



EE908 Assignment-4 Solution

eMasters in Communication Systems, IITK

EE908: Optimization in SPCOM

Instructor: Prof. Ketan Rajawat

Student Name: Venkateswar Reddy Melachervu

Roll No: 23156022

Q1. Using the concavity of the logarithm, show that $x^\theta y^{1-\theta} \leq \theta x + (1 - \theta)y$.

Solution:

Given inequality: $x^\theta y^{1-\theta} \leq \theta x + (1 - \theta)y$

Taking log both sides:

$$\log(x^\theta y^{1-\theta}) \leq \log(\theta x + (1 - \theta)y)$$

$$\Rightarrow \theta \log(x) + (1 - \theta) \log(y) \leq \log(\theta x + (1 - \theta)y)$$

Now let's make use of log concavity and Jensen's inequality to prove the above inequality.

\therefore Jensen's inequality for concavity of a function,

$$f(\sum_{i=1}^n \theta_i x_i) \geq \sum_{i=1}^n \theta_i f(x_i), \sum_{i=1}^n \theta_i = 1, \forall x_i \in \text{dom } f$$

Log(x) is a concave function and for any $x, y \in \text{dom}(\log), \theta \in [0,1]$

Applying Jensen's inequality:

$$\log(\theta x + (1 - \theta)y) \geq \theta \log(x) + (1 - \theta) \log(y)$$

$$\therefore \theta \log(x) + (1 - \theta) \log(y) \leq \log(\theta x + (1 - \theta)y)$$

QED

Q2. Show that the harmonic mean $f(x) = \left(\sum_{i=1}^n \frac{1}{x_i}\right)^{-1}$ is concave.

Solution:

Let's use the second order conditions $\nabla^2 f(x) < 0$ (opposite of PSD) to prove $f(x)$ is concave

$$\frac{\partial f(x)}{\partial x_i} = (\sum_{i=1}^n x_i^{-1})^{-2} x_i^{-2} = \left(\frac{f(x)}{x_i}\right)^2$$

$$\frac{\partial^2 f(x)}{\partial x_i \partial x_j} = \frac{2}{x_i} \left(\frac{f(x)}{x_i}\right) \left(\frac{f(x)}{x_j}\right)^2 = \frac{2}{f(x)} \left(\frac{f(x)^2}{x_i x_j}\right)^2 \text{ for } i \neq j$$

$$\frac{\partial^2 f(x)}{\partial x_i^2} = \frac{2}{f(x)} \left(\frac{f(x)^2}{x_i^2}\right)^2 - \frac{2}{x_i} \left(\frac{f(x)}{x_i}\right)^2 \text{ for } i = j$$

\therefore We need to show that

$$y^T \nabla^2 f(x) y = \frac{2}{f(x)} \left(\left(\sum_{i=1}^n \frac{y_i f(x)^2}{x_i^2} \right)^2 - \left(\sum_{i=1}^n \frac{y_i^2 f(x)^3}{x_i^3} \right) \right) \leq 0 \text{ for concavity of } f(x)$$

The above holds true following the Cauchy-Schwartz Inequality $a_i^T b_i \leq \|a_i\|_2 \|b_i\|_2$ where:

$$a_i = \left(\frac{f(x)}{x_i}\right)^{1/2}, b_i = y_i \left(\frac{f(x)}{x_i}\right)^{3/2} \text{ and } \sum_i a_i^2 = 1$$

QED



Q3. Prove the reverse Jensen's inequality for a convex f with $\text{dom } f = \mathbb{R}^n$, $\lambda_i > 0$ and $\lambda_1 - \sum_{i=2}^n \lambda_i = 1$
 $f(\lambda_1 x_1 - \lambda_2 x_2 - \dots - \lambda_n x_n) \geq \lambda_1 f(x_1) - \lambda_2 f(x_2) - \dots - \lambda_n f(x_n)$

Solution:

Given the function f is convex function, Jensen's inequality of this function f is:

$$\Rightarrow f(\lambda_1 x_1 + \lambda_2 x_2 + \dots + \lambda_n x_n) \leq \lambda_1 f(x_1) + \lambda_2 f(x_2) + \dots + \lambda_n f(x_n)$$

