

# Lecture Notes 01/25/2021

## Admin

→ upload to D2L

• HW #1 due 01/29/2021 @ 11:30 PM

→ Submit theory as a pdf (convert via word CamScanner, etc)

0 1 2 → upload code as a pdf

$p = [0.5 \ 0.2 \ 0.3]$

• show outputs / figures

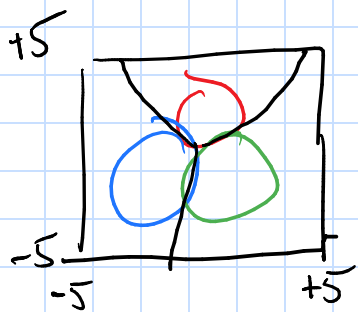
• Convert Jupyter notebooks to pdf

## Homework help

$g_i(x)$  → param:  $\mu_i, \Sigma_i, p(\omega_i)$   $\propto$  Posterior

$D_{Tr}$  → Learn  $\mu_1, \mu_2, \mu_3$   
 $\Sigma_1, \Sigma_2, \Sigma_3$

$D_{TE}$   $1 \times 1$   
 $[1 \times d] [d \times d] [d \times 1]$



$$g_i(x) = -\frac{1}{2} \underbrace{(x - \mu_i)^T \Sigma_i^{-1} (x - \mu_i)}_{\substack{\uparrow \\ \text{Assumed} \\ \text{column vectors}}} - \boxed{\frac{d}{2} \log(2\pi)}$$

2D  
100 samples

$$D = (100 \times 2)$$

$-\frac{1}{2} \log(|\Sigma_i|) + \log p(\omega_i)$

$$\underline{D[0].T}$$

np.linalg.transpose(x)

$$N \in \{0, 1, 2\}$$

$$N \rightarrow 2$$

$$p_0, p_1, p_2$$

$$\rightarrow p_1 + p_2 + p_3 = 1 \quad *$$

$$p_1, p_2, p_3 \in [0, 1]$$

$$\begin{array}{ccc} \downarrow & \downarrow & \downarrow \\ 0.7 & 0.25 & 0.05 \end{array}$$

$$r = \text{Sample} \left( 1000, \overset{\substack{\uparrow M \\ 0.7 \quad 0.95 \quad 1}}{[p_0, p_1, p_2]} \right) \quad \text{Look at the CDF}$$

$$r \in \mathcal{N}^{1000}$$

$$\downarrow \begin{array}{ccc} 0 & 1 & 2 \end{array}$$

$$p$$

$$c \rightarrow \text{cdf}$$

$$- \eta \sim \text{Uni}(0, 1)$$

$$0.6 \rightarrow 0$$

$$0.9 \rightarrow 1$$

for  $m$  in range( $M$ ):

$$etu \leftarrow \text{Sample Uni}(0, 1)$$

$$L \leftarrow c \leq etu$$

$$U \leftarrow c > etu$$

$$g(x) = \bar{w}^T x + w_0$$

Goal: Find  $\bar{w}$  and  $w_0$ .

↓  
weight  
vector

↓  
bias

$$w = \begin{bmatrix} w_0 \\ \bar{w} \end{bmatrix}$$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

$$l(w) = \sum_{i=1}^n (y_i - w^T x_i)^2 = (y - Xw)^T (y - Xw)$$

↓ target
↓ prediction

 ↓   ↓  
 $n \times d$     $d \times 1$   
 $\underbrace{\hspace{2cm}}$   
 $n \times 1$     $n \times 1$

We want the  $w$  that minimizes the loss function wrt  $w$ !

$$\frac{\partial L}{\partial w} = 2X^T(y - Xw) = 0$$

⇒ Solve for  $w$

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

How do we implement this?

Something to think about

- $X^T X$  must be invertible
- What if  $n$  and  $d$  are really large

(a) targets  $y_i \in \{\pm 1\}$     $y_i = 1.29$  [training]

(b)  $\hat{w} = (X^T X)^{-1} X^T y$

(c)  $\hat{y} = w^T x \rightarrow x$  is not from the training data