

- Tool for describing functions on different scales (or level of detail) via a multiresolution decomposition.
- Basis for $L^2(\mathbb{R})$ with special properties.

Example

Decomposition into different scales

$$\begin{aligned}
 f_3(x) &= f_2(x) + d_2(x) = f_1(x) + d_1(x) + d_2(x) = \dots = \\
 &= \underbrace{f_0(x)}_{\text{Average}} + \underbrace{d_0(x)}_{\text{detail 0}} + \underbrace{d_1(x)}_{\text{detail 1}} + \underbrace{d_2(x)}_{\text{detail 2}}
 \end{aligned}$$

Why?

- Explicit description: of f viewed on different scales: f_1, f_2, f_3, \dots and of the parts of f belonging to different scales: d_1, d_2, d_3, \dots
Useful for understanding / analyzing phenomena & in design of numerical algorithms.
- Size of $d_j(x) \rightarrow 0$ rapidly with j when f is piecewise smooth -
 \Rightarrow Can approximate f by just a few d_j
- Difference, $d_j(x)$ indicates where f is non-smooth
 \Rightarrow tool for ^{useful} e.g. edge detection & mesh refinement

Basis & inner product for L^2

$L^2(\mathbb{R})$ = space of square integrable functions on \mathbb{R}

$$\int_{\mathbb{R}} f^2 dx < \infty \iff f \in L^2(\mathbb{R})$$

Some generalizations of finite-dimensional (Matry: (vectors \rightarrow functions = "infinite length vectors"))

- Two functions f, g are orthogonal if

$$\langle f, g \rangle := \int_{\mathbb{R}} f(x)g(x)dx = 0$$

- Norm: $\|f\|_{L^2} = \sqrt{\langle f, f \rangle} = \sqrt{\int f^2 dx}$

- orthonormal basis (ONB)

$\{\phi_k(x)\}$ is an (ONB) if

$$\bullet f \in L^2 \Rightarrow \exists f_k: f(x) = \sum f_k \phi_k(x)$$

$$\bullet \langle \phi_k, \phi_l \rangle = \delta_{k-l}$$

$$\Rightarrow f_k = \langle f, \phi_k \rangle$$

- Parseval: $\|f\|^2 = \sum f_k^2$

- Cauchy-Schwarz: $|\langle f, g \rangle| \leq \|f\|_{L^2} \|g\|_{L^2}$

Example: $L^2([0, 2\pi])$ has basis

$$\text{Fourier } \left\{ \frac{\sin nx}{\sqrt{\pi}} \right\} \cup \left\{ \frac{\cos nx}{\sqrt{\pi}} \right\} \cup \left\{ \frac{1}{\sqrt{2\pi}} \right\}$$

$$\text{Polynomials } 1, x, x^2, \dots$$

(not orthogonal or normalized though)

Wavelet & scaling spaces

Example continued

Introduce function spaces $V_j, W_j \subset L^2(\mathbb{R})$ for the different scales:

V_j - "scaling spaces", spaces of functions viewed on scale j , " f_j "
Here: piecewise constant functions, piecewidth = 2^{-j}

W_j - "wavelet spaces", spaces of differences (detail) between level j & $j+1$, " d_j ".

Every $f \in V_{j+1}$ can be decomposed uniquely as $f = f_j + d_j$ with $f_j \in V_j$ & $d_j \in W_j$

$\Rightarrow V_{j+1} = V_j \oplus W_j$, direct sum

Moreover, here

$\langle f_j, d_j \rangle = 0$ 

$f_j \perp d_j \Rightarrow V_j \perp W_j$

W_j is "orthogonal complement of V_j in V_{j+1} "

In fact:

$f_j = P_{V_j} f$

$d_j = P_{W_j} f$

projections. (as defined $\langle f - f_j, g \rangle = 0 \forall g \in V_j$)

Remark: $V_{j+1} = W_j \oplus W_{j-1} \oplus \dots \oplus W_{j-k} \oplus V_{j-k}$

Bases for V_j & W_j

Example continued

$\{ \phi_{j,k} \}$ orthonormal basis for V_j

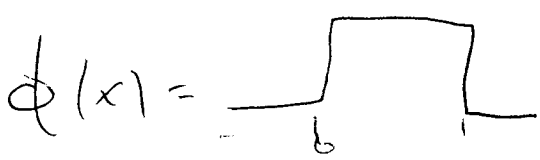
$\{ \psi_{j,k} \}$ orthonormal basis for W_j = the wavelets

Observation: These are all dilated and translated versions of two functions!

