

Homework 1

1) f and g are convex functions: $\mathbb{R}^n \rightarrow \mathbb{R}$

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

$$\Rightarrow g(x) + (1-\lambda)g(y) \geq g(\lambda x + (1-\lambda)y)$$

$$\begin{aligned} \textcircled{+} \quad & \Rightarrow f(x) + (1-\lambda)f(y) + \lambda g(x) + (1-\lambda)g(y) \geq f(\lambda x + (1-\lambda)y) + g(\lambda x + (1-\lambda)y) \\ & \geq (f+g)(x) + (1-\lambda)(f+g)(y) \geq (f+g)(\lambda x + (1-\lambda)y) \end{aligned}$$

so the function $f+g: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex

□

$$2) f(x) = \log \sum_{i=1}^n e^{x_i} = \log(e^{x_1} + \dots + e^{x_n})$$

$$\frac{\partial f}{\partial x_i} = \frac{\partial}{\partial x_i} \log(e^{x_1} + \dots + e^{x_n}) = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}}$$

$$\nabla f(x) = \frac{1}{\sum_{i=1}^n e^{x_i}} \begin{pmatrix} e^{x_1} \\ e^{x_2} \\ \vdots \\ e^{x_n} \end{pmatrix}$$

$$\frac{\partial^2 f}{\partial x_i^2} = \frac{\partial}{\partial x_i} \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}} = \frac{e^{x_i} \cdot \sum_{j=1}^n e^{x_j} - e^{2x_i}}{\left(\sum_{j=1}^n e^{x_j}\right)^2}$$

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial}{\partial x_j} \frac{e^{x_i}}{\sum_{k=1}^n e^{x_k}} = - \frac{e^{x_i} \cdot e^{x_j}}{\left(\sum_{k=1}^n e^{x_k}\right)^2}$$

$$H_f = - \frac{1}{\left(\sum_{k=1}^n e^{x_k}\right)^2} \begin{pmatrix} e^{2x_1} - e^{x_1} \sum_{k=1}^n e^{x_k} & e^{x_1+x_2} & \dots & e^{x_1+x_n} \\ e^{x_1+x_2} & e^{2x_2} - e^{x_2} \sum_{k=1}^n e^{x_k} & & \\ \vdots & & & \\ e^{x_1+x_n} & & & e^{2x_n} - e^{x_n} \sum_{k=1}^n e^{x_k} \end{pmatrix}$$

$$3) \quad f(x) = \frac{1}{1+e^{-x}} \quad f'(x) = f(x) \cdot (1-f(x))$$

$$\begin{aligned} f'(x) &= + \frac{e^{-x}}{(1+e^{-x})^2} = \frac{1}{1+e^{-x}} \cdot \frac{e^{-x}}{1+e^{-x}} = \\ &= \frac{1}{1+e^{-x}} \cdot \left(1 - \frac{1}{1+e^{-x}}\right) = f(x) \cdot (1-f(x)) \end{aligned}$$

□

$$5) \quad f: \mathbb{R}^n \rightarrow \mathbb{R}$$

$$f(x) = \sum_{i=1}^m \log(1+e^{a_i^T x})$$

$$\frac{\partial f}{\partial x_i} = \frac{\partial}{\partial x_i} \left(\log(1+e^{a_1^T x}) + \dots + \log(1+e^{a_m^T x}) \right) =$$

$$= \frac{\partial}{\partial x_i} \left(\log \left(1 + e^{a_{11}x_1 + \dots + a_{1n}x_n} \right) + \dots + \log \left(1 + e^{a_{m1}x_1 + \dots + a_{mn}x_n} \right) \right) =$$

$$= \frac{a_{1i} \cdot e^{a_1^T x}}{1 + e^{a_1^T x}} + \dots + \frac{a_{mi} \cdot e^{a_m^T x}}{1 + e^{a_m^T x}} = \cancel{\frac{1}{1+e^{a_i^T x}}} \cdot \sum_{j=1}^m \left(\frac{a_{ji} \cdot e^{a_j^T x}}{1 + e^{a_j^T x}} \right)$$

