

Quiz-2 (CS-709)

19-Oct-2011

Note: Please provide *rigorous and short* answers. Max. Marks=10

1. Using KKT conditions¹, describe the optimal set² of the following program:

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & c^\top x, \\ \text{s.t.} \quad & \|x\|_p \leq 1, \end{aligned}$$

where $\|x\|_p = (\sum_{i=1}^n |x_i|^p)^{\frac{1}{p}}$, $p \in \mathbb{R}, p > 1$ and $c \in \mathbb{R}^n$. The final expression for the optimal set should only involve parameters for the above problem i.e., should involve c and/or p alone.

[5 Marks]

2. A discrete random variable X takes on values x_1, x_2, \dots, x_n with probabilities p_1, p_2, \dots, p_n respectively³. For example, X could model the rolling of a die, in which case the $x_i = i$. In reality one does not know what numbers to assume for p_i given an application. In order to determine reasonable values for p_i , one usually performs simulations. Suppose in such simulations it was revealed that the j^{th} moment⁴ of X lies in the interval $[l_j, u_j]$. Here, $j = 1, \dots, m$.

¹Do not employ ANY non-trivial result other than KKT conditions while attempting this problem.

²Optimal set of a program (P) is the set of all optimal solutions of (P).

³In other words, $P[X = x_i] = p_i \forall i = 1, \dots, n$. Needless to say, we must have $p_i \geq 0 \forall i = 1, \dots, n$ and $\sum_{i=1}^n p_i = 1$.

⁴The j^{th} moment of X is defined as $\sum_{i=1}^n x_i^j p_i$

The goal is to find the “simplest” distribution for X , i.e., the values for the probabilities p_i with maximum entropy⁵, such that all the above simulation-determined constraints on the moments are satisfied. Express this problem as an ordinary convex program. Using any one of the duality schemes taught in lectures till now⁶, write down a dual of this program⁷.

[5 Marks]

⁵Entropy of the random variable X is defined as $-\sum_{i=1}^n x_i \log(x_i)$.

⁶Do not use Lagrange duality scheme, as I did not teach it yet.

⁷Also, after the quiz, attempt describing the optimal set for the primal and dual programs you wrote, in terms of x_i and/or l_i and/or u_i

Ans 1 KKT conditions ~~can be applied~~ for regular ^{differentiable} OCPs.
 Characterize optimality

So let's first pose the given problem as \rightarrow It is obvious that the constraint is ~~only~~ ^{can be} written as $g(x) = \sqrt[p]{\sum_i |x_i|^p} \leq 1 \leq 0$. However, this g is not differentiable. One way to do it is:

$$\begin{aligned} \{x \mid \sqrt[p]{\sum_i |x_i|^p} - 1 \leq 0\} &= \{x \mid \sum_i |x_i|^p - 1 \leq 0\} \quad \rightarrow \text{still not differentiable.} \\ &= \{x \mid \sum_i t_i^p - 1 \leq 0, \quad \left. \begin{array}{l} \sum_i t_i^p - 1 \leq 0, \\ |x_i| \leq t_i \leq 0 \end{array} \right\} \quad \rightarrow \text{differentiable} \\ &= \{(x, t) \mid \sum_i t_i^p - 1 \leq 0, \quad \left. \begin{array}{l} x_i - t_i \leq 0, \\ -t_i - x_i \leq 0 \end{array} \right\} \quad \rightarrow \text{not differentiable} \\ &\hspace{15em} \rightarrow \text{differentiable} \end{aligned}$$

Here the given program is equal to:

$$\begin{aligned} \min \quad & C^T x \\ \text{s.t.} \quad & x \in \mathbb{R}^n, \\ & t \in \mathbb{R}^n, \\ & \sum_i t_i^p - 1 \leq 0, \\ & x_i - t_i \leq 0, \quad -t_i - x_i \leq 0, \quad \forall i=1 \text{ to } n \end{aligned}$$

(I)

Note the following: ~~the point~~ $(\frac{0}{n}, t)$ where t is such that $\|t\|_p < 1$ is a point which ~~not~~ satisfies Slater's Condition.

- ① (I) is a regular, differentiable OCP
- ② Till now we just know that the optimal values of (I) and the given program are equal. We will later realize the relationship between their optimal solutions.

The number of constraints = $2n+1$. Hence the "dual" variable in KKT, say λ will be in \mathbb{R}^{2n+1} . Let the λ entry corresponding to $\sum_i t_i^p - 1 \leq 0$ be 's'

& the λ entries corresponding to $x_i - t_i \leq 0$ $\forall i=1 \dots n$ be μ

& the λ entries corresponding to $-t_i - x_i \leq 0$ $\forall i=1 \dots n$ be ν .

