

Solutions to hw2 homework on Convex
Optimization
<https://web.stanford.edu/class/ee364b/homework.html>

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2.1 (8 points, 1 point per question)

Let f be a convex function with domain in R^n . We fix $x \in \mathbf{int\,dom\,f}$ and $d \in R^n$. Recall the definition of the directional derivative of f at x along the direction d

$$f'(x, d) = \lim_{t \rightarrow 0} \frac{f(x + td) - f(x)}{t}$$

In this question we aim to show that $f'(x, d)$ exists and is finite, and that we have the following relationship between $\partial f(x)$ and $f'(x, d)$,

$$f'(x, d) = \sup_{g \in \partial f(x)} g^T d$$

(a) Show that the ratio $\frac{f(x+td)-f(x)}{t}$ is a nondecreasing function of $t > 0$. Deduce that $f'(x, d)$ exists and is either finite or equal to $-\infty$. We know from the lectures that, since $x \in \mathbf{int\,dom\,f}$, the subdifferential set ∂f is non - empty, convex and compact.

Solution:

Proof of non - decreasing. Definition of subgradient is

$$f(z) \geq f(x) + g^T(z - x)$$

let $z = x + td$; then

$$f(x + td) \geq f(x) + g^T(x + td - x)$$

or

$$f(x + td) - f(x) \geq tg^T d$$

dividing both part of the inequality by t (as $t > 0$, we can do it) gives

$$\frac{f(x+td) - f(x)}{t} \geq g^T d$$

as the right - hand side of the equation is not depends of t , differentiating by t gives

$$\partial \frac{f(x+td) - f(x)}{t} \geq 0$$

As the $\frac{\partial f'(x,d)}{\partial t} \geq 0$, it means the function $f'(x,d)$ is nondecreasing by variable t .

Proof of possible equality to $-\infty$.

The definition of convexity:

$$f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$$

where $0 < \theta < 1$.

let $t = 1 - \theta$, $0 < t < 1$. then

$$f((1 - t)x + ty) \leq (1 - t)f(x) + tf(y)$$

or

$$f(x + t(y - x)) \leq f(x) + t(f(y) - f(x))$$

as we can choose y any of the point in domain f , we can set $d = y - x$. Then

$$f(x + td) \leq f(x) + t(f(y) - f(x))$$

or

$$f(x + td) - f(x) \leq t(f(y) - f(x))$$

or

$$\frac{f(x + td) - f(x)}{t} \leq f(y) - f(x)$$

As $f(x)$ can be equal to ∞ on the domain of f , so $f'(x,d) = \frac{f(x+td) - f(x)}{t}$ can be less or equal than (for the infinity with sign minus it means strictly equal) $-\infty$ on the domain of f . This means that $f'(x,d)$ can be equal to $-\infty$ on domain of f .

(b) Let $g \in \partial f(x)$. Show that $f'(x,d) \geq g^T d$. Deduce that $f'(x,d)$ is finite and $f'(x,d) \geq \sup_{g \in \partial f(x)} g^T d$.

Solution:

We already shown that

$$f'(x,d) \geq g^T d$$

in part (a). We also shown in part (a) that

$$\frac{f(x + td) - f(x)}{t} \leq f(y) - f(x)$$

Second upper inequality means that $f'(x, d)$ is bounded from upper side (i.e it can't be equal to ∞), it means its value is finite.

As the first of upper inequalities is correct \forall subgradients in domain of f , it means, that it is correct for the supremum of these subgradients in domain f . It means that

$$f'(x, d) \geq \sup_{g \in \partial f(x)} g^T d.$$

In the remaining part of this question, we will establish the converse inequality $f'(x, d) \leq \sup_{g \in \partial f(x)} g^T d$, by showing the existence of a subgradient $g^* \in \partial f(x)$, such that $f'(x, d) \leq g^{*T} d$. We introduce two following sets

$$\begin{aligned} C_1 &= \{(z, t) \mid z \in \text{dom} f, f(z) < t\} \\ C_2 &= \{(y, v) \mid y = x + \alpha d, v = f(x) + \alpha f'(x, d), \alpha \geq 0\} \end{aligned}$$

(c) Prove that C_2 and C_1 are nonempty, convex and disjoint.

Solution:

C_1 is the epigraph of the convex function, therefore it is nonempty and convex.

C_2 is the nonempty set, because it have at least one point, which corresponds to $\alpha = 0, y = x, v = f(x)$. It is also a convex set, because $C_2^1 = \{y \mid y = x + \alpha d\}$ is a convex set as it is translated domain of f which is a convex set and $C_2^2 = \{v \mid v = f(x) + \alpha f'(x, d), \alpha \geq 0\}$ is either a straight line or a beam or a segment.

