

## Problem Set 4 — Solutions (Proximal Gradient and Subgradient Descent)

### Proximal Gradient and Subgradient Descent

Solve Exercises 26, 27, 28, 29 from the lecture notes.

**Exercise 26.** Prove Lemma 3.12!

**Hint:** It is useful to prove that with  $\mathbf{x}^*(p)$  as in (3.12) and satisfying (3.13),

$$\mathbf{x}^*(p) = \operatorname{argmin}\{\|\mathbf{x} - \mathbf{v}\| : \sum_{i=1}^d x_i = 1, x_{p+1} = \dots = x_d = 0\}.$$

**Solution:** We claim that for any  $1 \leq p \leq d$

$$\mathbf{x}^*(p) = \operatorname{argmin}\{\|\mathbf{x} - \mathbf{v}\| : \sum_{i=1}^d x_i = 1, x_{p+1} = \dots = x_d = 0\}.$$

- Assume for the moment that this claim is true. The claim means that if  $p_1 \leq p_2$ , then  $\|\mathbf{x}^*(p_1) - \mathbf{v}\| \geq \|\mathbf{x}^*(p_2) - \mathbf{v}\|$  since  $\mathbf{x}^*(p_2)$  is a solution of minimization problem with less constraints than for  $\mathbf{x}^*(p_1)$  (components  $p_1 + 1$  to  $p_2$  do not have to be equal to 0).

Now suppose Lemma 3.12 is wrong and  $\mathbf{x}^*(p^*)$  is not a solution and there exists another  $p \neq p^*$  such that  $\Pi_X(\mathbf{v}) = \mathbf{x}^*(p)$ . Notice that such  $p$  can be only smaller than  $p^*$  as for greater values  $p$ ,  $\mathbf{x}^*(p)$  (from Lemma 3.11) would have negative components and contradict Lemma 3.10. But for  $p < p^*$ ,  $\|\mathbf{x}^*(p) - \mathbf{v}\| \geq \|\mathbf{x}^*(p^*) - \mathbf{v}\|$ , so if  $\Pi_X(\mathbf{v}) = \mathbf{x}^*(p)$  then it has to hold that  $\|\mathbf{x}^*(p) - \mathbf{v}\| = \|\mathbf{x}^*(p^*) - \mathbf{v}\|$  and  $\mathbf{x}^*(p^*)$  is also a projection. We know that the projection on a convex set is unique, and thus  $\mathbf{x}^*(p) = \mathbf{x}^*(p^*)$ , which is impossible by the construction ( $p + 1$  component of  $\mathbf{x}^*(p)$  is equal to 0, and that of  $\mathbf{x}^*(p^*)$  is strictly positive), which leads to a contradiction.

- It remains only to prove our claim. That is, to show that for a given  $1 \leq p \leq d$  indeed

$$\mathbf{x}^*(p) = \operatorname{argmin}\{\|\mathbf{x} - \mathbf{v}\| : \sum_{i=1}^d x_i = 1, x_{p+1} = \dots = x_d = 0\},$$

provided that  $\mathbf{x}^*(p)$  satisfies conditions (3.12) and (3.13).

Let  $Y = \{\mathbf{x} \in \mathbb{R}^d : \sum_{i=1}^d x_i = 1, x_{p+1} = \dots = x_d = 0\}$ , and let  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  defined as  $f(\mathbf{x}) = \|\mathbf{v} - \mathbf{x}\|^2$ . To prove our claim, it suffices to show that  $\mathbf{x}^*(p) \in Y$  is a minimizer of  $f$  over  $Y$ . By the optimality condition of Lemma 1.27, it suffices to show that  $\nabla f(\mathbf{x}^*(p))^\top (\mathbf{x} - \mathbf{x}^*(p)) \geq 0$  for all  $\mathbf{x} \in Y$ . Because  $\nabla f(\mathbf{x}) = 2(\mathbf{v} - \mathbf{x})$ , we want to show that

$$-2(\mathbf{v} - \mathbf{x}^*(p))^\top (\mathbf{x} - \mathbf{x}^*(p)) \geq 0. \quad (1)$$

