

# Problem set 4, ORF523

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<2016-03-11 Fri>

## 1 Problem 1

Notations:

- $c^*$  the solution to the problem. It exists because every subset of  $\mathbb{R}$  has a supremum.
- $X = (x_1, x_2, x_3, x_4)$

$$f(X) = X^T \begin{pmatrix} 1 & -\frac{1}{2} & a & \frac{1}{10} \\ -\frac{1}{2} & 1 & b & c \\ a & b & 1 & -\frac{3}{10} \\ \frac{1}{10} & c & -\frac{3}{10} & 1 \end{pmatrix} X + \begin{pmatrix} 2 \\ -a \\ 0 \\ c \end{pmatrix}^T X := X^T S X + w^T X$$

- If  $S$  is not nonnegative semi definite, there exist  $X$  such that  $X^T S X < 0$ , and

$$f(\lambda X) = \lambda^2 X^T S X + \lambda w^T X \rightarrow_{\lambda \rightarrow \infty} -\infty$$

In order for the optimization problem to be finite, we therefore need to have  $S \geq 0$ .

- If  $S$  positive definite, Let  $\lambda_{\min}$  be its smallest eigen value. Then  $f(X) \geq \lambda_{\min} \|X\|^2 - \|w\| \|X\| \geq \lambda_{\min} (\|X\| - \frac{1}{2\lambda_{\min}} \|w\|)^2 + cte$  is bounded from below.

Let  $c^+$  be the solution to the following convex optimization problem:  $\max_{a,b,c,S \geq 0} c$

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```
1 n = 4
2 cvx_begin quiet
3 variable S(n,n) hermitian;
4 variable a;
5 variable b;
6 variable c;
7
8 maximize(c);
9 S == hermitian_semidefinite( n );
10 for i = 1:4
11     S(i, i) == 1
12 end
13
14 S(1, 2) == -1/2;
15 S(1, 3) == a;
16 S(1, 4) == 1/10;
17 S(2, 3) == b;
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18 S(2, 4) == c;
19 S(3, 4) == -3/10;
20 cvx_end
21
22 ans = [a b c]

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$$\begin{matrix} -0.054543 & -0.22906 & 0.81168 \end{matrix}$$

$0.8116 > c^+$  For all  $c > c^+$ , the optimization problem is not finite, so  $c^* \leq c^+$ .  
Let  $c^- = 0.8115$ , we check with CVX that

$$S = \begin{pmatrix} 1 & -\frac{1}{2} & a^- & \frac{1}{10} \\ -\frac{1}{2} & 1 & b^- & c^- \\ a^- & b^- & 1 & -\frac{3}{10} \\ \frac{1}{10} & c^- & -\frac{3}{10} & 1 \end{pmatrix} > 0$$

with  $a^- = -0.0682$ ,  $b^- = -0.2216$  The problem for  $c^-$  is then finite, so  $c^- \leq c^*$ .  
Conclusion:

$$0.9116 \leq c^* \leq 0.9117$$

or

$$c^* \approx 0.911$$

## 2 Alternative way

$$S = \begin{pmatrix} 1 & -\frac{1}{2} & a & \frac{1}{10} \\ -\frac{1}{2} & 1 & b & c \\ a & b & 1 & -\frac{3}{10} \\ \frac{1}{10} & c & -\frac{3}{10} & 1 \end{pmatrix}$$

With a change of variable  $x_3 \leftrightarrow x_4$ , we can rewrite  $S$ :

$$Q = \begin{pmatrix} 1 & -\frac{1}{2} & \frac{1}{10} & a \\ -\frac{1}{2} & 1 & c & b \\ \frac{1}{10} & c & 1 & -\frac{3}{10} \\ a & b & -\frac{3}{10} & 1 \end{pmatrix}$$

Note that  $Q \geq 0 \iff S \geq 0$ , and  $Q > 0 \iff S > 0$ .

