

MATH60005/70005: Optimisation (Autumn 24-25)

Chapter 8: solutions

Dr Dante Kalise, Dr Estefanía Loayza-Romero and Sara Bicego
Department of Mathematics
Imperial College London, United Kingdom
{dkaliseb,kloayzar,s.bicego21}@imperial.ac.uk

1. Solve the primal and dual problem for

$$\begin{array}{ll}\min & x_1^2 + x_2^2 + 2x_1 \\ \text{s.t.} & x_1 + x_2 = 0.\end{array}$$

2. Study the duality gap (difference between f^* and q^*) for the problem

$$\min \left\{ e^{-x_2} : \sqrt{x_1^2 + x_2^2} - x_1 \leq 0 \right\}.$$

3. Recompute the dual of the convex quadratic problem from the notes under that assumption that the matrix $\mathbf{Q} \geq 0$ instead of $\mathbf{Q} > 0$.
4. Consider the Chebyshev center problem where we have a set of points $\mathbf{a}_1, \dots, \mathbf{a}_m \in \mathbb{R}^n$ for which we seek a point $\mathbf{x} \in \mathbb{R}^n$ that is the center of a ball of minimum radius $r > 0$ containing the points

$$\begin{array}{ll}\min_{\mathbf{x}, r} & r \\ \text{s.t.} & \|\mathbf{x} - \mathbf{a}_i\| \leq r, \quad i = 1, 2, \dots, m.\end{array}$$

Compute the dual of this problem. (*Hint: use an equivalent formulation over the squared radius*)

Solutions

1. The primal problem has the following quadratic objective

$$f(\mathbf{x}) = \mathbf{x}^\top \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \mathbf{x} + 2 \begin{bmatrix} 1 & 0 \end{bmatrix} \mathbf{x}$$



which is convex (as the identity matrix is positive definite). Hence, KKT condition are in this case necessary and sufficient.

For the Lagrangian

$$\mathcal{L}(\mathbf{x}, \mu) = x_1^2 + x_2^2 - 2x_1 + \mu(x_1 + x_2)$$

we have the following KKT system:

$$\begin{cases} 2x_1 + 2 + \mu = 0 \\ 2x_2 + \mu = 0 \\ x_1 + x_2 = 0 \end{cases} \quad \begin{matrix} (\mu = -2x_2) \\ (x_1 = -x_2) \end{matrix} \quad \implies \quad (x_1^*, x_2^*) = \left(-\frac{1}{2}, \frac{1}{2} \right)$$

at which $f(\mathbf{x}^*) = -\frac{1}{2}$.

Since the objective function $f(\mathbf{x})$ is convex, and the linear equation is feasible, strong duality holds for this problem. For the associated Lagrangian $\mathcal{L}(\mathbf{x}, \mu)$ given above, we have

$$\mathbf{q}(\mu) = \min_{\mathbf{x} \in \mathbb{R}^2} \mathcal{L}(\mathbf{x}, \mu),$$

and

$$\nabla_{\mathbf{x}} \mathcal{L} = 0 \quad \iff \quad \begin{cases} 2x_1 + 2 + \mu = 0 \\ 2x_2 + \mu = 0 \end{cases} \quad \implies \quad \begin{cases} x_2 = -\frac{\mu}{2} \\ x_1 = -1 - \frac{\mu}{2} \end{cases} \quad (*)$$

for which the dual objective becomes

$$\begin{aligned} \mathbf{q}(\mu) &= \left(-1 - \frac{\mu}{2}\right)^2 + \left(-\frac{\mu}{2}\right)^2 + 2\left(-1 - \frac{\mu}{2}\right) + \mu\left(-1 - \frac{\mu}{2}\right) \\ &= -\frac{\mu^2}{2} - \mu - 1. \end{aligned}$$

Then, the dual problem reads

$$\max_{\mu} -\frac{\mu^2}{2} - \mu - 1$$

which is realized when $\mathbf{q}'(\mu) = 0$, hence at $\mu^* = -1$. Then, from (*) the minimizer is

$$(x_1^*, x_2^*) = \left(-\frac{1}{2}, \frac{1}{2} \right)$$

as in the solution of the primal.