$$\nabla f(x) = \left(\frac{\sum_{j=1}^m a_{ji} \cdot e^{a_j^T x}}{1 + e^a} \right)$$

$$\nabla f(x) = \left(\sum_{j=1}^m \frac{a_{j1} \cdot e^{a_j^T x}}{1 + e^{a_j^T x}}, \dots, \sum_{j=1}^m \frac{a_{jn} \cdot e^{a_j^T x}}{1 + e^{a_j^T x}} \right)^T$$

$$6) \quad a) \quad f: \mathbb{R}^n \rightarrow \mathbb{R} \quad f(x) = \log(1 + \|x\|^2)$$

$$\frac{\partial f}{\partial x_i} = \frac{\partial}{\partial x_i} \log(1 + x_1^2 + \dots + x_n^2) = \frac{2x_i}{1 + \|x\|^2}$$

$$\nabla f(x) = \frac{2}{1 + \|x\|^2} \cdot \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \frac{2x}{1 + \|x\|^2}$$

~~$$b) \quad f: \mathbb{R}^n \rightarrow \mathbb{R} \quad f(x) = \frac{1}{4} \|Ax - b\|^4$$~~

~~$$\nabla f(x) = 4 \cdot \frac{1}{4} \cdot (Ax - b)^3 \cdot (Ax - b) = 2 \cdot A^T \cdot (Ax - b)^3$$~~

~~$$\nabla f(x) = \nabla_x (Ax - b) + \frac{1}{4} \cdot (Ax - b)^3 = A^T \cdot (Ax - b)^3$$~~

$$c) \quad f: \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R} \quad f(x, y) = \frac{1}{2} \|xy^T - A\|^2$$

$$\nabla_x f(x, y) = 2 \cdot \frac{1}{2} \cdot (xy^T - A) \cdot \nabla_x (xy^T - A) = (xy^T - A)y$$

$$\nabla_y f(x, y) = 2 \cdot \frac{1}{2} \cdot (xy^T - A) \cdot \nabla_y (xy^T - A) = (xy^T - A)x$$

$$\nabla f(x, y) = \begin{cases} (xy^T - A)y \\ (xy^T - A)x \end{cases}$$

* because $y_1, y_2 > 0$,
 $\geq, 1 - \geq \geq 0$,
but only one of
them can be 0,
not both

$$7) \quad a) \quad f: \mathbb{R} \times \mathbb{R}_{++} \rightarrow \mathbb{R} \quad f(x, y) = \frac{x^2}{y}$$

We need that for all $x_1, x_2 \in \mathbb{R}, y_1, y_2 \in \mathbb{R}_{++}, \lambda \in [0, 1]$:

$$\lambda \frac{x_1^2}{y_1} + (1-\lambda) \frac{x_2^2}{y_2} \geq \frac{\lambda x_1 + (1-\lambda)x_2}{\lambda y_1 + (1-\lambda)y_2}$$

$$\begin{cases} y_1 > 0 \\ y_2 > 0 \\ (\lambda y_1 + (1-\lambda)y_2) > 0 \end{cases}$$

because $\lambda y_1 + (1-\lambda)y_2 > 0$
 $\lambda > 0, 1 - \lambda > 0$

$$\lambda^2 x_1^2 y_1 + \lambda(1-\lambda)x_1^2 y_2 + \lambda(1-\lambda)x_2^2 y_1 + (1-\lambda)^2 x_2^2 y_2$$

$$\geq \lambda^2 x_1^2 y_1 + 2\lambda(1-\lambda)x_1 x_2 y_1 y_2 + (1-\lambda)^2 x_2^2 y_1 y_2$$

$$\lambda(1-\lambda)x_1^2 y_2 + \lambda(1-\lambda)x_2^2 y_1 \geq 2\lambda(1-\lambda)x_1 x_2 y_1 y_2$$

otherwise:

$$x_1^2 y_2^2 + x_2^2 y_1^2 \geq 2x_1 x_2 y_1 y_2$$

$$(x_1 y_2 - x_2 y_1)^2 \geq 0 \quad \rightarrow \text{trivial}$$

if $\lambda = 0$ or 1 ,
this holds

□

$$b) f: \mathbb{R}_{++} \times \mathbb{R}_{++} \rightarrow \mathbb{R}$$

$$f(x, y) = x \cdot \log x - x \cdot \log y$$

We need that for all $x_1, x_2, y_1, y_2 \in \mathbb{R}_{++}, \lambda \in [0, 1]$

$$\begin{aligned} \lambda \cdot x_1 \cdot \log x_1 - \lambda \cdot x_1 \cdot \log y_1 + (1-\lambda) \cdot x_2 \cdot \log x_2 - (1-\lambda) \cdot x_2 \cdot \log y_2 \\ \geq (\lambda \cdot x_1 + (1-\lambda) \cdot x_2) \cdot \left(\log(\lambda x_1 + (1-\lambda)x_2) - \log(\lambda y_1 + (1-\lambda)y_2) \right) \end{aligned}$$

$$\log \left(\left(\frac{x_1}{y_1} \right)^{\lambda x_1} \cdot \left(\frac{x_2}{y_2} \right)^{(1-\lambda)x_2} \right) \geq \log \left(\frac{\lambda x_1 + (1-\lambda)x_2}{\lambda y_1 + (1-\lambda)y_2} \right)^{\lambda x_1 + (1-\lambda)x_2}$$

We have to check if the Hessian is PSD:

$$\frac{\partial f}{\partial x} = \log x + 1 - \log y$$

$$\frac{\partial f}{\partial y} = -\frac{x}{y}$$

$$\frac{\partial^2 f}{\partial x^2} = \frac{1}{x}$$

$$\frac{\partial^2 f}{\partial x \partial y} = -\frac{1}{y^2}$$

$$\frac{\partial^2 f}{\partial y^2} = \frac{x}{y^2}$$

$$\Rightarrow H_f = \begin{pmatrix} \frac{1}{x} & -\frac{1}{y} \\ -\frac{1}{y} & \frac{x}{y^2} \end{pmatrix}$$

As it is symmetric, it is enough to check if $H_{11} \geq 0$ and $H_{11} \cdot H_{22} - H_{12}^2 \geq 0$ because of Sylvester's criterion:

$$\frac{1}{x} \geq 0 \quad \checkmark, \text{ because } x > 0$$

$$\frac{1}{x} \cdot \frac{x}{y^2} - \left(-\frac{1}{y} \right)^2 = \frac{1}{y^2} - \frac{1}{y^2} = 0 \geq 0 \quad \checkmark \rightarrow \text{so } f \text{ is convex}$$

on $\mathbb{R}_{++} \times \mathbb{R}_{++}$

$$f: \mathbb{R}_+ \times \mathbb{R}_+ \rightarrow \mathbb{R}$$

8) a) $f(x_1, y) = xy$

$$\begin{array}{l} x_1=1 \\ y_1=0 \end{array} \quad \begin{array}{l} x_2=0 \\ y_2=1 \end{array} \quad \lambda = \frac{1}{2} \Rightarrow \begin{array}{l} \lambda x_1 + (1-\lambda)x_2 = \frac{1}{2} \\ \lambda y_1 + (1-\lambda)y_2 = \frac{1}{2} \end{array}$$

$$\frac{1}{2} \cdot f(1,0) + \frac{1}{2} \cdot f(0,1) \stackrel{?}{\geq} f\left(\frac{1}{2}, \frac{1}{2}\right)$$

$$0 + 0 \neq \frac{1}{4} \Rightarrow \text{not convex}$$

b) $f: \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$

$$f(x, y) = y \cdot e^x - x \cdot e^y$$

$$\begin{array}{l} x_1=0 \\ y_1=0 \end{array} \quad \begin{array}{l} x_2=-1 \\ y_2=-1 \end{array} \quad \lambda = \frac{1}{2}$$

