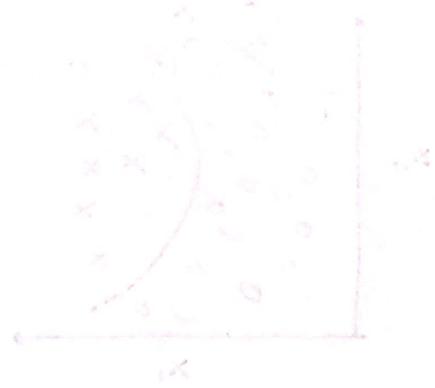


WEEK 4 - Application of graph

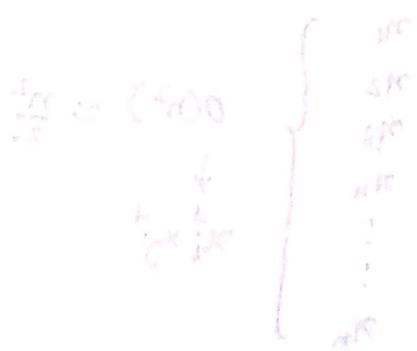
(Weighted undirected)

Given some weighted graph (with vertices & edges) find shortest path from vertex A to vertex B.



Given some weighted directed graph

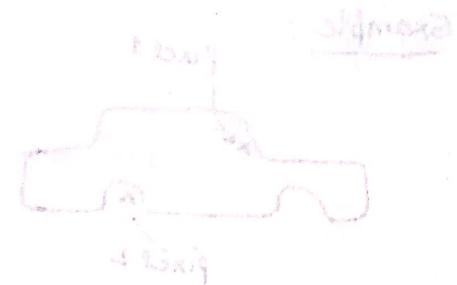
(u) ≤ 400



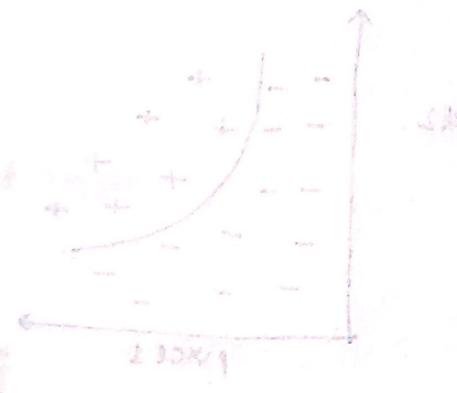
• Dijkstra

WEEK-4

shortest path (unweighted) ->
shortest path (weighted) ->



shortest path (unweighted) ->



($N \times N$) matrix of vertices)

shortest path (weighted) ->

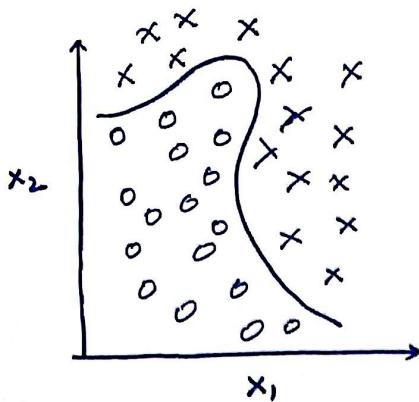


shortest path (weighted) ->



Neural Networks

(49)



$$h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \dots + \theta_n x_1^d x_2^d)$$

Non-linear hypothesis

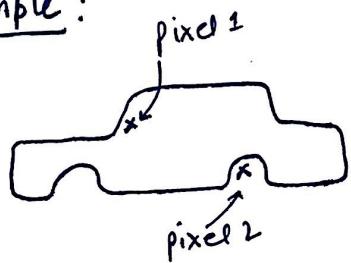
→ Linear/logistic regression works well when we have less features (i.e. 2 or 3)

$$\begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ \vdots \\ x_n \end{matrix} \quad O(n^2) \approx \frac{n^2}{2}$$

computationally expensive when ~~n~~ $n \rightarrow$ large

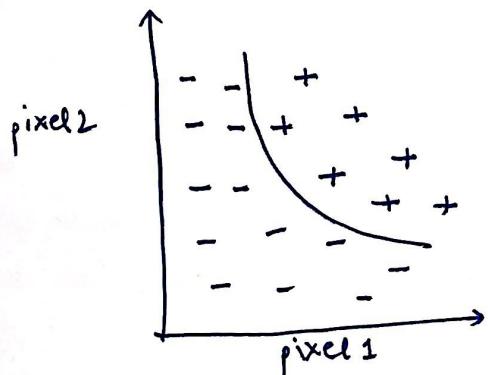
$$x_i x_j x_k \Rightarrow O(n^3)$$

Example:



learning algorithm.

