

# Homework 4

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## Question 1:

First, the feasible set of  $P$  is not empty, for instance  $(x, y)$  with  $x = (1, 0, \dots, 0)$  and  $y = (0, 1, 0, \dots, 0)$  is feasible, now, suppose that  $(x_1, y_1), (x_2, y_2)$  are two feasible points, we'll that that  $P$  is convex, i.e. that  $\lambda(x_1, y_1) + (1 - \lambda)(x_2, y_2)$  is a feasible point for any  $\lambda \in [0, 1]$ . Indeed  $\therefore$ , by linearity of the norm

$$(\lambda x_1 + (1 - \lambda)x_2)^t(\lambda x_1 + (1 - \lambda)x_2) = \lambda(x_1^t x_1) + (1 - \lambda)(x_2^t x_2) = 1.$$

The same argument applies for the second condition, finally, by linearity once again :

$$(\lambda x_1 + (1 - \lambda)x_2)^t(\lambda y_1 + (1 - \lambda)y_2) = \lambda x_1^t y_1 + (1 - \lambda)x_2^t y_2 = 0.$$

Therefore the convexity is proved.

Now for the LICQ, we derivate the three conditions to have  $(-2x, 0), (0, -2y), (y, x)$ , on a feasible point,  $x$  and  $y$  are of norm 1, therefore different than 0 and therefore orthogonal, hence they're linearly indepedent, therefore  $(-2x, 0), (0, -2y), (y, x)$  are (there's no solution to  $-2x = \lambda y$ ).

## Question 2 :

The optimal value of the relaxed problem is  $1/2(a_1 + b_1)$  where  $a_1, b_1$  are respectively the minimal eigenvalues of  $A$  and  $B$ . This follows from Linear Algebra II, we know it's a finite value because the matrices are SPD, to attain it, we need  $(x, y) = (v_{a_1}, v_{b_1})$  where those are the eigenvectors of  $a_1$  and  $b_1$  respectively of norm 1. The optimal value of the relaxed problem is better or equal to the one of the target problem (which is logical since it has less conditions), they're equal if and only if  $v_{a_1}; v_{b_1}$  are orthogonal (note that there can be multiple candidates for eigenvectors of norm 1), since that will make them respect the third condition and therefore be feasible in the target problem.

## Question 3 :

From now on, let  $z = (x, y)$  for simpler notation.

The following expression works :

$$L(z, \mu) = \frac{1}{2} z^t \begin{bmatrix} A - 2\mu_1 & \mu_3 \\ \mu_3 & B - 2\mu_2 \end{bmatrix} z + \mu_1 + \mu_2$$

where  $\mu_i$  designates the  $i$ -th coordinate of  $\mu$ , the symmetry of A and B guarantees the symmetry of the matrix, that we'll designate by  $H$  from now on.

#### Question 4:

We write the dual function  $L_D(\mu) = \inf L(z, \mu) = \inf (1/2)z^t H z + \mu^t \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$ . For  $L_D(\mu)$  to be finite, we need H to be SPD (which we can check with a computer if we have A, B and  $\mu$  since they're the only parameters), then we'd have that  $L_D(\mu) \geq \mu^t \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$  which proves it's finite. Then, the optimal value for  $\max L_D(\mu)$  can be rephrased :

$$\max \mu_1 + \mu_2 \text{ such that } H \text{ is SPD.}$$

If it's not SPD, then for any  $z$  such that  $z^t H z = a < 0$ ,  $\lambda z^t H \lambda z = \lambda^2 a < 0$ , since  $\lambda$  can be arbitrarily large, the solution is not finite. Hence, this is a necessary and sufficient condition.

#### Question 5:

If H is not SPD, then there's no optimal solution, if it is, then we can just take  $z = 0$  and get the solution  $\mu_1 + \mu_2$ , however, we know that this must be lesser or equal than  $1/2(a_1 + b_1)$  due to weak duality and Q2 (here  $a_1$  and  $b_1$  represent the smallest eigenvalues of A and B respectively); this makes sense since a necessary condition for H to be SPD is that  $a_1 \geq 2\mu_1$  and  $b_1 \geq \mu_2$  (otherwise, if  $a_1 < 2\mu_1$  for instance, then  $v_{a_1}^t H v_{a_1} = a_1 - 2\mu_1 < 0$  would be a contradiction).

