

Convex Optimisation
Homework 1

2.12. Let $H_n(a, b) = \{x \in \mathbb{R}^n \mid a^T x \leq b\}$, $a \in \mathbb{R}^n$, $b \in \mathbb{R}$.
 $(H_n(a, b)$ define ~~is~~ a halfspace and is convex)

a) $A(\alpha, \beta) = \{x \in \mathbb{R}^n \mid \alpha \leq a^T x \leq \beta\}$ convex?

As $A = H(a, \beta) \cap H(-a, -\alpha)$, A is convex. (intersection of convex sets)

b) $B(\alpha, \beta) = \{x \in \mathbb{R}^n \mid \forall i \in \{1, n\}, \alpha_i \leq x_i \leq \beta_i\}$ convex?

with $a_{ij} = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{otherwise} \end{cases}$ ($a_{ii}=1$, $a_{ij}=0$ for $i \neq j$), then B can be expressed as

$$B = \bigcap_{i=1}^n H(-\alpha_i, -\beta_i) \cap H(\alpha_i, \beta_i)$$

B is therefore convex.

c) $C_{a_1, b_1, a_2, b_2} = \{x \in \mathbb{R}^n \mid a_1^T x \leq b_1, a_2^T x \leq b_2\}$ is clearly convex as

$$C = H(a_1, b_1) \cap H(a_2, b_2)$$

d) $D(x_0, S) = \{x \in \mathbb{R}^n \mid \|x - x_0\|_2 \leq \|x - y\|_2 \text{ for } y \in S\}$ convex?

~~Let $x_1, x_2 \in D(x_0, S)$, then $\forall y \in S$, $\|x_1 - y\|_2 \leq \|x_0 - y\|_2$ and $\|x_2 - y\|_2 \leq \|x_0 - y\|_2$.~~

~~if $t x_1 + (1-t)x_2 - x_0\|_2 = \|t(x_1 - x_0) + (1-t)(x_2 - x_0)\|_2$~~

~~$\leq t\|x_1 - x_0\|_2 + (1-t)\|x_2 - x_0\|_2$ (triangle inequality)~~

~~$\leq t\|x_1 - y\|_2 + (1-t)\|x_2 - y\|_2$~~

$$D(x_0, S) = \bigcap_{y \in S} \{x \in \mathbb{R}^n \mid \|x - x_0\|_2 \leq \|x - y\|_2\}$$

$$= \bigcap_{y \in S} \{x \in \mathbb{R}^n \mid (x - x_0)^T (x - x_0) \leq (x - y)^T (x - y)\} \quad \text{by def of } \| \cdot \|_2^2$$

$$= \bigcap_{y \in S} \{x \in \mathbb{R}^n \mid (-2x_0 + 2y)^T x \leq y^T y - x_0^T x_0\}$$

$$= \bigcap_{y \in S} H(2(y - x_0), \|y\|_2^2 - \|x_0\|_2^2)$$

D is therefore convex.

e) $E(S, T) = \{x \in \mathbb{R}^n \mid \text{dist}(x, S) \leq \text{dist}(x, T)\}$ convex?

E is not convex: let's see a counterexample in \mathbb{R} :

$$S = \mathbb{R} \setminus [0, 1]$$

$$T = [0, 1]$$

Then we have clearly $E(S, T) = S$ which is not convex.

f) $F(S_1, S_2) = \{x \in \mathbb{R}^n \mid x + S_2 \subset S_1\}$ with S_1 convex.

Let $x, y \in F(S_1, S_2)$, $t \in [0, 1]$

Let $s \in tx + (1-t)y + S_2$, $s = tx + (1-t)y + s'$, $s' \in S_2$

then $s = t(x + s') + (1-t)(y + s')$.

as $x \in F(S_1, S_2)$, $x + s' \in S_1$ (because $x + S_2 \subset S_1$)

and $y + s' \in S_1$ (same reason)

Thanks to S_1 convexity, $s \in S_1$

Therefore $tx + (1-t)y + S_2 \subset S_1$

$tx + (1-t)y \in F(S_1, S_2)$

$F(S_1, S_2)$ is convex.

g) $G(\alpha, a, b) = \{x \in \mathbb{R}^n \mid \|x - ax\| \leq \alpha \|x - b\|\}$, $a \neq b$, $0 < \alpha \leq 1$. ?