50x50 pixel images \rightarrow 2500 pixels
 $n = 2500$ (7500 if RGB)



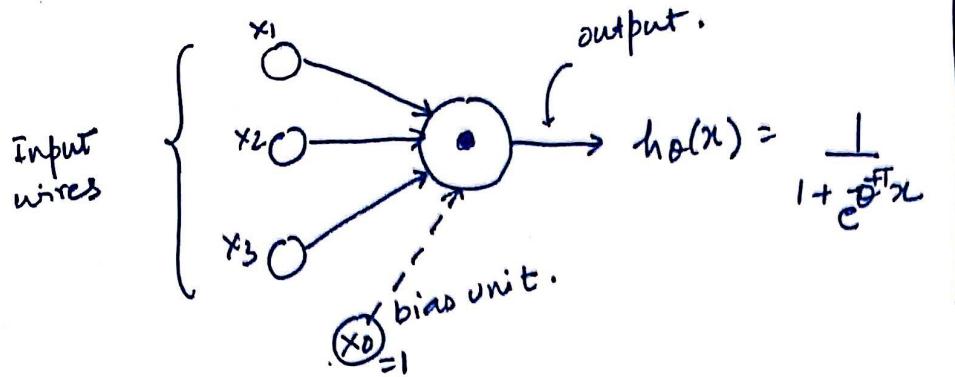
$$x = \begin{bmatrix} \text{Gray Scale} & \text{pixel 1 intensity} \\ & \vdots \\ & \text{pixel 2500} \end{bmatrix}$$

\rightarrow Car
 \rightarrow Not Car.

Quadratic features ($x_i x_j$)
 ≈ 3 million features.

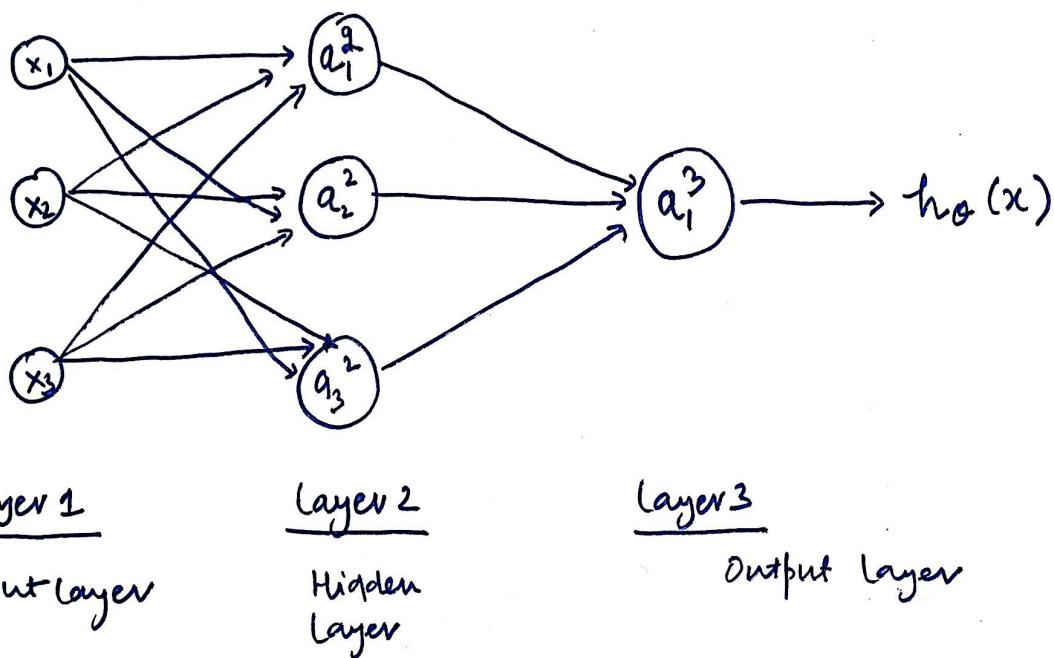
~~2500~~ 2500_{C_2}

Model Representation



single
Neuron model:
logistic unit.

