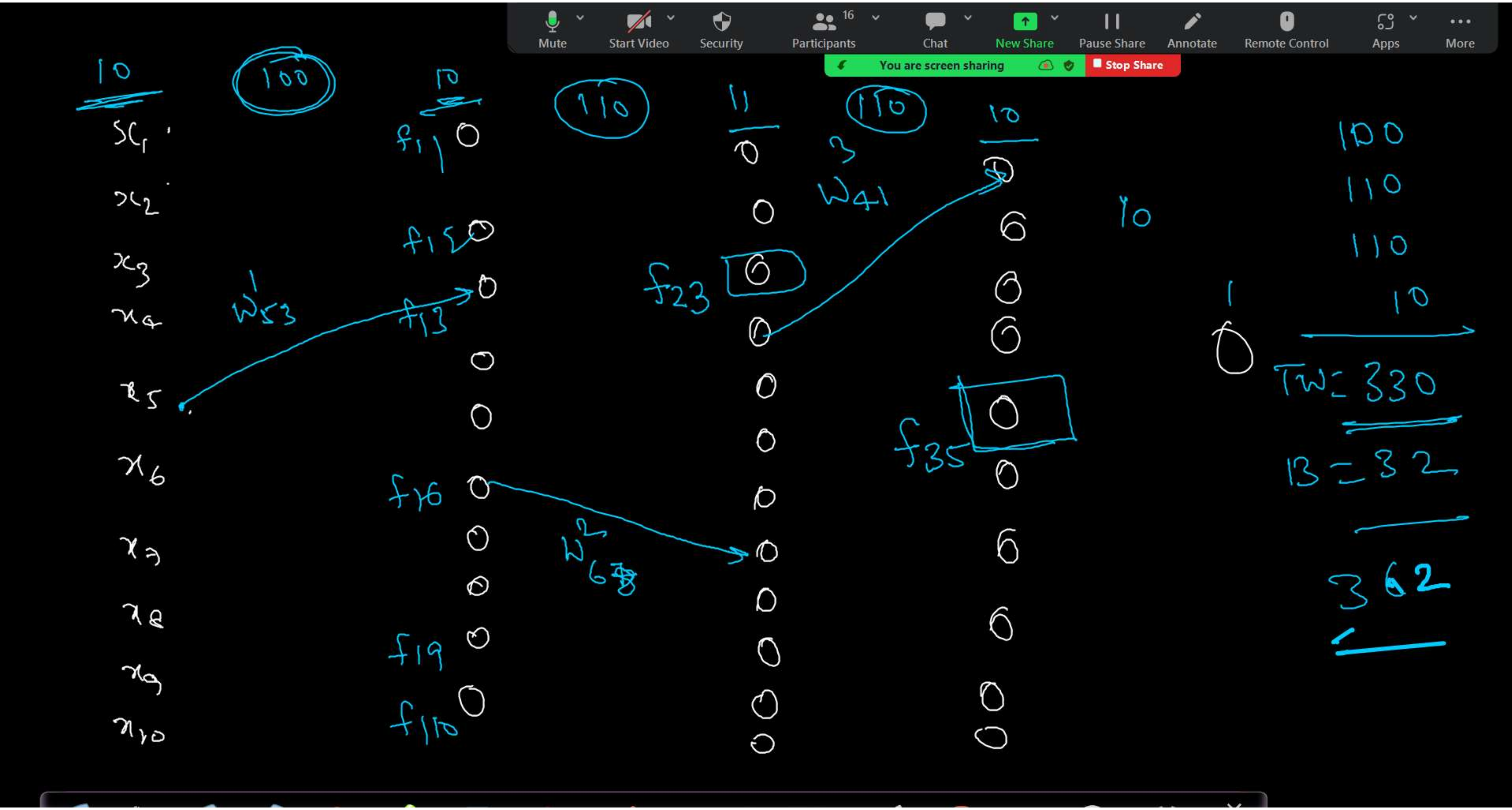
Copper

Xavier / Glorot

He ---

$$W_2 = \begin{bmatrix} w^2_{11} & w^2_{12} \\ w^2_{21} & w^2_{22} \\ w^2_{31} & w^2_{32} \end{bmatrix}_{3 \times 2}$$

