

∴ (a)  $(\log x)'' = -\frac{1}{x^2} < 0$ , so  $y = \log x$  is concave on  $(0, +\infty)$ .

Let  $k = \|x\|_0$ . Assume that  $x_i \neq 0$ ,  $i = 1, 2, \dots, k$ .

Then  $H(x) = -\sum_{i=1}^k x_i \log x_i = \sum_{i=1}^k x_i \log \frac{1}{x_i} \leq \log k \leq \log n$ .

(b)  $H(\bar{x}) = \log n$ , so  $\bar{x}$  is a maximum point.

Let  $C = \{x \in \Delta_{n-1} : x_i > 0, i = 1, 2, \dots, n\}$

If  $x \in C$ ,  $\nabla^2 H(x) = \text{diag}(-\frac{1}{x_1}, -\frac{1}{x_2}, \dots, -\frac{1}{x_n})$

Obviously  $\nabla^2 H(x)$  is negative definite, so  $H(x)$  is strictly concave on  $C$ . Thus  $\bar{x}$  is the unique maximum point on  $C$ .

If  $x \in \Delta_{n-1} \setminus C$ ,  $k < n$ ,  $H(x) \leq \log k < \log n$ .

Thus,  $\bar{x}$  is the unique maximum point on  $\Delta_{n-1}$ .

$$2. (a) \frac{(\mu-s)f(u) + (u-\mu)f(s)}{u-s} \geq f\left(\frac{\mu-s}{u-s} \cdot u + \frac{u-\mu}{u-s} \cdot s\right) = f(\mu)$$

$$(u-\mu)(f(\mu) - f(s)) \leq (\mu-s)(f(u) - f(\mu))$$

$$\text{so } \frac{f(\mu) - f(s)}{\mu-s} \leq \frac{f(u) - f(\mu)}{u-\mu}$$

$$(b) \text{ Let } \beta = \sup_{a < s < \mu} \frac{f(\mu) - f(s)}{\mu-s}, \exists u_0 \in (\mu, b), \forall s \in (a, \mu),$$

$$\frac{f(\mu) - f(s)}{\mu-s} \leq \frac{f(u_0) - f(\mu)}{u_0 - \mu} < +\infty, \text{ so } -\infty < \beta < +\infty.$$

$$\text{If } a < x < \mu, \frac{f(\mu) - f(x)}{\mu-x} \leq \beta, \text{ so } f(x) \geq f(\mu) + \beta(x-\mu)$$

$$\text{If } \mu < x < b, \frac{f(x) - f(\mu)}{x-\mu} \geq \beta \text{ (otherwise we can find } u_0,$$

$$\text{s.t. } \frac{f(\mu) - f(s)}{\mu-s} \leq \frac{f(u_0) - f(\mu)}{u_0 - \mu} < \beta, \text{ so } \beta \text{ is not the supremum)}$$

$$\text{so } f(x) \geq f(\mu) + \beta(x-\mu),$$

If  $x = \mu$ , the proposition is trivial.

$$(c) X \in (a, b), \text{ so } f(X) \geq f(\mu) + \beta(X-\mu)$$

$$E[f(X)] \geq E[f(\mu) + \beta(X-\mu)]$$

$$= E[f(\mu)] + \beta(E[X] - E[\mu])$$

$$= f(E[X]) \quad (\text{If } k \text{ is constant, then } E[k] = k.)$$

3.  $\|x\|$  is convex.  $x^3$  is increasing  $\Rightarrow \|x\|^3$  is convex.

$\Rightarrow \|Ax+b\|^3$  is convex.

$e^x$  is convex.  $f(x_1, x_2) = \log(x_1 + x_2)$  is increasing

$\Rightarrow \log(e^{x_1} + e^{x_2})$  is convex  $\Rightarrow \log(1 + e^{3x_1 + 2x_2})$  is convex

(Let  $\begin{pmatrix} x_1' \\ x_2' \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 3 & 2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$ .)

$\|Ax+b\|^3$  and  $\log(1 + e^{3x_1 + 2x_2})$  are convex

$\Rightarrow \max\{\|Ax+b\|^3, \log(1 + e^{3x_1 + 2x_2})\}$  is convex.

Sublevel sets of convex functions are convex sets, so  $S$  is convex.

4. (a) let  $f(x) = x_1^2 - 2x_1x_2 + x_2^2 + x_1 + x_2$ .

$$\nabla^2 f(x) = \begin{pmatrix} 2 & -2 \\ -2 & 2 \end{pmatrix}$$

$$|2| > 0, \quad \begin{vmatrix} 2 & -2 \\ -2 & 2 \end{vmatrix} = 0, \quad \text{so } \nabla^2 f(x) \succeq 0.$$

$f(x)$  is a convex function.

$x^2$  and  $e^x$  are convex functions. Similar to problem 4 of homework 3, we know that  $x_1^2 + e^{x_2}$  is a convex function. Let  $\begin{pmatrix} x_1' \\ x_2' \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$ . Then

$$(x_1 + x_2)^2 + e^{x_1 + x_2} = (x_1 - x_2)^2 + 4x_1x_2 + e^{x_1 + x_2}$$

is a convex function.

$x_1 - 3x_2$  is an affine function.

Thus, (a) is a convex optimization problem.

(b)  $6x_1^2 - 7x_2$  is not an affine function, so (b) is not a convex optimization problem.