

Nonlinear and Adaptive Approximation  
Foundations and Algorithms

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## Agenda

- I. Motivation and basic examples
- II. Wavelet bases, smoothness spaces, thresholding
- III. Isotropic and anisotropic adaptive finite elements

## Basic references

Ron DeVore, “Nonlinear approximation”, Acta Numerica, 1998.

Albert Cohen, “Numerical analysis of wavelet methods”, Elsevier North-Holland , 2003.

## Central problem in approximation theory

- $X$  normed space.
- $(\Sigma_N)_{N \geq 0} \subset X$  approximation subspaces ( $g \in \Sigma_N$  described by  $N$  or  $\mathcal{O}(N)$  parameters).
- Best approximation error  $\sigma_N(f) := \inf_{g \in \Sigma_N} \|f - g\|_X$ .

Problem 1: **characterise** those functions in  $f \in X$  having a certain rate of approximation

$$f \in X^r \Leftrightarrow \sigma_N(f) \lesssim N^{-r}$$

Here  $A \lesssim B$  means that  $A \leq CB$ , where the constant  $C$  is independent of the parameters defining  $A$  and  $B$ .

## Examples

**Linear approximation:**  $\Sigma_N$  space of dimension  $\mathcal{O}(N)$

- $\Sigma_N := \Pi_N$  polynomials of degree  $N$  in dimension 1
- $\Sigma_N := \{f \in C^r([0, 1]) ; f|_{[\frac{k}{N}, \frac{k+1}{N}]} \in \Pi_m, k = 0, \dots, N-1\}$  with  $0 \leq r \leq m$  fixed, splines with uniform knots.
- $\Sigma_N := \text{Vect}(e_1, \dots, e_N)$  with  $(e_k)_{k>0}$  a functional basis.

**Nonlinear approximation:**  $\Sigma_N + \Sigma_N \neq \Sigma_N$

- $\Sigma_N := \{\frac{p}{q}, p, q \in \Pi_N\}$  rational fractions
- $\Sigma_N := \{f \in C^r([0, 1]) ; f|_{[x_k, x_{k+1}]} \in \Pi_m, 0 = x_0 < \dots < x_N = 1\}$  with  $0 \leq r \leq m$  fixed, free knots splines.
- $\Sigma_N := \{\sum_{\lambda \in E} d_\lambda \psi_\lambda ; \#(E) \leq N\}$  set of all  $N$ -terms combination of a basis  $(\psi_\lambda)$ .

## Central problem in computational approximation

Problem 2: **practical realization** of  $f \mapsto f_N \in \Sigma_N$  such that

$$\|f - f_N\|_X \lesssim \sigma_N(f).$$

If  $\Sigma_N$  are linear spaces and  $P_N : X \rightarrow \Sigma_N$  are uniformly bounded projectors  $\|P_N\|_{X \rightarrow X} \leq C$ , then  $f_N := P_N f$  is a good choice, since for all  $g \in \Sigma_N$ ,

$$\begin{aligned} \|f - f_N\|_X &\leq \|f - g\|_X + \|g - f_N\|_X \\ &= \|f - g\|_X + \|P_N(g - f)\|_X \\ &\leq (1 + C)\|g - f\|_X, \end{aligned}$$

and therefore  $\|f - f_N\|_X \leq (1 + C)\sigma_N(f)$ .

**What about nonlinear spaces ?**

## Application 1: signal and image compression



Less information is needed in the homogeneous regions, more information is needed near the edges.

State of the art techniques: combine adaptive discretizations based on **wavelets** and appropriate **encoding strategies**.

## Application 2: statistical learning theory

Given a set of data  $(x_i, y_i)$ ,  $i = 1, 2, \dots, m$ , drawn independently according to a probability law, build a function  $f$  such that  $|f(x) - y|$  is small in the average ( $E(|f(x) - y|^2)$  as small as possible).

**Difficulty:** build the adaptive grid from **uncertain data**, update it as more and more samples are received.

## Application 3: adaptive numerical simulation of PDE's

Computing on a non-uniform grid is justified for solutions which displays isolated singularities (shocks).

**Difficulty:** the solution  $f$  is **unknown**. Build the grid which is best adapted to the solution. Use **a-posteriori** information, gained throughout the numerical computation.

## A basic example

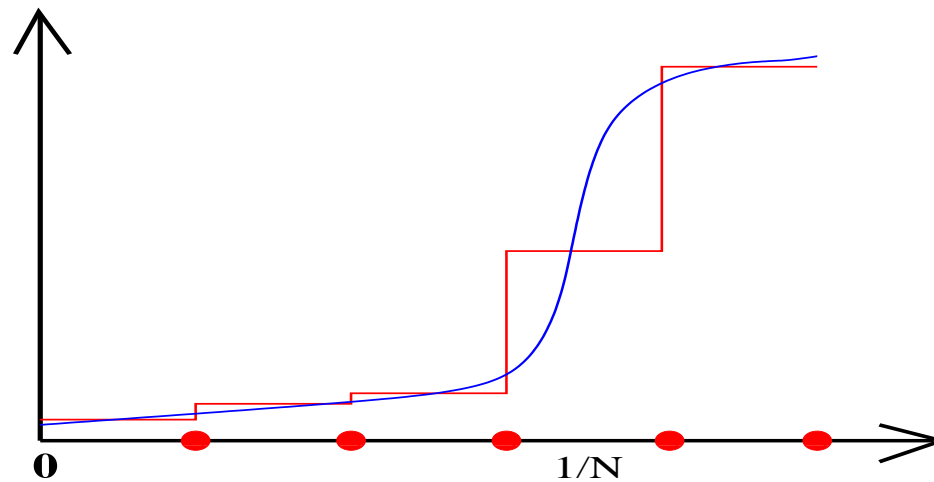
Approximation of  $f \in C([0, 1])$  by piecewise constant functions on a partition  $I_1, \dots, I_N$ , defining

$$f_N(x) = a_k := |I_k|^{-1} \int_{I_k} f, \quad \text{if } x \in I_k.$$

Local error:  $\|f - a_k\|_{L^\infty(I_k)} \leq \max_{x,y \in I_k} |f(x) - f(y)|$

