

Solutions to Problem Sheet 1

Solution (1.1)

(a) The gradient is given by

$$\nabla f = \begin{pmatrix} 3x^2 - 12y \\ -12x + 24y^2 \end{pmatrix}$$

Therefore

$$\begin{aligned} 3x^2 - 12y &= 0 \\ -12x + 24y^2 &= 0 \end{aligned}$$

The second equation implies $x = 2y^2$, therefore

$$3y^4 - 12y = 0 \Rightarrow y(y^3 - 1) = 0$$

Therefore $y_1 = 0, x_1 = 0$ or $y_2 = 1, x_2 = 2$. **(2)**

The Hessian is

$$\nabla^2 f(x, y) = \begin{pmatrix} 6x & -12 \\ -12 & 48y \end{pmatrix}$$

Its determinate is $\det \nabla^2 f = 288xy - 122$. **(2)**

Therefore

- $(0, 0) : \det \nabla^2 f(0, 0) = -122$ and f_{xx} at $x = 0$ is zero, hence it is a saddle point **(1)**
- $(2, 1) : \det \nabla^2 f(2, 1) = 12$ and $f_{xx}(2, 1) > 0$; hence it is a local minimum. **(1)**

(b) The gradient is given by **(1)**

$$\nabla f(x, y) = \begin{pmatrix} \cos(x) \cos(y) \\ -\sin(x) \sin(y) \end{pmatrix}$$

The optimality condition implies that (each row corresponding to the respective component of the equation system

$$\begin{aligned} x = \frac{\pi}{2} \quad \text{or} \quad x = \frac{3\pi}{2} \quad \text{or} \quad y = \frac{\pi}{2} \quad \text{or} \quad y = \frac{3\pi}{2} \\ x = 0 \quad \text{or} \quad x = \pi \quad \text{or} \quad y = 0 \quad \text{or} \quad y = \pi. \end{aligned}$$

This gives the following critical points **(2)**

$$\begin{aligned} P_1 = \left(\frac{\pi}{2}, 0\right), P_2 = \left(\frac{\pi}{2}, \pi\right), P_3 = \left(\frac{3\pi}{2}, 0\right), P_4 = \left(\frac{3\pi}{2}, \pi\right) \\ P_5 = \left(0, \frac{\pi}{2}\right), P_6 = \left(0, \frac{3\pi}{2}\right), P_7 = \left(\pi, \frac{\pi}{2}\right), P_8 = \left(\pi, \frac{3\pi}{2}\right). \end{aligned}$$

The Hessian is **(1)**

$$\nabla^2 f(x, y) = \begin{pmatrix} -\sin(x) \cos(y) & -\cos(x) \sin(y) \\ -\cos(x) \sin(y) & -\sin(x) \cos(y) \end{pmatrix}$$

The respective matrices are given by **(2)**

$$P_1 : \begin{pmatrix} -1 & 0 \\ 0 & -1 \end{pmatrix} \quad \text{maximum}$$

$$P_2 : \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \quad \text{minimum}$$

$$P_3 : \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \quad \text{minimum.}$$

$$P_4 : \begin{pmatrix} -1 & 0 \\ 0 & -1 \end{pmatrix} \quad \text{maximum}$$

$$P_5 : \begin{pmatrix} 0 & -1 \\ -1 & 0 \end{pmatrix} \quad \text{saddle}$$

$$P_6 : \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \quad \text{saddle}$$

$$P_7 : \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \quad \text{saddle}$$

$$P_8 : \begin{pmatrix} 0 & -1 \\ -1 & 0 \end{pmatrix} \quad \text{saddle}$$

Solution (1.2)

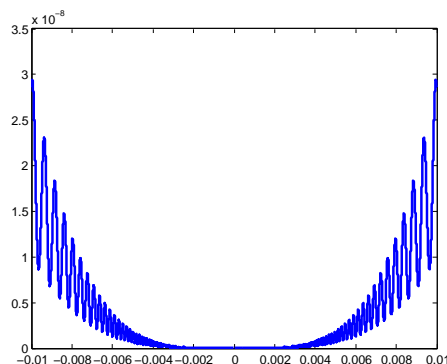
- (a) The function $f(x) = x^4$ has a strict minimum at $x = 0$, but the second derivative satisfies $f''(0) = 0$. **(1)**
- (b) We construct a function that has a strict minimizer x^* , but such that every open neighbourhood U of x^* contains other local minimizers. One such function is

$$f(x) = \begin{cases} x^4(\cos(1/x) + 2) & \text{for } x \neq 0 \\ 0 & \text{for } x = 0. \end{cases}$$