In order of  $Q$  to be positive semi-definite, the following submatrix has to have a non-negative determinant:

$$Q_1 = \begin{pmatrix} 1 & -\frac{1}{2} & \frac{1}{10} \\ -\frac{1}{2} & 1 & c \\ \frac{1}{10} & c & 1 \end{pmatrix}$$

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```

1 syms a b c;
2 S=[1,-1/2,a,1/10;-1/2,1,b,c;a,b,1,-3/10;1/10,c,-3/10,1];
3 Q_1 = [1 -1/2 1/10; -1/2 1 c; 1/10 c 1]

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$$\det(Q_1) = g(c) = -c^2 - \frac{1}{10}c + \frac{37}{50}$$

It has two roots  $r_1 = \frac{-1-3\sqrt{33}}{10}$ ,  $r_2 = \frac{-1+3\sqrt{33}}{10}$ . Since the leadin coefficient is negative, the polynomial is non-negative iff  $c \in [r_1, r_2]$ .

Let's now check that for  $c \in ]r_1, r_2[$ , there exist  $a, b$  that make  $Q > 0$ . Indeed, by using Sylvester criterion:

- $1 > 0$

•

$$\det \begin{pmatrix} 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 \end{pmatrix} = 1 - \frac{1}{4} > 0$$

- $\det(Q_1) > 0$

It remains to show that there exist to show that there exist  $a, b$  that make the following determinant positive:

$$\begin{aligned} P(a, b) &:= \begin{vmatrix} 1 & -\frac{1}{2} & \frac{1}{10} & a \\ -\frac{1}{2} & 1 & c & b \\ \frac{1}{10} & c & 1 & -\frac{3}{10} \\ a & b & -\frac{3}{10} & 1 \end{vmatrix} \\ &= a^2 c^2 - (3b)/100 - c/10 - ab - (3ac)/10 - (3bc)/5 - a^2 - (99b^2)/100 - c^2 - (3a)/50 - (abc)/5 + 269/400 \\ &= (c^2 - 1)a^2 - \frac{99}{100}b^2 - \left(\frac{3}{10}c + \frac{3}{50}\right)a - \left(\frac{3}{100} + \frac{3}{5}c\right)b - \left(\frac{c}{5} + 1\right)ab - c^2 - c/10 + \frac{269}{400} \\ &= - \begin{pmatrix} a \\ b \end{pmatrix}^T \underbrace{\begin{pmatrix} 1 - c^2 & \frac{c}{10} + \frac{1}{2} \\ \frac{c}{10} + \frac{1}{2} & \frac{99}{100} \end{pmatrix}}_R \begin{pmatrix} a \\ b \end{pmatrix} - \underbrace{\begin{pmatrix} \frac{3}{10}c + \frac{3}{50} \\ \frac{3}{100} + \frac{3}{5}c \end{pmatrix}}_v \begin{pmatrix} a \\ b \end{pmatrix} - \underbrace{c^2 - c/10 + \frac{269}{400}}_\alpha \\ &= \begin{pmatrix} a \\ b \end{pmatrix}^T R \begin{pmatrix} a \\ b \end{pmatrix} + v \begin{pmatrix} a \\ b \end{pmatrix} + \alpha \end{aligned}$$

$R$  is symmetric, By cholesky decomposition we can write it as  $R = U^T U$

$$U = \begin{pmatrix} \sqrt{1 - c^2} & \frac{c+5}{10\sqrt{1-c^2}} \\ 0 & \sqrt{\frac{g(c)}{1-c^2}} \end{pmatrix}$$

Let's do the change of variable  $(x, y) = U(a, b)$ :

$$\begin{aligned} P(a, b) &= - \begin{pmatrix} x \\ y \end{pmatrix}^T \begin{pmatrix} x \\ y \end{pmatrix} + \underbrace{(v^T U^{T-1})}_{u^T} \begin{pmatrix} x \\ y \end{pmatrix} + \alpha \\ &= -\left(x + \frac{u_1}{2}\right)^2 - \left(y + \frac{u_2}{2}\right)^2 + \alpha + \frac{u_1^2}{4} + \frac{u_2^2}{4} \end{aligned}$$

