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1 (a) $f(x) = x \log x$

$$\therefore f^*(y) = \sup_{x \in \text{dom}(f)} \{ yx - x \log x \}$$

Now,

$$\text{dom}(f) : x > 0, x \in \mathbb{R}$$

We show $yx - x \log x$ is concave

Proof: Let $f(x) = yx - x \log x$

$$\Rightarrow f'(x) = y - \left(\frac{1}{x} + \log x\right)$$

$$\Rightarrow f''(x) = +\frac{1}{x^2} < 0$$

$$\therefore f''(x) < 0 \quad \forall x \in \text{dom}(f)$$

$$\Rightarrow yx - x \log x \text{ is concave.}$$

Hence, to find the supremum of $yx - x \log x$, we can simply find its max value.

$$\therefore f'(x) = y - \left(\frac{1}{x} + \log x\right) = 0$$

$$\Rightarrow y = \frac{1}{x} + \log x \Rightarrow x = e^{y-1}$$

$$\therefore f^*(y) = yx - x \log x = x(1 + \log x) - x \log x$$
$$= x + x \log x - x \log x$$

$$\therefore f^*(y) = ye^{y-1} - e^{y-1}(y-1)$$
$$= e^{y-1}$$

$$\therefore \boxed{f^*(y) = e^{y-1}}, \quad \text{dom}(f^*) = \mathbb{R}$$

(b) $f(x) = \frac{1}{x}$

$$\therefore f^*(y) = \sup_{x \in \text{dom}(f)} \left\{ \frac{yx}{x} - \frac{1}{x} \right\}$$

Now,

$$\text{dom}(f) = x \neq 0$$

We show $yx - \frac{1}{x}$ is concave for $x > 0$

Proof: Let $u(x) = yx - \frac{1}{x}$

$$\Rightarrow u'(x) = y + \frac{1}{x^2}$$

$$\Rightarrow u''(x) = -\frac{2}{x^3}$$

$$\Rightarrow h''(x) < 0 \text{ for } x > 0$$

$$\therefore yx - \frac{1}{x} \text{ is concave for } x > 0$$

$$\therefore \text{Finding the max of } h: h'(x) = 0$$

$$\Rightarrow y + \frac{1}{x^2} = 0$$

$$\Rightarrow x = (-y)^{-\frac{1}{2}}$$

$$\therefore f^*(y) = y(-y)^{-\frac{1}{2}} - (-y)^{-\frac{1}{2}}$$

$$= \frac{-y - (-y)}{(-y)^{\frac{1}{2}}}$$

$$= \frac{2y}{(-y)^{\frac{1}{2}}} = +2(-y)^{\frac{1}{2}}, y < 0$$

$$\therefore \boxed{f^*(y) = \frac{2y}{(-y)^{\frac{1}{2}}}, \text{ dom}(f^*) = y < 0}$$

$$2. f(x) = x \log x - (x+1) \log(x+1)$$

$$\therefore D_f(P||Q) = \sum_x q(x) f\left(\frac{p(x)}{q(x)}\right)$$

$$= \sum_x \left[p(x) \log p(x) - \left(\frac{p(x)+q(x)}{q(x)}\right) \log\left(\frac{p(x)}{q(x)} + 1\right) \right]$$

$$= \sum_x \left[p(x) \log p(x) - p(x) \log q(x) - (p(x)+q(x)) \log(p(x)+q(x)) + (p(x)+q(x)) \log q(x) \right]$$

$$= \sum_x \left[p(x) \log p(x) - p(x) \log q(x) - p(x) \log(p(x)+q(x)) - q(x) \log(p(x)+q(x)) + p(x) \log q(x) + q(x) \log q(x) \right]$$

$$= \sum_x \left[p(x) \log\left(\frac{p(x)}{p(x)+q(x)}\right) + q(x) \log\left(\frac{q(x)}{p(x)+q(x)}\right) \right]$$

$$= \sum_x \left[p(x) \log\left(\frac{2p(x)}{p(x)+q(x)}\right) + q(x) \log\left(\frac{2q(x)}{p(x)+q(x)}\right) \right] - \sum p(x) \log 2 - \sum q(x) \log 2$$

$$= \sum_x p(x) \log\left(\frac{p(x)}{\frac{p(x)+q(x)}{2}}\right) + \sum_x q(x) \log\left(\frac{q(x)}{\frac{p(x)+q(x)}{2}}\right) - 2 \log 2$$

