

Convex Optimization

Homework #08

Submitted By: Rifat Bin Rashid

RUID: 237000174

Date: Apr 25, 2025

Problem 1:

Given, $a_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$, $a_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$, $a_3 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

$$C = \text{cone}\{a_1, a_2\}$$

$$C = \left\{ \theta_1 a_1 + \theta_2 a_2 \mid \theta_1, \theta_2 \geq 0 \right\}$$

This is all non-negative combinations of standard basis vectors a_1 & a_2

So, C fills the entire first quadrant of \mathbb{R}^2 .

$$D = \text{cone}\{a_1, a_2, a_3\}$$

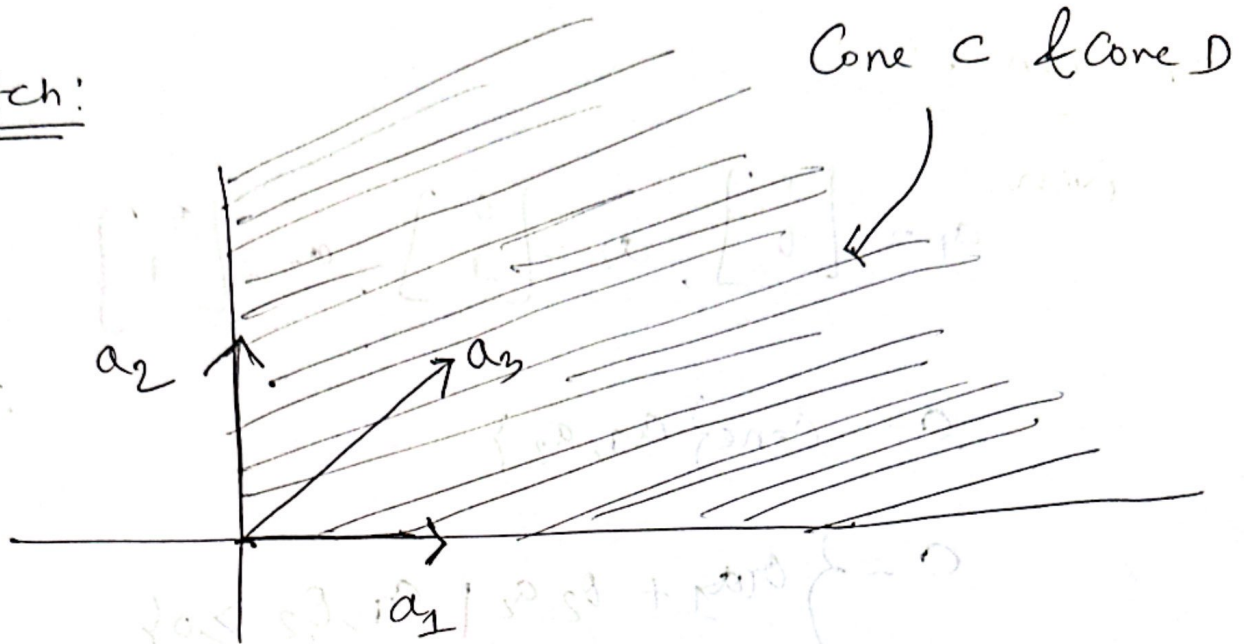
$$= \left\{ \theta_1 a_1 + \theta_2 a_2 + \theta_3 a_3 \mid \theta_1, \theta_2, \theta_3 \geq 0 \right\}$$

Here, $a_3 = a_1 + a_2$, so a_3 is already inside the cone generated by a_1 & a_2

So, adding a_3 doesn't change the cone

So, D also fills the first quadrant of \mathbb{R}^2

Sketch:



Problem 2

let's take

$$(\bar{x}, \bar{y}_1 + \bar{y}_2), (x', y'_1 + y'_2) \in S$$

with

$$(\bar{x}, \bar{y}_1) \in S_1 \quad (x', y'_1) \in S_1$$

$$(\bar{x}, \bar{y}_2) \in S_2 \quad (x', y'_2) \in S_2$$

now, for $\alpha \in [0, 1]$

$$\alpha (\bar{x}, \bar{y}_1 + \bar{y}_2) + (1-\alpha) (x', y'_1 + y'_2)$$

$$= \left(\alpha \bar{x} + (1-\alpha) x', \begin{pmatrix} \alpha \bar{y}_1 + (1-\alpha) y'_1 \\ \alpha \bar{y}_2 + (1-\alpha) y'_2 \end{pmatrix} \right)$$

This belongs to S

Because by convexity of S_1 :

$$(\alpha \bar{x} + (1-\alpha) x', \alpha \bar{y}_1 + (1-\alpha) y'_1) \in S_1$$

similarly, by convexity of S_2 :

$$(\alpha \bar{x} + (1-\alpha) x', \alpha \bar{y}_2 + (1-\alpha) y'_2) \in S_2$$

Hence, s is convex.