Notice that the first  $p$  coordinates of  $(\mathbf{v} - \mathbf{x}^*(p))$  are all equal to  $\Theta_p$ . Moreover, the last  $(d - p)$  coordinates of both  $\mathbf{x} \in Y$  and  $\mathbf{x}^*(p)$  are all equal to 0. Therefore, we get that  $(\mathbf{v} - \mathbf{x}^*(p))^\top (\mathbf{x} - \mathbf{x}^*(p))$  equals

$$(\Theta_p, \dots, \Theta_p, v_{p+1}, \dots, v_d)^\top (x_1 - v_1 + \Theta_p, \dots, x_p - v_p + \Theta_p, 0, \dots, 0)$$

Expanding this product, we get

$$(\mathbf{v} - \mathbf{x}^*(p))^\top (\mathbf{x} - \mathbf{x}^*(p)) = \Theta_p \sum_{i=1}^p (x_i - v_i + \Theta_p) = \Theta_p \left( \sum_{i=1}^p x_i - \sum_{i=1}^p v_i + p\Theta_p \right).$$

Because  $\mathbf{x} \in Y$ , we know that  $\sum_{i=1}^p x_i = 1$ , and since  $\Theta_p = \frac{1}{p}(\sum_{i=1}^p v_i - 1)$ , we get that

$$(\mathbf{v} - \mathbf{x}^*(p))^\top (\mathbf{x} - \mathbf{x}^*(p)) = \Theta_p \left( 1 - \sum_{i=1}^p v_i + p \frac{1}{p} \left( \sum_{i=1}^p v_i - 1 \right) \right) = 0.$$

That is, equation (1) holds, and by Lemma 1.27 we conclude that  $\mathbf{x}^*(p)$  is a minimizer of  $f$  over  $Y$  proving our claim.

**Exercise 27.** Prove Theorem 3.14!

**Solution:** From (3.17), the proximal step could be written as

$$\mathbf{x}_{t+1} = \operatorname{argmin}_{\mathbf{y} \in \mathbb{R}^d} \{g(\mathbf{x}_t) + \nabla g(\mathbf{x}_t)^\top (\mathbf{y} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{y} - \mathbf{x}_t\|^2 + h(\mathbf{y})\} = \operatorname{argmin}_{\mathbf{y} \in \mathbb{R}^d} \{\psi(\mathbf{y})\},$$

where the function  $\psi(\mathbf{y}) = g(\mathbf{x}_t) + \nabla g(\mathbf{x}_t)^\top (\mathbf{y} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{y} - \mathbf{x}_t\|^2 + h(\mathbf{y})$ . Note that  $\psi(\mathbf{y}) - \frac{L}{2} \|\mathbf{y} - \mathbf{x}_t\|^2$  is convex as  $h$  is convex. Note that Lemma 2.11 can also be defined for non-differentiable convex functions using subgradients, hence  $\psi$  is  $L$ -strongly convex. Although not discussed explicitly in the course, the definition of strong convexity Definition 2.10 can also be extended to non-differentiable convex functions using sub-gradients. Using this definition and the fact that 0 belongs to subgradient of  $\psi$  at  $\mathbf{x}_{t+1}$ , we have  $\psi(\mathbf{y}) \geq \psi(\mathbf{x}_{t+1}) + \frac{L}{2} \|\mathbf{y} - \mathbf{x}_{t+1}\|^2$ . This is equivalent to

$$\nabla g(\mathbf{x}_t)^\top (\mathbf{y} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{y} - \mathbf{x}_t\|^2 + h(\mathbf{y}) \geq \nabla g(\mathbf{x}_t)^\top (\mathbf{x}_{t+1} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{x}_{t+1} - \mathbf{x}_t\|^2 + h(\mathbf{x}_{t+1}) + \frac{L}{2} \|\mathbf{y} - \mathbf{x}_{t+1}\|^2,$$

