

[Special Topics] Homework 2  
Sudarshana Jagadeeshi  
CS 4301.001

1-1.

Slaters condition states that the inequality constraints must be satisfied strictly.  
(0.25, 0.25) accomplishes this as  $2(0.25) + 0.25 < 1$ ,  $0.25 > 0$ , and  $0.25 > 0$ .

1-2

$$2) L(x, y, \lambda) = (x^2 + y^2) + \lambda_1(2x + y - 1) + \lambda_2(-x) + \lambda_3(-y)$$

$$= \cancel{(x^2 + y^2)} + \sum_i \lambda_i (\cancel{2x + y - 1})$$

$$\frac{\partial L}{\partial x} = 2x + 2\lambda_1 - \lambda_2 = 0 \quad x = \frac{\lambda_2 - 2\lambda_1}{2}$$

$$\frac{\partial L}{\partial y} = 2y + \lambda_1 - \lambda_3 = 0 \quad y = \frac{\lambda_3 - \lambda_1}{2}$$

Substituting,

$$\min_{\lambda} \left( \frac{\lambda_2 - 2\lambda_1}{2} \right)^2 + \left( \frac{\lambda_3 - \lambda_1}{2} \right)^2 + \lambda_1 \left( \frac{\lambda_2 - 2\lambda_1}{2} + \frac{\lambda_3 - \lambda_1}{2} - 1 \right) + \lambda_2 \left( \frac{2\lambda_1 - \lambda_2}{2} \right) + \lambda_3 \left( \frac{\lambda_1 - \lambda_3}{2} \right)$$

$$\frac{\lambda_2^2 - 4\lambda_1\lambda_2 + 4\lambda_1^2}{4} + \frac{\lambda_3^2 - 2\lambda_1\lambda_3 + \lambda_1^2}{4}$$

$$+ \lambda_1\lambda_2 - 2\lambda_1^2 + \frac{\lambda_1\lambda_3 - \lambda_1^2}{2}$$

$$+ \frac{2\lambda_2\lambda_1 - \lambda_2^2}{2} + \frac{\lambda_1\lambda_3 - \lambda_3^2}{2}$$

$$= \frac{\lambda_2^2 - 4\lambda_1\lambda_2 + 4\lambda_1^2}{4} + \frac{\lambda_3^2 - 2\lambda_1\lambda_3 + \lambda_1^2}{4}$$

$$+ 4\lambda_1\lambda_2 - 8\lambda_1^2 + 2\lambda_1\lambda_3 - 2\lambda_1^2$$

$$+ 4\lambda_2\lambda_1 - 2\lambda_2^2 + 2\lambda_1\lambda_3 - 2\lambda_3^2$$

$$= -\lambda_2^2 + 4\lambda_1\lambda_2 + 5\lambda_1^2 - \lambda_3^2 + 2\lambda_1\lambda_3$$

$$\text{Final} = -5\lambda_1^2 - \lambda_2^2 - \lambda_3^2 + 4\lambda_1\lambda_2 + 2\lambda_1\lambda_3$$

$$\text{subject to } \left( \frac{\lambda_2 - 2\lambda_1}{2} \right)^2 + \left( \frac{\lambda_3 - \lambda_1}{2} \right)^2 = 1$$

$$\min_{\lambda} -[5\lambda_1^2 - \lambda_2^2 - \lambda_3^2 + 4\lambda_1\lambda_2 + 2\lambda_1\lambda_3]$$

$$\text{subject to } \left(\frac{\lambda_2 - 2\lambda_1}{2}\right)^2 + \left(\frac{\lambda_3 - \lambda_1}{2}\right)^2 - 1 = 0$$

$$\mathcal{L}(\lambda_1, \lambda_2, \lambda_3, \nu) = 5\lambda_1^2 - \lambda_2^2 - \lambda_3^2 + 4\lambda_1\lambda_2 + 2\lambda_1\lambda_3 + \nu \left[ \left(\frac{\lambda_2 - 2\lambda_1}{2}\right)^2 + \left(\frac{\lambda_3 - \lambda_1}{2}\right)^2 - 1 \right]$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_1} = 10\lambda_1 - 4\lambda_2 - 2\lambda_3$$

$$\min_{\lambda_1, \lambda_2, \lambda_3} \mathcal{L} \text{ is the dual}$$

2-1

The gradient w.r.t to each  $\lambda_i$  is:

