

TTK4135 Optimization and Control Spring 2013

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Exercise 4 Solution

Problem 1 (50 %) Quadratic Programming

a) A quadratic program

$$\min_{x} \quad q(x) = \frac{1}{2}x^{\top}Gx + x^{\top}c
\text{s.t.} \quad a_{i}^{\top}x = b_{i}, \quad i \in \mathcal{E}$$
(1a)

s.t.
$$a_i^{\top} x = b_i, \quad i \in \mathcal{E}$$
 (1b)

$$a_i^{\top} x \ge b_i, \qquad i \in \mathcal{I}$$
 (1c)

is convex if the Hessian matrix G is positive semidefinite. If G is positive definite, the QP is strictly convex.

Convexity is important because in the case of convex QPs, the problem is often similar in difficulty to a linear program, and the problem has only one solution. A nonconvex QP can be more challenging due to the possibility of several local minima and stationary points.

b) If the condition in Theorem 16.2 is changed from $Z^{T}GZ > 0$ to $Z^{T}GZ > 0$, all we can say about x^* is that it is a (local) solution of the equality constrained QP (16.3).

The proof is identical up until the equation

$$q(x) = \frac{1}{2}u^{\mathsf{T}}Z^{\mathsf{T}}GZu + q(x^*) \tag{2}$$

Now, since we have $Z^{\top}GZ \geq 0$, we can only conclude $q(x) \geq q(x^*)$, which shows that x^* is a local minimizer (not strict!).

c) We will apply Algorithm 16.3 to the quadratic program with

$$G = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \qquad c^{\top} = \begin{bmatrix} -2 & -5 \end{bmatrix}$$
(3a)

$$a_{1}^{\top} = \begin{bmatrix} 1 & -2 \end{bmatrix} \qquad a_{2}^{\top} = \begin{bmatrix} -1 & -2 \end{bmatrix} \qquad (3b)$$

$$a_{3}^{\top} = \begin{bmatrix} -1 & 2 \end{bmatrix} \qquad a_{4}^{\top} = \begin{bmatrix} 1 & 0 \end{bmatrix} \qquad (3c)$$

$$a_{5}^{\top} = \begin{bmatrix} 0 & 1 \end{bmatrix} \qquad b^{\top} = \begin{bmatrix} -2 & -6 & -2 & 0 & 0 \end{bmatrix} \qquad (3d)$$

$$a_1^{\mathsf{T}} = \begin{bmatrix} 1 & -2 \end{bmatrix} \qquad \qquad a_2^{\mathsf{T}} = \begin{bmatrix} -1 & -2 \end{bmatrix}$$
 (3b)

$$a_3^{\top} = \begin{bmatrix} -1 & 2 \end{bmatrix} \qquad \qquad a_4^{\top} = \begin{bmatrix} 1 & 0 \end{bmatrix}$$
 (3c)

$$a_5^{\mathsf{T}} = \begin{bmatrix} 0 & 1 \end{bmatrix} \qquad b^{\mathsf{T}} = \begin{bmatrix} -2 & -6 & -2 & 0 & 0 \end{bmatrix}$$
 (3d)

and $\{1,2,3,4,5\} \in \mathcal{I}$. Note that the objective function also has a constant element 7.25, but this has no effect on the solution. We start the algorithm at $x = [2, 0]^{\top}$, where constraints 3 and 5 are active. However, we set the initial working set W_0 to only contain constraint 3.

Let x_k , λ_k , p_k denote the variables x, λ , p at iteration k; let A_k the matrix $[A_i]_{i \in \mathcal{W}_k}$, that is, containing the vectors a_i which are in the working set at iteration k.

Iteration k = 0

Since only constraint 3 is active, A_0 will contain a_3 . To find the direction p, we solve the equality-constrained QP

$$\min_{p} \quad q(x) = \frac{1}{2} p^{\top} G p + g_0^{\top} p \tag{4a}$$

$$s.t. \quad a_3^{\top} p = 0 \tag{4b}$$

where $g_0 = Gx_0 + c$. (See equation (16.39) in the textbook.) From Chapter 16.1, we know that the solution to this problem can be found by solving the equation set

$$\begin{bmatrix} G & -A_0^{\mathsf{T}} \\ A_0 & 0 \end{bmatrix} \begin{bmatrix} p_0 \\ \lambda_0 \end{bmatrix} = \begin{bmatrix} -g_0 \\ 0 \end{bmatrix}$$
 (5a)

which gives

$$\begin{bmatrix} 2 & 0 & 1 \\ 0 & 2 & -2 \\ -1 & 2 & 0 \end{bmatrix} \begin{bmatrix} p_0 \\ \lambda_0 \end{bmatrix} = \begin{bmatrix} -2 \\ 5 \\ 0 \end{bmatrix}$$
 (5b)

This equation set has the solution $p_0 = [0.2, 0.1]^{\top}$ and $\lambda_0 = -2.4$. With this direction we get

$$x_1 = x_0 + p_0 = \begin{bmatrix} 2 \\ 0 \end{bmatrix} + \begin{bmatrix} 0.2 \\ 0.1 \end{bmatrix} = \begin{bmatrix} 2.2 \\ 0.1 \end{bmatrix}$$
 (6)

This point is feasible with respect to all constraints, so we do not need to find an α_0 at this iteration. Note that there also are no blocking constraints. Hence, the working set at the next iteration will be the same as in this iteration. We set k=1 and proceed to the next iteration.

