Lecture: Convex Functions

http://bicmr.pku.edu.cn/~wenzw/opt-2018-fall.html

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Introduction

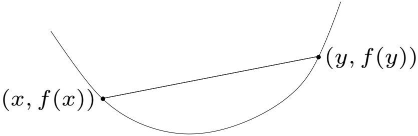
- basic properties and examples
- operations that preserve convexity
- the conjugate function
- quasiconvex functions
- log-concave and log-convex functions
- convexity with respect to generalized inequalities

Definition

$f : \mathbb{R}^n \to \mathbb{R}$ is convex if $\mathbf{dom}\, f$ is a convex set and

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

for all $x, y \in \mathbf{dom}\, f$, $0 \le \theta \le 1$



- f is concave if $-f$ is convex
- f is strictly convex if $\mathbf{dom}\, f$ is convex and

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

for $x, y \in \mathbf{dom}\, f$, $x \ne y$, $0 < \theta < 1$

Examples on $\mathbb{R}$

convex:

- affine: $ax + b$ on $\mathbb{R}$, for any $a, b \in \mathbb{R}$
- exponential: e^{ax}, for any $a \in \mathbb{R}$
- powers: x^α on $\mathbb{R}_{++}$, for $\alpha \geq 1$ or $\alpha \leq 0$
- powers of absolute value: $|x|^p$ on $\mathbb{R}$, for $p \geq 1$
- negative entropy: $x \log x$ on $\mathbb{R}_{++}$

concave:

- affine: $ax + b$ on $\mathbb{R}$, for any $a, b \in \mathbb{R}$
- powers: x^α on $\mathbb{R}_{++}$, for $0 \leq \alpha \leq 1$
- logarithm: $\log x$ on $\mathbb{R}_{++}$

Examples on $\mathbb{R}^n$ and $\mathbb{R}^{m\times n}$

affine functions are convex and concave; all norms are convex

examples on $\mathbb{R}^n$

- affine function $f(x) = a^T x + b$
- norms: $\|x\|_p = (\sum_{i=1}^n |x_i|^p)^{1/p}$ for $p \geq 1$; $\|x\|_\infty = \max_k |x_k|$

examples on $\mathbb{R}^{m\times n}$ ($m \times n$ matrices)

- affine function

$$f(X) = \mathrm{tr}(A^T X) + b = \sum_{i=1}^m \sum_{j=1}^n A_{ij} X_{ij} + b$$

- spectral (maximum singular value) norm

$$f(X) = \|X\|_2 = \sigma_{\max}(X) = (\lambda_{\max}(X^T X))^{1/2}$$

Restriction of a convex function to a line

$f : \mathbb{R}^n \to \mathbb{R}$ is convex if and only if the function $g : \mathbb{R} \to \mathbb{R}$,

$$g(t) = f(x + tv), \quad \mathrm{dom}\, g = \{t | x + tv \in \mathrm{dom}\, f\}$$

is convex (in t) for any $x \in \mathrm{dom}\, f, v \in \mathbb{R}^n$

can check convexity of f by checking convexity of functions of one variable

example. $f : \mathbb{S}^n \to \mathbb{R}$ with $f(X) = \log\det X$, $\mathrm{dom}\, f = \mathbb{S}^n_{++}$

$$\begin{aligned} g(t) = \log\det(X + tV) &= \log\det X + \log\det(I + tX^{-1/2}VX^{-1/2}) \\ &= \log\det X + \sum_{i=1}^{n} \log(1 + t\lambda_i) \end{aligned}$$

where λ_i are the eigenvalues of $X^{-1/2}VX^{-1/2}$

g is concave in t (for any choice of $X \succ 0$, V); hence f is concave

矩阵变量函数的导数

- 对于以$m \times n$ 矩阵X 为自变量的函数$f(X)$，若存在矩阵$G \in \mathbb{R}^{m\times n}$满足

$$\lim_{V\to 0} \frac{f(X+V) - f(X) - \langle G, V\rangle}{\|V\|} = 0,$$

其中$\|\cdot\|$是任意矩阵范数，就称矩阵变量函数f在X处Fréchet 可微，称G为f的Fréchet 导数.

