

Modulus of smoothness

Def The *difference operator* Δ_h^r . For $h \in \mathbb{R}^d$ we define $\Delta_h(f, x) = f(x+h) - f(x)$. For general $r \geq 1$ we define

$$\Delta_h^r(f, x) = \underbrace{\Delta_h \circ \dots \circ \Delta_h}_r(f, x) = \sum_{k=0}^r \binom{r}{k} (-1)^{r-k} f(x+kh).$$

Remarks

1. For $\Omega \subset \mathbb{R}^n$, we in fact modify to $\Delta_h^r(f, x) := \Delta_h^r(f, x, \Omega)$, where $\Delta_h^r(f, x) = 0$, in the case $[x, x+rh] \not\subset \Omega$. So for $\Omega = [a, b]$, $\Delta_h^r(f, x) = 0$ on $[b-rh, b]$, for any function.
2. As an operator on $L_p(\Omega)$, $1 \leq p \leq \infty$, we have that $\|\Delta_h^r\|_{L_p \rightarrow L_p} \leq 2^r$. Assume $\Omega = \mathbb{R}^n$, then

$$\|\Delta_h^r(f, \cdot)\|_p \leq \sum_{k=0}^r \binom{r}{k} \|f(\cdot+kh)\|_p = \sum_{k=0}^r \binom{r}{k} \|f\|_p = 2^r \|f\|_p$$

Def The *modulus of smoothness* of order r of a function $f \in L_p(\Omega)$, $0 < p \leq \infty$, at the parameter $t > 0$

$$\omega_r(f, t)_p := \sup_{|h| \leq t} \|\Delta_h^r(f, x)\|_{L_p(\Omega)}.$$

For $r = 1$ the modulus of smoothness is called the *modulus of continuity*.

Properties

1. $\omega_r(f, t)_p \leq 2^r \|f\|_{L_p(\Omega)}$.
2. $\omega_r(f, t)_p$ is non-decreasing in t
3. For $1 \leq p \leq \infty$ the *sub-linearity* property

$$|\Delta_h^r(f+g, x)| \leq |\Delta_h^r(f, x)| + |\Delta_h^r(g, x)|,$$

gives

$$\omega_r(f+g, t)_p \leq \omega_r(f, t)_p + \omega_r(g, t)_p.$$

4. For $N \geq 1$, $\omega_r(f, Nt)_p \leq N^r \omega_r(f, t)_p$, $1 \leq p \leq \infty$. We prove this using the property (**assignment**)

$$\Delta_{Nh}^r(f, x) = \sum_{k_1=0}^{N-1} \dots \sum_{k_r=0}^{N-1} \Delta_h^r(f, x+k_1h+\dots+k_rh).$$

Let's see the case $r = 1$,

$$\begin{aligned}
\Delta_{Nh}(f, x) &= f(x + Nh) - f(x) \\
&= f(x + Nh) - f(x + (N-1)h) + f(x + (N-1)h) - \dots + f(x + h) - f(x) \\
&= \sum_{k=0}^{N-1} \Delta_h(f, x + kh)
\end{aligned}$$

Then, for any $h \in \mathbb{R}^n$, $|h| \leq t$

$$\begin{aligned}
\|\Delta_{Nh}^r(f, \cdot)\|_p &\leq \sum_{k_1=0}^{N-1} \dots \sum_{k_r=0}^{N-1} \|\Delta_h^r(f, \cdot + k_1h + \dots + k_rh)\|_p \\
&= \sum_{k_1=0}^{N-1} \dots \sum_{k_r=0}^{N-1} \|\Delta_h^r(f, \cdot)\|_p \leq N^r \omega_r(f, t)_p.
\end{aligned}$$

Taking supremum over all $h \in \mathbb{R}^n$, $|h| \leq t$, gives $\omega_r(f, Nt)_p \leq N^r \omega_r(f, t)_p$.

5. From (4) we get for $1 \leq p \leq \infty$,

$$\omega_r(f, \lambda t)_p \leq (\lambda + 1)^r \omega_r(f, t)_p, \quad \lambda > 0$$

proof $\omega_r(f, \lambda t)_p \leq \omega_r(f, \lfloor \lambda + 1 \rfloor t)_p \leq (\lfloor \lambda + 1 \rfloor)^r \omega_r(f, t)_p \leq (\lambda + 1)^r \omega_r(f, t)_p$.