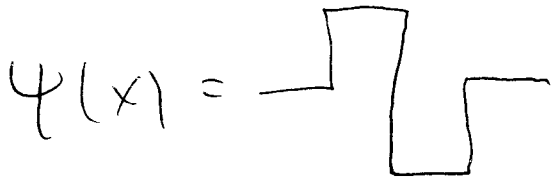
$$\phi_{j,k}(x) = 2^{j/2} \phi(2^j x - k)$$

$$\psi_{j,k}(x) = 2^{j/2} \psi(2^j x - k)$$

where



"scaling (shape) function"



"mother wavelet"

Moreover:

$$\int \phi(x) \phi(x-k) dx = \delta_k$$
$$\int \phi(x) \psi(x-k) dx = 0$$
$$\int \psi(x) \psi(x-k) dx = \delta_k$$

Since $V_{j+1} = V_j \oplus W_j$, $V_j \perp W_j$

the set $\{ \phi_{j,k} \} \cup \{ \psi_{j,k} \}$ is orthonormal basis for V_{j+1}

$$V_{j+1} = W_j \oplus W_{j-1} \oplus V_{j-1}$$

$\{ \psi_{j,k} \} \cup \{ \psi_{j-1,k} \} \cup \{ \phi_{j+1,k} \}$ ONB for V_{j+1}

$j \rightarrow \infty$, as before...
ONB for $L^2(\mathbb{R})$

Structure of wavelet system, summary

(5)

- Scaling & wavelet spaces V_j & W_j ; describing different scales
such that $V_{j+1} = V_j \oplus W_j$
finer scale average/coarse part difference/detail/fine part.

- Bases for V_j & W_j
 $V_j = \text{span} \{ \phi_{j,k} \}$ scaling functions
 $W_j = \text{span} \{ \psi_{j,k} \}$ wavelets
generated by scaling function & mother wavelet

$$\phi_{j,k}(x) = 2^{j/2} \phi(2^j x - k)$$

$$\psi_{j,k}(x) = 2^{j/2} \psi(2^j x - k)$$

$\Rightarrow \{ \phi_{j,k} \}$ basis for $L^2(\mathbb{R})$

- $\int \psi(x) dx = 0$ (\Rightarrow basic approximation property)

System described above called "Haar" system.
Simplest one possible, first proposed early 20th century.

Advantages:

- ϕ, ψ compactly supported (good for numerics)
- all bases orthogonal & $V_j \perp W_j$

Disadvantages:

- ϕ, ψ discontinuous
- $\int x^p \psi(x) dx \neq 0 \quad p > 0$

} relatively bad numerical & approximation properties

Generalize Haar and find better wavelet systems.

Examples

Wavelets - generalizations

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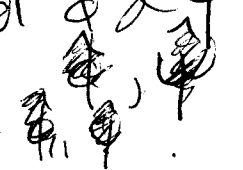
Want to create "better" wavelet systems than Haar, ~~with~~ ^{with} so

- Eg:
- Smoother wavelets
 - Wavelets with many vanishing moments:

$$\int \psi(x) x^p dx = 0 \quad p=0, \dots, M-1$$

(f. Haar: $M=1$)

Other "good" properties: \Rightarrow give good approximation prop.

- \otimes Compactly supported ϕ & ψ .
- Symmetric ϕ, ψ 
- etc. for $\hat{\phi}, \hat{\psi}$
- Orthonormal bases.

