

Subgradient Calculus

1:01 PM

Example abs(x), l-1 norm [Subgradient Contents](#)

g. Subgradient at x exist iff $\exists \{y_i\} \subseteq \text{dom} f$ s.t. $f(y_i) \leq f(x) + g_i^T(y_i - x)$

* Subgradient of $f(x) = |x|$ at x



$x > 0, f(x) = x \Rightarrow \partial f(x)_{x>0} = \{ \nabla f(x) \} = \{1\} = \text{sgn}(x)$

$x < 0, f(x) = -x \Rightarrow \partial f(x)_{x<0} = \{ \nabla f(x) \} = \{-1\} = \text{sgn}(x)$

$x = 0, f(x)$ not differentiable. $\nabla f(x)$ doesn't exist, $\forall g \in \mathbb{R} \quad f(y) = |y| = \max_{-1 \leq \alpha \leq 1} \alpha y \geq \alpha y \quad \forall y: |y| \leq 1 \rightarrow \forall y \in \text{dom} f \quad \{y\} \geq \alpha y \quad \forall -1 \leq \alpha \leq 1$
 $f(y) \geq f(0) + \alpha(y-0) \quad \forall -1 \leq \alpha \leq 1$

Use it to use the identity: $|z| = \max_{|t| \leq 1} tz$ for $z \in \mathbb{R}$
 e.g. $|-3| = \max_{-1 \leq t \leq 1} (-3)t = \max_{-1 \leq t \leq 1} -3t = 3$
 $|3| = \max_{-1 \leq t \leq 1} (3)t = \max_{-1 \leq t \leq 1} 3t = 3$ so it works!

by defn of subgradient, $g \in [-1, 1]$ is a subgradient of $f(x) = |x|$ at 0.

$\therefore \partial f(x)_{x=0} = [-1, 1]$

$$\partial |x| = \begin{cases} \text{sgn}(x), & \text{if } x \neq 0 \\ [-1, 1], & \text{if } x = 0 \end{cases}$$

subdifferential of abs(x)

$$\Leftrightarrow \max_{i \in \{1, \dots, n\}} |a_i| \leq 1 \Leftrightarrow \|g\|_\infty \leq 1$$

* Subgradient of l_1 norm function, $f(x) = \|x\|_1, x \in \mathbb{R}^n$ at $x=0$

$$f(y) = \|y\|_1 = \sum_{i=1}^n |y_i| = \sum_{i=1}^n \max_{|g_i| \leq 1} g_i y_i = \left(\max_{|g_1| \leq 1} g_1 y_1 \right) + \dots + \left(\max_{|g_n| \leq 1} g_n y_n \right) \geq g_1 y_1 + \dots + g_n y_n \quad \forall g_i \in [-1, 1] \quad \forall y_i \in \mathbb{R}$$

$$\Rightarrow f(y) \geq \sum_{i=1}^n g_i y_i \quad \forall g_i \in [-1, 1] \quad \forall y_i \in \mathbb{R} \quad \Leftrightarrow \|g\|_\infty \leq 1$$

$$\Leftrightarrow f(y) \geq f(0) + g^T(y-0) \quad \forall y \in \mathbb{R}^n \quad \Leftrightarrow \|g\|_\infty \leq 1$$

$$\Leftrightarrow g \in \partial f(0) \Leftrightarrow \|g\|_\infty \leq 1 \quad \text{Subgradient of } \| \cdot \|_1 \text{ at } 0$$

For general formula of subgradient of l-1 norm at any point, see: [subgradient of l-1 norm](#)

Subgradient Calculus

Subgradient Calculus:

* Chain rule: $h: \mathbb{R}^n \rightarrow \mathbb{R}^m, h: \mathbb{R}^m \rightarrow \mathbb{R}$

$$f = h \circ g \Leftrightarrow f(\Theta) = h(g(\Theta))$$

$$\partial f(x) = (\partial h(g(x)))^T \partial g(x) \quad \# \partial g(x) \text{ is the jacobian}$$

$$\text{If origin: } \nabla f(x) = (\nabla h(g(x)))^T \nabla g(x) = (\nabla h(g(x)))^T (\nabla g(x)) = \nabla h(g(x)) \nabla g(x)$$

$$\partial f(x) = \partial(h(g(x))) = \partial(h(g(x))) \partial g(x)$$

$$\text{Affine transformation: (Special case)} \quad \Theta = g(x) \quad f(x) = h(Ax+b)$$

