

## 1. Convex Functions

Definition: convex function:

$$f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y), \forall \theta = [0, 1]$$

strict version:

$$f(\theta x + (1 - \theta)y) < \theta f(x) + (1 - \theta)f(y), \forall \theta = (0, 1)$$

chord lies above the function

Definition concave function:

$$f(\theta x + (1 - \theta)y) \geq \theta f(x) + (1 - \theta)f(y)$$

chord lies below the function

For convenience we sometimes define an extended value function:

$$\tilde{f}(x) = \begin{cases} f(x), & x \in \text{dom}(f) \\ \infty, & \text{other wise} \end{cases}$$

if  $f(x)$  convex, then  $\tilde{f}$  is also convex

## 2. examples:

linear and affine functions are both convex and concave

 $\frac{1}{x}$  neither convex nor concave on domain of  $\mathbb{R}$  $\|*\|$  on  $\mathbb{R}^n$  is convex

## 3. sublevel set of a function

$$C(\alpha) = \{x \in \text{dom}(f) : f(x) \leq \alpha\}$$

For convex function, all sublevel sets are convex ( $\forall \alpha$ ). Converse is not true.

## 4. quasi-convex function: if its sublevel sets are all convex

5. epigraph of functions:  $\text{epi}(f) = \{(x, t) : x \in \text{dom}(f), f(x) \leq t\} \in \mathbb{R}^{n+1}, f \in \mathbb{R}^n \rightarrow \mathbb{R}$   
the set of space above the function $f$  is convex function  $\iff \text{epi}(f)$  is convex set

## 6. differentiable convex function

First order condition: suppose  $f$  is differentiable and domain of  $f$  is convex. Then:

$f$  is convex  $\iff (\forall x, x_0 \in \text{dom}(f)) f(x) \geq f(x_0) + \nabla f(x_0)^T(x - x_0)$

$f(x) + \nabla f(x_0)^T(x - x_0)$  is the 1st order approximation

the local information  $(f(x), \nabla f(x_0))$  gives global information about the function (global underestimator)

rough proof:

suppose  $f(x)$  is convex but  $(\exists x, x_0) f(x) < f(x_0) + \nabla f(x_0)^T(x - x_0)$

then this means the function should bend across the tangent line which violates the convexity

proof for converse direction:

suppose that  $(\exists x, x_0) f(x) \geq f(x_0) + \nabla f(x_0)^T(x - x_0)$

to show that  $f(x)$  is convex lets take  $x, y \in \text{dom}(f), z = \theta x + (1 - \theta)y$

for  $x, z$ :  $f(x) + \nabla f(z)^T(x - z)$

for  $y, z$ :  $f(y) + \nabla f(z)^T(y - z)$

$\theta f(x) + (1 - \theta)f(y) \geq f(z) + \nabla f(z)^T(\theta x - \theta z + (1 - \theta)y - (1 - \theta)z)$

$\theta f(x) + (1 - \theta)f(y) \geq f(\theta x + (1 - \theta)y)$

$f(x)$  is convex

7. second order condition: suppose  $f$  is twice differentiable and  $\text{dom}(f)$  is convex, then  $f(x)$  is convex  $\iff \nabla^2 f(x) \geq 0$  (PSD, eg: wrt.  $S_+^n$ )

proof for scalar case:

suppose that  $f(x)$  is convex, then the first-order condition holds

for  $x, y \in \text{dom}(f)$ :  $f(x) \geq f(y) + f'(y)(x - y)$

for  $y, x \in \text{dom}(f)$ :  $f(y) \geq f(x) + f'(x)(y - x)$

$f'(x)(y - x) \leq f(y) - f(x) \leq f'(y)(y - x)$

$f'(x)(y - x) \leq f'(y)(y - x) \implies 0 \leq (y - x)(f'(x) - f'(y))$

take  $y \rightarrow x$ :  $0 \leq f''(x)$

$f''(x) \geq \frac{f'(x+\delta x) - f'(x)}{\delta x}$

conversely, suppose that  $f'(z) \geq 0, \forall z \in \text{dom}(f)$ , take  $x, y \in \text{dom}(f)$  WLOG  $x < y$

$\int_x^y f''(z)(y - z)dz \geq 0$

$f''(z) \geq 0, (y - z) \geq 0 = I_1 + I_2$

$I_1 = \int_x^y f''(z) y dz - y f'(z)|_x^y = y(f'(y) - f'(x))$

$I_2 = -\int_x^y f''(z) z dz$

$dv = f''(z) dz \implies v = f'(z)$

$u = z \implies du = dz$

$I_2 = -z f'(z)|_x^y + \int_x^y f'(z) dz = -y f'(y) + x f'(x) + f(y) - f(x)$

$I_1 + I_2 = y f'(y) - y f'(x) - y f'(y) + x f'(x) + f(y) - f(x) \geq 0$

$\implies f(y) \geq f(x) + f'(x)(y - x)$  first order condition:  $x < y$

first order condition holds  $\implies f(x)$  convex

8. basic properties of convex functions:

(a)  $f(x)$  is convex  $\implies (\exists \alpha) \alpha f(x)$  is convex

(b)  $f_1, \dots, f_n$  convex  $\implies f_1 + \dots + f_n$  is convex

(c) if  $f(x)$  is convex  $\implies \forall g(x)$  affine,  $f(g(x))$  is convex  
eg:  $f(x) = \|Ax + b\|$  is convex.  $f(y) = \|y\|$  is convex

(d)  $f_1, \dots, f_n$  convex  $\implies \max\{f_1 + \dots + f_n\}$  is convex