EE 236B HW5 Zhiyuan Cao 304397496 02/16/2017

A3.21

(a)

Squaring both sides and use the observation in 4.26,

$$||[2y \ z_1 - z_2]^T||_2 \le z_1 + z_2$$

Expand this and we have

$$4y^2 + z_1^2 + z_2^2 - 2z_1z_2 \le z_1^2 + z_2^2 + 2z_1z_2$$

This is just $y^2 \le z_1 z_2$. To extend this to the case where n is a positive integer, first assume $n = 2^k$, and we have

$$y^{n} \leq (y_{11}y_{12})^{2^{k}-1} \leq (y_{21}y_{22})^{2k-2}(y_{23}y_{24})^{2k-2}$$

$$\leq \dots \leq (y_{k-1,1}y_{k-1,2})^{2}(y_{k-1,3}y_{k-1,4})^{2}\dots(y_{k-1,2^{k-1}-1}y_{k-1,2^{k-1}})^{2}$$

$$\leq z_{1}z_{2}\dots z_{2^{k}},$$

where we introduced variable y_{ij} , i = 1, ..., k - 1, $j = 1, ..., 2^{k-1}$ and have the following inequalities:

$$y_{k-1,j} \le (z_{2j-1}z_{2j})^{1/2}, j = 1, ..., 2^{k-1}$$

 $y_{i,j} \le (y_{i+1,2j-1}y_{i+1,2j})^{1/2}, i = 1, ..., k-2, j = 1, ..., 2^{i-1}$

With $2^k \le n \le 2^{k+1}$, we can write the original inequality as follow:

$$y^{2k+1} \le y^{2k+1-n} z_1 z_2 \dots z_n$$

and applied the same method above.

(b)

We can express α as p/q, where p,q>0 since α is a rational number greater than 1, and the original inequality can be written as:

$$x^{\alpha} = x^{p/q} \le t$$
$$x < t^{q/p} = (t^q)^{1/p}$$

Now we can apply the same method in (a) by setting $z_1, z_2, ..., z_{p-1} = 1$ and $z_p = t^q$.

For the second function, again we set $\alpha = -p/q$ and write the constraint as following:

$$(x^p t^q)^{1/(p+q)} \ge 1$$

and apply the same method by setting $z_1, ..., z_p = x$ and $z_{p+1}, ..., z_{p+q} = t$.

Add.1

(a)

For rule 2 we have

$$\log f = \log(\max\{g_1, g_2, ..., g_m\}) = \max\{\log g_1, \log g_2, ..., \log g_m\}$$

This is followed by logarithm function being monotonically increasing over R_{++} , which is the domain of f(x). since $\log g_i$, i = 1, ..., m are convex, $\log f$ is also convex since it is the supreme of a family of convex functions.

For rule 3 we have $h'(z_1, ..., z_n) = \log h(e^{z_1}, ..., e^{z_n})$ as convex and nondecreasing in each of its argument. Hence,

$$\log f(e^{y_1}, ..., e^{y_n}) = \log h(g_1(e^{y_1}, ..., e^{y_n}), ..., g_m(e^{y_1}, ..., e^{y_n}))$$
$$h'(\log g_1(e^{y_1}, ..., e^{y_n}), ..., \log g_m(e^{y_1}, ..., e^{y_n}))$$

From here we can establish convexity of $\log f$ from composition rule with h' convex and nondecreasing in each of its argument and $\log g_i$, i = 1, ..., n as a convex function.

