

Problem Set

Tikhonov regularization method

Problem. Let $(H, \langle \cdot, \cdot \rangle)$ be a finite dimensional space and $f : H \rightarrow \mathbb{R}$ a differentiable convex function. For any integer $k \geq 1$, we define x_k to be a minimizer of $f(\cdot) + \frac{1}{2k} \|\cdot\|^2$. For short we write

$$x_k \in \operatorname{argmin} \left\{ f(x) + \frac{1}{2k} \|x\|^2 : x \in H \right\}.$$

- 1/ Prove in a simple manner that f is bounded from below by an affine function.
- 2/ **a/** Show that a continuous function $g : H \rightarrow \mathbb{R}$ such that $g(x) \rightarrow +\infty$ as $\|x\| \rightarrow +\infty$ has at least a minimizer.
b/ (*) Use **1/** to establish that the function $f_k(x) = f(x) + \frac{1}{2k} \|x\|^2$ satisfies $f_k(x) \rightarrow +\infty$ as $\|x\| \rightarrow +\infty$.
c/ Show that the sequence $(x_k)_{k \in \mathbb{N}}$ is well defined and unique.
- 3/ Let us assume that $\operatorname{argmin} f \neq \emptyset$. Prove that $(x_k)_{k \in \mathbb{N}}$ is bounded.
- 4/ Prove that any convergent subsequence of $(x_k)_{k \in \mathbb{N}}$ has a its limit in $\operatorname{argmin} f$.
- 5/ One considers the set $S = \{x \in \operatorname{argmin} f \mid \|x\| \leq \|y\|, \forall y \in \operatorname{argmin} f\}$. Show that S contains a unique element.
- 6/ Prove that x_k converges to the unique element of S .
- 7/ Let us consider now that $f(x) = \frac{1}{2} \|Ax - b\|^2$ where A is a matrix in $\mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$ and $\|\cdot\|$ denote the usual euclidean norm on \mathbb{R}^m . Prove that f is convex, twice differentiable and has at least one minimizer.
- 8/ Let x^* be a minimizer of f . Prove that $\operatorname{argmin} f = x^* + \ker A$.
Express x_k as a function of data's problem.
Explain briefly what you understand of the purpose of Tikhonov's method.

On convex cones

The space \mathbb{R}^n is endowed with the Euclidean scalar product $\langle \cdot, \cdot \rangle$.

Exercise 1. We say that a closed convex cone is “self-dual” if $C^* = -C$. Establish that the following sets are auto-dual cones. In each case one must verify carefully

that the set is actually a cone and sketch a graphical representation for $n = 2, 3$.

a) $C_1 = \mathbb{R}_+^n$ (nonnegative orthant).

b) $C_2 = \{x \in \mathbb{R}^n : x_1 \geq 0, x_1^2 \geq x_2^2 + \dots + x_n^2\}$ (second-order cone).

Exercise 2. Compute the normal cone (at each point) of the following closed convex sets :

a) (*) $C_3 := \{x \in \mathbb{R}^n : \|x\| \leq 1\}$

b) (**) $C_4 := \{x \in \mathbb{R}^n : Ax \leq b\}$ $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$. For this case, one may simply conjecture a formula for the normal cone, the proof is difficult and is thus optional.

Correction

Problem

- 1/ Take any point \bar{x} and write the convex inequality at that point.
- 2/ **a/** Let u_k be a sequence such that $g(u_k) \rightarrow \inf g$. If u_k was not bounded there would exist $\|u_{k_p}\| \rightarrow +\infty$ which would imply $g(u_{k_p}) \rightarrow +\infty$. Hence u_k is bounded and converges up to an extraction to a point \bar{u} . By continuity we have $g(\bar{u}) = \inf g$.
- b/** The function f_k is continuous. By 1/ there exists $x^* \in \mathcal{E}$ and c such that

$$\begin{aligned} f_k(u) &\geq \langle x^*, u \rangle + c + \frac{1}{2k} \|u\|^2 \\ &\geq \frac{1}{2k} \|u\|^2 - \|x^*\| \|u\| + c. \end{aligned}$$

and the result follows from the fact that the limit of the polynomial $p(s) = \frac{1}{2k} s^2 - \|x^*\| s + c$ at $+\infty$ is $+\infty$.

