

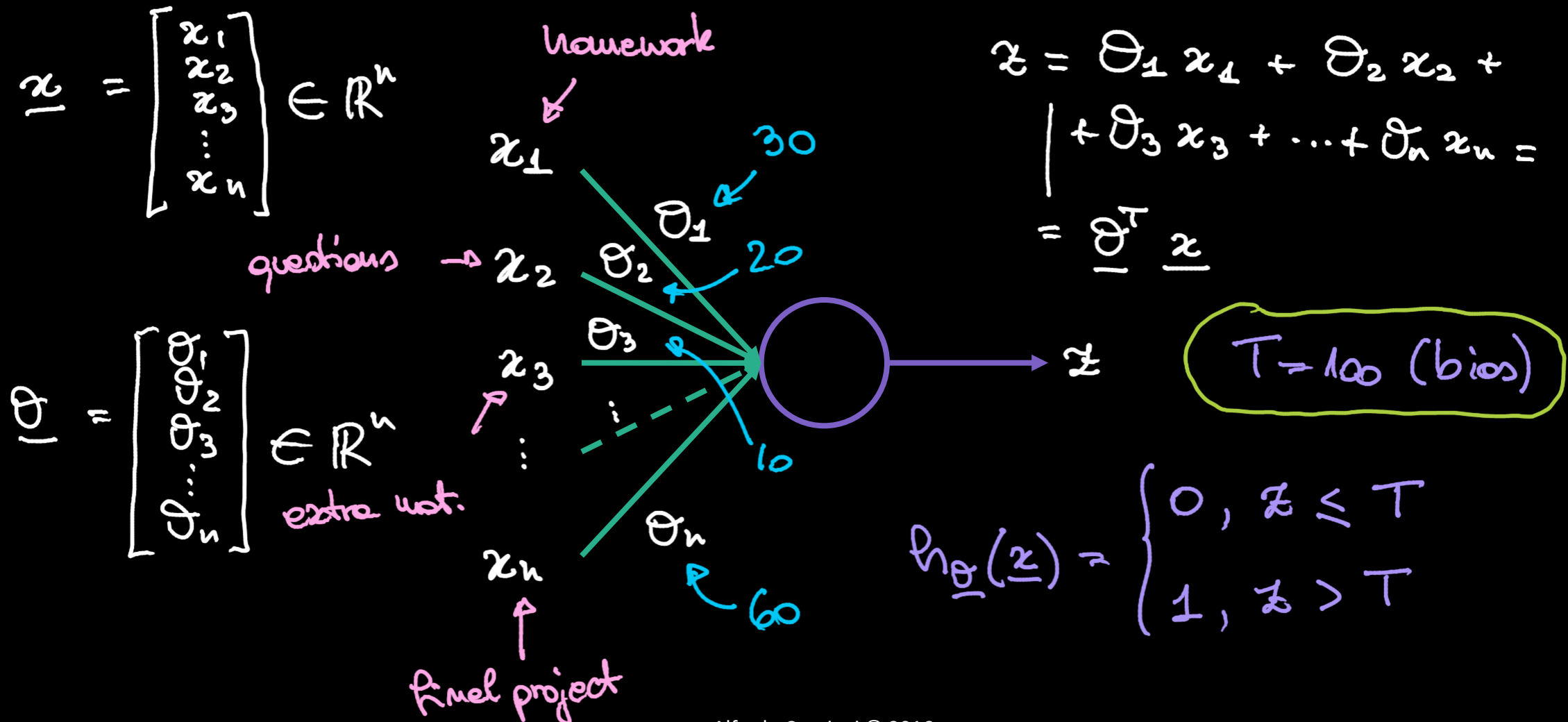
Practical 2.0

Neural Networks – feed forward (inference)

