

# Optimization

## Homework 1

Erika Rivadeneira  
erika.rivadeneira@cimat.mx

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1. Let  $f_1(x_1, x_2) = x_1^2 - x_2^2$ ,  $f_2(x_1, x_2) = 2x_1x_2$ . Represent the level sets associated with  $f_1(x_1, x_2) = 12$  and  $f_2(x_1, x_2) = 16$  on the same figure using Python. Indicate on the figure, the points  $\mathbf{x} = [x_1, x_2]^T$  for which  $f(\mathbf{x}) = [f_1(x_1, x_2), f_2(x_1, x_2)]^T = [12, 16]^T$

### Solution

Let's solve the equation system in order to find the intersection points. We have that

$$x_1^2 - x_2^2 = 12 \quad (1)$$

$$2x_1x_2 = 16 \quad (2)$$

From equation (2) we get that

$$x_2 = \frac{8}{x_1}$$

substituting  $x_2 = \frac{8}{x_1}$  in equation (1)

$$x_1^2 - \frac{64}{x_1^2} = 12$$

$$x_1^2(x_1^2 - 12) = 64$$

Then, the solution of the system is  $(-4, -2)$  and  $(4, 2)$

Finally, the corresponding plot of the level sets is

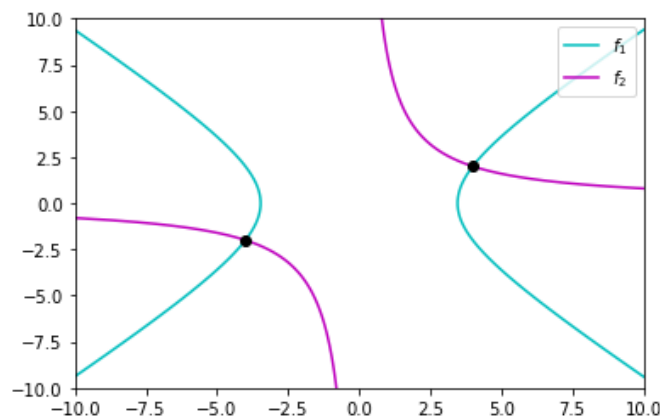


Figure 1: Level sets associated with  $f_1(x_1, x_2) = 12$  and  $f_2(x_1, x_2) = 16$

2. Consider the function  $f(\mathbf{x}) = (\mathbf{a}^T \mathbf{x}) (\mathbf{b}^T \mathbf{x})$ , where  $\mathbf{a}, \mathbf{b}$ , and  $\mathbf{x}$  are  $n$ -dimensional vectors. Compute the gradient  $\nabla f(\mathbf{x})$  and the Hessian  $\nabla^2 f(\mathbf{x})$ .

### Solution

Let's recall that the gradient of  $f(\mathbf{x})$  is defined as

$$\nabla f(\mathbf{x}) = \left[ \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \dots, \frac{\partial f}{\partial x_n} \right]^T$$
$$Df(\mathbf{x}) = \nabla f(\mathbf{x})^T$$

Then, we have that the gradient of  $f(x)$  is

$$\begin{aligned}\frac{\partial f}{\partial x_k} &= a_k \sum_{i=1}^n b_i x_i + b_k \sum_{i=1}^n a_i x_i \\ &= \sum_{j=1}^n (a_k b_j + b_k a_j) x_j\end{aligned}$$

Now, the Hessian  $\nabla^2 f(\mathbf{x})$  is given by

$$\nabla^2 f(\mathbf{x}) = \frac{\partial^2 f}{\partial x_i \partial x_j} = \begin{bmatrix} 2a_1 b_1 & a_1 b_2 + a_2 b_1 & \dots & a_1 b_n + a_n b_1 \\ a_2 b_1 + a_1 b_2 & 2a_2 b_2 & \dots & a_2 b_n + a_n b_2 \\ \vdots & \vdots & \ddots & \vdots \\ a_n b_1 + a_1 b_n & a_n b_2 + a_2 b_n & \dots & 2a_n b_n \end{bmatrix}$$