Hence,  $\mu_1 + \mu_2 \leq (1/2)a_1 + (1/2)b_1$ , therefore weak duality is respected. In addition, the upper bound is reached if  $\mu_3 = 0$ , making the optimal solution :  $\begin{bmatrix} \frac{a_1}{2} \\ \frac{b_1}{2} \\ 0 \end{bmatrix}$

#### Question 6:

The existence of a KKT point condition is satisfied, indeed, we know from Q1 that the LICQ is verified, plus we're working on a compact set (set the norm of x and y must be equal to 1), which guarantees the existence of a local minimum where a constraint qualification holds, and therefore by Theorem 8.26, the existence of a KKT point.

However, we'll need the computer to find valid Lagrange multipliers, and we need to solve the problem to compute them, hence we can't guarantee this condition before computing the problem (and neither can we confirm condition number 2 since it need Lagrange's multipliers as arguments).

#### Question 7:

We get

$$\nabla_x L_\beta(x, y, \mu) = Ax - 2\mu_1 x + \mu_3 y - 2\beta x(1 - x^t x) + \beta y x^t y.$$

$$\nabla_y L_\beta(x, y, \mu) = By - 2\mu_2 y + \mu_3 x - 2\beta y(1 - y^t y) + \beta x x^t y$$

## Question 8

Refer the attached code(also in the appendix of this file). alm.m generates the Lagrangian and its gradient.

## Question 9

Refer the attached code(also in the appendix of this file). With given initial settings, we have the following results.

```
1  z_min =  
2      -1.3695  
3      -0.2535  
4      -0.0107  
5       0.0825  
6       1.4721  
7      -1.2693  
8       0.9636  
9      -1.0786  
10      0.7410  
11      0.5569  
12  
13 L_min = -26.4171
```

Here,  $z = [x; y]$ , so

$$x = \begin{bmatrix} -1.3695 \\ -0.2535 \\ -0.0107 \\ 0.0825 \\ 1.4721 \end{bmatrix}, y = \begin{bmatrix} -1.2693 \\ 0.9636 \\ -1.0786 \\ 0.7410 \\ 0.5569 \end{bmatrix}, L_{min} = -26.4171$$

## Question 10

Each row of following is  $z_k = [x_k \ y_k]$ .

```
1  R1 =  
2      1.3349      0.4913     -0.4391      0.1087     -1.4509      0.9716     -0.7564      ...  
3      1.2123     -0.9557     -0.3235  
4      1.0365      0.4027     -0.3792      0.1000     -1.1276      0.7603     -0.5929      ...  
5      0.9649     -0.7630     -0.2499  
6      0.8481      0.3517     -0.3503      0.0978     -0.9235      0.6284     -0.4911      ...  
7      0.8132     -0.6450     -0.2035  
8      0.7350      0.3248     -0.3393      0.0989     -0.8012      0.5507     -0.4314      ...  
9      0.7253     -0.5764     -0.1761  
10     0.6708      0.3114     -0.3364      0.1007     -0.7318      0.5075     -0.3984      ...  
11     0.6767     -0.5383     -0.1610  
12     0.6360      0.3050     -0.3362      0.1022     -0.6941      0.4845     -0.3809      ...  
13     0.6508     -0.5180     -0.1530  
14     0.6177      0.3019     -0.3365      0.1031     -0.6743      0.4727     -0.3718      ...  
15     0.6374     -0.5074     -0.1489  
16     0.6083      0.3003     -0.3368      0.1036     -0.6642      0.4666     -0.3673      ...  
17     0.6306     -0.5020     -0.1468  
18     0.6036      0.2996     -0.3370      0.1038     -0.6591      0.4636     -0.3649      ...  
19     0.6272     -0.4992     -0.1458
```

At each iteration,  $f$  is calculated as following, converging around -6.4100(the last value).

```

1 R2 =
2   -27.0433
3   -16.6912
4   -11.5137
5    -8.9232
6    -7.6269
7    -6.9781
8    -6.6536
9    -6.4912
10   -6.4100

```

Also, each row of the following is  $h$  calculated at each iteration. Notice that the row values converges to  $[0 \ 0 \ 0]$ . The norm of  $h$  converges to 0.

```

1 R3 =
2   -3.3330   -3.0037    0.7584
3   -1.6619   -1.5051    0.3890
4   -0.8281   -0.7548    0.2002
5   -0.4126   -0.3786    0.1027
6   -0.2057   -0.1899    0.0523
7   -0.1027   -0.0951    0.0265
8   -0.0513   -0.0476    0.0133
9   -0.0256   -0.0238    0.0067
10  -0.0128   -0.0119    0.0033

