

Convexity

Statistics 710

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Prologue. There are interesting statistical problems in which an unknown function f , say, is to be estimated, subject to certain shape restrictions. For example, consider a regression problem

$$y_i = f(t_i) + \epsilon_i, \quad i = 1, \dots, n,$$

where $\epsilon_1, \dots, \epsilon_n$ are random errors with means 0 and finite variances and f is known (only) to be non-decreasing, or convex, or to satisfy some other shape restriction. For example, an average response may well be increasing with time, even though individual measures may not. Global warming provides a specific example. Assuming that the error are i.i.d. for simplicity, and letting $\theta_i = f(t_i)$, least squares estimation of θ requires minimizing a function of the form

$$\sum_{i=1}^n [y_i - \theta_i]^2$$

with respect to $\theta = [\theta_1, \dots, \theta_n]'$. Let \mathcal{F} denote the class of allowable f . Then $\theta \in \Omega := \{[f(t_1), \dots, f(t_n)] : f \in \mathcal{F}\}$, and the latter set is often convex. For example, if f is known to be non-decreasing, then

$$\Omega = \{\theta : -\infty < \theta_1 \leq \dots \leq \theta_n < \infty\},$$

a convex subset of \mathbb{R}^n .

Hilbert Spaces. Let \mathcal{H} denote a (real) Hilbert space. Thus, \mathcal{H} is a linear space together with a function $\langle \cdot, \cdot \rangle \rightarrow \mathbb{R}$ for which

$$\begin{aligned} \langle x, y \rangle &= \langle y, x \rangle, \\ \langle x, \alpha y + \beta z \rangle &= \alpha \langle x, y \rangle + \beta \langle x, z \rangle \end{aligned}$$

for all $x, y, z \in \mathcal{H}$ and $\alpha, \beta \in \mathbb{R}$, and

$$\langle x, x \rangle > 0$$

for all $x \neq 0$; and the norm in \mathcal{H} is defined by

$$\|x\| = \sqrt{\langle x, x \rangle};$$

and \mathcal{H} is complete in the metric $d(x, y) = \|x - y\|$.

Example 1 a) *Euclidean Space.* $\mathcal{H} = \mathbb{R}^m$ with $\langle x, y \rangle = x'y = x_1y_1 + \cdots + x_my_m$ or, more generally, $\langle x, y \rangle = x'Ay$, where A is a symmetric, positive definite matrix.

b) *More on Euclidean Space.* \mathcal{H} be the set of $m \times m$ matrices with $\langle x, y \rangle = \text{tr}(xy')$.

c) L^2 . Let $(\Omega, \mathcal{A}, \mu)$ is a measure space; and let $L^2(\Omega, \mathcal{A}, \mu)$ be the set of (equivalence classes) of square integrable functions with

$$\langle f, g \rangle = \int fg d\mu.$$

d) *Sobolov space.* Let \mathcal{S}_2 be the set of twice differentiable functions $f : [0, 1] \rightarrow \mathbb{R}$ for which $\int_0^1 f''(x)^2 dx < \infty$, and let

$$\langle f, g \rangle = f(0)g(0) + f'(0)g'(0) + \int_0^1 f(x)g(x)dx.$$

Remarks. The primary uses of convexity will be with $\mathcal{H} = \mathbb{R}^m$, and little is lost by focussing on this case. On the other hand many of the definitions extend to (even) more general linear spaces.

Some Properties. Let \mathcal{H} is a Hilbert space. Then *Schwarz' Inequality* asserts

$$\langle x, y \rangle \leq \|x\| \times \|y\|$$

for all $x, y \in \mathcal{H}$; and the *Parallelogram Laws* assert:

$$\begin{aligned} \|x + y\|^2 + \|x - y\|^2 &= 2\|x\|^2 + 2\|y\|^2, \\ \|x + y\|^2 - \|x - y\|^2 &= 4\langle x, y \rangle \end{aligned}$$

for all $x, y \in \mathcal{H}$.

Linear Functional. A function $f : \mathcal{H} \rightarrow \mathbb{R}$ is said to be a linear functional if $f[\alpha x + \beta y] = \alpha f(x) + \beta f(y)$ whenever $x, y \in \mathcal{H}$ and $\alpha, \beta \in \mathbb{R}$. For example, if $y \in \mathcal{H}$, then

$$f(x) = \langle x, y \rangle, \quad x \in \mathcal{H} \tag{1}$$

defines a continuous linear functional, a linear functional that is continuous in the metric. It is a theorem that *any continuous linear functional can be represented in the form (1) for some $y \in \mathcal{H}$ depending on the linear functional.*