$G(\alpha, a, b) = \{x \in \mathbb{R}^n \mid \underbrace{(1-\alpha)x^T x + 2(\alpha-a)^T x + \|a\|^2 - \alpha \|b\|^2}_{f(x)}, f \text{ convex.}} \leq 0\}$ (same as d))

Let $x, y \in G$, then $f(\alpha x + (1-\alpha)y) \leq \underbrace{tf(x)}_{\leq 0} + (1-t)\underbrace{f(y)}_{\leq 0} \leq 0$

therefore $\alpha x + (1-\alpha)y \in G \Rightarrow \underline{G \text{ is convex.}}$

3.21.

a) Let $g_i : \mathbb{R}^n \rightarrow \mathbb{R}$

$$x \mapsto \|Ax - b_i\|$$

g_i is convex ~~convex~~

(directly demonstrate with triangle inequality)

Then $f(x) = \max_{i=1}^r (g_i(x))$ is convex because pointwise maximum preserve convexity.

$$\begin{aligned} b) f(x) &= \sum_{i=1}^r |x|_{c,i} \quad (\text{sum of the } r \text{ largest components}) \\ &= \max_{1 \leq i_1 < i_2 < \dots < i_r} \sum_{k=1}^r |x|_{c,i_k} \\ &= \max_{1 \leq i_1 < i_2 < \dots < i_r} g_i(x) \end{aligned}$$

where $g_i(x) = \sum_{k=1}^r |x|_{c,i_k}$ which is also clearly convex thanks to the triangle inequality.

Therefore f is convex.

3.32 a) Let f, g convex functions, non-decreasing and positive. show that $f \cdot g$ is convex. ($f \cdot g(x) = f(x)g(x)$)

~~Proof by definition~~

~~$$f(x) + g(y) \geq f(tx + (1-t)y) + g(tx + (1-t)y)$$~~

Let $x, y \in \mathbb{R}^n$, $t \in [0, 1]$

$$\begin{aligned} fg \text{ convex} &\Leftrightarrow f \cdot g(tx + (1-t)y) \leq \underbrace{tf \cdot g(x) + (1-t)f \cdot g(y)}_{D_t(x, y)} \\ &\Leftrightarrow -f \cdot g(tx + (1-t)y) + tf \cdot g(x) + (1-t)f \cdot g(y) \geq 0. \end{aligned}$$

as f and g convex ~~and positive~~ and positives,

$$\begin{aligned} f \cdot g(tx + (1-t)y) &= \underbrace{f(tx + (1-t)y)}_{\geq 0} \underbrace{g(tx + (1-t)y)}_{\geq 0} \\ &\leq (f(x) + (1-t)f(y))(t g(x) + (1-t)g(y)) \end{aligned}$$

$$D_t(x, y) \geq t f_g(x) + (1-t)f_g(y) - (t f_g(x) + (1-t)f_g(y))(t g(x) + (1-t)g(y))$$

$$\begin{aligned}
 D_t(x, y) &\geq t f_g(x) + (1-t) f_g(y) - t^2 f_g(x) - (1-t)^2 f_g(y) - t [f_g(x)g(y) + f_g(y)g(x)] \\
 &\geq t(1-t)[f_g(x) + f_g(y) - f(x)g(y) - f(y)g(x)] \\
 &\geq t(1-t)(g(y) - g(x))(f(y) - f(x))
 \end{aligned}$$

or as f, g are both non increasing, $g(y) - g(x)$ is the same sign as $f(y) - f(x)$
therefore $D_t(x, y) \geq 0$

And $f \cdot g$ is convex.

b) Show that $f \cdot g$ is concave when f, g are concave, positive functions with $f \nearrow$ and $g \searrow$.

$f \cdot g$ concave $\Leftrightarrow D_t(x, y) \leq 0$

or as f, g concave and positives;

$$\begin{aligned}
 f(tx + (1-t)y)g(tx + (1-t)y) &\geq \cancel{f(tx)g(tx)} \\
 &\quad (+f(x) + (1-t)f(y))(t g(x) + (1-t)g(y)) \\
 \Rightarrow D_t(x, y) &\leq t f_g(x) + (1-t) f_g(y) - \text{_____} \\
 &\quad ; \text{ same calc as in a)} \\
 &\leq t(1-t)(g(y) - g(x))(f(y) - f(x)) \\
 &\leq 0 \quad \text{as } f \nearrow \text{ and } g \searrow \\
 &< 0
 \end{aligned}$$

Therefore $f \cdot g$ is concave.

c) Let f convex, non decreasing and positive function
 g concave, non increasing and positive function.