```

Lastly,  $\beta h$  calculated at each iteration is shown in each row of the following. Here, theses values does not converges to 0, but rather kept stable.

```

1 R4 =
2   -3.3330   -3.0037    0.7584
3   -3.3239   -3.0102    0.7779
4   -3.3124   -3.0192    0.8006
5   -3.3009   -3.0291    0.8216
6   -3.2916   -3.0376    0.8371
7   -3.2853   -3.0436    0.8468
8   -3.2816   -3.0473    0.8523
9   -3.2795   -3.0493    0.8552
10  -3.2785   -3.0504    0.8566

```

## Question 11

Each row of following is  $z_k = [x_k \ y_k]$ .

```

1 S1 =
2   1.3349    0.4911   -0.4391    0.1089   -1.4509    0.9717   -0.7564   ...
3   1.2122   -0.9557   -0.3235
4   0.5926    0.2931   -0.3230    0.0962   -0.6474    0.4849   -0.3805   ...
5   0.6199   -0.4859   -0.1617
6   0.6017    0.2962   -0.3318    0.1020   -0.6570    0.4603   -0.3623   ...
7   0.6228   -0.4960   -0.1446
8   0.5987    0.2988   -0.3371    0.1041   -0.6538    0.4609   -0.3629   ...
9   0.6237   -0.4963   -0.1449

```

6	0.5988	0.2988	-0.3372	0.1041	-0.6539	0.4605	-0.3626	...
	0.6237	-0.4965	-0.1447					
7	0.5988	0.2988	-0.3372	0.1041	-0.6539	0.4605	-0.3626	...
	0.6237	-0.4965	-0.1447					
8	0.5988	0.2988	-0.3372	0.1041	-0.6539	0.4605	-0.3626	...
	0.6237	-0.4965	-0.1447					
9	0.5988	0.2988	-0.3372	0.1041	-0.6539	0.4605	-0.3626	...
	0.6237	-0.4965	-0.1447					
10	0.5988	0.2988	-0.3372	0.1041	-0.6539	0.4605	-0.3626	...
	0.6237	-0.4965	-0.1447					

At each iteration,  $f$  is calculated as following, converging around -6.3288(the last value).

```

1 S2 =
2   -27.0430
3    -6.3392
4    -6.3353
5    -6.3290
6    -6.3289
7    -6.3288
8    -6.3288
9    -6.3288
10   -6.3288

```

Also, each row of the following is  $h$  calculated at each iteration. Notice that the row values converges to  $[0 \ 0 \ 0]$ . The norm of  $h$  converges to 0 and the convergence is faster than the quadratic penalty method.

```

1 S3 =
2   -3.3330  -3.0036  0.7586
3    0.0302  -0.0265  0.0335
4   -0.0019   0.0020  0.0074
5    0.0004  -0.0004  0.0003
6   -0.0000   0.0000  0.0000
7    0.0000  -0.0000  0.0000
8   -0.0000   0.0000  0.0000
9    0.0000  -0.0000  -0.0000
10  -0.0000   0.0000  -0.0000

```

Lastly,  $\mu_k$  is recorded in each row of the following.

```

1 S4 =
2      0      0      0
3   -3.3330  -3.0036  0.7586
4   -3.2727  -3.0566  0.8256
5   -3.2803  -3.0485  0.8552
6   -3.2773  -3.0516  0.8578
7   -3.2774  -3.0515  0.8582
8   -3.2774  -3.0515  0.8582
9   -3.2774  -3.0515  0.8582
10  -3.2774  -3.0515  0.8582

```

## Question 12

$\mu$  we figured out is  $[-3.2774 \ -3.0515 \ 0.8582]'$  Recall that

$$L(z, \mu) = \frac{1}{2} z^t \begin{bmatrix} A - 2\mu_1 & \mu_3 \\ \mu_3 & B - 2\mu_2 \end{bmatrix} z + \mu_1 + \mu_2$$

$\begin{bmatrix} A - 2\mu_1 & \mu_3 \\ \mu_3 & B - 2\mu_2 \end{bmatrix}$  has following eigenvalues.

```

1 ans =
2     -1.1210
3     -0.0000
4      0.8468
5      1.5289
6      4.7816
7      7.8188
8      9.7074
9     10.4000
10     32.7670
11     34.5590

```

As it has one negative eigenvalue, it is not positive definite. Thus,  $L$  is not convex.

