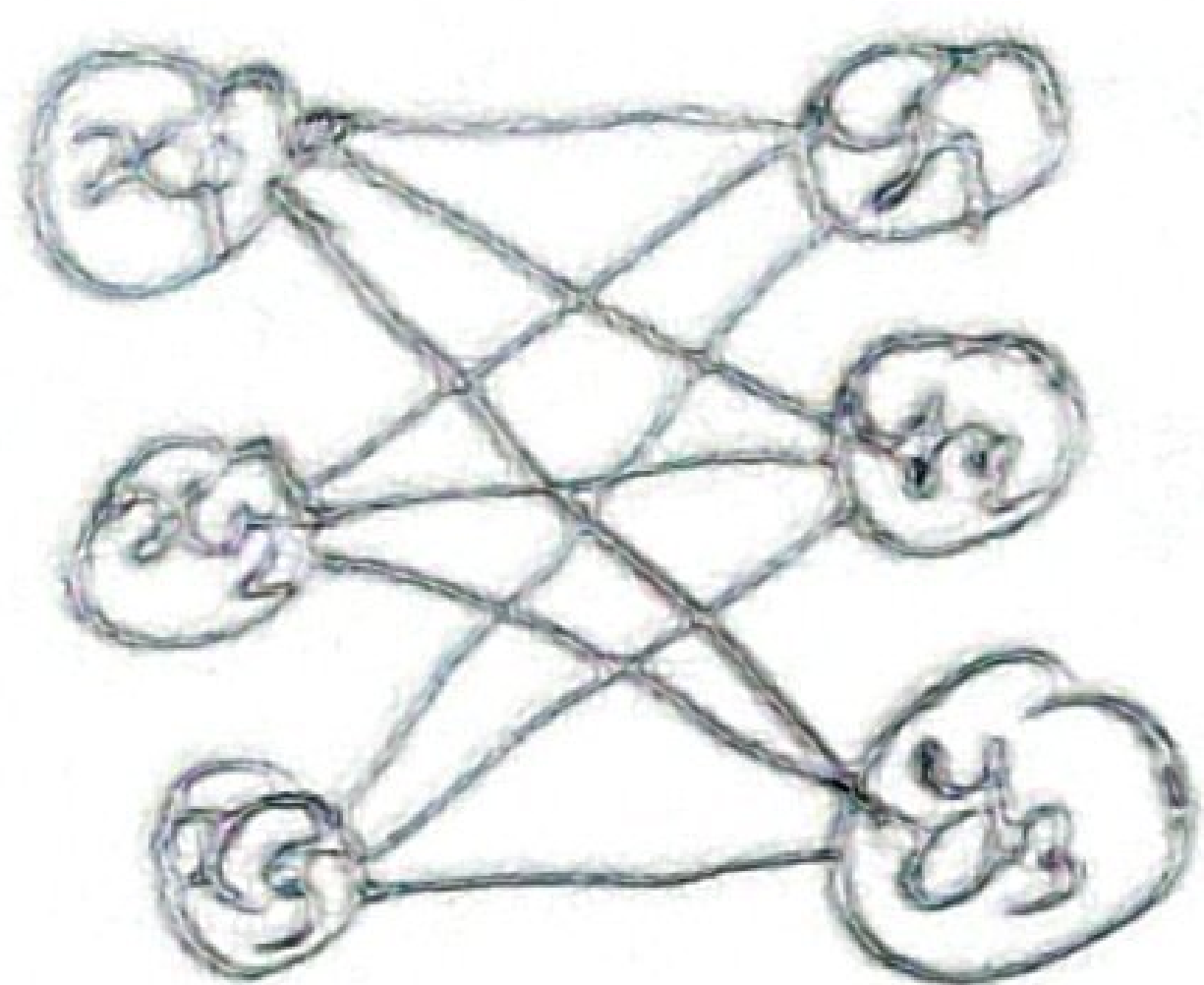


$$y_1 = \sigma(w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3 + b) = \sigma\left(\sum_i w_i x_i + b\right)$$

max + e

Artificial Neuron (single layer perceptron)

④ multiple perception to create a layer:

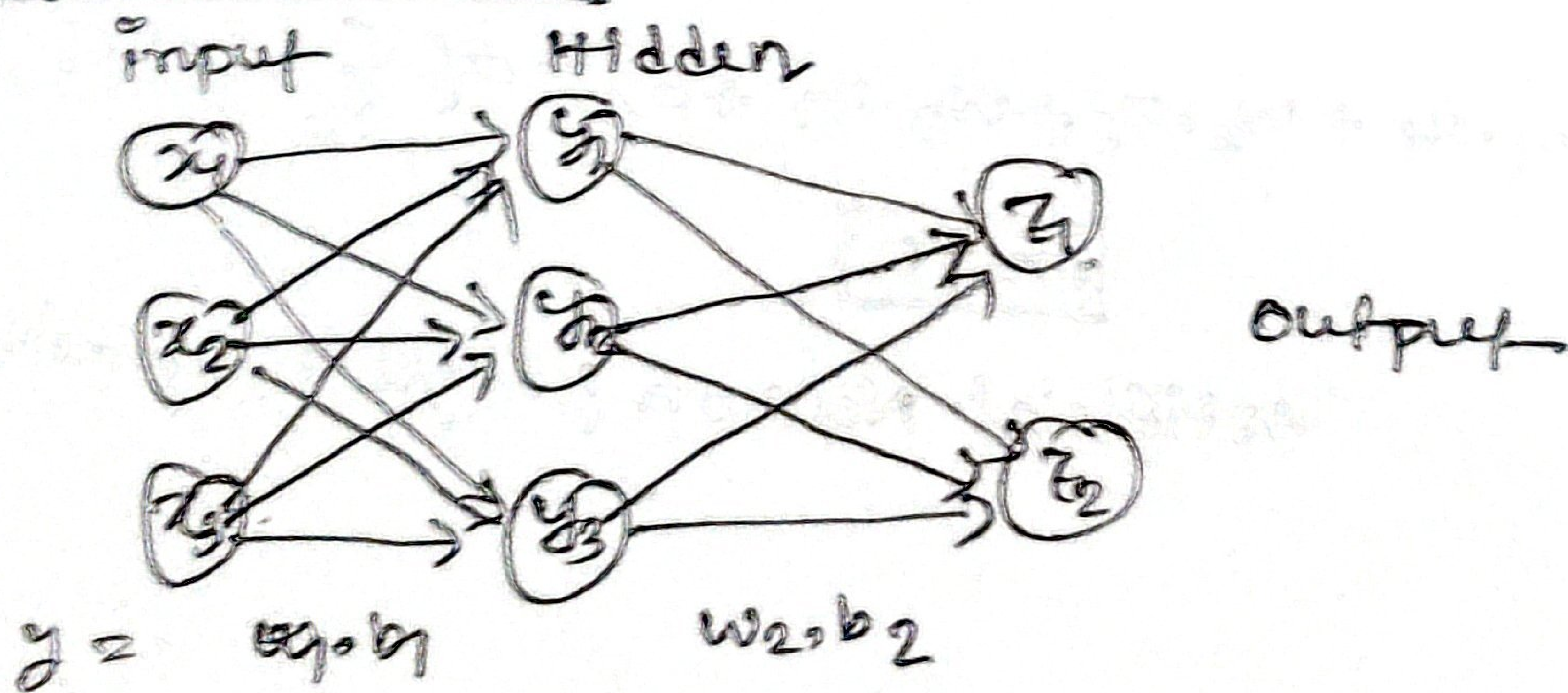


$$x \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

$$\begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = \begin{pmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \\ b_3 \end{pmatrix}$$

Finally $\cdot y = \sigma(w \cdot x + b)$

⑤ Hidden layers:



$$y = \sigma(w_1 \cdot x + b_1) \quad \text{input} \rightarrow \text{output}$$

$$z = \sigma(w_2 \cdot y + b_2)$$

↓
input for second layer.

$$z = \sigma(w_2 \cdot \sigma(w_1 \cdot x + b_1) + b_2)$$

② Activation function:

Non-Linear

It is a mathematical function that takes the weighted sum of the inputs and bias as input and then generates an output, typically used to add non-linearity to the model.

→ Sigmoid. $\sigma(x) = \frac{1}{1+e^{-x}}$; Range $\rightarrow (0,1)$

→ Hyperbolic Tangent, $\sigma(x) = \tanh(x)$; Range $(-1,1)$

→ Rectified Linear Unit, $\sigma(x) = \max(x, 0)$
(plus) \rightarrow Also (pos) $\rightarrow (-) \Rightarrow 0$ [Linear response]

→ Softmax - multi-class operation, $(0,1)$,
all class. will be 1.

Relu: (Rectified Linear unit):

$$\text{Relu}(x) = \max(0, x)$$

make negative values to zero, positive value remain unchanged.

Ex

$$x = -3, f(-3) = \max(0, -3) = 0$$

$$x = 2, f(2) = \max(0, 2) = 2$$

Hidden layers

⑥ Leaky ReLU: (Linear)

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha x & \text{if } x \leq 0 \end{cases}$$

α is a small positive coefficient such as, 0.01

Ex:

if, $\alpha = 0.01$, $x = -5$, then,

$$f(x) = 0.01 \times -5 = -0.05$$

⑦ ELU: (non-Linear)

$$f(x) = \begin{cases} x & \text{if } x \geq 0 \\ \alpha(e^x - 1) & \text{if } x < 0 \end{cases}$$

provide a non-zero gradient for negative values, which helps reduce the vanishing gradient effect,

⑧ Swish: $f(x) = x \cdot \sigma(x)$

$$= x \cdot f(x)$$

$$= x \cdot \frac{1}{1 + e^{-x}}$$

[combination of sigmoid]

$$\text{⑨ Tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Hidden layers $(-1, 1)$

much more complex

Sigmoid: For logistic function: ~~and~~

→ used output layer.

→ Binary class classification.

→ vanishing gradient problem, non-zero centered
Output, computational output is high.

Softmax: $(z)_i = \frac{e^{z_i}}{\sum_j e^{z_j}}$

⇒ For multiclass
problem
classification

Let's assume:

Score for 1st class = 2.0

" " 2nd " = 1.0

" " 3rd " = 0.5

• $e^{2.0} \approx 7.389$

• $e^{1.0} \approx 2.718$

• $e^{0.5} \approx 1.649$

total = $7.389 + 2.718 + 1.649 = 11.756$

Probability for class-1 = $\frac{7.389}{11.756} = 0.628$

" " " - 2 = $\frac{2.718}{11.756} = 0.231$

" " " - 3 = $\frac{1.649}{11.756} = 0.140$

Sum = 1.0, as expected.


Otecon

Oteseconazole INN 150 mg Capsule

④ For regression problem:

Linear activation problem: $f(x) = x$

input: x , output $= x$