

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

Proximal Gradient and Subgradient Descent

Solve Exercises 24, 25, 26, 27 from the lecture notes.

Exercise 24. 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 Θ_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 25. 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 $\psi(\mathbf{y}) = g(\mathbf{x}_t) + \nabla g(\mathbf{x}_t)^\top (\mathbf{y} - \mathbf{x}_t) + \frac{L}{2} \|\mathbf{y} - \mathbf{x}_t\|^2 + h(\mathbf{y})$ is strongly convex with the parameter L . Use an alternative definition of strongly convexity¹ and optimality of \mathbf{x}_{t+1} we have

$$\psi(\mathbf{x}_{t+1}) \leq \psi(\alpha \mathbf{x}_{t+1} + (1 - \alpha)\mathbf{y}) \leq \alpha \psi(\mathbf{x}_{t+1}) + (1 - \alpha)\psi(\mathbf{y}) - \frac{\alpha(1 - \alpha)L}{2} \|\mathbf{x} - \mathbf{y}\|^2, \quad \forall \alpha \in [0, 1].$$

Rearranging the terms give $\psi(\mathbf{y}) \geq \psi(\mathbf{x}_{t+1}) + \frac{\alpha L}{2} \|\mathbf{y} - \mathbf{x}_{t+1}\|^2$. By taking $\alpha = 1$ 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,

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

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

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

Exercise 26. 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

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

¹<https://xingyuzhou.org/blog/notes/strong-convexity>

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 $\mathbf{y}_{\varepsilon} = \varepsilon \text{sign}(\mathbf{g} - \nabla f(\mathbf{x}))_i \mathbf{e}_i + \mathbf{x}$ for small enough ε , where \mathbf{e}_i is the i -th coordinate vector. Substituting \mathbf{y}_{ε} and dividing both sides with $\|\mathbf{y} - \mathbf{x}\|$ we get

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

We see that on the left hand side ε 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 27. 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 λ 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/

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 μ 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 μ 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

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

which is equivalent to show $\mathbf{z}^\top (\mathbf{I} - \mathbf{G}) \mathbf{z} \geq 0$ for all $\mathbf{z} \in \mathbb{R}^n$. Since \mathbf{G} is symmetric and $\sum_{j=1}^n \mathbf{G}_{ij} = 1$, we have $\sum_{i=1}^n z_i^2 = \sum_{i=1}^n \sum_{j=1}^n \mathbf{G}_{ij} z_i^2 = \sum_{i=1}^n \sum_{j=1}^n \mathbf{G}_{ij} z_j^2 = \sum_{i=1}^n \sum_{j=1}^n \mathbf{G}_{ij} (z_i^2 + z_j^2)/2$. Then

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

In Exercise 13 we know that $L = 2\|\mathbf{I} - \mathbf{G}\|$. $\|\mathbf{I} - \mathbf{G}\| \leq 1$ (TBD).

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 μ 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} .