- 设$f(X)$为矩阵变量函数，如果对任意方向$V \in \mathbb{R}^{m\times n}$，存在矩阵$G \in \mathbb{R}^{m\times n}$ 满足

$$\lim_{t\to 0} \frac{f(X+tV) - f(X) - t\langle G, V\rangle}{t} = 0,$$

那们称f 关于X Gateaux 可微. 满足上式的G称为f在X处的Gateaux 导数.

矩阵变量函数的导数

- 当f是Fréchet 可微函数时f也是Gateaux 可微且两种导数相等.
- 和Fréchet 导数的定义进行对比不难发现，Gateaux 导数实际上是方向导数的某种推广，它针对一元函数考虑极限，因此计算Gateaux 导数是更容易实现的.
- 从二者定义容易看出，若f是Fréchet 可微的，则f也是Gateaux 可微的，且f 的Fréchet 导数和Gateaux 导数是相等的. 但这一命题反过来不一定成立.

矩阵变量函数的导数

考虑二次函数：$f(X,Y)=\frac{1}{2}\|XY-A\|_F^2$，其中$(X,Y)\in\mathbb{R}^{m\times p}\times\mathbb{R}^{p\times n}$. 对变量$Y$，取任意方向$V$以及充分小的$t\in\mathbb{R}$有

$$\begin{aligned} f(X,Y+tV)-f(X,Y) &= \frac{1}{2}\|X(Y+tV)-A\|_F^2-\frac{1}{2}\|XY-A\|_F^2 \\ &= \langle tXV, XY-A\rangle+\frac{1}{2}t^2\|XV\|_F^2 \\ &= t\left\langle V, X^{\mathrm{T}}(XY-A)\right\rangle+\mathcal{O}(t^2). \end{aligned}$$

由定义可知$\frac{\partial f}{\partial Y}=X^{\mathrm{T}}(XY-A)$.
对变量X，取任意方向V以及充分小的$t\in\mathbb{R}$，有

$$\begin{aligned} f(X+tV,Y)-f(X,Y) &= \frac{1}{2}\|(X+tV)Y-A\|_F^2-\frac{1}{2}\|XY-A\|_F^2 \\ &= \langle tVY, XY-A\rangle+\frac{1}{2}t^2\|VY\|_F^2 \\ &= t\left\langle V, (XY-A)Y^{\mathrm{T}}\right\rangle+\mathcal{O}(t^2). \end{aligned}$$

由定义可知$\frac{\partial f}{\partial X}=(XY-A)Y^{\mathrm{T}}$.

Extended-value extension

extended-value extension $\tilde{f}$ of f is

$$\tilde{f}(x) = f(x), \quad x \in \operatorname{dom} f, \qquad \tilde{f}(x) = \infty, \quad x \notin \operatorname{dom} f$$

often simplifies notation; for example, the condition

$$0 \leq \theta \leq 1 \quad \Longrightarrow \quad \tilde{f}(\theta x + (1-\theta)y) \leq \theta \tilde{f}(x) + (1-\theta)\tilde{f}(y)$$

(as an inequality in $\mathbb{R} \cup \{\infty\}$), means the same as the two conditions

- $\operatorname{dom} f$ is convex
- for $x, y \in \operatorname{dom} f$,

$$0 \leq \theta \leq 1 \quad \Longrightarrow \quad f(\theta x + (1-\theta)y) \leq \theta f(x) + (1-\theta)f(y)$$