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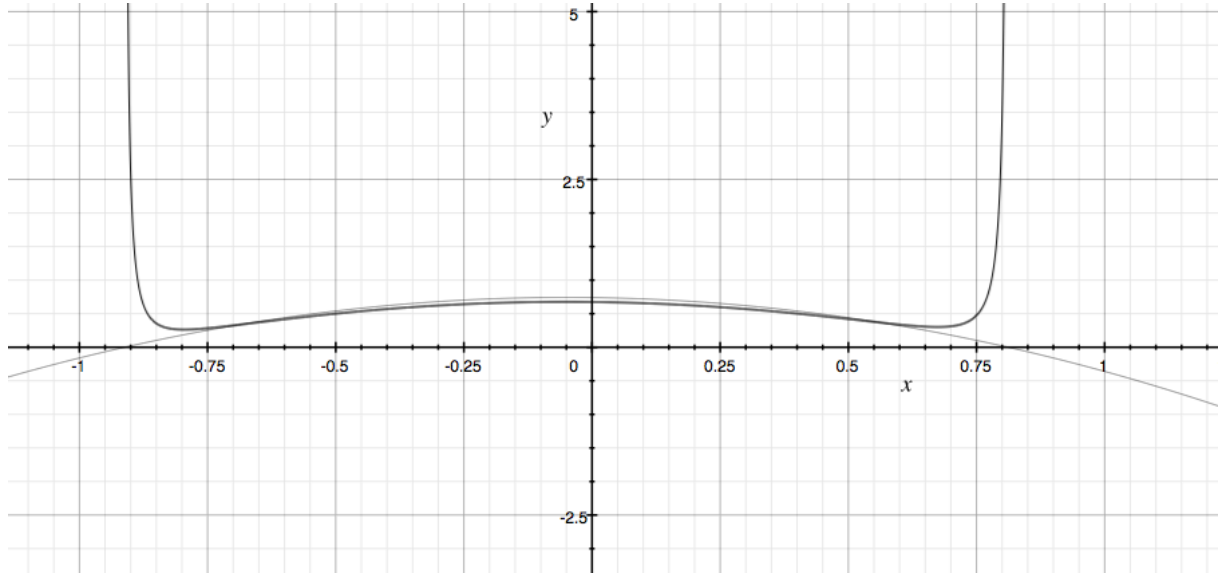
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1  assume(c < 1/2 & c > 0)
2  R = [(1-c^2), (c/10 + 1/2); (c/10+1/2), 99/100];
3  U = chol(R, 'real');
4  u = v'*(U')^(-1);

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This polynomial can be non negative at some point if and only if  $\alpha + \frac{u_1^2}{4} + \frac{u_2^2}{4} \geq 0$ , we use matlab to calculate that expression, we plot it:



Which shows that it is always positive between the roots.

**As a conclusion:**

- for  $r_1 < c < r_2$ , there is  $a, b$  that make  $S > 0$ , and therefore the problem bounded.
- for  $c > r_2$ , all  $a, b$  make  $S$  not semi-definite, and therefore the problem not bounded.
- we conclude that  $c^* = r_2 = \frac{-1+3\sqrt{33}}{10}$

### 3 Problem 2

1. Let  $\|A\|_{\text{dual}} = \max_{\|X\|_{\text{op}} \leq 1} \langle Y, X \rangle$  and let's prove that  $\|A\|_* = \|A\|_{\text{dual}}$

**Lemma 3.1** *If  $A = U\Lambda V^T$  be the SVD decomposition of  $A$ , then  $\|A\|_* = \text{Tr}(\Lambda)$*

- Let  $A = U\Lambda V^T$  be the SVD decomposition of  $A$ , then  $\langle A, UV^T \rangle = \text{Tr}(V\Lambda U^T UV^T) = \text{Tr}(V\Lambda V^T) = \text{Tr}(\Lambda) = \|A\|_*$ . Note that  $\|UV^T\|_{\text{op}} = 1$  because  $UV^T$  is orthogonal. We have just proved that  $\|A\|_* \leq \|A\|_{\text{dual}}$
- Let  $X$  be a matrix st  $\|X\|_{\text{op}} \leq 1$ ,  $\langle A, X \rangle = \text{Tr}(A^T X) = \text{Tr}(V\Lambda U^T X) = \text{Tr}(\Lambda U^T X V) = \sum \Lambda_{ii} (U^T X V)_{ii} = \sum \Lambda_{ii} \underbrace{u_i^T X v_i}_{\leq \|X\|_{\text{op}}} \leq \|X\|_{\text{op}} \|\Lambda\|_* \leq \|A\|_*$ . so  $\|A\|_* \geq \|A\|_{\text{dual}}$
- As a conclusion  $\|A\|_* = \max_{\|X\|_{\text{op}} \leq 1} \langle Y, X \rangle$ , and  $\|\cdot\|_{\text{op}}$  is the dual of  $\|\cdot\|_*$

