

# Homework 3

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1. (a) True  
(b) True  
(c) True  
(d) True  
(e) True
2. For each following function,  $\text{dom}(f) = \mathbb{R}^n$  is a convex set. Therefore, we only need to show the Jensen inequality holds to prove that each function is convex.

(a)  $\forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^n, \forall t \in [0, 1],$

$$\begin{aligned} f(t\mathbf{x} + (1-t)\mathbf{y}) &= \max(tx_1 + (1-t)y_1, \dots, tx_n + (1-t)y_n) \\ &\leq t \max(x_1, \dots, x_n) + (1-t) \max(y_1, \dots, y_n) \\ &= tf(\mathbf{x}) + (1-t)f(\mathbf{y}) \end{aligned}$$

(b)  $\forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^n, \forall t \in [0, 1],$

$$\begin{aligned} f(t\mathbf{x} + (1-t)\mathbf{y}) &= \|t\mathbf{x} + (1-t)\mathbf{y}\|_p \\ &\leq \|t\mathbf{x}\|_p + \|(1-t)\mathbf{y}\|_p && (\because \text{Subadditivity}) \\ &= t\|\mathbf{x}\|_p + (1-t)\|\mathbf{y}\|_p && (\because \text{Homogeneity}) \\ &= tf(\mathbf{x}) + (1-t)f(\mathbf{y}) \end{aligned}$$

(c)  $\forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^n, \forall t \in [0, 1],$

$$\begin{aligned} f(t\mathbf{x} + (1-t)\mathbf{y}) &= \log \left( \sum_{i=1}^n e^{tx_i + (1-t)y_i} \right) \\ &= \log \left( \sum_{i=1}^n e^{tx_i} e^{(1-t)y_i} \right) \\ &\leq \log \left[ \left\{ \sum_{i=1}^n (e^{tx_i})^{\frac{1}{t}} \right\}^t \left\{ \sum_{i=1}^n (e^{(1-t)y_i})^{\frac{1}{1-t}} \right\}^{1-t} \right] && (\because \text{Hölder's inequality}) \\ &= t \log \left( \sum_{i=1}^n e^{x_i} \right) + (1-t) \log \left( \sum_{i=1}^n e^{y_i} \right) \\ &= tf(\mathbf{x}) + (1-t)f(\mathbf{y}) \end{aligned}$$

3. (a) *Proof.*

$\Rightarrow \forall x, y \in \text{dom}(f), \forall t \in (0, 1],$

$$\begin{aligned} f(y) &= \frac{tf(y) + (1-t)f(x) - (1-t)f(x)}{t} \\ &\geq \frac{f(ty + (1-t)x) - (1-t)f(x)}{t} \quad (\because \text{Convexity}) \\ &= f(x) + \frac{f(x + t(y-x)) - f(x)}{t} \end{aligned}$$

Since  $f$  is differentiable, we get

$$\begin{aligned} f(y) &= \lim_{t \rightarrow 0^+} f(y) \\ &\geq \lim_{t \rightarrow 0^+} \left( f(x) + \frac{f(x + t(y-x)) - f(x)}{t} \right) \\ &= f(x) + f'(x)(y-x) \end{aligned}$$

$\Leftarrow$ ) Let  $z = tx + (1-t)y$  for any  $x, y \in \text{dom}(f), t \in [0, 1]$ . By the inequality,

$$\begin{aligned} tf(x) + (1-t)f(y) &\geq t(f(z) + f'(z)(x-z)) + (1-t)(f(z) + f'(z)(y-z)) \\ &= f(z) + f'(z)(tx + (1-t)y - z) \\ &= f(z) = f(tx + (1-t)y) \end{aligned}$$

which means that  $f$  is convex. □

(b) *Proof.*

As we already proved (a), let's prove that  $\forall x, y \in \text{dom}(f), f(y) \geq f(x) + f'(x)(y-x) \iff \forall z \in \text{dom}(f), f''(z) \geq 0$  to solve this problem.