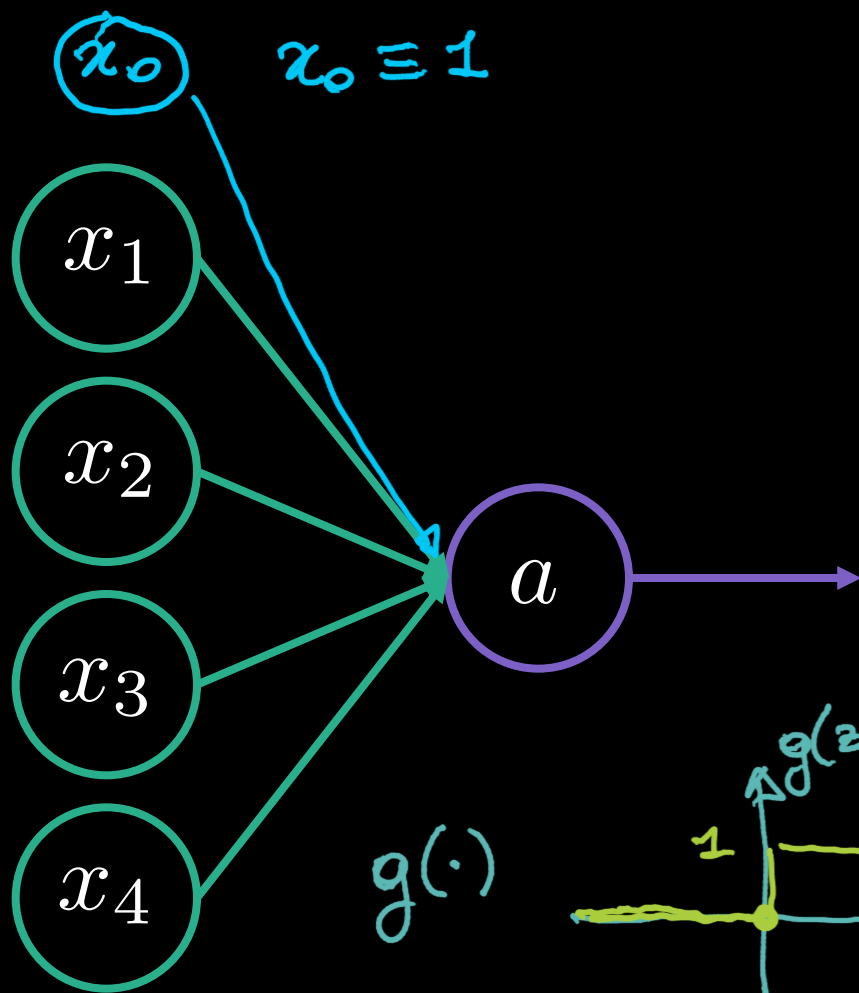
Overview

- Perceptron
 - Embedded threshold
 - Step activation function
- Logistic unit
- Neural network
 - Architecture
 - Equations

Perceptron (I) (1950s, Frank Rosenblatt)



Perceptron (II)



$$\begin{aligned} z &:= \underline{\theta}^T \underline{x} = \\ &= \theta_0 \cdot 1 + \theta_1 x_1 + \dots + \\ &\quad + \theta_n x_n \end{aligned}$$

$$\underline{x} = \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^{n+1}$$

$$\underline{\theta} = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_n \end{bmatrix} \in \mathbb{R}^{n+1}$$

$$h_{\underline{\theta}}(\underline{x}) = \begin{cases} 0, & z \leq 0 \\ 1, & z > 0 \end{cases}$$

$z = \underline{\theta}^T \underline{x}$
 θ_0

$$= g(z) = g(\underline{\theta}^T \underline{x}) = a$$

$$\underline{\theta} = \begin{bmatrix} -100 \\ 30 \\ 20 \\ 10 \\ 50 \end{bmatrix}$$

$$\underline{x} = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix} \in \mathbb{R}^{n+1}$$