Let's now prove that the nuclear norm is indeed a norm:

- If  $\|A\|_* = 0$ , then  $\forall i \leq m \wedge n \sigma_i(A) = 0$ , If  $U\Lambda V$  the SVD of  $A$ , then  $\Lambda = 0$ , and therefore  $A = 0$ .
- If  $\alpha > 0$ ,  $\alpha A = U(\alpha\Lambda)V^T$ , and therefore  $\|\alpha A\|_* = \text{Tr}(\alpha\Lambda) = \alpha \text{Tr}(\Lambda) = \alpha \|A\|_*$
- If  $\alpha < 0$ ,  $\alpha A = (-U)(-\alpha\Lambda)V^T$ , we conclude in the same way as before.
- $\|A+B\|_* = \max_{\|X\|_{\text{op}} \leq 1} \langle A+B, X \rangle = \max_{\|X\|_{\text{op}} \leq 1} \langle A, X \rangle + \langle B, X \rangle \leq \max_{\|X\|_{\text{op}} \leq 1} \langle A, X \rangle + \max_{\|X\|_{\text{op}} \leq 1} \langle B, X \rangle$  (Where we have used the fact that  $\sup(S_1 + S_2) \leq \sup S_1 + \sup S_2$  for any two sets  $S_1, S_2$ ), so  $\|A+B\|_* \leq \|A\|_* + \|B\|_*$

1.

Let's first find unit sphere

$A = \begin{pmatrix} x & y \\ y & z \end{pmatrix}$ , Let  $\lambda_1, \lambda_2$  be its eigen values.

$$\begin{aligned}
\|A\|_* = 1 &\iff |\lambda_1| + |\lambda_2| = 1 \\
&\iff \lambda_1^2 + \lambda_2^2 + 2|\lambda_1\lambda_2| = 1 \\
&\iff (\lambda_1 + \lambda_2)^2 + -2\lambda_1\lambda_2 + 2|\lambda_1\lambda_2| = 1 \\
&\iff \text{Tr}(A)^2 + 2(|\det(A)| - \det(A)) = 1 \\
&\iff (\text{Tr}(A)^2 = 1 \text{ and } \det(A) \geq 0) \text{ or } (\text{Tr}(A)^2 - 4\det(A) = 1 \text{ and } \det(A) \leq 0) \\
&\iff ((x+z)^2 = 1 \text{ and } xz \geq y^2) \text{ or } ((x+z)^2 - 4(xz - y^2) = 1 \text{ and } xz \leq y^2) \\
&\iff ((x+z)^2 = 1 \text{ and } xz \geq y^2) \text{ or } ((x-z)^2 + 4y^2 = 1 \text{ and } xz \leq y^2)
\end{aligned}$$

Let's do the linear change of variable

$$\begin{aligned}
u &= \frac{x+z}{\sqrt{2}} \\
v &= \sqrt{2}y \\
w &= \frac{x-z}{\sqrt{2}}
\end{aligned}$$

Which can also be written in matrix form as:

$$\begin{pmatrix} u \\ w \\ v \end{pmatrix} = \underbrace{\begin{pmatrix} \cos(-\frac{\pi}{4}) & -\sin(-\frac{\pi}{4}) & 0 \\ \sin(-\frac{\pi}{4}) & \cos(-\frac{\pi}{4}) & 0 \\ 0 & 0 & \frac{1}{\sqrt{2}} \end{pmatrix}}_R \begin{pmatrix} x \\ z \\ y \end{pmatrix}$$

The linear transformation  $R$  is then a rotation of  $-\frac{\pi}{4}$  in the  $(X, Z)$  plane, and a scaling of  $\frac{1}{\sqrt{2}}$  along the  $Y$  axis.

To find the shape of the unit cylinder, we work in the  $(u, v, w)$  space, and then we apply to inverse transformation of  $R$ .