**Linear case:**  $I_k = [\frac{k}{N}, \frac{k+1}{N}]$  uniform partition.

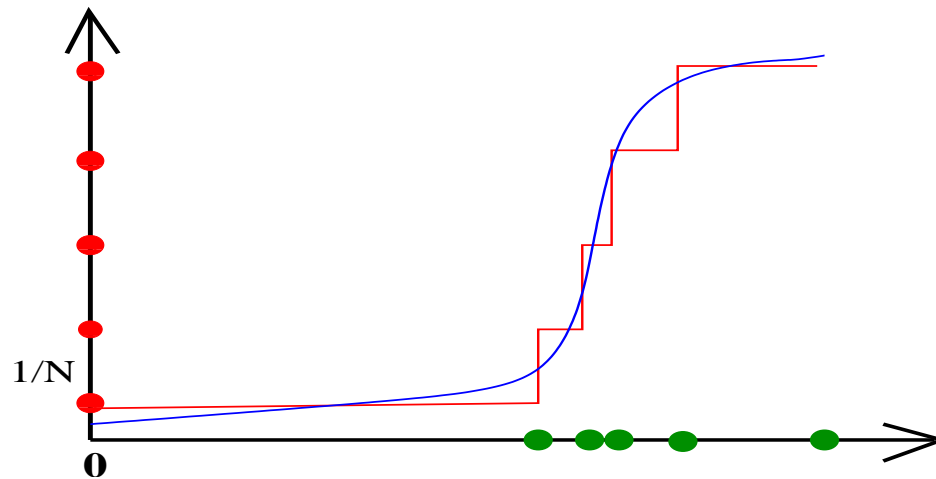
$$f' \in L^\infty \Leftrightarrow \|f - f_N\|_{L^\infty} \leq CN^{-1} \quad (C = \sup |f'|).$$





**Nonlinear case:**  $I_k$  free partition. If  $f' \in L^1$ , choose the partition such that equilibrates the total variation  $\int_{I_k} |f'| = N^{-1} \int_0^1 |f'|$ .

$$f' \in L^1 \Leftrightarrow \|f - f_N\|_{L^\infty} \leq CN^{-1} \quad (C = \int_0^1 |f'|).$$



**Approximation rate governed by different smoothness spaces !**

**Example:**  $f(t) = t^\alpha$  with  $0 < \alpha < 1$ , then  $f'(t) = \alpha t^{\alpha-1}$  is in  $L^1$ , not in  $L^\infty$ . Nonlinear approximation rate  $N^{-1}$  outperforms linear approximation rate  $N^{-\alpha}$ .

## Towards an algorithm: equilibrating the error

Fix a tolerance  $\varepsilon > 0$  and build a partition  $I_1, \dots, I_N$  such that

$$\varepsilon/2 \leq \|f - a_k\|_{L^\infty(I_k)} \leq \varepsilon.$$

Thus  $\|f - f_N\|_{L^\infty} \leq \varepsilon$ . If in addition  $f' \in L^1$ , then

$$\int |f'| \geq \sum_{k=1}^N \int_{I_k} |f'| \geq \sum_{k=1}^N \|f - a_k\|_{L^\infty(I_k)} \geq N\varepsilon/2,$$

and therefore

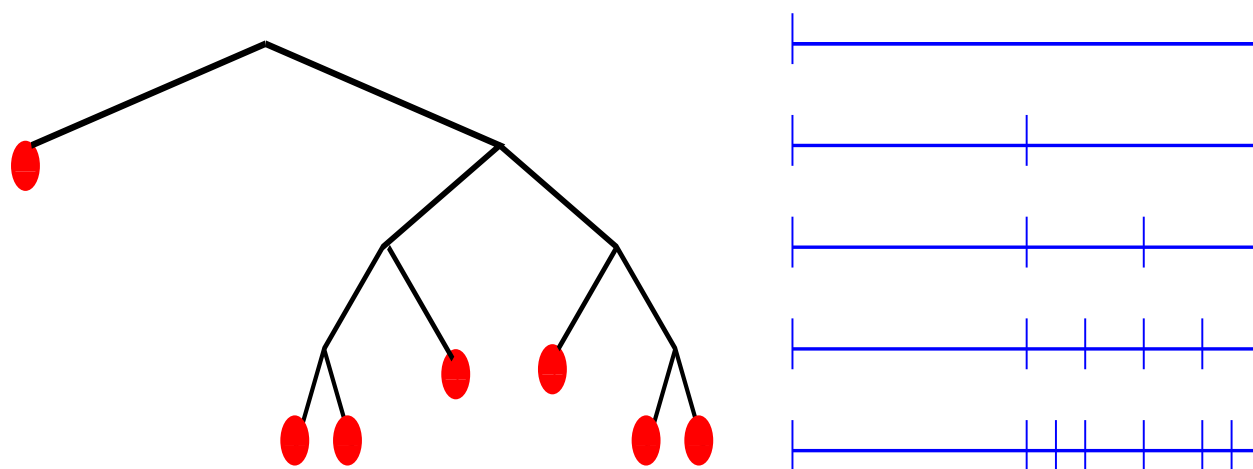
$$\|f - f_N\|_{L^\infty} \leq \varepsilon \leq 2CN^{-1},$$

with  $C = \int_0^1 |f'|$ .

Can we achieve this in practice by a simple algorithm ?