- sigmoid(logistic) activation fn. := Neuron
- parameters \approx weights θ

Neural Network:

a_i^j = "activation" of unit i in layer j

Q_j = matrix of weights controlling fn. mapping from layer j to layer $j+1$.

$$a_1^{(2)} = g(\theta_{10}' x_0 + \theta_{11}' x_1 + \theta_{12}' x_2 + \theta_{13}' x_3) = g(z_1^{(2)})$$

$$a_2^{(2)} = g(\theta_{20}' x_0 + \theta_{21}' x_1 + \theta_{22}' x_2 + \theta_{23}' x_3) = g(z_2^{(2)})$$

$$a_3^{(2)} = g(\theta_{30}' x_0 + \theta_{31}' x_1 + \theta_{32}' x_2 + \theta_{33}' x_3) = g(z_3^{(2)})$$

$$\begin{aligned} h_\theta(x) &= a_1^{(3)} = g(\theta_{10}^2 a_0^{(2)} + \theta_{11}^2 a_1^{(2)} + \theta_{12}^2 a_2^{(2)} + \theta_{13}^2 a_3^{(2)}) \\ \text{final o/p.} &= g(z_1^{(3)}) \end{aligned}$$

→ if network has s_j units in layer j , s_{j+1} units in layer $j+1$

then θ^j will be of dimension $\left[s_{j+1} \times (s_j + 1) \right]$

$\therefore \theta^1 \Rightarrow 3 \times 4$ matrix.

→ Vectorized implementation

$$a_0^1 = x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad z^{(2)} = \begin{bmatrix} z_1^{(2)} \\ z_2^{(2)} \\ z_3^{(2)} \end{bmatrix}$$

$$\left\{ \begin{array}{l} z^{(2)} = \theta^1 x \\ a^{(2)} = g(z^{(2)}) \\ \downarrow \quad \quad \quad \downarrow \\ \mathbb{R}^{3 \times 1} \quad \quad \quad \mathbb{R}^{3 \times 1} \end{array} \right\} \quad a^{(1)}$$

