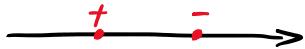


HW1 Tao Ni

2019年2月21日 星期四 下午5:10

1. (a)



The threshold classifier: $f(x) = \begin{cases} +1 & x > c \\ -1 & x < c \end{cases}$

cannot shatter the configuration shown above.

$$\therefore VC(c) = 1$$

(b)



In this configuration, the interval classifier always has to contain the negative point if he tries to contain all the positive points.

Therefore, $VC([a, b]) = 2$.

2. (a) $l(\theta | x) = f(x_1, x_2, \dots, x_n | \theta) = \prod_{i=1}^n \frac{1}{\theta} e^{-\frac{x_i}{\theta}}$

$$L(\theta | x) = -\sum_{i=1}^n \lg \theta - \sum_{i=1}^n \frac{x_i}{\theta} = -n \lg \theta - \sum_{i=1}^n \frac{x_i}{\theta}$$
$$\underset{\theta}{\operatorname{argmax}} L(\theta | x) = \frac{\partial L(\theta | x)}{\partial \theta} = 0$$
$$\Rightarrow -\frac{n}{\theta} + \sum_{i=1}^n x_i \cdot \frac{1}{\theta^2} = 0 \Rightarrow \theta = \frac{1}{n} \sum_{i=1}^n x_i$$

(b) $l(\theta | x) = f(x_1, x_2, \dots, x_n | \theta) = \prod_{i=1}^n 2\theta \cdot x_i^{2\theta-1}$

$$L(\theta | x) = n \lg 2\theta + (2\theta - 1) \sum_{i=1}^n \lg x_i$$

$$\underset{\theta}{\operatorname{argmax}} L(\theta | x) = \frac{\partial L(\theta | x)}{\partial \theta} = 0$$

$$\Rightarrow \frac{2n}{2\theta} + 2 \sum_{i=1}^n \lg x_i = 0 \Rightarrow \theta = \frac{-n}{2 \sum_{i=1}^n \lg x_i}$$

$$(c) l(\theta | X) = \prod_{i=1}^n \frac{1}{2\theta} = \frac{1}{(2\theta)^n}$$

to maximize $l(\theta | X)$ equals to minimize θ .

$$\because x \leq 2\theta \quad \therefore \theta = \max \left\{ \frac{x_1}{2}, \frac{x_2}{2}, \dots, \frac{x_n}{2} \right\}$$

3. (a) $P(C_1 | X=0) \propto P(X=0 | C_1) \cdot P(C_1) = p_1 \cdot P(C_1)$
 $P(C_2 | X=0) \propto P(X=0 | C_2) \cdot P(C_2) = p_2 \cdot P(C_2)$
 if $p_1 \cdot P(C_1) > p_2 \cdot P(C_2)$ then we classify $X=0$ as C_1
 else we classify $X=0$ as C_2 .

$$P(C_1 | X=1) \propto P(X=1 | C_1) \cdot P(C_1) = (1-p_1) \cdot P(C_1)$$

$$P(C_2 | X=1) \propto P(X=1 | C_2) \cdot P(C_2) = (1-p_2) \cdot P(C_2)$$

if $(1-p_1) \cdot P(C_1) > (1-p_2) \cdot P(C_2)$ then classify $X=1$ as C_1 .

else classify $X=1$ as C_2 .

$$(b) P(C_1 | X) \propto P(X | C_1) \cdot P(C_1) = \prod_{i=1}^d P_{1i}^{1-x_i} \cdot (1-P_{1i})^{x_i} \cdot P(C_1)$$

(1) →

$$P(C_2 | X) \propto P(X | C_2) \cdot P(C_2)$$

$$\stackrel{(2) \rightarrow}{=} P(C_2) \cdot \prod_{i=1}^d P_{2i}^{1-x_i} \cdot (1-P_{2i})^{x_i}$$

if ① > ②, then classify X as C_1

else classify \mathbf{x} as C_2 .

(c) for sample $(0, 0)$, $P(C_1) = 0.2$

$$P(C_1 | (0, 0)) = \frac{P((0, 0) | C_1) P(C_1)}{P((0, 0))} = \frac{0.2 \times p_{11} \times p_{12}}{0.2 \times p_{11} \times p_{12} + 0.8 \times p_{21} \times p_{22}} = 0.02$$

$$P(C_2 | (0, 0)) = 1 - P(C_1 | (0, 0)) = 0.973$$

$P(C_1) = 0.6$:

$$P(C_1 | (0, 0)) = \frac{0.6 \times 0.6 \times 0.1}{0.6 \times 0.6 \times 0.1 + 0.4 \times 0.6} = 0.143$$

$$P(C_2 | (0, 0)) = 1 - 0.143 = 0.857$$

$P(C_1) = 0.8$

$$P(C_1 | (0, 0)) = \frac{0.8 \times 0.6 \times 0.1}{0.8 \times 0.6 \times 0.1 + 0.2 \times 0.6} = 0.308$$

$$P(C_2 | (0, 0)) = 1 - 0.308 = 0.692$$

for others samples:

posterior	$(0, 1)$	$(1, 0)$	$(1, 1)$	
$P(C_1) = 0.2$	0.692	0.027	0.693	C_1
	0.308	0.973	0.307	C_2
$P(C_1) = 0.6$	0.931	0.143	0.931	C_1
	0.069	0.857	0.069	C_2
$P(C_1) = 0.8$	0.973	0.307	0.973	C_1
	0.027	0.693	0.027	C_2

4. validation_err_rate:

σ	0.00001	0.0001	0.001	0.01	0.1	1	2	3	
err	0.54	0.54	0.54	0.54	0.51	0.515	0.455	0.46	

σ	4	5	6	
err	0.46	0.46	0.46	

test_err_rate: 44.5%