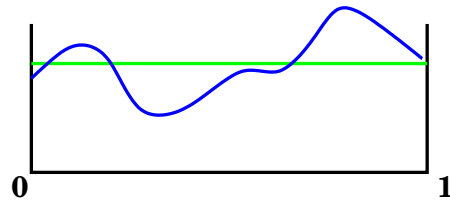
## Adaptive greedy splitting

Split intervals  $I$  into two equal parts as long as  $\|f - a_I\|_{L^\infty(I)} > \varepsilon$ , the final adaptive partition is built when  $\|f - a_I\|_{L^\infty(I)} \leq \varepsilon$  holds for all intervals (leaves of the decision tree).

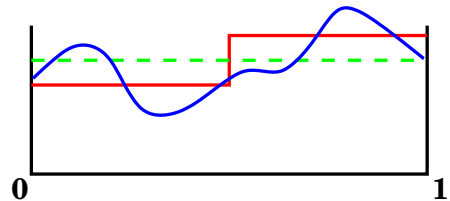
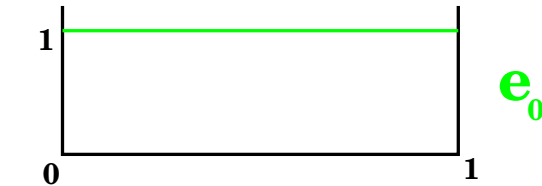


Limitation to **dyadic intervals**. In turn  $f' \in L^1$  is not sufficient to ensure that  $\|f - f_N\|_{L^\infty} \lesssim N^{-1}$ , but it can be shown that a slightly stronger condition ( $f' \in L(\log L)$  or  $L^p$  for any  $p > 1$ ) suffices.

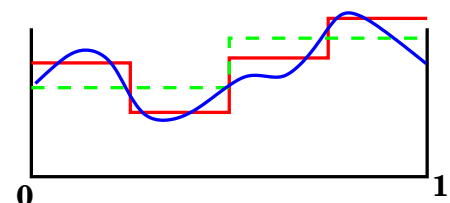
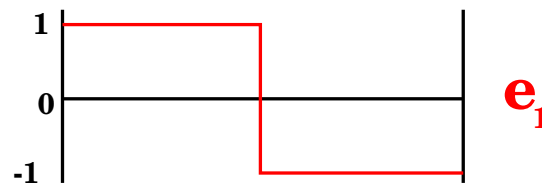
## Multiscale decompositions into wavelet bases: the Haar system



$$\mathbf{f} = \langle \mathbf{f}, \mathbf{e}_0 \rangle \mathbf{e}_0$$



$$+ \langle \mathbf{f}, \mathbf{e}_1 \rangle \mathbf{e}_1$$



$$+ \langle \mathbf{f}, \mathbf{e}_2 \rangle \mathbf{e}_2 + \langle \mathbf{f}, \mathbf{e}_3 \rangle \mathbf{e}_3$$

$$\dots = \sum_{\lambda} \mathbf{f}_{\lambda} \Psi_{\lambda}$$

$$\mathbf{f}_{\lambda} := \langle \mathbf{f}, \Psi_{\lambda} \rangle$$

$$\psi_{\lambda}(x) := 2^{j/2} \psi(2^j x - k), \quad \lambda = (j, k), \quad j \geq 0, \quad k \in \mathbb{Z}, \quad |\lambda| = j = j(\lambda).$$

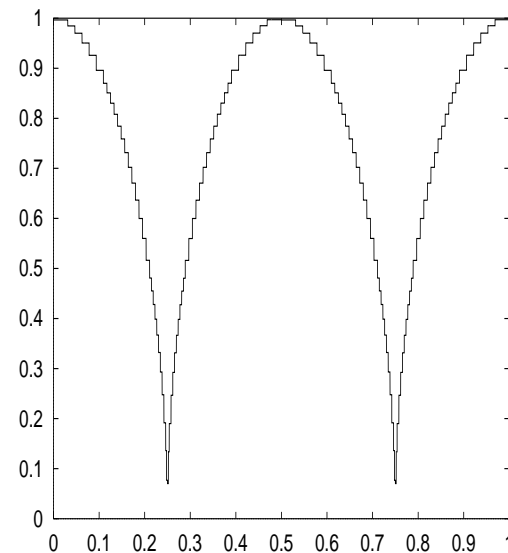
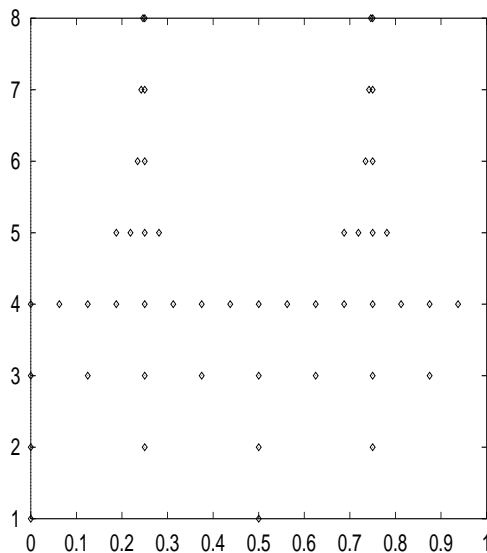
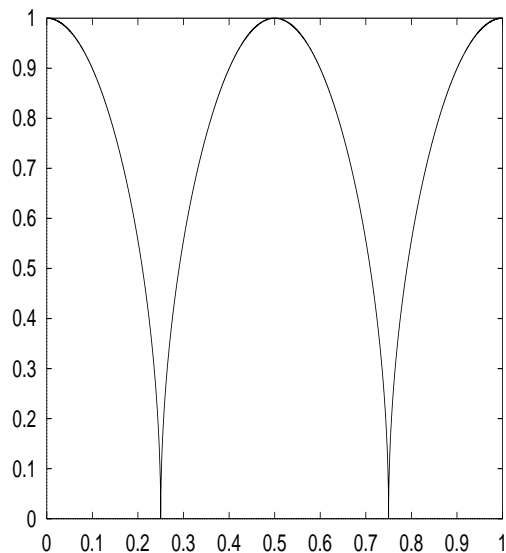
More general wavelets are constructed from similar multiscale approximation processes, using **smoother functions** such as splines, finite elements... In  $d$  dimension  $\psi_{\lambda}(x) := 2^{dj/2} \psi(2^j x - k)$ ,  $k \in \mathbb{Z}^d$ .

