## LUNDS TEKNISKA HÖGSKOLA MATEMATISKA INSTITUTIONEN

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**1.** a) The Hessian *H* must be positive semidefinite. Necessarily,

$$\det H = -(a+2)^2 \ge 0 \quad \Leftrightarrow \quad a = -2.$$

For this value of a we can complete the squares

$$x^T H x = (x_1 - 2x_2 + x_3)^2 \ge 0, \ \forall x \in \mathbb{R}^3,$$

hence, the matrix is positive semidefinite by definition. Answer: a = -2.

b) If the minimum exists then it is a stationary point of f. The function is convex, therefore, a stationary point is the global minimum. Thus, the minimum exists  $\Leftrightarrow$  a stationary point exists  $\Leftrightarrow$  there exists a solution to

$$\nabla f(x,y,z) = 2(x+y+z) \begin{bmatrix} 1\\1\\1 \end{bmatrix} + \begin{bmatrix} a\\b\\c \end{bmatrix} = \begin{bmatrix} 0\\0\\0 \end{bmatrix} \quad \Leftrightarrow \quad a=b=c.$$

<u>Answer</u>: a = b = c.

- c) See the book, Lemma 1, p. 43.
- **2. a)** The function is convex iff  $-\ln(y x^2)$  is convex. Try  $h(x, y) = x^2 y$  convex,  $g(t) = -\ln|t|, t < 0$ , increasing  $(g'(t) = -\frac{1}{t} > 0)$  and convex  $(g''(t) = \frac{1}{t^2} > 0)$ , hence, g(h(x, y)) is convex. Answer: Yes.
  - **b)** Yes,  $q_{\epsilon} \to +\infty$  when (x, y) approaches the boundary  $y = x^2$ .
  - c) The minimum of  $q_{\epsilon}$  on  $D_q$  exists because the function is convex and there is a feasible stationary point

$$\nabla q_{\epsilon} = \begin{bmatrix} 1 + \epsilon \frac{2x}{y - x^2} \\ 1 - \epsilon \frac{1}{y - x^2} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \Leftrightarrow \quad \begin{cases} y - x^2 + 2x\epsilon = 0, \\ y - x^2 - \epsilon = 0. \end{cases} \quad \Leftrightarrow \quad \begin{cases} x = -\frac{1}{2}, \\ y = \frac{1}{4} + \epsilon \end{bmatrix}$$

which is the minimum of  $q_{\epsilon}$ . It converges to (-1/2, 1/4), hence, it is the global minimum of the constrained problem.

**3.** a) The dual problem is

$$\min(6y_1 + 7y_2 + 2y_3) \qquad \text{subject to} \quad \begin{cases} y_1 + 3y_2 + 3y_3 \geq 1, \\ 3y_1 + 5y_2 + y_3 \geq 4, \\ y_1 + y_2 + y_3 \geq 3, \\ y_2 \geq 0, \ y_3 \leq 0. \end{cases}$$

The CSP gives  $y_2 = y_3 = 0$  and  $y_1 + y_2 + y_3 = 3$ , that is y = (3, 0, 0). It is dual feasible, hence, both solutions are optimal.

**b**) The statement 2 is equivalent to

$$A^T y = 0, \ b^T y > 0$$

has no solution. Rewriting it as the standard (first) Farkas alternative

$$\begin{bmatrix} A^T \\ -A^T \end{bmatrix} y \le 0, \quad b^T y > 0$$

makes the second alternative

$$\begin{bmatrix} A & -A \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = b, \quad \begin{bmatrix} u \\ v \end{bmatrix} \ge 0$$

being solvable. Denote x = u - v to conclude that it is equivalent to the statement 1.

**4.** a) Since all  $g_k$  are convex we have

$$g(\lambda z_1 + (1-\lambda)z_2) = \begin{bmatrix} g_1(\lambda z_1 + (1-\lambda)z_2) \\ g_2(\lambda z_1 + (1-\lambda)z_2) \\ \vdots \\ g_n(\lambda z_1 + (1-\lambda)z_2) \end{bmatrix} \le \begin{bmatrix} \lambda g_1(z_1) + (1-\lambda)g_1(z_2) \\ \lambda g_2(z_1) + (1-\lambda)g_2(z_2) \\ \vdots \\ \lambda g_n(z_1) + (1-\lambda)g_n(z_2) \end{bmatrix} = \lambda g(z_1) + (1-\lambda)g(z_2)$$

Now we have convexity of h by definition from

$$\underbrace{f(g(\lambda z_1 + (1 - \lambda)z_2))}_{h(\lambda z_1 + (1 - \lambda)z_2)} \stackrel{(1)}{\leq} f(\lambda g(z_1) + (1 - \lambda)g(z_2)) \stackrel{(2)}{\leq} \lambda \underbrace{f(g(z_1))}_{h(z_1)} + (1 - \lambda)\underbrace{f(g(z_2))}_{h(z_2)}.$$

where (1) follows from the above relation and f being coordinate-wise increasing, and (2) follows from convexity of f.

**b)** The function  $h_1$  is convex since

$$h_1(x, y, z) = \sqrt{x^6 + y^6 + z^6} = \sqrt{(|x|^3)^2 + (|y|^3)^2 + (|z|^3)^2}$$

can be split as  $h = f \circ g$  where

$$f(g_1, g_2, g_3) = \sqrt{g_1^2 + g_2^2 + g_3^2} = ||g||, \qquad g(x, y, z) = (|x|^3, |y|^3, |z|^3).$$

Here all  $g_k(x, y, z)$  are convex and f is convex and coordinate-wise increasing.