- c/** By the previous result f_k has a minimizer. Since f_k is also strictly convex as a sum of a strictly convex function $\frac{1}{2k} \|\cdot\|^2$ and a convex function, the minimizer is unique.
- 3/ Let a be in $\operatorname{argmin} f$. By definition $f(x_k) + \frac{1}{2k} \|x_k\|^2 \leq f(a) + \frac{1}{2k} \|a\|^2$ (*), thus
$$\|x_k\|^2 \leq 2k(f(a) - f(x_k)) + \|a\|^2 \leq \|a\|^2.$$
- 4/ One can simply pass to the limit in (*) just above. One obtains the result.
Alternative proof : we have $\nabla f(x_k) + \frac{1}{k} x_k = 0$ hence if x^* is a limit point of x_k we have $\nabla f(x^*) = 0$ (we have seemingly used the continuity of the gradient here but it is not necessary, why?). By convexity this means that x^* is a minimizer of f .
- 5/ S exactly defines the projection of 0 on the nonempty closed convex set $\operatorname{argmin} f$. Observe indeed that $\emptyset \neq \operatorname{argmin} f = [f \leq \min f]$. Thus by continuity and convexity of f , $\operatorname{argmin} f$ is closed and convex.
- 6/ f is twice differentiable as a composition of smooth functions. Its hessian (...) is given by $A^T A$ which is positive semidefinite, indeed

$$\langle A^T A x, x \rangle = \langle A x, A x \rangle = \|A x\|^2 \geq 0, \quad \forall x \in H.$$

The rest has already been done.

- 7/ By convexity : x minimizes f if and only if $\nabla f(x) = A^T A x - A^T b = 0$. Thus $\operatorname{argmin} f \supset x^* + \operatorname{Ker} A$. Conversely if x minimizes f then $A^T A x = A^T b$. Hence $A^T A(x - x^*) = 0$ therefore $\langle A^T A(x - v), x - v \rangle = 0$, i.e. $\|A(x - v)\|^2 = 0$.
Differentiating f_k gives $x_k = (\frac{1}{k} \operatorname{Id} + A^T A)^{-1} (A^T A b)$ where the invertibility of $\frac{1}{k} \operatorname{Id} + A^T A$ comes from the fact that $A^T A$ is positive semidefinite.

Exercise 1

a) Just apply the definitions.

b) Observe that $n \geq 2$ (¹). We establish that $-C_2 \subset C_2^*$. Let (z_1, \dots, z_n) in $-C_2$ and (x_1, \dots, x_n) in C_2 . By Cauchy-Schwarz inequality

$$\begin{aligned} z_1x_1 + z_2x_2 + \dots + z_nx_n &\leq z_1x_1 + \sqrt{z_2^2 + \dots + z_n^2} \sqrt{x_2^2 + \dots + x_n^2} \\ &\leq z_1x_1 - z_1x_1 \\ &= 0. \end{aligned}$$

We establish that $-C_2 \supset C_2^*$. Fix (v_1, \dots, v_n) in C_2^* . One has

$$v_1x_1 + v_2x_2 + \dots + v_nx_n \leq 0 \tag{1}$$

for all (x_1, \dots, x_n) in C_2 . Choose x so that

$$x_1 = \sqrt{v_2^2 + \dots + v_n^2}, \quad x_i = v_i \text{ for all } i \geq 2.$$

Using (1), one obtains

$$v_1 \sqrt{v_2^2 + \dots + v_n^2} \leq -v_2^2 - \dots - v_n^2$$

which yields $v_1 \leq 0$ and $v_1^2 = v_2^2 + \dots + v_n^2$, i.e. $-v \in C_2$.

Exercise 2 a) In the interior we of course have *as always*: $N_{C_3}(x) = \{0\}$, $x \in \text{int } C_3$. Assume thus x is on the boundary of C_3 .

The most simple way at this stage of the classes is certainly to observe that

$$C_3 = \left[\|\cdot\|^2 \leq 1 \right]$$

where $f = \|\cdot\|^2$ is a convex smooth function. The Slater condition being clearly satisfied (take $x_0 = 0$), we thus have

$$N_{C_3}(x) = \mathbb{R}_+ \nabla f(x) = \mathbb{R}_+(2x) = \mathbb{R}_+x.$$

A more down-to-earth but geometrical method is to consider curves of the form

$$t \rightarrow x_y(t) = (\cos t)x + (\sin t)y$$

where y is any normal vector to x such that $\|y\| = 1$. This curve is drawn on the sphere and its velocity at zero is y . By definition

$$\lim_{t \rightarrow 0^+} \frac{1}{t} (x_y(t) - x) \in T_{C_3}(x)$$

that is $y \in T_{C_3}(x)$. Hence $T_{C_3}(x) \supset (\mathbb{R}x)^\perp$. This implies $N_{C_3}(x) \subset \mathbb{R}x$ and the result easily follows since $-x$ cannot be in the normal cone ($\langle -x, 0 - x \rangle = 1$).

b) It relies on Farkas lemma as done in Theorem 32 of the Static Optimization lecture notes.

1. Observe C_2 is the epigraph of a norm, it is thus convex.