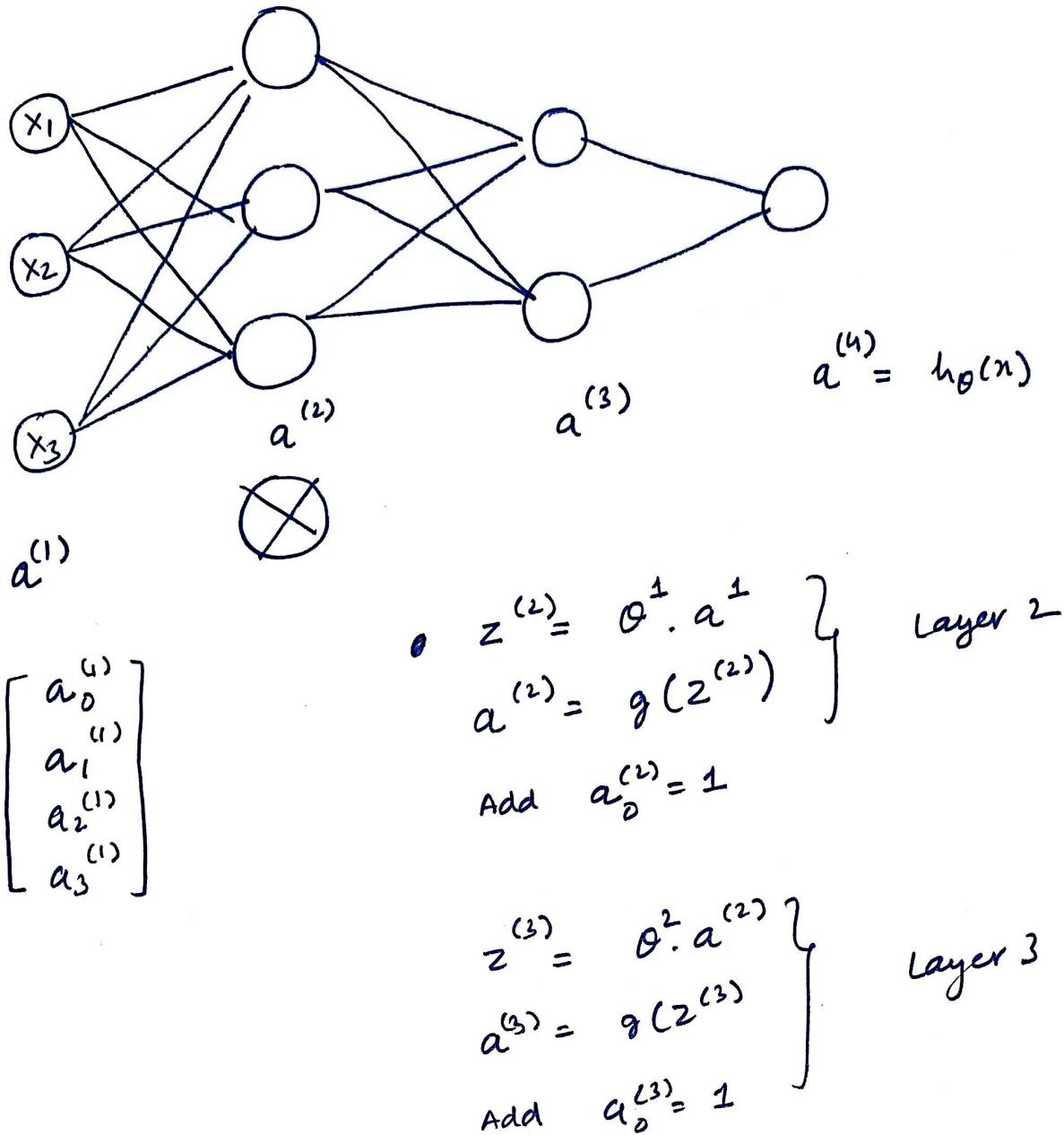
$$\rightarrow \text{Add } a_0^{(2)} = 1$$

Forward propagation

$$\left\{ \begin{array}{l} z^{(3)} = \theta^2 a^{(2)} \\ h_\theta(x) = a^{(3)} = g(z^{(3)}) \end{array} \right\}$$

example: different neural architecture

(52)

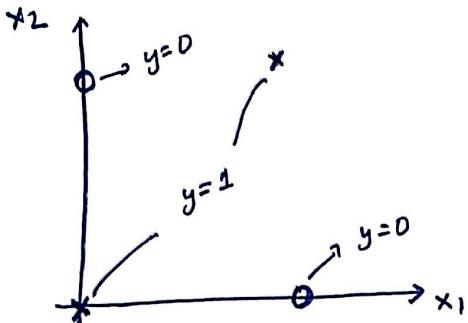


Examples & Intuitions 1 : Non-linear classification example

XOR/NXOR

$$\text{NOT } (x_1 \text{ XOR } x_2) \rightarrow x_1 \text{ NXOR } x_2$$

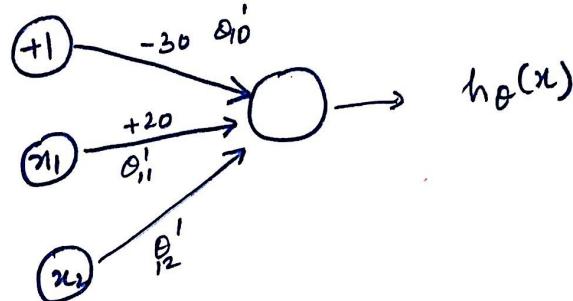
XOR.