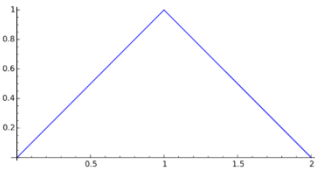
Theorem [connection between Sobolev and modulus] For $g \in W_p^r(\Omega)$, $1 \leq p \leq \infty$, we have that

$$\omega_r(g, t)_{L_p(\Omega)} \leq C(r, d) t^r |g|_{W_p^r(\Omega)}, \quad \forall t > 0.$$

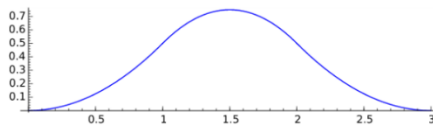
B-splines

- Definition by convolution $N_1 = \mathbf{1}_{[0,1]^n}$. In general, $N_r := N_{r-1} * N_1 = \int_{\mathbb{R}^n} N_{r-1}(x-t) N_1(t) dt$.

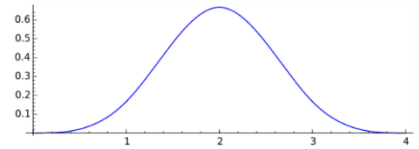
$$N_2(x) = N_1 * N_1(x) = \int_0^1 \mathbf{1}_{[0,1]}(x-t) dt = \int_{\max(x-1, 0)}^{\min(x, 1)} dt = \begin{cases} 0 & x < 0 \\ x & 0 \leq x < 1 \\ 2-x & 1 \leq x \leq 2 \\ 0 & x > 2 \end{cases}$$



N_2



N_3



N_4

- Properties:
 - Order r
 - Support $[0, r]^n$
 - Piecewise polynomial of degree $r-1$ with breakpoints (knots) at the integers

- Smoothness $r - 2$, thus in Sobolev W_p^{r-1} .
- $\int_{\mathbb{R}^n} N_r(x) dx = 1$
- Tensor-product in multivariate case

Let's see how we get the property of $\int_{\mathbb{R}^n} N_r(x) dx = 1$. Let $f, g \in L_1(\mathbb{R}^n)$ then

$$\int_{\mathbb{R}^n} f * g(x) dx = \int_{\mathbb{R}^n} f \int_{\mathbb{R}^n} g$$

Proof of Theorem ($\Omega = \mathbb{R}$). Here, we use the fact that for $h > 0$, $\Delta_{-h}^r(f, x) = \Delta_h^r(f, x - rh)$. So W.L.G, for any $0 \leq t$, we can work with $0 < h \leq t$.

Define $N_r(x, h) := h^{-1} N_r(x/h)$, $h > 0$. Let $g \in C^1(\mathbb{R})$. Then

$$\begin{aligned} h^{-1} \Delta_h(g, x) &= h^{-1} (g(x+h) - g(x)) \\ &= h^{-1} \int_x^{x+h} g'(u) du \\ &= \int_{\mathbb{R}} g'(x+u) N_1(u, h) du \end{aligned}$$

More generally, $g \in C^r(\mathbb{R})$

$$h^{-r} \Delta_h^r(g, x) = \int_{\mathbb{R}} g^{(r)}(x+u) N_r(u, h) du$$

To see that we apply induction

$$\begin{aligned} h^{-r} \Delta_h^r(g, x) &= h^{-1} h^{-(r-1)} (\Delta_h^{r-1}(g, x+h) - \Delta_h^{r-1}(g, x)) \\ &= h^{-1} \left(\int_{\mathbb{R}} g^{(r-1)}(x+h+u) N_{r-1}(u, h) du - \int_{\mathbb{R}} g^{(r-1)}(x+u) N_{r-1}(u, h) du \right) \\ &= h^{-1} \int_x^{x+h} \int_{-\infty}^{\infty} g^{(r)}(v+u) N_{r-1}(u, h) dudv \\ &= \int_{-\infty}^{\infty} N_{r-1}(u, h) \left(h^{-1} \int_x^{x+h} g^{(r)}(v+u) dv \right) du \\ &= \int_{-\infty}^{\infty} N_{r-1}(u, h) \left(\int_{-\infty}^{\infty} g^{(r)}(v+u) N_1(v-x, h) dv \right) du \\ &= \int_{-\infty}^{\infty} N_{r-1}(u, h) \left(\int_{-\infty}^{\infty} g^{(r)}(x+y) N_1(y-u, h) dy \right) du \\ &= \int_{-\infty}^{\infty} g^{(r)}(x+y) \left(\int_{-\infty}^{\infty} N_{r-1}(u, h) N_1(y-u, h) du \right) dy \\ &= \int_{-\infty}^{\infty} g^{(r)}(x+y) N_r(y, h) dy \end{aligned}$$