Then $\frac{1}{g}$ ~~is non decreasing and positive function~~
~~is concave~~
 ~~$f(tx + (1-t)y) \geq f(x)$~~

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And moreover $\frac{1}{g}$ is convex!

$$\begin{aligned} \frac{1}{g(tx + (1-t)y)} &\leq \frac{1}{t g(x) + (1-t) g(y)} && (\text{because } g \text{ concave}) \\ &\leq t \frac{1}{g(x)} + (1-t) \frac{1}{g(y)} && (\text{because } x \mapsto \frac{1}{x} \text{ is convex}) \end{aligned}$$

Therefore $\frac{P}{\int} = f \cdot \frac{1}{g}$ is convex (from a)

3.36

a) ~~is~~ is equivalent to b) with $r=1$.

b) $f^*(y) = \sup_{x \in \mathbb{R}^n} x^T y - f(x)$

$$= \sup_{x \in \mathbb{R}^n} \underbrace{\sum_{i=1}^n x_i y_i - \sum_{i=1}^n x_i}_{g_y(x)}, \quad r \in [0, n].$$

* if $\exists y_i < 0$, then with $x_i = -t e_i$, $g_y(x) = -t y_i$ $t \geq 0$

$$g_y(x) \rightarrow +\infty \quad \text{so} \quad f^*(y) = +\infty.$$

* if $\exists y_i > 1$ then $x_i = t e_i \Rightarrow g_y(x_i) = (y_i - 1)x_i \rightarrow +\infty$ ($t \geq 0$)

Let assume that $y \in [0, 1]$ and with $x_i = t \begin{pmatrix} 1 \\ 0 \end{pmatrix}$

$$g_y(x_i) = t \left(\sum_{j=1}^n y_j - r \right)$$

$$\text{if } \sum_{j=1}^n y_j > r \quad g_y(x_i) \rightarrow +\infty$$

$$\sum_{j=1}^n y_j < r \quad g_y(x_i) \xrightarrow[t \rightarrow -\infty]{} +\infty$$

so $f^*(y) = +\infty$ with $\sum y_j \neq r$. and with $y \notin [0, 1]$.

Now assume that $\sum y_j = r$ and $y \in (0, 1)$.

Let $x \in \mathbb{R}^n$ and i_1, i_2, \dots, i_n a permutation of $\{1, \dots, n\}$

such that $x_{i_1} \geq x_{i_2} \geq \dots \geq x_{i_n}$

$$\begin{aligned}
 g_{\gamma}(x) &= \sum_{i=1}^n x_i y_i - \sum_{i=1}^r x_{i_k} \\
 &= \sum_{i=1}^n x_i y_i - \sum_{k=1}^r x_{i_k} \\
 &= \sum_{k=1}^r x_{i_k} y_{i_k} - \sum_{k=1}^r x_{i_k}
 \end{aligned}$$

~~$$\begin{aligned}
 g_{\gamma}(x) &= \sum_{k=1}^r \underbrace{(y_{i_k} - 1)}_{\leq 0} x_{i_k} + \sum_{k=r+1}^n x_{i_k} y_{i_k}
 \end{aligned}$$~~

We have $\forall k, k \leq r \quad x_{i_k} \geq x_{i_r}$ and $\forall k \geq r+1 \quad x_{i_k} \leq x_{i_r}$

$$\begin{aligned}
 g_{\gamma}(x) &\leq \underbrace{-\sum_{k=1}^r y_{i_k} x_{i_r}}_{\leq 0} + \sum_{k=r+1}^n x_{i_r} y_{i_k} \\
 &\leq x_{i_r} \left(\sum_{k=1}^r y_{i_k} - \sum_{k=1}^r 1 \right) \\
 &\leq x_{i_r} \left(\underbrace{\sum_{i=1}^n y_i - r}_{=0} \right) \\
 &\leq 0
 \end{aligned}$$

