Subgradient and Subdifferencial

Seminar

Optimization for ML. Faculty of Computer Science. HSE University





Main notions recap

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For a domain set $E \in \mathbb{R}^n$ and a function $f: E \to \mathbb{R}$:

• A vector $g \in \mathbb{R}^n$ is called **subgradient** of the function f at $x \in E$ if $\forall y \in E$

$$f(y) \ge f(x) + g^T(y - x)$$

• A set $\partial f(x)$ is called **subdifferential** of the function f at $x \in E$ if:

$$\partial f(x) = \{ g \in \mathbb{R}^n \mid f(y) \ge f(x) + g^T(y - x) \} \forall y \in E$$

• $f(\cdot)$ is called **subdifferentiable** at point $x \in E$ if $\partial f(x) \neq \emptyset$

Connection between subdifferentiation and convexity

Connection between subdifferentiation and convexity

If $f: E \to \mathbb{R}$ is subdifferentiable on the **convex** subset $S \in E$ then f is convex on S.

- The inverse is generally incorrect
- There is no sense to derive the subgradient of nonconvex function.

Connection between subdifferentiation and differentiation

- $\ensuremath{\P}$ CConnection between subdifferentiation and differentiation
 - 1) If $f:E \to \mathbb{R}$ is convex and differentiable at $x \in \operatorname{int} E$ then $\partial f(x) = \{\Delta f(x)\}$
 - 2) If $f:E\to\mathbb{R}$ is convex and for $x\in \mathrm{int}\; E\;\partial f(x)=\{s\}$ then f is differentiable at x and $\Delta f(x)=s$
- Derive the subdifferencial of a differentiable function is overkill.

Main notions recap

Question

Find the subgradient of the function

$$f(x) = -\sqrt{x}$$



Subdifferentiation rules

1)
$$f: E \to \mathbb{R}, x \in E, c > 0$$

$$\Rightarrow \partial(cf)(x) = c\partial f(x)$$

2)
$$f: F \to \mathbb{R}, g: G \to \mathbb{R}, x \in F \cap G$$

$$\Rightarrow \partial(f+g)(x) \supseteq \partial f(x) + \partial g(x)$$

3)
$$T: V \to W = Ax + b$$
, $g: W \to \mathbb{R}$, $x_0 \in V$

$$\Rightarrow \partial(g \circ T)(x_0) \supseteq A^* \partial(g)(T(x_0))$$

 $i \in I(x)$

4)
$$f(x) = \max(f_1(x), \dots, f_m(x)), I(x) = \{i \in 1 \dots m | f_i(x) = f(x)\}$$

$$\Rightarrow \partial f(x) \supseteq \mathsf{Conv}(\ \ \ \ \ \ \ \ \partial f_i(x))$$

If abovementioned functions are convex and x is inner point then all inequalities turn into equalities.

Question

Find the subgradient of the function f(x) + g(x) if

$$f(x) = -\sqrt{x}$$
 when $x \ge 0$

$$g(x) = -\sqrt{-x}$$
 when $x \le 0$



Question

- 1) Find the subgradient of the function $f(x) = ||Ax b||_1$;
- 2) For task $f(x) = \frac{1}{2}||Ax b||_2^2 + \lambda ||x||_1 \to \min_x$ say which lambdas lead to $x_{opt} = 0$

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Question

Check the differentiability of the function

$$f(A) = \sup_{||x||_2 = 1} x^T A x, \text{ where } A \in \mathbb{S}^n, \, x \in \mathbb{R}^n$$

