

Problem 2

HW 9 | Daniil Glukhovskiy

Differentiating $f(x) = \frac{1}{2} x^T C x - m^T x$, get

$$\nabla f(x) = Cx - m^T.$$

We estimate partial derivative of f w.r.t. x_1 :

$$\begin{aligned}\frac{\partial f}{\partial x_1} &= 0.5113x_1 + 0.2451x_2 + 0.2175x_3 - 1.2938 \leq \\ &\leq |0.5113x_1| + |0.2451x_2| + |0.2175x_3| - 1.2938 \leq \\ &\leq 0.5113 + 0.2451 + 0.2175 - 1.2938 < 0,\end{aligned}$$

so, unless $x_1 = 1$, we could increase x_1 and leave x_2 and x_3 the same in order to decrease f . Thus minimum is achieved with $x_1 = 1$.

Similarly, estimate $\frac{\partial f}{\partial x_2}$:

$$\begin{aligned}\frac{\partial f}{\partial x_2} &= 0.2175x_1 + 0.1144x_2 + 0.4094x_3 + 1.1919 \geq \\ &\geq -|0.2175x_1| - |0.1144x_2| - |0.4094x_3| + 1.1919 \geq \\ &\geq -0.2175 - 0.1144 - 0.4094 + 1.1919 > 0,\end{aligned}$$

so, unless $x_3 = -1$, we could decrease x_3 in order to decrease f . Thus minimum is achieved with $x_3 = -1$

Finally, with determined $x_1 = 1$ and $x_3 = -1$,

$$\begin{aligned}\frac{\partial f}{\partial x_2} &= 0.2451x_1 + 0.3551x_2 + 0.1144x_3 - 0.1307 = \\ &= 0.2451 + 0.3551x_2 - 0.1144 - 0.1307 = \\ &= 0.3551x_2.\end{aligned}$$

Thus minimum could not be achieved when $x_2 < 0$ (as we could decrease f by increasing x_2) or when $x_2 > 0$ (could decrease f by decreasing x_2). Thus minimum is at $x_2 = 0$.

That is, $x_{\text{sol}} = (1, 0, -1)$ is a minimizer.

Problem 3

Original problem is equivalent to the following:

$$\underset{y}{\text{minimize}} \quad k^T y \quad \text{subject to} \quad y \leq 0, \quad \text{where } k = A^{-1} m^T \quad (\#).$$

Indeed, consider a bijection $\varphi: x \rightarrow Ax - b$ from the set of admissible values of the original problem to the set of admissible values of problem (#).

- It is bijection since A is invertible
- $k^T \varphi(x) = k^T(Ax - b) = m^T A^{-1}(Ax - b) = m^T x - m^T A^{-1} b$, so objective function of original problem evaluated at x differs from objective function of problem (#) evaluated at $\varphi(x)$ by constant.

Thus, if x^* is a minimizer of the original problem, $y^* = \varphi(x^*)$ is a minimizer of problem (#) and vice versa. So we could solve problem (#).

minimize $k^T y$ subject to $y \leq 0$. (*)

If any entry of k is positive, minimizer would not exist. Indeed, suppose j -th entry of k is positive number a . Then $k^T \begin{pmatrix} 0 \\ \vdots \\ -n \\ \vdots \\ 0 \end{pmatrix} = an \rightarrow -\infty$ as $n \rightarrow \infty$, and $y_n = \begin{pmatrix} 0 \\ \vdots \\ -n \\ \vdots \\ 0 \end{pmatrix}$ is admissible.

Thus, for minimizer to exist we must have $k \leq 0$.

Then $\inf_{y \leq 0} k^T y = 0$ is achieved, in particular, at $y^* = 0$.

Thus original problem has finite minimizer whenever $k = (A^{-1})^T m \leq 0$. Optimal value of objective function is then $m^T A^{-1} b$, achieved, in particular, at $x^* = \varphi^{-1}(0) = A^{-1} b$.

Problem 4

a) $x \in [2, 4]$ are feasible (since quadratic function with positive leading coeff. is negative between its roots).