x_1	x_2	y
0	0	0
0	1	1
1	0	1
1	1	0

$$x_1 \text{ XOR } x_2 = x_1 \cdot \bar{x}_2 + x_2 \cdot \bar{x}_1$$

Example: AND
 $x_1, x_2 \in \{0, 1\}$
 $y = x_1 \text{ AND } x_2$

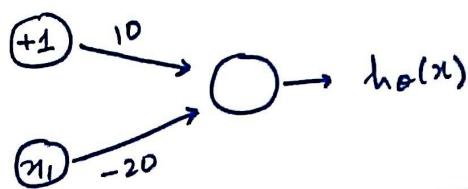


$$h_\theta(x) = g(-30 + 20x_1 + 20x_2) = x_1 \text{ AND } x_2$$

$\uparrow \theta_{10}'$ $\uparrow \theta_{11}'$ $\uparrow \theta_{12}'$

x_1	x_2	$h_\theta(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(10) \approx 0$
1	1	$g(10) \approx 1$

example: Negation:

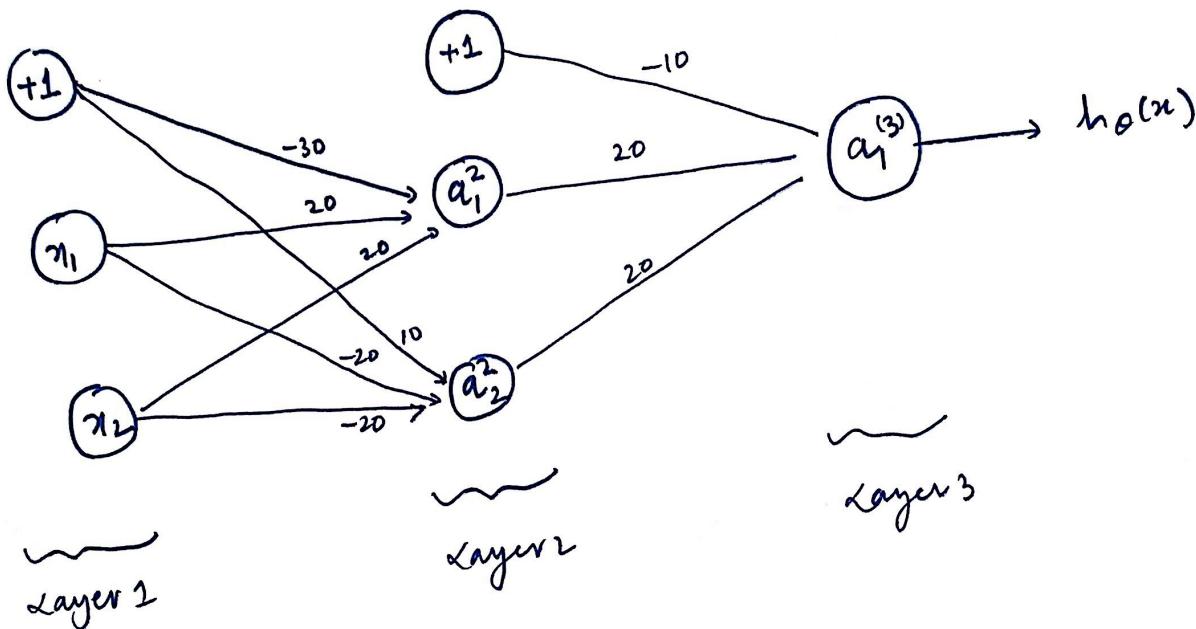


x_1	$h_\theta(x)$
0	1
1	0

$$h_\theta(x) = g(10 - 20x_1)$$

intuition: put large negative weight in front of the variable you want to negate.