Proof of disjointedness:

We should show that there is exists a nonzero vector $(a, \beta) \in R^n \times R$ such as

$$a^T(x + \alpha d) + \beta(f(x) + \alpha f'(x, d)) \leq a^T z + \beta w$$

for all $\alpha \geq 0, z \in \text{dom} f$, and $f(z) < w$.

Solution: As we shown earlier,

$$f'(x, d) \leq f(y) - f(x)$$

where $x, y \in \text{dom} f$. As x, y can be any points in domain f , it follows that

$$f'(x, d) \leq \min_{z \in \text{dom} f} (f(z)) - \max_{z \in \text{dom} f} (f(z))$$

Lets just derive equation for β .

$$\beta(f(x) + \alpha f'(x, d) - w) \leq a^T(z - x - \alpha d)$$

or

$$\beta \leq \frac{a^T(z - x - \alpha d)}{f(x) + \alpha f'(x, d) - w}$$

I don't know how to solve items (e) - (g)

(h) Let $A \in R^{m \times n}$, $b \in R^m$, $\lambda > 0$, and fix a direction $d \in R^n$. Consider the function $\frac{1}{2}\|Ax - b\|_2^2 + \lambda\|x\|_1$. Compute $f'(0, d)$. Remark: you can either compute it directly by using the definition of the directional derivative, or, use the variational formula $f'(0, d) = \sup_{g \in \partial f(0)} g^T d$.

Solution:

$$\nabla\|x\|_1 = \text{sign}(x)$$

$$\nabla\|Ax - b\|_2^2 = \nabla((Ax - b)^T(Ax - b)) = 2(Ax - b)^T A$$

see <https://math.stackexchange.com/questions/606646/matrix-derivative-ax-btax-b> and <http://www.math.uwaterloo.ca/~hwolkowi/matrixcookbook.pdf>

So,

$$\nabla(\frac{1}{2}\|Ax - b\|_2^2 + \lambda\|x\|_1) = 2(Ax - b)^T A + \lambda \text{sign}(x)$$

Then

$$f'(0, d) = d^T((Ax - b)^T A + \lambda[-1, 1]_n)$$

where $[-1, 1]_n$ is a vector in R^n with component values in range $-1 \leq x_i \leq 1$, $i \in 1, \dots, n$.

2.2 (4 Points)

In this question, we will show that a subgradient of the function $h(x) = \min_{z \in C} \|x - z\|_2$ is

$$g = \frac{x - z^*}{\|x - z^*\|_2}$$

where C is a compact set in R^n , x is a given point in R^n , which does not belong to C , and

$z^* = P_C(x) := \arg \min_{z \in C} \|x - z\|_2$ denotes the Euclidean projection of x onto C (which exists and is unique).

(a) (0.5 point) Use the fact that $\|x - z\|_2 = \max_{u: \|u\|_2 \leq 1} u^T(x - z)$ to transform the minimization problem $h(x) = \min_{z \in C} \|x - z\|_2$ into the following saddle point problem

$$\min_{z \in C} \max_{u: \|u\|_2 \leq 1} u^T(x - z)$$

Solution:

We get it by substituting expression $\max_{u: \|u\|_2 \leq 1} u^T(x - z)$ instead the expression $\|x - z\|_2$.

(b) (2 points) Now, we will use (a simple version of) the Sion's minimax theorem, which can be stated as follows.

Let $X \subseteq \mathbb{R}^n$, $Y \subseteq \mathbb{R}^n$, be compact and convex sets. Let f be a real valued function on $X \times Y$ such that

- $f(x, \cdot)$ is continuous and concave on Y , $\forall x \in X$.
- $f(\cdot, y)$ is continuous and convex on X , $\forall y \in Y$.

Then, we have

$$\min_{x \in X} \max_{y \in Y} f(x, y) = \max_{y \in Y} \min_{x \in X} f(x, y)$$

Further, there exists a (saddle) point $(x^*, y^*) \in X \times Y$ such that

$$f(x^*, y^*) = \min_{x \in X} f(x, y^*) = \max_{y \in Y} f(x^*, y) = \min_{x \in X} \max_{y \in Y} f(x, y) = \max_{y \in Y} \min_{x \in X} f(x, y)$$

Apply Sion's minimax theorem to conclude that

$$\min_{z \in C} \max_{u: \|u\|_2 \leq 1} u^T(x - z) = \max_{u: \|u\|_2 \leq 1} \min_{z \in C} u^T(x - z)$$

Define $u^* = \frac{x - z^*}{\|x - z^*\|_2}$. Show that (z^*, u^*) is a saddle point of the above minimax problem.