Then  $2xz = u^2 - w^2$ , and

$$\begin{aligned}
\|A\|_* = 1 &\iff (2u^2 = 1 \text{ and } u^2 - w^2 \geq v^2) \text{ or } (2w^2 + 2v^2 = 1 \text{ and } u^2 - w^2 \leq v^2) \\
&\iff (u^2 = \frac{1}{2} \text{ and } u^2 \geq v^2 + w^2) \text{ or } (w^2 + v^2 = \frac{1}{2} \text{ and } u^2 \leq v^2 + w^2) \\
&\iff (u = \pm \frac{1}{2} \text{ and } \frac{1}{2} \geq v^2 + w^2) \text{ or } (w^2 + v^2 = \frac{1}{2} \text{ and } -\frac{1}{2} \leq u \leq \frac{1}{2})
\end{aligned}$$

$\{u = \pm \frac{1}{2} \text{ and } \frac{1}{2} \geq v^2 + w^2\}$  is two centered disks of radius  $\frac{1}{\sqrt{2}}$  in the plane  $u = \pm \frac{1}{2}$ .  $\{w^2 + v^2 = \frac{1}{2} \text{ and } -\frac{1}{2} \leq u \leq \frac{1}{2}\}$  is the lateral surface of the cylinder of radius  $\frac{1}{\sqrt{2}}$  and axis  $u$

**Conclusion:** In  $(u, v, w)$  space, the unit sphere  $S(0, 1)$  is the basis and lateral surface of the cylinder with radius  $u$ , radius  $\frac{1}{\sqrt{2}}$ , and height 1.

**Lemma 3.2** *The unit ball  $B(0, 1)$  is the convex hull of the unit sphere  $S(0, 1)$ .*

$B(0, 1)$  is convex containing  $S(0, 1)$ . If  $x, y \in S(0, 1)$ , and  $\alpha \in (0, 1)$ , then  $|\alpha x + (1 - \alpha)y|_* \leq \alpha|x|_* + (1 - \alpha)|y|_* \leq 1$  because of the triangular inequality.

$B(0, 1)$  is then a cylinder.