## Approximating functions by wavelet bases

- **Linear (uniform) approximation** at resolution level  $j$  by taking the truncated sum  $f \mapsto P_j f := \sum_{|\lambda| < j} f_\lambda \psi_\lambda$ .

- **Nonlinear (adaptive) approximation** obtained by **thresholding**

$$f \mapsto \mathcal{T}_\Lambda f := \sum_{\lambda \in \Lambda} f_\lambda \psi_\lambda, \quad \Lambda = \Lambda(\eta) = \{\lambda \text{ s.t. } |f_\lambda| \geq \eta\}.$$



## Wavelet thresholding applied to an image

Decomposition and reconstruction with 4096 largest coefficients.



Sparse representations (significant coefficients concentrated near the edges)  $\Rightarrow$  adaptive approximation by thresholding. Results in important applications in image processing (compression, denoising).

## Wavelet analysis of local smoothness

- If  $f$  is bounded on  $S_\lambda := \text{Supp}(\psi_\lambda)$ , an obvious estimate is

$$|f_\lambda| = |\langle f, \psi_\lambda \rangle| \leq \sup_{t \in S_\lambda} |f(t)| \int |\psi_\lambda| = 2^{-|\lambda|/2} \sup_{t \in S_\lambda} |f(t)|.$$

- If  $f$  is  $C^1$  on  $S_\lambda$ , a finer estimate is

$$\begin{aligned} |f_\lambda| &= \inf_{c \in \mathbb{R}} |\langle f - c, \psi_\lambda \rangle| \\ &\leq \inf_{c \in \mathbb{R}} \|f - c\|_{L^\infty(S_\lambda)} \|\psi_\lambda\|_{L^1} \\ &\leq 2^{-3|\lambda|/2} \sup_{t \in S_\lambda} |f'(t)|. \end{aligned}$$

- If  $f$  is Hölder continuous of exponent  $\alpha$  on  $S_\lambda$ , i.e.

$|f(x) - f(y)| \leq C|x - y|^\alpha$ , for some  $\alpha \in (0, 1]$ , we have the intermediate estimate  $|f_\lambda| \leq C2^{-|\lambda|(\alpha+1/2)}$ .

Decay of wavelet coefficients influenced by **local smoothness**.

## Fourier analysis of global smoothness

Decomposition of a (1-periodic) function in Fourier series

$$f(t) = \sum_{n \in \mathbb{Z}} c_n(f) e^{i2\pi nt}, \text{ with } c_n(f) := \int_0^1 f(t) e^{-i2\pi nt} dt.$$

If  $f, f', \dots, f^{(m)}$  are continuous over  $\mathbb{R}$ , we can apply  $n$  times the integration by part to obtain

$$\begin{aligned} |c_n(f)| &= |(i2\pi n)^{-1} c_n(f')| \\ &= \dots |(i2\pi n)^{-m} c_n(f^{(m)})| \\ &\leq |i2\pi n|^{-m} \int_0^1 |f^{(m)}| \lesssim n^{-m}. \end{aligned}$$

$\Rightarrow$  Fast decay if  $f$  is **smooth**.

However, if  $f$  is smooth everywhere except at some discontinuity point  $x \in [0, 1]$ , we cannot hope better than  $|c_n(f)| \lesssim n^{-1}$

Decay of Fourier coefficients influenced by **global smoothness**.

Wavelet representations are thus more appropriate for piecewise smooth functions.



## Summary

- Adaptive methods relate to nonlinear approximation
- Adaptive partitions requires less smoothness than uniform partitions for a given convergence rate
- Adaptive splitting algorithm: aims to equilibrate the local error
- Wavelet thresholding builds an adaptive partition
- Thresholding might not be effective in other bases

## A general framework for wavelet bases

Mallat and Meyer (1986): a **multiresolution approximation (MRA)** is a sequence of nested spaces  $V_j \subset V_{j+1} \subset \dots$  of  $L^2(\mathbb{R}^d)$ , such that:

- $\overline{\cup V_j} = L^2$ , i.e.  $\lim_{j \rightarrow +\infty} \|f - P_j f\|_{L^2} = 0$  for all  $f \in L^2$  where  $P_j$  is the  $L^2$ -orthogonal projector.
- There exists a **scaling function**  $\varphi \in V_0$  such that

$$\varphi_{j,k}(t) = 2^{j/2} \varphi(2^j t - k), \quad k \in \mathbb{Z}^d,$$

constitute a **Riesz basis** of  $V_j$  (Riesz basis in Hilbert spaces: basis  $(e_n)$  such that  $\|(x_n)\|_{\ell^2} \sim \|\sum x_n e_n\|_H$ ).

For piecewise constant functions we had  $\varphi = \chi_{[0,1]}$ . In this case

$$\|f - P_j f\|_{L^p} \leq 2^{-j} \|f'\|_{L^p},$$

but no better rate such as  $2^{-mj} \|f^{(m)}\|_p$  (first order accuracy).

Raising the accuracy:  $V_j$  should contain higher order polynomials.

Example : B-spline of degree  $N$

$$\varphi(x) = \chi_{[0,1]} * \cdots * \chi_{[0,1]} = (*)^{N+1} \chi_{[0,1]},$$

Remark: except for  $N = 0$ , the functions  $\varphi_{j,k}$  are **not orthogonal**.