And $g_{\gamma}(0) = 0$

therefore $f^*(\gamma) = \begin{cases} 0 & \text{if } \gamma \in \{0, 1\}^n \text{ and } \sum y_i = r \\ +\infty & \text{otherwise.} \end{cases}$

case $r=1$ (answer to a))

$$f^*(\gamma) = \begin{cases} 0 & \text{if } \gamma \geq 0 \text{ and } \sum y_i = 1 \\ +\infty & \text{otherwise.} \end{cases} \quad (\sum y_i = 1 \text{ and } \gamma \geq 0 \Rightarrow \gamma \leq 1)$$

case $r=n$

$$\begin{aligned}
 g_{\gamma}(x) &= \sum_{i=1}^n x_i y_i - \sum_{i=1}^n x_i \\
 &= \sum (y_{i_c} - 1) x_i
 \end{aligned}$$

~~if $\exists y_i \neq 1$ then with $x_r = t e_i$, $g_{\gamma}(x_r) = (y_i - 1) t$~~

and with

~~if $\gamma = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix}$, $g_{\gamma}(x) = 0 \quad \forall x$.~~

$\rightarrow +\infty$

$t \rightarrow +\infty$

$$g^*(y) = \begin{cases} 0 & \text{if } y = (1) \\ +\infty & \text{otherwise.} \end{cases}$$

$$= \begin{cases} 0 & \text{if } y \in [0, 1]^n \text{ and } \sum y_i = n \quad (\Leftrightarrow y = (1)) \\ +\infty & \text{otherwise.} \end{cases}$$

c) $f^*(y) = \sup_{x \in \mathbb{R}} \frac{(xy - \max_i(a_i x + b_i))}{g_y(x)}$

We can assume that $\forall i, j, a_i < a_j$. Indeed if $a_i = a_j$ then b_i has to be different than b_j (otherwise it's redundant) but then ~~if $b_i > b_j$ then $b_i < b_j$~~ only one is relevant (~~as~~ the one with the bigger b_i is always above the other).

It's then easy to see that there are m ^{linear} pieces in f :

$$\cdot [-\infty, x_1], [x_i, x_{i+1}] \quad i \in \{1, m-1\} \quad [x_{m-1}, +\infty]$$

$$\hookrightarrow a_i x + b_i \quad \hookrightarrow a_{i+1} x + b_{i+1} \quad \hookrightarrow a_m x + b_m$$

where (x_i, p_i) is the intersection point of two defined by $\begin{cases} y = a_i x + b_i \\ y = a_{i+1} x + b_{i+1} \end{cases}$

$$\Rightarrow x_i = \frac{b_{i+1} - b_i}{a_{i+1} - a_i}$$

* Now if $y < a_1$ with ~~$x < x_1$ and $x > x_{m-1}$~~ and $x < x_1$ then $g_y(x) = xy - a_1 x - b_1$

$$= \underbrace{(y-a_1)x}_{< 0}$$

$$g_y(x) \rightarrow +\infty \quad x \rightarrow -\infty$$

Done $f^*(y) = +\infty$

* if $y > a_m$, with $x > x_{m-1}$. $g_y(x) = x(y - a_m) - b_m > 0$

$$\Rightarrow f^*(y) = +\infty \quad x \xrightarrow{x \rightarrow +\infty}$$

* $a_1 \leq y \leq a_m$

~~g_y~~ g_y is increasing until x reaches the linear piece where g grows too much.

Let assume $a_i \leq y \leq a_{i+1}$

for $x \leq x_i$, g_y is non decreasing (as the slope of f is smaller than y)
 for $x \geq x_i$, g_y is non increasing

Therefore $f^*(y) = g_y(x_i)$

$$= y \frac{b_i - b_{i+1}}{a_{i+1} - a_i} - a_i \frac{b_i - b_{i+1}}{a_{i+1} - a_i} - b_i$$

$$= (y - a_i) x_i - b_i$$

f^* is also a linear piecewise function

$$f^*(y) = \begin{cases} +\infty & y < a_1 \text{ or } y > a_m \\ (y - a_i) x_i - b_i & \text{if } a_i \leq y \leq a_{i+1} \end{cases}$$

d) $f^*(y) = \sup_{x \in \mathbb{R}_{++}} \frac{(yx - x^p)}{g_y(x)}$

* $p > 1$

if $y < 0$, g_y is non increasing on \mathbb{R}_{++}

therefore $f^*(y) = g_y(0) = 0$.

