

Backpropagation in Practice:

function [jVal, gradient] = costFunction(theta)
 $\hookrightarrow \mathbb{R}^{n+1}$ $\longrightarrow \mathbb{R}^{n+1}$
optTheta = fminunc(@cost

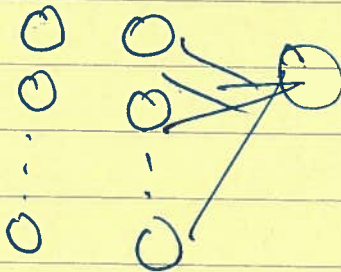
Neural Network ($L=4$)

$H^{(1)}, H^{(2)}, H^{(3)} \rightarrow$ matrices (Theta1, Theta2, Theta3)
 $D^{(1)}, D^{(2)}, D^{(3)} -$ matrices (D1, D2, D3)
"Unroll into vectors"

Example

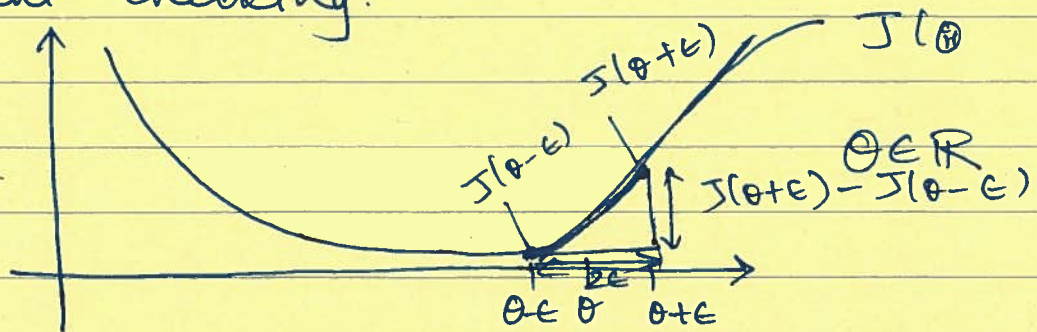
$$s_1 = 10, s_2 = 10, s_3 = 1$$

$$H^{(1)} \in \mathbb{R}^{10 \times 11}, H^{(2)} \in \mathbb{R}^{10 \times 11}, H^{(3)} \in \mathbb{R}^{1 \times 11}$$



$$D^{(1)} \in \mathbb{R}^{10 \times 11}, D^{(2)} \in \mathbb{R}^{10 \times 11}, D^{(3)} \in \mathbb{R}^{1 \times 11}$$

Gradient Checking:



$$\frac{dJ(\theta)}{d\theta} \approx \frac{J(\theta + \epsilon) - J(\theta - \epsilon)}{2\epsilon} \quad \bigg| \quad \frac{J(\theta + \epsilon) - J(\theta)}{\epsilon}$$

$$\epsilon = 10^{-4}$$

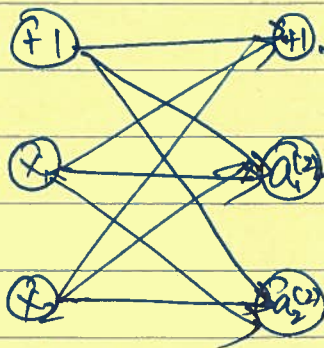
2 sided Difference.

One sided difference

$$\frac{4 - 0.1 - 0.01^3 - 1}{(1.01)^3 - (0.99)^3} = \frac{2.8999}{0.02}$$

Random Initialization

Zero initialization



$$h_{ij}^{(l)} = 0 \text{ for all } i, j, l$$

$$a_1^{(2)} = a_2^{(2)}$$

$$h_{01}^{(1)} = h_{02}^{(1)}$$

$$\text{Also } \delta_1^{(2)} = \delta_2^{(2)}$$

$$\frac{\partial J(H)}{\partial h_{01}^{(1)}} = \frac{\partial J(H)}{\partial h_{02}^{(1)}}$$

$$a_1^{(2)} = a_2^{(2)}$$

$$\Delta_{ij}^{(2)} := \Delta_{ij}^{(2)} + \delta_i^{(3)} \times (a^{(2)})_j$$

$$\Delta^{(2)} := \Delta^{(2)} + \delta^{(3)} \cdot (a^{(2)})^T$$

$$\Theta_1, \Theta_2$$

$$5 \times 3, 4 \times 6$$

$$\text{reshape}((16:39), 4, 6)$$

$$J(\theta) = 2\theta^4 + 2$$

$$\theta = 1 \quad \epsilon = 0.01$$

④ Using grad check can help verify if backprop is bug free
 * For comp efficiency, after we have per. if our neural net overfits to a set, increase λ .

⑤ $J(\theta)$ is too large
 plot $J(\theta)$ number of iteration and make sure dec

if NN using grad descent,

if you run algorithm twice with diff random initialization, gd may converge to two diff solⁿ