$$W_3 = \begin{bmatrix} w^3_{11} \\ w^3_{21} \end{bmatrix}_{2 \times 1}$$



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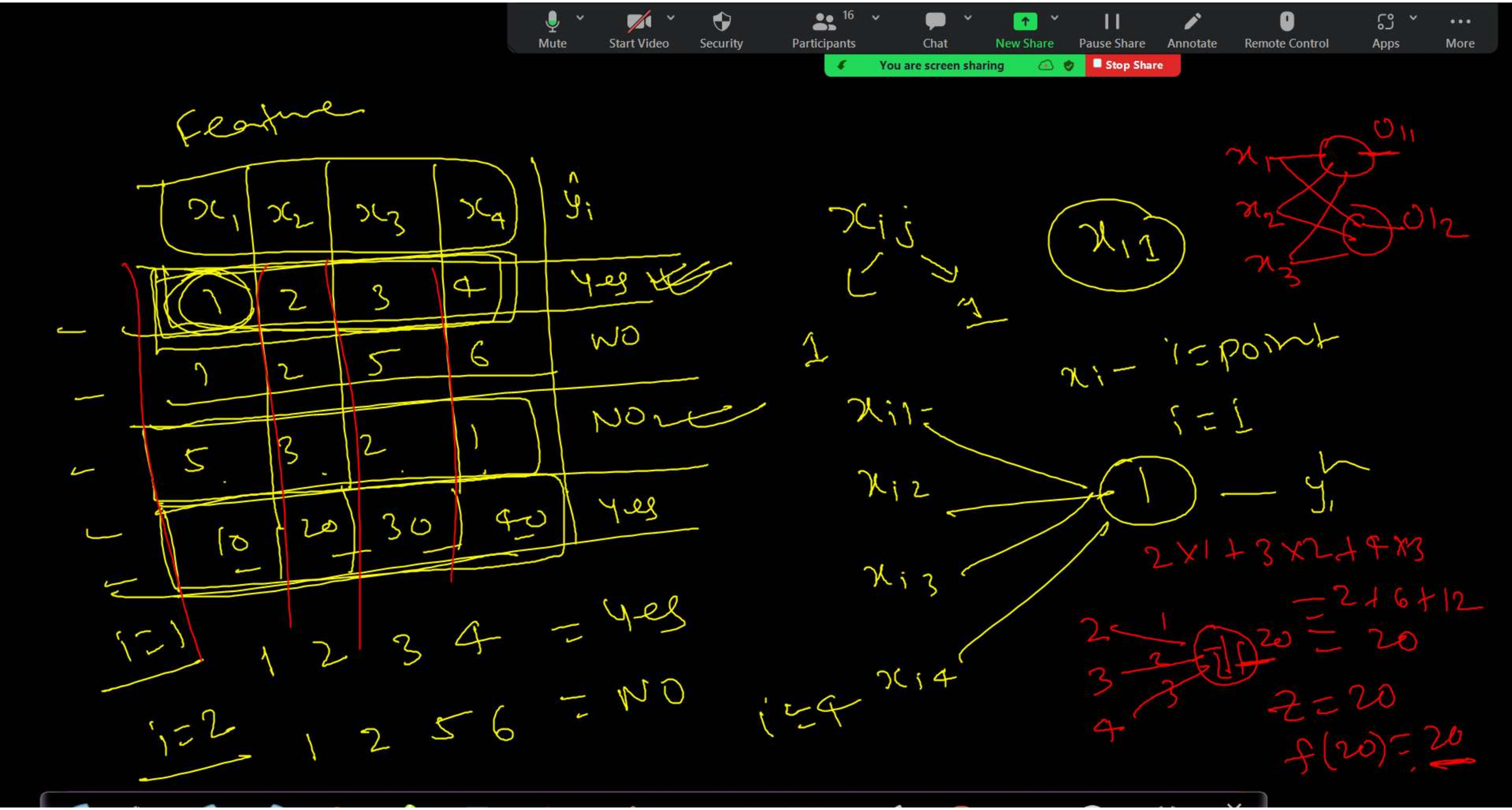
10
100
10
110
11
110
10
x_1
x_2
x_3
x_4
x_5
x_6
x_7
x_8
x_9
x_{10}
f_{11}
f_{12}
f_{13}
f_{16}
f_{19}
f_{110}
f_{23}
f_{35}
W^1_{53}
W^2_{68}
W^3_{41}
10
100
110
110
10
TW = 330
B = 32
362



