

## Exercise 8

Lorenzo Vigo

Optimization: 8<sup>th</sup> November 2021

**Exercise 8.** To be delivered before 9-XI-2021 as: Ex08-YourSurname.pdf

Given a vector  $\mathbf{y}$ , consider the problem

$$\text{maximize } \mathbf{y}^T \mathbf{x}$$

$$\text{subject to: } \mathbf{x}^T \mathbf{Q} \mathbf{x} \leq 1$$

where  $\mathbf{Q}$  is a positive definite symmetric matrix. Show that the optimal value is  $\sqrt{\mathbf{y}^T \mathbf{Q}^{-1} \mathbf{y}}$ , and use this fact to establish the inequality

$$(\mathbf{x}^T \mathbf{y})^2 \leq (\mathbf{x}^T \mathbf{Q} \mathbf{x})(\mathbf{y}^T \mathbf{Q}^{-1} \mathbf{y})$$

We are presented with a problem that is equivalent to the following constrained optimization problem:

$$\min f(x) = -\mathbf{y}^T x$$

$$\text{subject to } g(x) = 1 - x^T \mathbf{Q} x \geq 0$$

We will follow the same steps as in Exercise 7 to begin with:

$$L(x, \lambda) = f(x) - \lambda g(x)$$

$$X = \{x | 1 - x^T \mathbf{Q} x \geq 0\}$$

We will use the Theorem of sufficient conditions seen in class. The Karush-Kuhn-Tucker conditions generate the following equations, with  $\lambda > 0$ :

$$\nabla L(x, \lambda) = -\mathbf{y} + 2\lambda \mathbf{Q} x = 0$$

$$\lambda(1 - x^T \mathbf{Q} x) = 0$$

We are using that  $\mathbf{Q}$  is symmetrical and positive definite. So now, we get that:

$$x = \frac{1}{2\lambda} \mathbf{Q}^{-1} \mathbf{y}$$

From the second condition, knowing that  $\lambda > 0$ :

$$\begin{aligned} 1 &= x^T Q x \\ 1 &= \frac{1}{2\lambda} (y^T Q^{-1}) Q (Q^{-1} y) \\ 1 &= \frac{1}{2\lambda} y^T Q^{-1} y \\ 2\lambda &= \sqrt{y^T Q^{-1} y} \end{aligned}$$

Therefore:

$$x = \frac{1}{\sqrt{y^T Q^{-1} y}} Q^{-1} y$$

And in the original function, as we wanted to prove:

$$y^T x = \frac{y^T}{\sqrt{y^T Q^{-1} y}} Q^{-1} y = \sqrt{y^T Q^{-1} y}$$

To prove the last inequality, we will consider the case where  $(x^T y)^2 = ((y^T x)^T)^2$  is maximized, that is when the base is maximized. In that case we already know that:

$$x = \frac{1}{2\lambda} Q^{-1} y$$

We will be using that  $y^* = 2\lambda Q x^*$ . We are changing notations in order not to confound generic  $x, y$  and their values when the function is maximized.

$$\begin{aligned} (x^T y)^2 &= (2\lambda x^T Q x^*)^2 \\ (x^T y)^2 &= (2\lambda)^2 (x^T Q x^*)^T (x^T Q x^*) \end{aligned}$$

Now, applying the Cauchy-Schwartz inequality:

$$(x^T y)^2 < (x^T Q x)(y^T Q^{-1} y)$$

As for the second condition of the Theorem of sufficient conditions we used during this exercise, we know that  $\nabla^2 f(x) = 0$  and that  $\nabla^2 g(x) = -2Q$ . Therefore, for any  $z$ :

$$z^T [2Q] z = 2(z^T Q z) > 0$$

Which is true because  $Q$  is positive definite.