

$$f \text{ Convex} \longrightarrow f_i(\theta u_i + (1-\theta)u_r) \leq \theta f_i(u_i) + (1-\theta)f_i(u_r), i=1, \dots, n \quad (a-1)$$

$$u_i, u_r \rightarrow g(u_i) \leq g(u_r) \longrightarrow g \circ f(\theta u_i + (1-\theta)u_r) \leq g(\theta f(u_i) + (1-\theta)f(u_r))$$

$$\underline{g \text{ is Convex}} \longrightarrow g \circ f(\theta u_i + (1-\theta)u_r) \leq \theta g \circ f(u_i) + (1-\theta)g \circ f(u_r)$$

$$\implies g \circ f \text{ is Convex}$$

$$f \text{ Convex strictly} \longrightarrow f(\theta u_i + (1-\theta)u_r) < \theta f(u_i) + (1-\theta)f(u_r) \quad (b)$$

$$u_i, u_r \rightarrow g(u_i) < g(u_r) \longrightarrow g \circ f(\theta u_i + (1-\theta)u_r) < g(\theta f(u_i) + (1-\theta)f(u_r))$$

$$\underline{g \text{ is Convex}} \longrightarrow g \circ f(\theta u_i + (1-\theta)u_r) < \theta g \circ f(u_i) + (1-\theta)g \circ f(u_r)$$

$$\implies g \circ f \text{ is strictly Convex}$$

$$f(x) - h(x) = f(x) - x^T w + \underbrace{\sup(x^T w - f(x))}_{g(x)} = -g(x) + \sup(g(x)) \quad -2$$

تاریخچه

$$g(x) \leq \sup_{\text{همه } w} g(x) \implies f(x) - h(x) = \sup(g(x)) - g(x) \geq 0$$

$$\implies f(x) \geq h(x)$$

$$\begin{array}{ccc} x^T x & \longrightarrow & 1 - x^T x \\ \text{Convex} & & \underline{\text{Concave}} \end{array}$$

از طرف می‌دانیم $\|x\|_2^2$ Convex است و اگر تابع $Ax+b$ affine ترکیب کنیم، $\|Ax+b\|_2^2$ Convex است.

ادامه صفحه بعد

می دانیم که تابع h برای $y > 0$ $Convex$ است: $y > 0 \rightarrow \frac{\partial h}{\partial n} \geq 0$ $\left(\frac{\partial h}{\partial y} \leq 0 \right)$ $\left(\|z\|_2 < 1 \right)$
 $h = \frac{x^2}{y}$ $y > 0$ $Convex$ $\frac{\partial h}{\partial y} \leq 0$ $f = \log(x)$

$$g(x) = (\|Ax - b\|^2 + 1 - x^T x)$$

Convex Concave

$$f'' = g'(x)^T \nabla^2 \log(x) g'(x) + \nabla \log(x)^T g''(x)$$

جواب: $\gamma_0 \quad \gamma_0 \Rightarrow f'' \geq 0$

$\begin{matrix} h \nearrow \\ \text{Gruen} \\ \searrow \end{matrix} \Rightarrow \begin{matrix} \text{Gruen} \\ \text{=1} \end{matrix}$

$\delta_1^- : \quad \downarrow$
 $>_0$ \ll_0 $\ll_0 \Rightarrow f'' >_0$

$$\text{Conver} \frac{\|Ax - b\|^r}{1 - x^T x} \leftarrow$$

$$f(x) = \prod_{i=1}^n (1 - e^{-x_i})^{a_i}$$

$$\frac{\partial f}{\partial \pi_i} = \frac{\lambda_i (1 - e^{-\pi_i})^{\lambda_i - 1} e^{-\pi_i}}{1 - e^{-\pi_i}} \prod_{i=1}^n (1 - e^{-\pi_i})^{\lambda_i} = \frac{\lambda_i}{-1 + e^{\pi_i}} \prod_{i=1}^n (1 - e^{-\pi_i})^{\lambda_i}$$

$$\frac{\partial f}{\partial \pi_i \partial \pi_j} = \frac{\lambda_i \lambda_j}{(e^{\pi_i} - 1)(e^{\pi_j} - 1)} \sum_{i=1}^n \frac{\pi_i}{\pi_i} (1 - e^{-\pi_i})^{\lambda_i}$$

$$\frac{\partial^r f}{\partial x_i^r} = \frac{\lambda_i^r}{(e^{x_{i-1}})^r} \frac{\pi}{i} (1 - e^{-x_i})^{\lambda_i} - \frac{\lambda_i}{(e^{x_{i-1}})^r} \frac{\pi}{i} (1 - e^{-x_i})^{\lambda_i} = \frac{\lambda_i (\lambda_i - 1)}{(e^{x_{i-1}})^r} \frac{\pi}{i} (1 - e^{-x_i})^{\lambda_i}$$