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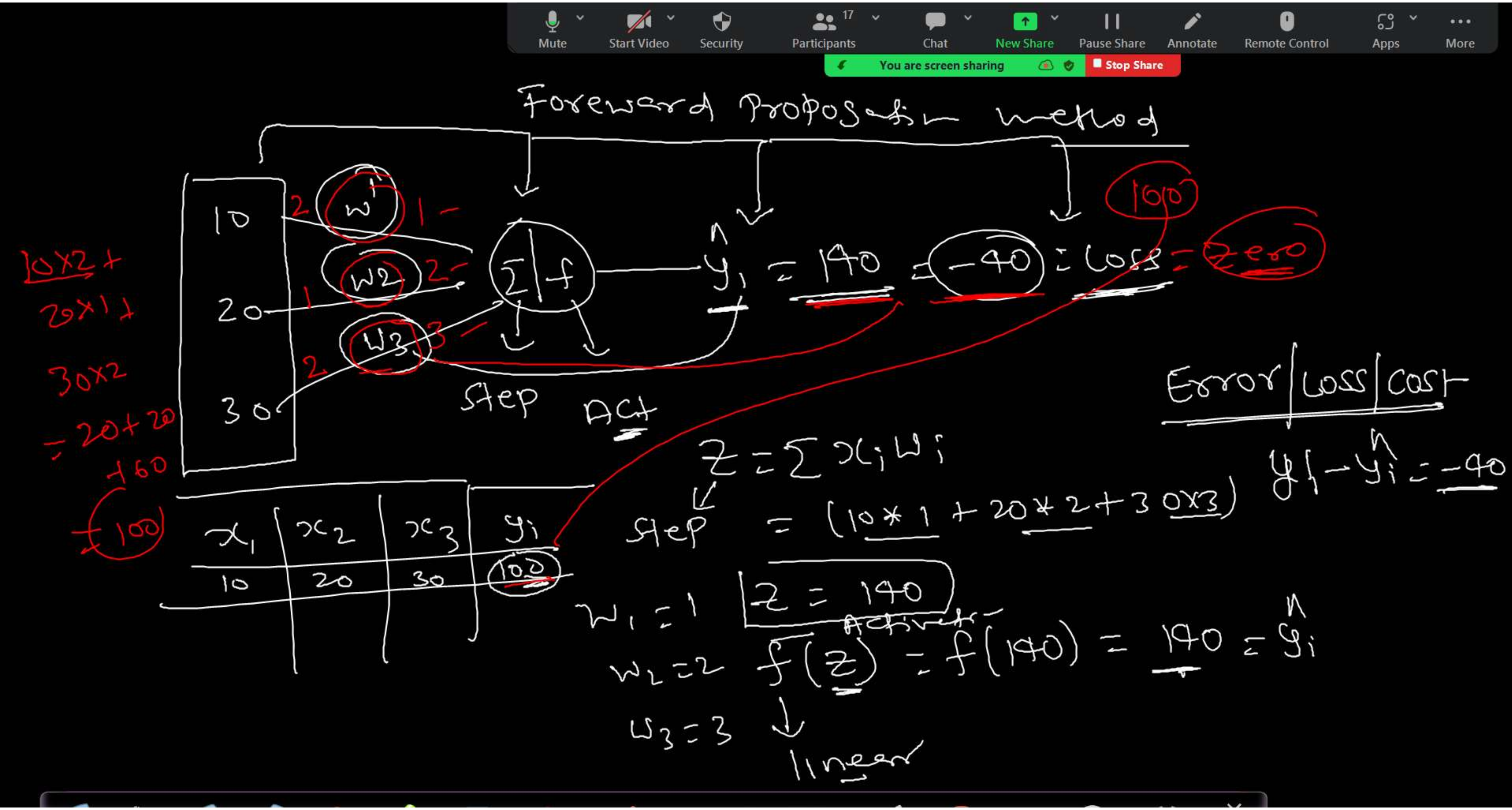
Feature
x1 x2 x3 x4
ŷi
1 2 3 4 yes
1 2 5 6 NO
5 3 2 1 NO
10 20 30 40 yes
i=1 1 2 3 4 = yes
i=2 1 2 5 6 = NO
xij
x11
xi — i=point
i=1
xi1
xi2
xi3
xi4
i=4
yi
2×1+3×2+4×3
=2+6+12
=20
z=20
f(20)=20
x1 x2 x3
O11 O12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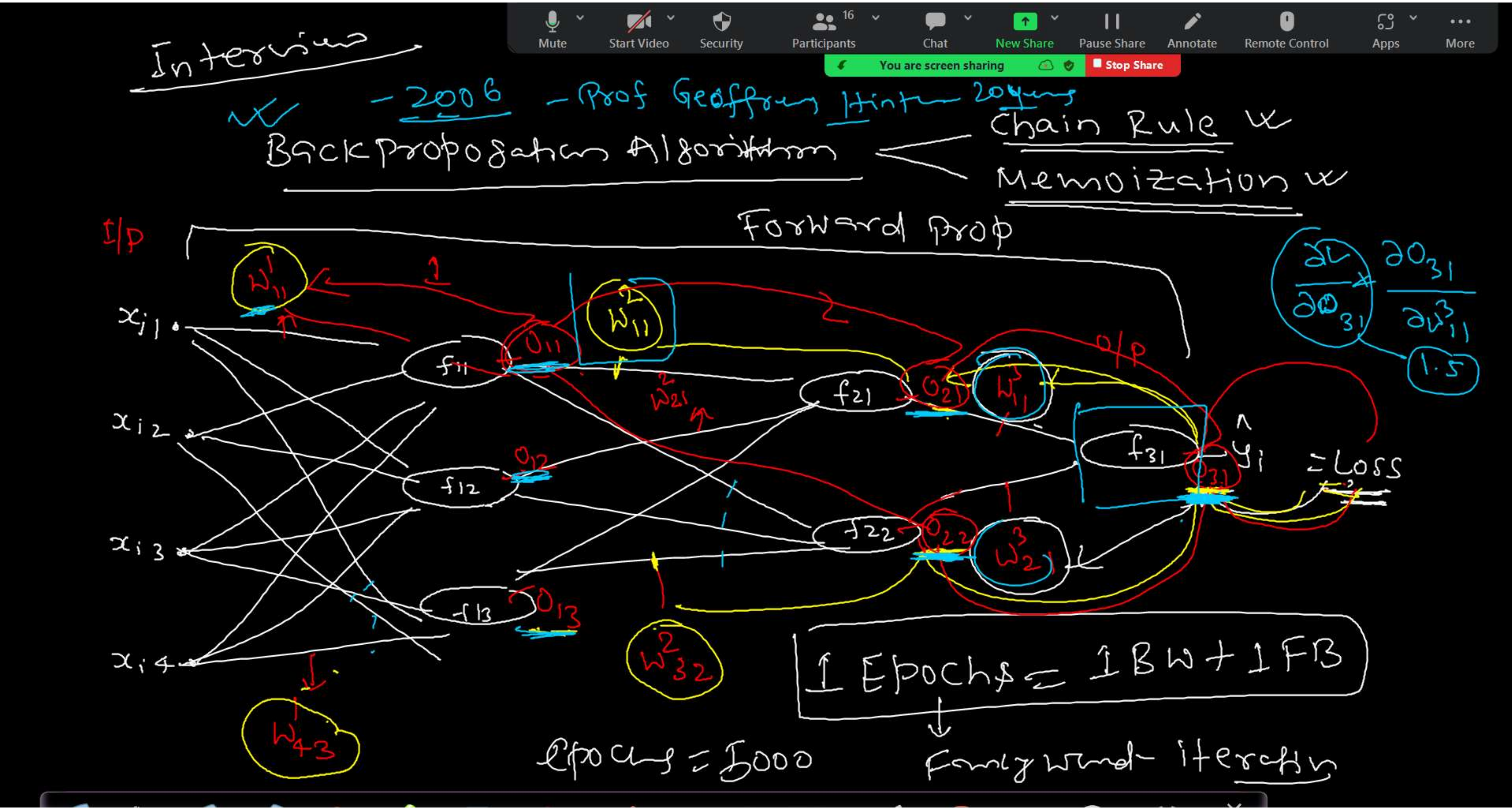
Foreward Proposation method
10
20
30
w1
w2
w3
Σ | f
ŷ1 = 140 = -40 = Loss = zero
100
Step
Act
Error | Loss | cost
10×2 + 20×1 + 30×2 = 20 + 20 + 60 = 100
x1 | x2 | x3 | yi
10 | 20 | 30 | 100
z = Σ xi wi
step = (10 * 1 + 20 * 2 + 30 × 3)
yi - ŷi = -40
w1 = 1
z = 140
Activate
w2 = 2
f(z) = f(140) = 140 = ŷi
w3 = 3
linear