We have that:

$\left(\begin{bmatrix} x^* \\ t^* \end{bmatrix}, \begin{bmatrix} s^* \\ \mu^* \\ \nu^* \end{bmatrix} \right)$ is a KKT point \iff

Feasibility: $\sum_i t_i^p - 1 \leq 0, x_i - t_i \leq 0, -t_i - x_i \leq 0; s \in \mathbb{R} \geq 0, \mu \in \mathbb{R}^n \geq 0, \nu \in \mathbb{R}^n \geq 0$

complementary slackness: $s(\sum_i t_i^p - 1) = 0, \mu_i(x_i - t_i) = 0, \nu_i(t_i + x_i) = 0 \forall i$

gradient condition: $\frac{\partial L(\begin{bmatrix} x^* \\ t^* \end{bmatrix}, \begin{bmatrix} s^* \\ \mu^* \\ \nu^* \end{bmatrix})}{\partial x_i} = 0 \forall i$
 $\frac{\partial L(\begin{bmatrix} x^* \\ t^* \end{bmatrix}, \begin{bmatrix} s^* \\ \mu^* \\ \nu^* \end{bmatrix})}{\partial t_i} = 0 \forall i$

where $L\left(\begin{bmatrix} x^* \\ t^* \end{bmatrix}, \begin{bmatrix} s^* \\ \mu^* \\ \nu^* \end{bmatrix}\right) = c^T x + s\left(\sum_i t_i^p - 1\right) + \sum_{i=1}^n \mu_i(x_i - t_i) + \sum_{i=1}^n \nu_i(t_i + x_i)$

$$\textcircled{1} \Rightarrow c_i + \mu_i - \nu_i = 0 \forall i$$

$$\textcircled{2} \Rightarrow s p t_i^{p-1} - \mu_i - \nu_i = 0 \forall i$$

Now suppose $C_j = 0$ for some j ,

then $\mu_j^* = \gamma_j^* = \frac{\sum p t_j^{*p-1}}{2} \quad (\because \textcircled{1} \& \textcircled{2})$

Also from $\textcircled{4}$ we get: $t_j^{*p-1} \chi_j^* - t_j^* = 0$
 $t_j^* + t_j^{*p-1} \chi_j^* = 0 \Rightarrow t_j^* = 0$

$\Downarrow \quad (\textcircled{3})$
 $\chi_j^* = 0 \quad - \quad \textcircled{R1}$

(this case actually is ~~easy~~ easy to see from the problem itself.)

Suppose $C_j \neq 0$ for some j , then,

$\textcircled{1} \& \textcircled{2} \Leftrightarrow \quad \left. \begin{aligned} \frac{C_j + \sum p t_j^{*p-1}}{2} &= \gamma_j^* \\ \frac{\sum p t_j^{*p-1} - C_j}{2} &= \mu_j^* \end{aligned} \right\} \quad \textcircled{5}$

Now because of $\textcircled{4}$, it is easy to see that both γ_j^* & μ_j^* cannot be ^{non} zero: if they were non-zero, then $\chi_j^* = t_j^* = 0 \Leftrightarrow \chi_j^* = 0$,
 $\chi_j^* + t_j^* = 0 \quad \checkmark \quad t_j^* = 0$,
 which is impossible by $\textcircled{5}$ as $C_j \neq 0$.

\therefore At least one of them is zero $\Rightarrow C_j = \sum p t_j^{*p-1}$ (here $\mu_j^* = 0$)
 $C_j = -\sum p t_j^{*p-1}$ (here $\gamma_j^* = 0$)

\checkmark This shows both cannot be zero... either $\mu_j^* = 0$ & $\gamma_j^* = 0$
 Also $\sum p \neq 0$ $\gamma_j^* \neq 0$ & $\mu_j^* \neq 0$

~~Now $\mu_j^* = 0 \Rightarrow y_j^* \neq 0 \Rightarrow x_j^* = t_j^*$~~

Also we know from (3), that $t_j^* \geq 0$

Here, if $c_j^* > 0$, then $c_j = s^* p t_j^{*p-1}$ and $\mu_j^* = 0 \Rightarrow y_j^* \neq 0$
 i.e. $x_j^* = -\left(\frac{c_j}{s^* p}\right)^{1/p-1}$ $x_j^* = -t_j^*$

if $c_j^* < 0$, then $c_j = -s^* p t_j^{*p-1}$ and $y_j^* = 0 \Rightarrow \mu_j^* = 0$
 $\Rightarrow x_j^* = \left(\frac{-c_j}{s^* p}\right)^{1/p-1}$ $x_j^* = t_j^*$