Rearranging terms and subtracting  $h(\mathbf{x}_t)$  from both sides,

$$\nabla g(\mathbf{x}_t)^\top (\mathbf{y} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{y} - \mathbf{x}_t\|^2 - \frac{L}{2} \|\mathbf{y} - \mathbf{x}_{t+1}\|^2 + h(\mathbf{y}) - h(\mathbf{x}_t) \geq \nabla g(\mathbf{x}_t)^\top (\mathbf{x}_{t+1} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{x}_{t+1} - \mathbf{x}_t\|^2 + h(\mathbf{x}_{t+1}) - h(\mathbf{x}_t)$$

As the function  $g$  is  $L$ -smooth, we can estimate the right side as  $g(\mathbf{x}_t)^\top (\mathbf{x}_{t+1} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{x}_{t+1} - \mathbf{x}_t\|^2 \geq g(\mathbf{x}_{t+1}) - g(\mathbf{x}_t)$ , and because  $g$  is convex, on the left side we estimate  $\nabla g(\mathbf{x}_t)^\top (\mathbf{y} - \mathbf{x}_t) \leq g(\mathbf{y}) - g(\mathbf{x}_t)$ . Putting this together

$$f(\mathbf{y}) - f(\mathbf{x}_t) + \frac{L}{2} \|\mathbf{y} - \mathbf{x}_t\|^2 - \frac{L}{2} \|\mathbf{y} - \mathbf{x}_{t+1}\|^2 \geq f(\mathbf{x}_{t+1}) - f(\mathbf{x}_t)$$

This holds for any  $\mathbf{y} \in \mathbb{R}^d$ . Lets take  $\mathbf{y} = \mathbf{x}^*$  and sum up the inequation above from  $t = 0$  to  $t = T - 1$

$$\sum_{t=0}^{T-1} (f(\mathbf{x}^*) - f(\mathbf{x}_t)) + \frac{L}{2} \|\mathbf{x}^* - \mathbf{x}_0\|^2 - \frac{L}{2} \|\mathbf{x}^* - \mathbf{x}_T\|^2 \geq f(\mathbf{x}_T) - f(\mathbf{x}_0)$$

or equivalently,

$$\sum_{t=1}^T (f(\mathbf{x}_t) - f(\mathbf{x}^*)) \leq \frac{L}{2} \|\mathbf{x}^* - \mathbf{x}_0\|^2 - \frac{L}{2} \|\mathbf{x}^* - \mathbf{x}_T\|^2 \leq \frac{L}{2} \|\mathbf{x}^* - \mathbf{x}_0\|^2.$$

Note that  $\mathbf{x}_{t+1}$  is the minima of  $\psi(\mathbf{y})$ . Hence we have,

$$\psi(\mathbf{x}_{t+1}) \leq \psi(\mathbf{x}_t)$$

From definition of  $\psi$ ,  $\psi(\mathbf{x}_t) = g(\mathbf{x}_t) + h(\mathbf{x}_t) = f(\mathbf{x}_t)$ ,

$$\psi(\mathbf{x}_{t+1}) = g(\mathbf{x}_t) + \nabla g(\mathbf{x}_t)^\top (\mathbf{x}_{t+1} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{x}_{t+1} - \mathbf{x}_t\|^2 + h(\mathbf{x}_{t+1}),$$

$$\text{Using smoothness of } g, g(\mathbf{x}_{t+1}) \leq g(\mathbf{x}_t) + \nabla g(\mathbf{x}_t)^\top (\mathbf{x}_{t+1} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{x}_{t+1} - \mathbf{x}_t\|^2,$$

$$\text{Hence, } f(\mathbf{x}_{t+1}) = g(\mathbf{x}_{t+1}) + h(\mathbf{x}_{t+1}) \leq \psi(\mathbf{x}_{t+1}).$$

Combining these we have  $f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t)$  for each  $0 \leq t \leq T$

$$f(\mathbf{x}_t) - f(\mathbf{x}^*) \leq \frac{1}{T} \sum_{t=1}^T (f(\mathbf{x}_t) - f(\mathbf{x}^*)) \leq \frac{L}{2T} \|\mathbf{x}^* - \mathbf{x}_0\|^2.$$

**Exercise 28.** Prove Lemma 4.2, meaning that a function that is differentiable at  $\mathbf{x}$  has at most one subgradient there, namely  $\nabla f(\mathbf{x})$ .

