1. Consider applying the basic Newton method to minimise the function

$$h(x_1, x_2) = x_1^2 + x_2^2 - x_1 x_2 + 3x_2 - 1$$

on  $\mathbb{R}^2$ , starting from the point  $\boldsymbol{x}^{(1)} = (1, 1)^{\top}$ .

(i) Calculate the Newton direction  $s^{(1)}$  for h at  $x^{(1)}$ .

Solution. The gradient and Hessian are given by

$$\nabla h(\boldsymbol{x}) = \begin{pmatrix} 2x_1 - x_2 \\ 2x_2 - x_1 + 3 \end{pmatrix}, \ \nabla^2 h(\boldsymbol{x}) = \begin{pmatrix} 2 & -1 \\ -1 & 2 \end{pmatrix}.$$

The Newton direction  $s^{(1)}$  satisfies

$$\nabla^2 h(\boldsymbol{x}^{(1)}) \boldsymbol{s}^{(1)} = \begin{pmatrix} 2 & -1 \\ -1 & 2 \end{pmatrix} \boldsymbol{s}^{(1)} = -\nabla h(\boldsymbol{x}^{(1)}) = \begin{pmatrix} -1 \\ -4 \end{pmatrix}.$$

By row reduction:

$$\begin{pmatrix} 2 & -1 & | & -1 \\ -1 & 2 & | & -4 \end{pmatrix} \rightarrow \begin{pmatrix} 1 & -\frac{1}{2} & | & -\frac{1}{2} \\ 1 & -2 & | & 4 \end{pmatrix} \rightarrow \begin{pmatrix} 1 & -\frac{1}{2} & | & -\frac{1}{2} \\ 0 & -\frac{3}{2} & | & \frac{9}{2} \end{pmatrix},$$

giving  $\mathbf{s}^{(1)} = (-2, -3)^{\top}$ .

(ii) Is the Newton direction  $\mathbf{s}^{(1)}$  a descent direction for h at  $\mathbf{x}^{(1)}$ . Give reasons for your answer.

**Solution.** It is a descent direction as

$$\nabla h(\boldsymbol{x}^{(1)})^{\top} \boldsymbol{s}^{(1)} = \begin{pmatrix} 1 & 4 \end{pmatrix} \begin{pmatrix} -2 \\ -3 \end{pmatrix} = -14 < 0.$$

(iii) Find the next Newton iterate  $x^{(2)}$ .

Solution. 
$$\boldsymbol{x}^{(2)} = \boldsymbol{x}^{(1)} + \boldsymbol{s}^{(1)} = (1,1)^{\top} + (-2,-3)^{\top} = (-1,-2)^{\top}.$$

(iv) Stating reasons, show that  $x^{(2)}$  is the unique global minimiser for the function h.

**Solution.** The point  $x^{(2)}$  is a stationary point because

$$\nabla h(\boldsymbol{x}^{(2)}) = \begin{pmatrix} (2)(-1) - (-2) \\ (2)(-2) - (-1) + 3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}.$$

Moreover,  $\nabla^2 h(\boldsymbol{x}) = \begin{pmatrix} 2 & -1 \\ -1 & 2 \end{pmatrix}$  with  $\operatorname{tr}(\nabla^2 h(\boldsymbol{x})) = 4 > 0$  and  $\det(\nabla^2 h(\boldsymbol{x})) = 3 > 0$  has positive eigenvalues, so  $\nabla^2 h(\boldsymbol{x})$  is positive definite for all  $\boldsymbol{x} \in \mathbb{R}^2$ . Hence, h is a strictly convex function over  $\mathbb{R}^2$ . Hence, the stationary point  $\boldsymbol{x}^{(2)}$  is the unique global minimiser.