Negating both sides:

$$\Rightarrow -f(\lambda_1 x_1 + \lambda_2 x_2 + \dots + \lambda_n x_n) \geq -\lambda_1 f(x_1) - \lambda_2 f(x_2) - \dots - \lambda_n f(x_n)$$

$$\Rightarrow -f\left(\sum_{i=1}^n \lambda_i x_i\right) \geq -\sum_{i=1}^n \lambda_i f(x_i)$$

Since $\lambda_1 - \sum_{i=2}^n \lambda_i = 1$

$$\Rightarrow -f(\lambda_1 x_1 + \lambda_2 x_2 + \dots + \lambda_n x_n) \geq -\lambda_1 f(x_1) - (\lambda_1 - 1)$$

$$-f(\lambda_1 x_1 + \lambda_1 - 1) \geq -\lambda_1 f(x_1) - (\lambda_1 - 1)$$

Reversing the signs both sides,

$$f(\lambda_1 x_1 + \lambda_1 - 1) \leq \lambda_1 f(x_1) + (\lambda_1 - 1)$$

This is valid and holds as per Jensen's inequality

QED

Q4. Give an example of a function $f(x)$ whose epigraph is (a) half-space, (b) norm cone, and (c) polyhedron.

Solution:

Let's define a function $f(x) = \|x\|_2 = \sqrt{x_1^2 + x_2^2}, x \in \mathbb{R}^2$ - Euclidean norm.

This function satisfies all three cases:

(a) Half-space:

- The epigraph of $f(x)$ as a half-space can be represented as $\{(x_1, x_2, t) \mid \sqrt{x_1^2 + x_2^2} \geq t\}$
- This corresponds to the region above or on the circle centered at the origin with radius t

(b) Norm cone

- The epigraph of $f(x)$ as a norm cone can be represented as $\{(x_1, x_2, t) \mid \sqrt{x_1^2 + x_2^2} \leq t\}$
- This represents the cone-like region expanding from the origin outward.

(c) Polyhedron

- The epigraph of $f(x)$ as a polyhedron is the set of points (x_1, x_2, t) such that $\sqrt{x_1^2 + x_2^2} \leq t$
- This represents circular region in 2D space

So, the function $f(x) = \|x\|_2 = \sqrt{x_1^2 + x_2^2}$ satisfies all three cases: it represents a half-space, a norm cone, and a polyhedron.

QED

Q5. Let $x, y \in \mathbb{R}_{++}^n$ be two vectors. We need to show that the Itakura-Saito distance, defined as

$$D_{IS}(x, y) = \sum_{i=1}^n \left(\frac{x_i}{y_i} - \log\left(\frac{x_i}{y_i}\right) - 1 \right)$$

is always positive, using the following steps:

(a) Show that for a convex differentiable function f , the Bregman divergence:

$$D(x, y) = f(x) - f(y) - \Delta f(y)^T(x - y)$$





is always non-negative.

Solution:

Let's prove that $D(x, y) = f(x) - f(y) - \nabla f(y)^T(x - y) \geq 0$ for all x, y . f is convex differentiable:

So, as per the first order convex condition (gradient-based)

$$f(x) \geq f(y) + \nabla f(y)^T(x - y)$$

Let's substitute the above equation into Bregman divergence:

$$\begin{aligned} D(x, y) &= f(x) - f(y) - \nabla f(y)^T(x - y) \\ &\geq [f(y) - \nabla f(y)^T(x - y)] - f(y) - \nabla f(y)^T(x - y) \\ &\geq 0 \\ \text{QED} \end{aligned}$$

(b) Show that for the convex function $f(x) = -\sum_{i=1}^n \log(x_i)$, it holds that $D(x, y) = D_{IS}(x, y)$.