$$\frac{1}{2} \cdot f(0,0) + \frac{1}{2} \cdot f(-1,-1) \stackrel{?}{\geq} f\left(-\frac{1}{2}, -\frac{1}{2}\right)$$

$$0 + \frac{1}{2} \cdot (e^{-1} + e^1) \geq \frac{1}{2} \cdot e^{-\frac{1}{2}} + \frac{1}{2} \cdot e^{\frac{1}{2}}$$

$$e^{-1} + e^1 \geq e^{-\frac{1}{2}} + e^{\frac{1}{2}}$$

$$e^{-1} - e^{-\frac{1}{2}} + e^1 - e^{\frac{1}{2}} \geq 0$$

$$e^{\frac{1}{2}} (e^{-\frac{1}{2}} - 1) - e^{-\frac{1}{2}} (e^{\frac{1}{2}} - 1) \geq 0$$

$$(e^{-\frac{1}{2}} - e^1) (e^{-\frac{1}{2}} - e^0) \geq 0$$

$$\begin{array}{l} x_1=2 \\ y_1=0 \end{array} \quad \begin{array}{l} x_2=2 \\ y_2=2 \end{array} \quad \lambda = \frac{1}{2} \Rightarrow \begin{array}{l} \lambda x_1 + (1-\lambda)x_2 = 2 \\ \lambda y_1 + (1-\lambda)y_2 = 1 \end{array}$$

$$\frac{1}{2} \cdot f(2,0) + \frac{1}{2} \cdot f(2,2) \stackrel{?}{\geq} f(2,1)$$

$$\frac{1}{2} \cdot (-2) + \frac{1}{2} \cdot 0 \stackrel{?}{\geq} e^2 - 2e$$

$$0 \neq (e-1)^2 \Rightarrow \text{not convex}$$

$$9) \min_{\substack{x_1 > 0 \\ x_2 > 0}} \frac{1}{x_1 \cdot x_2} + x_1 + x_2$$

find critical points:

$$\begin{aligned} \frac{\partial f}{\partial x_1} &= -\frac{1}{x_1^2 \cdot x_2} + 1 = 0 \Rightarrow x_1^2 \cdot x_2 = 1 \quad \left. \begin{array}{l} x_1 - \frac{1}{x_1^4} = 1 \\ \frac{1}{x_1^3} = 1 \end{array} \right\} \\ \frac{\partial f}{\partial x_2} &= -\frac{1}{x_1 \cdot x_2^2} + 1 = 0 \Rightarrow x_1 \cdot x_2^2 = 1 \end{aligned}$$

$$\begin{array}{l} \underline{x_1 = 1} \\ \underline{x_2 = 1} \end{array}$$

Check if local minimum:

$$\frac{\partial^2 f}{\partial x_1^2} = \frac{2}{x_1^3 \cdot x_2}$$

$$\frac{\partial^2 f}{\partial x_2^2} = \frac{2}{x_1 \cdot x_2^3} \rightarrow D(1,1) = \frac{2}{1^3 \cdot 1} \cdot \frac{2}{1 \cdot 1^3} - \left(\frac{1}{1^2 \cdot 1^2}\right)^2 = 3 > 0$$

$$\frac{\partial^2 f}{\partial x_1 \partial x_2} = \frac{1}{x_1^2 \cdot x_2^2} \quad \frac{\partial^2 f(1,1)}{\partial x_1^2} = \frac{2}{1^3 \cdot 1} = 2 > 0 \Rightarrow \text{local minimum}$$

Prove that f is convex

Because of Sylvester's criterion it is enough to check if $H_{11} \geq 0$ and $H_{11} H_{22} - H_{12}^2 \geq 0$, so H_f is PSD, so f is convex.

