Quiz 2

NAME: SID:

The quiz lasts 1h30. Notes are *not* allowed, except for a one-page, two sided cheat sheet.

- 1. In this problem we examine the convexity of various functions.
 - (a) For a given $k \in \{1, ..., n\}$ we define the function $s_k : \mathbb{R}^n \to \mathbb{R}$ with values given by

$$s_k(x) = \sum_{i=1}^k x_{[i]},$$

where $x_{[i]}$ is the *i*-th largest component of x. Show that s_k is a convex function. Hint: express s_k as the maximum of linear functions. You can try with n=3, k=2 first.

(b) Assume n = 2k - 1 is odd. Consider the average absolute deviation from the median of the components of x, which is the function $\phi : \mathbb{R}^n \to \mathbb{R}$ with values given by

$$\phi(x) = \frac{1}{n} \sum_{i=1}^{n} |x_i - \text{med}(x)|,$$

where $\operatorname{med}(x) = x_{[k]}$ denotes the *median* of the components of x, i.e., a number that leaves half of the entries of x on its left and half on its right. Show that ϕ is convex. *Hint:* express ϕ in terms of s_k, s_{k-1} and the sum of the components of x.

Solution:

(a) For n=3, k=2, we have

$$s_2(x) = \max(x_1 + x_2, x_2 + x_3, x_3 + x_1).$$

More generally:

$$s_k(x) = \max_{(i_1,\dots,i_k)\in\{1,\dots,n\}^k} x_{i_1} + \dots + x_{i_k}.$$

This shows that s_k is the point-wise maximum of linear function, hence it is convex.

(b) We have, for n = 2k - 1 odd:

$$\phi(x) = \sum_{i=1}^{k-1} (x_{[i]} - x_{[k]}) + \sum_{i=k+1}^{n} (x_{[k]} - x_{[i]}) = \sum_{i=1}^{k-1} x_{[i]} - \sum_{i=k+1}^{n} x_{[i]} = s_{k-1}(x) + s_k(x) - \sum_{i=1}^{n} x_i,$$

which shows that ϕ is convex.

2. A version of the so-called (convex) trust-region problem amounts to finding the minimum of a convex quadratic function over an Euclidean ball, that is

$$\begin{aligned} & \min_{x} & & \frac{1}{2}x^{\top}Hx + c^{\top}x + d \\ & \text{s.t.} & & x^{\top}x \leq r^{2}, \end{aligned}$$

where H > 0, and r > 0 is the given radius of the ball. Prove that the optimal solution to this problem is unique and it is given by

$$x(\lambda^*) = -(H + \lambda^* I)^{-1} c,$$

where $\lambda^* = 0$ if $||H^{-1}c||_2 \le r$, or otherwise λ^* is the unique value such that

$$||(H + \lambda^* I)^{-1} c||_2 = r.$$

Solution 1 (A trust-region problem) The Lagrangian of this problem can be written as

$$\mathcal{L}(x,\lambda) = \frac{1}{2}x^{\mathsf{T}}Hx + c^{\mathsf{T}}x + d + \frac{\lambda}{2}(x^{\mathsf{T}}x - r^2)$$
$$= \frac{1}{2}x^{\mathsf{T}}(H + \lambda I)x + c^{\mathsf{T}}x + d - \frac{\lambda}{2}r^2.$$

The Lagrangian is strongly convex, hence it has a unique minimizer

$$x^*(\lambda) = -(H + \lambda I)^{-1}c.$$

The optimal solution of the problem is $x^*(\lambda^*)$, where λ^* is the optimal solution of the dual problem

$$\max_{\lambda \ge 0} g(\lambda),$$

with

$$g(\lambda) \doteq -\frac{1}{2}c^{\mathsf{T}}(H+\lambda I)^{-1}c+d-\frac{\lambda}{2}r^{2}.$$

Let $H = U\Lambda U^{\top}$ be a spectral factorization of H, where U is orthogonal, and $\Lambda = \operatorname{diag}(\lambda_1, \ldots, \lambda_n) \succ 0$. We can write $(H + \lambda I) = U(\Lambda + \lambda I)U^{\top}$, hence

$$g(\lambda) = d - \frac{\lambda}{2}r^2 - \frac{1}{2}\sum_{i=1}^n \frac{\tilde{c}_i^2}{\lambda_i + \lambda},$$

where \tilde{c}_i are the entries of $\tilde{c} \doteq U^{\top} c$, and it holds that

$$g'(\lambda) \doteq \frac{\mathrm{d}g}{\mathrm{d}\lambda} = -\frac{1}{2}r^2 + \frac{1}{2}\sum_{i=1}^n \frac{\tilde{c}_i^2}{(\lambda_i + \lambda)^2}$$
$$= -\frac{1}{2}r^2 + \frac{1}{2}\|(H + \lambda I)^{-1}c\|_2^2.$$

Notice that the term $\|(H + \lambda I)^{-1}c\|_2$ is strictly decreasing over $\lambda \geq 0$. Hence, if $g'(0) \leq 0$ then $g(\lambda) < 0$ for all $\lambda > 0$, which means that $g(\lambda)$ is decreasing for positive λ , hence the maximum is at the boundary point where $\lambda = 0$. If otherwise g'(0) > 0, then the concave function g has a maximum over $\lambda > 0$, at the point where the derivative g' is zero, that is where

$$||(H + \lambda I)^{-1}c||_2^2 = r^2,$$

which is what we needed to prove. The value of λ satisfying this equation can be found numerically via any univariate search technique. For instance, one may use Newton method, starting with some initial $\lambda > 0$, and iteratively updating

$$\lambda \leftarrow \lambda - \frac{g'(\lambda)}{g''(\lambda)},$$

where $g''(\lambda)$ is the second derivative

$$g''(\lambda) \doteq \frac{\mathrm{d}^2 g}{\mathrm{d}\lambda^2} = -\sum_{i=1}^n \frac{\tilde{c}_i^2}{(\lambda_i + \lambda)^3}.$$

3. Let B_i , $i=1,\ldots,m$, be m given Euclidean balls in \mathbb{R}^n , with centers x_i , and radii $\rho_i \geq 0$. We wish to find a ball B of minimum radius that contains all the B_i , $i=1,\ldots,m$. Explain how to cast this problem into a known convex optimization format.

Solution 2 (Robust sphere enclosure) Let $c \in \mathbb{R}^n$ and $r \geq 0$ denote the center and radius of the enclosing ball B, respectively. We express the given balls B_i as

$$B_i = \{x : x = x_i + \delta_i, \|\delta_i\|_2 \le \rho_i\}, \quad i = 1, \dots, m.$$

We have that $B_i \subseteq B$ if and only if

$$\max_{x \in B_i} ||x - c||_2 \le r.$$

But

$$\max_{x \in B_i} \|x - c\|_2 = \max_{\|\delta_i\|_2 \le \rho_i} \|x_i - c + \delta_i\|_2 = \|x_i - c\|_2 + \rho_i.$$

The problem is then cast as the following SOCP

$$\min_{c,r} r \text{s.t.} ||x_i - c||_2 + \rho_i \le r, i = 1, ..., m.$$