Add.2

The scalarized problem is clear a GP since it can be written as the following form

minimize
$$\sum_{i=1}^{6} w_i + ut$$
 subject to
$$w_i - w_{max} + 1 \le 1 \qquad i = 1, ..., 6$$

$$w_{min} - w_i + 1 \le 1 \qquad i = 1, ..., 6$$

$$T_i - t + 1 \le 1, \qquad i = 1, ..., 3$$

Where the objective function and constraints are posinomials.

```
clc;clear;
c_1 = [1.5 1 5]';
w_max = 10;
w_min = 0.1;
```

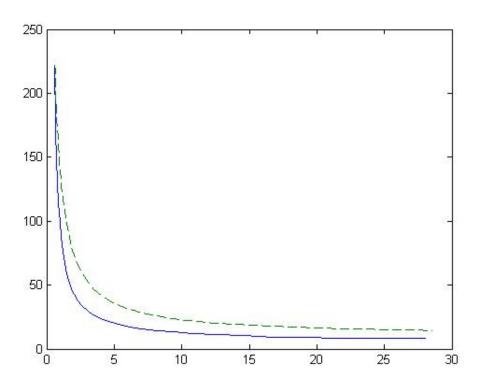


Figure 1: Comparison

```
n = 50;
u = logspace(-3,3,n);
a_1 = zeros(1,n);
d_1 = zeros(1,n);
for i=1:n
    cvx_begin gp
    variables t w(6)
    C = w;
    R = 1./w;
    minimize(sum(w) + u(i)*t)
    subject to
    w / w_max <= 1.0;
    w_min ./ w <= 1;
    (C(3) + c_1(1)) * sum(R([1,2,3])) ...
    + C(2) * sum(R([1,2])) ...
    + (sum(C([1,4,5,6])) + sum(c_1([2,3]))) * R(1) <= t;
    (C(5) + c_1(2)) * sum(R([1,4,5])) ...
    + C(4) * sum(R([1,4])) ...
    + (C(6) + c_1(3)) * sum(R([1,4])) ...
```

```
+ (sum(C([1,2,3])) + c_1(1)) * R(1) <= t;
    (C(6) + c_1(3)) * sum(R([1,4,6])) ...
    + C(4) * sum(R([1,4])) ...
    + sum(C([1,2,3]) + c_1(1)) * R(1) ...
    + (C(5) + c_1(2)) * sum(R([1,4])) \le t;
    cvx_end
    d_1(i) = t;
    a_1(i) = sum(w);
end;
n=100;
ws = logspace(-1,1,n);
a_2 = zeros(1,n);
d_2 = zeros(1,n);
for i=1:length(ws)
    w = ws(i)*ones(6,1);
    a_2(i) = sum(w);
    C = w;
    R = 1./w;
    t1 = (C(3) + c_1(1)) * sum(R([1,2,3])) ...
    + C(2) * sum(R([1,2])) ...
    + (sum(C([1,4,5,6])) + sum(c_1([2,3]))) * R(1);
    t2 = (C(5) + c_1(2)) * sum(R([1,4,5])) ...
    + C(4) * sum(R([1,4])) ...
    + (C(6) + c_1(3)) * sum(R([1,4])) ...
    + (sum(C([1,2,3])) + c_1(1)) * R(1);
    t3 = (C(6) + c_1(3)) * sum(R([1,4,6])) ...
    + C(4) * sum(R([1,4])) ...
    + sum(C([1,2,3]) + c_1(1)) * R(1) ...
    + (C(5) + c_1(2)) * sum(R([1,4]));
    d_2(i) = max([t1, t2, t3]);
end;
plot(a_1, d_1, '-', a_2, d_2, '--');
Add.3
```

(a) ⇒

Provided that $X \in S^n$, We introduce $\nu = [\nu_1, \nu_2]^T$, Since $X \succeq 0$, we have

$$\nu^T X \nu = [\nu_1^T, \nu_2^T] \begin{bmatrix} 0 & B \\ B^T & C \end{bmatrix} \begin{bmatrix} \nu_1 \\ \nu_k \end{bmatrix} = 2\nu_1^T B \nu_2 + \nu_2^T C \nu_2 \ge 0$$

for any ν . set $\nu_1 = -tB\nu_2$ and we have

$$-2t||B\nu_2|| + \nu_2^T C \nu_2 \ge 0$$

with $t \to -\infty$, we must have B = 0 to satisfy the condition. This also shows $C \succeq 0$.

 \Leftarrow

Provided that B = 0 and $C \succeq 0$, we can introduce $\nu = [\nu_1, \nu_k]^T$ and show $\nu X \nu \geq 0$.