$$\therefore \nabla f(x) = \nabla(h(Ax+b))$$

$$\begin{aligned} \nabla f(x) &= \nabla(h(Ax+b)) = \nabla_{Ax+b} h(Ax+b) \cdot \nabla_x (Ax+b) \quad \{ \nabla_x (Ax+b) = \nabla_x Ax = \left(\frac{\partial}{\partial x_j} \sum_k a_{jk} x_k \right)_{j=1}^n = \left(\sum_k a_{jk} \frac{\partial x_k}{\partial x_j} \right)_{j=1}^n = \left(\sum_k a_{jk} \delta_{jk} \right)_{j=1}^n = (a_j)_{j=1}^n = A \} \\ &= (\nabla h(\Theta))_{\Theta=Ax+b}^T A \end{aligned}$$

$$\text{So for differentiable case: } \nabla f(x) = (\nabla h(\Theta))_{\Theta=Ax+b}^T A = A^T (\nabla h(\Theta))_{\Theta=Ax+b}^T = A^T \nabla h(\Theta)_{\Theta=Ax+b}$$

Extending to subgradient:

$$\partial f(x) = A^T (\partial h(\Theta))_{\Theta=Ax+b} \quad \Theta=Ax+b \in \text{int dom} h$$

* Example:

$$f(x) = |a^T x - b| = (abs \circ a^T \Theta - b)(x) = abs(a^T x - b)$$

pretend differentiable $\nabla f(x) = ?$

$$\nabla f(x) = \nabla_{Ax+b} abs(a^T x - b) \cdot \nabla_x (a^T x - b) = \left(\begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix} \right)_{\Theta=a^T x - b}^T \left(\begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix} \right)$$

$$\therefore \partial f(x) = \partial f(x)^T = \left(\begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix} \right)_{\Theta=a^T x - b}^T \cdot \left(\begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix} \right)$$

// $Df(x) = D_{a^T x + b} \quad D_x(a^T x - b) = \begin{pmatrix} D_x | 0 \end{pmatrix} \quad D_x(a^T x - b) = \begin{pmatrix} D_x | 0 \end{pmatrix} \quad D_x(a^T x - b)$

$\therefore \partial f(x) = Df(x)^T = \left(\begin{pmatrix} D_x | 0 \end{pmatrix} \right)_{D_x(a^T x - b)}^T \quad D_x(a^T x - b)$

$= \left(D_x(a^T x - b) \right)^T \left(\begin{pmatrix} D_x | 0 \end{pmatrix} \right)_{D_x(a^T x - b)}^T$

$= \underbrace{D_x(a^T x - b)}_a \left(\begin{pmatrix} \partial | 0 \end{pmatrix} \right)_{D_x(a^T x - b)} \rightarrow \text{not differentiable, hence subgradient}$

$\partial | 0 = \begin{cases} \text{sgn } 0, & 0 \neq 0 \\ [-1, 1], & 0 = 0 \end{cases}$

$= a \left(\text{sgn}(a^T x - b) \notin a^T x - b \neq 0 \right) + [-1, 1] \notin a^T x - b = 0 \}$

* Sum or linear combination

$f(x) = \alpha h(x) + \beta g(x)$

$\alpha \in \mathbb{R}, \beta \in \mathbb{R}$

$\forall x \in \text{relint dom } h \cap \text{relint dom } g \quad \partial f(x) = \alpha \partial h(x) + \beta \partial g(x)$

$\Leftrightarrow \partial(\alpha h(x) + \beta g(x)) = \alpha \partial h(x) + \beta \partial g(x)$ // proper parsing all elements of $\partial h(x)$ are multiplied by α } all the elements of these resultant sets are added together.

Example: $f(x) = \sum_{i=1}^n |a_i^T x + b|$

$\partial f(x) = \partial \left(\sum_{i=1}^n |a_i^T x + b| \right) = \sum_{i=1}^n \partial |a_i^T x + b| = \sum_{i=1}^n \left(a_i \left(\text{sgn}(a_i^T x - b) \notin a_i^T x - b \neq 0 \right) + [-1, 1] \notin a_i^T x - b = 0 \right)$ (i)

note: $\partial f(x) = \partial \|x\|_1 = \partial \sum_{i=1}^n |x_i| = \partial \sum_{i=1}^n |e_i^T x + 0| = \sum_{i=1}^n e_i \left(\text{sgn}(e_i^T x + 0) \notin e_i^T x + 0 \neq 0 \right) + [-1, 1] \notin e_i^T x + 0 = 0$

$= \sum_{i=1}^n e_i \text{sgn}(x_i) \notin x_i \neq 0 \} + [-1, 1] \notin x_i = 0 \}$

(subgradient of ℓ_1 norm)