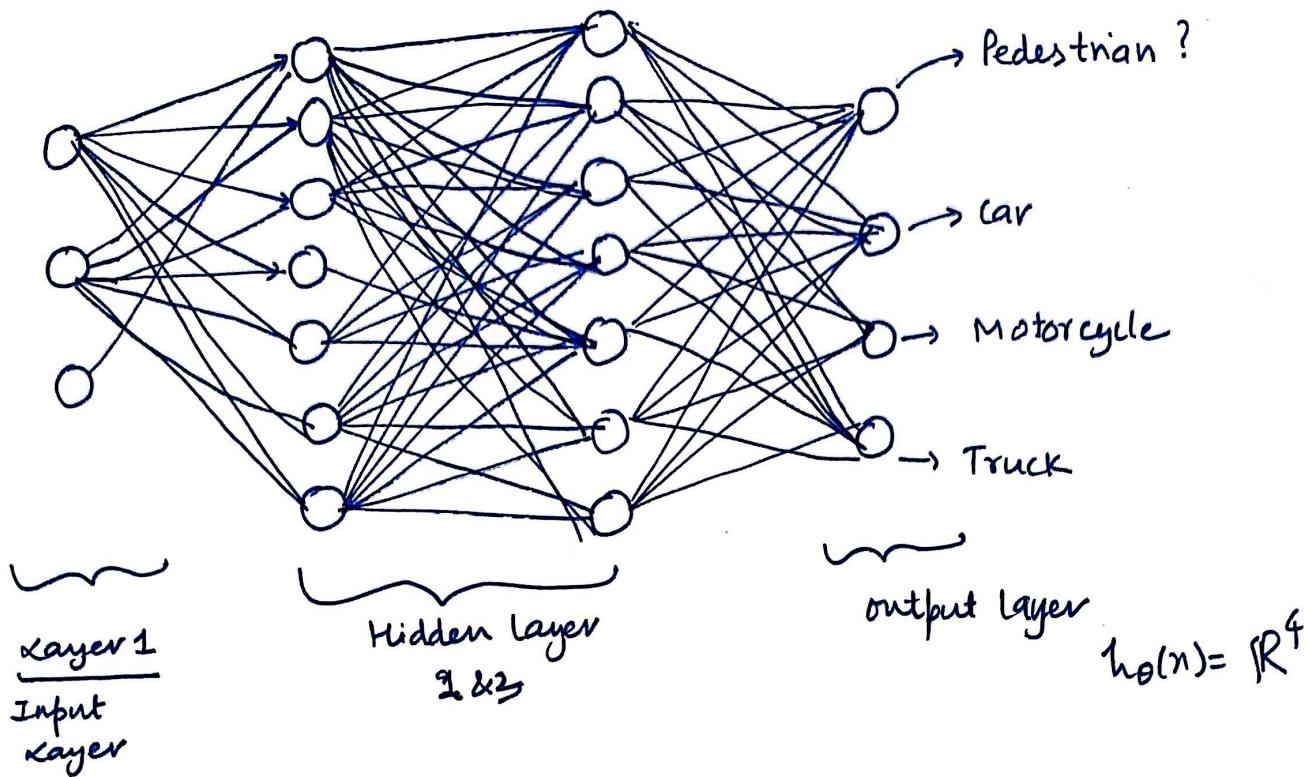
x_1 XNOR x_2



x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\theta(x)$
0	0	0	1	1
0	1	0	0	0
1	0	0	0	0
1	1	1	0	1

$$h_\theta(x) = a_1^{(3)} = g(z_1^{(3)})$$

Multi-class Classification : One. Vs. All



$$h_{\theta}(x) = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad \text{when pedestrian}$$

$$h_{\theta}(x) = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad \text{etc.}$$

when motorcycle

$$h_{\theta}(x) = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \quad \text{when car}$$

Training set : $(x^1, y^1), (x^2, y^2) \dots (x^m, y^m)$

y^i will be one of $\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$

$$\frac{h_{\theta}(x^i) \approx y^{(i)}}{\mathbb{R}^4}$$

predict : Neural network.

function p = predict(theta1, theta2, x)

%

m = size(x, 1);

p = zeros(size(x, 1), 1); % 5000 x 1

x = [ones(size(x, 1), 1) x]; % 5000 x 401

out_1 = sigmoid(x * theta1');

~~out_1~~

out_1 = [ones(size(out_1), 1) output 1];

out_2 = sigmoid(out_1 * theta2');

p = max(out_2, [], 2)

end