First-order condition

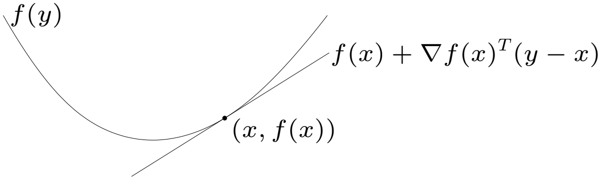
f is **differentiable** if $\mathrm{dom}\, f$ is open and the gradient

$$\nabla f(x) = \left(\frac{\partial f(x)}{\partial x_1}, \frac{\partial f(x)}{\partial x_2}, \ldots, \frac{\partial f(x)}{\partial x_n} \right)$$

exists at each $x \in \mathrm{dom}\, f$

1st-order condition: differentiable f with convex domain is convex iff

$$f(y) \geq f(x) + \nabla f(x)^T (y - x) \quad \text{for all } x, y \in \mathrm{dom}\, f$$



first-order approximation of f is global underestimator

Second-order conditions

f is **twice differentiable** if $\mathbf{dom}\, f$ is open and the Hessian $\nabla^2 f(x) \in \mathbb{S}^n$,

$$\nabla^2 f(x)_{ij} = \frac{\partial^2 f(x)}{\partial x_i \partial x_j}, \quad i, j = 1, \ldots, n,$$

exists at each $x \in \mathbf{dom}\, f$

2nd-order conditions: for twice differentiable f with convex domain

- f is convex if and only if

$$\nabla^2 f(x) \succeq 0 \quad \text{for all } x \in \mathbf{dom}\, f$$

- if $\nabla^2 f(x) \succ 0$ for all $x \in \mathbf{dom}\, f$, then f is strictly convex

Examples

quadratic function: $f(x) = (1/2)x^T Px + q^T x + r$ (with $P \in \mathbb{S}^n$)

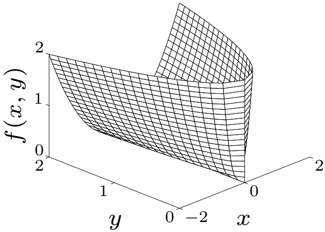
$$\nabla f(x) = Px + q, \qquad \nabla^2 f(x) = P$$

convex if $P \succeq 0$

least-squares objective: $f(x) = \|Ax - b\|_2^2$

$$\nabla f(x) = 2A^T(Ax - b), \quad \nabla^2 f(x) = 2A^T A$$

convex (for any A)



quadratic-over-linear: $f(x,y) = x^2/y$

$$\nabla^2 f(x,y) = \frac{2}{y^3} \begin{bmatrix} y \\ -x \end{bmatrix} \begin{bmatrix} y \\ -x \end{bmatrix}^T \succeq 0$$

convex for $y > 0$

log-sum-exp: $f(x) = \log \sum_{k=1}^n \exp x_k$ is convex

$$\nabla^2 f(x) = \frac{1}{\mathbf{1}^T z}\mathrm{diag}(z) - \frac{1}{(\mathbf{1}^T z)^2} z z^T \qquad (z_k = \exp x_k)$$

to show $\nabla^2 f(x) \succeq 0$, we must verify that $v^T \nabla^2 f(x) v \geq 0$ for all v:

$$v^T \nabla^2 f(x) v = \frac{(\sum_k z_k v_k^2)(\sum_k z_k) - (\sum_k v_k z_k)^2}{(\sum_k z_k)^2} \geq 0$$

since $(\sum_k v_k z_k)^2 \leq (\sum_k z_k v_k^2)(\sum_k z_k)$ (from Cauchy-Schwartz inequality)

geometric mean: $f(x) = (\prod_{k=1}^n x_k)^{1/n}$ on $\mathbb{R}_{++}^n$ is concave (similar proof as for log-sum-exp)

适当函数

- **适当函数**: 给定广义实值函数f 和非空集合$\mathcal{X}$. 如果存在$x \in \mathcal{X}$ 使得$f(x) < +\infty$，并且对任意的$x \in \mathcal{X}$，都有$f(x) > -\infty$，那么称函数f 关于集合$\mathcal{X}$ 是适当的.
- 概括来说，适当函数f的特点是“至少有一处取值不为正无穷”，以及“处处取值不为负无穷”. 对最优化问题$\min_x f(x)$，适当函数可以帮助去掉一些我们不感兴趣的函数，从而在一个比较合理的函数类中考虑最优化问题.
- 对于适当函数f，规定其定义域

$$\mathbf{dom} f = \{x \mid f(x) < +\infty\}.$$

正是因为适当函数的最小值不可能在函数值为无穷处取到，因此$\mathbf{dom} f$的定义方式是自然的.

