Optimization and Computational Linear Algebra for Data Science
Homework 11: Optimality conditions

Due on December 5, 2020

- Unless otherwise stated, all answers must be mathematically justified.
- Partial answers will be graded.
- Your submission has to be uploaded to Gradescope. Indicate Gradescope the page on which each problem is written.
- You can work in groups but each student must write his/her own solution based on his/her own understanding of the problem. Please list on your submission the students you work with for the homework (this will not affect your grade).
- Problems with a ($\star$) are extra credit, they will not (directly) contribute to your score of this homework. However, for every 4 extra credit questions successfully answered your lowest homework score get replaced by a perfect score.
- If you have any questions, feel free to contact me (`lm4271@nyu.edu`) or to stop at the office hours.

Problem 11.1 (2 points)**.** *Let $f, g : \mathbb{R}^3 \to \mathbb{R}$ be the functions defined by*

$$f(x,y,z) = 2x^2 + y^2 + \frac{1}{2}z^2 + 4x - 6y - z + 1 \quad \text{and} \quad g(x,y,z) = -xyz + x + y + z.$$

Compute the critical points of f and g and determine if they are global/local maximizers/minimizers or saddle points.

Problem 11.2 (3 points)**.** *We consider the following constrained optimization problem:*

$$\text{minimize} \quad x - y + z \quad \text{subject to} \quad x^2 + y^2 + z^2 = 1 \quad \text{and} \quad x + y + z = 1. \tag{1}$$

We admit that this minimization problem has (at least) one solution (this comes from the fact that a continuous function on a compact set attains its minimum).

Using Lagrange multipliers, show that (1) has a unique solution and compute its coordinates.

Problem 11.3 (2 points)**.** *Let $u \in \mathbb{R}^n$ be a vector such that for all $i \neq j$, $|u_i| \neq |u_j|$. We consider the constrained optimization problem*

$$\text{maximize} \quad \langle u, x \rangle \quad \text{subject to} \quad \|x\|_1 \leq 1.$$

(a) *Show that this problem has a unique solution x^* and give the expression of x^* in terms of u (Lagrange multipliers are not needed here).*

(b) *Give a graphical interpretation.*

Problem 11.4 (3 points). **We will prove the spectral theorem in this problem: you are therefore not allowed to use the spectral theorem and its consequences to solve this exercise.**

Let A be an $n \times n$ symmetric matrix. We consider the following optimization problem

$$\text{maximize} \quad x^{\mathsf{T}} A x \quad \text{subject to} \quad \|x\| = 1. \tag{2}$$

This optimization problem admits a solution (this comes from the fact that a continuous function on a compact set achieved its maximum) that we denote by v_1.

(a) *Using Lagrange multipliers, show that v_1 is an eigenvector of A.*

(b) *We now consider the optimization problem*

$$\text{maximize} \quad x^{\mathsf{T}} A x \quad \text{subject to} \quad \|x\| = 1 \quad \text{and} \quad \langle x, v_1 \rangle = 0. \tag{3}$$

For the same reason as above, this problem admits a solution that we denote by v_2. Show that v_2 is an eigenvector of A that is orthogonal to v_1.

(c) *We now consider the optimization problem*

$$\text{maximize} \quad x^{\mathsf{T}} A x \quad \text{subject to} \quad \|x\| = 1 \quad \text{and} \quad \langle x, v_1 \rangle = 0 \quad \text{and} \quad \langle x, v_2 \rangle = 0. \tag{4}$$

Again, this problem admits a solution that we denote by v_3. Show that v_3 is an eigenvector of A that is orthogonal to v_1 and v_2.

Conclusion: by repeating this procedure, we obtain an orthonormal family $v_1, \dots, v_n$ of eigenvectors of A. This proves the spectral theorem (without using any linear algebra result!).

Problem 11.5 ($\star$). *We consider here a simple portfolio optimization problem. Assume that we can invest in n financial assets. Each asset i has a return of X_i (X_i is a random variable) meaning that investing $w\$$ in the asset i will generate a return of $w \times X_i$ \$. We introduce*

$$r_i = \mathbb{E}[X_i],$$
$$\Sigma = \mathrm{Cov}(X, X) = \mathbb{E}\big[(X - r)(X - r)^{\mathsf{T}}\big]$$

that are respectively the average return and the covariance matrix of the returns. We assume that the covariance matrix Σ is invertible. We represent a portfolio (an investment strategy) by a vector $w = (w_1, \dots, w_n) \in \mathbb{R}^n$, where each coordinate w_i represents the amount invested on the asset i. We allow w_i to be negative, which means that it is possible to "short" a security. The expected return of the portfolio is then

$$R(w) = \mathbb{E}\left[\sum_{i=1}^{n} w_i X_i\right] = \sum_{i=1}^{n} w_i r_i$$

and its variance is

$$\begin{aligned} V(w) &= \mathrm{Var}\left(\sum_{i=1}^{n} w_i X_i\right) = \mathbb{E}\left[\left(\sum_{i=1}^{n} w_i (X_i - r_i)\right)^2\right] = \mathbb{E}\left[\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j (X_i - r_i)(X_j - r_j)\right] \\ &= w^{\mathsf{T}} \Sigma w. \end{aligned}$$

We want here to invest a total amount of m\$ on the assets. Given an targeted expected return μ*, we would like to find a portfolio* w *such that* $R(w) = \mu$ *and* $\sum_{i=1}^{n} w_i = m$ *for which the variance* $V(w)$ *is minimal. That is, we aim at solving the following problem:*

$$\textit{minimize} \quad V(w) \quad \textit{subject to} \quad R(w) = \mu \quad \textit{and} \quad \sum_{i=1}^{n} w_i = m. \tag{5}$$

Let $\mathbb{1}$ *denotes the all-ones vector of dimension* n*. We assume that* $r \notin \mathrm{Span}(\mathbb{1})$*. Show that the matrix*

$$M = \begin{pmatrix} \mathbb{1}^\top \Sigma^{-1} \mathbb{1} & \mathbb{1}^\top \Sigma^{-1} r \\ \mathbb{1}^\top \Sigma^{-1} r & r^\top \Sigma^{-1} r \end{pmatrix}$$

is invertible and that the unique solution to (5) *is*

$$w^* = \Sigma^{-1} \begin{pmatrix} | & | \\ \mathbb{1} & r \\ | & | \end{pmatrix} M^{-1} \begin{pmatrix} m \\ \mu \end{pmatrix}.$$