Problem 3:

let $y_1, y_2 \in C$

By definition, $\forall x \in C$,

$$y_1^T x \leq 1 \quad \& \quad y_2^T x \leq 1 \quad \dots (i)$$

Now, let's take: $y = \theta y_1 + (1-\theta)y_2$, $\theta \in [0, 1]$

for any $x \in C$,

$$\begin{aligned} y^T x &= (\theta y_1 + (1-\theta)y_2)^T x \\ &= \theta y_1^T x + (1-\theta)y_2^T x \end{aligned}$$

$$\begin{aligned} \text{But, } y_1^T x &\leq 1, \quad y_2^T x \leq 1 \quad [\text{from (i)}] \\ &\& \quad \theta \in [0, 1] \end{aligned}$$

$$\underline{\text{So}} \quad y^T x \leq \theta \cdot 1 + (1-\theta) \cdot 1 = 1$$

So, $y^T x \leq 1 \quad \forall x \in C$

$$\text{so, } y \in C^0$$

so, C^0 is convex.

Problem 4:

hypograph of g : $[\text{hyp}(g)]$

$$\text{hyp}(g) = \{ (y, t) \mid y \in \text{dom}(g), t \leq g(y) \}$$

This is the set of all the points lying on or below the graph of $g(y)$.

now, if $\text{hyp}(g)$ is convex $\rightarrow g$ is concave.

Now,

g is inverse of f

$$\text{so, } t \leq g(y)$$

$$\Rightarrow f(t) \leq y \quad (f \text{ is increasing})$$

$$\text{so, } \text{hyp}(g) = \{ (y, t) \mid f(t) \leq y, t \in (a, b), y \in (f(a), f(b)) \}$$

Now, let's take, $(y_1, t_1), (y_2, t_2) \in \text{hyp}(g)$

$$\text{So, } \begin{aligned} f(t_1) &\leq y_1 \\ f(t_2) &\leq y_2 \end{aligned} \quad \text{--- (i)}$$

So, for any $\theta \in [0, 1]$,

$$\begin{aligned} \text{Let, } (y, t) &= \theta(y_1, t_1) + (1-\theta)(y_2, t_2) \\ &= (\theta y_1 + (1-\theta)y_2, \theta t_1 + (1-\theta)t_2) \end{aligned}$$

Since f is convex,

$$f(t) = f(\theta t_1 + (1-\theta)t_2) \leq \theta f(t_1) + (1-\theta)f(t_2)$$

$$\xrightarrow{\text{from (i)}} f(t) \leq \theta y_1 + (1-\theta)y_2 = y$$

$$\text{So, } f(t) \leq y \implies (y, t) \in \text{hyp}(g)$$

So $\text{hyp}(g)$ is convex

Hence, $\boxed{g \text{ is concave}}$

Problem 5:

Restricting to a line:

$$\text{let, } g(t) = f(z + tV) = \ln((z + tV)^{-1})$$

$$\text{where, } z > 0 \text{ (P.D.)}$$

$$\& V \in S^n$$

Now,

$$(z + tV)^{-1} = z^{-\frac{1}{2}} \left(I + t z^{-\frac{1}{2}} V z^{-\frac{1}{2}} \right) z^{-\frac{1}{2}}$$

$$= z^{-\frac{1}{2}} \left(I + t \tilde{V} \right)^{-1} z^{-\frac{1}{2}}$$

$$\text{where, } \tilde{V} = z^{-\frac{1}{2}} V z^{-\frac{1}{2}}$$

Now, \tilde{V} is symmetric, so it can be diagonalized.

$$\tilde{V} = Q \Lambda Q^T$$

where, Q is an orthogonal matrix ($QQ^T = I$)

Λ is diagonal matrix

Now,

$$\begin{aligned} I + t\tilde{V} &= I + tQ\Lambda Q^T \\ &= Q(I + t\Lambda)Q^T \quad ; \text{ because } Q \\ &\quad \text{is orthogonal} \end{aligned}$$

So, $(I + t\tilde{V})^{-1} = Q(I + t\Lambda)^{-1}Q^T$

So, $g(t) = \text{tr}((I + t\tilde{V})^{-1}) = \text{tr}(Q^{-1/2}Q(I + t\Lambda)^{-1}Q^T Q^{-1/2})$