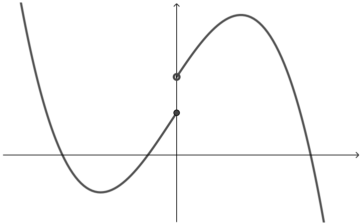
下半连续函数

- 设$f:\mathbb{R}^n\to\overline{\mathbb{R}}$为广义实值函数，若$\operatorname{epi} f$为闭集，则称$f$为**闭函数**.
- 设广义实值函数$f:\mathbb{R}^n\to\overline{\mathbb{R}}$，若对任意的$x\in\mathbb{R}^n$，有

$$\liminf_{y\to x} f(y)\geq f(x),$$

  则$f(x)$为**下半连续函数**

- 设广义实值函数$f:\mathbb{R}^n\to\overline{\mathbb{R}}$，则以下命题等价：
  1. $f(x)$的任意α-下水平集都是闭集；
  2. $f(x)$是下半连续的；
  3. $f(x)$是闭函数.



Epigraph and sublevel set

α**-sublevel set** of $f : \mathbb{R}^n \to \mathbb{R}$:

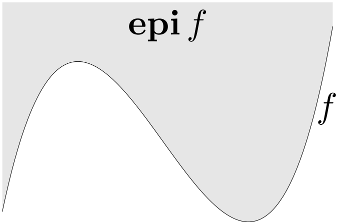
$$C_\alpha = \{x \in \operatorname{dom} f | f(x) \leq \alpha\}$$

sublevel sets of convex functions are convex (converse is false)

epigraph of $f : \mathbb{R}^n \to \mathbb{R}$:

$$\operatorname{epi} f = \{(x, t) \in \mathbb{R}^{n+1} | x \in \operatorname{dom} f, f(x) \leq t\}$$

f is convex if and only if $\operatorname{epi} f$ is a convex set



Monotonicity

- A mapping $F : \mathbb{R}^n \to \mathbb{R}^n$ is monotone if

$$\langle F(x) - F(y), x - y \rangle \geq 0, \qquad x, y \in \mathbb{R}^n.$$

- A mapping $F : \mathbb{R}^n \to \mathbb{R}^n$ is uniformly monotone if there exists a constant $c > 0$ such that

$$\langle F(x) - F(y), x - y \rangle \geq c\|x - y\|^2, \qquad x, y \in \mathbb{R}^n.$$

- Suppose that $f(x) : \mathbb{R}^n \to \mathbb{R}$ is differentiable, then $f(x)$ is convex if and only if $\nabla f(x)$ is monotone.

Jensen's inequality

basic inequality: if f is convex, then for $0 \leq \theta \leq 1$,

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

extension: if f is convex, then

$$f(\mathbf{E}z) \leq \mathbf{E}f(z)$$

for any random variable z

basic inequality is special case with discrete distribution

$$\text{prob}(z = x) = \theta, \quad \text{prob}(z = y) = 1 - \theta$$

Operations that preserve convexity

practical methods for establishing convexity of a function

1. verify definition (often simplified by restricting to a line)
2. for twice differentiable functions, show $\nabla^2 f(x) \succeq 0$
3. show that f is obtained from simple convex functions by operations that preserve convexity
   - nonnegative weighted sum
   - composition with affine function
   - pointwise maximum and supremum
   - composition
   - minimization
   - perspective

Positive weighted sum & composition with affine function

nonnegative multiple: αf is convex if f is convex, $\alpha \geq 0$

sum: $f_1 + f_2$ convex if f_1, f_2 convex (extends to infinite sums, integrals)

composition with affine function: $f(Ax + b)$ is convex if f is convex

examples

- log barrier for linear inequalities

$$f(x) = -\sum_{i=1}^{m} \log(b_i - a_i^T x), \quad \mathrm{dom}\, f = \{x | a_i^T x < b_i, i = 1, \ldots, m\}$$