Iteration k = 1

We now solve the same QP as above, except that we now have $g_1 = Gx_1 + c = [2.4, -4.8]^{\top}$. This gives the equation set

$$\begin{bmatrix} 2 & 0 & 1 \\ 0 & 2 & -2 \\ -1 & 2 & 0 \end{bmatrix} \begin{bmatrix} p_1 \\ \lambda_1 \end{bmatrix} = \begin{bmatrix} -2.4 \\ 4.8 \\ 0 \end{bmatrix}$$
 (7)

with the solution $p_1 = [0, 0]^{\top}$ and $\lambda_1 = -2.4$. Since $p_1 = 0$ and $\lambda_1 < 0$, we remove the constraint with the most negative multiplier from the working set. With only one constraint in the working set, the working set will now be empty. Furthermore, $x_2 = x_1 + 0 = x_1$. We set k = 2 and proceed to the next iteration.

Iteration k = 2

Now that we have an empty working set, so A_2 is an empty matrix. The direction p is then found from the unconstrained QP

$$\min_{p} \quad q(x) = \frac{1}{2} p^{\top} G p + g_2^{\top} p \tag{8}$$

where $g_2 = Gx_2 + c = [2.4, -4.8]^{\top}$. Solving the equation set

$$\begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} p_2 = \begin{bmatrix} -2.4 \\ 4.8 \end{bmatrix} \tag{9}$$

gives the solution $p_2 = [-1.2, 2.4]^{\top}$. (There are no multipliers due to the absence of constraints in the working set.) Note that the solution to the unconstrained problem is $p_2 = G^{-1}(-g_2)$, that $\nabla^2 q(x_2) = G$, and that $\nabla q(x_2) = Gx_2 + c$. Hence, we can write $p_2 = -(\nabla^2 q(x_2))^{-1} \nabla q(x_2)$, which is the Newton direction (see equation (2.15) in the textbook). Setting $x_3 = x_2 + p_2 = [1, 2.5]^{\top}$ gives an infeasible point (constraint 1 is violated), so a step-length parameter α_2 must be found. $a_i^{\top} p_2 < 0$ for i = 1, 2, and 4, so

$$\alpha_2 = \min\left(1, \ \frac{b_1 - a_1^{\top} x_2}{a_1^{\top} p_2}, \ \frac{b_2 - a_2^{\top} x_2}{a_2^{\top} p_2}, \ \frac{b_4 - a_4^{\top} x_2}{a_4^{\top} p_2}\right)$$

$$= \min\left(1, \ \frac{2}{3}, \ 1, \ \frac{11}{6}\right) = \frac{2}{3}$$
(10)

As the minimum value corresponds to corresponds to constraint 1 (a blocking constraint), this constraint is added to the working set. That is, $W_3 = \{1\}$. x at the next iteration is then found from

$$x_3 = x_2 + \alpha_2 p_2 = \begin{bmatrix} 1.4\\1.7 \end{bmatrix} \tag{11}$$

We set k = 3 and proceed to the next iteration.

Iteration k = 3

We now have $g_3 = Gx_3 + c = [0.8, -1.6]^{\top}$ and $A_3 = a_1$. Then, the KKT system that solves the QP for the direction p_3 becomes

$$\begin{bmatrix} G & -A_3^{\top} \\ A_3 & 0 \end{bmatrix} \begin{bmatrix} p_3 \\ \lambda_3 \end{bmatrix} = \begin{bmatrix} -g_3 \\ 0 \end{bmatrix}$$
 (12a)

which gives

$$\begin{bmatrix} 2 & 0 & -1 \\ 0 & 2 & 2 \\ 1 & -2 & 0 \end{bmatrix} \begin{bmatrix} p_3 \\ \lambda_3 \end{bmatrix} = \begin{bmatrix} -0.8 \\ 1.6 \\ 0 \end{bmatrix}$$
 (12b)

The solution to this equation set is $p_3 = [0, 0]^{\top}$ and $\lambda_0 = 0.8$. Hence, we can conclude that we have found the solution. That is, $x^* = [1.4, 1.7]^{\top}$.

