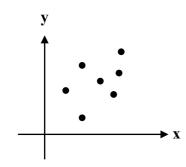
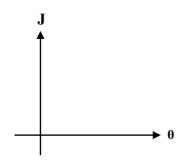
## SC201 Lecture 4

## **Supervised Learning**

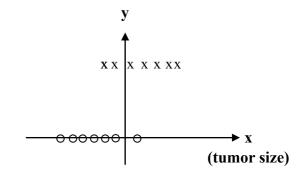
< \_\_\_\_\_ regression >



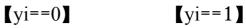
$$\theta =$$

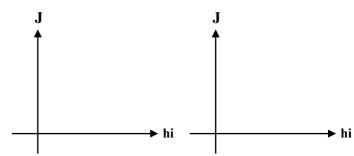


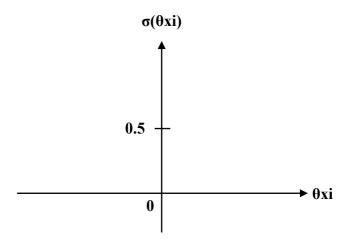
< \_\_\_\_\_ regression >



$$\theta =$$

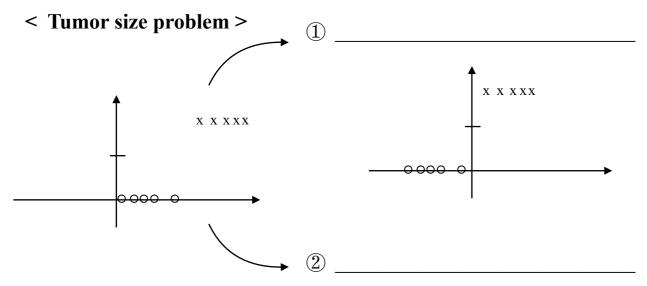


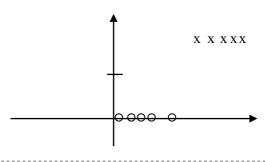




$$\theta xi$$
 \_\_\_\_\_\_,  $\sigma(\theta xi)$  \_\_\_\_\_

$$\theta xi$$
 \_\_\_\_\_ ,  $\sigma(\theta xi)$  \_\_\_\_\_





visualize.py

• It is possible to raise xi to exponent (\_\_\_\_\_\_)

feature  $xi \rightarrow \theta xi + b \rightarrow$ \_\_\_\_\_\_

feature xi, xi<sup>2</sup>  $\rightarrow$  \_\_\_\_\_  $\rightarrow$  \_\_\_\_\_

< Maximum Likelihood Estimation >

The origin of \_\_\_\_\_



● 機率最大化

Maximize  $(hi)^{yi} (1-hi)^{1-yi} = Maximize$ 

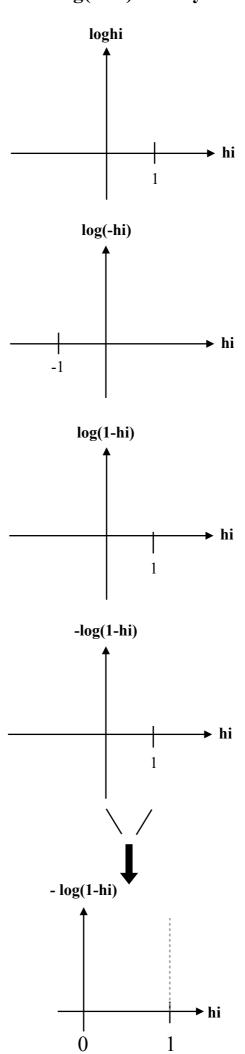
= Maximize \_\_\_\_\_ = Maximize \_\_\_\_\_

= Minimize \_\_\_\_\_ **→ J** = \_\_\_\_\_

0

1

< L = -log(1-hi) when yi==0> stanCode



### **Gradient Descent**

#### < Batch Gradient Descent > BGD

$$\theta = \theta - \alpha \left( \frac{d}{d\theta} \right)$$

where J =

$$\frac{dj}{d\theta} =$$

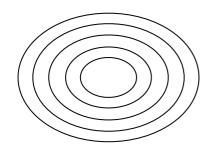
• Compute the gradient using

\_\_\_\_

- Move \_\_\_\_\_ towards the optimum
- \_\_\_\_update

• \_\_\_\_\_RAM needed

•





#### < Stochastic Gradient Descent > SGD

$$\theta = \theta - \alpha \left( \frac{d}{d\theta} \right)$$

where L = \_\_\_\_\_

$$\frac{dL}{d\theta} =$$
 \_\_\_\_\_\_

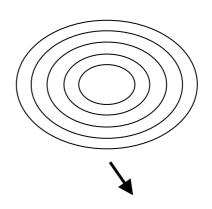
• Compute the gradient using

\_\_\_\_\_

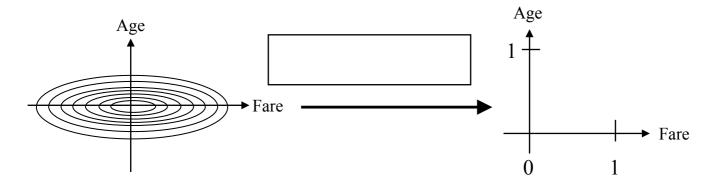
- \_\_\_\_\_learning process

  (often \_\_\_\_\_ from optimum)
- \_\_\_\_update
- \_\_\_\_\_RAM

•



(bounce around min)



### Normalization

| <b>Define Model (hi)</b> | hi = |
|--------------------------|------|
| . ,                      |      |

**Define Loss Function** L = \_\_\_\_\_

# Find the best parameters (weights)

$$\frac{dL}{dWi} =$$