$$\lim_{\alpha \rightarrow 0} U_\alpha(x) = \lim_{\alpha \rightarrow 0} \frac{x^{\alpha-1}}{\alpha} \stackrel{\text{هوسپیتال}}{=} \lim_{\alpha \rightarrow 0} \frac{\frac{d}{d\alpha}(x^{\alpha-1})}{\frac{d}{d\alpha}(\alpha)} = \lim_{\alpha \rightarrow 0} x^\alpha \ln x = \underline{\ln x} = U_0(x) \quad (a-d)$$

$$\frac{d}{d\alpha} (U_\alpha(x)) = \frac{d}{d\alpha} \left(\frac{x^{\alpha-1}}{\alpha} \right) = \frac{1}{\alpha} \frac{\alpha}{x} x^\alpha = x^{\alpha-1} > 0 \Rightarrow \text{Monotone Increasing} \quad (b)$$

$x > 0$
 $0 < \alpha \leq 1$

$$\frac{d^2}{d\alpha^2} (U_\alpha(x)) = \frac{d}{d\alpha} \left(x^{\alpha-1} \right) = \frac{x^{\alpha-1}}{\alpha-1} \leq 0 \Rightarrow \text{Concave}$$

$\alpha \leq 1 \rightarrow \alpha-1 \leq 0$
 $\alpha = 1 \rightarrow 0 \leq 0$

(a-e) میدانیم $\log \sum_i \exp(g_i(x))$ در صورت محسوب بودن $g_i(x)$ ، محسوب است. از طرفی $a_i^T x + b_i$ محسوب

است پس $\log \sum_i \exp(a_i^T x + b_i)$ محسوب است $-\log \sum_i \exp(a_i^T x + b_i)$ مقعر است.

$$\left. \begin{array}{l} h(x) = -\log(x) \text{ , Concave , non-increasing} \\ g(x) = -\log \sum_i \exp(a_i^T x + b_i) \text{ , Concave} \end{array} \right\} \Rightarrow \text{Conven}$$

$$\left. \begin{array}{l} h(x) = -\sqrt{y}x \text{ , Conven} \\ g(x) = (u, v - \frac{x^T x}{u}) \end{array} \right\} \Rightarrow \log = -\sqrt{uv - x^T x} \quad (b)$$

$\frac{\partial h}{\partial x} = -\frac{\sqrt{y}}{2\sqrt{y}x} \leq 0 \rightarrow \text{decreasing}$
 $\frac{\partial h}{\partial y} = -\frac{\sqrt{x}}{2\sqrt{xy}}$
 $\frac{\partial g}{\partial u} = -\frac{1}{u} \leq 0 \rightarrow \text{decreasing}$
 $\frac{\partial g}{\partial v} = \frac{1}{u} > 0 \rightarrow \text{increasing}$

میدانیم $\frac{x^T x}{u}$ محسوب است پس $-\frac{x^T x}{u}$ مقعر است و چون v مقعر است، $v - \frac{x^T x}{u}$ مقعر است.

$$\left. \begin{array}{l} h(x) = -\log(x) \text{ , Concave , non-increasing} \\ g(x) = (u, v - \frac{x^T x}{u}) \end{array} \right\} \Rightarrow \log = -\log(uv - x^T x) \text{ (Conven)}$$

$\frac{\partial g}{\partial u} = -\frac{1}{u} \leq 0 \rightarrow \text{decreasing}$
 $\frac{\partial g}{\partial v} = \frac{1}{u} > 0 \rightarrow \text{increasing}$

$$\frac{\partial h}{\partial x} = -\frac{1}{x} \text{ , } \frac{\partial^2 h}{\partial x^2} = \frac{1}{x^2} \Rightarrow \nabla^2 h > 0 \Rightarrow \text{Conven}$$

$$\frac{\partial h}{\partial y} = \frac{1}{y} \text{ , } \frac{\partial h}{\partial y} = 0 \Rightarrow \nabla h < 0 \rightarrow \text{non-increasing}$$