~~Now $s^* = 0$, take from (4) we have $\sum t_i^* = 1$~~

~~9. either works,~~
 From above we get, $|x_j^*| = t_j^* = \left(\frac{|c_j|}{s^* p}\right)^{1/p-1}$

Now since, $s^* \neq 0$, we get from (4), that $\sum t_i^* = 1$

$$\Rightarrow \frac{\sum_{j=1}^n (|c_j|)^{1/p-1}}{s^{*p/p-1} p^{1/p-1}} = 1$$

$$\Rightarrow s^* = \frac{\left(\sum_{j=1}^n |c_j|^{p/p-1}\right)^{1/p}}{p^{1/p}}$$

\Rightarrow i.e. $x_j^* = -\frac{c_j^{1/p-1}}{\left(\sum_{j=1}^n |c_j|^{p/p-1}\right)^{1/p}}$ when $c_j^* > 0$ $x_j^* = \frac{(-c_j)^{1/p-1}}{\left(\sum_{j=1}^n |c_j|^{p/p-1}\right)^{1/p}}$ when $c_j^* < 0$

(R2)
(R3)

Introducing KKT conditions are:
Combining (R1), (R2), (R3), we get:

$$x_j^* = \begin{cases} - (|c_j|)^{1/p-1} & \text{if } c_j \geq 0 \\ \frac{\left(\sum_{i=1}^n |c_i|^{p/(p-1)} \right)^{1/p}}{(|c_j|)^{1/p-1}} & \text{else} \end{cases}$$

minimum

Since this x^* is such that $\|x^*\|_p \leq 1$ & achieves optimal value of the given problem for $C^T x$, we have that this is the optimal solution of the given problem also! Here the optimal set is the singleton having the above x^* .
(From this x^* , it is also clear that the optimal value of the given problem is $- \|c\|_q$, where $\frac{1}{p} + \frac{1}{q} = 1$.)

② $\min_{p_i \geq 0} \sum_{i=1}^n p_i \log p_i$ (I)

s.t. $\sum_{i=1}^n p_i = 1, l_i \leq a_i^T x \leq u_i \quad \forall i = 1 \text{ to } m$

where $a_i = \begin{bmatrix} x_1^i \\ \vdots \\ x_n^i \end{bmatrix}$

~~Convexity~~ \mathcal{P} is a PCP. i.e.

$$\textcircled{I} = \min_{p \in \mathcal{P}} f(p)$$

s.t. $a_i^T p \leq b_i \quad i = 1 \text{ to } 2m$
 $a_0^T p = b_0$

where $f(p) = \sum_{i=1}^m p_i \log p_i$, $\mathcal{P} = \{p \in \mathbb{R}^n / p_i \geq 0 \forall i\}$

$$a_0 = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}_{n \times 1}$$

$$b_0 = 1$$

we actually know, that $1^T p = 1 \Leftrightarrow$ $1^T p \leq 1$
 $-1^T p \leq -1$

~~convexity~~ \rightarrow let corresponding dual variables be $\lambda \rightarrow$ signs will be unrestricted

$$\begin{aligned} a_i &= \bar{a}_i & a_{i+m} &= -\bar{a}_i & \text{for } i=1 \text{ to } m. \\ b_i &= u_i & b_{i+m} &= -l_i \end{aligned}$$

dual variable $\lambda \in \mathbb{R}^m$ dual variable $\mu \in \mathbb{R}^m$

By the PCP duality derived in lecture, we get:

$$\textcircled{I} = \max_{p \in \mathbb{R}^n, \lambda \in \mathbb{R}^m, \mu \in \mathbb{R}^m} -f\left(-\sum_{i=1}^m \lambda_i \bar{a}_i + \sum_{i=1}^m \mu_i \bar{a}_i - \rho \mathbf{1}\right) - \sum_{i=1}^m u_i \lambda_i + \sum_{i=1}^m l_i \mu_i - \rho$$

\textcircled{II}

s.t. $\lambda \geq 0, \mu \geq 0$

Now $f^*(y) = \max_{p_i \geq 0} y^T p - \sum_i p_i \log p_i \xrightarrow{\text{at optimality}} y_i - 1 - \log p_i = 0 \forall i$

$$\Rightarrow p_i = e^{y_i - 1}$$

$$\therefore f^*(y) = \sum_{i=1}^n y_i e^{y_i - 1} - \sum_{i=1}^n (y_i - 1) e^{y_i - 1} = \sum_{i=1}^n e^{y_i - 1}$$

Substituting in \textcircled{II} gives the dual.