

# 最佳化 HW2 REB121011 期末考題

1. • (Homework) Prove the convexity of the following functions:

- $\log(x)$  on the positive real line;
- $\exp(x)$  on the real line;
- $x^4$  on the real line;
- $\|x\|_2^2$  on the  $n$ -dimensional space  $\mathbb{R}^n$  (for any  $n \geq 2$ ).

Note that the convexity of the domain of each function should be verified.

- A set  $C$  is said to be a **convex set** if for any  $x_1, x_2 \in C$ , the line segment connecting  $x_1$  and  $x_2$  also belongs to  $C$ ; precisely,

$$\theta x_1 + (1 - \theta)x_2 \in C, \quad \forall \theta \in [0, 1], \quad x_1, x_2 \in C.$$

- A function  $f$  is called a **convex function** if the following two conditions hold true:

1. The function domain  $D$  is a convex set.

2. For  $\lambda \in [0, 1]$ ,  $x, y \in D$ ,

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y). \quad (5.1)$$

•  $f(x) = -\log(x), \quad x \in \mathbb{R}^+$

1)  $\mathbb{R}^+$  is a convex set:

For any  $x_1, x_2 \in \mathbb{R}^+$ ,

$$\theta x_1 + (1 - \theta)x_2 \in \mathbb{R}^+, \quad \forall \theta \in [0, 1]$$

2) eqn (5.1):

For  $\lambda \in [0, 1]$ ,  $x_1, x_2 \in \mathbb{R}^+$

$$\begin{aligned} \lambda f(x_1) + (1 - \lambda)f(x_2) &= -\lambda \log(x_1) - (1 - \lambda)\log(x_2) \\ &= -[\lambda \log(x_1) + (1 - \lambda)\log(x_2)] \\ &= -\log(x_1^\lambda \cdot x_2^{1-\lambda}) \end{aligned}$$

$$f(\lambda x_1 + (1 - \lambda)x_2) = -\log(\lambda x_1 + (1 - \lambda)x_2)$$

加權算術不等式:

$$p_1 x_1 + \dots + p_n x_n \geq x_1^{p_1} \cdots x_n^{p_n}, \quad \forall x_i \in \mathbb{R}^+, \quad \forall i = 1, \dots, n, \quad \sum_{i=1}^n p_i = 1$$

$$\therefore \lambda x_1 + (1 - \lambda)x_2 \geq x_1^\lambda x_2^{1-\lambda}$$

$$\therefore -\log(\lambda x_1 + (1 - \lambda)x_2) \leq -\log(x_1^\lambda x_2^{1-\lambda})$$

$$\Rightarrow \lambda f(x_1) + (1 - \lambda)f(x_2) \geq f(\lambda x_1 + (1 - \lambda)x_2)$$

By 1), 2),  $\forall x \in \mathbb{R}^+$ ,  $f(x) = -\log(x)$  is a convex function.

•  $f(x) = e^x, \quad x \in \mathbb{R}$

1)  $\mathbb{R}$  is a convex set:

For any  $x_1, x_2 \in \mathbb{R}$ ,

$$\theta x_1 + (1 - \theta)x_2 \in \mathbb{R}, \quad \forall \theta \in [0, 1]$$

2) eqn (5.1):

For  $\lambda \in [0,1]$ ,  $x_1, x_2 \in \mathbb{R}$

$$\lambda f(x_1) + (1-\lambda)f(x_2) = \lambda e^{x_1} + (1-\lambda)e^{x_2}$$

$$f(\lambda x_1 + (1-\lambda)x_2) = e^{\lambda x_1 + (1-\lambda)x_2}$$

加權算幾不等式:

$$p_1 x_1 + \cdots + p_n x_n \geq x_1^{p_1} \cdots x_n^{p_n}, \forall x_i \in \mathbb{R}^+, \forall i=1, \dots, n, \sum_{i=1}^n p_i = 1$$

$\because e^k \in \mathbb{R}^+, \forall k \in \mathbb{R}$

$$\therefore \lambda e^{x_1} + (1-\lambda)e^{x_2} \geq e^{\lambda x_1} \cdot e^{(1-\lambda)x_2} = e^{\lambda x_1 + (1-\lambda)x_2}$$

$$\Rightarrow \lambda f(x_1) + (1-\lambda)f(x_2) \geq f(\lambda x_1 + (1-\lambda)x_2)$$

By 1), 2),  $f(x) = e^x$  is a convex function.

