# Optimization methods Graded Assignment 1

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- 1. (1 point) Correct points:
  - 1. Whether it has 5 extremums in the segment [-4; 4]
  - 2. If the global minimum is zero
  - 3. Whether the global maximum is unique
  - 4. If the number of local minimums is finite
  - 5. Whether the number of local maximums is countable
  - 6. If the function is smooth and continuous
- 2. (3 points) Verifying Convexity of Sets
  - (a) Given  $S_a \subseteq \mathbb{R}^n$  defined by a polynomial P(x), verify convexity:

For 
$$x, y \in S_a, \lambda \in [0, 1]$$
, check if  $\lambda x + (1 - \lambda)y \in S_a$ .

(b) For  $S_b \subseteq \mathbb{R}^2$  with  $xy \leq k, k \in \mathbb{R}$ , analyze:

Convexity if 
$$\forall x, y \in S_b, \lambda x + (1 - \lambda)y \in S_b$$
.

(c) Let  $S_c$  be matrices in  $\mathbb{R}^{n\times n}$  with diagonal criteria. Confirm:

Linear combinations preserve conditions:  $\lambda A + (1 - \lambda)B \in S_c, \forall A, B \in S_c$ .

(d) For  $S_d$  with min/max element bounds in  $\mathbb{R}^n$ , test convexity:

If 
$$x, y \in S_d$$
, then  $\lambda x + (1 - \lambda)y \in S_d, \forall \lambda \in [0, 1]$ .

(e) Given  $S_e$  of matrices with rank r, verify:

Convexity if 
$$\forall A, B \in S_e, \lambda A + (1 - \lambda)B$$
 has rank  $r, \forall \lambda \in [0, 1]$ .

3. (2 points) Convexity Preservation Under Maps

#### Linear Map Case:

Assume f is a linear map, i.e., f(x) = Ax for some matrix A.

- Take any two points  $x, y \in f^{-1}(C)$ .
- By definition of preimage,  $f(x), f(y) \in C$ .
- Since C is convex, for any  $\lambda \in [0,1], \lambda f(x) + (1-\lambda)f(y) \in C$ .
- Using linearity,  $f(\lambda x + (1 \lambda)y) = \lambda Ax + (1 \lambda)Ay = \lambda f(x) + (1 \lambda)f(y) \in C$ .

• Thus,  $\lambda x + (1 - \lambda)y \in f^{-1}(C)$ , proving convexity.

# Perspective Map Case:

Assume f is a perspective map, i.e.,  $f(x,t) = \frac{x}{t}$  for  $x \in \mathbb{R}^n, t \in \mathbb{R} \setminus \{0\}$ .

- Consider two points  $(x_1, t_1), (x_2, t_2) \in f^{-1}(C)$ .
- By definition,  $f(x_1, t_1), f(x_2, t_2) \in C$ .
- For  $\lambda \in [0, 1]$ , check  $\lambda f(x_1, t_1) + (1 \lambda)f(x_2, t_2) \in C$ .
- Note:  $f(\lambda(x_1, t_1) + (1 \lambda)(x_2, t_2)) = \frac{\lambda x_1 + (1 \lambda)x_2}{\lambda t_1 + (1 \lambda)t_2}$ .
- If  $\lambda t_1 + (1 \lambda)t_2 \neq 0$ ,  $\frac{\lambda x_1 + (1 \lambda)x_2}{\lambda t_1 + (1 \lambda)t_2} \in C$ .
- Hence,  $\lambda(x_1, t_1) + (1 \lambda)(x_2, t_2) \in f^{-1}(C)$ , proving convexity.
- 4. (2 points) Convexity Characterization of Sets in  $\mathbb{R}^n$

#### **Proof:**

If C is convex:

- For  $x, y \in C$ ,  $\lambda x + (1 \lambda)y \in C$  for  $\lambda \in [0, 1]$ .
- Hence,  $\alpha x, \beta y \in C$  for  $\alpha, \beta \geq 0$ .
- Therefore,  $\alpha x + \beta y \in \alpha C + \beta C$ .
- It follows that  $(\alpha + \beta)C \subseteq \alpha C + \beta C$ .

If  $(\alpha + \beta)C = \alpha C + \beta C$ :

- For  $x, y \in C$ ,  $\alpha = \lambda$ ,  $\beta = 1 \lambda$ ,  $\lambda \in [0, 1]$ .
- Then,  $\lambda x + (1 \lambda)y \in \lambda C + (1 \lambda)C = (\lambda + 1 \lambda)C = C$ .
- $\bullet$  Thus, C is convex.