

Class Notes: DL

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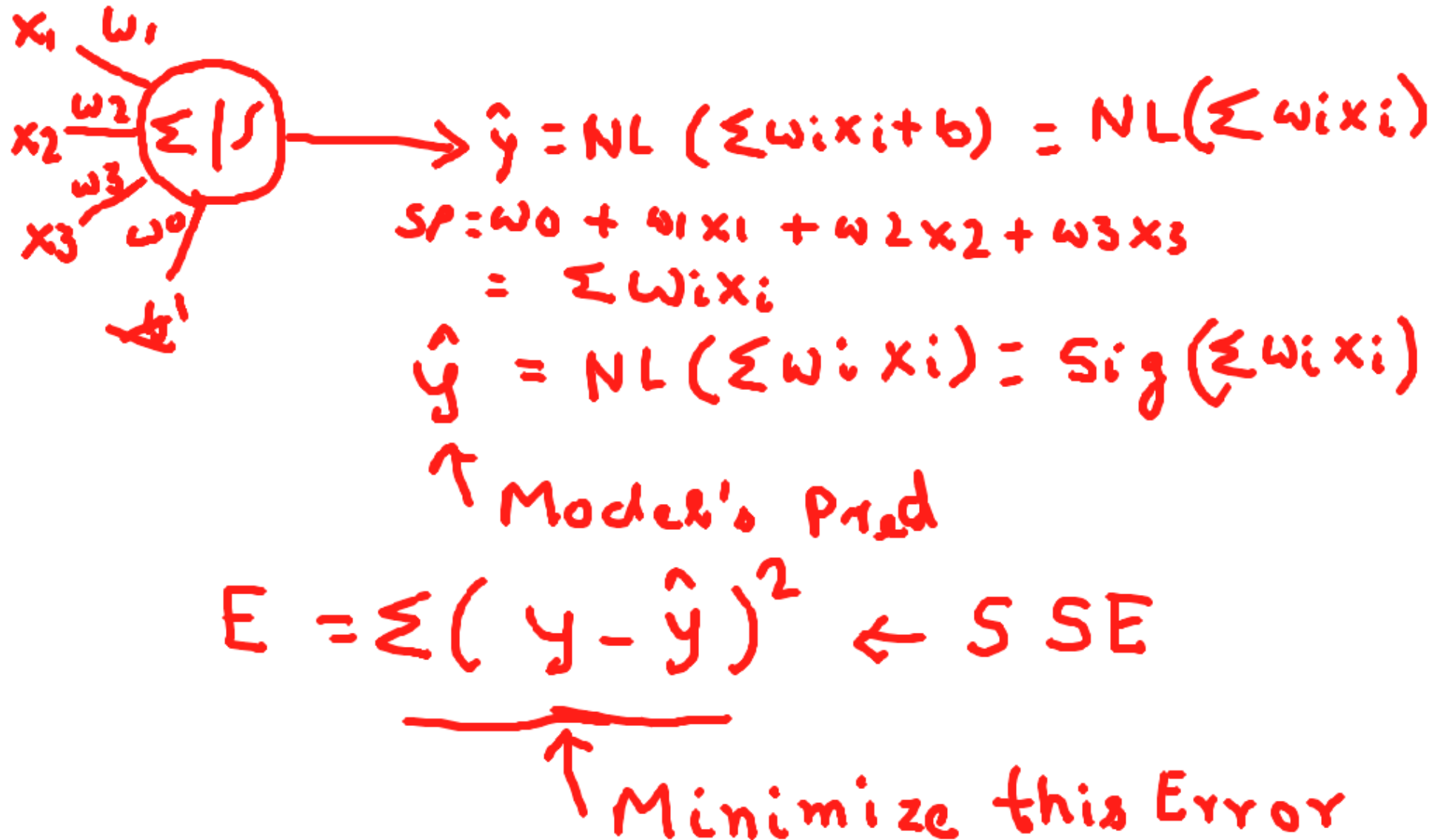
Data

- Data sufficiency
- Data Quality
- Some examples of evaluating information inside data

