

\mathcal{D}_1 is convex

P1(a) Proof: $\|x-a\| \leq \|x-b\|$ That is $\|x-a\|^2 \leq \|x-b\|^2$

$$\text{Or } -2a^T x + \|a\|^2 \leq -2b^T x + \|b\|^2$$

$$\Leftrightarrow 2(b^T - a^T)x \leq \|b\|^2 - \|a\|^2$$

$$\text{for } x, y \in \mathbb{R} \quad \lambda x + (1-\lambda)y \rightarrow 2(b^T - a^T)(\lambda x + (1-\lambda)y)$$

$$= \lambda \cdot 2(b^T - a^T)x + (1-\lambda) \cdot 2(b^T - a^T)y$$

$$\leq \lambda(\|b\|^2 - \|a\|^2) + (1-\lambda)(\|b\|^2 - \|a\|^2)$$

$$= \|b\|^2 - \|a\|^2 \rightarrow \text{So it is a convex set}$$

~~\mathcal{D}_2~~ \mathcal{D}_2 is convex Proof: let $f(x, t) = x^T x - t = \|x\|^2 - t$

$$\text{convex, id } \nabla f(x, t) = \begin{pmatrix} 2x \\ -1 \end{pmatrix}, \nabla^2 f(x, t) = \begin{pmatrix} 2I & 0 \\ 0 & 0 \end{pmatrix} \geq 0.$$

By Hessian, $\nabla^2 g$ is positive for $(x, t) \in \mathbb{R}^n \times \mathbb{R}$, g is convex $\rightarrow \mathcal{D}_2$ is

(b) $\mathbb{R}_+^2 = \{x \in \mathbb{R}^2, x \geq 0\}$ So the set is $x_1 x_2 \geq 0$ for $x \in \mathbb{R}^2, x \geq 0$ convex

$x_1 x_2 \geq 0$ that is $f(x_1, x_2) := -\log x_1 - \log x_2 \leq 0$

$$\text{gradient } \nabla f(x_1, x_2) = \begin{pmatrix} -\frac{1}{x_1} \\ -\frac{1}{x_2} \end{pmatrix}, \nabla^2 f(x_1, x_2) = \begin{pmatrix} \frac{1}{x_1^2} & 0 \\ 0 & \frac{1}{x_2^2} \end{pmatrix}$$

$\nabla^2 f > 0$ on $\mathbb{R}_+^2 \rightarrow f$ is convex $\rightarrow \mathcal{D}_2$ is convex

(c) let $x, y \in \mathbb{R}$ $\lambda \in [0, 1]$ $(x, f(x)), (y, f(y)) \in S$.

By convex of S . $\lambda(x, f(x)) + (1-\lambda)(y, f(y)) = (\lambda x + (1-\lambda)y, \lambda f(x) + (1-\lambda)f(y)) \in S$.

$$\rightarrow f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)f(y)$$

Since $x, y \in \mathbb{R}$ $\lambda \in [0, 1] \rightarrow f$ convex on \mathbb{R} .

P2(a) False. let $g(x) = x^2, f(x) = -x^2, f(g(x)) = -x^2$

where $g(x), f(x)$ convex and $f(g(x))$ concave.

(b) True. $x, y \in \mathbb{R}$ $\lambda \in [0, 1]$ convex of $g \rightarrow g(\lambda x + (1-\lambda)y) \leq \lambda g(x) + (1-\lambda)g(y)$

I is convex $g(\mathbb{R}) \subset \mathbb{R} \rightarrow \lambda g(x) + (1-\lambda)g(y) \in I$.

f is nondecreasing, $f(g(\lambda x + (1-\lambda)y)) \leq f(\lambda g(x) + (1-\lambda)g(y)) \leq \lambda f(g(x)) + (1-\lambda)f(g(y))$

So $f \circ g$ is convex.