$$= 2 \text{JSD}(P, Q) - \log 4$$

$$\therefore \boxed{D_f(P||Q) = 2 \text{JSD}(P, Q) - \log 4}$$

$$3. f(x) = x \log x - (1+x) \log(1+x)$$

$$\therefore f^*(y) = \sup_{x \in \text{dom}(f)} \{ yx - f(x) \}$$

$$= \sup_{x \in \text{dom}(f)} \{ yx - x \log x + (x+1) \log(x+1) \}$$

Now,

$$\text{dom}(f) : x > 0 \wedge x > -1$$

$$= x > 0$$

We show that $yx - x \log x + (x+1) \log(x+1)$ is concave

$$\text{let } g(x) = yx - x \log x + (x+1) \log(x+1)$$

$$\Rightarrow g'(x) = y - (\log x + 1) + \log(x+1) + 1$$

$$= y - \log x + \log(x+1)$$

$$\Rightarrow g''(x) = -\frac{1}{x} + \frac{1}{x+1} = \frac{-x-1+x}{x(x+1)} = \frac{-1}{x(x+1)}$$

$$\Rightarrow g''(x) < 0 \quad \forall x > 0 \quad [\because \text{dom}(f) = x > 0]$$

$\therefore g(x)$ is concave.

\therefore supremum of $g(x)$ is its maximum value.

$$\therefore g'(x) = y - \log x + \log(x+1) = 0$$

$$\Rightarrow \log\left(\frac{x+1}{x}\right) = y$$

$$\Rightarrow x = (-1 + e^y)^{-1} = \frac{1}{e^y - 1}$$

~~$$\therefore f^*(y) = \frac{y}{e^y - 1} - \frac{\log(e^y - 1)}{e^y - 1} + \log\left(\frac{e^y}{e^y - 1}\right) + \log\left(\frac{e^y}{e^y - 1}\right)$$~~
~~$$= \frac{y}{e^y - 1} - \frac{\log(e^y - 1)}{e^y - 1} + \frac{y}{e^y - 1} - \frac{\log(e^y - 1)}{e^y - 1} + -y - \log(e^y - 1)$$~~

$$\therefore f(x) = x \log x - (x+1) \log(x+1)$$

$$= x \log\left(\frac{x}{x+1}\right) - \log(x+1)$$

$$\Rightarrow f\left(x = \frac{1}{e^y - 1}\right) = \frac{1}{e^y - 1} \log\left(\frac{1}{e^y}\right) - \log\left(\frac{e^y}{e^y - 1}\right)$$

$$= \frac{y}{e^y - 1} - \log\left(\frac{e^y}{e^y - 1}\right)$$

$$\therefore f^*(y) = \frac{y}{e^y - 1} - \frac{y}{e^y - 1} + \log\left(\frac{e^y}{e^y - 1}\right)$$

$$= \log\left(\frac{1}{1 - e^{-y}}\right) = -\log(1 - e^{-y})$$

$$\therefore \boxed{f^*(y) = -\log(1 - e^{-y})}$$

4. A function is 1-Lipschitz if,

$$|f(x) - f(y)| \leq 1 \cdot \|x - y\|, \quad \forall x, y \in \text{dom}(f)$$

$$\text{let } x = y + h$$

$$\Rightarrow |f(y+h) - f(y)| \leq \|y+h - y\|_2$$

$$\Rightarrow |f(y+h) - f(y)| \leq \|h\|$$

$$\Rightarrow \frac{|f(y+h) - f(y)|}{\|h\|} \leq 1.$$

$$\Rightarrow \left| \frac{f(y+h) - f(y)}{h} \right| \leq 1.$$

$$\Rightarrow \lim_{h \rightarrow 0} \left| \frac{f(y+h) - f(y)}{h} \right| \leq \lim_{h \rightarrow 0} 1.$$

$$\Rightarrow |f'(y)| \leq 1.$$

$$\Rightarrow |\nabla f(x)| \leq 1 \quad \forall x \in \text{dom}(f)$$

$$\therefore \boxed{|\nabla f(x)| \leq 1 \quad \forall x \in \text{dom}(f)}$$

$$7. v^T (I - vv^T) v$$

$$= v^T (v - vv^T v)$$

$$= v^T (v - v) = 0 \quad [\because v^T v = 1]$$

$\therefore v$ and $(I - vv^T)v$ are orthogonal.

Next,

$$(x^T v)^T (I - vv^T) x$$

$$= v^T (x^T v) (x - vv^T x)$$

$$= v^T (x^T v) x - v^T (x^T v) vv^T x$$

$$\text{let } x^T v \text{ be } k$$

$$= k v^T x - k v^T v v^T x$$

$$= k v^T x - k v^T x \quad [\because v^T v = 1]$$

$$= 0$$

$\therefore (x^T v)v$ and $(I - vv^T)x$ is orthogonal.