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Interview
2006 - Prof Geoffrey Hinton
Backpropogation Algorithm
Chain Rule
Memoization
Forward Prop
I/P
O/P
x_{i1}
x_{i2}
x_{i3}
x_{i4}
f_{11}
f_{12}
f_{13}
f_{21}
f_{22}
f_{31}
O_{11}
O_{12}
O_{13}
O_{21}
O_{22}
O_{31}
W^1_{11}
W^2_{11}
W^2_{21}
W^3_{11}
W^3_{21}
W^2_{32}
W^1_{43}
$\hat{y}_i$
= Loss
$\frac{\partial L}{\partial O_{31}} \times \frac{\partial O_{31}}{\partial w^3_{11}}$
1.5
1 Epochs = 1 BW + 1 FB
Epochs = 5000
iteration

Chain Rule

$$\frac{\partial y}{\partial x} = \frac{\partial y}{\partial u} \cdot \frac{\partial u}{\partial v} \cdot \frac{\partial v}{\partial x}$$

$$\frac{\partial L}{\partial w^3_{11}} = \boxed{\frac{\partial L}{\partial O_{31}}} * \frac{\partial O_{31}}{\partial w^3_{11}}$$

$$\frac{\partial L}{\partial w^3_{21}} = \boxed{\frac{\partial L}{\partial O_{31}}} * \frac{\partial O_{31}}{\partial w^3_{21}}$$

$$\frac{\partial L}{\partial w^2_{11}} = \boxed{\frac{\partial L}{\partial O_{31}}} * \frac{\partial O_{31}}{\partial O_{21}} * \frac{\partial O_{21}}{\partial w^2_{11}}$$

$$\frac{\partial L}{\partial w^2_{32}} = \boxed{\frac{\partial L}{\partial O_{31}}} * \frac{\partial O_{31}}{\partial O_{22}} * \frac{\partial O_{22}}{\partial w^2_{32}}$$

$$\frac{\partial L}{\partial w^1_{11}} = \frac{\partial L}{\partial O_{31}} * \frac{\partial O_{31}}{\partial O_{21}} * \frac{\partial O_{21}}{\partial O_{11}} * \frac{\partial O_{11}}{\partial w^1_{11}} + \frac{\partial L}{\partial O_{31}} * \frac{\partial O_{31}}{\partial O_{22}} * \frac{\partial O_{22}}{\partial O_{11}} * \frac{\partial O_{11}}{\partial w^1_{11}}$$

$$\frac{\partial L}{\partial w^1_{11}} = \boxed{\frac{\partial L}{\partial O_{31}}} * \frac{\partial O_{11}}{\partial w^1_{11}} \left\{ \frac{\partial O_{31}}{\partial O_{21}} * \frac{\partial O_{21}}{\partial O_{11}} + \frac{\partial O_{31}}{\partial O_{22}} * \frac{\partial O_{22}}{\partial O_{11}} \right\}$$