**Solution:** Let  $\mathbf{g}$  be a subgradient at  $\mathbf{x}$ . Together with differentiability at  $\mathbf{x}$  (Definition 1.5), we derive the inequality

$$(\mathbf{g} - \nabla f(\mathbf{x}))^\top (\mathbf{y} - \mathbf{x}) \leq r_{\mathbf{x}}(\mathbf{y} - \mathbf{x})$$

for all  $\mathbf{y}$  in some neighborhood of  $\mathbf{x}$ , where  $r_{\mathbf{x}}$  is a sublinear error function ( $r_{\mathbf{x}}(\mathbf{v})/\|\mathbf{v}\| \rightarrow 0$  as  $\mathbf{v} \rightarrow 0$ ). Then it should also hold for all  $\mathbf{y}_\varepsilon = \varepsilon \mathbf{e}_i + \mathbf{x}$  for small enough  $\varepsilon$ , where  $\mathbf{e}_i$  is the  $i$ -th coordinate vector. Substituting  $\mathbf{y}_\varepsilon$  and dividing both sides with  $\|\mathbf{y} - \mathbf{x}\|$  we get

$$\frac{(\mathbf{g} - \nabla f(\mathbf{x}))^\top (\varepsilon \mathbf{e}_i)}{\varepsilon \|\mathbf{e}_i\|} \leq \frac{r_{\mathbf{x}}(\varepsilon \mathbf{e}_i)}{\|\varepsilon \mathbf{e}_i\|}$$

We see that on the left hand side  $\varepsilon$  cancels and the term does not depend on it, while the right part goes to zero as  $\varepsilon \rightarrow 0$  since  $r_{\mathbf{x}}$  is sublinear function. This means that the left part has to be zero, i.e.  $(\mathbf{g} - \nabla f(\mathbf{x}))^\top \mathbf{e}_i = 0$  and this should hold for any  $i$ . This is possible only when  $\mathbf{g} = \nabla f(\mathbf{x})$ .

**Exercise 29.** Prove the easy direction of Lemma 4.3, meaning that the existence of subgradients everywhere implies convexity!

**Solution:** Let's assume that we have subgradients everywhere. With  $\mathbf{g} \in \partial f(\lambda \mathbf{x} + (1 - \lambda)\mathbf{y})$ , (4.1) yields

$$\begin{aligned} f(\mathbf{x}) &\geq f(\lambda \mathbf{x} + (1 - \lambda)\mathbf{y}) + \mathbf{g}^\top ((1 - \lambda)(\mathbf{x} - \mathbf{y})), \\ f(\mathbf{y}) &\geq f(\lambda \mathbf{x} + (1 - \lambda)\mathbf{y}) + \mathbf{g}^\top (\lambda(\mathbf{y} - \mathbf{x})). \end{aligned}$$

Adding up these two inequalities with multiples  $\lambda$  and  $1 - \lambda$  cancels the subgradient terms and yields

$$\lambda f(\mathbf{x}) + (1 - \lambda)f(\mathbf{y}) \geq f(\lambda \mathbf{x} + (1 - \lambda)\mathbf{y}),$$

which is convexity.

## Random Walks

Gradient descent turns up in a surprising number of situations which apriori have nothing to do with optimization. In this exercise, we will see how performing a random walk on a graph can be seen as a special case of gradient descent.