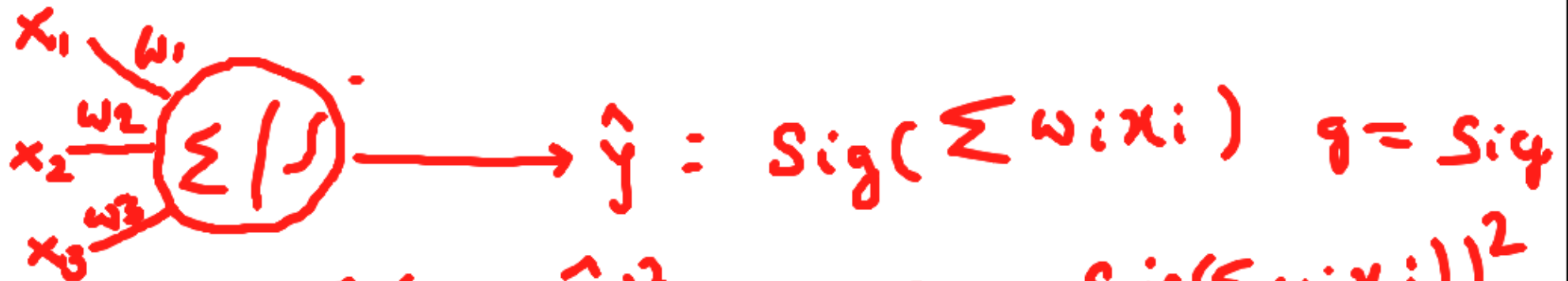
Basics of Deep Learning

- Deep learning emulation of human brain
- Deep Learning – layered architecture, hierarchical extraction of features
- Deep learning – every unit is capable of linear and non linear processing.

Training a neuron



Minimizing the Error



$$E = \Sigma (y - \hat{y})^2 = \Sigma (y - \text{sig}(\Sigma w_i x_i))^2$$

$$= \Sigma (y - g(\Sigma w_i x_i))^2$$

Minimize this Error
 $E \rightarrow 0$

Car at a vel v , apply brake (multiple)

$$\boxed{-\frac{dv}{dt}}$$

$\rightarrow E \rightarrow 0$
 Scaling

$$\boxed{-\eta \frac{\partial E}{\partial w_i} = \Delta w_i}$$

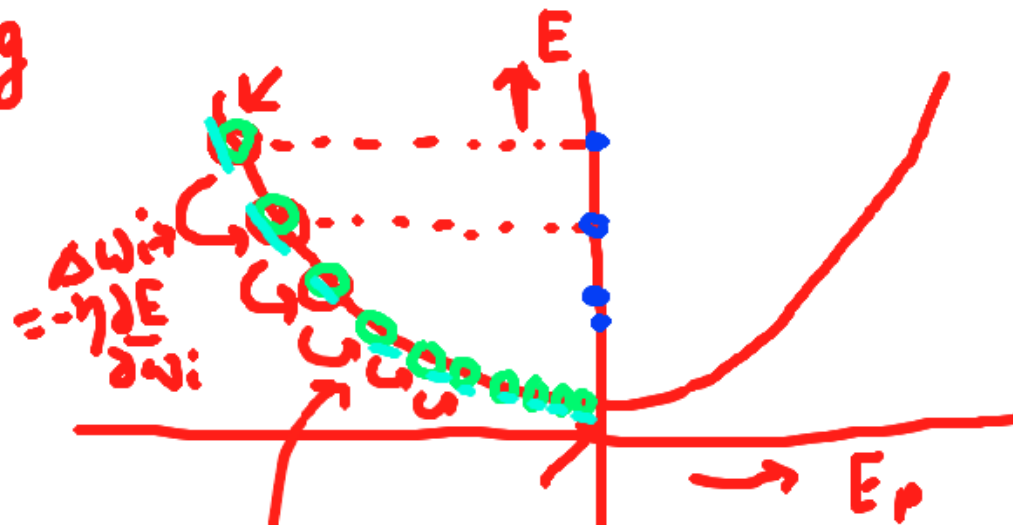
Training and Gradient Descent

→ $\Delta w_i = -\eta \frac{\partial E}{\partial w_i}$ ← Minimize the Error

← Multiple Times

Scaling
Learning
Rate

$$E = \sum (y - \hat{y})^2 = \sum (y - g(\sum w_i x_i))^2$$



↓ Grad ↓

Gradient Descent

Derivative of sigmoid

$$\begin{aligned} y(x) = \text{Sig}(x) &= \frac{1}{1+e^{-x}} & \frac{d}{dx}(\text{Sig}(x)) &= \frac{d}{dx}\left(\frac{1}{1+e^{-x}}\right) \\ &= \frac{d}{dx} \frac{1}{u} & \frac{d}{dx} u^{-1} &= -1 \cdot u^{-1-1} \cdot \frac{du}{dx} \\ &= -1 \cdot (1+e^{-x})^{-2} \cdot \frac{d}{dx}(1+e^{-x}) &= \frac{-1}{(1+e^{-x})^2} \cdot (0+e^{-x} \cdot (-1)) \\ &= \frac{e^{-x}}{(1+e^{-x})^2} = \frac{1}{(1+e^{-x})} \cdot \frac{e^{-x}}{(1+e^{-x})} = g(x) \cdot \frac{e^{-x}+1-1}{1+e^{-x}} \\ &= g(x) \cdot \left(1 - \frac{1}{1+e^{-x}}\right) = g(x) \cdot (1 - g(x)) \end{aligned}$$