2. Consider the equality constrained optimization problem

(P<sub>1</sub>) 
$$\min_{\boldsymbol{x} \in \mathbb{R}^3} -x_1 x_2 x_3$$
  
 $s.t.$   $x_1 + x_2 + x_3 - 40 = 0$   
 $x_1 + x_2 - x_3 = 0$ ,

where  $f(\mathbf{x}) = -x_1x_2x_3$ ,  $c_1(\mathbf{x}) = x_1 + x_2 + x_3 - 40$  and  $c_2(\mathbf{x}) = x_1 + x_2 - x_3$ . It is **given** that  $\mathbf{x}^* = (10, 10, 20)^{\top}$  is a regular constrained stationary point for (P1) with the Lagrange multipliers  $\lambda_1^* = 150$  and  $\lambda_2^* = 50$ . Using the second-order sufficient optimality conditions, determine whether or not  $\mathbf{x}^*$  is a (strict) local minimiser for (P1).

**Solution.** The Lagrangian function is  $L(\boldsymbol{x}, \boldsymbol{\lambda}) = f(\boldsymbol{x}) + \lambda_1 c_1(\boldsymbol{x}) + \lambda_2 c_2(\boldsymbol{x})$  with gradient and Hessian

$$\nabla L(\boldsymbol{x}, \boldsymbol{\lambda}) = \begin{pmatrix} -x_2 x_3 + \lambda_1 + \lambda_2 \\ -x_1 x_3 + \lambda_1 + \lambda_2 \\ -x_1 x_2 + \lambda_2 - \lambda_2 \end{pmatrix}, \ \nabla^2 L(\boldsymbol{x}, \boldsymbol{\lambda}) = \begin{pmatrix} 0 & -x_3 & -x_2 \\ -x_3 & 0 & -x_1 \\ -x_2 & -x_1 & 0 \end{pmatrix}, \ \nabla^2 L(\boldsymbol{x}^*, \boldsymbol{\lambda}^*) = \begin{pmatrix} 0 & -20 & -10 \\ -20 & 0 & -10 \\ -10 & -10 & 0 \end{pmatrix}.$$

The matrix  $\nabla^2 L(\boldsymbol{x}^*, \boldsymbol{\lambda}^*)$  is not positive definite. So, to calculate the reduced Hessian matrix, we want to find  $Z^* = (\alpha, \beta, \gamma)^{\top} \in \mathbb{R}^{3 \times 1}$  with full rank such that

$$(Z^*)^{\top} \left( \nabla c_1(\boldsymbol{x}^*) \quad \nabla c_2(\boldsymbol{x}^*) \right) = (Z^*)^{\top} \begin{pmatrix} 1 & 1 \\ 1 & 1 \\ 1 & -1 \end{pmatrix} = \left( \alpha + \beta + \gamma \quad \alpha + \beta - \gamma \right) = \begin{pmatrix} 0 & 0 \end{pmatrix}.$$

This means

$$\alpha + \beta + \gamma = 0$$
, and  $\alpha + \beta - \gamma = 0$ .

This gives  $\gamma = 0$  and  $\alpha = -\beta$ . So  $Z^*$  is of the form  $Z^* = (-\beta, \beta, 0), \beta \neq 0$ . Choose  $Z^* = (-1, 1, 0)^{\top}$ . The reduced Hessian is

$$W^* = (Z^*)^{\top} \nabla L(\boldsymbol{x}^*, \boldsymbol{\lambda}^*) Z^* = \begin{pmatrix} -1 & 1 & 0 \end{pmatrix} \begin{pmatrix} 0 & -20 & -10 \\ -20 & 0 & -10 \\ -10 & -10 & 0 \end{pmatrix} \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} = 40,$$

which is positive definite  $(1 \times 1)$  matrix. By the second-order sufficient optimality condition,  $\boldsymbol{x}^*$  is a strict local minimiser.

## 3. Consider the convex optimization problem

(P2) 
$$\min_{\mathbf{x} \in \mathbb{R}^2} e^{-2(x_1 + x_2)}$$
  
subject to  $e^{x_1} + e^{x_2} - 4 \le 0$ .

(i) Find a constrained stationary point  $z^*$  of the problem (P2).