In turn the orthogonal projector  $P_j$  is **not local**. New difficulties:

- Define numerically simple projectors  $P_j$  onto  $V_j$ .
- Construct wavelet bases  $(\psi_\lambda)$  which characterize the difference between two successive levels of projection so that

$$f = P_0 f + \sum_{j \geq 0} Q_j f, \quad Q_j f := P_{j+1} f - P_j f = \sum_{|\lambda|=j} f_\lambda \psi_\lambda$$

Recall that  $\psi_\lambda(x) = 2^{dj/2} \psi(2^j x - k)$  and  $|\lambda| := j$  when  $\lambda = (j, k)$ .

Several approaches: orthogonal wavelets, biorthogonal wavelets, finite element wavelets...

## Wavelet characterizations of functions spaces

Let  $f = \sum f_\lambda \psi_\lambda$ ,  $f_\lambda = \langle f, \tilde{\psi}_\lambda \rangle$ .

-  $L^2$  characterized by  $\|f\|_{L^2}^2 \sim \|P_0 f\|_{L^2}^2 + \sum_{j \geq 0} \|Q_j f\|_{L^2}^2 \sim \sum |f_\lambda|^2$ .

- Sobolev space  $H^t = W^{t,2}$  characterized by

$$\|f\|_{H^t}^2 \sim \|P_0 f\|_{L^2}^2 + \sum_{j \geq 0} 2^{2tj} \|Q_j f\|_{L^2}^2 \sim \sum 2^{2t|\lambda|} |f_\lambda|^2 \sim \sum \|f_\lambda \psi_\lambda\|_{H^t}^2.$$

**Hints:** (i)  $\psi_\lambda^{(t)}(x) = 2^{t|\lambda|} (\psi^{(t)})_\lambda(x)$ , (ii)  $\|f\|_{H^t}^2 \sim \int (1 + |\omega|^{2t}) |\hat{f}(\omega)|^2$

- Besov-Sobolev space  $B_{p,p}^t$  characterized by

$$\begin{aligned} \|f\|_{B_{p,p}^t}^p &\sim \|P_0 f\|_{L^p}^p + \sum_{j \geq 0} 2^{ptj} \|Q_j f\|_{L^p}^p \sim \sum 2^{pt|\lambda|} \|f_\lambda \psi_\lambda\|_{L^p}^p \\ &\sim \sum 2^{pt|\lambda|} 2^{pd(1/2-1/p)|\lambda|} |f_\lambda|^p \sim \sum \|f_\lambda \psi_\lambda\|_{B_{p,p}^t}^p. \end{aligned}$$

Remark:  $B_{p,p}^t = W^{t,p}$  if  $t \notin \mathbb{N}$  or  $p = 2$  and  $B_{\infty,\infty}^t = C^t$  if  $t \notin \mathbb{N}$ .

All this holds **provided that  $\psi_\lambda$  has enough smoothness**

## Linear multiscale approximation

From the characterization of  $H^t$ , we get  $\|Q_j f\|_{L^2} \lesssim 2^{-jt} \|f\|_{H^t}$  and therefore

$$f \in H^t \Rightarrow \|f - P_j f\|_{L^2} \leq \sum_{l \geq j} \|Q_l f\|_{L^2} \lesssim 2^{-tj}.$$

and in a similar manner

$$f \in W^{t,p} \Rightarrow \|f - P_j f\|_{L^p} \lesssim 2^{-tj}.$$

We actually have a finer result

$$f \in B_{p,q}^t \Leftrightarrow (2^{tj} \|f - P_j f\|_{L^p})_{j \geq 0} \in \ell^q.$$

Besov spaces are thus **characterized** from the rate of linear multiscale approximation.

These results are very similar to (uniform) finite element approximation since  $V_j \sim V_h$  with  $h \sim 2^{-j}$ .

## Finite element approximation results

- $V_h$ : finite element space based on a uniform discretization of a domain  $\Omega \subset \mathbb{R}^d$  with mesh size  $h$ .
- $N := \dim(V_h) \sim \text{vol}(\Omega)h^{-d}$
- $W^{s,p} := \{f \in L^p(\Omega) \text{ s.t. } D^\alpha f \in L^p(\Omega), |\alpha| \leq s\}$

Classical finite element approximation theory (Bramble-Hilbert, Ciarlet-Raviart, Deny-Lions, Strang-Fix): provides with the classical estimate

$$f \in W^{s+t,p} \Rightarrow \inf_{g \in V_h} \|f - g\|_{W^{s,p}} \leq Ch^t \sim CN^{-t/d},$$

assuming that  $V_h$  has enough polynomial reproduction and is contained in  $W^{s,p}$ .

Measuring sparsity in a representation  $f = \sum f_\lambda \psi_\lambda$

**Intuition:** the number of coefficients above a threshold  $\eta$  should not grow too fast as  $\eta \rightarrow 0$ .

**Weak spaces:**  $(f_\lambda) \in w\ell^p$  if and only if

$$\text{Card}\{\lambda \text{ s.t. } |f_\lambda| > \eta\} \leq C\eta^{-p},$$

or equivalently, the decreasing rearrangement  $(f_n^*)_{n>0}$  of  $(|f_\lambda|)$  satisfies

$$f_n^* \leq Cn^{-1/p}.$$

The representation is **sparser** as  $p \rightarrow 0$ . If  $p < 2$  and  $(\psi_\lambda)$  is an orthonormal basis, an equivalent statement is in terms of **best**

**$N$ -term approximation:** if  $f_N := \sum_{N \text{ largest } |f_\lambda|} f_\lambda \psi_\lambda$ , then

$$\|f - f_N\|_{L^2} = \left[ \sum_{n \geq N} |f_n^*|^2 \right]^{1/2} \lesssim N^{-s}, \quad 1/p = s + 1/2.$$

## Nonlinear wavelet approximation in $L^2$

Recall that  $B_{p,p}^t$  is characterized by

$$\|f\|_{B_{p,p}^t}^p \sim \sum 2^{pt|\lambda|} 2^{pd(1/2-1/p)|\lambda|} |f_\lambda|^p$$

Assume that  $f \in B_{p,p}^t$  with  $1/p = 1/2 + t/d$ . In this case

$$\|f\|_{B_{p,p}^t} \sim \|(f_\lambda)\|_{\ell^p},$$

and therefore  $(f_\lambda) \in w\ell^p$ . If  $f_N := \sum_{N \text{ largest } |f_\lambda|} f_\lambda \psi_\lambda$ , we have

$$\|f - f_N\|_{L^2} \lesssim N^{-t/d}.$$

For linear approximation, the same rate is achieved under the stronger condition  $f \in H^t$ .