8. (a) $L(x, v) = x^T x + v^T (Ax - b)$, $x \in \mathbb{R}^n$, $A \in \mathbb{R}^{m \times n}$, $v \in \mathbb{R}^m$, $b \in \mathbb{R}^m$

(b) $g(v) = \inf_{x \in \text{dom}(f)} \{ x^T x + v^T (Ax - b) \}$
 $= \inf_{x \in \mathbb{R}^n} \{ x^T x + v^T (Ax - b) \}$

~~(c)~~ ~~$g'(v)$~~ = We can see that the above expression is convex, hence, we can directly differentiate it and find the minima.

\therefore let $f(x) = x^T x + v^T (Ax - b)$

$\Rightarrow \nabla f(x) = 2x + A^T v = 0$

$\Rightarrow x = -\frac{1}{2} (A^T v)$

$\therefore f(x = -\frac{1}{2} (A^T v)) = \frac{1}{2} (A^T v)^T \frac{(A^T v)}{2} + v^T (A \times \frac{1}{2} (A^T v) - b)$

$= \frac{1}{4} v^T A A^T v + \frac{-v^T A A^T v}{2} - v^T b$

$= -\frac{1}{4} v^T A A^T v - v^T b$

$\therefore \boxed{g(v) = -\frac{1}{4} v^T A A^T v - v^T b}$

(c) To check for concavity, we can show that $-\nabla^2 g$ is positive definite.

Also, AA^T is a symmetric matrix — (1)

$\therefore \nabla g(v) = -\frac{1}{4} \times 2 A A^T v - b$ [$\because \nabla_x [x^T A x] = \begin{cases} 2Ax & \text{if } A \text{ is symmetric} \\ 0 & \text{if } A \text{ is skew-sym.} \end{cases}$]

$\Rightarrow -\nabla^2 g(v) = \frac{1}{2} A A^T$

$\therefore AA^T$ is a symmetric matrix \Rightarrow it is positive semi-definite.

$\therefore -\nabla^2 g(v) \geq 0$

$\therefore g(v)$ is concave.

(d) Slater's condition for this case:

① \rightarrow There is no inequality to be satisfied

\rightarrow Primal problem is feasible

\rightarrow Case 1: $b \in R(A) \rightarrow p^* = d^*$

Case 2: $b \notin R(A) \rightarrow p^* = -\infty$ and $d^* = -\infty$

\therefore Slater's condition is always satisfied and strong duality holds true.

\rightarrow (because of Slater's condition)

(e) Since, $p^* = d^*$, ~~hence~~ hence the lower bound d^* is tight to p^* .

$$7. v = \left[\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}} \right]^T$$

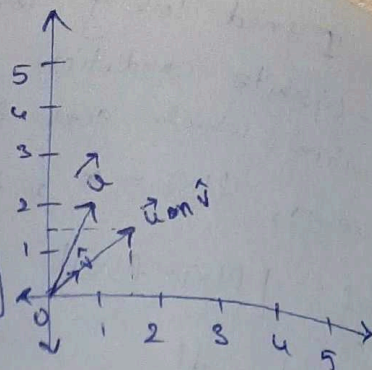
$$\text{let } u = [1, 2]^T$$

$$\therefore, \text{Component of } u \text{ along } v = \frac{u^T v}{\|v\|} \cdot \frac{v}{\|v\|}$$

$$= \frac{[1 \ 2] \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}}{1} \cdot \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$= \frac{3}{\sqrt{2}} \left[\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}} \right]^T$$

$$= \left[\frac{3}{2}, \frac{3}{2} \right]^T$$



$$\text{Component of } u \text{ along } (I - vv^T)v = u \cdot (I - vv^T)v$$

$$= \text{since } (I - vv^T)v \text{ is a null vector}$$

$$= [0, 0]^T$$

6. Given L-Lipschitz function, $f: \mathbb{R}^n \rightarrow \mathbb{R}$

$$|f(x) - f(y)| \leq L \cdot \|x - y\|_2 \quad \text{--- (1)}$$

Here, we choose distance metric $d() = \| \cdot \|_2$ (L-2 norm)

$$\text{let } \epsilon > 0 \text{ and } \delta = \frac{\epsilon}{L}$$

$$\therefore, \text{ if } \|x - y\|_2 < \delta$$

$$\Rightarrow \|x - y\|_2 < \frac{\epsilon}{L}$$

$$\Rightarrow L \cdot \|x - y\|_2 < \epsilon$$

$$\Rightarrow |f(x) - f(y)| < \epsilon \quad [\text{from (1)}]$$

$$\therefore, |f(x) - f(y)| < \epsilon$$

Hence from the given, if $\|x - y\|_2 < \delta$ then $|f(x) - f(y)| < \epsilon$, the function f is continuous.

