

CSE-5819 Written Assignment 1

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Q1. Linear Algebra and Probability

(1)

Answers:

For given vectors, can get:

$$x_2 - x_1 = [0.7, 0, -0.5, -0.2]$$

$$x_3 - x_1 = [0, 0.8, 0.5, 0]$$

$$x_4 - x_1 = [0.8, -0.1, 0.2, -0.2]$$

Then execute the result of different norm functions:

	$x_2 - x_1$	$x_3 - x_1$	$x_4 - x_1$	My final answer
(a) L_0	3	2	4	x_3
(b) L_1	1.4	1.3	1.3	x_3, x_4
(c) L_2	$\sqrt{0.78}$	$\sqrt{0.89}$	$\sqrt{0.73}$	x_4
(d) L_∞	0.7	0.8	0.8	x_2

(2)

Answers:

$$E[(X - X')^2]$$

$$= E[X^2 - 2XX' - X'^2]$$

$$= E[X^2] - 2E[XX'] + E[X'^2]$$

$$= E[X^2] - 2E[X]E[X'] + E[X'^2]$$

$$= \mu_1^2 + \sigma^2 - 2\mu_1^2 + \mu_1^2 + \sigma^2$$

$$= 2\sigma^2$$

(3)

Answer:

Firstly, use $w=2$ to re-write the $p(x)$ function:

$$p(x) = 0 \quad \text{if } x < 0$$

$$p(x) = 1 - \frac{x}{2} \quad \text{if } 0 \leq x \leq 2$$

$$p(x) = 0 \quad \text{if } x > 2$$

Then:

$$p(x=1 \mid w=2) = 1 - \frac{1}{2} = 0.5$$

(4)

Answer:

Firstly, write the likelihood function

$$L(\lambda \mid x) = \prod_{i=1}^N p(x_i \mid \lambda) = \prod_{i=1}^N \lambda e^{-\lambda x_i} = \lambda^N e^{-\lambda \sum_{i=1}^N x_i}$$

Secondly, execute the log

$$\ell(\lambda \mid x) = \log(L(\lambda \mid x)) = N \log(\lambda) - \lambda \sum_{i=1}^N x_i$$

Finally MLE:

$$\frac{\partial \ell(\lambda \mid x)}{\partial \lambda} = \frac{N}{\lambda} - \sum_{i=1}^N x_i = 0$$

$$\lambda = \frac{N}{\sum_{i=1}^N x_i}$$

Q2. Introduction to Optimization

(1)

Answer:

(a)

False

Reason: the definition of optimization problem is

$$\min_x f(x)$$

$$s.t. x \in F$$

So I think it is a minimization problem.

(b)

Here I use the $f''(x) > 0$? to judge whether $f(x)$ is convex on $-\infty < x < c$

$$f'(x) = \frac{\partial f(x)}{\partial x} = \frac{2x(c-x) + x^2}{(c-x)^2} = \frac{2xc - x^2}{(c-x)^2}$$

$$\begin{aligned} f''(x) &= \frac{\partial f'(x)}{\partial x} \\ &= \frac{2(c-x)^3 - 2(2xc - x^2)(x-c)}{(c-x)^4} \\ &= \frac{2(c^2 - 2cx + x^2 + 2xc - x^2)}{(c-x)^3} \\ &= \frac{2c^2}{(c-x)^3} \end{aligned}$$

When $-\infty < x < c$, The result for $f''(x) > 0$ is always True. So it is convex.

(2)

Answer:

When use Lagrange multipliers, we can get:

$$\begin{aligned} L(x, y, \lambda) &= 6xy + \lambda \left(\frac{x^2}{9} + \frac{y^2}{16} - 1 \right) \\ &= 6xy - \frac{\lambda}{9} x^2 + \frac{\lambda}{16} y^2 - \lambda \end{aligned}$$

Then, calculate:

$$\frac{\partial L}{\partial x} = 6y + \frac{2\lambda}{9}x = 0$$

$$\frac{\partial L}{\partial y} = 6x + \frac{\lambda}{8}y = 0$$

$$\frac{\partial L}{\partial \lambda} = \frac{x^2}{9} + \frac{y^2}{16} - 1 = 0$$

Based on these equations,

$$y = -\frac{\lambda}{27}x$$

$$y = -\frac{48}{\lambda}x$$

$$\frac{x^2}{9} + \frac{y^2}{16} = 1$$

Then, use the first and second equation, we can get $\lambda^2 = (48*27)$

Finally, we can get:

$$x = \pm\sqrt{\frac{9}{2}}$$

$$y = \pm 2\sqrt{2}$$

Q3. Linear Regression

Answer:

(a)

$$L(w) = (y - Xw - \varepsilon)^T (y - Xw - \varepsilon)$$

Because the ε obeys the normalization distribution, It is a scalar, Then

$$\begin{aligned} L(w) &= (y - Xw)^T (y - Xw) \\ &= (y^T - w^T X^T)(y - Xw) \\ &= y^T y - y^T Xw - w^T X^T y + w^T X^T Xw \\ &= y^T y - 2y^T Xw + w^T X^T Xw \end{aligned}$$

Then

$$\begin{aligned} \frac{\partial L(w)}{\partial w} &= 0 - 2y^T X + 2w^T X^T X = 0 \\ w^T X^T X &= y^T X \end{aligned}$$

Finally, transpose both sides of the equal sign, We can get the w based on X and y

$$\begin{aligned} X^T Xw &= X^T y \\ w &= (X^T X)^{-1} (X^T y) \end{aligned}$$

(b)

$$X^T X = \begin{Bmatrix} 6 & 8 \\ 8 & 14 \end{Bmatrix}$$

$$X^T y = \begin{Bmatrix} 13 \\ 17 \end{Bmatrix}$$

=>

$$(X^T X)^{-1} = \begin{Bmatrix} 0.7 & -0.4 \\ -0.4 & 0.3 \end{Bmatrix}$$

$$w = \begin{Bmatrix} 2.3 \\ -0.1 \end{Bmatrix}$$