- (any) norm of affine function: $f(x) = \|Ax + b\|$

Pointwise maximum

if $f_1, \ldots, f_m$ are convex, then $f(x) = \max\{f_1(x), \ldots, f_m(x)\}$ is convex

examples

- piecewise-linear function: $f(x) = \max_{i=1,\ldots,m}(a_i^T x + b_i)$ is convex
- sum of r largest components of $x \in \mathbb{R}^n$:

$$f(x) = x_{[1]} + x_{[2]} + \cdots + x_{[r]}$$

is convex ($x_{[i]}$ is ith largest component of x)

proof:

$$f(x) = \max\{x_{i_1} + x_{i_2} + \cdots + x_{i_r} | 1 \leq i_1 < i_2 < \cdots < i_r \leq n\}$$

Pointwise supremum

if $f(x, y)$ is convex in x for each $y \in \mathcal{A}$, then

$$g(x) = \sup_{y \in \mathcal{A}} f(x, y)$$

is convex

examples

- support function of a set C : $S_C(x) = \sup_{y \in C} y^T x$ is convex
- distance to farthest point in a set C :

$$f(x) = \sup_{y \in C} \|x - y\|$$

- maximum eigenvalue of symmetric matrix: for $X \in \mathbb{S}^n$,

$$\lambda_{\max}(X) = \sup_{\|y\|_2 = 1} y^T X y$$

Composition with scalar functions

composition of $g : \mathbb{R}^n \to \mathbb{R}$ and $h : \mathbb{R} \to \mathbb{R}$:

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

f is convex if
g convex, h convex, $\tilde{h}$ nondecreasing
g concave, h convex, $\tilde{h}$ nonincreasing

- proof (for $n = 1$, differentiable g, h)

$$f''(x) = h''(g(x))g'(x)^2 + h'(g(x))g''(x)$$

- note: monotonicity must hold for extended-value extension $\tilde{h}$

examples

- $\exp g(x)$ is convex if g is convex
- $1/g(x)$ is convex if g is concave and positive

Vector composition

composition of $g : \mathbb{R}^n \to \mathbb{R}^k$ and $h : \mathbb{R}^k \to \mathbb{R}$:

$$f(x) = h(g(x)) = h(g_1(x), g_2(x), ..., g_k(x))$$

f is convex if $\begin{array}{l} g_i \text{ convex}, h \text{ convex}, \tilde{h} \text{ nondecreasing in each argument} \\ g_i \text{ concave}, h \text{ convex}, \tilde{h} \text{ nnonincreasing in each argument} \end{array}$

proof (for $n = 1$, differentiable g, h)

$$f''(x) = g'(x)^T \nabla^2 h(g(x)) g'(x) + \nabla h(g(x))^T g''(x)$$

examples

- $\sum_{i=1}^m \log g_i(x)$ is concave if g_i are concave and positive
- $\log \sum_{i=1}^m \exp g_i(x)$ is convex if g_i are convex

Minimization

if $f(x, y)$ is convex in (x, y) and C is a convex set, then

$$g(x) = \inf_{y \in C} f(x, y)$$

is convex

examples

- $f(x, y) = x^T A x + 2x^T B y + y^T C y$ with

$$\begin{bmatrix} A & B \\ B^T & C \end{bmatrix} \succeq 0, \quad C \succ 0$$

  minimizing over y gives $g(x) = \inf_y f(x, y) = x^T (A - BC^{-1} B^T) x$
  g is convex, hence Schur complement $A - BC^{-1} B^T \succeq 0$

- distance to a set: $\mathrm{dist}(x, S) = \inf_{y \in S} \|x - y\|$ is convex if S is convex