The function  $h_2$  is not convex. Set y = z = 0 to get the restriction  $\sqrt[3]{|x|}$  that is not convex.

c) The Hessian is

$$H = \begin{bmatrix} 2 & 4y \\ 4y & 4x + 12(1+a)y^2 \end{bmatrix}.$$

It is positive-semidefinite in the set iff

$$\det H = 8(x + (1 + 3a)y^2) \ge 0, \quad \forall x \ge 0.$$

It is equivalent to  $1 + 3a \ge 0 \Leftrightarrow a \ge -\frac{1}{3}$ . <u>Answer</u>:  $a \ge -\frac{1}{3}$ .

## 5. Existence of the minimum.

Use x + y = 4 and x, y > 0 to conclude that x, y are bounded from above. Take x = y = 2, z = 1/4. Then it is enough to consider  $xy + 2 \ln z \le 4 - 2 \ln 4 \le 2$  $\Rightarrow \ln z \le 1$ , hence z is bounded from above as well.

Now use  $xyz \ge 1$  to prove that x, y, z are bounded away from 0 from below. It makes the set compact. The minimum exists by Weierstrass theorem.

We set  $X = \{(x, y, z) \colon x > 0, y > 0, z > 0\},\$ 

$$g(x, y, z) = 1 - xyz, \quad h(x, y, z) = x + y - 4$$

 $\frac{CQ \text{ points. No such.}}{KKT \text{ points.}}$ 

$$\begin{pmatrix}
y - uyz + v &= 0, & (1) \\
x - uxz + v &= 0, & (2) \\
\frac{2}{z} - uxy &= 0, & (3) \\
u(1 - xyz) &= 0, & (4) \\
u &\geq 0, & (5) \\
\text{feasibility} & (6)
\end{cases}$$

u = 0 makes (3) impossible. For u > 0 we get xyz = 1 and u = 2 from (3). The first two equations yields

$$v = y(2z - 1) = x(2z - 1) \implies (x - y)(2z - 1) = 0.$$

If x = y then  $x + y = 4 \Rightarrow x = y = 2$  and  $xyz = 1 \Rightarrow z = 1/4$ , hence, (2, 2, 1/4) is a KKT point with  $f = 4 - 2 \ln 4 = 4 - 4 \ln 2$ .

If  $2z = 1 \Leftrightarrow z = 1/2$  then xy = 2 from (3) which together with x + y = 4 implies that x, y solves the quadratic equation

$$t^2 - 4t + 2 = 0 \quad \Leftrightarrow \quad t = 2 \pm \sqrt{2}.$$

Another KKT point is  $(2 \pm \sqrt{2}, 2 \mp \sqrt{2}, 1/2), f = 2 - 2 \ln 2.$ <u>Answer</u>:  $(2 \pm \sqrt{2}, 2 \mp \sqrt{2}, 1/2).$ 

## 6. a) Write down the Lagrange function

$$L(x, u) = x^{2} - 12x + y^{2} + 2y + u_{1}(x^{2} + y - 4) + u_{2}(-x^{2} + y^{2} + 1) =$$
  
=  $(1 + u_{1} - u_{2})x^{2} - 12x + (1 + u_{2})y^{2} + (2 + u_{1})y + u_{2} - 4u_{1}.$ 

Minimization w.r.t.  $y \ge 0$  is clearly at y = 0. Minimization w.r.t. x depends on:

if  $1 + u_1 - u_2 \le 0$  then  $\inf_x L = -\infty$ . if  $1 + u_1 - u_2 \ge 0$  then the function L is convex in x and

if  $1 + u_1 - u_2 > 0$  then the function L is convex in x and

$$L'_{x} = 2(1+u_{1}-u_{2})x - 12 = 0 \quad \Leftrightarrow \quad x = \frac{6}{1+u_{1}-u_{2}}$$

hence it is the minimum. It gives

$$\Theta(u) = \begin{cases} -\frac{36}{1+u_1-u_2} - 4u_1 + u_2, & \text{if } 0 \le u_2 < 1+u_1, \\ -\infty & \text{otherwise.} \end{cases}$$

Let us see if there is a stationary point w.r.t.  $u_1$ 

$$\Theta_{u_1}' = \frac{36}{(1+u_1-u_2)^2} - 4 = 0 \quad \Leftrightarrow \quad 1+u_1-u_2 = 3 \quad \Leftrightarrow \quad u_1 = u_2 + 2.$$

This  $u_1$  maximizes  $\Theta$  as the dual function is concave. It is left to maximize w.r.t.  $u_2 \ge 0$  for the found  $u_1$ 

$$\Theta = -12 - 4(u_2 + 2) + u_2 = -20 - 3u_2.$$

The function is decreasing, hence, the maximum is at  $u_2 = 0$ . Therefore,  $\bar{u}_2 = 0$ ,  $\bar{u}_1 = 2$  and  $\Theta(\bar{u}) = -20$ . The candidate x, y from above is  $\bar{x} = 6/3 = 2$ ,  $\bar{y} = 0$  gives  $f(\bar{x}, \bar{y}) = -20 = \Theta(\bar{u})$ , thus, the optimal point is (2, 0).

b)

$$\Theta(u,v) = \inf_{x \in X} L(x,u,v) \le L(x,u,v) = f(x) + \underbrace{u^T g(x)}_{\le 0} + v^T \underbrace{h(x)}_{=0} \le f(x).$$