x_0

Logistic unit

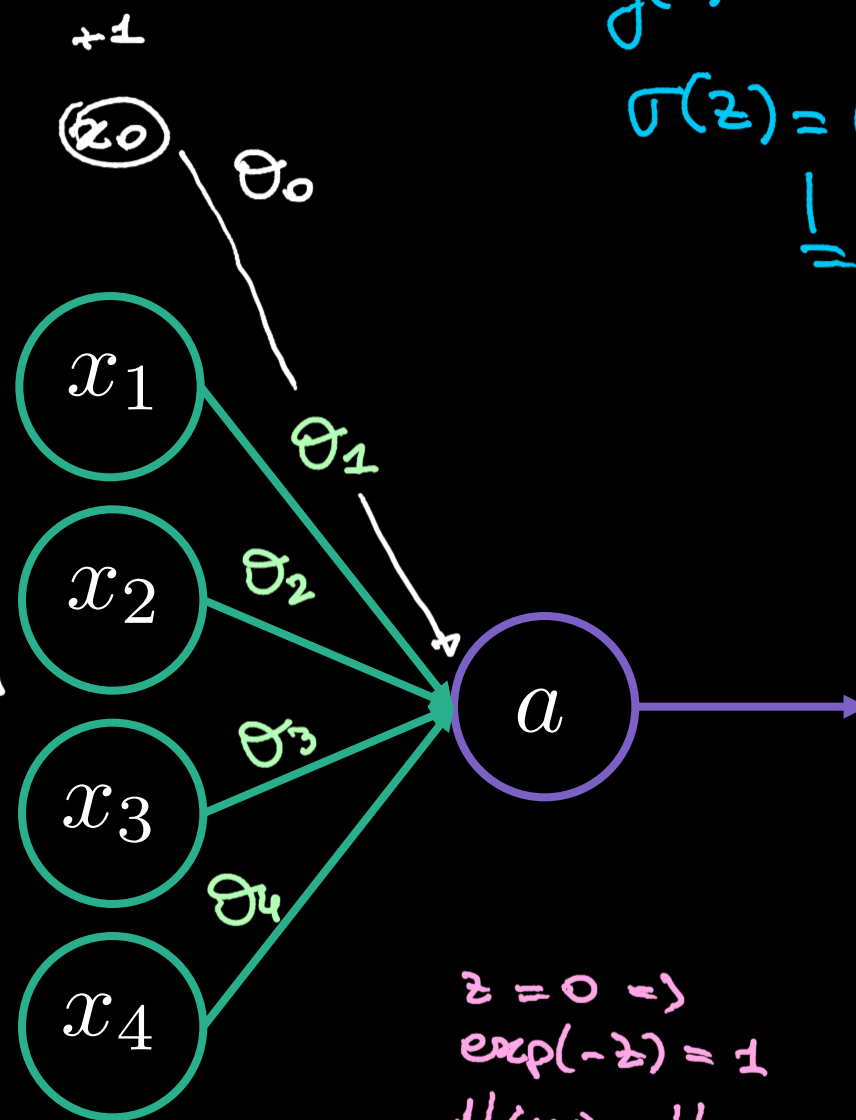
$$\underline{x} \in \mathbb{R}^{n+1}$$

$$\underline{\theta} \in \mathbb{R}^{n+1}$$

$$z = \underline{\theta}^T \underline{x}$$

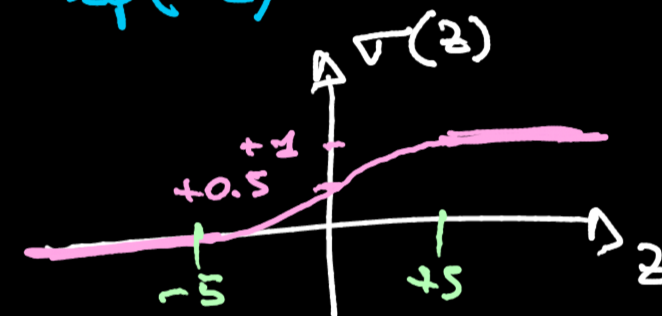
$$h_{\underline{\theta}}(\underline{x}) = \sigma(z) \in [0, 1]$$

$$h_{\underline{\theta}}(\underline{x}) \stackrel{?}{>} 0.5$$



$$g(\cdot) = \sigma(\cdot) \Rightarrow$$

$$\sigma(z) = (1 + \exp(-z))^{-1} = \frac{1}{1 + \exp(-z)}$$



$$\begin{aligned} z &\rightarrow -\infty \\ -z &\rightarrow +\infty \Rightarrow \exp(-z) \rightarrow +\infty \\ 1/(1 + \exp(-z)) &\rightarrow 0^+ \end{aligned}$$

$$\begin{aligned} z &\rightarrow +\infty \\ -z &\rightarrow -\infty \Rightarrow \exp(-z) \rightarrow 0^+ \\ 1/(1 + \underbrace{\exp(-z)}_{\rightarrow 0^+}) &\rightarrow 1 \end{aligned}$$

$$\begin{aligned} z = 0 &\Rightarrow \\ \exp(-z) &= 1 \\ 1/(1+1) &= 1/2 \end{aligned}$$