- $f(x) = x^4, x \in \mathbb{R}$

1)  $\mathbb{R}$  is a convex set:

For any  $x_1, x_2 \in \mathbb{R}$ ,

$$\theta x_1 + (1-\theta)x_2 \in \mathbb{R}, \forall \theta \in [0,1]$$

2)  $f'' > 0$ :

$$f(x) = x^4, f'(x) = 4x, f''(x) = 4 > 0$$

By 1), 2),  $f(x) = x^4$  is a convex function.

- $f(x) = \|x\|_2^2, x \in \mathbb{R}^n, n \geq 2$

1)  $\mathbb{R}^n$  is a convex set:

For any  $\begin{cases} x_1 = (x_{11}, x_{12}, \dots, x_{1n}) \in \mathbb{R}^n, n \geq 2 \\ x_2 = (x_{21}, x_{22}, \dots, x_{2n}) \in \mathbb{R}^n, n \geq 2 \end{cases}$

$$\theta x_1 + (1-\theta)x_2$$

$$= (\theta x_{11} + (1-\theta)x_{21}, \theta x_{12} + (1-\theta)x_{22}, \dots, \theta x_{1n} + (1-\theta)x_{2n}) \in \mathbb{R}^n, n \geq 2, \forall \theta \in [0,1]$$

2) eqn (5.1):

For  $\lambda \in [0,1], x_1, x_2 \in \mathbb{R}^n$

$$\text{Let } h(x) = x^2, g(x) = \|x\|_2 \Rightarrow h \circ g = \|x\|_2^2$$

$$\lambda g(x_1) + (1-\lambda)g(x_2) = \lambda \|x_1\|_2 + (1-\lambda)\|x_2\|_2$$

$$= \|\lambda x_1 + (1-\lambda)x_2\|_2$$

$$\geq \|\lambda x_1 + (1-\lambda)x_2\|_2 \quad \text{by 三角不等式}$$

$$= g(\lambda x_1 + (1-\lambda)x_2)$$

$\Rightarrow g(x) = \|x\|_2$  is a convex function

$$h'(x) = 2x, h''(x) = 2 > 0$$

$\Rightarrow h(x) = x^2$  is a convex function

$\because h(x)$  &  $g(x)$  is convex function

$\therefore hg$  is a convex function

By 1), 2),  $f(x) = \|x_2\|^\alpha, x \in \mathbb{R}^n, \alpha \geq 2$  is a convex function.

2.

- (Homework) Prove that the set  $C = \{X \mid X \succeq A_i, i = 1, \dots, m\}$  (for symmetric  $A_i \in \mathbb{S}^n$ ) is also a convex set.

[Hint: the intersection of some convex sets is still a convex set.]

$$\text{Let } C = \bigcap_{i=1}^m C_i, \quad C_i = \{X \mid X \succeq A_i\}$$

Given  $M \in \mathbb{S}^n, M \succeq 0$  means  $M$  is a PSD matrix  $\Rightarrow v^T M v \geq 0, \forall v \in \mathbb{R}^n$

$X \succeq A_i$  means that  $X - A_i \succeq 0$  is PSD

Given  $x, y \in C_i, \alpha \in [0, 1]$

$$\begin{aligned} & v^T (\alpha x + (1-\alpha)y - A_i) v \\ &= \alpha v^T (X - A_i) v + (1-\alpha)v^T (Y - A_i) v \\ &\geq 0 + (1-\alpha)0 = 0 \end{aligned}$$

meaning that  $\alpha x + (1-\alpha)y \succeq A_i$  as well.