The problem and iteration sequence is illustrated in Figure 1.

d) We write the problem in Example 16.4 as

$$\min_{x} \quad q(x) = \frac{1}{2}x^{\mathsf{T}}Gx + x^{\mathsf{T}}c \tag{13a}$$

$$s.t. \quad Ax - b \ge 0 \tag{13b}$$

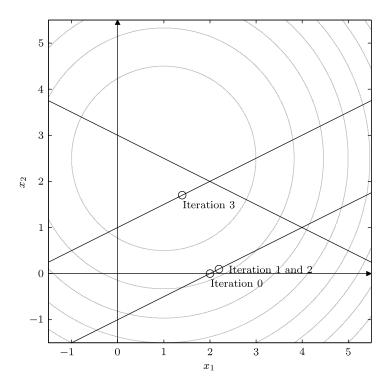


Figure 1: Contour plot with constraints and iterations for Problem 1.

where

$$G = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \qquad c = \begin{bmatrix} -2 \\ -5 \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & -2 \\ -1 & -2 \\ -1 & 2 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \qquad b = \begin{bmatrix} -2 \\ -6 \\ -2 \\ 0 \\ 0 \end{bmatrix}$$

$$(14a)$$

The Lagrangian for this problem is

$$\mathcal{L}(x,\lambda) = \frac{1}{2}x^{\mathsf{T}}Gx + x^{\mathsf{T}}c - \lambda^{\mathsf{T}}(Ax - b)$$
 (15)

Hence, the dual objective is

$$f(\lambda) = \inf_{x} \mathcal{L}(x, \lambda) = \inf_{x} \frac{1}{2} x^{\top} G x + x^{\top} c - \lambda^{\top} (Ax - b)$$
 (16)

Since G > 0 and the Lagrangian is a strictly convex quadratic function, the infimum with respect to x is where $\nabla_x \mathcal{L}(x, \lambda) = 0$. That is:

$$\nabla_x \mathcal{L}(x,\lambda) = \frac{1}{2} G^\top x + \frac{1}{2} G x + c - (\lambda^\top A)^\top, \qquad G = G^\top$$
$$= G x + c - A^\top \lambda = 0 \tag{17}$$

We can now write the dual problem in three different forms. One form is obtained by writing x as $x = G^{-1}(A^{T}\lambda - c)$ and substitute in the dual objective to get

$$f(\lambda) = \frac{1}{2} (A^{\top} \lambda - c)^{\top} G^{-1} G G^{-1} (A^{\top} \lambda - c) + (A^{\top} \lambda - c)^{\top} G^{-1} c - \lambda^{\top} (A G^{-1} (A^{\top} \lambda - c) - b)$$
(18)

After some rearranging, we can write

$$f(\lambda) = \frac{1}{2} (A^{\top} \lambda - c)^{\top} G^{-1} (A^{\top} \lambda - c)$$

$$+ A^{\top} \lambda G^{-1} c - c^{\top} G^{-1} c$$

$$- \lambda^{\top} A G^{-1} A^{\top} \lambda + \lambda^{\top} A G^{-1} c + \lambda^{\top} b$$

$$\Rightarrow f(\lambda) = \frac{1}{2} (A^{\top} \lambda - c)^{\top} G^{-1} (A^{\top} \lambda - c)$$

$$- (A^{\top} \lambda - c)^{\top} G^{-1} (A^{\top} \lambda - c) + \lambda^{\top} b$$

$$\Rightarrow f(\lambda) = -\frac{1}{2} (A^{\top} \lambda - c)^{\top} G^{-1} (A^{\top} \lambda - c) + \lambda^{\top} b$$

$$(19)$$

The dual problem can then be formulated as

$$\max_{\lambda} f(\lambda) = -\frac{1}{2} (A^{\mathsf{T}} \lambda - c)^{\mathsf{T}} G^{-1} (A^{\mathsf{T}} \lambda - c) + \lambda^{\mathsf{T}} b$$
 (20a)

s.t.
$$\lambda \ge 0$$
 (20b)

Alternatively, the dual problem can be formulated in both x and λ as

$$\max_{x,\lambda} \quad \frac{1}{2} x^{\top} G x + x^{\top} c - \lambda^{\top} (Ax - b)$$
 (21a)

s.t.
$$Gx + c - A^{\mathsf{T}}\lambda = 0$$
 (21b)

$$\lambda > 0 \tag{21c}$$

A third option is to reformulate the constraint as $(c - A^{\top} \lambda)^{\top} = -x^{\top} G x$, and substitute into the objective function to get

$$\max_{x,\lambda} \quad -\frac{1}{2}x^{\top}Gx + \lambda^{\top}b \tag{22a}$$

s.t.
$$Gx + c - A^{\mathsf{T}}\lambda = 0$$
 (22b)