$$\frac{2}{x_1^3 \cdot x_2} \geq 0 \checkmark, \text{ because } x_1, x_2 > 0$$

$$\frac{2}{x_1^3 \cdot x_2} \cdot \frac{2}{x_1 \cdot x_2^3} - \left(\frac{1}{x_1^2 \cdot x_2^2}\right)^2 = \frac{4}{x_1^4 \cdot x_2^4} - \frac{1}{x_1^4 \cdot x_2^4} = \frac{3}{x_1^4 \cdot x_2^4} \geq 0 \checkmark$$

thus H_f is PSD, thus f is convex, thus every local minimum is global minimum, so the solution of the problem: $(x_1, x_2) = (1, 1)$

the minimum value: $\frac{1}{1 \cdot 1} + 1 + 1 = 3$

$$10) f(x) = \frac{1}{2} \langle Ax, x \rangle + \langle b, x \rangle + c$$

We know that $f(x) \geq d \quad \forall x \in \mathbb{R}^n$
 $\exists d \in \mathbb{R}$

We need that A is PSD $\Leftrightarrow \langle Ax, x \rangle \geq 0 \quad \forall x \in \mathbb{R}^n$

Let's suppose $\exists x' \in \mathbb{R}^n$ s.t. $\langle Ax', x' \rangle < 0$

in this case $\forall \lambda > 0$: $\langle A\lambda x', \lambda x' \rangle = \lambda^2 \cdot \langle Ax', x' \rangle < 0$

and $\langle b, \lambda x' \rangle = \lambda \langle b, x' \rangle$, so even if $\langle b, x' \rangle > 0$,

We will be able to find a $\lambda \geq 0$ such that

$\lambda^2 \cdot \langle Ax', x' \rangle + \lambda \langle b, x' \rangle < d - c$, which is a contradiction,

so such x' cannot exist $\rightarrow \langle Ax, x \rangle \geq 0 \quad \forall x \in \mathbb{R}^n$

$\hookrightarrow A \text{ is } \underline{\text{PSD}}$

$$12) f(x, y) = \sin(\pi x y^2)$$

linear approximation of f at $(1, 1)$:

$$L(x, y) = f(x_0, y_0) + f_x(x_0, y_0)(x - x_0) + f_y(x_0, y_0)(y - y_0)$$

$$f_x(x, y) = \pi y^2 \cdot \cos(\pi x y^2)$$

$$f_x(1, 1) = \pi \cdot 1^2 \cdot \cos \pi = -\pi$$

$$f_y(1, 1) = \sin \pi = 0$$

$$f_y(x, y) = 2\pi x y \cos(\pi x y^2)$$

$$f_y(1, 1) = 2\pi \cdot 1 \cdot 1 \cdot \cos \pi = -2\pi$$

$$L(x, y) = 0 + (-\pi) \cdot (x - 1) + (-2\pi) \cdot (y - 1) = -\pi x - 2\pi y + 3\pi$$

$$L(1, 1) = -\pi - 2\pi + 3\pi = 0$$

$$\text{so } f(1, 1) = L(1, 1)$$

\hookrightarrow it is always equal at (x_0, y_0)

$$13) Q(x,y) = f(x_0, y_0) + f_x(x_0, y_0)(x - x_0) + f_y(x_0, y_0)(y - y_0) + \frac{1}{2} \cdot \left(f_{xx}(x_0, y_0)(x - x_0)^2 + 2f_{xy}(x_0, y_0)(x - x_0)(y - y_0) + f_{yy}(x_0, y_0)(y - y_0)^2 \right)$$

$$f_{xx}(x, y) = -\pi \cdot y^4 \cdot \sin(\pi \cdot xy^2)$$

$$f_{xx}(1, 1) = -\pi \cdot 1^4 \cdot \sin \pi = 0$$

$$f_{yy}(x, y) = 2\pi \cdot x \cos(\pi \cdot xy^2) - 4\pi^2 \cdot x^2 \cdot y^2 \sin(\pi \cdot xy^2)$$

