

# ML w2 multivariate linear regression

Multiple Features

## Multiple Features

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 \dots + \theta_n x_n$$

$\uparrow$   
 $x_0 = 1$

$$X = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^{n+1} \quad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_n \end{bmatrix} \in \mathbb{R}^{n+1}$$

Transpose

$$[\theta_0, \theta_1, \theta_2 \dots \theta_n]^T \times \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$\theta^T$   
 $(n+1) \times 1$  matrix

X

$$h_{\theta} = \theta^T X$$

## Feature Scaling

$$-1 \leq x_1 \leq 1 \text{ range.}$$

- Dividing by maximum value.

e.g.  $\frac{x_2}{2500}$  size of feet  $< 2500$

$\frac{x_2}{5}$  bedroom  $< 5$ .

- make features approximately zero mean.

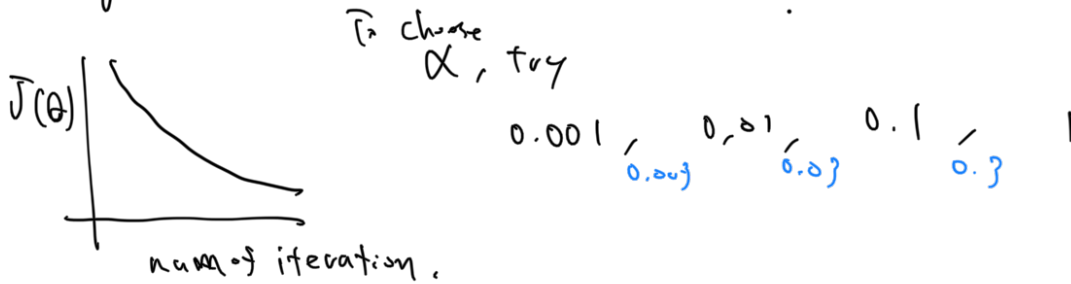
e.g.  $x_1 = \frac{\text{size} - 1000}{2000}$

$x_2 = \frac{\text{size} - 2}{5}$

average value of feature

$$x_1 \leftarrow \frac{x_1 - \mu_1}{s_1} \quad \leftarrow \text{range (max - min)}$$

Learning Rate.



Feature Scaling with Polynomial Regression

$$h_{\theta}(x) = \theta_0 + \theta_1(\text{size}) + \theta_2 \sqrt{\text{size}} \quad \text{size range: } 1 \sim 1000$$

model.

$$h_{\theta}(x) = \theta_0 + \theta_1 \underbrace{\frac{\text{size}}{1000}} + \theta_2 \underbrace{\frac{\sqrt{\text{size}}}{32}}$$

← Feature scaling (without mean normalization)

Normal Equation. 正规方程式

$$X = \begin{bmatrix} 1 & 204 & 5 & 1 & \dots \\ 1 & 1416 & 3 & 2 & \dots \\ 1 & 1514 & 3 & 2 & \dots \\ 1 & 862 & 2 & 1 & \dots \end{bmatrix} \quad y = \begin{bmatrix} 460 \\ 232 \\ 315 \\ 178 \end{bmatrix}$$

examples  $(x^{(1)}, y^{(1)}), \dots, (x^{(m)}, y^{(m)})$ ;  $n$ : features.

$$x^{(i)} = \begin{bmatrix} x_0^{(i)} \\ x_1^{(i)} \\ x_2^{(i)} \\ \vdots \\ x_n^{(i)} \end{bmatrix} \in \mathbb{R}^{n+1}$$

design matrix

$$X = \begin{bmatrix} x^{(1)T} \\ x^{(2)T} \\ \vdots \\ x^{(m)T} \end{bmatrix}$$

exampler.

E.g.

$$X = \begin{bmatrix} 1 & x_1^{(1)} \\ 1 & x_1^{(2)} \\ \vdots & \vdots \\ 1 & x_1^{(m)} \end{bmatrix} \quad y = \begin{bmatrix} y^{(1)} \\ \vdots \\ y^{(m)} \end{bmatrix}$$

$$y = \theta x$$

$$A = (X^T X)^{-1} X^T y$$

$$\theta = \frac{1}{x} y \quad (?)$$

inverse.

octave

$$\text{pinv}(X' * X) * X' * y$$

$$O(n^3)$$

Normal equation Noninvertibility.

$X^T X$  non invertible.

- Redundant features.  $x_1$  feet,  $x_2$  meter  $\rightarrow x_2 = (3.28)^2 x_1$
- Too many features (e.g.  $m \leq n$ ) delete features or use regularization

Vectorization

$$h_{\theta}(x) = \sum_{j=0}^n \theta_j x_j$$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \end{bmatrix}$$

$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \end{bmatrix}$$

$$\text{prediction} = \theta^T x;$$

transpose

$$\theta : \theta - \delta$$

$\mathbb{R}^{n+1}$  (delta)

$\mathbb{R}^{n+1}$  (vector)

$\mathbb{R}^{n+1}$  Real number

vector delta

$$\text{where } \delta = \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x^{(i)}$$

$$n=2$$

$$\delta = \begin{bmatrix} \delta_0 \\ \delta_1 \\ \delta_2 \end{bmatrix} \begin{bmatrix} (h_{\theta}(x^{(1)}) - y^{(1)}) \cdot x^{(1)} \\ (h_{\theta}(x^{(2)}) - y^{(2)}) \cdot x^{(2)} \\ \vdots \end{bmatrix}$$