Solution:

$$\text{Given } f(x) = -\sum_{i=1}^n \log(x_i),$$

$$D(x, y) = f(x) - f(y) - \nabla f(y)^T(x - y)$$

$$\therefore \nabla f(x) = \left(-\frac{1}{x_1}, -\frac{1}{x_2}, \dots, -\frac{1}{x_n}\right)$$

$$\therefore D(x, y) = -\sum_{i=1}^n \log(x_i) + \sum_{i=1}^n \log(y_i) - \left(-\frac{1}{x_1}, -\frac{1}{x_2}, \dots, -\frac{1}{x_n}\right)^T (x - y)$$

$$= -\sum_{i=1}^n \log(x_i) + \sum_{i=1}^n \log(y_i) + \sum_{i=1}^n \frac{x_i}{y_i} - n$$

$$\text{Let's compute } D_{IS}(x, y) = \sum_{i=1}^n \left(\frac{x_i}{y_i} - \log\left(\frac{x_i}{y_i}\right) - 1\right)$$

$$= \sum_{i=1}^n \left(\frac{x_i}{y_i} - \log\left(\frac{x_i}{y_i}\right)\right) - n$$

Let's compare both:

$$D(x, y) = -\sum_{i=1}^n \log(x_i) + \sum_{i=1}^n \log(y_i) + \sum_{i=1}^n \frac{x_i}{y_i} - n$$

$$= -(\sum_{i=1}^n \log(x_i) - \sum_{i=1}^n \log(y_i)) + \sum_{i=1}^n \frac{x_i}{y_i} - n$$

$$= \sum_{i=1}^n \frac{x_i}{y_i} - (\sum_{i=1}^n \log(x_i) - \sum_{i=1}^n \log(y_i)) - n$$

$$= \sum_{i=1}^n \frac{x_i}{y_i} - \left(\sum_{i=1}^n \log\left(\frac{x_i}{y_i}\right)\right) - n$$

$$= \sum_{i=1}^n \left(\frac{x_i}{y_i} - \log\left(\frac{x_i}{y_i}\right)\right) - n = D_{IS}(x, y)$$

$$\therefore D(x, y) = D_{IS}(x, y)$$

QED

(c) Along similar lines, prove that the generalized KL divergence:

$$D_{KL}(x, y) = \sum_{i=1}^n \left(x_i \log\left(\frac{x_i}{y_i}\right) - x_i + y_i\right)$$

is always positive.

Solution:

We aim to prove that $D_{KL}(x, y) \geq 0$ for all non-negative x, y i.e.

$$D_{KL}(x, y) = \sum_{i=1}^n \left(x_i \log\left(\frac{x_i}{y_i}\right) - x_i + y_i\right) \geq 0$$

Jensen's inequality for a convex function $f(x) = -\log(x)$





$$-\log \left(\sum_{i=1}^n \theta_i \frac{x_i}{y_i} \right) \leq \sum_{i=1}^n \theta_i \left(-\log \left(\frac{x_i}{y_i} \right) \right)$$

Rewriting the above:

$$-\log \left(\sum_{i=1}^n \theta_i \frac{x_i}{y_i} \right) \leq \sum_{i=1}^n \theta_i (-\log(x_i) + \log(y_i))$$

$$\Rightarrow -\log \left(\sum_{i=1}^n \theta_i \frac{x_i}{y_i} \right) \leq -\sum_{i=1}^n \theta_i \log(x_i) + \sum_{i=1}^n \theta_i \log(y_i)$$

$$\Rightarrow \log \left(\sum_{i=1}^n \theta_i \frac{x_i}{y_i} \right) \geq \sum_{i=1}^n \theta_i \log(x_i) - \sum_{i=1}^n \theta_i \log(y_i)$$

Substituting the inequality into KL divergence:

$$D_{KL}(x, y) = \sum_{i=1}^n \left(x_i \log \left(\frac{x_i}{y_i} \right) - x_i + y_i \right) \geq \sum_{i=1}^n x_i \log(x_i) + \sum_{i=1}^n x_i \log(y_i) - \sum_{i=1}^n x_i + \sum_{i=1}^n y_i$$

Simplifying:

$$D_{KL}(x, y) \geq \sum_{i=1}^n y_i - \sum_{i=1}^n x_i$$

Since x_i, y_i are non-negative for all i , $y_i - x_i$ is non-negative

QED

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