if $y > 0$ let's find g_y maximum:

$$g_y'(x) = y - p x^{p-1}, \quad g_y'(x) = 0 \Leftrightarrow x = \left(\frac{y}{p}\right)^{\frac{1}{p-1}}$$

$$\hookrightarrow g_y' \begin{matrix} 0 \\ y + \left(\frac{y}{p}\right)^{\frac{1}{p-1}} - \dots \\ g(x) \end{matrix}$$

The maximum is reached at $\left(\frac{y}{p}\right)^{\frac{1}{p-1}}$

$$\begin{aligned} f^*(y) &= g_y\left(\left(\frac{y}{p}\right)^{\frac{1}{p-1}}\right) = y \left(\frac{y}{p}\right)^{\frac{1}{p-1}} - \left(\frac{y}{p}\right)^{\frac{p}{p-1}} \\ &= y^{\frac{p}{p-1}} \left[\left(\frac{1}{p}\right)^{\frac{1}{p-1}} - \left(\frac{1}{p}\right)^{\frac{p}{p-1}} \right] \\ &= \left(\frac{p-1}{p}\right) y^{\frac{p}{p-1}} \left(p \left(\frac{1}{p}\right)^{\frac{1}{p-1}} - \left(\frac{1}{p}\right)^{\frac{p}{p-1}}\right) \\ &= (p-1) \left(\frac{y}{p}\right)^{\frac{p}{p-1}} \end{aligned}$$

$$f^*(y) = \begin{cases} (p-1) \left(\frac{y}{p}\right)^{\frac{p}{p-1}} & \text{if } y > 0 \\ 0 & \text{otherwise} \end{cases}$$

(3)

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* $\rho < 0$

$$\text{if } \gamma > 0, \quad g_\gamma(x) = \gamma x - x^\rho \xrightarrow[x \rightarrow +\infty]{} +\infty \quad (\text{since } x^\rho \rightarrow 0 : \rho < 0)$$

$$\text{then } f^*(\gamma) = +\infty$$

if $\gamma \leq 0$ let's compute the maximum of g_γ .

$$g'_\gamma(x) = 0 \Leftrightarrow x = \left(\frac{\gamma}{\rho}\right)^{\frac{1}{\rho-1}}$$

g'_γ	$\begin{cases} -\infty & \gamma > 0 \\ +\infty & \gamma = 0 \\ -\infty & \gamma < 0 \end{cases}$	$\begin{cases} +\infty & \gamma > 0 \\ 0 & \gamma = 0 \\ -\infty & \gamma < 0 \end{cases}$
g_γ	$\begin{cases} +\infty & \gamma > 0 \\ 0 & \gamma = 0 \\ -\infty & \gamma < 0 \end{cases}$	

$$f^*(\gamma) = g_\gamma\left(\left(\frac{\gamma}{\rho}\right)^{\frac{1}{\rho-1}}\right) = (\rho-1)\left(\frac{\gamma}{\rho}\right)^{\frac{\rho}{\rho-1}}$$

$$\text{so } f^*(\gamma) = \begin{cases} (\rho-1)\left(\frac{\gamma}{\rho}\right)^{\frac{\rho}{\rho-1}} & \text{if } \gamma \leq 0 \\ +\infty & \text{otherwise} \end{cases}$$

$$\text{e) } f^*(\gamma) = \sup_{x \in \mathbb{R}_{++}^n} \left(\gamma^T x + (1+x)^\frac{1}{\rho} \right)$$