**Solution.** Let  $c_1(x_1, x_2) := e^{x_1} + e^{x_2} - 4$ . Suppose that the constraint is active at  $\boldsymbol{z}^*$ , i.e.,  $c_1(z_1^*, z_2^*) = e^{z_1^*} + e^{z_2^*} - 4 = 0$ . The Lagrangian function is  $L(\boldsymbol{x}, \lambda_1) = e^{-2(x_1 + x_2)} + \lambda_1(e^{x_1} + e^{x_2} - 4)$ . For  $\boldsymbol{z}^*$  to be a constrained stationary point, we require  $\nabla_{\boldsymbol{z}} L(\boldsymbol{z}^*, \lambda_1^*) = \boldsymbol{0}$  and  $c_1(\boldsymbol{z}^*) = 0$  for some  $\lambda_1^*$ , i.e.,

$$-2e^{-2(z_1^*+z_2^*)} + \lambda_1^*e^{z_1^*} = 0, (1)$$

$$-2e^{-2(z_1^*+z_2^*)} + \lambda_1^* e^{z_2^*} = 0. (2)$$

$$e^{z_1^*} + e^{z_2^*} - 4 = 0. (3)$$

Subtracting Eqn. (1) from Eqn. (2) yields  $\lambda_1^*(e^{z_2^*}-e^{z_1^*})=0$ . Then either  $\lambda_1^*=0$  or  $e^{z_1^*}=e^{z_2^*}$ . If  $\lambda_1^*=0$ , then Eqn. (1) implies  $-2e^{-2(z_1^*+z_2^*)}=0$  which is not possible. So,  $e^{z_1^*}=e^{z_2^*}$ , and  $z_1^*=z_2^*$ . Now, Eqn. (3) gives  $z_1^*=z_2^*=\log 2$ . Finally, from Eqn. (1),  $\lambda_1^*=2^{-4}$ . Hence,  $\boldsymbol{z}^*=(\log 2,\log 2)$  is a constrained stationary point with the Lagrange multiplier  $\lambda_1^*=2^{-4}$ .

(ii) Is  $z^*$  of part (i) the only constrained stationary point for the problem (P2)? Give reasons for your answer.

**Solution.** Suppose that the constraint is not active at  $z^*$ , i.e.,  $e^{z_1^*} + e^{z_2^*} - 4 < 0$ . Then, the first-order necessary optimality condition requires

$$\nabla_{\mathbf{z}}(e^{-2(z_1^*+z_2^*)}) = \begin{pmatrix} -2e^{-2(z_1^*+z_2^*)} \\ -2e^{-2(z_1^*+z_2^*)} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix},$$

which is not possible. Hence,  $z^* = (\log 2, \log 2)$  is the **only** constrained stationary point.

- (iii) Explain why the constrained stationary point  $z^*$  of part (i) is a global minimizer for the problem (P2). Solution. It is given that (P<sub>2</sub>) is a convex problem, and we have found  $\lambda_1^* > 0$  for the active inequality constraint. By the KKT sufficient optimality conditions, the constrained stationary point  $z^*$  is a global minimiser.
- (iv) Stating clear reasons, show that  $\mathbf{z}^*$  of part (i) is the unique global minimizer for the problem (P2). Solution. Suppose that  $\mathbf{y}^* = (y_1^*, y_2^*)$  is another global minimiser for  $(P_2)$ . Then, it is a regular local minimizer because  $\nabla c_1(\mathbf{y}^*) = (e^{y_1^*}, e^{y_2^*})^{\top} \neq 0$ . So, by the first-order necessary optimality conditions, it must be a constrained stationary point for  $(P_2)$ . By part (ii),  $\mathbf{z}^*$  is the only constrained stationary point for  $(P_2)$ , so  $\mathbf{z}^* = \mathbf{y}^*$ . Note that the constraint cannot be active at  $\mathbf{y}^*$ . Otherwise, the first-order necessary optimality condition gives

$$\nabla_{\boldsymbol{y}^*}(e^{-2(y_1^*+y_2^*)}) = \begin{pmatrix} -2e^{-2(z_1^*+z_2^*)} \\ -2e^{-2(z_1^*+z_2^*)} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix},$$

which is not possible. Hence,  $z^*$  is the unique global minimiser for  $(P_2)$ .