Multiresolution analysis

One can show that we ^{just} need to find spaces V_j & a scaling function $\phi(x)$ that forms a multiresolution analysis: (MRA).
i.e. V_j & ϕ satisfy:

1. $\dots \subset V_j \subset V_{j+1} \subset \dots \subset L^2$
nested spaces

2. $f(t) \in V_j \iff f(2t) \in V_{j+1}$
~~spaces~~ describe ~~have~~ different scales

3. $\bigcup V_j = L^2 \quad \bigcap V_j = \{0\}$ (technical)

4. $\{\phi(x-k)\}$ is an ON-basis for V_0

From these requirements it then follows that a full wavelet system can be created:

- $\phi_{j,k}(x) := 2^{j/2} \phi(2^j x - k)$ is an ON basis for V_j (Exercise)
- W_j spaces defined as orthogonal complement of V_j in V_{j+1} ($V_{j+1} = V_j \oplus W_j$, $V_j \perp W_j$)
- There exists a mother wavelet $\psi(x)$ such that $\psi_{j,k}(x) := 2^{j/2} \psi(2^j x - k)$ is an ON basis for W_j (and for $L^2(\mathbb{R})$)

- There are many examples of V_j & ϕ satisfying 1) - 4).
- of particular interest for numerical computations are those with compact support for ϕ & ψ . (Discovered in '88' by Daubechies.)
- The orthogonality condition can be relaxed, and non-orthogonal wavelet systems can also be built.

Filter coefficients

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Since $\phi \in V_0 \subset V_1$ and V_1 is spanned by $\{\phi\}$
 $\phi_{1,k}(x) = \sqrt{2} \phi(2x-k)$ we can find $\{h_k\}$ such that

$$(*) \quad \phi(x) = \sum_k \sqrt{2} h_k \phi(2x-k)$$

This is called a refinement equation

The $\{h_k\}$ are the (lowpass) filter coefficients for the wavelet system. Characterizes it.

Similarly, since $\psi \in W_0 \subset V_1$,

$$\psi(x) = \sum_k \sqrt{2} g_k \phi(2x-k)$$

for some (highpass) filter coefficients $\{g_k\}$,

Example: Haar: $h_k = \left\{ \frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}} \right\}$ $\sqrt{2} + \sqrt{2} = 2$
 $g_k = \left\{ \frac{1}{\sqrt{2}}, -\frac{1}{\sqrt{2}} \right\}$ $\sqrt{2} - \sqrt{2} = 0$

Note: Compact support of $\phi, \psi \Leftrightarrow$
 $\{h_k, g_k\}$ finite length (FIR) filter
or (impulse response)

= finite # non-zero entries

① We can build \perp wavelet systems directly from filter coefficients because of the following

If $\sum_k h_k h_{k+2l} = \delta_l = \begin{cases} 1 & l=0 \\ 0 & \text{else} \end{cases}$

(**) $\sum_k h_k = \sqrt{2}$

plus some technical assumptions

(e.g. $\sum_k |h_k| |k|^\epsilon < \infty \quad \epsilon > 0$, $\left(\hat{h}(\xi) \geq \delta > 0 \right)_{|\xi| \leq \pi/2}$)
 $\left(\begin{aligned} \hat{h}(\xi) &= \frac{1}{\sqrt{2}} \sum_k h_k e^{ik\xi} = \frac{1}{2} (1 + e^{i\xi}) \hat{f}(\xi/2) \\ \sum_k |f_k| |k|^\epsilon &< \infty \quad \epsilon > 0 \\ |\hat{f}(\xi)| &< 2^{N-1} \end{aligned} \right) \Rightarrow \text{given regular } \phi$

Then

- (*) defines a scaling function
- $g_k = (-1)^k h_{1-k}$ defines a mother wavelet $\psi(x)$
- which together defines an MRA.

Finding compactly supported ^{orthogonal} wavelets

Finding finite length $\{h_k\}$ satisfying (**)

Exercise: Show that (**) are necessary conditions if (*) holds & $\{\phi(x-k)\}$ are orthogonal.