Now, let's see the proof for $p = 1$. Let $|h| \leq t$

$$\begin{aligned}
\int_{\mathbb{R}} |\Delta_h^r(g, x)| dx &\leq h^r \int_{\mathbb{R}} \int_{\mathbb{R}} |g^{(r)}(x+u)| |N_r(u, h)| du dx \\
&\leq h^r \int_{\mathbb{R}} |N_r(u, h)| du \int_{\mathbb{R}} |g^{(r)}(x+u)| dx \\
&\leq t^r \int_{\mathbb{R}} |g^{(r)}(x)| dx \\
&\leq t^r |g|_{W_1^r(\mathbb{R})}.
\end{aligned}$$

For general $1 \leq p < \infty$ we need Minkowski's inequality (**assignment**). It says that for measurable non-negative functions φ, ρ

$$\left\{ \int_A \left(\int_B \varphi(y) \rho(x, y) dy \right)^p dx \right\}^{1/p} \leq \int_B \varphi(y) \left(\int_A \rho(x, y)^p dx \right)^{1/p} dy$$

Or written differently

$$\left\| \int_B \varphi(y) \rho(\cdot, y) dy \right\|_{L_p(A)} \leq \int_B \varphi(y) \left\| \rho(\cdot, y) \right\|_{L_p(A)} dy$$

Using it we have

$$\begin{aligned}
\int_{\mathbb{R}} |\Delta_h^r(g, x)|^p dx &\leq h^{pr} \int_{\mathbb{R}} \left(\int_{\mathbb{R}} |g^{(r)}(x+u)| |N_r(u, h)| du \right)^p dx \\
&\leq h^{pr} \left(\int_{\mathbb{R}} |N_r(u, h)| \left\| g^{(r)}(\cdot+u) \right\|_{L_p(\mathbb{R})} du \right)^p \\
&\leq h^{pr} \left(\int_{\mathbb{R}} |N_r(u, h)| \left\| g^{(r)} \right\|_{L_p(\mathbb{R})} du \right)^p \\
&\leq t^{pr} \left\| g^{(r)} \right\|_{L_p(\mathbb{R})}^p \\
&= t^{pr} |g|_{W_p^r(\mathbb{R})}^p.
\end{aligned}$$

For a general function $g \in W_p^r(\mathbb{R})$ we use a density argument. ♦

Corollary From the theorem we get that $\Delta_h^r(P, x) = 0$ for any $P \in \Pi_{r-1}$ and therefore $\omega_r(P, t)_p = 0$.

Marchaud inequalities

We know that for any $1 \leq k < r$, $1 \leq p \leq \infty$,

$$\omega_r(f, t)_p = \sup_{|h| \leq t} \left\| \Delta_h^r(f) \right\|_p = \sup_{|h| \leq t} \left\| \Delta_h^{r-k} \Delta_h^k(f) \right\|_p \leq 2^{r-k} \sup_{|h| \leq t} \left\| \Delta_h^k(f) \right\|_p = 2^{r-k} \omega_k(f, t)_p.$$

The direct inverse cannot be true. If we take $\Omega = [a, b]$ and a polynomial $P \in \Pi_{r-1}$, then for any $h > 0$,

$$\Delta_h^r(P, x) = h^r \int_{-\infty}^{\infty} P^{(r)}(x+y) N_r(y, h) dy = 0.$$

So $\omega_r(P, t)_p = 0$, but we don't necessarily have $\omega_k(P, t)_p = 0$ for $0 \leq k < r$.

Theorem $\Omega = \mathbb{R}$. For any $1 \leq k < r$

$$\omega_k(f, t)_p \leq ct^k \int_t^\infty \frac{\omega_r(f, s)_p}{s^{k+1}} ds, \quad t > 0.$$

The K-functional

For two Banach spaces $X_1 \subset X_0$ the corresponding K-functional

$$K(f, t, X_0, X_1) := \inf_{f=f_0+f_1} \|f_0\|_{X_0} + t\|f_1\|_{X_1}$$

$$K(f, t, L_p(\Omega), W_p^r(\Omega)) := \inf_{g \in W_p^r(\Omega)} \|f - g\|_{L_p(\Omega)} + t\|g\|_{W_p^r(\Omega)}, \quad 1 \leq p \leq \infty.$$

Theorem [Equivalence of K-functional and modulus] For $\Omega \subseteq \mathbb{R}^n$ There exist $C_1, C_2 > 0$, such that for any $t > 0$

$$C_1 K_r(f, t^r)_p \leq \omega_r(f, t)_p \leq C_2 K_r(f, t^r)_p. \quad (1.1)$$

It is easy to show that C_2 depends only on r , but the constant C_1 further depends on the geometry of Ω .

