

#4.  $\phi''(x) \geq 0$  then  $\phi(x)$  is convex.

pf)  $\forall x_1, x_2 \in \mathbb{C}, x_1 \leq x_2, \eta \in (0,1)$

$$\frac{\phi(\eta x_1 + (1-\eta)x_2) - \phi(x_1)}{(1-\eta)(x_2 - x_1)} = \phi'(x_3) \quad \exists x_3 \in (x_1, \eta x_1 + (1-\eta)x_2) \text{ by Mean Value Theorem}$$

$$\frac{\phi(x_2) - \phi(\eta x_1 + (1-\eta)x_2)}{\eta(x_2 - x_1)} = \phi'(x_4) \quad \exists x_4 \in (\eta x_1 + (1-\eta)x_2, x_2) \text{ by M.V.T.}$$

$$\frac{\phi'(x_4) - \phi'(x_3)}{x_4 - x_3} = \frac{1}{(x_4 - x_3)} \frac{1}{(x_2 - x_1)} \left( \frac{\phi(x_2) - \phi(\eta x_1 + (1-\eta)x_2)}{\eta} - \frac{\phi(\eta x_1 + (1-\eta)x_2) - \phi(x_1)}{(1-\eta)} \right) = \phi''(c) \geq 0$$

$\exists c \in (x_3, x_4)$  by M.V.T

$$\therefore (1-\eta)(\phi(x_2) - \phi(\eta x_1 + (1-\eta)x_2)) \geq \eta(\phi(\eta x_1 + (1-\eta)x_2) - \phi(x_1))$$

$$\Leftrightarrow \eta \phi(x_1) + (1-\eta)\phi(x_2) \geq \phi(\eta x_1 + (1-\eta)x_2) \quad \square$$

o/pt,  $D_{KL}(p||q) \geq 0$   $\stackrel{a}{=} \text{v.l.}$

$$\text{pf) } f(x) = -\ln(x) \Rightarrow f'(x) = -\frac{1}{x} \Rightarrow f''(x) = \frac{1}{x^2} \geq 0 \quad (x > 0)$$

$\therefore$  since  $f''(x) > 0$ ,  $f(x)$  is convex. Therefore, by Jensen's inequality ( $P(I=i) = p_i$ )

$$\begin{aligned} D_{KL}(p||q) &= \mathbb{E}_I \left[ \log\left(\frac{p_I}{q_I}\right) \right] = -\mathbb{E}_I \left[ -\log\left(\frac{q_I}{p_I}\right) \right] \geq -\log\left(\mathbb{E}_I \left[ \frac{q_I}{p_I} \right]\right) \\ &= -\log\left(\sum_{i=1}^n p_i \frac{q_i}{p_i}\right) = -\log(1) = 0. \end{aligned}$$

$$D_{KL}(p||q) \geq 0 \quad \square$$

#5  $\phi''(x) > 0$  then  $\phi(x)$  is strictly convex:

pf)  $x_1 < x_2$ ,  $\eta \in (0, 1)$

$$\frac{\phi(\eta x_1 + (1-\eta)x_2) - \phi(x_1)}{(1-\eta)(x_2 - x_1)} = \phi'(x_3) \quad \exists x_3 \in (x_1, \eta x_1 + (1-\eta)x_2) \text{ by M.V.T}$$

$$\frac{\phi(x_2) - \phi(\eta x_1 + (1-\eta)x_2)}{\eta(x_2 - x_1)} = \phi'(x_4) \quad \exists x_4 \in (\eta x_1 + (1-\eta)x_2, x_2) \text{ by M.V.T}$$

$$\frac{\phi'(x_4) - \phi'(x_3)}{x_4 - x_3} = \phi''(c) > 0 \quad \exists c \in (x_3, x_4) \text{ by M.V.T}$$

$$\Leftrightarrow (1-\eta)(\phi(x_2) - \phi(\eta x_1 + (1-\eta)x_2)) > \eta(\phi(\eta x_1 + (1-\eta)x_2) - \phi(x_1))$$

$$\Leftrightarrow \eta \phi(x_1) + (1-\eta)\phi(x_2) > \phi(\eta x_1 + (1-\eta)x_2) : \text{strictly convex!} \quad \square$$

o/21,  $D_{KL}(p||q) > 0$  (p ≠ q)  $\Leftrightarrow \exists |z|$ .

$f(x) = -\ln(x) \Rightarrow f''(x) = \frac{1}{x^2} > 0$  ( $x > 0$ ) o/22  $f$  is strictly convex.  $\therefore$  By Jensen,

$$\phi(\mathbb{E}[X]) < \mathbb{E}[\phi(X)] \text{ holds for non constant r.v } X.$$

Consider random variable  $\frac{p_I}{q_I}$  where  $P(I=i) = p_i$ . Since  $p \neq q$ ,  $\frac{p_I}{q_I}$  is a non constant r.v

$$\therefore D_{KL}(p||q) = \mathbb{E}_I \left[ -\log \frac{p_I}{q_I} \right] > -\log \left( \mathbb{E}_I \left[ \frac{p_I}{q_I} \right] \right) = -\log \left( \sum_{i=1}^n p_i \cdot \frac{p_i}{p_i} \right) = -\log 1 = 0$$

$$\therefore D_{KL}(p||q) > 0 \quad \square$$

$$\#6 \quad f_{\theta}(x) = u^T \sigma(ax+b) = \sum_{j=1}^p u_j \sigma(a_j x + b_j)$$

$$\frac{\partial f_{\theta}(x)}{\partial u_j} = \sigma(a_j x + b_j) \quad \text{or} \quad \nabla_u f_{\theta}(x) = (\sigma(a_1 x + b_1), \dots, \sigma(a_p x + b_p)) = \underline{\sigma(ax+b)}$$

$$\begin{aligned} \frac{\partial f_{\theta}(x)}{\partial b_j} &= u_j \sigma'(a_j x + b_j) \quad \text{or} \quad \nabla_b f_{\theta}(x) = (u_1 \sigma'(a_1 x + b_1), \dots, u_p \sigma'(a_p x + b_p)) \\ &= \sigma'(ax+b) \odot u = \begin{pmatrix} a_1 x + b_1 & & 0 \\ & a_2 x + b_2 & \\ 0 & & \ddots & \\ & & & a_p x + b_p \end{pmatrix} \begin{pmatrix} u_1 \\ \vdots \\ u_p \end{pmatrix} = \text{diag}(\sigma'(ax+b)) u \end{aligned}$$

$$\begin{aligned} \frac{\partial f_{\theta}(x)}{\partial a_j} &= u_j \sigma'(a_j x + b_j) x \quad \text{or} \quad \nabla_a f_{\theta}(x) = x (u_1 \sigma'(a_1 x + b_1), \dots, u_p \sigma'(a_p x + b_p)) \\ &= (\sigma'(ax+b) \odot u) x = x \begin{pmatrix} a_1 x + b_1 & & 0 \\ & a_2 x + b_2 & \\ 0 & & \ddots & \\ & & & a_p x + b_p \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_p \end{pmatrix} = (\text{diag}(\sigma'(ax+b)) u) x \end{aligned}$$