So,  $C_i$  is convex,  $\forall i = 1, \dots, m$

Also, we know if  $A$  &  $B$  are convex sets, then  $A \cup B$  is also a convex set.

and we know  $C_i$  is a convex set  $\forall i = 1, \dots, m$

$$\text{So, } \bigcap_{i=1}^m C_i = C = \{X \mid X \succeq A_i, i = 1, \dots, m\} \text{ is a convex set.}$$

3.

- (Homework) Prove the equality in (5.7).

[Hint: you can assume that  $S_2 = \mathbb{R}^m$ .]

$$z^{q+1} := \text{prox}_{\frac{1}{c}f_2}(Ax^q - d^q).$$

ADMM handles convex optimization problems of the following form

$$\min_{x \in S_1, z \in S_2} f_1(x) + f_2(z), \quad \text{s.t. } z = Ax$$

Where  $f_1: \mathbb{R}^n \rightarrow \mathbb{R}$  and  $f_2: \mathbb{R}^m \rightarrow \mathbb{R}$  are convex functions,

$A$  is an  $m \times n$  matrix and  $S_1 \subseteq \mathbb{R}^n, S_2 \subseteq \mathbb{R}^m$  are convex sets.

Transform the formula into

$$\min_{\substack{x \in S_1 \\ z \in S_2}} L(x, z, q) = \min_{\substack{x \in S_1 \\ z \in S_2}} f_1(x) + f_2(z) + \frac{c}{2} \|Ax - z - q\|_2^2$$

$$\begin{aligned} \Rightarrow \hat{z}^q &= \operatorname{argmin}_{\substack{\hat{z} \in S_2 \\ \hat{z} \in S_2}} L(X^q, \hat{z}, q^q) \\ &= \operatorname{argmin}_{\substack{\hat{z} \in S_2 \\ \hat{z} \in S_2}} f_1(x) + f_2(\hat{z}) + \frac{c}{2} \|Ax^q - \hat{z} - q^q\|_2^2 \\ &= \operatorname{argmin}_{\substack{\hat{z} \in S_2 \\ \hat{z} \in S_2}} f_2(\hat{z}) + \frac{c}{2} \|Ax^q - \hat{z} - q^q\|_2^2 \quad (\because f_1(x) \text{ is constant for } \hat{z}) \\ &= \operatorname{argmin}_{\substack{\hat{z} \in S_2 \\ \hat{z} \in S_2}} f_2(\hat{z}) + \frac{c}{2} \|v - \hat{z}\|_2^2 \quad (\text{let } v = Ax^q - q^q) \\ &= \operatorname{argmin}_{\substack{\hat{z} \in S_2 \\ \hat{z} \in S_2}} \frac{1}{c} f_2(\hat{z}) + \frac{1}{2} \|v - \hat{z}\|_2^2 \quad (\text{multiply by } \frac{1}{c}) \\ &= \operatorname{prox}_{\frac{1}{c} f_2}(v) \quad (\because \operatorname{prox}_f(v) = \operatorname{argmin}_x [f(x) + \frac{1}{2} \|x - v\|_2^2]) \\ &= \operatorname{prox}_{\frac{1}{c} f_2}(Ax^q - q^q) \end{aligned}$$

4.

- (Homework) Please implement the above CVX command. Please demo your code based on the FIR filter parameterized by  $\{h_i\}_{i=-n}^n$ .