2. We consider

$$\min e^{-x_2} \quad \text{s.t.} \quad \sqrt{x_1^2 + x_2^2} - x_1 \leq 0$$

for which the feasible set is $\{\mathbf{x} : x_2 = 0, x_1 \geq 0\}$, hence Slater's condition cannot be satisfied, and so only weak duality holds ($f^* > q^*$). Since optimality requires $x_2 = 0$, we have that for the primal, $f^* = 1$. Moving now to the dual problem, we have associated Lagrangian

$$\mathcal{L}(\mathbf{x}, \lambda) = e^{-x_2} + \lambda(\sqrt{x_1^2 + x_2^2} - x_1), \quad \lambda \geq 0,$$



for which the dual objective is $q(\mu) = \min_{\mathbf{x} \in \mathbb{R}^2} \mathcal{L}(\mathbf{x}, \mu)$. Note that $\mathcal{L} \geq 0$, but for any $\varepsilon > 0$, we have

$$\mathbf{x}_\varepsilon = \left(\frac{x_{2,\varepsilon}^2 - \varepsilon^2}{2\varepsilon}, \ln(\varepsilon) \right) \implies \sqrt{x_{1,\varepsilon}^2 + x_{2,\varepsilon}^2} - x_{1,\varepsilon} = \varepsilon \implies \mathcal{L}(\mathbf{x}_\varepsilon, \lambda) = (1 + \lambda)\varepsilon$$

and so

$$q(\mu) = \min_{\mathbf{x} \in \mathbb{R}^2} \mathcal{L}(\mathbf{x}, \mu) \iff \min_{\varepsilon > 0} \mathcal{L}(\mathbf{x}_\varepsilon, \lambda) \iff \min_{\varepsilon > 0} (1 + \lambda)\varepsilon \rightarrow 0 \quad \forall \lambda \geq 0.$$

Thus, $q(\mu) = 0$ and the dual solution is given by

$$\max_{\lambda \geq 0} \{0\} = \mathbf{q}^* = 0.$$

3. The quadratic problem from the notes is

$$\min_{\mathbf{x} \in \mathbb{R}^n} \mathbf{x}^\top Q \mathbf{x} + 2\mathbf{f}^\top \mathbf{x}, \quad \text{s.t.} \quad A\mathbf{x} \leq \mathbf{b},$$

where we assume $Q \succeq 0$. This implies that Q is not necessarily invertible, but there exists a matrix $D \in \mathbb{R}^{n \times n}$ such that $Q = D^\top D$. Thus, the quadratic problem is equivalent to

$$\min_{\mathbf{x} \in \mathbb{R}^n} \mathbf{x}^\top D^\top D \mathbf{x} + 2\mathbf{f}^\top \mathbf{x}, \quad \text{s.t.} \quad A\mathbf{x} \leq \mathbf{b},$$

which in turns is equivalent to

$$\min_{\mathbf{x}, \mathbf{z} \in \mathbb{R}^n} \|\mathbf{z}\|^2 + 2\mathbf{f}^\top \mathbf{x}, \quad \text{s.t.} \quad \begin{cases} A\mathbf{x} \leq \mathbf{b} \\ \mathbf{b}\mathbf{z} = D\mathbf{x} \end{cases}$$

The associated Lagrangian

$$\mathcal{L}(\mathbf{x}, \mathbf{z}, \lambda, \mu) = \|\mathbf{z}\|^2 + 2\mathbf{f}^\top \mathbf{x} + 2\lambda^\top (A\mathbf{x} - \mathbf{b}) + 2\mu^\top (\mathbf{z} - D\mathbf{x})$$

it is separable with respect to \mathbf{x} and \mathbf{z} , hence the objective for the dual problem can be computed as

$$q(\lambda, \mu) = \underbrace{\min_{\mathbf{z}} \left(\|\mathbf{z}\|^2 + 2\mu^\top \mathbf{z} \right)}_{(a)} + 2 \underbrace{\min_{\mathbf{x}} \left(\mathbf{f}^\top \mathbf{x} + \lambda^\top A\mathbf{x} - \mu^\top D\mathbf{x} \right)}_{(b)} - 2\lambda^\top \mathbf{b}$$

(a) by first order optimality conditions, we have

$$\nabla_{\mathbf{z}} \left(\|\mathbf{z}\|^2 + 2\mu^\top \mathbf{z} \right) = 0 \implies 2\mathbf{z} + 2\mu = 0 \implies \mathbf{z}^* = -\mu$$

(b) we can rearrange the objective and obtain

$$\min_{\mathbf{x}} \left((\mathbf{f}^\top + \lambda^\top A - D^\top \mu) \mathbf{x} \right) = \begin{cases} 0 & \mathbf{f} + A^\top \lambda - D^\top \mu = 0 \\ -\infty & \text{otherwise} \end{cases}$$