We are given an *undirected* graph  $G(V, E)$  with vertices  $V = [n]$  labelled 1 through  $n$ , and edges  $E \subseteq [n]^2$  such that if  $(i, j) \in E$ , then  $(j, i) \in E$ . Further, we assume that the graph is *regular* in the sense that every edge has the same degree. Let  $d$  be the degree of each node such that if we denote  $\mathcal{N}(i) = \{j : (i, j) \in E\}$  to be the neighbors of  $i$ , then  $|\mathcal{N}(i)| = d$ . We assume that every node is connected to itself and so  $(i, i) \in \mathcal{N}(i)$ .

Now we start our random walk from node 1, jumping randomly from a node to its neighbor. More precisely, suppose at time step  $t$  we are at node  $i_t$ . Then  $i_{t+1}$  is picked uniformly at random from  $\mathcal{N}(i_t)$ . If we run this random walk for a large enough  $T$  steps, we expect that  $\Pr(i_T = j) = 1/n$  for any  $j \in [n]$ . This is called the stationary distribution.

**Problem A.** Let us represent the position at time step  $t$  in the graph with  $\mathbf{e}_{i_t} \in \mathbb{R}^n$  where the  $i_t$ th coordinate is 1 and all others are 0. Then, the vector  $\mathbf{x}_t = \mathbb{E}[\mathbf{e}_{i_t}]$  denotes the probability distribution over the  $n$  nodes of the graph. Further, let us denote  $\mathbf{G} \in \mathbb{R}^{n \times n}$  be the transition probability matrix such that

$$\mathbf{G}_{i,j} = \begin{cases} \frac{1}{d} & \text{if } (i, j) \in E \\ 0 & \text{otherwise.} \end{cases}$$

Show that

$$\mathbf{x}_{t+1} = \mathbf{G}\mathbf{x}_t \tag{2}$$

**Solution:** Let look at one coordinate  $j$  of random vector  $\mathbf{x}_{t+1} = \mathbb{E}[\mathbf{e}_{i_{t+1}}]$ . Then by the law of total probability, the expectation of this coordinate would be

$$\begin{aligned} [\mathbf{x}_{t+1}]_j &= \mathbb{E}[\mathbf{e}_{i_{t+1}}]_j = \Pr([\mathbf{e}_{i_{t+1}}]_j = 1) = \sum_k \Pr(i_{t+1} = j | i_t = k) \Pr(i_t = k) = \sum_k \Pr(i_{t+1} = j | i_t = k) \Pr([\mathbf{e}_{i_t}]_k = 1) \\ &= \sum_k \Pr(i_{t+1} = j | i_t = k) \mathbb{E}[\mathbf{e}_{i_t}]_k = \sum_k \Pr(i_{t+1} = j | i_t = k) [\mathbf{x}_t]_k \end{aligned}$$

Note, that for  $k : (j, k) \notin E$ ,  $\Pr(i_{t+1} = j | i_t = k) = 0 = \mathbf{G}_{j,k}$  and for  $k : (j, k) \in E$ ,  $\Pr(i_{t+1} = j | i_t = k) = \frac{1}{d} = \mathbf{G}_{j,k}$ . This means that

$$[\mathbf{x}_{t+1}]_j = \sum_k \mathbf{G}_{jk} [\mathbf{x}_t]_k,$$

or equivalently

$$\mathbf{x}_{t+1} = \mathbf{G} \mathbf{x}_t \quad (3)$$

**Problem B.** Simulate the random walk above over a torus and confirm that we indeed converge to a uniform distribution over the nodes. What is the *rate* at which this convergence occurs?

Follow the Python notebook provided here:

[github.com/epfml/OptML\\_course/tree/master/labs/ex04/](https://github.com/epfml/OptML_course/tree/master/labs/ex04/)

**Problem C.** Define  $\mu = \frac{1}{n} \mathbf{1}_n$  be a vector of all  $1/n$ , and a objective function  $f : \mathcal{S} \rightarrow \mathbb{R}$  as

$$f(\mathbf{x}) = (\mathbf{x} - \mu)^\top (\mathbf{I} - \mathbf{G})(\mathbf{x} - \mu),$$

defined over the probability simplex  $\mathcal{S} \subseteq \mathbb{R}^n$  where  $\mathcal{S} = \{\mathbf{v} : \mathbf{1}_n^\top \mathbf{v} = 1, v_i \geq 0\}$ .