From question 1,  $LICQ$  holds. Thus, the strong duality follows.

## Appendix: Code

### 0.1 main.mlx

```

1 global A B n
2 A = [ 2 4 4 5 9;
3 4 4 8 7 5;
4 4 8 2 8 5;
5 5 7 8 6 5
6 9 5 5 5 2 ];
7 B = [ 4 8 3 6 8;
8 8 4 4 5 2;
9 3 4 2 8 5;
10 6 5 8 4 7;
11 8 2 5 7 8 ];
12 n = 5;
13
14 eig(A)
15 eig(B)
16
17 %Problem 8
18 [L, gradL] = alm(randn(10, 1), randn(3, 1), 1);
19
20 %Problem 9
21 beta = 1.42;
22 mu = [1; 2; -3];
23 x0 = [1; 0; -1; 2; 1];
24 y0 = [1; 2; 0; 1; 2];
25 z0 = [x0; y0];
26 [z_min, L_min] = fminunc(@(z) alm(z, mu, beta), z0)
27
28 f = @f;
29 f(z_min);
30 h = @h;

```

```

31 h(z_min);
32
33 %Problem 10
34 %
35 z0 = randi(5, 10, 1);
36 mu = [0; 0; 0];
37 R = cell(9, 4);
38
39 for i = 1:9
40     beta = 2^(i-1);
41     z_min = fminunc(@(z) alm(z, mu, beta), z0);
42
43     R(i, 1) = {z_min};
44     R(i, 2) = {f(z_min)};
45     R(i, 3) = {h(z_min)};
46     R(i, 4) = {beta*h(z_min)};
47     z0 = z_min;
48 end
49
50 R1 = cell2mat(R(:, 1))'
51 R2 = cell2mat(R(:, 2))'
52 R3 = cell2mat(R(:, 3))'
53 R4 = cell2mat(R(:, 4))'
54 f(z_min)
55 h(z_min)
56
57 %Problem 11
58 % ALM Method
59 z0 = randi(5, 10, 1);
60 mu = [0; 0; 0];
61 S = cell(9, 4);
62 for i = 1:9
63     beta = 2^(i-1);
64     z_min = fminunc(@(z) alm(z, mu, beta), z0);
65     %R(i, :) = [z_min, f(z_min), h(z_min), beta*h(z_min)];
66     S(i, 1) = {z_min};
67     S(i, 2) = {f(z_min)};
68     S(i, 3) = {h(z_min)};
69     S(i, 4) = {mu};
70
71     mu = mu + beta*h(z_min);
72     z0 = z_min;
73 end
74
75 S1 = cell2mat(S(:, 1))'
76 S2 = cell2mat(S(:, 2))'
77 S3 = cell2mat(S(:, 3))'
78 S4 = cell2mat(S(:, 4))'
79 f(z_min)
80 h(z_min)
81
82 %Problem 12
83 mu
84 test = [0 0 0]
85 X = zeros(10);
86 X(1:n, 1:n) = A-2*mu(1)*eye(n)
87 X(n+1:2*n, n+1:2*n) = B-2*mu(2)*eye(n)
88 X(1:n, n+1:2*n) = mu(3)*eye(n)
89 X(n+1:2*n, 1:n) = mu(3)*eye(n)

```

## 0.2 alm.m

```

1 function [L,gradL] = alm(z, mu, beta)
2 %Returns L_\beta(z, mu), grad L_\beta(z, mu)
3     global A B n
4     f = @f;
5     h = @h;
6
7     x = z(1:n, 1);
8     y = z(n+1:end, 1);
9
10    L = f(z) + mu'*h(z) + beta/2*norm(h(z))^2;
11    gradLx = A*x - 2*mu(1)*x + mu(3)*y - 2*beta*x*(1-x'*x) + beta*y*x'*y;
12    gradLy = B*y - 2*mu(2)*y + mu(3)*x - 2*beta*x*(1-y'*y) + beta*x*x'*y;
13    gradL = [gradLx; gradLy];
14 end

```

## 0.3 f.m

```

1 function f = f(z)
2     global A B n
3     x = z(1:n, 1);
4     y = z(n+1:end, 1);
5     f = 1/2*(x'*A*x+y'*B*y);
6 end

```

## 0.4 h.m

```

1 function h = h(z)
2     global n
3     x = z(1:n, 1);
4     y = z(n+1:end, 1);
5     h = [1-x'*x; 1-y'*y; x'*y];
6 end

```