Convex Sets. Recall that a subset $\mathcal{H}_0 \subseteq \mathcal{H}$ is called a linear subspace if it is closed under addition and scalar multiplication: that is $\alpha x + \beta y \in \mathcal{H}_0$ whenever $x, y \in \mathcal{H}_0$ and $\alpha, \beta \in \mathbb{R}$. Similarly, a subset $C \subseteq \mathcal{L}$ is said to *convex* if it contains the line joining any two of its elements; that is $\alpha x + (1 - \alpha)y \in C$ whenever $x, y \in C$ and $0 \leq \alpha \leq 1$. A convex set C is said to be a *cone* if $\alpha x \in C$ whenever $x \in C$ and $\alpha \geq 0$ in which case $\alpha x + \beta y \in C$ whenever $x, y \in C$ and $0 \leq \alpha, \beta < \infty$. Any linear subspace is a convex cone. Any ball, $B = \{x \in \mathcal{H} : \|x\| \leq c\}$ is a convex set (since $\|\alpha x + (1 - \alpha)y\| \leq \alpha\|x\| + (1 - \alpha)\|y\| \leq c$ whenever $\|x\|, \|y\| \leq c$, but not a convex cone).

Example 2 If $f_i, i \in I$ are continuous linear functionals, then

$$C = \{x \in \mathcal{H} : f_i(x) \geq 0, \text{ for all } i \in I\}$$

is a convex cone.

Projections. If C is a closed convex set and $z \in \mathcal{H}$, then there is a $x \in C$ for which

$$\|x - z\| = \inf_{y \in C} \|y - z\|; \quad (2)$$

and x is the unique point in C for which

$$\langle y - x, x - z \rangle \geq 0 \quad (3)$$

for all $y \in C$. For the existence, let i denote the infimum and let $y_n \in C$ be a sequence for which $\|y_n - z\| \rightarrow i$. Then

$$\|y_n - y_m\|^2 = \|y_n - z\|^2 + \|y_m - z\|^2 - 2\langle y_n - z, y_m - z \rangle$$

and

$$\begin{aligned} 2\langle y_n - z, y_m - z \rangle &= \frac{\|y_n + y_m - 2z\|^2 - \|y_n - y_m\|^2}{2} \\ &= 2\left\| \frac{y_n + y_m}{2} - z \right\|^2 - \frac{\|y_n - y_m\|^2}{2} \end{aligned}$$

by the parallelogram law. So,

$$\begin{aligned} \frac{1}{2}\|y_n - y_m\|^2 &= \|y_n - z\|^2 + \|y_m - z\|^2 - 2\left\| \frac{y_n + y_m}{2} - z \right\|^2 \\ &\leq \|y_n - z\|^2 + \|y_m - z\|^2 - 2i^2 \\ &\rightarrow 0 \end{aligned}$$

as $m, n \rightarrow \infty$. Thus, y_n is a Cauchy sequence and, therefore, a convergent sequence. Let $x = \lim_{n \rightarrow \infty} y_n$. Then $x \in C$, since C is closed, and $\|x - z\| = \lim_{n \rightarrow \infty} \|y_n - z\| = i$. For (3): If $y \in C$ and $0 < t < 1$, then $x + t(y - x) = (1 - t)x + ty \in C$, so that

$$0 \leq \|[x + t(y - x)] - z\|^2 - \|x - z\|^2 = 2t\langle y - x, x - z \rangle + t^2\|y - x\|^2$$

and, therefore,

$$\langle y - x, x - z \rangle \geq -t\|y - x\|^2/2.$$

The inequality (3) then follows by letting $t \rightarrow 0$. Finally, it must be shown that only one $x \in C$ can satisfy (3). If x_1 and x_2 both satisfy (3), then

$$\begin{aligned}\langle x_2 - x_1, x_1 - z \rangle &\geq 0, \\ \langle x_1 - x_2, x_2 - z \rangle &\geq 0\end{aligned}$$

by setting $y = x_2$ and $y = x_1$. Adding these two inequalities then gives

$$-\|x_1 - x_2\|^2 = \langle x_1 - x_2, x_2 - x_1 \rangle \geq 0$$

and, therefore, $x_1 = x_2$. The element $x \in C$ is called *the projection of z onto C* and denoted by $\Pi_C(z)$.

If C is a convex cone, then setting $y = x/2$ and $y = 2x$ in (3) shows that $\langle x, x - z \rangle = 0$. So, x is the unique element of C for which

$$x \in C \quad \text{and} \quad \langle y, z - x \rangle = 0 \tag{4}$$

for all $y \in C$; and if C is a linear subspace, then $\pm y \in C$ whenever $y \in C$, so that (4) becomes

$$\langle x, z - x \rangle = 0 \quad \text{and} \quad \langle y, z - x \rangle \leq 0 \tag{5}$$

The Separation Theorems. For these suppose that \mathcal{H} is a finite dimensional linear space—for example, $\mathcal{H} = R^m$.