Minimal value is 5, achieved at $x=2$ (since $x^2 + 1$ is increasing).

b) Lagrange dual function:

$$L(\lambda) = \inf_{x \in [2, 4]} \{x^2 + 1 + \lambda(x-2)(x-4)\}$$

For $\lambda > 0$ parabola points up, so we perform

the minimization as following: $\frac{d}{dx} (x^2 + 1 + \lambda(x-2)(x-4)) = 0$

$\Leftrightarrow 2x + 2\lambda x - 6\lambda = 0 \Leftrightarrow x = \frac{3\lambda}{1+\lambda}$. This extremum point is between 2 and 4 if $2 \leq \frac{3\lambda}{1+\lambda} \leq 4 \Leftrightarrow$

$$\Leftrightarrow 2+2\lambda \leq 3\lambda \leq 4+4\lambda \Leftrightarrow \lambda \geq 2. \text{ So for } \lambda \geq 2 \text{ minimum is achieved at } \frac{3\lambda}{1+\lambda} \text{ and } L(\lambda) = \left(\frac{3\lambda}{1+\lambda}\right)^2 + 1 + \lambda \left(\frac{\lambda-2}{1+\lambda}\right)\left(\frac{-\lambda-4}{1+\lambda}\right) = \frac{9\lambda^2 + 1 + 2\lambda + \lambda^2 - \lambda^3 - 2\lambda^2 + 8\lambda}{(1+\lambda)^2} = \frac{-\lambda^3 + 8\lambda^2 + 10\lambda + 1}{(1+\lambda)^2} = \frac{1+9\lambda-\lambda^2}{1+\lambda}$$

For $0 < \lambda < 2$, $\frac{3\lambda}{1+\lambda} < 2$, so function is increasing on $[2, 4]$. Then minimum is at $x=2$, so $L(\lambda)=5$.

Summarizing, $L(\lambda) = \begin{cases} \frac{1+9\lambda-\lambda^2}{1+\lambda}, & \text{if } \lambda \geq 2 \\ 5, & \text{if } 0 < \lambda < 2 \end{cases}$

Now solve dual problem:

minimize $-L(\lambda)$ subject to $\lambda \geq 0$

$$\frac{dL}{d\lambda} = 0 \Leftrightarrow \begin{cases} 0 < \lambda \leq 2 \text{ or} \\ (-2\lambda+9)(1+\lambda) - (1+9\lambda-\lambda^2) = 0, \lambda > 2 \end{cases} \Leftrightarrow$$

$$\Leftrightarrow \begin{cases} 0 \leq \lambda \leq 2 \text{ or} \\ \lambda = -4 \text{ or} \\ \lambda = 2 \end{cases} \quad \underbrace{\text{so minima are achieved on } [0, 2]}_{\text{feasible}}$$

$$-L(2) = 5$$

$$-L(\infty) = +\infty$$

Since $\min(\text{dual}) = -L(2) = 5 = \min(\text{original})$,
strong duality holds,

Problem 5:

We aim to show that $F(tx + (1-t)y) \leq tF(x) + (1-t)F(y)$ for all $t \in [0, 1]$. For it write:

$$\begin{aligned}
 tF(x) + (1-t)F(y) &= t \int_0^x f(s) \frac{ds}{x} + (1-t) \int_0^y f(s) \frac{ds}{y} = \begin{cases} \omega = s/x \text{ in 1st int.} \\ \omega = s/y \text{ in 2nd int.} \end{cases} \\
 &= t \int_0^1 f(\omega x) d\omega + (1-t) \int_0^1 f(\omega y) d\omega = \int_0^1 t f(\omega x) + (1-t) f(\omega y) d\omega \geq \\
 &\geq \int_0^1 f(tx + (1-t)y) d\omega = \int_0^1 f(s) \frac{ds}{tx + (1-t)y} = \frac{1}{tx + (1-t)y} \int_0^{tx + (1-t)y} f(s) ds \\
 &\quad \uparrow \text{convexity of } f \\
 &\quad s = \omega(tx + (1-t)y) \\
 &= F(tx + (1-t)y), \text{ as desired. } \square
 \end{aligned}$$

Problem 1

Turned out to be the hardest problem, but I managed! "Idee Adyru" is the image of "Jeff Bezos" under the letter wise action of the backward-shift operator acting on English alphabet.