Perspective

the **perspective** of a function $f : \mathbb{R}^n \to \mathbb{R}$ is the function $g : \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}$,

$$g(x, t) = tf(x/t), \quad \mathrm{dom}\, g = \{(x, t) | x/t \in \mathrm{dom}\, f, t > 0\}$$

g is convex if f is convex

examples

- $f(x) = x^T x$ is convex; hence $g(x, t) = x^T x/t$ is convex for $t > 0$
- negative logarithm $f(x) = -\log x$ is convex; hence relative entropy $g(x, t) = t \log t - t \log x$ is convex on $\mathbb{R}^2_{++}$
- if f is convex, then

$$g(x) = (c^T x + d)f\left((Ax + b)/(c^T x + d)\right)$$

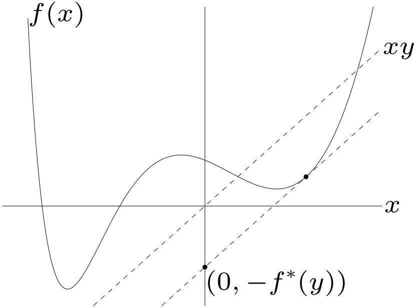
is convex on $\{x | c^T x + d > 0, (Ax + b)/(c^T x + d) \in \mathrm{dom}\, f\}$

The conjugate function

the **conjugate** of a function f is

$$f^*(y) = \sup_{x \in \text{dom } f} (y^T x - f(x))$$

- f^* is convex (even if f is not)
- will be useful in chapter 5



examples

- negative logarithm $f(x) = -\log x$

$$f^*(y) = \sup_{x>0}(xy + \log x) = \begin{cases} -1 - \log(-y) & y < 0 \\ \infty & \text{otherwise} \end{cases}$$

- strictly convex quadratic $f(x) = (1/2)x^T Qx$ with $Q \in \mathbb{S}^n_{++}$

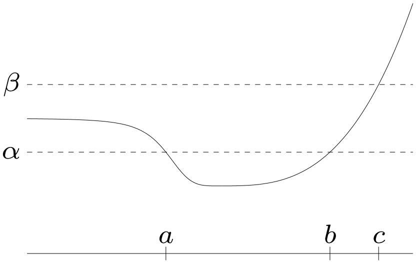
$$f^*(y) = \sup_x (y^T x - (1/2)x^T Qx) = \frac{1}{2} y^T Q^{-1} y$$

Quasiconvex functions

$f : \mathbb{R}^n \to \mathbb{R}$ is quasiconvex if $\mathrm{dom}\, f$ is convex and the sublevel sets

$$S_\alpha = \{x \in \mathrm{dom}\, f | f(x) \leq \alpha\}$$

are convex for all α



- f is quasiconcave if $-f$ is quasiconvex
- f is quasilinear if it is quasiconvex and quasiconcave

Examples

- $\sqrt{|x|}$ is quasiconvex on $\mathbb{R}$
- $\operatorname{ceil}(x) = \inf\{z \in \mathbb{Z} | z \geq x\}$ is quasilinear
- $\log x$ is quasilinear on $\mathbb{R}_{++}$
- $f(x_1, x_2) = x_1 x_2$ is quasiconcave on $\mathbb{R}^2_{++}$
- linear-fractional function

$$f(x) = \frac{a^T x + b}{c^T x + d}, \quad \operatorname{dom} f = \{x | c^T x + d > 0\}$$

  is quasilinear
- distance ratio

$$f(x) = \frac{\|x - a\|_2}{\|x - b\|_2}, \quad \operatorname{dom} f = \{x | \ \|x - a\|_2 \leq \|x - b\|_2\}$$

  is quasiconvex

internal rate of return

- cash flow $x = (x_0, \ldots, x_n)$; x_i is payment in period i (to us if $x_i > 0$)
- we assume $x_0 < 0$ and $x_0 + x_1 + \cdots + x_n > 0$
- present value of cash flow x, for interest rate r:

$$\mathrm{PV}(x, r) = \sum_{i=0}^{n} (1+r)^{-i} x_i$$

- internal rate of return is smallest interest rate for which $\mathrm{PV}(x, r) = 0$:

$$\mathrm{IRR}(x) = \inf\{r \geq 0 \mid \mathrm{PV}(x, r) = 0\}$$

IRR is quasiconcave: superlevel set is intersection of open halfspaces

$$\mathrm{IRR}(x) \geq R \quad \Longleftrightarrow \quad \sum_{i=0}^{n} (1+r)^{-i} x_i > 0 \text{ for } 0 \leq r < R$$