3. Let  $f(x) = \frac{1}{1+e^{-x}}$  and  $g(\mathbf{z}) = f(\mathbf{a}^T \mathbf{z} + b)$  with  $\|\mathbf{a}\|_2 = 1$ . Show that

$$D_a g(\mathbf{z}) = g(\mathbf{z})(1 - g(\mathbf{z})) \quad (3)$$

### Solution

By the directional derivative and since  $\|\mathbf{a}\|_2 = 1$  we have that

$$\begin{aligned}D_a g(\mathbf{z}) &= \lim_{h \rightarrow 0} \frac{f(\mathbf{a}^T(\mathbf{z} + h\mathbf{a}) + b) - f(\mathbf{a}^T \mathbf{z} + b)}{h} \\ &= \lim_{h \rightarrow 0} \frac{f(\mathbf{a}^T \mathbf{z} + b + h) - f(\mathbf{a}^T \mathbf{z} + b)}{h} \\ &= f'(\mathbf{a}^T \mathbf{z} + b)\end{aligned}$$

Let's note that

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

Then,

$$D_a g(\mathbf{z}) = f'(\mathbf{a}^T \mathbf{z} + b) = \frac{e^{-(\mathbf{a}^T \mathbf{z} + b)}}{1 + e^{-(\mathbf{a}^T \mathbf{z} + b)}}$$

Now, from (3) we get

$$\begin{aligned}g(\mathbf{z})(1 - g(\mathbf{z})) &= \frac{1}{1 + e^{-(\mathbf{a}^T \mathbf{z} + b)}} \left( 1 - \frac{1}{1 + e^{-(\mathbf{a}^T \mathbf{z} + b)}} \right) \\ &= \frac{1}{1 + e^{-(\mathbf{a}^T \mathbf{z} + b)}} - \frac{1}{(1 + e^{-(\mathbf{a}^T \mathbf{z} + b)})^2} \\ &= \frac{e^{-(\mathbf{a}^T \mathbf{z} + b)}}{(1 + e^{-(\mathbf{a}^T \mathbf{z} + b)})^2}\end{aligned}$$

Therefore,

$$D_a g(\mathbf{z}) = f'(\mathbf{a}^T \mathbf{z} + b) = \frac{e^{-(\mathbf{a}^T \mathbf{z} + b)}}{(1 + e^{-(\mathbf{a}^T \mathbf{z} + b)})^2} = g(\mathbf{z})(1 - g(\mathbf{z}))$$

4. Compute the gradient of

$$f(\theta) \stackrel{\text{def}}{=} \frac{1}{2} \sum_{i=1}^n [g(\mathbf{x}_i) - g(\mathbf{A}\mathbf{x}_i + \mathbf{b})]^2$$

with respect to  $\theta$ , where  $\theta = [a_{11}, a_{12}, a_{21}, a_{22}, b_1, b_2]^T$ ,  $\mathbf{x}_i \in \mathbb{R}^2$ ,  $\mathbf{A} \in \mathbb{R}^{2 \times 2}$ ,  $\mathbf{b} \in \mathbb{R}^2$  are defined as follows

$$\begin{aligned}\mathbf{A} &= \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \\ \mathbf{b} &= [b_1, b_2]^T\end{aligned}$$

and  $g : \mathbb{R}^2 \rightarrow \mathbb{R} \in \mathcal{C}^1$ .

**Solution**

Let's note that

$$Ax_i + b = \begin{bmatrix} a_{11}x_1 + a_{12}x_2 + b_1 \\ a_{21}x_1 + a_{22}x_2 + b_2 \end{bmatrix}$$

Then,

$$D_\theta(Ax_i + b) = \begin{bmatrix} x_1 & x_2 & 0 & 0 & 1 & 0 \\ 0 & 0 & x_1 & x_2 & 0 & 1 \end{bmatrix}$$

Therefore, we get that

$$\begin{aligned} \nabla f(\theta) &= - \sum_{i=1}^n (g(x_i) - g(Ax_i + b)) D_\theta g(Ax_i + b) D_\theta(Ax_i + b) \\ &= - \sum_{i=1}^n (g(x_i) - g(Ax_i + b)) \left( \frac{dg}{dv_1}, \frac{dg}{dv_2} \right) \begin{bmatrix} x_1 & x_2 & 0 & 0 & 1 & 0 \\ 0 & 0 & x_1 & x_2 & 0 & 1 \end{bmatrix} \end{aligned}$$