Neural network (I)

$$x_0 = 1$$

$$\Delta_2 = 4$$

$$a_0^{(2)} = 1$$

$$\Theta^{(1)}$$

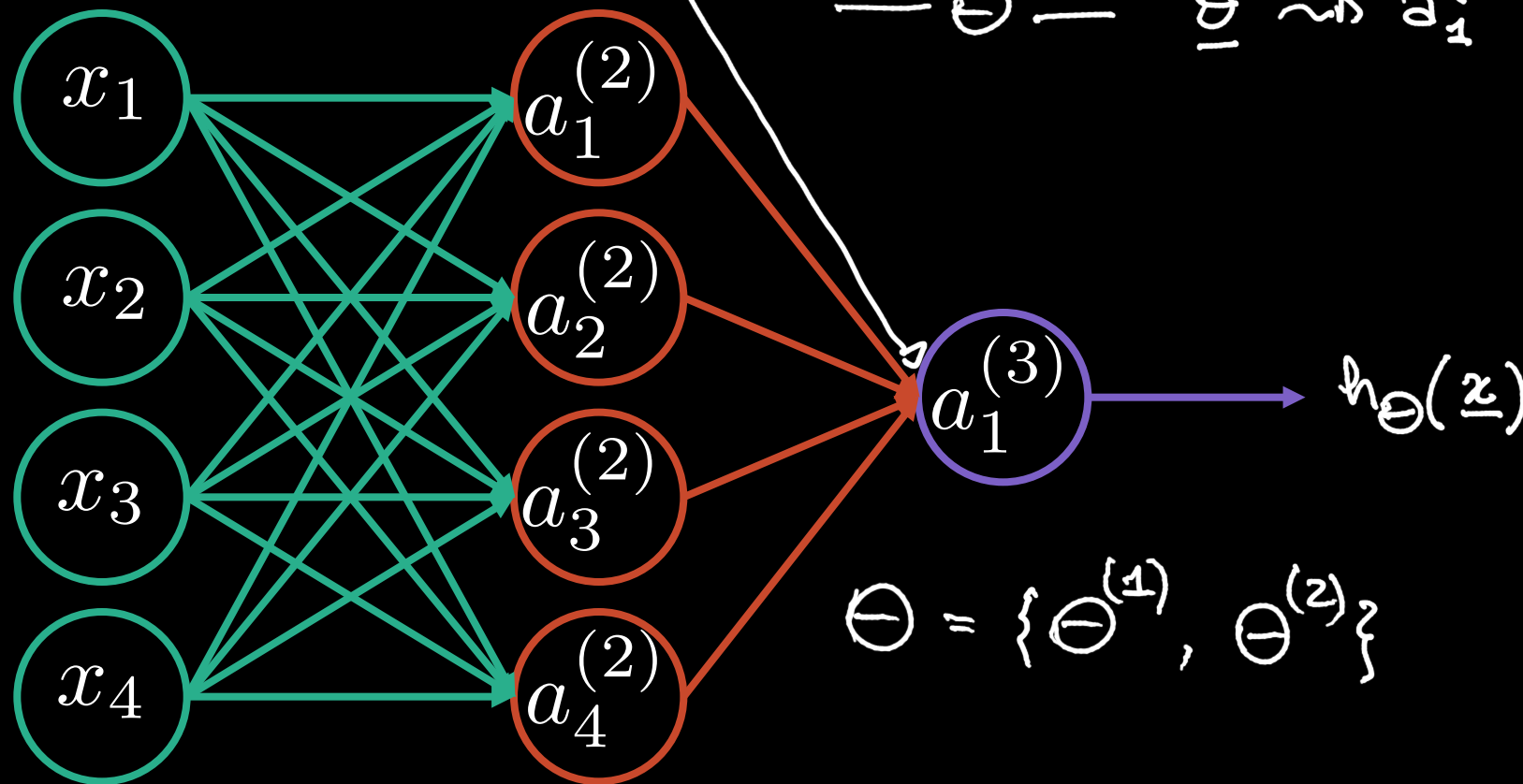
$$\Theta^{(1)}$$

$$\theta \sim a_1^{(2)}$$

$$\theta \sim a_2^{(2)}$$

$$\Theta^{(2)}$$

$$\theta \sim a_1^{(3)} = h_{\Theta}(z)$$



$$\Theta = \{\Theta^{(1)}, \Theta^{(2)}\}$$

$$\Delta_1 = 4$$

Input layer

Hidden layer

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Output layer

$$\Delta_L = \Delta_3 = 1$$

Neural network (II)