$$f_{yy}(1, 1) = 2\pi \cdot 1 \cdot \cos \pi - 4\pi^2 \cdot 1 \cdot \sin \pi = -2\pi$$

$$f_{xy}(x, y) = 2\pi y \cos(\pi \cdot xy^2) - 2\pi^2 \cdot y^2 \sin(\pi \cdot xy^2)$$

$$f_{xy}(1, 1) = 2\pi \cdot 1 \cdot \cos \pi - 2\pi^2 \cdot 1 \cdot \sin \pi = -2\pi$$

$$\begin{aligned} Q(x, y) &= -\pi x - 2\pi y + 3\pi + \frac{1}{2} \cdot \left(0 \cdot (x-1)^2 + 2 \cdot (-2\pi) \cdot (x-1)(y-1) - 2\pi \cdot (y-1)^2 \right) = \\ &= -\pi x - \underbrace{2\pi y + 3\pi}_{+2\pi x + 2\pi y} + \underbrace{2\pi x y - 2\pi x y - 2\pi}_{-\pi y^2} + \underbrace{2\pi y - \pi}_{-\pi y^2} = \\ &= -\pi y^2 - 2\pi x y + \pi x + 2\pi y \end{aligned}$$

$$Q(1, 1) = -\pi - 2\pi + \pi + 2\pi = 0$$

so $f(1, 1) = Q(1, 1) \rightarrow$ it is always true at (x_0, y_0)

$$14) f(x, y) = \sin(x^2 + y) + y$$

$$\left. \begin{array}{l} \frac{\partial f}{\partial x} = 2x \cdot \cos(x^2 + y) = 0 \\ \frac{\partial f}{\partial y} = \cos(x^2 + y) + 1 = 0 \end{array} \right\} \text{if } x = 0 :$$

$$\left. \begin{array}{l} \cos y + 1 = 0 \\ \cos y = -1 \Rightarrow y = \pi + k \cdot 2\pi \\ y = \pi + k \cdot 2\pi \quad | \quad k \in \mathbb{Z} \end{array} \right\}$$

So the critical points:

$$(x, y) = (0, \pi + k \cdot 2\pi)$$

$$k \in \mathbb{Z}$$

if $x \neq 0 :$

$$\begin{array}{l} \cos(x^2 + y) = 0 \\ \cos(x^2 + y) = -1 \end{array}$$

$$16) \quad 1-t \leq e^{-t}$$

$$f(t) = e^{-t} + t - 1$$

$$\frac{\partial f}{\partial t} = -e^{-t} + 1 = 0 \Leftrightarrow e^{-t} = 1 \\ t = 0$$

$$\frac{\partial^2 f}{\partial t^2} = e^{-t} \Rightarrow \frac{\partial^2 f(0)}{\partial t^2} = e^0 = 1 \Rightarrow \text{it is a local minimum}$$



$e^{-t} > 0 \quad \forall t \in \mathbb{R} \Rightarrow f$ is convex on \mathbb{R}

so all local minimums are global minimums, thus

$$f(t) \geq 0 \quad \forall t \Leftrightarrow 1-t \leq e^{-t} \quad \forall t$$

□

6) b) $f: \mathbb{R}^n \rightarrow \mathbb{R}$

$$f(x) = \frac{1}{4} \|Ax - b\|^4$$

$$g(x) := \frac{1}{2} \|Ax - b\|^2 \rightarrow f(x) = g^2(x)$$

$$\nabla f(x) = 2 \cdot g(x) \cdot \nabla g(x)$$

From the lectures we know that $\nabla g(x) = A^T \cdot (Ax - b)$,
hence

$$\nabla f(x) = 2 \cdot \frac{1}{2} \cdot \|Ax - b\|^2 \cdot A^T \cdot (Ax - b) = \|Ax - b\|^2 \cdot A^T \cdot (Ax - b)$$

$$11) \text{ a)} f(x) = \frac{1}{2} \|Ax - b\|^2$$

We know that for $\forall A, x: \|Ax\| \leq \|A\| \cdot \|x\|$ (for $\|\cdot\|_2$)