Approximation properties

Basic approximation mechanism of wavelets:
vanishing moments. (and space localization)

Definition: Mother wavelet $\psi(x)$ has M vanishing moments if

$$\int x^p \psi(x) dx = 0, \text{ for } p=0, 1, \dots, M-1$$

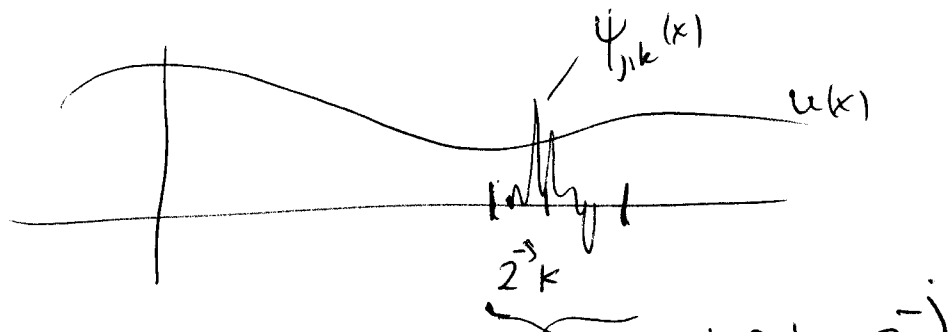
- Implies that $\int p(x)\psi(x)dx = 0$ when $p(x)$ polynomial of degree $< M$
- Same holds for $\psi_{j,k}(x)$ (Exercise.)
- There exist compactly supported wavelets with arbitrary many vanishing moments. (Daubechies, 'PAM 88')

Suppose $u(x) = \sum u_{j,k} \psi_{j,k}(x)$ is smooth $\in C^M(\mathbb{R})$

Then coefficients given by

$$u_{j,k} = \langle u, \psi_{j,k} \rangle = \int_{\Omega} u(x) \psi_{j,k}(x) dx$$

where $\Omega = \text{support of } \psi_{j,k}(x)$



Taylor expansion around x_0

$$u(x) = u(x_0) + (x-x_0)u'(x_0) + \dots + \frac{(x-x_0)^{M-1}}{(M-1)!} u^{(M-1)}(x_0) + \frac{(x-x_0)^M}{M!} R(x)$$

$$\Rightarrow u_{j,k} = \int_{\Omega} \underbrace{\sum_{n=0}^{M-1} u^{(n)}(x_0) \frac{(x-x_0)^n}{n!} \psi_{j,k}(x)}_{=0 \text{ since } \psi \text{ has } M \text{ vanishing moments!}} dx + \int_{\Omega} \frac{(x-x_0)^M}{M!} R(x) \psi_{j,k}(x) dx$$

$$\Rightarrow |u_{j,k}| \leq \int_{\Omega} \frac{|x-x_0|^M}{M!} |R(x)| \cdot |\psi_{j,k}(x)| dx$$

Note: $|x-x_0| \leq |\Omega|$
 $|R(x)| \leq \sup_{x \in \Omega} |u^{(M)}(x)|$

$$\Rightarrow |u_{j,k}| \leq \frac{|\Omega|^M}{M!} \cdot \sup_{x \in \Omega} |u^{(M)}(x)| \cdot \int_{\Omega} |\psi_{j,k}(x)| dx$$

Cauchy Schwarz: $\int_{\Omega} fg dx \leq \left(\int_{\Omega} f^2 dx \cdot \int_{\Omega} g^2 dx \right)^{1/2}$

$$\Rightarrow \int_{\Omega} |\psi_{j,k}(x)| dx \leq \left(\int_{\Omega} 1^2 dx \cdot \int_{\Omega} \psi_{j,k}^2 dx \right)^{1/2} \leq |\Omega|^{1/2}$$

$$\therefore |u_{j,k}| \leq \frac{|\Omega|^{M+1/2}}{M!} \cdot \sup_{x \in \Omega} |u^{(M)}(x)| \leq C 2^{-j(M+1/2)} \sup_{x \in \Omega} |u^{(M)}(x)|$$

- $u_{j,k}$ decay rapidly with j when $u(x)$ smooth & M large.
 (details) locally around $\psi_{j,k}$

- Most $u_{j,k}$ can be neglected. Just need to keep those where $u(x)$ has abrupt changes / discontinuities.

- Wavelet approximates also piecewise smooth

Time-frequency analysis

Localization in time & frequency
 a special property of wavelet bases.

Consider three ways to represent a signal.

