

Homework exercise

Eugene Lykhovyd

1 Main section

The main problem: given $h_k > 0, k = 0, \dots, N$ prove that

$$\Delta_N = \frac{R^2 + \sum_{i=0}^N h_i^2}{2 \sum_{i=0}^N h_i}$$

is a convex function of h_k .

In this proof we will use the following inequalities:

Theorem 1 (Cauchy inequality). *For positive a and b it holds $\frac{a+b}{2} \geq \sqrt{ab}$.*

Theorem 2 (Cauchy-Bunyakovsky-Schwarz inequality). *Let $x_1, x_2 \in \mathbb{R}^n$. Then $(x_1, x_2) \leq \|x_1\| \cdot \|x_2\|$.*

Let's prove the following lemma.

Lemma 1. *Let $x_1, x_2 \in \mathbb{R}_+^n$, i.e. all coordinates are positive. Let $\mathbf{1}$ denote a vector of all ones. Then it holds*

$$2(x_1, x_2) \leq \frac{\|x_1\|^2}{(x_1, \mathbf{1})}(x_2, \mathbf{1}) + \frac{\|x_2\|^2}{(x_2, \mathbf{1})}(x_1, \mathbf{1})$$

Proof. By Cauchy inequality (noticing everything is positive)

$$\frac{\frac{\|x_1\|^2}{(x_1, \mathbf{1})}(x_2, \mathbf{1}) + \frac{\|x_2\|^2}{(x_2, \mathbf{1})}(x_1, \mathbf{1})}{2} \geq \sqrt{\frac{\|x_1\|^2}{(x_1, \mathbf{1})}(x_2, \mathbf{1}) \frac{\|x_2\|^2}{(x_2, \mathbf{1})}(x_1, \mathbf{1})} = \|x_1\| \cdot \|x_2\|$$

Then by Cauchy-Bunyakovsky-Schwarz inequality $\|x_1\| \cdot \|x_2\| \geq (x_1, x_2)$. QED \square

The next lemma will prove the hard part of the function we want to show convexity later.

Lemma 2. *Let $x \in \mathbb{R}_+^n$. Then the function $f(x) = \frac{\sum_{i=1}^n x_i^2}{\sum_{i=1}^n x_i}$ is convex.*

Proof. Firstly, notice that $f(x) = \frac{\|x\|^2}{(x,1)}$.

Take $x_1, x_2 \in \mathbb{R}_+^n$. Fix any $\lambda \in [0; 1]$. We prove convexity by definition. For the only inequality we apply the lemma above.

$$\begin{aligned}
f(\lambda x_1 + (1 - \lambda)x_2) &= \frac{\|\lambda x_1 + (1 - \lambda)x_2\|^2}{(\lambda x_1 + (1 - \lambda)x_2, 1)} = \frac{\lambda^2\|x_1\|^2 + 2\lambda(1 - \lambda)(x_1, x_2) + (1 - \lambda)^2\|x_2\|^2}{\lambda(x_1, 1) + (1 - \lambda)(x_2, 1)} \leq \\
&\leq \frac{\lambda^2\|x_1\|^2 + \lambda(1 - \lambda) \left(\frac{\|x_1\|^2}{(x_1, 1)}(x_2, 1) + \frac{\|x_2\|^2}{(x_2, 1)}(x_1, 1) \right) + (1 - \lambda)^2\|x_2\|^2}{\lambda(x_1, 1) + (1 - \lambda)(x_2, 1)} = \\
&= \frac{\lambda\|x_1\|^2 \left(\lambda + (1 - \lambda) \frac{(x_2, 1)}{(x_1, 1)} \right) + (1 - \lambda)\|x_2\|^2 \left((1 - \lambda) + \lambda \frac{(x_1, 1)}{(x_2, 1)} \right)}{\lambda(x_1, 1) + (1 - \lambda)(x_2, 1)} = \\
&= \frac{\lambda\|x_1\|^2 \left(\frac{\lambda(x_1, 1) + (1 - \lambda)(x_2, 1)}{(x_1, 1)} \right) + (1 - \lambda)\|x_2\|^2 \left(\frac{\lambda(x_1, 1) + (1 - \lambda)(x_2, 1)}{(x_2, 1)} \right)}{\lambda(x_1, 1) + (1 - \lambda)(x_2, 1)} = \\
&= \lambda \frac{\|x_1\|^2}{(x_1, 1)} + (1 - \lambda) \frac{\|x_2\|^2}{(x_2, 1)} = \lambda f(x_1) + (1 - \lambda)f(x_2)
\end{aligned}$$

□

Now basically we are almost done. Here is an easy proof of the next auxiliary function.

Lemma 3. *Let $x \in \mathbb{R}_+^n$. Then the function $g(x) = \frac{1}{\sum_{i=1}^n x_i}$ is convex.*

Proof. Every partial derivative of g is $\frac{\partial^2 g}{\partial x_i \partial x_j} = \frac{2}{\left(\sum_{i=1}^n x_i\right)^3}$. Then the hessian of g is

$H_g = \frac{2}{\left(\sum_{i=1}^n x_i\right)^3} J_n$ where J_n is the matrix of all ones. From J_n is positive semidefinite, we immediately conclude that H_g is positive semidefinite and $g(x)$ is convex on \mathbb{R}_+^n . □

And the final result.

Theorem 3. Δ_N is convex.

Proof. Rewrite $\Delta_N = \frac{R^2}{2}g(h) + \frac{1}{2}f(h)$. Sum of convex functions multiplied by positive scalars is convex. □