Derivative of Error

$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i} \Delta \leftarrow \text{Multiple times (Epochs)}$$

$$\frac{\partial E}{\partial w_i} = \frac{\partial}{\partial w_i} \left(\sum (y - \hat{y})^2 \right)$$

$$= \frac{\partial}{\partial w_i} \left(\sum (y - g(\sum w_i x_i))^2 \right) \quad \frac{\partial}{\partial w_i} u^2 = 2 \cdot u \cdot \frac{\partial u}{\partial w_i}$$

$$= 2 \sum (y - g(\sum w_i x_i)) \cdot \frac{\partial}{\partial w_i} (y - g(\sum w_i x_i))$$

$$= 2 \sum (y - g(\sum w_i x_i)) \cdot (0 - \frac{\partial}{\partial w_i} g(\sum w_i x_i))$$

Derivative of Error, dependencies

$$\begin{aligned}\frac{\partial E}{\partial w_i} &= 2 \sum (y - g(\sum w_i x_i)) \cdot \left(0 - \frac{\partial}{\partial w_i} g(\sum w_i x_i)\right) \\ &= 2 \sum (y - g(\sum w_i x_i)) \cdot (-g'(w_i x_i) \cdot (1 - g(\sum w_i x_i))) \\ &\quad \cdot \frac{\partial}{\partial w_i} (\sum w_i x_i) \\ &= -2 \sum (y - g(\sum w_i x_i)) \cdot g(\sum w_i x_i) (1 - g(\sum w_i x_i)) \\ &\quad \cdot x_i\end{aligned}$$

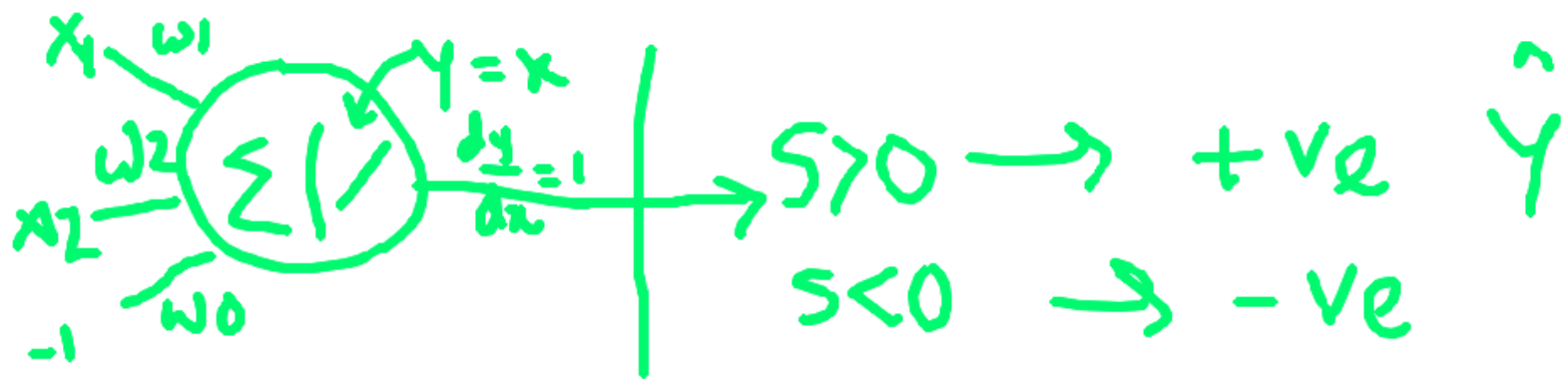
$$\boxed{\frac{\partial E}{\partial w_i} = -2 \sum (y - g(\sum w_i x_i)) \cdot g(\sum w_i x_i) \cdot (1 - g(\sum w_i x_i)) \cdot x_i}$$

→ Der from True Val

→ Der (Act Fn)

→ Input

$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i} \quad \frac{\partial E}{\partial w_i} \Rightarrow 0 \quad \text{Trg will stop}$$



| | \hat{y} | y | |
|---------|-----------|------|------------------|
| $S < 0$ | -1 | -1 | } Corr |
| $S > 0$ | 1 | $+1$ | |
| $S < 0$ | -1 | $+1$ | } opposing Error |
| $S > 0$ | $+1$ | -1 | |