Solution:

C is compact and convex. u defined on the closed sphere S of unity radius, therefore its domain is compact and convex also. The function $f(u, z) = u^T(x - z)$ is linear in sense of both $f(z, \cdot)$ on C and $f(\cdot, u)$ on S . It means that it is concave and convex in both cases. So, applying Sion's minimax theorem we have:

$$\min_{z \in C} \max_{u: \|u\|_2 \leq 1} u^T(x - z) = \max_{u: \|u\|_2 \leq 1} \min_{z \in C} u^T(x - z)$$

where $f(z, u) = u^T(x - z)$ and there exist a saddle point (z^*, u^*) in $C \times S$ such that

$$f(z^*, u^*) = \min_{z \in C} f(z, u^*) = \max_{u \in S} f(z^*, u) = \min_{z \in C} \max_{u \in S} f(z, u) = \max_{z \in C} \min_{u \in S} f(z, u)$$

define $u^* = \frac{x - z^*}{\|x - z^*\|_2}$. It is evident, that u^* is the solution of the problem $\max_{u: \|u\|_2 \leq 1} u^T(x - z)$. Also, this is evident, that the point z^* is the solution of the problem $z^* = P_C(x) := \arg \min_{z \in C} \|x - z\|_2$. Then, by Sion's theorem the point $(z^*, u^*) : f(z^*, u^*) = \min_{z \in C} f(z, u^*)$, where $f(z, u^*) = u^{*T}(x - z)$ is a saddle point of the problem

$$\min_{z \in C} \max_{u \in S} u^T(x - z)_2.$$

(c) (1.5 points) Using the 'max-min' representation of $h(x)$, compute a sub-gradient of h at x .

Solution:

$$g = u \nabla(x - z^*) = u = \frac{x - z^*}{\|x - z^*\|_2}$$

2.3 (4 points)

For this question, you need to submit your code in addition to any description of your algorithm. Let Σ be an $n \times n$ diagonal matrix with entries $\sigma_1 \geq \dots \geq \sigma_n$ and y a given vector in R^n . Consider the compact convex sets $\mathcal{E} = \{z \in R^n \mid \|\Sigma^{\frac{1}{2}}z\|_2 \leq 1\}$ and $B = \{z \in R^n \mid \|z - y\|_\infty \leq 1\}$.

(a) (2 points) Formulate an optimization problem and propose an algorithm in order to

find a point $x \in \mathcal{E} \cap B$. You can assume that $\mathcal{E} \cap B$ is not empty. Your algorithm must be provably converging (although you do not need to prove it and you can simply refer to the lectures' slides).

Solution:

As Σ is a diagonal matrix, $\|\Sigma^{\frac{1}{2}}z\|_2 = \|\lambda^T z\|_2$, where $\lambda \in R^n$, and $\lambda = (\sqrt{\sigma_1}, \dots, \sqrt{\sigma_n})$. It means that \mathcal{E} is an ellipse in R^n with the center in the point $(0)^n$. The set B is a cube in R^n with edge length 2 and with the center at the point y .

Reference to lecture slides - Finding a point in the intersection of convex sets, slides to 2-nd lection, p. 18.

ecludian projection of point to ellipse <https://www.geometrictools.com/Documentation/DistancePointEllips>
<https://math.stackexchange.com/questions/1775174/distance-function-of-the-ellipse-in-mathbb{R}^n>

ecludian projection of point to cube
<https://math.stackexchange.com/questions/3390029/projecting-a-point-onto-a-hypercube>
a version of the alternating projections algorithm
An algorithm himself can be the following:

1. Begins from the point $x^{(0)} = 0^n$, $x^{(0)} \in \mathcal{E}$, and then applying the alternate projection method to this point and sets \mathcal{E} and B , i.e. we are calculating the $x^{(1)} = P_B(x^{(0)})$, $x^{(2)} = P_{\mathcal{E}}(x^{(1)})$, $x^{(3)} = P_B(x^{(2)})$, and so on. We are checking also if the point $x^{(k)}$ is in the both sets on each step. As the both sets are closed and have intersection by the task, we have a guarantee, that we eventually will get a solution of the task.