* if $\exists y_i \geq 0$ with $x_t = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} + \underbrace{t e_t}_{t \rightarrow +\infty}$

$$g_\gamma(x) = \sum y_i + t y_t + (1+t)^\frac{1}{\rho}$$

$$\xrightarrow[t \rightarrow +\infty]{} +\infty$$

$$\Rightarrow f^*(\gamma) = +\infty$$

* $\gamma < 0$ consider $x_t = \log\left(-\frac{t}{\gamma}\right)$, $t > 0$

$$g_\gamma(x_t) = -nt + \left(\pi - \frac{t}{\gamma}\right)^{\frac{1}{n}}$$

$$= t\left(\left(\pi - \frac{1}{\gamma}\right)^{\frac{1}{n}} - n\right)$$

* if $\left(\pi - \frac{1}{\gamma}\right)^{\frac{1}{n}} > n$

$$g_\gamma(x_t) \rightarrow +\infty$$

\downarrow

$$\Rightarrow f^*(\gamma) = +\infty$$

* $\left(\pi - \frac{1}{\gamma}\right)^{\frac{1}{n}} \leq n$

Then $g_\gamma(x) = \sum x_i y_i + (\pi x_i)^{\frac{1}{n}}$

but the geometric mean inequality states that

$$\frac{1}{n} \sum_{i=1}^n x_i (-y_i) \geq \left(\prod_{i=1}^n x_i (-y_i)\right)^{\frac{1}{n}}$$

$$\geq \left(\pi - y_i\right)^{\frac{1}{n}} \left(\pi x_i\right)^{\frac{1}{n}}$$

$$\geq \frac{1}{n} (\pi x_i)^{\frac{1}{n}} \quad (\pi - y_i \geq \frac{1}{n} \Leftrightarrow \pi - \frac{1}{\gamma} \leq n)$$

$$\Leftrightarrow 0 \geq g_\gamma(x)$$

or and $g_\gamma(0^+) = 0$

Therefore $f^*(\gamma) = 0$

$$f^*(\gamma) = \begin{cases} 0 & \text{if } \gamma < 0 \quad (\pi y_i)^{\frac{1}{n}} \geq \frac{1}{n} \\ +\infty & \text{otherwise} \end{cases}$$

g) $f^*(\gamma) = \sup_{\substack{x \in \mathbb{R}^n, t \in \mathbb{R} \\ t > \|x\|_2}} \underbrace{\gamma^t x + \log(t^2 - x^t x)}_{g_{\gamma, 0}(x, t)} + ct$

* if $c \geq 0$, then with $x = 0$, $g_{\gamma, 0}(0, t) = ct + \log(t^2)$

$$\begin{matrix} \rightarrow t \rightarrow \\ \downarrow \rightarrow t \rightarrow \end{matrix}$$

$$\Rightarrow f^*(\gamma, c) = +\infty$$

Now if $\alpha \geq -\|y\|_2$ then with $x_\alpha = \alpha y$

$$t_\alpha = \|x_\alpha\|_2 + 1 = \alpha \|y\|_2 + 1$$

$$\begin{aligned} g_{\gamma, u}(x_\alpha, t_\alpha) &= \alpha \sum x_i^2 + \alpha u \|y\|_2 + u + \log((\epsilon \|y\|_2 + \alpha)^2 - \alpha^2 \gamma^2) \\ &= \alpha (\underbrace{\|y\|_2^2 + u \|y\|_2}_{\text{So it's zero}}) + u + \log(1 + 2\alpha \|y\|_2) \\ &= \alpha \|y\|_2 (\underbrace{\|y\|_2 + u}_{\geq 0}) + u + \log(1 + 2\alpha \|y\|_2) \end{aligned}$$

$$\therefore g_{\gamma, u}(x_\alpha, t_\alpha) \xrightarrow[\alpha \rightarrow \infty]{} +\infty$$

$$g^*(\gamma, u) = +\infty$$

Therefore $\alpha < -\|y\|_2 \leq 0$.

As $-g_{\gamma, u}$ is coercive and continuous, $g_{\gamma, u}$ has a unique global maximizer.

Let's compute the derivatives of $g_{\gamma, u}$:

$$\nabla_x g_{\gamma, u}^{(x)} = \gamma - \frac{2x}{\epsilon^2 - x^2}, \quad \nabla_t g_{\gamma, u}(x, t) = u + \frac{2t}{\epsilon^2 - x^2}$$

