



KTH Mathematics

**SF2822 Applied nonlinear optimization, final exam**  
**Monday May 20 2013 8.00–13.00**  
**Brief solutions**

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1. (a) If  $p$  is a nonzero vector in  $\mathbb{R}^4$ , then

$$p^T H p = p^T (I + e e^T) p = p^T p + (p^T e)^2 \geq p^T p > 0.$$

Hence,  $H$  is positive definite.

- (b) We may write  $A = (N \ B)$ , where  $B = I$  and  $N = -e$ , where  $e$  is the vector of ones. Then, a matrix  $Z$  whose columns form a basis for the nullspace of  $A$  is given by

$$Z = \begin{pmatrix} I \\ -B^{-1}N \end{pmatrix} = \begin{pmatrix} 1 \\ e \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}.$$

- (c) The step to the minimizer is given by  $Z p_Z$ , where

$$Z^T H Z p_Z = -Z^T (H \bar{x} + c).$$

Insertion of numerical values gives  $20 p_Z = 20$ , i.e.,  $p_Z = 1$ . Hence the optimal  $x$  is given by

$$x = \bar{x} + Z p_Z = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix}.$$

The Lagrange multipliers are then given by  $Hx + c = A^T \lambda$ , i.e.,

$$\begin{pmatrix} -2 \\ -1 \\ -1 \\ 4 \end{pmatrix} = \begin{pmatrix} -1 & -1 & -1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{pmatrix},$$

i.e.,  $\lambda = (-1 \ -1 \ 4)^T$ .

- (d) Since  $H$  is positive definite, the optimal solution  $x$  is unique. As  $A$  has full row rank, the Lagrange multiplier vector  $\lambda$  is unique. Since no component of  $\lambda$  is zero, no constraint can be omitted without  $x$  being changed.

2. Constraint 3 is in the working set at the initial point, i.e.,  $\mathcal{W} = \{3\}$ . With  $H = I$  and  $c = 0$  we obtain

$$\begin{pmatrix} H & A_{\mathcal{W}}^T \\ A_{\mathcal{W}} & 0 \end{pmatrix} \begin{pmatrix} p^{(0)} \\ -\lambda_{\mathcal{W}}^{(0)} \end{pmatrix} = - \begin{pmatrix} Hx^{(0)} + c \\ 0 \end{pmatrix}.$$

Insertion of numeric values gives

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} p_1^{(0)} \\ p_2^{(0)} \\ -\lambda_3^{(1)} \end{pmatrix} = - \begin{pmatrix} 8 \\ 0 \\ 0 \end{pmatrix}$$

We obtain

$$p^{(0)} = \begin{pmatrix} -8 & 0 \end{pmatrix}^T, \quad \lambda^{(1)} = \begin{pmatrix} 0 & 0 & 0 \end{pmatrix}^T.$$

The maximum steplength is given by

$$\alpha_{\max} = \min_{i: a_i^T p^{(0)} < 0} \frac{a_i^T x^{(0)} - b_i}{-a_i^T p^{(0)}} = \frac{1}{4},$$

where the minimum is attained for  $i = 1$ . Consequently,  $\alpha^{(0)} = 1/4$  so that

$$x^{(1)} = x^{(0)} + \alpha^{(0)} p^{(0)} = \begin{pmatrix} 8 \\ 0 \end{pmatrix} + \frac{1}{4} \begin{pmatrix} -8 \\ 0 \end{pmatrix} = \begin{pmatrix} 6 \\ 0 \end{pmatrix},$$

with  $\mathcal{W} = \{1, 3\}$ . The solution to the corresponding equality-constrained quadratic program is given by

$$\begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} p_1^{(1)} \\ p_2^{(1)} \\ -\lambda_1^{(2)} \\ -\lambda_3^{(2)} \end{pmatrix} = - \begin{pmatrix} 6 \\ 0 \\ 0 \\ 0 \end{pmatrix}.$$

We obtain

$$p^{(1)} = \begin{pmatrix} 0 & 0 \end{pmatrix}^T, \quad \lambda^{(2)} = \begin{pmatrix} 6 & 0 & -6 \end{pmatrix}^T.$$

As  $p^{(1)} = 0$ , it follows that  $x^{(2)} = x^{(1)}$  and the corresponding equality-constrained problem has been solved. However, since  $\lambda_3^{(2)} < 0$ , constraint 3 is deleted so that  $\mathcal{W} = \{1\}$ . The solution to the corresponding equality-constrained quadratic program is given by

$$\begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} p_1^{(2)} \\ p_2^{(2)} \\ -\lambda_1^{(3)} \end{pmatrix} = - \begin{pmatrix} 6 \\ 0 \\ 0 \end{pmatrix}.$$

We obtain

$$p^{(2)} = \begin{pmatrix} -3 & 3 \end{pmatrix}^T, \quad \lambda^{(3)} = \begin{pmatrix} 3 & 0 & 0 \end{pmatrix}^T.$$