1. Show that  $f$  defined above is convex and compute its smoothness constant.
2. Show that running gradient descent on  $f$  with the correct step-size is equivalent to the random walk step (2).
3. Prove that  $\mathbf{x}_t$  converges to the distribution  $\mu$  at a linear rate i.e. for the random walk on a torus with  $n$  nodes,

$$\|\mathbf{x}_t - \mu\|_2^2 \leq \left(1 - \frac{1}{n}\right)^t \|\mathbf{x}_0 - \mu\|_2^2 \leq \left(1 - \frac{1}{n}\right)^t.$$

*Hint: Use that the two largest eigenvalues of  $\mathbf{G}$  are 1 and  $1 - \frac{1}{n}$ . Also  $\mathbf{G}\mu = \mu$  and so  $\mu$  is the eigenvector corresponding to eigenvalue 1.*

**Solution:**

1. By the second order characterization of convexity (Lemma 1.17) the function is convex if its hessian is positive semidefinite. Lets show that

$$\nabla^2 f(\mathbf{x}) = 2(\mathbf{I} - \mathbf{G}) \succeq 0$$

For any vector  $\mathbf{z}$

$$\begin{aligned} \mathbf{z}^\top (\mathbf{I} - \mathbf{G}) \mathbf{z} &= \sum_{i=1}^n z_i^2 - \sum_{i=1}^n \sum_{j=1}^n \mathbf{G}_{ij} z_i z_j = d \sum_{i=1}^n \frac{1}{d} z_i^2 - \sum_{i=1}^n \sum_{j:(i,j) \in E} \frac{1}{d} z_i z_j = \\ &= (d-1) \sum_{i=1}^n \frac{1}{d} z_i^2 - \sum_{i=1}^n \sum_{j < i: (i,j) \in E} \frac{2}{d} z_i z_j = \sum_{i=1}^n \frac{1}{d} \sum_{j < i: (i,j) \in E} z_i^2 + z_j^2 - 2z_i z_j \\ &= \sum_{i=1}^n \frac{1}{d} \sum_{j < i: (i,j) \in E} (z_i - z_j)^2 \geq 0. \end{aligned}$$

where we used that the  $\mathbf{G}$  is symmetric because the graph is undirected and that every row of  $\mathbf{G}$  had exactly  $d$  non-zero elements.

Let us prove now that the function  $f$  is  $L$ -smooth with smoothness constant  $L = 2$ . From Ex. 11 we know that  $L = 2\|\mathbf{I} - \mathbf{G}\|$ , and we claim that  $\|\mathbf{I} - \mathbf{G}\|$  is less than 1. As we already showed above,

$$\mathbf{z}^\top (\mathbf{I} - \mathbf{G}) \mathbf{z} = \sum_{i=1}^n \frac{1}{d} \sum_{j < i: (i,j) \in E} (z_i - z_j)^2.$$

Using that  $z_i > 0 \forall i$ ,

$$\mathbf{z}^\top (\mathbf{I} - \mathbf{G}) \mathbf{z} \leq \frac{1}{d} \sum_{i=1}^n \sum_{j < i: (i,j) \in E} z_i^2 + z_j^2 = \frac{d-1}{d} \sum_{i=1}^n z_i^2 < \|\mathbf{z}\|^2$$

This means that  $\|\mathbf{I} - \mathbf{G}\| < 1$ .