[Hint: you can freely specify a suitable size  $(n, P)$ , frequency samples  $\{\omega_1, \dots, \omega_P\} \in [0, \pi]$ , as well as the desired frequency response  $H_{\text{des}}(\omega_p)$  with “symmetry” (i.e.,  $h_i = h_{-i}$ .)]

```
>> n = 5;
P = 10;
omega = linspace(0, pi, P);
Hdes = cos(rand(P, 1));

cvx_begin
    variables h(n+1) t;
    minimize(t);

    subject to
        for p = 1 : P
            a=0;
            for i=2:n+1
                a=a+h(i) * cos(omega(p) * (i-1));
            end
            abs(Hdes(p) - h(1) - 2 * a) <= t;
        end
    end
cvx_end

Calling SDPT3 4.0: 30 variables, 17 equality constraints
For improved efficiency, SDPT3 is solving the dual problem.
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```

```
num. of constraints = 17
dim. of socp var = 20, num. of socp blk = 10
dim. of linear var = 10
number of nearly dependent constraints = 1
To remove these constraints, re-run sqip.m with OPTIONS.rmdpconstr = 1.
*****
SDPT3: Infeasible path-following algorithms
*****
version predcorr gam expon scale_data
NT 1 0.000 1 0
it pstep dstep pinfeas dinfeas gap prim-obj dual-obj cputime
```

```
0|0.000|0.000|1.5e+01|1.0e+01||1.1e+03| 0.000000e+00| 0.000000e+00| 0:0:0| chol 1 1
1|1.000|1.000|17.1e-04||1.0e+01|-4.730565e-03 -1.455363e+01| 0:0:0| chol 1 1
2|1.000|0.953|1.9e-07||1.4e-02|6.9e-01|-1.018598e-02 -6.752633e-01| 0:0:0| chol 1 1
3|0.946|0.986|5.8e-08||1.2e-03|2.0e-01|-9.310840e-02 -2.910260e-01| 0:0:0| chol 1 1
4|0.894|0.877|1.7e-08||2.3e-04|3.6e-02|-1.225229e-01 -1.581126e-01| 0:0:0| chol 1 1
5|0.909|1.000|8.8e-09||1.0e-05||1.0e-02|-1.375094e-01 -1.479250e-01| 0:0:0| chol 1 1
6|0.957|1.000|1.2e-08||1.0e-06||1.6e-03|-1.414233e-01 -1.430077e-01| 0:0:0| chol 1 1
7|0.891|0.991|17.5e-09||1.1e-07||1.7e-04|-1.421724e-01 -1.423386e-01| 0:0:0| chol 1 1
8|1.000|0.912|1.5e-07||2.0e-08||3.0e-05|-1.422611e-01 -1.422908e-01| 0:0:0| chol 1 1
9|0.995|1.000|5.7e-09||2.3e-09||6.0e-07|-1.422758e-01 -1.422764e-01| 0:0:0| chol 1 1
10|0.994|0.997|14.2e-10||1.3e-10||7.7e-09|-1.422761e-01 -1.422761e-01| 0:0:0|
stop: max(relative gap, infeasibilities) < 1.49e-08
```

```
-----  
number of iterations = 10  
primal objective value = -1.42276097e-01  
dual objective value = -1.42276103e-01  
gap := trace(XZ) = 7.71e-09  
relative gap = 6.00e-09  
actual relative gap = 5.15e-09  
rel. primal infeas (scaled problem) = 4.24e-10  
rel. dual " " " = 4.35e-10  
rel. primal infeas (unscaled problem) = 0.00e+00  
rel. dual " " " = 0.00e+00  
norm(X), norm(y), norm(Z) = 9.1e-01, 8.4e-01, 5.8e-01  
norm(A), norm(b), norm(C) = 1.3e+01, 2.0e+00, 3.7e+00  
Total CPU time (secs) = 0.07  
CPU time per iteration = 0.01  
termination code = 0  
DIMACS: 4.2e-10 0.0e+00 8.0e-10 0.0e+00 5.1e-09 6.0e-09
```

```
-----  
Status: Solved  
Optimal value (cvx_optval): +0.142276
```