The maximum steplength is given by

$$\alpha_{\max} = \min_{i: a_i^T p^{(2)} < 0} \frac{a_i^T x^{(2)} - b_i}{-a_i^T p^{(2)}} = \frac{4}{3},$$

where the minimum is attained for  $i = 2$ . Since  $\alpha_{\max} > 1$ , we let  $\alpha^{(2)} = 1$  so that

$$x^{(3)} = x^{(2)} + p^{(2)} = \begin{pmatrix} 6 \\ 0 \end{pmatrix} + \begin{pmatrix} -3 \\ 3 \end{pmatrix} = \begin{pmatrix} 3 \\ 3 \end{pmatrix}.$$

Since  $\lambda^{(3)} \geq 0$ , the optimal solution has been found.

3. (a) The problem  $(QP)$  is a convex quadratic program. The primal part of the trajectory is obtained as minimizer to the barrier-transformed problem

$$(P_\mu) \quad \min \quad \frac{1}{2}x_1^2 + \frac{1}{2}x_2^2 - \mu \ln(x_1 - 1)$$

under the implicit condition that  $x_1 + 1 > 0$ . The first-order optimality conditions of  $(P_\mu)$  gives

$$\begin{aligned} x_1(\mu) - \frac{\mu}{x_1(\mu) - 1} &= 0, \\ x_2(\mu) &= 0. \end{aligned}$$

Since  $(QP)$  is a convex problem,  $(P_\mu)$  is an unconstrained convex problem, taking into account the implicit constraint  $x_1 - 1 > 0$ . Therefore, the first-order necessary optimality conditions are sufficient for global optimality.

The first-order optimality conditions give  $x_2(\mu) = 0$ , and  $x_1(\mu)$  is given by

$$x_1^2(\mu) - x_1(\mu) - \mu = 0,$$

i.e.,

$$x_1(\mu) = \frac{1}{2} + \sqrt{\frac{1}{4} + \mu},$$

where the plus sign has been chosen for the square root to enforce  $x_1(\mu) - 1 > 0$ .

The dual part of the trajectory, i.e.  $\lambda(\mu)$ , is normally given by  $\lambda_i(\mu) = \mu/g_i(x(\mu))$ ,  $i = 1, \dots, m$ . Here we only have one constraint, so

$$\lambda(\mu) = \frac{\mu}{x_1(\mu) - 1} = \frac{\mu}{-\frac{1}{2} + \sqrt{\frac{1}{4} + \mu}} = \frac{1}{2} + \sqrt{\frac{1}{4} + \mu}.$$

- (b) As  $\mu \rightarrow 0$  it follows that  $x(\mu) \rightarrow (1 \ 0)^T$  and  $\lambda(\mu) \rightarrow 1$ . Let  $x^* = (1 \ 0)^T$  and  $\lambda^* = 1$ . Then  $x^*$  and  $\lambda^*$  satisfy the first-order optimality conditions of  $(QP)$ . Since  $(QP)$  is a convex problem, this is sufficient for global optimality of  $(QP)$ .

- (c) We have

$$\|x(\mu) - x^*\|_2 = -\frac{1}{2} + \sqrt{\frac{1}{4} + \mu} = -\frac{1}{2} + \frac{1}{2}\sqrt{1 + 4\mu} = \mu + o(\mu).$$

This is as expected. We would expect  $\|x(\mu) - x^*\|_2$  to be of the order  $\mu$  near an optimal solution where regularity holds.

4. (a) The point  $x^{(0)}$  is not feasible, as  $g_2(x^{(0)}) < 0$ . Hence, it cannot be a local minimizer.

(b) The QP subproblem becomes

$$\begin{aligned} & \text{minimize} && \frac{1}{2}p^T \nabla_{xx}^2 \mathcal{L}(x^{(0)}, \lambda^{(0)})p + \nabla f(x^{(0)})^T p \\ & \text{subject to} && \nabla g_i(x^{(0)})^T p \geq -g_i(x^{(0)}), \quad i = 1, 2, 3. \end{aligned}$$

Insertion of numerical values gives

$$\begin{aligned} & \min && \frac{1}{2}p_1^2 + \frac{1}{2}p_2^2 \\ & \text{subject to} && p_1 + p_2 \geq -2, \\ & && p_1 \geq 1, \\ & && p_2 \geq -1. \end{aligned}$$

If we let  $p^{(0)}$  denote the optimal solution of the QP subproblem, we obtain  $x^{(1)} = x^{(0)} + p^{(0)}$ . We obtain  $\lambda^{(1)}$  as the Lagrange multipliers of the QP subproblem.

The quadratic program is convex, and the optimal solution is given by  $p^{(0)} = (1 \ 0)^T$ , so that  $x^{(2)} = x^{(0)} + p^{(0)} = (1 \ 0)^T$ . The Lagrange multiplier of the quadratic program is given by  $\lambda^{(1)} = (0 \ 1)^T$ .

**5.** (See the course material.)