2. The gradient of  $f$  is

$$\nabla f(\mathbf{x}) = 2(\mathbf{I} - \mathbf{G})(\mathbf{x}_t - \mu) = 2(\mathbf{I} - \mathbf{G})\mathbf{x}_t - 2(\mu - \mathbf{G}\mu) = 2(\mathbf{I} - \mathbf{G})\mathbf{x}_t.$$

The last equality followed since  $\mathbf{G}\mu = \mu$ . With the stepsize  $\gamma = \frac{1}{L} = \frac{1}{2}$  gradient descent will take form

$$\mathbf{x}_{t+1} = \mathbf{x}_t - \frac{1}{2} \nabla f(\mathbf{x}_t) = \mathbf{x}_t - \frac{1}{2} 2(\mathbf{I} - \mathbf{G})\mathbf{x}_t = \mathbf{G}\mathbf{x}_t.$$

Since our problem is constrained to the set  $\mathcal{S}$ , we have to make sure  $\mathbf{x}_{t+1}$  also lies in  $\mathcal{S}$ . This is easy to verify.

3. To show the linear convergence rate, we first will prove that function  $f$  restricted to the set  $\mathcal{S}$  is strongly convex with parameter  $\frac{2}{n}$ . Then, the convergence rate would follow from the Theorem 2.11.

To find strong convexity coefficient we need to show a lower bound on  $(\mathbf{y} - \mathbf{x})^\top \nabla^2 f(\mathbf{x})(\mathbf{y} - \mathbf{x}) = (\mathbf{y} - \mathbf{x})^\top 2(\mathbf{I} - \mathbf{G})(\mathbf{y} - \mathbf{x})$  for  $\mathbf{x}, \mathbf{y} \in \mathcal{S}$ . For that we will find the minimum

$$\min_{\mathbf{y}, \mathbf{x} \in \mathcal{S}} \frac{(\mathbf{y} - \mathbf{x})^\top (\mathbf{I} - \mathbf{G})(\mathbf{y} - \mathbf{x})}{\|\mathbf{y} - \mathbf{x}\|^2}$$

First, let's show that  $\mathbf{y} - \mathbf{x} \perp \mu \forall \mathbf{x}, \mathbf{y} \in \mathcal{S}$ . Indeed,

$$(\mathbf{y} - \mathbf{x})^\top \mu = \mathbf{y}^\top \mu - \mathbf{x}^\top \mu = \frac{1}{n} - \frac{1}{n} = 0.$$

Here we used that  $\sum_i y_i = 1$  and  $\sum_i x_i = 1$ .

Then

$$\min_{\mathbf{y}, \mathbf{x} \in \mathcal{S}} \frac{(\mathbf{y} - \mathbf{x})^\top (\mathbf{I} - \mathbf{G})(\mathbf{y} - \mathbf{x})}{\|\mathbf{y} - \mathbf{x}\|^2} \geq \min_{\mathbf{z} \perp \mu} \frac{\mathbf{z}^\top (\mathbf{I} - \mathbf{G})\mathbf{z}}{\|\mathbf{z}\|^2}.$$

Recall that  $\mu$  is the principal eigenvector. Then, the right hand side of the above equation characterizes the second largest eigenvalue. In the basis of orthonormal eigenvectors  $\{\mathbf{v}_i\}_{i=1}^n$  of  $\mathbf{I} - \mathbf{G}$  vector  $\mathbf{z}$  is represented as  $\mathbf{z} = \sum_{i=2}^n \alpha_i \mathbf{v}_i$ , because it is orthogonal to  $\mathbf{v}_1 = \mu$ . Then

$$\min_{\mathbf{z} \perp \mu} \frac{\mathbf{z}^\top (\mathbf{I} - \mathbf{G})\mathbf{z}}{\|\mathbf{z}\|^2} = \min_{\alpha_2, \dots, \alpha_n} \frac{\sum_{i=2}^n \alpha_i^2 \lambda_i}{\sum_{i=2}^n \alpha_i^2} = \lambda_2 = \frac{1}{n}.$$

This shows that  $f$  is  $\frac{2}{n}$  strongly convex when restricted to  $\mathcal{S}$ .