(b)

$$AA^{+} = [Q1Q2] \begin{bmatrix} \Lambda_{1} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} Q_{1}^{T} \\ Q_{2}^{T} \end{bmatrix} Q_{1}\Lambda_{1}^{-1}Q_{1}^{T} = Q_{1}Q_{1}^{T}$$

$$A^{+}A = Q_{1}\Lambda_{1}^{-1}Q_{1}^{T}[Q1Q2] \begin{bmatrix} \Lambda_{1} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} Q_{1}^{T} \\ Q_{2}^{T} \end{bmatrix} = Q_{1}Q_{1}^{T}$$

$$I - AA^{+} = I - A^{+}A = [Q_1 \ Q_2] \begin{bmatrix} Q_1^T \\ Q_2^T \end{bmatrix} - Q_1Q_1^T = Q_2Q_2^T$$

(c)

 \Rightarrow

Let

$$A = [Q_2^T \ Q_1^T] \begin{bmatrix} 0 & 0 \\ 0 & \Lambda \end{bmatrix} \begin{bmatrix} Q_2 \\ Q_1 \end{bmatrix}$$

$$\nu X \nu = [\nu_1^T, \nu_2^T, \nu_3^T] \begin{bmatrix} 0 & 0 & Q_2^T B \\ 0 & \Lambda & Q_1^T B \\ B^T Q_2 & B^T Q_1 & C \end{bmatrix} \begin{bmatrix} \nu_1 \\ \nu_2 \\ \nu_3 \end{bmatrix} = \geq 0$$

Based on (a), we must have $B^TQ_2 = 0$, which is equivalent to $(I - AA^+)B = 0$. Also we must have

$$\begin{bmatrix} & \Lambda & Q_1^T B \\ & B^T Q_1 & C \end{bmatrix} \succeq 0$$

Apply the general Schur Component and we have $C - B^T Q_1 \Lambda Q_1^T B = C - B^T A^+ B \ge 0$.

A3.11

(a)

The problem can be written as:

minimize
$$t$$
 subject to
$$\begin{bmatrix} F(x) & c^T \\ c & t \end{bmatrix} \succeq 0$$

This is followed by Schur Component with $t - c^T F^{-1}(x)c \ge 0$.

(b)

The problem can be written as:

minimize
$$t$$
 subject to
$$\begin{bmatrix} F(x) & c^T \\ c & t \end{bmatrix} \succeq 0, \quad i = 1, ..., K$$

(c)

$$f(x) = \lambda_{max}(F^{-1}(x)) \le t \Leftrightarrow F^{-1}(x) \le tI$$

Therefore the problem is formed as followed

minimize
$$t$$
 subject to
$$\begin{bmatrix} F(x) & I \\ I & tI \end{bmatrix} \succeq 0$$

(d)

$$E[c^{T}F^{-1}c] = E[\bar{c}^{T}F^{-1}\bar{c} + (c - \bar{c})^{T}F^{-1}(c - \bar{c})]$$

$$= E[\bar{c}^{T}F^{-1}\bar{c}] + E[\sum_{i=1}^{m} \sum_{j=1}^{m} f_{ij}y_{i}y_{j}]$$

$$= \bar{c}^{T}F^{-1}\bar{c} + \mathbf{tr}(F^{-1}S)$$

where $y_i = c_i - \bar{c}_i$. If we factor S as $S = \sum_{k=1}^m c_k c_k^T$ the problem is equivalent to

minimize
$$\bar{c}^T F^{-1} \bar{c} + \sum_{k=1}^m c_k^T F(x)^{-1} c_k$$

which is equivalent to

minimize
$$t_0 + \sum_k t_k$$
subject to
$$\begin{bmatrix} F(x) & \bar{c}^T \\ \bar{c}^T & t_0 \end{bmatrix} \succeq 0$$

$$\begin{bmatrix} F(x) & c_k^T \\ c_k^T & t_k \end{bmatrix} \succeq 0, \qquad k = 1, ..., m$$