Examples

1. Sample values

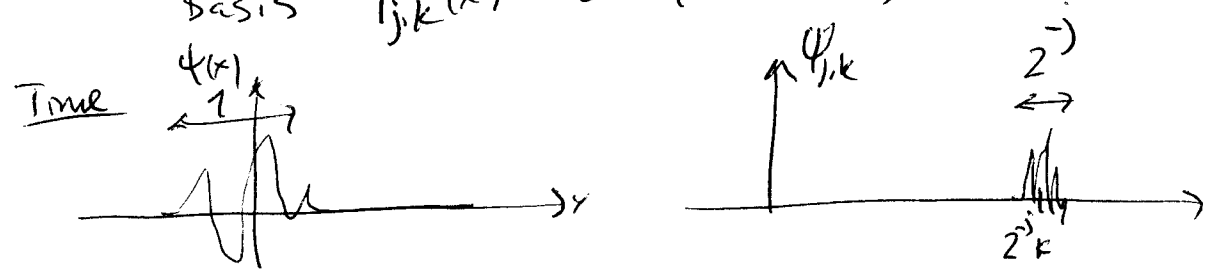
Basis: $\delta(x-x_j)$ Fourier transform: $e^{-i\omega x_j}$

2. ~~Power~~ ~~base~~ ~~frequency~~ Fourier decomposition

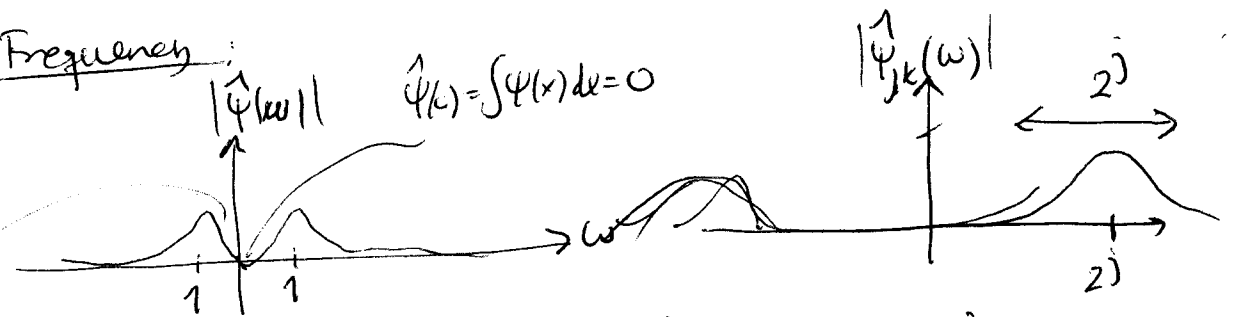
Basis: $e^{i\omega_j x}$ Fourier transform $\delta(\omega-\omega_j)$

3. Wavelets:

Basis $\psi_{j,k}(x) = 2^{j/2} \psi(2^j x - k)$



Frequency:



$$\begin{aligned} \hat{\psi}_{j,k}(\omega) &= \int 2^{j/2} \psi(2^j x - k) e^{-i\omega x} dx = \{y = 2^j x - k\} \\ &= 2^{-j/2} \int \psi(y) e^{-i\omega 2^{-j}(y+k)} dy = \\ &= 2^{-j/2} e^{i\omega 2^{-j} k} \hat{\psi}(\omega 2^{-j}) \end{aligned}$$

Note: $\hat{\psi}^{(p)}(\omega) = \mathcal{F}((ix)^p \psi(x)) \Rightarrow \int x^p \psi(x) dx = \frac{1}{i^p} \hat{\psi}^{(p)}(0) = 0$

1) Define $\hat{h}(\xi) = \frac{1}{\sqrt{2}} \sum h_n e^{in\xi} \sim$ Fourier transform of $\{h_n\}$ / Generating function

2) $\sum_k h_k = \sqrt{2} \iff \hat{h}(0) = 1$

$\sum_k h_k h_{k+2\ell} = \delta_\ell \iff |\hat{h}(\xi)|^2 + |\hat{h}(\xi+\pi)|^2 = 1$