(a - v)

$$f(x) = \|x\|^r, \quad h(x) = \sum_i x_i - 1$$

$$L(x) = \|x\|^r + v(\mathbf{1}^T x - 1)$$

$$\begin{cases} \frac{\partial L}{\partial x_i} = r x_i^{r-1} + v = 0 \quad i=1, \dots, n \rightarrow x_i^* = -\frac{v}{r} \quad i=1, \dots, n \end{cases}$$

$$\begin{cases} \mathbf{1}^T x^* - 1 = 0 \rightarrow \sum_i x_i^* = 1 \rightarrow -\frac{n v}{r} = 1 \rightarrow v = -\frac{r}{n} \Rightarrow x_i^* = \frac{1}{n} \quad i=1, \dots, n \end{cases}$$

$$f(x) = \sum_i x_i - 1, \quad h(x) = \|x\|^r - 1$$

(b)

$$L(x) = \mathbf{1}^T x - 1 + v(x^T x - 1)$$

$$\begin{cases} \frac{\partial L}{\partial x_i} = 1 + 2v x_i^* = 0 \quad i=1, \dots, n \rightarrow x_i^* = -\frac{1}{2v} \end{cases}$$

$$\begin{cases} x^T x - 1 = 0 \rightarrow \sum_i x_i^{*2} = 1 \rightarrow \frac{n}{4v^2} = 1 \rightarrow v = \frac{\sqrt{n}}{2} \Rightarrow x_i^* = -\frac{1}{\sqrt{n}} \quad i=1, \dots, n \end{cases}$$

$$\text{minimize } \|z - x\|^r$$

$$x \in \mathbb{R}^n$$

$$\text{s.t. } Ax = 0$$

$$m \times n$$

$$L(x, v) = (z - x)^T (z - x) + v Ax \rightarrow$$

$$\frac{\partial L}{\partial x} = v(x - z) + A^T v^T = 0 \rightarrow x = z - \frac{A^T v^T}{v}$$

$$g(v) = \inf_x L(x, v) = -\frac{1}{\epsilon} v A A^T v^T + v A z$$

Dual Problem \rightarrow

$$\begin{aligned} \text{maximize } & -\frac{1}{\epsilon} v A A^T v^T + v A z \\ & = -\frac{1}{\epsilon} \|v A\|_F^2 + v A z \end{aligned}$$

$$\begin{aligned} & -\frac{1}{\epsilon} (A^T v + z)^T (A^T v + z) \\ & - z^T z \\ & \downarrow \\ & \|z\|^2 \end{aligned}$$

$$\underset{x}{\text{minimize}} \sum_k x_k \log\left(\frac{x_k}{y_k}\right)$$

(a-9)

$$\text{s.t.} \quad Ax = b \rightarrow \sum_k a_k x_k = b$$

$$1^T x = 1 \rightarrow \sum_k x_k = 1$$

$$L(x, v) = \sum_k x_k \log\left(\frac{x_k}{y_k}\right) + \underbrace{v_1}_{1 \times n} \left(\sum_k a_k x_k - b \right) + v_2 \left(\sum_k x_k - 1 \right)$$

$$\frac{\partial L}{\partial x_i} = \log\left(\frac{x_i}{y_i}\right) + y_i + v_1 a_k + v_2 \quad i=1, \dots, n \rightarrow x_i^* = y_i e^{-y_i - v_1 a_k - v_2}$$

$$g(v) = \sum_k y_k (-y_k - v_1 a_k - v_2) e^{-y_k - v_1 a_k - v_2} + v_1 \left(\sum_k a_k y_k e^{-y_k - v_1 a_k - v_2} - b \right) + v_2 \left(\sum_k y_k e^{-y_k - v_1 a_k - v_2} - 1 \right)$$

$$= - \sum_k y_k^2 e^{-y_k - v_1 a_k - v_2} \approx v_1 b - v_2$$

$$\sum_k y_k^2 e^{-y_k - v_1 a_k - v_2} = - \log \sum_k y_k^2 e^{-y_k - v_1 a_k - v_2}$$

Dual
Problem

$$\text{maximize} \quad - \sum_k y_k^2 e^{-y_k - v_1 a_k - v_2} - v_1 b - v_2$$

(b)

$$\frac{\partial}{\partial v_2} g(v_1, v_2) = + e^{-v_2} \sum_k y_k^2 e^{-y_k - v_1 a_k} - 1 = 0 \rightarrow v_2^* = + \log \sum_k y_k^2 e^{-y_k - v_1 a_k}$$

$$\text{sub } \frac{\partial}{\partial v_1} g(v_1, v_2) = - \sum_k y_k^2 e^{-y_k - v_1 a_k} - \log \sum_k y_k^2 e^{-y_k - v_1 a_k} - v_1 b - \log \sum_k y_k^2 e^{-y_k - v_1 a_k}$$

$$= - \frac{\sum_k y_k^2 e^{-y_k - v_1 a_k}}{\sum_k y_k^2 e^{-y_k - v_1 a_k}} - v_1 b - \log \sum_k y_k^2 e^{-y_k - v_1 a_k}$$

$$= -1 \underbrace{(-v_1)}_{z^T} b - \log \sum_k \underbrace{y_k^2 e^{-y_k}}_{y_k} e^{-\underbrace{v_1}_{z^T} a_k}$$

$$\Rightarrow \text{maximize} \quad b^T z - \log \sum_k y_k e^{a_k^T z}$$