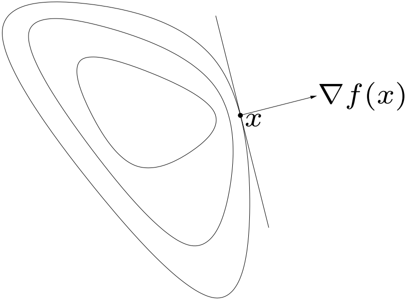
Properties

modified Jensen inequality: for quasiconvex f

$$0 \leq \theta \leq 1 \quad \Longrightarrow \quad f(\theta x + (1-\theta)y) \leq \max\{f(x), f(y)\}$$

first-order condition: differentiable f with cvx domain is quasiconvex iff

$$f(y) \leq f(x) \quad \Longrightarrow \quad \nabla f(x)^T (y - x) \leq 0$$



sums of quasiconvex functions are not necessarily quasiconvex

Log-concave and log-convex functions

a positive function f is log-concave if $\log f$ is concave:

$$f(\theta x + (1-\theta)y) \geq f(x)^{\theta} f(y)^{1-\theta} \quad \text{for } 0 \leq \theta \leq 1$$

f is log-convex if $\log f$ is convex

- powers: x^a on $\mathbb{R}_{++}$ is log-convex for $a \leq 0$, log-concave for $a \geq 0$
- many common probability densities are log-concave, $e.g.$, normal:

$$f(x) = \frac{1}{\sqrt{(2\pi)^n \det \Sigma}} e^{-\frac{1}{2}(x-\bar{x})^T \Sigma^{-1} (x-\bar{x})}$$

- cumulative Gaussian distribution function Φ is log-concave

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-u^2/2} du$$

Properties of log-concave functions

- twice differentiable f with convex domain is log-concave if and only if
$$f(x)\nabla^2 f(x) \preceq \nabla f(x)\nabla f(x)^T$$
for all $x \in \mathbf{dom}\, f$
- product of log-concave functions is log-concave
- sum of log-concave functions is not always log-concave
- integration: if $f : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}$ is log-concave, then
$$g(x) = \int f(x,y)dy$$
is log-concave (not easy to show)

consequences of integration property

- convolution $f * g$ of log-concave functions f , g is log-concave

$$(f * g)(x) = \int f(x-y)g(y)dy$$

- if $C \subseteq \mathbb{R}^n$ convex and y is a random variable with log-concave pdf then

$$f(x) = \text{prob}(x + y \in C)$$

  is log-concave

  proof: write $f(x)$ as integral of product of log-concave functions

$$f(x) = \int g(x+y)p(y)dy, \quad g(u) = \begin{cases} 1 & u \in C \\ 0 & u \notin C, \end{cases}$$

  p is pdf of y

example: yield function

$$Y(x) = \text{prob}(x + w \in S)$$

- $x \in \mathbb{R}^n$: nominal parameter values for product
- $w \in \mathbb{R}^n$: random variations of parameters in manufactured product
- S: set of acceptable values

if S is convex and w has a log-concave pdf, then

- Y is log-concave
- yield regions $\{x | Y(x) \geq \alpha\}$ are convex

Convexity with respect to generalized inequalities

$f : \mathbb{R}^n \to \mathbb{R}^m$ is K-convex if $\mathrm{dom}\, f$ is convex and

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

for $x, y \in \mathrm{dom}\, f$, $0 \le \theta \le 1$

example $f : \mathbb{S}^m \to \mathbb{S}^m$, $f(X) = X^2$ is $\mathbb{S}^m_+$-convex

proof: for fixed $z \in \mathbb{R}^m$, $z^T X^2 z = \|Xz\|_2^2$ is convex in X , $i.e.$,

$$z^T(\theta X + (1-\theta)Y)^2 z \le \theta z^T X^2 z + (1-\theta) z^T Y^2 z$$

for $X, Y \in \mathbb{S}^m$, $0 \le \theta \le 1$

therefore $(\theta X + (1-\theta)Y)^2 \preceq \theta X^2 + (1-\theta)Y^2$