Proof: $|\hat{h}(\xi)|^2 + |\hat{h}(\xi+\pi)|^2 =$
 $= \sum_{k,\ell} h_k e^{ik\xi} \cdot h_\ell e^{-i\ell\xi} + h_k e^{ik(\xi+\pi)} \cdot h_\ell e^{-i\ell(\xi+\pi)}$
 $= \sum_{k,\ell} h_k h_\ell e^{i(k-\ell)\xi} (1 + e^{i(k-\ell)\pi}) = \sum_{k,\ell} h_k h_\ell e^{i(k-\ell)\xi} (1 + (-1)^{k-\ell})$
 $= \sum_{k,\ell} h_k h_{k+2\ell} e^{-i\ell\xi} = 1 \iff \sum_k h_k h_{k+2\ell} = \delta_\ell$

3) Compactly supported $\iff \{h_n\}$ finite length
 $\iff \hat{h}(\xi) = P(e^{i\xi})$, P some polynomial with real coeff.

4) M vanishing moments \Rightarrow
 $\hat{h}(\xi) = \left(\frac{1+e^{i\xi}}{2}\right)^M \cdot Q(e^{i\xi})$ Q some polynomial, real coeff.

(Follows from:
 $\hat{\psi}(2\xi) = e^{-i(\xi+\pi)} \hat{h}(\xi+\pi) \cdot \hat{\phi}(\xi)$ and
 the fact that $\frac{\partial^p}{\partial \xi^p} \hat{\psi}(0) = 0$
 $0 \leq p \leq M$

5) We get:

$$\dot{Q}(1) = 1$$

$$\left| \frac{1+e^{i\xi}}{2} \right|^{2M} |Q(e^{i\xi})|^2 + \left| \frac{1-e^{i\xi}}{2} \right|^{2M} |Q(-e^{i\xi})|^2 = 1$$

Make ansatz for $Q = c_0 + c_1 z + c_2 z^2 + \dots$

Solve for c_0, c_1, c_2, \dots etc.

Ex: $M=1 \Rightarrow Q=1$ since $|1+z|^2 + |1-z|^2 = 1+|z|^2$
 $\Rightarrow \hat{h}(\xi) = \frac{1+e^{i\xi}}{2} \Rightarrow h_n = \frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}$ i.e. Haar

Ex: $M=2 \Rightarrow Q = a + b z$ with
 $a = \frac{1+\sqrt{3}}{2}$ $b = \frac{1-\sqrt{3}}{2}$

$$\hat{h}(\xi) = \left(\frac{1+e^{i\xi}}{2} \right)^2 (a + b e^{i\xi})$$

$$= \underbrace{\frac{a}{4}}_{h_0/\sqrt{2}} + \underbrace{\frac{2a+b}{4}}_{h_1/\sqrt{2}} e^{i\xi} + \underbrace{\frac{2b+a}{4}}_{h_2/\sqrt{2}} e^{i2\xi} + \underbrace{\frac{b}{4}}_{h_3/\sqrt{2}} e^{i3\xi}$$

\Rightarrow Daubechies 4.

Wavelet transforms

Suppose we have a function $u(x) \in V_j$ given,

$$u(x) = \sum_k u_k \phi_{j+1,k}(x)$$

In Numerical algorithms we only need to keep track of the $\{u_k\}$ coefficients. Suppose they are given.

Note: If $\phi_{j+1,k}$ is Haar $\rightarrow u_k \sim$ sample values of $u(x)$ at $x=2^j k$
(actually $2^{j/2} u_k(x)$)

In general $u_k \sim$ local average of $u(x)$ at $x=2^j k$.
 \approx sample value.

We want to decompose $u(x)$ into a wavelet representation:

$$u(x) = \sum_{j=0}^j d_j(x) + u_0(x) = \sum_{j,k} b_{j,k}^f \psi_{j,k}(x) + \sum_k d_0^f \phi_{0,k}(x) \quad (*)$$

We start with one step:

$$u(x) = \underbrace{u_j(x)}_{\in V_j} + \underbrace{d_j(x)}_{\in W_j} =: \sum u_{j,k}^c \phi_{j,k}(x) + \sum u_{j,k}^f \psi_{j,k}(x) \quad (*)$$

Then:

$$\left. \begin{aligned} u_{j,k}^c &= \langle u, \phi_{j,k} \rangle = \sum_l u_l h_{l-2k} \\ u_{j,k}^f &= \langle u, \psi_{j,k} \rangle = \sum_l u_l g_{l-2k} \end{aligned} \right\} \text{Exercise}$$

\therefore The transform $\{u_k\} \rightarrow \{u_{j,k}^c\} \cup \{u_{j,k}^f\}$
can be done only using filter coefficients g_{l-2k} & h_{l-2k}

• For compactly supported wavelets, computing $u_{j,k}^c$ & $u_{j,k}^f$ can be done in $O(1)$ time.

