

HW 1

1. Prove: f is convex $\Leftrightarrow \forall x_1, \dots, x_k \in D, \alpha_1, \dots, \alpha_k \in [0, 1], \sum_{i=1}^k \alpha_i = 1$:

if D is convex and $\forall x, y \in D$,
 $\forall t \in [0, 1]: f(tx + (1-t)y) \leq tf(x) + (1-t)f(y)$
 $f(\sum_{i=1}^k \alpha_i x_i) \leq \sum_{i=1}^k \alpha_i f(x_i)$

(\Leftarrow) If right side holds for all $x_i \in D$, we can choose α_i such that two of them are not 0: let's take α_1 and $\alpha_2 = 1 - \alpha_1$.
 Then:

$f(\alpha_1 x_1 + (1 - \alpha_1) x_2) \leq \alpha_1 f(x_1) + (1 - \alpha_1) f(x_2)$
 holds for every x_1, x_2, α_1 , which is exactly the definition for convex functions. $\alpha_1 + 1 - \alpha_1 = 1$.

(\Rightarrow) We will prove this by induction

$k=2$: holds by definition: $f(\underbrace{tx_1 + (1-t)y}_{\alpha_1 x_1 + \alpha_2 x_2}) \leq tf(x) + (1-t)f(y)$ ✓

$k \rightarrow k+1$ $f(\sum_{i=1}^{k+1} \alpha_i x_i) \leq \sum_{i=1}^{k+1} \alpha_i f(x_i)$

We know: $f(\sum_{i=1}^k \alpha_i x_i) \leq \sum_{i=1}^k \alpha_i f(x_i) \quad \forall \alpha_i \in [0, 1], \sum_{i=1}^k \alpha_i = 1, \forall x_i \in D$.

$f(t \cdot \sum_{i=1}^k \alpha_i x_i + (1-t)x_{k+1}) \leq t \cdot f(\sum_{i=1}^k \alpha_i x_i) + (1-t)f(x_{k+1}) \leq$
 \uparrow \uparrow
 f convex k -th step of induction

$\leq t \left(\sum_{i=1}^k \alpha_i f(x_i) \right) + (1-t)f(x_{k+1}) = \sum_{i=1}^k t \alpha_i f(x_i) + (1-t)f(x_{k+1})$

$\sum_{i=1}^k t \alpha_i + 1 - t = t \cdot \underbrace{\sum_{i=1}^k \alpha_i}_1 + 1 - t = 1$

$= \sum_{i=1}^{k+1} \beta_i f(x_i)$ with $\beta_i = t \cdot \alpha_i$ for $i=1, \dots, k$ and $1-t = \beta_{k+1}$

Since this holds for every t and every α_i (where $\sum \alpha_i = 1$),
 it holds for every $\beta_i; i=1, \dots, k+1$, if $\sum_{i=1}^{k+1} \beta_i = 1$.

We can also write: $f(\sum_{i=1}^{k+1} \beta_i x_i) \leq \sum_{i=1}^{k+1} \beta_i f(x_i)$ □

2. f is L -Lip. if $\forall x, y \in D: |f(x) - f(y)| \leq L \|x - y\|$

Prop. 26: f is L -Lip. iff. $\|\nabla f\| \leq L$

\Rightarrow The smallest possible L is $L = \max \|\nabla f\|$

$$\nabla f = [2x + e^x - y, 2y - x]$$

$$\|\nabla f\| = \sqrt{(2x + e^x - y)^2 + (2y - x)^2}$$

$$\operatorname{argmax} \|\nabla f\| = \operatorname{argmax} \|\nabla f\|^2$$

We are searching for max of fun $g(x, y) = (2x + e^x - y)^2 + (2y - x)^2$

$$g'_x(x, y) = 2(2x + e^x - y) \cdot (2 + e^x) + 2(2y - x) \cdot (-1) = 0$$

$$g'_y(x, y) = 2(2x + e^x - y) \cdot (-1) + 2(2y - x) \cdot 2 = 0$$

$$-4x + 2e^x + 2y + 2y - 4x = 0$$

$$y = \frac{1}{5}(4x + e^x)$$

$$8x + 2e^x - 2y + 2xe^x + 2e^{2x} - 2ye^x + 2y + 2x = 0$$

$$5x - \frac{4}{5}(4x + e^x) + 2e^x + e^{2x} + 2xe^x - \frac{1}{5}(4x + e^x)e^x = 0$$

$$\frac{9}{5}x + \frac{6}{5}e^x + \frac{4}{5}e^{2x} + \frac{6}{5}xe^x = 0$$

$$9x + 6e^x + 4e^{2x} + 6xe^x = 0$$

$$3x(3 + 2e^x) + 2e^x(3 + 2e^x) = 0$$

$$(3 + 2e^x)(3x + 2e^x) = 0$$

$$1. \quad 3 + 2e^x = 0$$

$$e^x = -\frac{3}{2} \quad \times$$

$$2. \quad 3x + 2e^x = 0$$

\Downarrow minimum
not interested

$$\|\nabla f\| = \sqrt{(2x + e^x - \frac{4}{5}x - \frac{1}{5}e^x)^2 + (\frac{4}{5}x + \frac{1}{5}e^x - x)^2} =$$

$$= \sqrt{(\frac{6}{5}x + \frac{4}{5}e^x)^2 + (\frac{2}{5}x + \frac{2}{5}e^x)^2} = \sqrt{(\frac{2}{5} \cdot 0)^2 + (\frac{1}{5} \cdot 0)^2} = 0$$