P3 ① $f(x) = \sqrt{1+x^2}, f'(x) = \frac{1}{2}(1+x^2)^{-\frac{1}{2}}(-2x), f''(x) = -(1+x^2)^{-\frac{1}{2}} + -\frac{1}{4}(1+x^2)^{-\frac{3}{2}}(4x^2)$

all continuous and differentiable on $\mathbb{R} \setminus \{0\}$

$$\text{for } f''(x) \text{ that is } \frac{2x\sqrt{1+x^2} + x^2}{x^4(1+x^2)} = \frac{3x^2 + 2}{x^3(1+x^2)\sqrt{1+x^2}} > 0 \text{ for } x \neq 0$$

f convex on $\mathbb{R} \setminus \{0\}$

$$\textcircled{2} \quad f(w) := \frac{1}{2}\|Ax-b\|^2 + \mu\|Lx\|_1$$

$\frac{1}{2}\|x\|^2$ is convex $\rightarrow x \mapsto \frac{1}{2}\|\lambda x + b\|^2$ is a linear and convex function

By triangle inequality, L_1 norm $\|\lambda x + (1-\lambda)y\|_1 \leq \lambda \|x\|_1 + (1-\lambda)\|y\|_1$, $\lambda \in [0, 1]$
 $\rightarrow x \mapsto \|x\|_1$ is convex. $\rightarrow x \mapsto \|Lx\|_1$ is a convex function

$\rightarrow f$ convex

$$\textcircled{3} \text{ let } g(x, y) = \frac{1}{2}\|x\|^2 \quad g_i(x, y) = \ln(1 + e^{-b_i(a_i^T x + y)})$$

$$f = \sum g_i \geq g_i \geq g + \sum g_i, \quad g \text{ and } g_i \text{ is convex}$$

mapping $g_i: z \mapsto \gamma(z) = \ln(1 + e^z)$ affine-linear func. $(x, y) \mapsto h_i(x, y) := -b_i(a_i^T x + y)$
 h_i convex $\rightarrow g_i$ convex when y convex

$$\text{for } g_i'(z) = \left(\frac{e^z}{1+e^z}\right)' = \frac{e^z}{(1+e^z)^2} > 0 \rightarrow g_i \text{ convex}$$

$$\text{Hessian of } g \quad \nabla^2 g(x, y) = \begin{pmatrix} I & 0 \\ 0 & 0 \end{pmatrix} \geq 0 \quad \text{where } \nabla^2 g(x, y) \in \mathbb{R}^{(n+m) \times (n+m)}$$

So f convex.

(b) Constraints are linear and convex. Mapping $(x, w) \mapsto \sum_i \frac{1}{2} \|w_i\|^2$ is linear and convex

So just prove convexity of the function define $\gamma: \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$, $\gamma(u, v) = \frac{u^2}{1+v}$

$$\text{So } \sum_{i=1}^m \frac{(a_i^T x - b_i)^2}{1+w_i} = \sum_{i=1}^m \gamma(a_i^T x - b_i, e_i^T w), \quad e_i = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ i \end{bmatrix}$$

$$\nabla \gamma(u, v) = \begin{pmatrix} \frac{2u}{1+v} \\ -\frac{u^2}{(1+v)^2} \end{pmatrix}, \quad \nabla^2 \gamma(u, v) = \begin{pmatrix} \frac{2}{1+v} & -\frac{2u}{(1+v)^2} \\ -\frac{2u}{(1+v)^2} & \frac{2u^2}{(1+v)^3} \end{pmatrix}$$

$$\text{so } \text{tr}(\nabla^2 \gamma(u, v)) = \frac{2}{1+v} \left(1 + \frac{u^2}{\frac{2u^2}{(1+v)^2}} \right) > 0.$$

$$\text{det}(\nabla^2 \gamma(u, v)) = \frac{4u^2}{(1+v)^4} - \frac{4u^2}{(1+v)^4} = 0 \quad \forall (u, v) \in \mathbb{R} \times \mathbb{R}^+$$

So $\nabla^2 \gamma > 0$ on $\mathbb{R} \times \mathbb{R}^+$ So γ is convex

$\text{So } (x, w) \mapsto \gamma(a_i^T x - b_i, e_i^T w)$ is convex

\rightarrow The function is convex.

P4 Lagrangian func. is $\mathcal{L}(y, \lambda) = \frac{1}{2}\|y - x\|^2 + \lambda(a^T y - b)$

Primal $a^T y = b$

$$\text{Stationary } \frac{\partial \mathcal{L}}{\partial y} = y - x + \lambda a = 0 \quad y = x - \lambda a$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = a^T y - b \quad \text{or} \quad a^T(x - \lambda a) = b \rightarrow \lambda = \frac{a^T x - b}{a^T a}$$

$$\rightarrow y = x - \frac{a^T x - b}{a^T a} a.$$