$$\lambda > 0 \tag{22c}$$

e) The dual optimization problem can be used to give an over-estimate of $q(\bar{x}) - q(x^*)$ (q is the primal objective), when x^* is not known. Any feasible \bar{x} and any $\bar{\lambda} \geq 0$ will give $f(\bar{\lambda}) \leq q(x^*)$ (f is the dual objective). Therefore,

$$q(\bar{x}) - q(x^*) \le q(\bar{x}) - f(\bar{\lambda}) \tag{23}$$

Problem 2 (50 %) Production Planning and Quadratic Programming

Two reactors, R_I and R_{II} , produce two products A and B. To make 1000 kg of A, 2 hours of R_I and 1 hour of R_{II} are required. To make 1000 kg of B, 1 hour of R_I and 3 hours of R_{II} are required. The order of R_I and R_{II} does not matter. R_I and R_{II} are available for 8 and 15 hours, respectively. We want to maximize the total profit from the two products.

The profit now depends on the production rate:

- the profit from A is $3 0.4x_1$ per tonne produced,
- the profit from B is $2 0.2x_2$ per tonne produced,

where x_1 is the production of product A and x_2 is the production of product B (both in tonnes).

a) The total profit from selling the two products is

$$p(x) = (3 - 0.4x_1)x_1 + (2 - 0.2x_2)x_2 \tag{24}$$

Since we want to maximize p(x), we minimize the negative of p(x). Hence, the objective function for the minimization problem is

$$f(x) = -p(x) = -(3 - 0.4x_1)x_1 - (2 - 0.2x_2)x_2 = \frac{1}{2}x^{\mathsf{T}} \underbrace{\begin{bmatrix} 0.8 & 0\\ 0 & 0.4 \end{bmatrix}}_{G} x + \underbrace{\begin{bmatrix} -3 & -2 \end{bmatrix}}_{c^{\mathsf{T}}} x \quad (25)$$

Note that G > 0. The availability constraints can be formulated as $2x_1 + x_2 \le 8$ and $x_1 + 3x_2 \le 15$; nonnegative production rates are formulated $x_1 \ge 0$ and $x_2 \ge 0$. We then have the optimization problem

$$\min_{x} \quad q(x) = \frac{1}{2}x^{\mathsf{T}}Gx + x^{\mathsf{T}}c \tag{26a}$$

s.t.
$$-2x_1 - x_2 \ge -8$$
 (26b)

$$-x_1 - 3x_2 \ge -15 \tag{26c}$$

$$x_1 \ge 0 \tag{26d}$$

$$x_2 \ge 0 \tag{26e}$$

- b) A contour plot with constraints and iterations indicated is illustrated in Figure 2. Code for producing a contour plot in MATLAB is attached at the end of this solution.
- c) The modifications that have to be made to the file qp_prodplan.m so that it solves the problem formulated in a) is attached at the end of this solution. We see in Figure 2 that as opposed to the linear case in exercise 3, the solution is not at a point of intersection between constraints. The solution and all iterations are indicated in Figure 2.

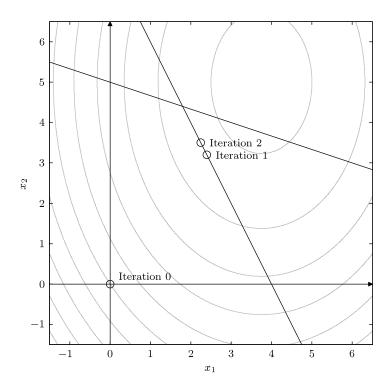


Figure 2: Contour plot with constraints and iterations for Problem 2.

- d) See Problem 1 c) and the textbook for an explanation of the active set algorithm.
- e) As mentioned, the solution is not found at a corner point of the feasible area. For linear programs, the solution is always at a point of intersection between constraints. For quadratic programs, the solution may be at any point in the feasible area, including the interior (where no constraints are active).

```
1 % Code for making a contour plot for Problem 2.
x1_1 = -1.5; x1_h = 6.5;
x2_1 = -1.5; x2_h = 6.5;
_{4} res = 0.01;
5 [x1, x2] = meshgrid(x1_l:res:x2_h, x1_l:res:x2_h);
f = -(3-0.4*x1).*x1 - (2-0.2*x2).*x2;
_{7} levels = (-12:2:8)';
[C, h] = contour(x1, x2, f, levels, 'Color', .7*[1 1 1]);
9 set(h, 'ShowText', 'on', 'LabelSpacing', 300); % For text labels
1 % Changes made to the file qp_prodplan.m
2 % Quadratic objective (MODIFY THESE)
_{3} G = [0.8 0;
      0 0.4]; % Remember the factor 1/2 in the objective
5 C = [-3; -2];
6 % Linear constraints (MODIFY THESE)
_{7} A = [2 1 ;
      1 3];
9 b = [8; 15];
```