The Supporting Hyperplane Theorem: If C is a convex set and $z \notin C^\circ$, the interior of C , then there is an $0 \neq w \in \mathcal{H}$ for which

$$\langle w, y \rangle \geq \langle w, z \rangle \tag{6}$$

for all $y \in C$. Suppose first the $z \notin \bar{C}$, the closure of C , and let $x = \Pi_C(z)$ and $w = x - z$. Then, $w \neq 0$, and

$$\langle w, z \rangle - \langle w, y \rangle = \langle x - z, z - y \rangle = \langle x - z, z - x \rangle + \langle x - z, x - y \rangle \leq 0,$$

for all $y \in C$ by (3). If $z \in \bar{C} - C^\circ$, then there are $z_n \in \bar{C}'$ for which $\|z_n - z\| \rightarrow 0$ as $n \rightarrow \infty$ and $w_n \in \mathcal{H}$ for which $\|w_n\| = 1$ for all n and $\langle w_n, y \rangle \geq \langle w_n, z \rangle$ for all $y \in C$. The sequence w_n is precompact, since it is bounded; and if w denotes any limit point, then $\|w\| = 1$ and (6) holds.

The Separating Hyperplane Theorem: C_1 and C_2 are disjoint convex sets, then there is an $0 \neq w \in \mathcal{H}$ for which

$$\langle w, y_1 \rangle \geq \langle w, y_2 \rangle \quad (7)$$

for all $y_1 \in C_1$ and $y_2 \in C_2$. To see this let $C = \{y_1 - y_2 : y_1 \in C_1, y_2 \in C_2\}$. Then C is a convex set for which $0 \notin C$. So, by the Supporting Hyperplane Theorem, there is an $w \neq 0$ for which $\langle w, y \rangle \geq \langle w, 0 \rangle = 0$, and (7) follows by writing $y = y_1 - y_2$.

Problem 1 In the Supporting Hyperplane Theorem, show that if $z \notin \bar{C}$, then w may be chosen so that $\inf_{y \in C} \langle w, y \rangle > \langle w, z \rangle$.

Convex Functions. If C is a convex subset of \mathcal{H} a function $f : C \rightarrow \mathbb{R}$ is said to be convex if $f[\alpha x + (1 - \alpha)y] \leq \alpha f(x) + (1 - \alpha)f(y)$ whenever $x, y \in C$ and $0 \leq \alpha \leq 1$; and f is said to be strictly convex if there is strict inequality whenever $x \neq y$ and $0 < \alpha < 1$.

Clearly if $f : C \rightarrow \mathbb{R}$ is (strictly) convex and $C_0 \subseteq C$ is a convex subset of C , then the restriction of f to C_0 is convex. Conversely, if C is convex, $f : C \rightarrow \mathbb{R}$, and the restriction of f to every line $L(x, y) = \{\alpha x + (1 - \alpha)y : 0 \leq \alpha \leq 1\}$ is strictly convex, then f is (strictly) convex. For if $x, y \in C$ and $g(t) = f[tx + (1 - t)y]$ is convex in $0 \leq t \leq 1$, then

$$f[tx + (1 - t)y] = g(t) \leq tg(1) + (1 - t)g(0) = tf(y) + (1 - t)f(x).$$

Derivatives of Convex Functions. If $-\infty \leq a < b \leq \infty$ and $f : (a, b) \rightarrow \mathbb{R}$ is convex, then

$$-\infty < f'_\ell(y) = \lim_{x \uparrow y} \frac{f(x) - f(y)}{x - y} < \infty$$

and

$$-\infty \leq f'_r(z) = \lim_{w \downarrow z} \frac{f(w) - f(z)}{w - z} < \infty$$

exist for $a < y \leq b$ and $a \leq z < b$. f'_ℓ and f'_r are both non-decreasing, and

$$-\infty < f'_\ell(x) \leq f'_r(x) < \infty$$

for $a < x < b$. If $-\infty < a < b < \infty$ and f is convex on $[a, b]$, then $-\infty \leq f'_r(a) < \infty$ and $-\infty < f'_\ell(b) \leq \infty$ exist, possibly infinite. To see this, let $a \leq x < y < z \leq b$. Then

$$y = \frac{(z - y)x + (y - x)z}{z - x}$$

so that

$$f(y) \leq \left(\frac{z - y}{z - x} \right) f(x) + \left(\frac{y - x}{z - x} \right) f(z). \quad (8)$$

Subtracting $f(x)$ from both sides of (8) leads to

$$\frac{f(y) - f(x)}{y - x} \leq \frac{f(z) - f(x)}{z - x}. \quad (9)$$

Thus, the difference quotients $[f(y) - f(x)]/(y - x)$ are increasing in y , and

$$-\infty \leq f'_r(x) = \inf_{y>x} \frac{f(y) - f(x)}{y - x} < \infty$$

exists. The existence of f'_ℓ can be established similarly.