Hence, any L-Lipschitz ^{continuous} function is continuous.

Hence, proved.

5. I tried looking for a function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ which follows 1-Lipschitz condition equality. But I couldn't guess any such function which goes from $\mathbb{R}^n \rightarrow \mathbb{R}$.

However, $f(x) = x$, $x \in \mathbb{R}$ satisfies the condition

Proof: $|f(x) - f(y)|$

$$= |x - y|$$

$$= \|x - y\|_2$$

Hence, $f(x) = x$, $x \in \mathbb{R}$ follows 1-Lipschitz equality.

9). $d(x, y) = \|x - y\|_2$, $x, y \in \mathbb{R}^n$

We first assume that $d(x, y)$ is convex and then prove it.

Proof: Using the condition of convexity,

$$f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)f(y), \quad x, y \in \mathbb{R}^n, \lambda \in [0, 1]$$

$$\Rightarrow \|\lambda x + (1-\lambda)y\|_2 \leq \lambda \|x\|_2 + (1-\lambda)\|y\|_2$$

$$\Rightarrow \|\lambda x + (1-\lambda)y\|_2^2 \leq \lambda^2 \|x\|_2^2 + (1-\lambda)\|y\|_2^2 + 2\lambda(1-\lambda)\|x\|_2\|y\|_2$$

[Squaring both sides]

10).

9). $d(x, y) = \|x - y\|_2$, $x, y \in \mathbb{R}^n$

For simplicity we will denote $d(x)$ as $f(x) = \sqrt{x^T x}$, $x \in \mathbb{R}^n$

$$\therefore \nabla f(x) = \frac{1}{2\sqrt{x^T x}} \cdot 2x = \frac{x}{\|x\|_2} \quad [\because \nabla(x^T x) = 2x]$$

Now,

$$\nabla^2 f(x) = \nabla_x \left[\frac{x}{\|x\|_2} \right]$$

$$= \frac{\nabla_x (x) \cdot \|x\|_2 - x \cdot \nabla_x (\|x\|_2)}{\|x\|_2^3}$$

$$\frac{\partial^2 f(x)}{\partial x_i \partial x_j} = \begin{cases} \frac{1}{\|x\|_2} - \frac{x_i^2}{\|x\|_2^3} & i=j \\ 0 & i \neq j \end{cases}$$

$$\therefore \nabla^2 f(x) = \begin{bmatrix} c_1 & 0 & \dots & 0 \\ 0 & c_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & c_n \end{bmatrix}_{n \times n}, \quad c_i = \frac{1}{\|x\|_2} - \frac{x_i^2}{\|x\|_2^3}$$

As we can see, $\nabla^2 f(x)$ has all diagonal elements non-zero and others are zero. Such a matrix always has positive eigenvalues.

$\therefore \nabla^2 f(x)$ is positive definite.

$\therefore f(x)$ is convex

\Rightarrow L-2 norm is convex function.

Next,

Convexity is defined such that $\nabla^2 f(x) \succ 0$ and $\text{dom}(f)$ is a convex set. Above we did not show explicitly that $\text{dom}(f)$ is convex as \mathbb{R}^n is convex is trivial.

But given $A \subset \mathbb{R}^n$ and A is convex, $f(x)$ will still be convex since it meets both the conditions $\rightarrow \nabla^2 f(x) \succ 0$ and $\text{dom}(f) = A$ is convex.

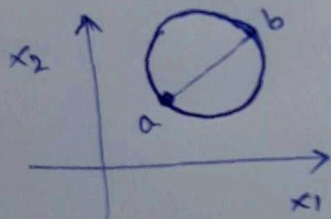
Hence, this proves the last statement of the question.

Next,

Let $A \subset \mathbb{R}^n$. $f(x)$ will not be convex in this $\text{dom}(f) = A$, if A is non-convex. There are many examples of such subsets \rightarrow

One example is that of a hollow circle.

Suppose we consider the case of $A \subset \mathbb{R}^2$ for simplicity, we define A as the points of a circle without the interior, only the boundary.



Here, if we connect any two points, it will include points which are not in the set. Hence, A is non-convex.