Proof of the easy direction Let $f \in L_p(\Omega)$ and let $g \in W_p^r(\Omega)$. Then

$$\begin{aligned} \omega_r(f, t)_p &\leq \omega_r(f - g, t)_p + \omega_r(g, t)_p \\ &\leq 2^r \|f - g\|_{L_p(\Omega)} + C(r) t^r \|g\|_{W_p^r(\Omega)} \\ &\leq C(r) \left(\|f - g\|_{L_p(\Omega)} + t^r \|g\|_{W_p^r(\Omega)} \right) \end{aligned}$$

Taking infimum over all possible $g \in W_p^r(\Omega)$ we obtain the right hand side of (1.1). ♦

Applications of K-functionals

The K-functional appears in many applications such as denoising. Balance between approximation and smoothness.

1. Least squares of ‘soft version’

$$\min_{g \in \sum \alpha_k N_r(\cdot, k)} \|f - g\|_2^2 + t \|g^{(2)}\|_2^2.$$

2. Denoising with TV minimization

$$\min_g \|f - g\|_2 + t \|g\|_{TV}$$

Lip spaces

Def $0 < \alpha \leq 1$, $|f(x) - f(y)| \leq M|x - y|^\alpha$. $|f|_{Lip(\alpha)} := \inf M$. For $1 \leq p \leq \infty$,

$$|f|_{lip(\alpha,p)} := \sup_{t>0} t^{-\alpha} \omega_1(f,t)_p.$$

Example For $f(x) = x^\alpha$, $0 < \alpha \leq 1$, $f \in Lip(\alpha)$, $f \notin Lip(\beta)$, $\beta > \alpha$.

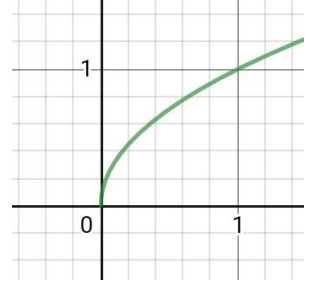
Proof

(i) Assume $f \in Lip(\beta)$, $\beta > \alpha$. Then for $0 < x \leq 1$,

$$x^\alpha - 0^\alpha = x^\alpha \leq M(x-0)^\beta = Mx^\beta \Rightarrow x^{\alpha-\beta} \leq M \Rightarrow \text{contradiction}$$

(ii) We use the inequality $(a+b)^\alpha \leq a^\alpha + b^\alpha$. Assume w.l.g $x \geq y$, we set $a = y, b = x - y$ and obtain

$$x^\alpha \leq y^\alpha + (x-y)^\alpha \Rightarrow x^\alpha - y^\alpha \leq (x-y)^\alpha.$$



However, for any $0 < \alpha \leq 1$, $f(x) = x^\alpha \in Lip(1,1)$, because

$$\begin{aligned} \int_0^1 |f'(x)| dx &= 1 \Rightarrow f' \in L_1 \\ &\Rightarrow \omega_1(f,t)_1 \leq t |f'|_1 = t \\ &\Rightarrow |f|_{Lip(1,1)} = \sup_{t>0} t^{-1} \omega_1(f,t)_1 = 1 \end{aligned}$$

Generalized Lip are a special case of Besov spaces. For any $\alpha > 0$, let $r := \lfloor \alpha \rfloor + 1$,

$$|f|_{B_{p,\infty}^\alpha} := \sup_{t>0} t^{-\alpha} \omega_r(f,t)_p.$$

Linear approximation of Lip functions

Theorem: Let $f \in Lip(\alpha)$. With the linear method of uniform piecewise constants, we have

$$E_N(f)_{L_\infty([0,1])} := \inf_{\phi \in S(N_1)^{1/N}} \|f - \phi\|_\infty \leq N^{-\alpha} |f|_{Lip(\alpha)}.$$

Proof [Classic technique] Recall that for $g \in C^1[0,1]$, we constructed $\phi_g \in S(N_1)^{1/N}$, such that

$$E_N(g)_\infty \leq \|g - \phi_g\|_\infty \leq N^{-1} |g|_{1,\infty}. \text{ Therefore,}$$

$$\begin{aligned} \|f - \phi_g\|_\infty &\leq \|f - g\|_\infty + \|g - \phi_g\|_\infty \\ &\leq \|f - g\|_\infty + N^{-1} |g|_{1,\infty} \end{aligned}$$