We need to look at border values:

$$x = -2: \|\nabla f\| = \sqrt{(-4 + e^{-2} - y)^2 + (2y + 2)^2} \rightarrow \text{is maximal when } y \text{ is the biggest}$$

But it is smaller than (because we add e^{x^2} to the abs. value)

$$x = 2: \|\nabla f\| = \sqrt{(4 + e^2 - y)^2 + (2y - 2)^2} \rightarrow \text{when } y = -2$$

$$= \sqrt{(6 + e^2)^2 + (-6)^2} = \sqrt{36 + 12e^2 + e^4 + 36} = \sqrt{72 + 12e^2 + e^4} =$$

$$\approx 14.672$$

$$\nabla f = [2x + e^x - y, 2y - x]$$

Def: f is β -smooth if $\forall x, y \in D : \|\nabla f(x) - \nabla f(y)\| \leq \beta \|x - y\|$

Prop. 2.8.: f is β -smooth $\Leftrightarrow \|\nabla^2 f\| \leq \beta$. \Leftrightarrow all eigenvalues are on $[0, \beta]$

$$\nabla^2 f = \begin{bmatrix} 2 + e^x & -1 \\ -1 & 2 \end{bmatrix}$$

eigenvalues: $(2 + e^x - \lambda)(2 - \lambda) - 1 = 0$

$$\lambda^2 + 4 + 2e^x - \lambda(2 + e^x + 2) - 1 = 0$$

$$\lambda^2 - (4 + e^x)\lambda + 2e^x + 3 = 0$$

$$\lambda_{1,2} = \frac{4 + e^x \pm \sqrt{16 + 8e^x + e^{2x} - 4e^x - 12}}{2} = \frac{4 + e^x \pm \sqrt{4 + e^{2x}}}{2}$$

$$\Rightarrow \text{max \& eigenvalue is at } x=2: \lambda_1 = \frac{4 + e^2 + \sqrt{4 + e^4}}{2} = \beta \approx 9,522$$

f is α -strongly convex if $f(x) - \frac{\alpha}{2} \|x\|^2$ is convex

Prop. 2.11.: \hookrightarrow iff each eigenvalue of $\nabla^2 f$ is $\geq \alpha$.

The smallest eigenvalue of $\nabla^2 f$ is at $x=-2$:

$$\lambda_2 = \frac{4 + e^{-2} - \sqrt{4 + e^{-4}}}{2} \approx 1,07 = \alpha$$

f is convex if $\nabla^2 f$ is PSD. (for all $x, y \in K$)

$$\det(\nabla^2 f) = 4 + 2e^x - 1 = 3 + 2e^x \geq 0 \quad \forall x(, y)$$

$$2 + e^x > 0 \quad \forall x(, y)$$

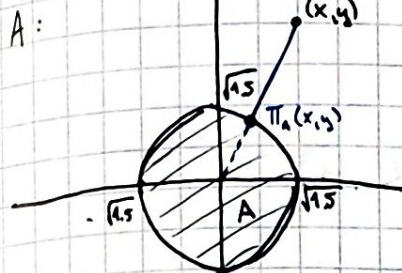
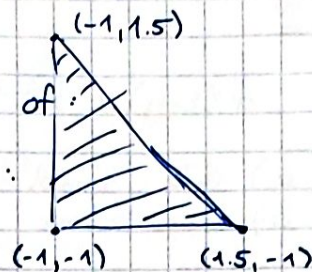
$\Rightarrow \boxed{+} \rightarrow \& H_f = \nabla^2 f \text{ PD} \Rightarrow f \text{ is convex everywhere.}$

3. Projections $\mathbb{R}^2 \rightarrow K$ to the closest points of:

A: $x^2 + y^2 \leq 1.5$

B: $[-1, 1] \times [-1, 1]$

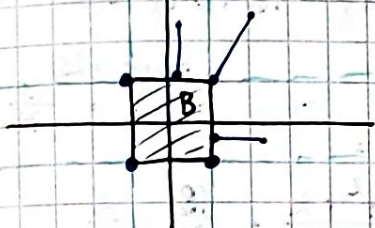
C:



$$\Pi_A(x, y) = \begin{cases} (x, y) & \text{if } (x, y) \in A \\ \frac{\sqrt{1.5}}{\sqrt{x^2 + y^2}} \cdot (x, y) & \text{otherwise} \end{cases}$$

