

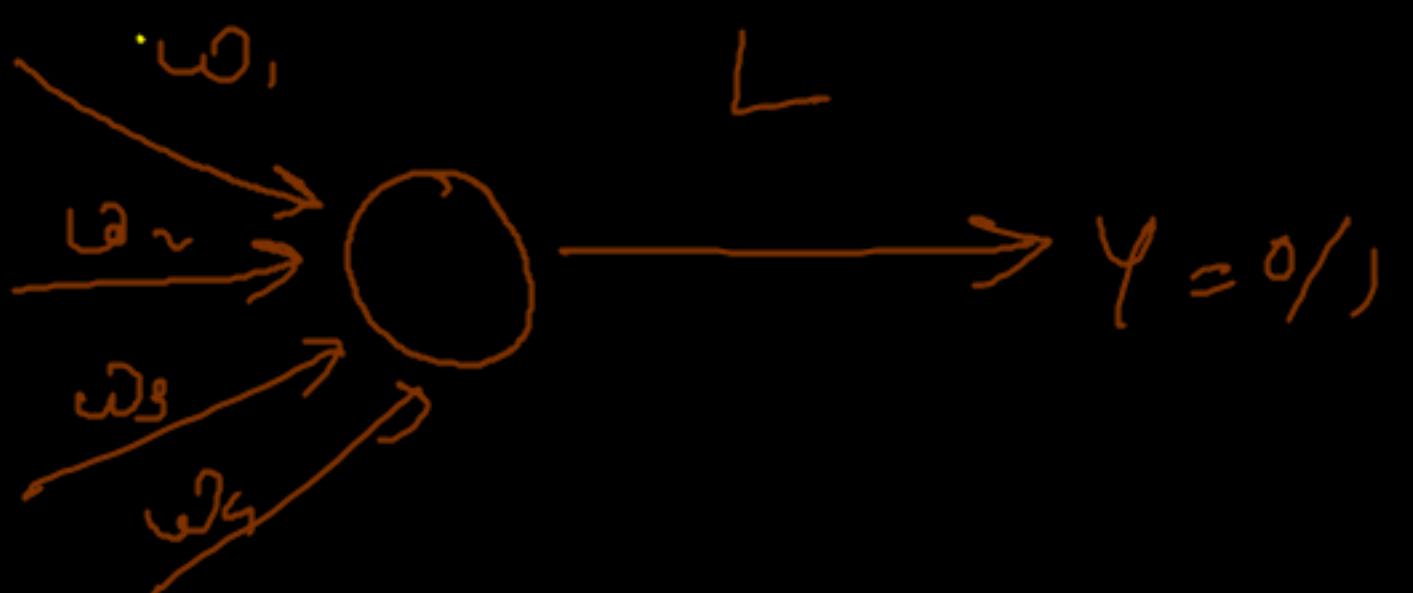
## Optimisation

Step-3 (optimise weight for single Neural N/w) :-

(a) initialize the weight  $w_i$ 's  $\rightarrow$  Randomly.