$(q\text{-sum}) * x(i)$

<https://colab.research.google.com/drive/13qxjrX9OcVPcd1ZwUCdDYuyRGSAJ8sO?usp=sharing>

2-2

$$L(\lambda, \nu, \mu) = \frac{1}{2} \|q - \sum_{m=1}^M \lambda_m x^{(m)}\|_2^2$$

$$+ \nu \left[ \sum_{m=1}^M \lambda_m - 1 \right] + \sum_{m=1}^M \mu_m \lambda_m$$

$$\frac{\partial L}{\partial \lambda_k} = \frac{1}{2} \|q - x^{(k)}\|_2^2 + \nu + \mu_k = 0$$

$$= \frac{1}{2} (-2x_0 q_0$$

$$(q_0 - \lambda_0 x_0)^2 + (q_1 - \lambda_1 x_1)^2 + \dots + (q_M - \lambda_M x_M)^2$$

$$q_0^2 - 2\lambda_0 x_0 q_0 + \lambda_0^2 x_0^2$$

$$-2x_0 q_0 + 2\lambda_0 x_0^2 + \nu + \mu_k = 0$$

$$\lambda_0 = \frac{2x_0 q_0 - \nu - \mu_k}{2x_0^2}$$

Thus:

$$L(\lambda, \nu, \mu) = \frac{1}{2} \|q - \sum_{m=1}^M \frac{2x_m q_m - \nu - \mu_m}{2x_m^2}\|_2^2$$

$$+ \nu \left[ \sum_{m=1}^M \frac{2x_m q_m - \nu - \mu_m}{2x_m^2} - 1 \right]$$

$$+ \sum_{m=1}^M \mu_m \frac{2x_m q_m - \nu - \mu_m}{2x_m^2}$$

3-1

Probably not. The function is not smooth, and there is no neighborhood around a point, so the derivative will not exist.

3-2-a

It ceases to be a subgradient when  $w$  takes sufficiently large values. It will no longer underestimate data point  $y(m)$ .

3-2-b

Rewrite the constraint in order to eliminate the  $y$ . The problem then becomes:

maximize over  $w$  (argmin over points  $(y(m) - w^T(x(m) - x))$ )

i.e. we must find the optimal point first and then optimize over  $w$  for each iteration.

[https://colab.research.google.com/drive/1WIUCNled6KcgJk\\_OqXrDkGdy\\_U4BZgZ?usp=sharing](https://colab.research.google.com/drive/1WIUCNled6KcgJk_OqXrDkGdy_U4BZgZ?usp=sharing)

3-2-c



Construct the Dual.

$$\max_{w \in \mathbb{R}^n, m \in \{1, \dots, M\}} y^{(m)} - w^T (x^{(m)} - q_{\text{new}})$$

$$w_1^2 + w_2^2 + w_3^2 \leq \gamma^2$$

subject to  $\|w\|_2^2 \leq \gamma^2$

$$\mathcal{L}(w, \lambda) = y^{(m^*)} - w^T (x^{(m^*)} - q) + \lambda \left[ \sum_{m=1}^M w_m^2 - \gamma^2 \right]$$

$$\frac{\partial \mathcal{L}}{\partial w_m} = - (x^{(m^*)} - q) + 2\lambda w_m = 0$$

$$\therefore w_m = \frac{(x^{(m^*)} - q)}{2\lambda} \quad \text{or} \quad w = \frac{x - q_{\text{new}}}{2\lambda}$$

$$\max_{\lambda} \mathcal{L}(\lambda) = y^{(m^*)} - \frac{(x^{(m^*)} - q_{\text{new}})^T (x^{(m^*)} - q_{\text{new}})}{2\lambda}$$

$$+ \lambda \left[ \sum_{m=1}^M \left( \frac{\|x^{(m)} - q_{\text{new}}\|_2^2}{4\lambda^2} \right) - \gamma^2 \right]$$

$$= y^{(m^*)} - \frac{\|x^{(m^*)} - q_{\text{new}}\|_2^2}{2\lambda} + \frac{\|x^{(m^*)} - q_{\text{new}}\|_2^2}{4\lambda} - \lambda \gamma^2$$

3-2-d

<https://colab.research.google.com/drive/1D0gUWAXJpealGwmBKLkZ1K9WR5ndePfq?usp=sharing>