Π_A shortens each vector to length of $\sqrt{1.5}$, keeps its direction

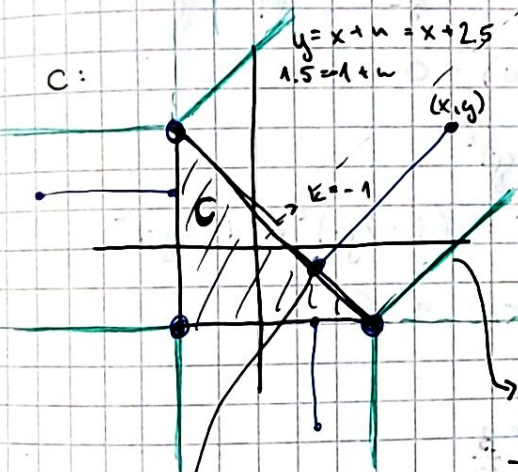
B:



$$\Pi_B(x, y) = (\Pi_{B1}(x), \Pi_{B2}(y))$$

$$\Pi_{B1}(x) = \begin{cases} x & ; -1 \leq x \leq 1 \\ -1 & ; x < -1 \\ 1 & ; x > 1 \end{cases}$$

C:



$$\Pi_C(x, y) = \begin{cases} (x, y) & ; (x, y) \in C \\ (-1, y) & ; x < -1, y \in (-1, 1.5) \\ (-1, 1.5) & ; x < -1, y > 1.5 \\ (-1, -1) & ; x < -1, y < -1 \\ (x, -1) & ; x \in (-1, 1.5), y < -1 \\ (1.5, -1) & ; x > 1.5, y < -1 \\ \frac{1}{2}(0.5 - y + x, 0.5 + y - x) & ; \text{otherwise} \end{cases}$$

$k = 1$
 $y = x + u$
 $-1 = 1.5 + u$
 $u = -2.5$

$x \geq \max(1.5, y + 2.5)$

$(x, y) = \Pi(x, y) + ($
 $\hookrightarrow y = x + u \rightarrow n_1 = y_1 - x_1$
 $\left. \begin{aligned} -x + 0.5 &= x + (y_1 - x_1) \\ \frac{1}{2}(0.5 - y_1 + x_1) &= x \end{aligned} \right\}$
 $y = -x + 0.5$
 $y = \frac{1}{2}(0.5 - y_1 + x_1) + y_1 - x_1 = \frac{1}{2}(0.5 + y_1 - x_1)$

$$4. f(x, y) = x^2 + 2y^2. \quad x_1 = (1, 1)$$

a) GD: find minimum of $f(x_2)$

b) How close to actual min of $f: x^*$ can we get? $\min \|x^* - x_2\|^2$

$$\text{GD: } x_{k+1} = x_k - \gamma \nabla f(x_k)$$

$$x_2 = x_1 - \gamma \nabla f(x_1)$$

$$a) \nabla f = [2x, 4y] \longrightarrow \nabla f(x_1) = [2, 4]$$

$$x_2 = [1 - 2\gamma, 1 - 4\gamma]$$

$$f(x_2) = (1 - 2\gamma)^2 + 2(1 - 4\gamma)^2$$

$$\frac{\partial f(x_2)}{\partial \gamma} = 2(1 - 2\gamma) \cdot (-2) + 4(1 - 4\gamma) \cdot (-4) = -4 + 8\gamma - 16 + 64\gamma = 0$$

$$\min f(x_2) = f(x_2) \Big|_{\gamma = \frac{20}{72}} = \left(\frac{32}{72}\right)^2 + 2 \cdot \left(-\frac{8}{72}\right)^2 = \frac{32^2 + 2 \cdot 8^2}{72^2} = \frac{4^2 + 2}{9^2} = \frac{18}{81} = \frac{2}{9}$$

$72\gamma = 20$
 $\gamma = \frac{20}{72} = \frac{5}{18}$

b) Actual minimum of $f(x, y)$ is $f(0, 0) = 0$

$$\|x^* - x_2\| = \|x_2\| = \sqrt{(1 - 2\gamma)^2 + (1 - 4\gamma)^2}$$

γ at min is equal to γ at min of $\|x_2\|^2 = (1 - 2\gamma)^2 + (1 - 4\gamma)^2$

$$\frac{\partial \|x_2\|^2}{\partial \gamma} = -2 \cdot 2 \cdot (1 - 2\gamma) - 4 \cdot 2 \cdot (1 - 4\gamma) = 0$$

$$-2 + 4\gamma - 4 + 16\gamma = 0$$

$20\gamma = 6$
 $\gamma = \frac{3}{10}$

$$\|x_2\| \Big|_{\gamma = \frac{3}{10}} = \sqrt{\left(\frac{4}{10}\right)^2 + \left(-\frac{2}{10}\right)^2} = \sqrt{\frac{4+1}{25}} = \frac{\sqrt{5}}{5}$$