(b) (2 points) Implement your algorithm with the following data: $n = 2$, $y = (7/4, 0)$, $\sigma_1 = 1$, $\sigma_2 = 0.5$ and $x = (0, 4)$. Plot the objective value of your optimization problem versus the number of iterations.

<https://www.geometricktools.com/Documentation/DistancePointEllipseEllipsoid.pdf>

The rectangle vertices are $\{(-1/4, 2), (1/4, -2), (15/4, 2), (15/4, -2)\}$, the ellipse equation is $x^2 + y^2/2 \leq 1$.

Coordinates of the point found by the algorithm are $(0, 1.4142)$, the code is in the file `2_3_b_solution.py`.

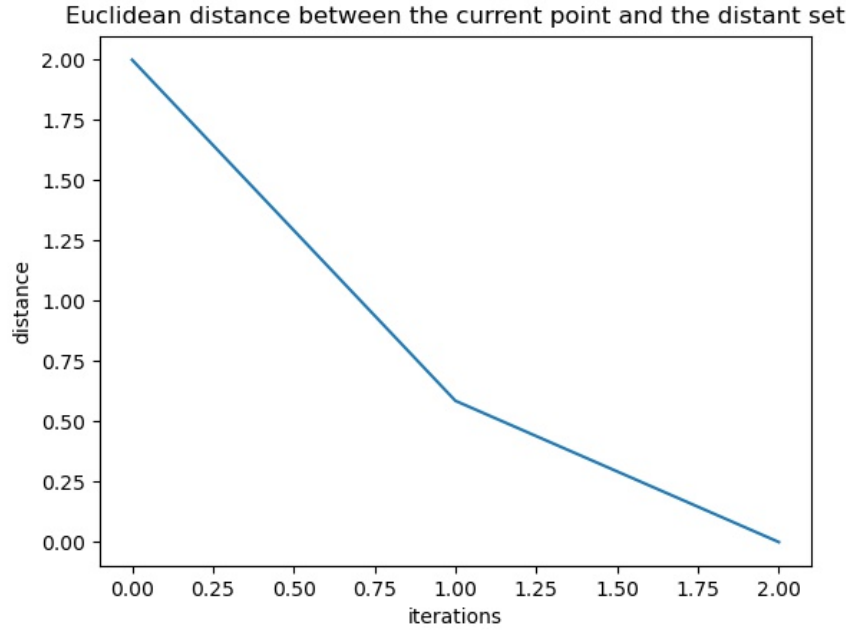


Figure 1: Euclidean distance between the current point and the distant set.

2.4 (4 points)

Consider the optimization problem

$$\text{minimize} \quad \left\{ f(x_1, \dots, x_J) := \frac{1}{2} \|b - \sum_{j=1}^J A_j x_j\|_2^2 + \lambda \cdot \left\| \sum_{j=1}^J x_j^2 \right\|_2 \right\},$$

with variable $x_1, \dots, x_J \in R^n$, and problem data $A_1, \dots, A_J \in R^{m \times n}$, $b \in R^m$, and $\lambda > 0$. We will apply the subgradient method.

(a) (2 points) Show that the subgradient method with Polyak's step length updates the current point to a point at which the first order (linear) approximation has value f^* (optimal value).

Solution

As noted in 02-subgrad_method_notes.pdf p. 9, the Polyak step length determined as

$$\alpha_k = \frac{f(x^{(k)}) - f^*}{\|g^{(k)}\|_2^2}$$

where g is the subgradient, f^* is the optimal value. This is the consequence of the fact that

$$f(x^{(k)} - \alpha g^{(k)}) \approx f(x^{(k)}) + g^{(k)T}(x^{(k)} - \alpha g^{(k)} - x^{(k)}) = f(x^{(k)}) - \alpha g^{(k)T} g^{(k)}$$

Replacing the lefthand side with f^* and solving for α gives the step length above.

$$\begin{aligned} \frac{1}{2} \|b - \sum_{j=1}^J A_j x_j\|_2^2 &= (b - \sum_{j=1}^J A_j x_j)^T (b - \sum_{j=1}^J A_j x_j) \\ &= b^T b - 2b^T \sum_{j=1}^J A_j x_j + \sum_{j=1}^J x_j^T A_j^T \sum_{j=1}^J A_j x_j \end{aligned}$$

Further we have

$$\nabla_k b^T b = 0$$

$$\nabla_k b^T \sum_{j=1}^J A_j x_j = b^T A_k$$

$$\nabla_k \sum_{j=1}^J x_j^T A_j^T \sum_{j=1}^J A_j x_j = 2A_k^T \sum_{j=1}^J A_j x_j$$