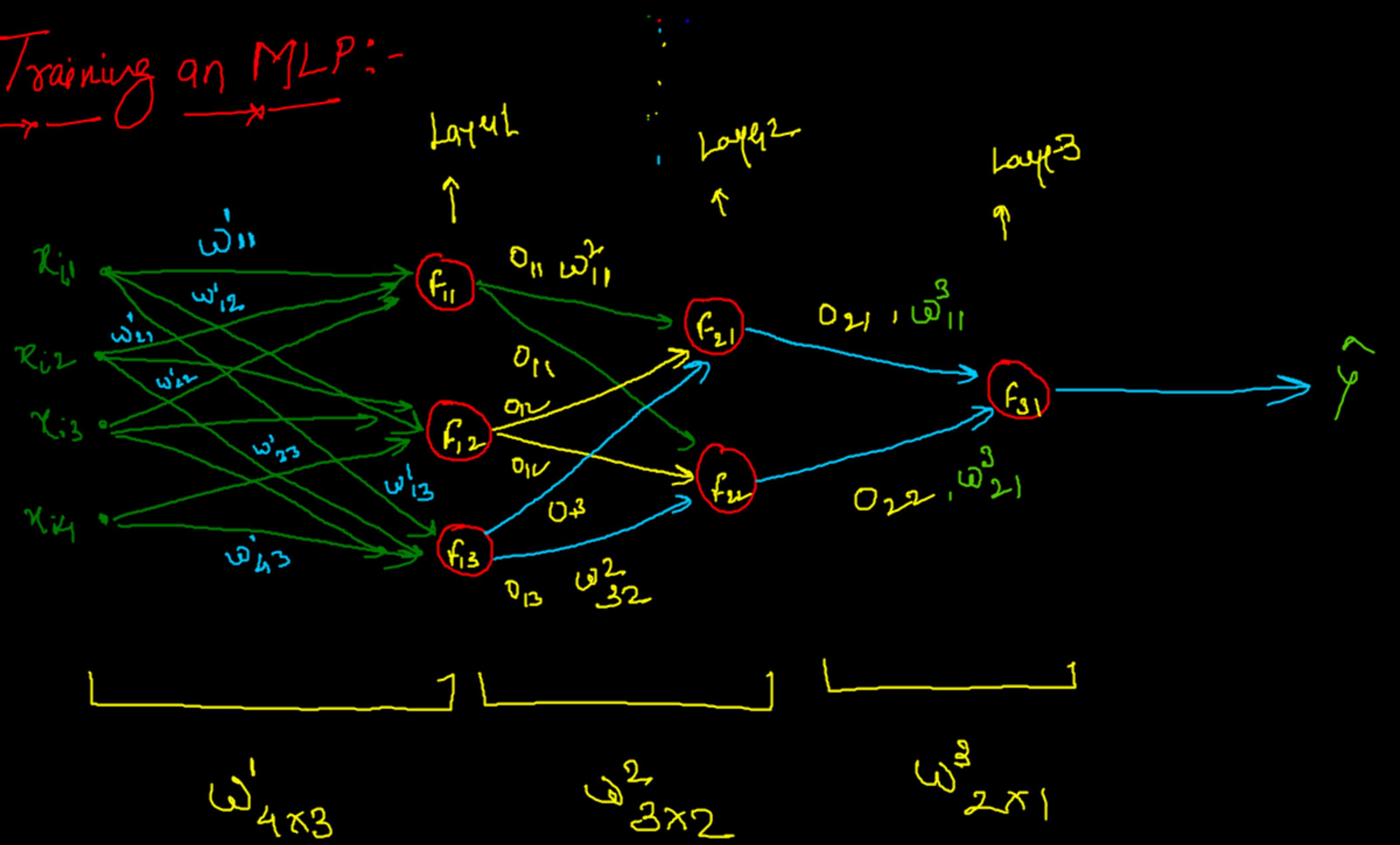
(b)

$$\nabla_w L = \begin{bmatrix} \frac{\partial L}{\partial w_1} \\ \frac{\partial L}{\partial w_2} \\ \frac{\partial L}{\partial w_3} \\ \vdots \end{bmatrix}$$



Training an MLP :-

Notation



$$\left[ \begin{array}{c} \omega_{ij}^k \\ \vdots \\ \omega_{ij}^1 \end{array} \right] \quad \begin{array}{l} i \rightarrow \text{layer} \\ j \rightarrow \text{from} \\ k \rightarrow \text{to} \end{array}$$

$\omega_{ij}^k \rightarrow i \rightarrow \text{layer No.}$   
 $\omega_{ij}^k \rightarrow j \rightarrow \text{input (Neuron)}$

⇒ Some need to optimised  $\omega_{4x3}^1, \omega_{3x2}^2, \omega_{2x1}^3 = 20$  weights.

Step-1

Loss function -  $L = \sum_{i=1}^n (y - \hat{y})^2 + \text{Reg.}$ ,  $\text{Sq. Loss} = L_i = (y_i - \hat{y}_i)^2$

Aim  $\rightarrow \min L_{\text{Loss}}$  w.r.t.  $\omega_{ij}^k$

Step-2

① initialize -  $\omega_{ij}^k$  = randomly / many methods

②  $(\omega_{ij}^k)_{\text{new}} = (\omega_{ij}^k)_{\text{old}} - \eta \left( \frac{\partial L}{\partial \omega_{ij}^k} \right)_{\text{old}}$

Aim  $\rightarrow \left( \frac{\partial L}{\partial \omega_{ij}^k} \right)_{\omega \rightarrow \text{old}} \rightarrow \text{find if.}$

③ perform update until the convergence ( $\omega_{\text{new}} \approx \omega_{\text{old}}$ )

To calculate  $\left( \frac{dL}{d\omega_{ij}} \right)$

→ For  $\omega^3$  :-

$$\frac{dL}{d\omega_{11}^3} = \frac{dL}{dO_{31}} \times \frac{dO_{31}}{d\omega_{11}^3}$$

→ chain rule.

→ For  $\omega^2$  :-

$$\frac{dL}{d\omega_{11}^2} = \frac{dL}{dO_{31}} \times \frac{dO_{31}}{dO_{21}} \times \frac{dO_{21}}{d\omega_{11}^2}$$

→ chain rule

$$\frac{dL}{d\omega_{21}^2} = \frac{dL}{dO_{31}} \times \frac{dO_{31}}{dO_{21}} \times \frac{dO_{21}}{d\omega_{21}^2}$$

→ chain rule



$\rightarrow F_{\sigma \tau} \omega^1$



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