## Nonlinear approximation results

$N$ -terms approximations:  $\Sigma_N := \{\sum_{\lambda \in \Lambda} d_\lambda \psi_\lambda ; \#(\Lambda) \leq N\}$ .

- Rate of decay governed by **weaker smoothness conditions** ( DeVore): with  $1/q = 1/p + t/d$

$$f \in W^{s+t,q} \Rightarrow \inf_{g \in \Sigma_N} \|f - g\|_{W^{s,p}} \leq CN^{-t/d},$$

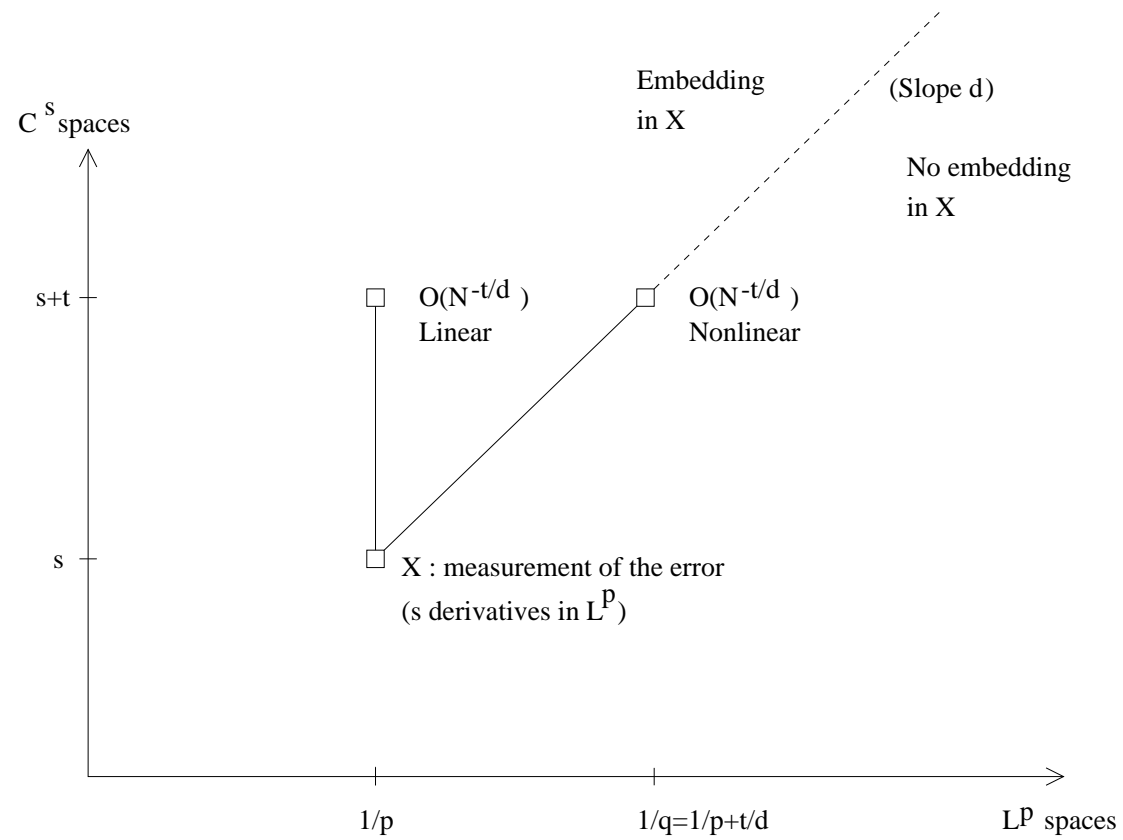
- For most error norm  $X$  (e.g.  $L^p$ ,  $W^{s,p}$ ,  $B_{p,q}^s$ ), a near optimal approximation is obtained by **thresholding**: if  $f = \sum_\lambda f_\lambda \psi_\lambda$ , and  $f_N := \sum_{N \text{ largest } \|f_\lambda \psi_\lambda\|_X} f_\lambda \psi_\lambda$ , we then have

$$\|f - f_N\|_X \leq C \inf_{g \in \Sigma_N} \|f - g\|_X$$

with  $C$  independent of  $f$  and  $N$ .

- Remark: similar theory for adaptive finite element on  $N$  triangles with isotropy constraints (minimal angle condition).

## Pictorial interpretation of approximation results



## Greedy bases

Let  $(\psi_\lambda)$  be a basis in a Banach space  $X$  with  $\|\psi_\lambda\|_X = 1$  for all  $\lambda$ .