Now, From cyclic property of trace:

$$\text{tr}(ABC) = \text{tr}(BCA) = \text{tr}(CAB)$$

So, $g(t) = \text{tr}\left(Q^T Q^{-1/2}Q(I + t\Lambda)^{-1}\right)$

Now, $Q^T Q^{-1/2}Q$ is symmetric

$(I + t\Lambda)^{-1}$ is diagonal with entries $(1 + t\lambda_i)^{-1}$

So, $g(t) = \sum_{i=1}^n (Q^T Q^{-1/2}Q)_{ii} (1 + t\lambda_i)^{-1}$

This is a weighted sum of functions of the form:

$$(1 + t \lambda_i)^{-1}$$

Now, let, $\phi_i(t) = \frac{1}{1 + t \lambda_i}$

So, $\phi_i'(t) = -\lambda_i (1 + t \lambda_i)^{-2}$

$$\phi_i''(t) = 2\lambda_i^2 (1 + t \lambda_i)^{-3}$$

Here,

$$(1 + t \lambda_i)^{-3} > 0 \text{ when } 1 + t \lambda_i > 0$$

This is true if t is in a region where $2 + t \lambda_i > 0$

So, $\phi_i''(t) \geq 0 \rightarrow$ so $\frac{1}{1 + t \lambda_i}$ is convex

Now, a positive weighted sum of convex functions is convex

So, $\boxed{g(t) \text{ is convex}}$

Problem 6:-

Hence each $\|A^{(i)}x - b^{(i)}\|$ is convex

Because,

⊛ norm $\|\cdot\|$ is convex

⊛ $A^{(i)}x - b^{(i)}$ is affine in x

So, the composition $\|A^{(i)}x - b^{(i)}\|$ is convex

Since convex functions composed with affine function remain convex.

Now, let, $f_i(x) = \|A^{(i)}x - b^{(i)}\|$ is convex

So, $f(x) = \max \{f_1(x), \dots, f_n(x)\}$ is the pointwise maximum of convex functions.

for $\theta \in [0, 1]$ then, $\forall x, y \in \mathbb{R}^n$:

$$f(\theta x + (1-\theta)y) = \max_i \|A^{(i)}(\theta x + (1-\theta)y) - b^{(i)}\|$$

By convexity of each f_i :

$$\begin{aligned} & \|A^{(i)}(\theta x + (1-\theta)y) - b^{(i)}\| \\ & \leq \theta \|A^{(i)}x - b^{(i)}\| + (1-\theta) \|A^{(i)}y - b^{(i)}\| \end{aligned}$$

Taking maximum over i :

$$\begin{aligned} f(\theta x + (1-\theta)y) & \leq \theta \max_i \|A^{(i)}x - b^{(i)}\| \\ & + (1-\theta) \max_i \|A^{(i)}y - b^{(i)}\| \\ & = \theta f(x) + (1-\theta) f(y) \end{aligned}$$

Thus, f is convex.

Problem 7:

Given, $\log \sum_{i=1}^n e^{y_i}$ is convex

So, $g(x) = \log \left(\sum_{i=1}^n e^{a_i^T x + b_i} \right)$ is convex

because it is a composition of log-sum-exp function & an affine mapping after that

So, $-g(x)$ is concave

Now, $h(y) = -\log y$ is convex & decreasing

Because, $\nabla^2 h(y) = \frac{1}{y^2} > 0$ for $y > 0$

So, $f(x) = h(-g(x))$ is convex,

Because,

$-g(x)$ is concave
 $h(y)$ is convex & decreasing
 $\left. \begin{array}{l} \text{if } \phi \text{ is convex \& decreasing} \\ \text{and if } \psi \text{ is concave} \end{array} \right\} \Rightarrow \text{then } \phi(\psi(x)) \text{ is convex}$

Problem 8:

f & g are convex.

So, $\forall x, y \in I$ & $\theta \in [0, 1]$

$$f(\theta x + (1-\theta)y) \leq \theta f(x) + (1-\theta)f(y) \quad \text{--- (1)}$$

$$g(\theta x + (1-\theta)y) \leq \theta g(x) + (1-\theta)g(y) \quad \text{--- (2)}$$

Now,

$$h(x) = f(x) g(x)$$

$$h(\theta x + (1-\theta)y) = f(\theta x + (1-\theta)y) \cdot g(\theta x + (1-\theta)y)$$

$$\leq \left(\theta f(x) + (1-\theta)f(y) \right) \left(\theta g(x) + (1-\theta)g(y) \right)$$

[using (1) & (2)]

So,

$$h(\theta x + (1-\theta)y) \leq \theta^2 f(x) g(x) + \theta(1-\theta)[f(x)g(y) + f(y)g(x)] + (1-\theta)^2 f(y)g(y)$$

Now,
if f and g are nondecreasing, then for $x \leq y$:

$$f(x) \leq f(y)$$

$$g(x) \leq g(y)$$

So,

$$f(x)g(y) + f(y)g(x) \leq f(x)g(x) + f(y)g(y)$$

for f & g are nonincreasing, the same inequality holds because the signs align.

So,

$$h(\theta x + (1-\theta)y) \leq \theta^2 f(x)g(x) + \theta(1-\theta)[f(x)g(y) + f(y)g(x)] + (1-\theta)^2 f(y)g(y)$$

$$h(\theta x + (1-\theta)y) \leq \theta^2 h(f(x)g(x)) + (1-\theta)^2 h(f(y)g(y)) + 2\theta(1-\theta)h(f(x)g(y))$$

$$h(\theta x + (1-\theta)y) \leq \theta h(x) + (1-\theta) h(y)$$

So, h is convex on I