We also know that $\nabla f(x) = A^T(Ax - b)$

$$\begin{aligned} \|\nabla f(x) - \nabla f(y)\| &= \|A^T(Ax - b) - A^T(Ay - b)\| = \\ &= \|A^T Ax - A^T Ay + A^T b - A^T b\| = \|A^T A(x - y)\| \leq \\ &\leq \|A^T A\| \cdot \|x - y\| \Rightarrow \text{for } \forall L \geq \|A^T A\| \\ &\quad f \text{ is } L\text{-smooth} \end{aligned}$$

$$b) f(x) = \sqrt{1 + \|x\|^2}$$

$$\nabla f(x) = \frac{x}{\sqrt{1 + \|x\|^2}}$$

We need: $\forall x, y \in \mathbb{R}^n$:

$$\left\| \frac{x}{\sqrt{1 + \|x\|^2}} - \frac{y}{\sqrt{1 + \|y\|^2}} \right\| \leq L \|x - y\|$$

$$\| \cdot \|^2 \leq \| \cdot \|^2$$

$$\left(\frac{x}{\sqrt{1 + \|x\|^2}} - \frac{y}{\sqrt{1 + \|y\|^2}} \right)^T \left(\frac{x}{\sqrt{1 + \|x\|^2}} - \frac{y}{\sqrt{1 + \|y\|^2}} \right) \leq L \cdot (x - y)^T (x - y)$$

$$\frac{x^T x}{1 + \|x\|^2} - \frac{2}{\sqrt{1 + \|x\|^2} \sqrt{1 + \|y\|^2}} x^T y + \frac{y^T y}{1 + \|y\|^2} \leq L (x^T x - 2x^T y + y^T y)$$

$L = 1$ is a good choice: $\frac{x^T x}{1 + \|x\|^2} \leq x^T x$, because $1 + \|x\|^2 \geq 1$

$$\frac{y^T y}{1 + \|y\|^2} \leq y^T y$$
, because $1 + \|y\|^2 \geq 1$

$$-\frac{2 x^T y}{\sqrt{1 + \|x\|^2} \sqrt{1 + \|y\|^2}} \leq -2 x^T y$$
, because $\sqrt{1 + \|x\|^2} \cdot \sqrt{1 + \|y\|^2} \geq 1$

so $\forall L \geq 1$ f is L -smooth

$$c) f(x) = x^3 \quad x \in [3, 3]$$

$$\nabla f(x) = f'(x) = 3x^2$$

$$\|\nabla f(x) - \nabla f(y)\| = \|3x^2 - 3y^2\| = 3|x^2 - y^2| = \\ = 3|x+y||x-y| \leq 3 \cdot 3+3 \cdot |x-y| = 18|x-y|, \text{ so}$$

$\forall L \geq 18 \quad f \text{ is } L\text{-smooth}$

$$17) f \text{ convex} \Leftrightarrow \forall x, y \quad f(y) \geq f(x) + \langle \nabla f(x), y-x \rangle \quad [1]$$

$$\|y\|^2 = \|x + y - x\|^2$$

$$\|y\|^2 = \|x\|^2 + 2\langle x, y - x \rangle + \|y - x\|^2$$

$$\frac{\mu}{2} \|y\|^2 = \frac{\mu}{2} \|x\|^2 + \langle \nabla f(x), y - x \rangle + \frac{\mu}{2} \|y - x\|^2 \quad [2]$$

Adding 1) + 2) :

$$f(y) + \frac{\mu}{2} \|y\|^2 \geq f(x) + \frac{\mu}{2} \|x\|^2 + \langle \nabla f(x), y - x \rangle + \langle \nabla f(x), y - x \rangle + \\ + \frac{\mu}{2} \|y - x\|^2$$

$$\downarrow \text{because } \nabla F(x) = \nabla f(x) + \nabla \frac{\mu}{2} \|x\|^2 = \nabla f(x) + \mu x$$

$$F(y) \geq F(x) + \langle \nabla F(x), y - x \rangle + \frac{\mu}{2} \|y - x\|^2$$