$\Rightarrow \forall x, y \in \text{dom}(f),$

$$\begin{aligned} f'(x)(y-x) &= f(x) + f'(x)(y-x) - f(x) \\ &\leq f(y) - f(x) \\ &\leq f(y) - (f(y) + f'(y)(x-y)) \\ &= f'(y)(y-x) \end{aligned}$$

Thus, we have

$$\begin{aligned} f''(x) &= \lim_{y \rightarrow x} \frac{f'(y) - f'(x)}{y-x} \\ &= \lim_{y \rightarrow x} \frac{(f'(y) - f'(x))(y-x)}{(y-x)^2} \\ &\geq 0 \end{aligned}$$

$\Leftarrow$ ) By the mean value version of the Taylor's theorem,

$$\forall x, y \in \text{dom}(f), \exists z \in [x, y] \text{ s.t. } f(y) = f(x) + f'(x)(y-x) + \frac{1}{2}f''(z)(y-x)^2$$

Since  $f''(z) \geq 0$ , we can get

$$f(y) \geq f(x) + f'(x)(y-x)$$

Thus,  $f$  is convex iff  $\forall z \in \text{dom}(f), f''(z) \geq 0$ . □

4. The Lagrangian of the primal problem is as follows.

$$\mathcal{L}(\mathbf{w}, b, \boldsymbol{\lambda}) = \frac{1}{2} \mathbf{w}^\top \mathbf{w} + \sum_{i=1}^N \lambda_i \{1 - y_i(\mathbf{w}^\top \mathbf{x}_i + b)\}$$

Then we can rewrite the primal problem with the Lagrangian.

$$\begin{aligned} & \underset{\mathbf{w}, b}{\text{minimize}} && \sup_{\boldsymbol{\lambda}} \mathcal{L}(\mathbf{w}, b, \boldsymbol{\lambda}) \\ & \text{s.t.} && \boldsymbol{\lambda} \geq \mathbf{0} \end{aligned}$$

We can use  $\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = 0$  and  $\frac{\partial \mathcal{L}}{\partial b} = 0$  to derive  $\inf_{\mathbf{w}, b} \mathcal{L}(\mathbf{w}, b, \boldsymbol{\lambda})$ .

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \mathbf{w}} &= \mathbf{w}^\top - \sum_{i=1}^N \lambda_i y_i \mathbf{x}_i^\top \Rightarrow \mathbf{w} = \sum_{i=1}^N \lambda_i y_i \mathbf{x}_i \\ \frac{\partial \mathcal{L}}{\partial b} &= - \sum_{i=1}^N \lambda_i y_i = 0 \Rightarrow \sum_{i=1}^N \lambda_i y_i = 0 \end{aligned}$$

By using these conditions, we have

$$\begin{aligned} \inf_{\mathbf{w}, b} \mathcal{L}(\mathbf{w}, b, \boldsymbol{\lambda}) &= \frac{1}{2} \mathbf{w}^\top \mathbf{w} + \sum_{i=1}^N \lambda_i - \mathbf{w}^\top \sum_{i=1}^N \lambda_i y_i \mathbf{x}_i - \left( \sum_{i=1}^N \lambda_i y_i \right) b \\ &= \frac{1}{2} \mathbf{w}^\top \mathbf{w} + \sum_{i=1}^N \lambda_i - \mathbf{w}^\top \mathbf{w} \\ &= -\frac{1}{2} \left( \sum_{i=1}^N \lambda_i y_i \mathbf{x}_i \right)^\top \left( \sum_{i=1}^N \lambda_i y_i \mathbf{x}_i \right) + \sum_{i=1}^N \lambda_i \\ &= -\frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \lambda_i \lambda_j y_i y_j \mathbf{x}_i^\top \mathbf{x}_j + \sum_{i=1}^N \lambda_i \end{aligned}$$

Thus, the Lagrangian dual problem of the primal is as below.

$$\begin{aligned} & \underset{\boldsymbol{\lambda}}{\text{maximize}} && \sum_{i=1}^N \lambda_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \lambda_i \lambda_j y_i y_j \mathbf{x}_i^\top \mathbf{x}_j \\ & \text{s.t.} && \boldsymbol{\lambda} \geq \mathbf{0}, \\ & && \sum_{i=1}^N \lambda_i y_i = 0 \end{aligned}$$

There exist  $\mathbf{w}$  and  $b$  that satisfy  $1 - y_i(\mathbf{w}^\top \mathbf{x}_i + b) \leq 0$  for  $i = 1, \dots, N$ . Thus,  $(2\mathbf{w}, 2b)$  is strictly feasible;  $1 - y_i((2\mathbf{w})^\top \mathbf{x}_i + (2b)) \leq -1 < 0$ . Since the convex problem satisfies the Slater's condition, the strong duality holds.