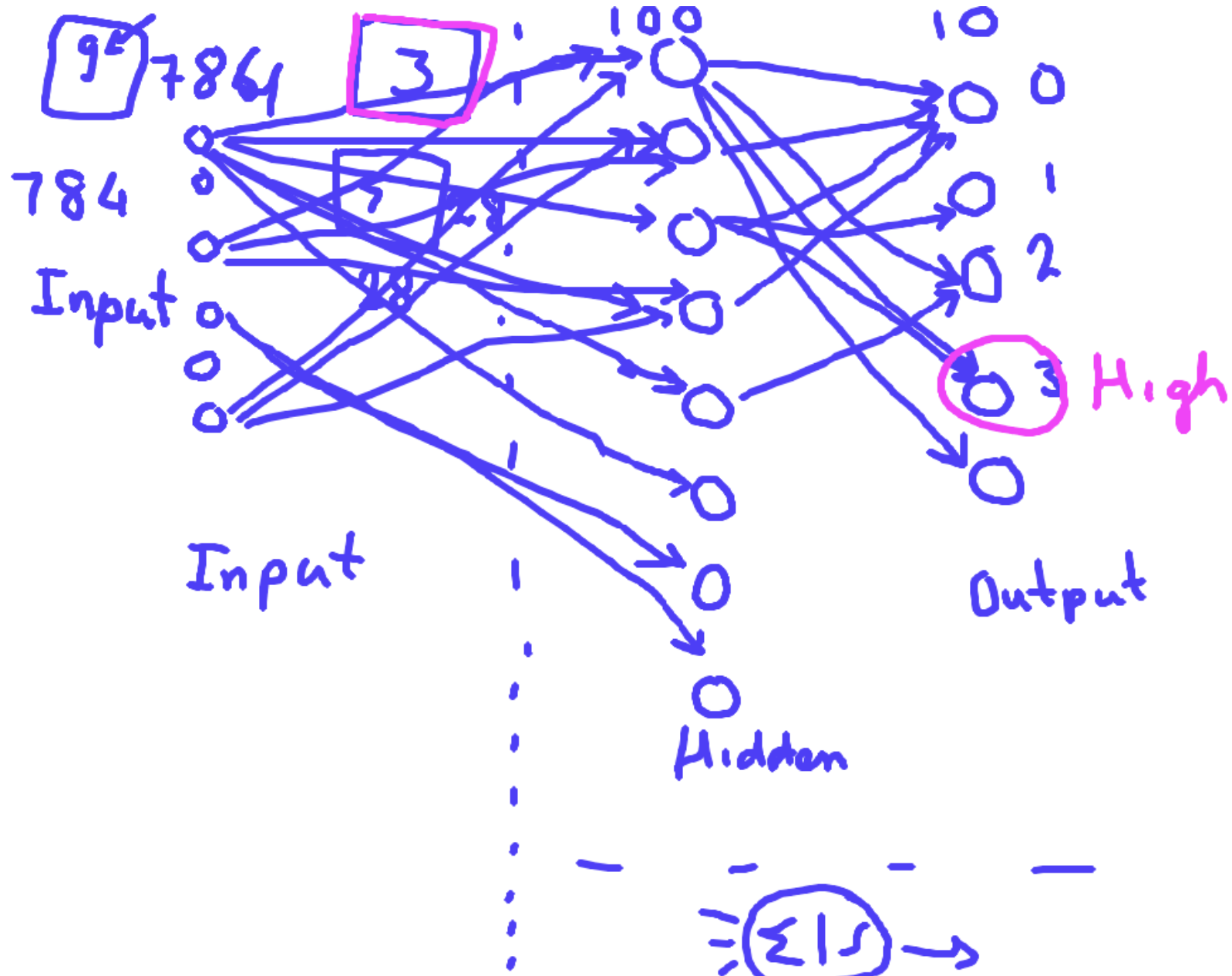
$S \cdot y \leq 0 \leftarrow \text{For } E$

$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i} = \eta \cdot y_i \cdot x_i$$

$$\frac{\partial E}{\partial w_i} = -2 \sum (\text{Der } F T_r) \cdot \text{Der}(\text{Act}) \cdot x_i$$

$$\frac{\partial E}{\partial w_i} = -2 \cdot 2 y_i \cdot 1 \cdot x_i = \underline{\underline{-4 \cdot y_i \cdot x_i}}$$

Building and connecting ANN



Tensorflow Intro