Thus, the dual objective reads

$$\mathbf{q}(\lambda, \mu) = \min_{\mathbf{x}, \mathbf{q}} \mathcal{L}(\mathbf{x}, \mathbf{z}, \lambda, \mu) = \begin{cases} -\|\mu\|^2 - 2\lambda^\top b & f + A^\top \lambda - D^\top \mu = 0 \\ -\infty & \text{otherwise} \end{cases}$$

and since $\{-\infty\} \notin \text{Dom}(\mathbf{q})$, we can write the dual problem as

$$\max_{\substack{\mu \in \mathbb{R}^n \\ \lambda \in \mathbb{R}_+^m}} -\|\mu\|^2 - 2\lambda^\top b \quad \text{s.t.} \quad f + A^\top \lambda - D^\top \mu = 0.$$

4. We consider the set $\{\mathbf{a}_i\}_{i=1}^m \subset \mathbb{R}^n$ of data points encircled by a ball of radius r and center \mathbf{x} :

$$\min_{\mathbf{x}, r} r \quad \text{s.t.} \quad \|\mathbf{x} - \mathbf{a}_i\| \leq r \quad i = 1, \dots, m,$$

which is equivalent to

$$\min_{\mathbf{x}, \gamma} \gamma \quad \text{s.t.} \quad \|\mathbf{x} - \mathbf{a}_i\|^2 \leq \gamma \quad i = 1, \dots, m.$$

The associated Lagrangian is

$$\mathcal{L}(\mathbf{x}, \gamma, \lambda) = \gamma + \sum_{i=1}^m \lambda_i (\|\mathbf{x} - \mathbf{a}_i\|^2 - \gamma), \quad \lambda \geq 0,$$

for which the dual objective becomes

$$\mathbf{q}(\lambda) = \min_{(\mathbf{x}, \gamma) \in X} \mathcal{L}(\mathbf{x}, \gamma, \lambda) = \underbrace{\gamma \left(1 - \sum_{i=1}^m \lambda_i\right)}_0 + \sum_{i=1}^m \lambda_i (\|\mathbf{x} - \mathbf{a}_i\|^2).$$

We take $X = \mathbb{R}^{n+1}$, without imposing any restriction on γ (which should be positive, as $\gamma = r^2$). Assuming $\lambda \in \Delta_m$, we have

$$\sum_{i=1}^m \lambda_i \|\mathbf{x} - \mathbf{a}_i\|^2 = \sum_{i=1}^m \lambda_i (\|\mathbf{x}\|^2 - 2\mathbf{a}_i^\top \mathbf{x} + \|\mathbf{a}_i\|^2) = \underbrace{\|\mathbf{x}\|^2 \left(\sum_{i=1}^m \lambda_i\right)}_1 - 2 \left(\sum_{i=1}^m \lambda_i \mathbf{a}_i^\top\right) \mathbf{x} + \left(\sum_{i=1}^m \lambda_i \|\mathbf{a}_i\|^2\right),$$

and so

$$\mathbf{q}(\lambda) = \min_{\mathbf{x}} \left(\|\mathbf{x}\|^2 - 2 \left(\sum_{i=1}^m \lambda_i \mathbf{a}_i^\top\right) \mathbf{x} + \left(\sum_{i=1}^m \lambda_i \|\mathbf{a}_i\|^2\right) \right).$$

By first order optimality conditions, we have

$$\mathbf{x}^* = \sum_{i=1}^m \lambda_i \mathbf{a}_i^\top = A\lambda$$



for the matrix A having as i -th column the coordinate of the point \mathbf{a}_i , for $i = 1, \dots, m$.
Thus

$$\mathbf{q}(\lambda) = \|A\lambda\|^2 - 2 \underbrace{(A\lambda)^\top (A\lambda)}_{\|A\lambda\|^2} + \sum_{i=1}^m \lambda_i \|\mathbf{a}_i\|^2 = \begin{cases} -\|A\lambda\|^2 + \sum_{i=1}^m \lambda_i \|\mathbf{a}_i\|^2 & \lambda \in \Delta_m \\ -\infty & \text{otherwise} \end{cases}$$

for which the dual problem reads

$$\max_{\lambda \geq 0} \left(-\|A\lambda\|^2 + \sum_{i=1}^m \lambda_i \|\mathbf{a}_i\|^2 \right) \quad \text{s.t.} \quad \lambda \in \Delta_m.$$

