



# Homework 1

Consider a **convex optimization** problem

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & g(x) \leq 0 \\ & h(x) = 0 \end{aligned}$$

Its PHR Augmented Lagrangian is defined as

$$\mathcal{L}_\rho(x, \lambda, \mu) := f(x) + \frac{\rho}{2} \left\{ \left\| h(x) + \frac{\lambda}{\rho} \right\|^2 + \left\| \max \left[ g(x) + \frac{\mu}{\rho}, 0 \right] \right\|^2 \right\} - \frac{1}{2\rho} \left\{ \|\lambda\|^2 + \|\mu\|^2 \right\}$$

where  $\rho > 0, \mu \succeq 0$ .

Prove that **the PHR Lagrangian is always convex with respect to x.**



## Homework 2

Provided a low-dimensional strictly convex QP solver that only solves:

$$\min_{x \in \mathbb{R}^n} \frac{1}{2} x^T M_Q x + c_Q^T x, \text{ s.t. } A_Q x \leq b_Q$$

where  $M_Q \succ 0$ .

Please design a scheme to approximately solve the case where  $M_Q \succeq 0$  but  $M_Q \neq 0$ .

You can **combine the low-dimensional strictly convex QP solver with a “proximal” term**.

A C++ version of the solver is provided as below:

<https://github.com/ZJU-FAST-Lab/SDQP>

A test example for a positive semi-definite case:

$$M_Q = \begin{pmatrix} 2 & -1 & 0 \\ 0 & 1 & -1 \\ 2 & -2 & 1 \end{pmatrix} \quad c_Q = \begin{pmatrix} 1 \\ 3 \\ -2 \end{pmatrix} \quad A_Q = \begin{pmatrix} 0 & -1 & -2 \\ -1 & 1 & -3 \\ 1 & -2 & 0 \\ -1 & -2 & -1 \\ 3 & 5 & 1 \end{pmatrix} \quad b_Q = \begin{pmatrix} -1 \\ 2 \\ 7 \\ 2 \\ -1 \end{pmatrix} \quad x^* = \begin{pmatrix} -\frac{38}{3} \\ \frac{25}{6} \\ \frac{109}{6} \end{pmatrix}$$



## Homework 3

Please solve the SOCP below via Conic ALM.

$$\begin{aligned} \min_{a,b,c,d,e,f,g \in \mathbb{R}} \quad & a + 2b + 3c + 4d + 5e + 6f + 7g \\ \text{s.t.} \quad & \|(7a + 1, 6b + 3, 5c + 5, 4d + 7, 3e + 9, 2f + 11, g + 13)\| \leq a + 1. \end{aligned}$$

The approximate solution is:

$$(-0.127286, -0.506097, -1.01317, -1.77744, -3.06097, -5.66462, -13.7682)$$