$f(x)$

$x \qquad\qquad h($

$g(x)$

$$\frac{\partial L}{\partial x} = \frac{\partial h}{\partial f} * \frac{\partial f}{\partial x} + \frac{\partial h}{\partial g} * \frac{\partial g}{\partial x}$$

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Memoization : it is not memorization, it is called

Memoization → Dynamic Programming

computer science

$$\frac{\partial L}{\partial w^3_{11}} = \boxed{\frac{\partial L}{\partial O_{31}}} \times \frac{\partial O_{31}}{\partial w^3_{11}}$$

$$\frac{\partial L}{\partial w^3_{21}} = \boxed{\frac{\partial L}{\partial O_{31}}} \times \frac{\partial O_{31}}{\partial w^3_{21}}$$

Compute once & reuse it.

* → The core idea of memoization is this

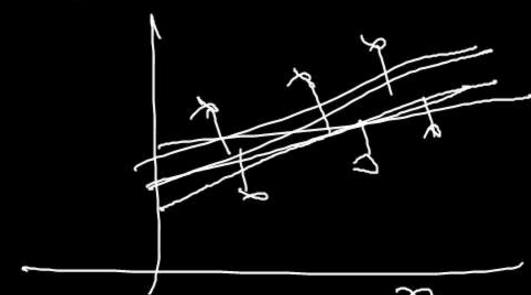
→ if there is any operation that is used many times, it's good idea to compute once & then store it for reuse purpose

→ This concept is known as Memoization

① Define Loss Function (example - Regression)

$Y = m_1 x_1 + m_2 x_2 + c$

$$\boxed{L = \underbrace{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}_{\text{Sq-Loss fn:}} + \text{regularization}}$$



$$\text{Error} = \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$

② Optimization

$$\boxed{\text{Loss (minimize)}}$$

$\downarrow$

Weight & bias

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③ Gradient Descent (Batch GD, Mini-batch GD, SGD)

(i) initialize w_{ij}^{k} randomly — lots of technique → we will cover later

(ii) Update weight — Rule :-

Formula:- $$\left(w_{ij}^{k}\right)_{new} = \left(w_{ij}^{k}\right)_{old} - \eta * \frac{\partial L}{\partial w_{old}}$$ ← V.V.Imp. BackProp.

η → eta / learning Rate (0 to 1.0)

$w_{old} = 50$

$w_{new} = 50 - 1 * 5$

$w_{new} = 45$

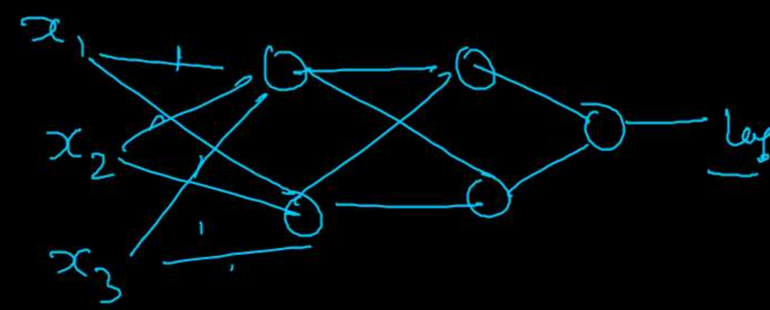
(ii) Perform updates till the convergence.

NOTE :- convergence means the new weight value and the old weight value are very close to each other.

$$\left\{\begin{array}{l} W_{old} = 50 \\ W_{new} = 49.9995 \\ W_{new_2} = 49.9998 \\ W_{new_3} = 49.9997 \end{array}\right.$$

2.45

Back-Prop



1. Initialize weight - randomly
2. epochs (1BP + 1FB) → Forward Prop
   → compute loss
   → compute derivatives (Chain Rule + memoization)
   → update weight in a backward prop
3. repeat step 2 till the convergence.