$a_i^{(j)}$: i -th activation in layer j

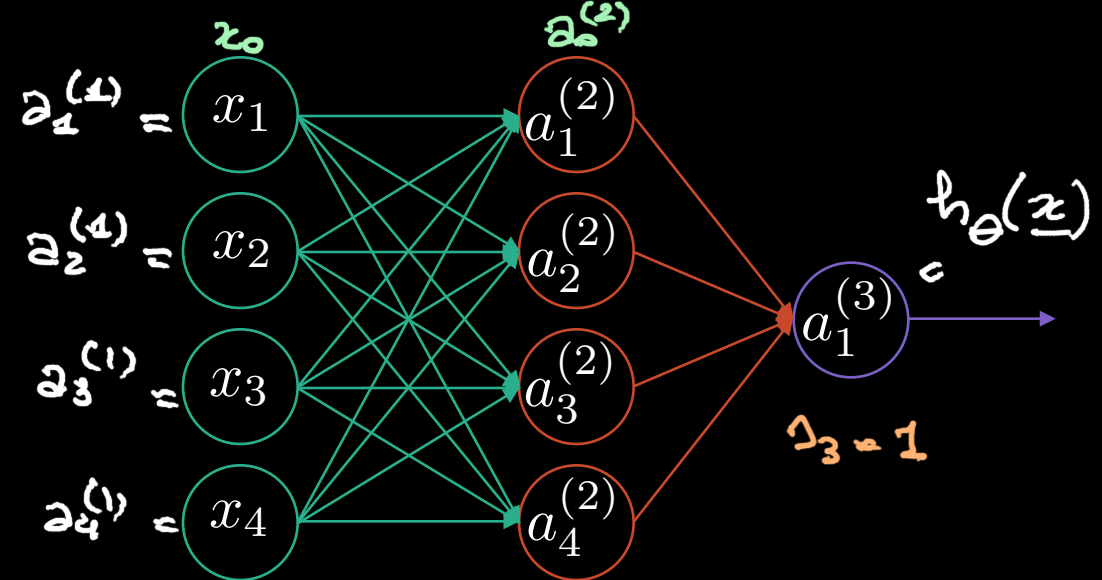
$\Theta^{(j)}$: collection of mappings to go from layer j to $j+1$

$$a_1^{(2)} = \sigma \left(\underbrace{\Theta_{10}^{(1)}}_{+1} x_0 + \Theta_{11}^{(1)} x_1 + \dots + \Theta_{14}^{(1)} x_4 \right)$$

$$a_2^{(2)} = \sigma \left(\Theta_{20}^{(1)} x_0 + \Theta_{21}^{(1)} x_1 + \dots + \Theta_{24}^{(1)} x_4 \right)$$

$$a_4^{(2)} = \sigma \left(\Theta_{40}^{(1)} x_0 + \Theta_{41}^{(1)} x_1 + \dots + \Theta_{44}^{(1)} x_4 \right)$$

$$h_{\Theta}(x) = a_1^{(3)} = \sigma \left(\Theta_{10}^{(2)} a_0^{(2)} + \Theta_{11}^{(2)} a_1^{(2)} + \dots + \Theta_{14}^{(2)} a_4^{(2)} \right)$$



S_j : # elements for layer j

$$\underline{a}^{(2)} = \begin{bmatrix} a_1^{(2)} \\ a_2^{(2)} \\ \vdots \\ a_4^{(2)} \end{bmatrix} \in \mathbb{R}^{\Delta_2}$$

$$= \sigma \left(\Theta^{(1)} \underline{x} \right)$$

$\Theta^{(j)} \in \mathbb{R}^{\Delta_{j+1} \times (\Delta_j + 1)}$

$\Delta_{j+1} \times \left\{ \begin{bmatrix} \vdots \\ \vdots \end{bmatrix} \right\}_{\Delta_j} = \left\{ \begin{bmatrix} \vdots \\ \vdots \end{bmatrix} \right\}_{\Delta_{j+1}}$

$\hat{\underline{a}}^{(2)} = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \Rightarrow h_{\Theta}(x) = \sigma \left(\Theta^{(2)} \hat{\underline{a}}^{(2)} \right)$