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TMA4180  
Optimisation I  
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**Solutions to exercise set 2**

- 1 a)  $\nabla f(x, y, z) = (4x + y - 6, x + 2y + z - 7, y + 2z - 8)$ , so critical/stationary point(s) of  $f$ , that is, points for which  $\nabla f = 0$ , must satisfy the system

$$\begin{bmatrix} 4 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 6 \\ 7 \\ 8 \end{bmatrix}.$$

The unique solution is  $(x, y, z) = (6, 6, 17)/5$ .

- b) Since  $f$  is twice continuously differentiable—in fact, smooth—around  $(6, 6, 17)/5$ , this point will be a strict local minimum provided the Hessian of  $f$  is symmetric positive definite (SPD) there. Now, for every  $(x, y, z)$ ,

$$\nabla^2 f = \begin{bmatrix} 4 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix}.$$

All three eigenvalues of  $\nabla^2 f$  are positive, and thus it is SPD.

- c) Function  $f$  is strictly convex because  $\nabla^2 f$  is SPD. Hence, local minimisers are global minimisers, and we conclude that  $(6, 6, 17)/5$  is a (*the*, in fact) global minimum.

- 2 Let  $u \in \mathbb{R}^n$  be arbitrary. Using the hint, note first that stationary points of  $f_u$  are solutions to the equation  $\nabla f(x) = u$ , because  $\nabla f_u(x) = \nabla f(x) - u$ . Thus it suffices to show that  $f_u$  has a critical point, and in particular, we look for a global minimum, which is guaranteed to exist provided  $f_u$  is coercive (it is continuously differentiable and therefore lower semi-continuous). Now,  $f$  is certainly more than coercive: it grows superlinearly—faster than linear in the sense of the norm—to  $+\infty$  as  $\|x\| \rightarrow \infty$ . (Indeed,

$$f(x) = \frac{f(x)}{\|x\|} \cdot \|x\| \rightarrow +\infty \cdot (+\infty) = +\infty \quad \text{as} \quad \|x\| \rightarrow \infty.)$$

Moreover, from Cauchy–Schwarz’ inequality we have  $u^\top x \leq \|u\|\|x\|$ , and so

$$f_u(x) = \frac{f(x)}{\|x\|} \|x\| - u^\top x \geq \left( \frac{f(x)}{\|x\|} - \|u\| \right) \|x\|.$$

Since  $f(x)/\|x\| \rightarrow +\infty$  as  $\|x\| \rightarrow \infty$ , the first part in the parenthesis will eventually be larger than  $\|u\|$ , no matter which  $u$  we consider. Therefore  $f_u(x) \rightarrow +\infty$  as  $\|x\| \rightarrow \infty$ , and  $f_u$  is coercive.

- 3 We utilise that twice continuously differentiable functions are convex if and only if their Hessian matrix is (symmetric) positive semi-definite. Routine calculations yield that

$$\nabla^2 f(x, y) = \frac{e^{x+y}}{(e^x + e^y)^2} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}.$$

The exponential terms are positive, and the constant matrix has eigenvalues 0 and 2. As such,  $\nabla^2 f$  is positive semi-definite, and  $f$  is convex.

- 4 On  $\mathbb{R}_{>0} = (0, \infty)$ , the map  $-\log x$  is strictly convex because  $(-\log x)'' = x^{-2} > 0$ . Thus

$$-\log(\alpha x + \beta y) \leq \alpha(-\log x) + \beta(-\log y) = -\log(x^\alpha y^\beta),$$

(where  $\beta = 1 - \alpha$ ) or

$$\log(x^\alpha y^\beta) \leq \log(\alpha x + \beta y),$$

with equality if and only if  $x = y$ . Exponentiating each side gives the arithmetic-geometric mean inequality.

- 5 Denote by  $C \subseteq \mathbb{R}^n$  the set of minimisers of  $f$ , and let  $x, y \in C$  and  $\alpha \in (0, 1)$ . Then  $f(x) = \min f = f(y)$  by assumption, and convexity of  $f$  yields that

$$f(\alpha x + (1 - \alpha)y) \leq \alpha f(x) + (1 - \alpha)f(y) = \min f.$$

Hence, by definition of  $\min f$ , we must have  $f(\alpha x + (1 - \alpha)y) = \min f$ . In other words,  $\alpha x + (1 - \alpha)y \in C$ , so  $C$  is convex.

- 6 Suppose that  $f$  has two global minimisers  $x$  and  $y$ . Since the set of minimisers is convex, it follows that  $\alpha x + (1 - \alpha)y$  is also a global minimiser for any  $\alpha \in (0, 1)$ . But

$$f(\alpha x + (1 - \alpha)y) < \alpha f(x) + (1 - \alpha)f(y) = \min f$$

by strict convexity of  $f$ , which contradicts the fact that  $x$  and  $y$  are global minimisers. Therefore  $f$  has at most one global minimiser.

Every exponential map  $f: x \mapsto a^x$  with  $a > 0$  and  $a \neq 1$  is strictly convex, but admits no local (and thus no global) minimiser on  $\mathbb{R}$ . Indeed, since  $f'(x) = a^x \ln a$ , it follows that  $f$  is strictly increasing for  $a > 1$  and strictly decreasing for  $0 < a < 1$ . Moreover, strict convexity is a consequence of  $f''(x) = a^x (\ln a)^2 > 0$ .

- 7 Geometrically, the idea is as follows: consider a sphere of some radius  $R$  around the global minimum  $x^*$ . Let  $C \subset \mathbb{R}^n \times \mathbb{R}$  be the circular convex cone with vertex  $(x^*, f(x^*))$ , and that touches the minimum of  $f$  on the sphere. Note that this minimum is greater than  $f(x^*)$  by strict convexity of  $f$ . Then  $(x, f(x))$  lies within  $C$  whenever  $\|x - x^*\| \geq R$  because  $f$  is convex, and so  $f$  blows up for large  $x$  (since the cone “blows up”).

Concretely, let  $R = 1$  and  $c$  be the minimum of  $f$  on the sphere  $\{y : \|y - x^*\| = 1\}$ . Let  $x$  be any point outside the sphere, that is,  $\|x - x^*\| \geq 1$ . Then we can consider a corresponding point  $y$  on the sphere as the convex combination

$$y = x^* + \frac{1}{\|x - x^*\|}(x - x^*) = \left(1 - \frac{1}{\|x - x^*\|}\right)x^* + \frac{1}{\|x - x^*\|}x.$$

By convexity of  $f$  we have

$$f(y) \leq \left(1 - \frac{1}{\|x - x^*\|}\right)f(x^*) + \frac{1}{\|x - x^*\|}f(x),$$

and since  $f(y) \geq c$ , this yields

$$f(x) \geq f(x^*) + (c - f(x^*))\|x - x^*\|.$$

Observing that  $c > f(x^*)$  by strict convexity of  $f$  (why?), we may let  $\|x\| \rightarrow \infty$  and conclude that  $f(x) \rightarrow +\infty$ , as desired.