Next, subtracting $f(y)$ from both sides of (8) leads to

$$\frac{f(y) - f(x)}{y - x} \leq \frac{f(z) - f(y)}{z - y}, \quad (10)$$

and iterating (10),

$$\frac{f(x) - f(t)}{x - t} \leq \frac{f(y) - f(x)}{y - x} \leq \frac{f(z) - f(y)}{z - y} \leq \frac{f(w) - f(z)}{w - z} \quad (11)$$

for $a \leq t < x < y < z < w \leq b$. That $-\infty < f'_\ell(y) \leq f'_r(y) < \infty$ for $a < y < b$ follows, as does the monotonicity of f'_ℓ and f'_r .

As a consequence: *If $a < x < y$, then*

$$f(y) - f(x) = \int_x^y f'_r(w)dw; \quad (12)$$

and if $-\infty < a < b < \infty$ and f is continuous on $[a, b]$, then (12) holds also when $x = a$ or $y = b$.

Gateaux Derivatives. If $G \subseteq \mathcal{H}$, then an $x \in G$ is called an inner point iff: for every $y \in G$, $(1 - \alpha)x + \alpha y \in G$ for sufficiently small α . Any interior point is an inner point. If $f : G \rightarrow \mathbb{R}$ and x is an inner point, then f is said to have a Gateaux derivative at x if

$$df_x(y) := \lim_{t \downarrow 0} \frac{f[(1 - t)x + ty] - f(x)}{t} \quad (13)$$

exists (finite) for each $y \in G$. Then the function df_x is called the (extended) Gateaux derivative of f and x . If df_x is a continuous linear functional, then there is an element of \mathcal{H} , also denoted by df_x for which

$$df_x(y) = \langle df_x, y \rangle$$

for all $y \in \mathcal{H}$. For example, if G is an open subset of \mathbb{R}^m and $f : G \rightarrow \mathbb{R}$ is continuously differentiable, then

$$df(x; y) = \nabla f(x)'y$$

where $\nabla f(x)$ denotes the gradient,

$$\nabla f(x) = \left[\frac{\partial f}{\partial x_1}, \dots, \frac{\partial f}{\partial x_m} \right]'$$

If f has a Gateaux derivative at every $x \in C$, then f is said to be *Gateaux differentiable on C* .

Problem 2 *Suppose that C is an convex, open subset of \mathbb{R}^m and the f is twice continuously differentiable on C . Then f is convex iff*

$$\nabla^2 f(x) = \left[\frac{\partial^2 f(x)}{\partial x_j \partial x_i} : i, j = 1, \dots, m \right]$$

is non-negative definite for all $x \in C$.

If $C \subseteq \mathcal{H}$ and $f : C \rightarrow \mathbb{R}$ convex, then f has an *extended Gateaux derivative* $df_x^e : C \rightarrow \mathbb{R}$ at every $x \in C$ in the following sense: the limit in (13) exists for all y of the form $y = z - x$, where $z \in C$. For if $z \in C$, then $g(t) = f([x + t(z - x)]) = f[(1 - t)x + tz]$ is convex on $[0, 1]$ and, therefore, $g'_r(0)$ exists (possibly $-\infty$). Write

$$df_x^e(y) = \lim_{t \downarrow 0} \frac{f[x + ty] - f(x)}{t} \quad (14)$$

for $y \in C - x$. It is clear the $df_x^e(y)$ agrees with $df_x(y)$ when the latter exists.

Convex Optimization. *Let C be a convex set. Then a necessary and sufficient condition for $x^* \in C$ to minimize f is that*

$$df_{x^*}^e(y - x^*) \geq 0 \quad (15)$$

for all $y \in C$. To proof is easy. First if x^* minimizes f on C and $y \in C$, then $f[(1-t)x^* + ty] \geq f(x^*)$, so that

$$0 \leq \frac{f[x^* + t(y - x^*)] - f(x^*)}{t} \rightarrow df_{x^*}^e(y - x^*)$$

as $t \downarrow 0$. Conversely, if (15) is satisfied and $y \in C$, then $g(t) = f[(1 - t)x^* + ty]$ defines a convex function on $[0, 1]$ for which

$$g'_r(0) = df_{x^*}^e(x; y - x^*) \geq 0$$

and, therefore, $g_r(t) \geq 0$ for all $0 \leq t \leq 1$. It then follows that

$$f(y) - f(x^*) = g(1) - g(0) = \int_0^1 g'_r(t) dt \geq 0.$$

as required.

The result does not assert that the minimum is attained.

Rockafellar [2] provides a more more comprehensive account of convexity. Edwards [1] has a nice chapter on calculus in linear spaces.

References

[1] Edwards, C.H. (1973). *Advanced Calculus of Several Variables*. Academic Press.

[2] Rockafellar, R. (1970). *Convex Analysis*. Princeton.