\Leftrightarrow
F is μ -strongly convex

$$4) \text{ a) } f(x) = \|x\| = \sqrt{x_1^2 + \dots + x_n^2}$$

$f(x)$ is not differentiable at 0 , hence it is not differentiable

f is diff. if $\forall x, \forall v \in \mathbb{R}^n : \lim_{h \rightarrow 0} \frac{|f(x+hv) - f(x)|}{h}$ exists

$x=0$:

$$\lim_{h \rightarrow 0} \frac{|f(x+hv) - f(x)|}{h} = \lim_{h \rightarrow 0} \frac{\|hv\|}{h} = \lim_{h \rightarrow 0} \frac{|h| \cdot \|v\|}{h} =$$

$$= \|v\| \cdot \lim_{h \rightarrow 0} \frac{|h|}{h}, \text{ which does not exist, because}$$

$$\lim_{h \rightarrow 0+} \frac{|h|}{h} = \lim_{h \rightarrow 0+} \frac{h}{h} = 1$$

$$\lim_{h \rightarrow 0-} \frac{|h|}{h} = \lim_{h \rightarrow 0-} -\frac{h}{h} = -1$$

$$\text{b) } f(x) = \|x\|_1 = |x_1 + \dots + x_n|$$

$f(x)$ is not differentiable, because it is not differentiable at 0 :

$$\lim_{h \rightarrow 0} \frac{|f(x+hv) - f(x)|}{h} = \lim_{h \rightarrow 0} \frac{|hv|}{h} = \|v\| \cdot \lim_{h \rightarrow 0} \frac{|h|}{h}, \text{ which}$$

does not exist as we have previously seen

$$\text{c) } f(x) = \frac{\|x\|^2}{x_1}$$

we need $\forall x, v \in \mathbb{R}^n$. Keep in mind that f is not defined if $x_1 = 0$

$$\lim_{h \rightarrow 0} \frac{|f(x+hv) - f(x)|}{h} = \lim_{h \rightarrow 0} \frac{\frac{\|x+hv\|^2}{x_1 + hv} - \frac{\|x\|^2}{x_1}}{h} =$$

exists

15) $f(x) = x^4$ is a counter-example

$$\nabla^2 f(x) = 12x^2 \Rightarrow \text{if } x=0 \quad \nabla^2 f(x) > 0 \text{ is not true,}$$

but $f(x)$ is strictly convex:

First I show $g(x) = x^2$ is strictly convex:

$$\forall x, y, \lambda \in (0, 1):$$

$$\lambda x^2 + (1-\lambda)y^2 > (\lambda x + (1-\lambda)y)^2$$

$$\lambda x^2 + (1-\lambda)y^2 > \lambda^2 x^2 + 2\lambda(1-\lambda)xy + (1-\lambda)^2 y^2$$

$$\lambda(1-\lambda)x^2 - 2\lambda(1-\lambda)xy + (1-\lambda)\lambda y^2 > 0 \quad | : \begin{matrix} \lambda \neq 0 \\ (1-\lambda) \neq 0 \end{matrix}$$

$$x^2 - 2xy + y^2 > 0$$

$$(x-y)^2 > 0$$

, because $x \neq y$

now x^4 :

$$\forall x, y, \lambda \in (0, 1):$$

$$\lambda x^4 + (1-\lambda)y^4 \stackrel{?}{>} (\lambda x + (1-\lambda)y)^4$$

$$\left((\lambda x + (1-\lambda)y)^2 \right)^2$$

$$(\lambda x^2 + (1-\lambda)y^2)^2$$

$$\lambda(x^2)^2 + (1-\lambda)(y^2)^2$$

$$\lambda x^4 + (1-\lambda)y^4$$

because x^2 is
strictly convex

because x^2 is
strictly convex

\Downarrow
 $f(x) = x^4$ is strictly convex