---

```

1 import matplotlib
2 import matplotlib.pyplot as plt
3 from mpl_toolkits.mplot3d import Axes3D
4 import np
5
6 num_points = 30
7
8 # Construct cylinder
9 # base
10 x=np.linspace(-1,1,num_points)
11 z=np.linspace(-1,1,num_points)
12 X, Z=np.meshgrid(x,z)
13 Y=np.sqrt(1-X**2)
14
15 P = map(lambda u: u.ravel(), [X, Y, Z])
16 P[0] = np.concatenate((P[0], X.ravel()))
17 P[1] = np.concatenate((P[1], (-Y.ravel())))
18 P[2] = np.concatenate((P[2], Z.ravel()))
19
20 # lateral surface
21 t=np.linspace(0,1,num_points)
22 theta=np.linspace(0, 2*np.pi,num_points)
23 T, Theta = np.meshgrid(t, theta)
24
25 X = np.cos(Theta)*T
26 Y = np.sin(Theta)*T
27 Z = X*0 + 1
28 P[0] = np.concatenate((P[0], X.ravel()))
29 P[1] = np.concatenate((P[1], Y.ravel()))
30 P[2] = np.concatenate((P[2], Z.ravel()))
31
32 P[0] = np.concatenate((P[0], X.ravel()))
33 P[1] = np.concatenate((P[1], Y.ravel()))
34 P[2] = np.concatenate((P[2], -Z.ravel()))
35
36 # Inverse transformation
37 R = np.array([[1, 0, 1], [0, 2, 0], [1,0,-1]]) / np.sqrt(2)
38 P = np.array(P)
39 P = np.dot(np.linalg.inv(R), P)
40
41 # Plot
42 fig = plt.figure()
43 ax = fig.add_subplot(111, projection='3d')
44 ax.scatter(*P)
45 plt.xlabel('x')
46 plt.ylabel('y')
47 plt.zlabel('z')
48 plt.show()
49 fig.savefig('cylinder.png')

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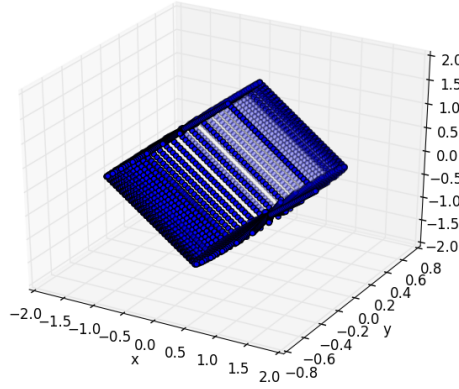


Figure 1: Shape of the unit nuclear ball

3.

**Lemma 3.3** For  $Y \in \mathbb{R}^{n \times m}$

$$\|Y\|_{op} \leq 1 \iff \begin{pmatrix} I_n & Y \\ Y^T & I_m \end{pmatrix} \geq 0$$

Proof:  $\|Y\|_{op} \leq 1 \iff \forall x \in \mathbb{R}^n \leq 1 x^T Y^T Y x \leq x^T I_m x \iff Y^T I_n Y \leq I_m$  We conclude by Schur lemma.

Back to the problem, we can write the nuclear norm as a solution to an SDP:

$$\begin{aligned} \|X\|_* &= \max_{\|Y\|_{op} \leq 1} \langle X, Y \rangle = \max_{\begin{pmatrix} I_n & Y \\ Y^T & I_m \end{pmatrix} \geq 0} \langle X, Y \rangle \\ &= \max_{\underbrace{\begin{pmatrix} I_n & Y \\ Y^T & I_m \end{pmatrix} \geq 0}_Z} \langle X, Y \rangle \\ &= \frac{1}{2} \max_{Z \geq 0, Z \in C} \underbrace{\langle \begin{pmatrix} 0 & X \\ X^T & 0 \end{pmatrix}, Z \rangle}_{X'} \end{aligned}$$

Where

- $C = \{Z \in \mathbb{R}^{(n+m) \times (n+m)} : \langle E_{ij}, Z \rangle = 1_{i=j} \text{ for } (i, j) \in \mathcal{I}\}$  is a set defined by affine inequalities
- $E_{ij}$  is the  $(n+m) \times (n+m)$  matrix with 0 every where except on the entries  $(i, j)$  and  $(j, i)$  where it is equal to 1.
- $\mathcal{I} = \{(i, j) \in [1, n+m]^2, ((i \vee j) \leq n) \text{ or } (n < (i \wedge j))\}$

The feasible set  $\{Z \geq 0, Z \in C\} \equiv \{Y : \|Y\|_{op} \leq 1\}$  is the unit ball of a norm, so it is strictly feasible.

The dual of this SDP can then be written as:

$$\min_{\mu \in \mathbb{R}^{\mathcal{I}}, \sum_{(i,j) \in \mathcal{I}} \mu_{ij} E_{ij} \geq X'} \langle \mu, b \rangle$$

Where  $b_{ij} = 1_{ij}$

The feasible set of this program can be written as:

$$\{(\mu_1, \mu_2) \in \mathbb{R}^{n \times n} \times \mathbb{R}^{m \times m} \mid \begin{pmatrix} \mu_1 & X \\ X^T & \mu_2 \end{pmatrix} \geq 0\}$$

This set also strictly feasible, indeed, since adding  $t$  times the identity matrix shift all the eigen values, for  $t \in \mathbb{R}$  large enough, we have that:

$$\begin{pmatrix} tI_n & X \\ X^T & tI_m \end{pmatrix} > 0$$

This proves that the primal and dual are equal.

Now, we can rewrite the original problem  $\min_{\mathcal{A}(X)=c} |X|_*$  where  $\mathcal{A}$  any linear functional as:  $\min_{\mathcal{A}(X)=c} |X|_* = \min_{\mathcal{A}(X)=c} \max_{|Y|_{op} \leq 1} \langle X, Y \rangle = \min_{X, \mu, \mathcal{A}(X)=c, \sum \mu_i A_i \geq X'} \mu^T b$  Where  $b, X'$  are the same as defined above. This is obviously an SDP.

## 4 Problem 3

1.

Let's first show the following:

**Lemma 4.1** *a Matrix  $D$  is a distance matrix of some points  $x_1, \dots, x_n$  iff there exist  $X \geq 0, X \in \mathbb{R}^{n \times n}$  such that  $D_{ij} = X_{ii} + X_{jj} - 2X_{ij}$*

Indeed, if  $D$  is the distance matrix of  $x_1, \dots, x_n$ , let  $X = (\langle x_i, x_j \rangle)_{ij}$ . Then:

- $D_{ij} = \|x_i - x_j\|^2 = \langle x_i, x_i \rangle + \langle x_j, x_j \rangle - 2\langle x_i, x_j \rangle = X_{ii} + X_{jj} - 2X_{ij}$ .
- $X$  is symmetric because  $\langle \cdot, \cdot \rangle$  is symmetric.
- Let  $y \in \mathbb{R}^n$   $y^T X y = \sum_{ij} \langle x_i, x_j \rangle y_i y_j = \|\sum y_i x_i\|_2^2 \geq 0$ , so  $X \geq 0$

For the converse, let  $X$  a psd such that  $D_{ij} = X_{ii} + X_{jj} - 2X_{ij}$ . By Cholesky decomposition, let

$$M = \begin{pmatrix} m_1^T \\ \vdots \\ m_n^T \end{pmatrix} \in \mathbb{R}^{n \times n} \text{ s.t } X = M M^T, \text{ eg } X_{ij} = m_i^T m_j, \text{ so that } D_{ij} = \|m_i - m_j\|^2$$

Using this Lemma, to solve the problem we have to check only if  $D$  can be written as  $D_{ij} = X_{ii} + X_{jj} - 2X_{ij}$  for some matrix  $X \geq 0$ . e.g. check if the following SDP is feasible

$$\{X \geq 0; D_{ij} = X_{ii} + X_{jj} - 2X_{ij}\}$$

2. Take

$$D = \begin{pmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 2 \\ 1 & 1 & 2 & 0 \end{pmatrix}$$

It trivially verifies the triangular inequality.

Suppose it is a distance matrix, then by the lemma, there exist 4 points  $x_1, x_2, x_3, x_4$  in  $\mathbb{R}^4$  such that  $\|x_i - x_j\| = D_{ij}, i, j = 1, \dots, 4$

- $x_2, x_3, x_4 \in B(x_1, 1)$
- $|x_4 - x_3| = 2$ , so  $[x_4, x_3]$  is a diameter in  $B(x_1, 1)$ , so  $x_1 \in \frac{x_3 + x_4}{2}$
- $|x_2 - x_4| + |x_2 - x_3| = 1 + 1 = |x_4 - x_3|$ , so  $x_2 \in [x_3, x_4]$ , so  $x_2 = \frac{x_4 - x_3}{2} = x_1$
- But  $|x_2 - x_1| = 1 \neq 0$ , contradiction

Conclusion:  $D$  is not a distance matrix.



## 5 Problem 4

1.

$$A_1 = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}$$

$$A_2 = \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix}$$

$$A_2 A_1 = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}$$

$A_1, A_2$  and  $A_2 A_1$  are triangular, so the eigen values are all in the diagonal, e.g  $\rho(A_1) = \rho(A_2) = 0$ , but  $\rho(A_2 A_1) = 1$ .

2.

The following program:

---