The basis is **greedy** if and only if for all  $f \in X$  and  $N > 0$ ,

$$\|f - \sum_{N \text{ largest } |f_\lambda|} f_\lambda \psi_\lambda\|_X \leq C \inf_{g \in \Sigma_N} \|f - g\|_X.$$

The basis is **unconditional** if and only if there exists  $C > 0$  such that

$$|x_\lambda| \leq |y_\lambda| \text{ for all } \lambda \Rightarrow \left\| \sum x_\lambda \psi_\lambda \right\|_X \leq C \left\| \sum y_\lambda \psi_\lambda \right\|_X.$$

The basis is **democratic** if and only if there exists  $C > 0$  such that

$$\#(E) = \#(F) \Rightarrow \left\| \sum_{\lambda \in E} \psi_\lambda \right\|_X \leq C \left\| \sum_{\lambda \in F} \psi_\lambda \right\|_X.$$

Two results due to Temlyakov:

1. Greedy  $\Leftrightarrow$  unconditional and democratic.
2. Wavelet are democratic in  $L^p$  and  $W^{m,p}$  when  $1 < p < +\infty$ .

## General program for PDE's

- **Theoretical:** revisit **regularity theory for PDE's**. Solutions of certain PDE's might have substantially higher regularity in the scale governing nonlinear approximation than in the scale governing linear approximation. Examples : hyperbolic conservation laws (DeVore and Lucier 1987), elliptic problems on corner domains (Dahlke and DeVore, 1997).
  - **Numerical:** develop for the unknown  $u$  of the PDE  $\mathcal{F}(u) = 0$  appropriate **adaptive resolution strategies** which perform essentially as well as thresholding : produce  $\tilde{u}_N$  with  $N$  terms such that  $\|u - \tilde{u}_N\|$  has the same rate of decay  $N^{-s}$  as  $\|u - u_N\|$  in some prescribed norm, if possible in  $\mathcal{O}(N)$  computation.
- Remark:** similar goals can be formulated for **adaptive finite elements** with  $N$  being the number of elements.

## Adaptive finite element approximation theory

In all the following we will work with the error metric

$$X = L^p(\Omega).$$

For simplicity we take

$$\Omega = [0, 1]^2,$$

and we only work with piecewise affine finite elements.

We want to discuss the differences in approximation capabilities between :

- (i) Uniform and isotropic (shape regular) triangulations
- (ii) Adaptive and isotropic triangulations
- (iii) Adaptive and anisotropic triangulations

## Uniform and isotropic triangulations

If  $(\mathcal{T}_h)_{h>0}$  is a family of uniform and isotropic triangulations, and  $V_h$  the corresponding piecewise affine finite element space, then

$$f \in W^{s,p} \Rightarrow \inf_{f_h \in V_h} \|f - f_h\|_{L^p} \leq Ch^{\min\{s,2\}} |f|_{W^{s,p}}.$$

Since  $N = \#(\mathcal{T}_h) \sim h^{-2}$ , this gives the convergence rate  $N^{-\frac{\min\{s,2\}}{2}}$ .

In particular

$$f \in W^{2,p} \Rightarrow \|f - f_N\|_{L^p} \leq CN^{-1} |f|_{W^{2,p}},$$

and

$$f \in C^2 \Rightarrow \|f - f_N\|_{L^\infty} \leq CN^{-1} |f|_{C^2}.$$

Remark : almost an “if and only if” result (one needs  $B_{p,\infty}^s$  in place of  $W^{s,p}$ )

## Adaptive and isotropic triangulations

Consider here  $X = L^\infty$ . If  $R$  is a reference triangle and  $I_R$  the interpolation operator, we have by Sobolev imbedding,

$$\|f - I_R f\|_{L^\infty(R)} \lesssim \|f - I_R f\|_{W^{2,1}(R)},$$

and this by Bramble-Hilbert lemma

$$\|f - I_R f\|_{L^\infty(R)} \lesssim |f|_{W^{2,1}(R)}.$$

The constant in this estimate is invariant by isotropic scaling : for any isotropic triangle  $T$

$$\|f - I_T f\|_{L^\infty(T)} \leq C |f|_{W^{2,1}(T)}.$$

Given  $f \in C(\Omega)$ , assume that for any prescribed  $\varepsilon > 0$ , we can find a triangulation  $\mathcal{T}_N$ , with  $N = \#(\mathcal{T}_N) = N(\varepsilon)$  such that the local error is equidistributed in the sense that

$$\varepsilon/2 \leq \|f - I_T f\|_{L^\infty(T)} \leq \varepsilon, \quad T \in \mathcal{T}_N.$$

Then obviously  $\|f - f_N\|_{L^\infty} \leq \varepsilon$ . Moreover if  $f \in W^{2,1}$ , we have

$$N\varepsilon/2 \leq \sum_{T \in \mathcal{T}_N} \|f - I_T f\|_{L^\infty(T)} \leq C \sum_{T \in \mathcal{T}_N} |f|_{W^{2,1}(T)} = C|f|_{W^{2,1}},$$

and therefore

$$f \in W^{2,1} \Rightarrow \|f - f_N\|_{L^\infty} \leq CN^{-1}|f|_{W^{2,1}}.$$

The rate of smoothness  $N^{-1}$  is governed by weaker smoothness condition than for uniform partition.

For  $X = L^p$  : equidistributing the local  $L^p$  error yields

$$f \in W^{2,q} \Rightarrow \|f - f_N\|_{L^p} \leq CN^{-1}|f|_{W^{2,q}}, \quad 1/q = 1/p + 1.$$



## A greedy approach to error equidistribution

- 1) Given  $f \in L^p$  and some prescribed  $\varepsilon > 0$ , we start from an initial coarse triangulation  $\mathcal{T}_2$  (split  $\Omega$  into two triangles).
- 2) Given  $\mathcal{T}_k$  we consider the triangle  $T$  where the error  $\|f - f_k\|_{L^p(T)}$  is maximal. If it is larger than  $\varepsilon$ , then split  $T$  into four sub-triangles of similar shape using the three midpoints. This gives a new (generally non-conforming) triangulation  $\mathcal{T}_{k+3}$ .
- 3) Stop when all triangles have local error less than  $\varepsilon$ .