We explain the construction of this function:

1. Start out with $g(x) = \cos(1/x) + 2$ for $x \neq 0$ and $g(0) = 1$. This function has minimizers $x_0 = 0$ and $x_k = 1/(\pi(2k + 1))$ for $k \geq 0$, with values $g(x_k) = 1$ at all minimizers. Therefore, any open interval around 0 contains (infinitely many) local minimizers x_k other than $x_0 = 0$.
2. Multiply x^4 to the function: $f(x) = x^4 g(x)$. This ensures that $f(0) = 0$ and $f(x) > 0$ for $x \neq 0$. There are still local minima in every neighbourhood of 0. To see this, compute the derivative

$$f'(x) = x^2(4x \cos(1/x) + \sin(1/x) + 8x). \quad (1)$$



Set $z_m = 1/(\pi/2 + m\pi)$ for $m > 0$. Since $\sin(1/z_m) = \sin(\pi/2 + m\pi) = 1$ for m even and -1 for m odd, and for m sufficiently large the contribution of the other terms is negligible (as the z_m become arbitrary small), the derivative (1) changes signs between successive z_m . Since $f'(x)$ is continuous, it has roots between any z_m and z_{m+1} for large enough m , and these correspond to maxima and minima of f .

The function is in $C^2(\mathbb{R})$. For $x \neq 0$ this is clear, and to verify this at $x = 0$, one shows that the right and left limits as $x \rightarrow 0$ of $f'(x)$ and $f''(x)$ coincide (they are in fact 0).

Note the subtle point that one minimizer x^* can have local minimizers that are arbitrary close: while each open interval I surrounding x^* has another local minimizer \tilde{x} , every such \tilde{x} has an interval \tilde{I} surrounding it where this \tilde{x} is the only minimizer! (4)

Note: there is no unique way of solving this, and any sensible function with the desired properties will do the job. A solution that is based on the right idea but that is otherwise incomplete is worth two points.

Solution (1.3) The general procedure is as follows: we first make an educated guess as to whether the function could be convex or not. If we think it is not convex, then it is enough to find a *counterexample*: find points in S for which the line segment joining them is not completely contained in S . If we think it is convex, then we can show that for any two points the line segment joining them is in S .

(a) This set is not convex: take $\mathbf{x} = (1, 0, 0)^\top$ and $\mathbf{y} = (-1, 0, 0)^\top$, then $\frac{1}{2}\mathbf{x} + \frac{1}{2}\mathbf{y} = \mathbf{0} \notin S$.

(b) This set is convex: if $\mathbf{x}, \mathbf{y} \in S$, then $1 \leq x_1 - x_2 < 2$ and $1 \leq y_1 - y_2 < 2$, and

$$\lambda x_1 + (1-\lambda)y_1 - \lambda x_2 - (1-\lambda)y_2 = \lambda(x_1 - x_2) + (1-\lambda)(y_1 - y_2) < \lambda 2 + (1-\lambda)2 = 2,$$

with the same argument giving the lower bound.

- (c) This set is convex. In fact, S is the unit ball of the 1-norm

$$\|\mathbf{x}\|_1 = \sum_{i=1}^n |x_i|.$$

Given $\mathbf{x}, \mathbf{y} \in S$,

$$\|\lambda \mathbf{x} + (1 - \lambda) \mathbf{y}\|_1 \leq \lambda \|\mathbf{x}\|_1 + (1 - \lambda) \|\mathbf{y}\|_1 \leq \lambda \cdot 1 + (1 - \lambda) \cdot 1 = 1.$$

- (d) This set is convex. Here, one needs to show that convex combinations preserve symmetry and positive definiteness of a matrix. The symmetry is clear. As for the positive definiteness, let $\mathbf{x} \neq \mathbf{0}$ be given. Then

$$\mathbf{x}^\top (\lambda \mathbf{A} + (1 - \lambda) \mathbf{B}) \mathbf{x} = \lambda \mathbf{x}^\top \mathbf{A} \mathbf{x} + (1 - \lambda) \mathbf{x}^\top \mathbf{B} \mathbf{x} \geq 0,$$

which shows that positive definiteness is also preserved.