```

1  A1 = [-1 -1; -4 0] / 4;
2  A2 = [3 3; -2 1] / 4;
3
4  cvx_begin sdp
5  variable P(2, 2)
6  minimize(P(2, 1))
7  P >= 1
8  A1 * P * A1' <= P
9  A2 * P * A2' <= P
10 cvx_end
11
12 ans=P

```

---

proves that there exist  $P \geq 0$  such that:

$$A_1' P A_1 \leq P, A_2' P A_2 \leq P$$

**Lemma 5.1** *Let  $A, B \geq 0$ , If  $A \geq 0$ , then  $B'AB \geq 0$*

**Proof 5.2** *Indeed, for  $x \in \mathbb{R}^n$ ,  $x'B'ABx = (Bx)'A(Bx) \geq 0$*

Let  $\Sigma$  be a product of term of the form  $A_1$  or  $A_2$

Let's prove by induction on the size on the number of terms  $\Sigma$ , that  $\Sigma'P\Sigma \leq P$ .

Indeed, let  $\Sigma$  be of size  $n + 1$ , without loss of generality  $\Sigma = \Sigma_1 A_1$ , with  $\Sigma_1$  of size  $n$ .

$$\text{Then } \Sigma'P\Sigma = A_1' \underbrace{\Sigma_1'P\Sigma_1}_{\leq P} A_1 \leq A_1' P A_1 \leq A_1.$$

By lyapounouv theorem,  $\Sigma$  is then stable, or equivalently  $\{A_1, A_2\}$  is stable.