5. Show that  $\kappa(\mathbf{A}) \geq 1$  where  $\|\mathbf{A}\| = \max_x \frac{\|\mathbf{A}x\|}{\|x\|}$ . (Hint: show that  $\|\mathbf{A}\mathbf{B}\| \leq \|\mathbf{A}\|\|\mathbf{B}\|$ )

**Solution**

Let's prove that  $\|AB\| \leq \|A\|\|B\|$  first. Let's note that

$$\|A\| = \max_x \frac{\|Ax\|}{\|x\|} \geq \frac{\|Ay\|}{\|y\|} \Rightarrow \|Ay\| \leq \|A\|\|y\| \quad (4)$$

Now, considering (4) we get

$$\begin{aligned} \|AB\| &= \max_x \frac{\|ABx\|}{\|x\|} \\ &\leq \max_x \frac{\|A\|\|Bx\|}{\|x\|} \\ &\leq \max_x \frac{\|A\|\|B\|\|x\|}{\|x\|} \\ &= \|AB\| \end{aligned}$$

Therefore, we have proven that

$$\|AB\| \leq \|A\|\|B\| \quad (5)$$

Now, by using (5) and the definition of the condition number of a matrix we get

$$\begin{aligned} \kappa(A) &= \|A\|\|A^{-1}\| \\ &\geq \|A \cdot A^{-1}\| \\ &= \|I\| = 1 \end{aligned}$$

6. Show that  $x - \sin x = o(x^2)$ , as  $x \rightarrow 0$

**Solution**

We know by definition that

$$\lim_{x \rightarrow a} \frac{f(x)}{g(x)} = 0$$

Then, using L'Hopital we get

$$\begin{aligned} \lim_{x \rightarrow 0} \frac{x - \sin(x)}{x^2} &= \lim_{x \rightarrow 0} \frac{1 - \cos(x)}{2x} \\ &= \lim_{x \rightarrow 0} \frac{\sin(x)}{2} = 0 \end{aligned}$$

Therefore, we have proven that  $x - \sin(x) = o(x^2)$  as  $x \rightarrow 0$

7. Suppose that  $f(\mathbf{x}) = o(g(\mathbf{x}))$ . Show that for any given  $\epsilon > 0$ , there exists  $\delta > 0$  such that if  $0 < \|\mathbf{x}\| < \delta$ , then  $|f(\mathbf{x})| < \epsilon|g(\mathbf{x})|$ , i.e,  $f(\mathbf{x}) = O(g(\mathbf{x}))$  for  $0 < \|\mathbf{x}\| < \delta$

**Solution**

Let's assume that  $f(x) = o(g(x))$ . Then by definition of  $o(\cdot)$  we have that

$$\lim_{x \rightarrow 0} \frac{f(x)}{g(x)} = 0$$

Then, by definition of limit for all  $\epsilon > 0$  there exists  $\delta > 0$  such that if  $\|x - 0\| < \delta$  then

$$\begin{aligned} \left| \frac{f(x)}{g(x)} - 0 \right| &< \epsilon \\ \Rightarrow |f(x)| &< \epsilon|g(x)| \end{aligned}$$

which is the definition of  $O(\cdot)$

8. Show that if functions  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  and  $g : \mathbb{R}^n \rightarrow \mathbb{R}$  satisfy  $f(x) = -g(x) + o(g(x))$  and  $g(x) > 0$  for all  $x \neq \mathbf{0}$ , then for all  $x \neq \mathbf{0}$  sufficiently small, we have  $f(x) < 0$

**Solution**

We have that

$$f(x) + g(x) = o(g(x))$$

Then, by definition of  $o(\cdot)$  we get

$$\begin{aligned} \lim_{x \rightarrow 0} \frac{f(x) + g(x)}{g(x)} &= \lim_{x \rightarrow 0} \frac{f(x)}{g(x)} + 1 = 0 \\ \Rightarrow \lim_{x \rightarrow 0} \frac{f(x)}{g(x)} &= -1 \end{aligned}$$

Therefore,  $f(x) < 0$  since  $g(x) > 0$  by hypothesis.