Let x^*, t^* an extremum of $g_{\gamma, u}$. Then:

$$\begin{cases} \nabla_x g_{\gamma, u}(x^*, t^*) = 0 \\ \nabla_t g_{\gamma, u}(x^*, t^*) = 0 \end{cases} \Leftrightarrow \begin{cases} \gamma = \frac{2x^*}{\epsilon^2 - \|x^*\|_2^2} \\ u = \frac{-2t^*}{\epsilon^2 - \|x^*\|_2^2} \end{cases}$$

$$\text{We can notice that } u^2 \gamma^2 = \frac{4}{\epsilon^2 - \|x^*\|_2^2}$$

$$\Leftrightarrow t^{*2} - \|x^*\|^2 = \frac{4}{u^2 - \|y\|^2} \quad (1)$$

$$\begin{aligned} (1) &\Leftrightarrow (t^{*2} - \|x^*\|^2)\gamma = \frac{4\gamma}{u^2 - \|y\|^2} \\ &\Leftrightarrow x^* = \frac{2\gamma}{u^2 - \|y\|^2} \end{aligned}$$

$$(1) \Leftrightarrow (t^* - \|x^*\|)u = \frac{4u}{u^2 - 4\gamma^2}$$

$$\Leftrightarrow t^* = \frac{-2u}{u^2 - \|y\|^2}$$

$g_{\gamma, u}$ has only one extremum at x^*, t^* (maximum)

$$\text{with } x^* = \frac{\gamma^t y}{u^2 - \gamma^t y}, \quad t^* = \frac{-2u}{u^2 - \gamma^t y}$$

$$g_{\gamma, u}(x^*, t^*) = \frac{2\gamma^t y}{u^2 - \gamma^t y} - \frac{2u^2}{u^2 - \gamma^t y} + \log\left(\frac{4u^2 - \gamma^t y}{(u^2 - \gamma^t y)^2}\right)$$

$$= -2 + \log(4) - \log(u^2 - \gamma^t y)$$

≥ 0 because $u < -\|\gamma\|_2$ so
 $\Rightarrow u^2 > \|\gamma\|_2^2$

or as $g_{\gamma, u}(0, t) = ut + \log(t^*)$

$$\begin{array}{c} \rightarrow -\infty \\ t \rightarrow \infty \end{array} \quad (u < 0)$$

$$\Rightarrow \exists x, t \quad (x < 0, t \text{ big enough}) \quad g_{\gamma, u}(x, t) < g_{\gamma, u}(x^*, t^*)$$

~~Therefore x^*, t^* is the maximum of $g_{\gamma, u}$~~

$$\Rightarrow f^*(\gamma, u) = 2(\log(2) - 2) - \log(u^2 - \gamma^t y)$$

$$f^*(\gamma, u) = \begin{cases} 2(\log(2) - 2) - \log(u^2 - \gamma^t y) & \text{if } u < -\|\gamma\|_2 \\ +\infty & \text{otherwise.} \end{cases}$$

* - $g_{\gamma, u}$ coercive:

$$\text{if } \gamma^t x < 0 \quad \text{then} \quad g_{\gamma, u}(x, t) < 0 + ut + \log\left(\frac{t^2 - x^t x}{\|\gamma\|_2^2}\right) \leq ut + \log(t^2)$$

if $\|x, t\|_2 \rightarrow +\infty$; as $t \geq \|\gamma\|_2$ then t also grows to infinity.

$$\begin{aligned} \Rightarrow \lim_{\|x, t\|_2 \rightarrow +\infty} (g_{\gamma, u}(x, t)) &\leq \lim_{\|x, t\|_2 \rightarrow +\infty} (ut + \log(t^2)) \\ &< \lim_{t \rightarrow +\infty} (ut + \log(t^2)) \\ &\rightarrow -\infty \quad (u < 0) \end{aligned}$$

Therefore $-g_{\gamma, u}$ is coercive

if $\gamma^t x \geq 0$, then $\gamma^t x = |\gamma^t x| \leq \|\gamma\|_2 \|x\|_2$ (Cauchy Schwartz)

$$\begin{aligned} g_{\gamma, u}(x, t) &\leq \|\gamma\|_2 \|x\|_2 + ut + \log(t^2) \\ &\leq (\|\gamma\|_2 + u)t + \log(t^2) \quad (\|x\|_2 \leq t) \end{aligned}$$

$$\Rightarrow \lim_{\|x, t\|_2 \rightarrow +\infty} g_{\gamma, u}(x, t) = -\infty \quad \Rightarrow -g_{\gamma, u} \text{ is coercive.}$$