For a sequence $\{g_k\}$, with $K_1(f, N^{-1})_\infty = \lim_{k \rightarrow \infty} \|f - g_k\|_\infty + N^{-1} |g_k|_{1,\infty}$, we get

$$\|f - \phi_{g_k}\|_\infty \leq \|f - g_k\|_\infty + N^{-1} \|g_k\|_{1,\infty} \xrightarrow{k \rightarrow \infty} K_1(f, N^{-1})_\infty.$$

Using the equivalence of the modulus of smoothness and K-functional,

$$\begin{aligned} E_N(f)_\infty &\leq K_1(f, N^{-1})_\infty \\ &\leq \omega_1(f, N^{-1})_\infty \\ &\leq N^{-\alpha} |f|_{Lip(\alpha)}. \end{aligned}$$

Inverse Theorem: Assume $E_N(f)_\infty \leq MN^{-\alpha}$, $N \geq 1$. Then, $f \in Lip(\alpha)$.

Intuition $0 \leq y < x \leq 1$. Let $x = y + h$, $(N+1)^{-1} \leq h \leq N^{-1}$. If $x, y \in [kN^{-1}, (k+1)N^{-1}]$, then with the approximation constant approximation c_k in that interval,

$$\begin{aligned} |f(x) - f(y)| &\leq |f(x) - c_k| + |f(y) - c_k| \\ &\leq 2MN^{-\alpha} \\ &\leq 2M|x - y|^\alpha \end{aligned}$$

However, since they might not fall in the same interval, there is a mixing argument.

So linear approximation is kind of limited when α is small. The problem is that we're not spending enough 'budget' in the vicinity of zero.

Adaptive / Nonlinear / Sparse approximation

Remark This is the univariate version of the ML decision trees and random forests we will review later

Denote

$$\Sigma_N := \left\{ \sum_{j=0}^{N-1} c_j \mathbf{1}_{[t_j, t_{j+1})} : T = \{t_j\}, 0 = t_0 < t_1 < \dots < t_N = 1 \right\}, \quad \sigma_N(f)_\infty := \inf_{g \in \Sigma_N} \|f - g\|_\infty,$$

$$Var(f) := \sup_T \left\{ \sum |f(t_{j+1}) - f(t_j)| \right\}.$$

If f' exists a.e., $Var(f) = \|f'\|_1$. Why?

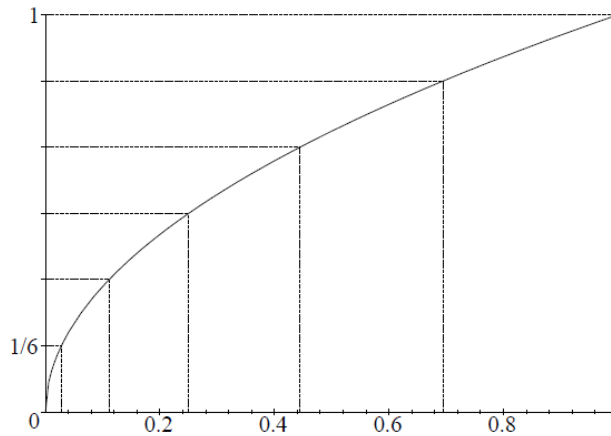
$$\int_0^1 |f'(x)| dx = \lim_{h \rightarrow 0} \sum_k h \frac{|f((k+1)h) - f(kh)|}{h}.$$

Let's go back to the examples $f(x) = x^\alpha$. In our case $\|f'\|_1 = Var(f) = 1$.

Now create a partition where $Var_{[t_j, t_{j+1}]}(f) \leq \frac{Var(f)}{N}$. If a_j is the median value in $[t_j, t_{j+1}]$, then

$|f(x) - a_j| \leq \frac{\text{Var}(f)}{2N}$, $\forall x \in [t_j, t_{j+1}]$. This gives a free knot spline $g \in \Sigma_N$ with

$$\|f - g\|_\infty \leq \frac{\text{Var}(f)}{2N} \leq \frac{1}{2N}, \quad f(x) = x^\alpha, \quad 0 < \alpha \leq 1.$$



In our example, to obtain an equidistant partition of the range, we choose $t_j = \left(\frac{j}{N}\right)^{1/\alpha}$.

So we see the advantage of nonlinear approximation for the family $f(x) = x^\alpha$, $0 < \alpha < 1$,

$$E_N(f) \sim N^{-\alpha}, \quad \sigma_N(f) \sim N^{-1}.$$