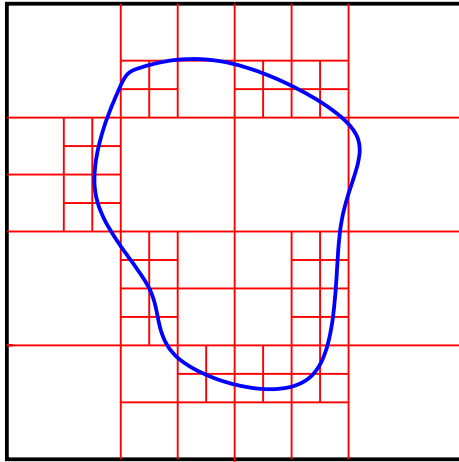
This does not exactly equidistributes the error, but one has for  $X = L^p$  and any  $q$  such that  $1/q > 1/p + 1$

$$f \in W^{2,q} \Rightarrow \|f - f_N\|_{L^p} \leq CN^{-1} |f|_{W^{2,q}}.$$

Remark : the triangulation can be made conforming without changing the convergence rate.

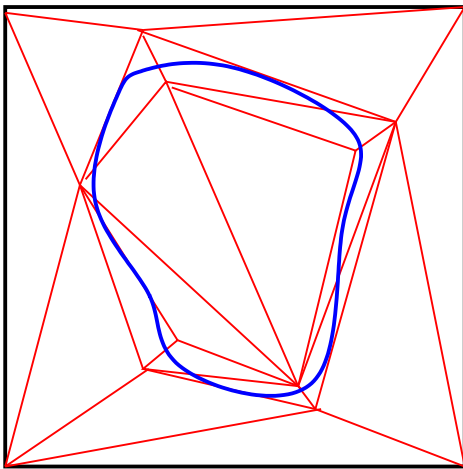
## When do we need anisotropy ?

Sharp gradients or jump discontinuities on curved edges :  $f = \chi_{\Omega}$ ,  
with  $\partial\Omega$  smooth.



$f_N =$  piecewise affine function  
on  $N$  optimally selected squares

$$\Rightarrow \|f - f_N\|_{L^2} \sim N^{-1/2}$$



$f_N =$  piecewise affine function  
on  $N$  optimally selected triangles

$$\Rightarrow \|f - f_N\|_{L^2} \sim N^{-1}$$

## $C^n - C^m$ models

The function  $f$  is  $C^n - C^m$  if it is piecewise  $C^n$  with jump discontinuities on piecewise  $C^m$  curves.

If  $f \in C^n - C^m$ , then there exists triangulations  $(\mathcal{T}_N)_{N>0}$  such that

$$\|f - f_N\|_{L^p} \lesssim N^{-\frac{\min\{n,2\}}{2}} + N^{-m/p}.$$

In particular if  $f \in C^2 - C^2$ , the rate is  $N^{-1}$  in  $L^p$  for  $p \leq 2$ .

### Drawbacks of this model:

- lacks a rigorous quantitative definition
- does not describe smooth yet sharp transitions.
- does not lead to a natural algorithm

More quantitative models based on the regularity of [level sets](#)  
(DeVore, Petrova, Wojtaszczyk)

## Hessian based models

A very heuristic computation:

A “good” triangle around  $x$  has aspect ratio of the ellipsoid

$$E(x) := \{\langle H(x)v, v \rangle \leq 1\}$$

where  $H(x) = |D^2 f(x)|$ , i.e. it is an isotropic triangle with respect to the distorted metric induced  $H$ .

For such a triangle  $T$ , if  $(\lambda_1, \lambda_2)$  are the eigenvalues of  $H$  and  $(h_1, h_2)$  the heights of  $T$  in the corresponding directions, we have  $h_1/h_2 \approx \sqrt{\lambda_2/\lambda_1}$ . Therefore and if  $D^2 f$  does not vary too much on  $T$  one has

$$\begin{aligned} \|f - I_T f\|_{L^\infty(T)} &\leq \lambda_1 h_1^2 + \lambda_2 h_2^2 \\ &\approx h_1 h_2 \sqrt{\lambda_1 \lambda_2} \\ &\approx |T| (\det(H(x)))^{1/2} \approx \int_T \sqrt{\det(H(x))}. \end{aligned}$$

Now, assuming that

$$E(f) := \int_{\Omega} \sqrt{\det(H(x))} < +\infty$$

and that  $\mathcal{T}_N$  is designed such that each triangle has the optimal aspect ratio and  $\int_T \sqrt{\det(H(x))} \approx N^{-1} E(f)$ , we obtain

$$\|f - f_N\|_{L^\infty} \leq CN^{-1} E(f).$$

By similar heuristics for  $X = L^p$ , we can obtain adaptive anisotropic triangulations with error estimates of the type

$$\|f - f_N\|_{L^p} \leq CN^{-1} \|\sqrt{\det(H)}\|_{L^q}, \quad 1/q = 1/p + 1.$$

Non-linear quantities :  $E(f + g)$  not controlled by  $E(f) + E(g)$ .

## Making it more rigorous (Shen-Sun-Xu, Babenko)

- $E(f) = 0$  for a degenerate Hessian (univariate  $f$ ), yet error is non-zero : replace  $H$  by a majorant of the type  $H + \varepsilon I$ .
- Requires enough smoothness on  $f$  so that the triangulation  $\mathcal{T}_N$  can indeed be constructed for  $N > N_0(f, \varepsilon)$

### Two drawbacks:

- The construction of the triangulation is based on the Hessian : not robust to noise, does not apply to arbitrary  $L^p$  functions.
- The construction is non-hierarchical.

A greedy alternative (Dyn, Hecht, Mirebeau, A.C.): Coarse triangulation  $\Rightarrow$  select triangle with largest local  $L^p$  error  $\Rightarrow$  choose the mid-point bisection that best reduces this error  $\Rightarrow$  split  $\Rightarrow$  iterate.... until prescribed accuracy or number of triangles is met.