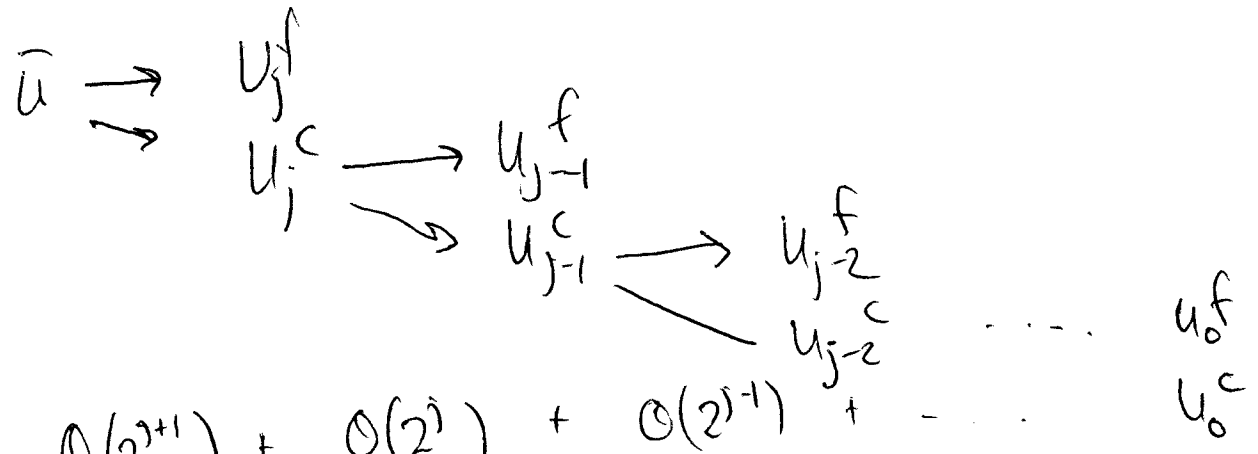
Suppose now $u(x)$ is of finite length / compact support say $c \in [0,1]$.

\Rightarrow # coefficients on level $j+1$ is $2^{j+1} = N$

Let $\bar{u} = \{u_k\}$, vector $\in \mathbb{R}^{2^j}$.
 $U_j^f = \{u_{j,k}^f\}$ $U_j^c = \{u_{j,k}^c\} \in \mathbb{R}^{2^j}$

Transform $\bar{u} \rightarrow U_j^f \cup U_j^c$ cost $O(2^{j+1})$

To do the full transform (*) we continue this hierarchically:



Cost $O(2^{j+1}) + O(2^j) + O(2^{j-1}) + \dots + U_0^f$
 U_0^c

Total cost $\sum_{k=0}^{j+1} 2^k = 2^{j+2} - 1 = O(2^{j+1}) = O(N)$

where N is the total number of unknowns we started from.

\therefore Wavelet transform cost $O(N)$

FFT = $O(N \log N)$

Inverse transform done

In matrix form we can write

$$U = \begin{pmatrix} U_j^f \\ U_j^c \end{pmatrix} = \underbrace{\begin{pmatrix} g_0 & g_1 & g_2 & \dots \\ & g_0 & g_1 & \dots \\ \hline h_0 & h_1 & h_2 & \dots \\ & h_0 & h_1 & h_2 & \dots \end{pmatrix}}_{W_j} \begin{pmatrix} \bar{u} \\ u \end{pmatrix}$$

then:

$$W_j^T W_j = \underline{I} \quad (\text{orthonormal})$$

W_j sparse (when h, g FIR)

Numerical homogenization

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Example

$$\partial_x r(\frac{x}{\epsilon}) \partial_x u^\epsilon = f \quad u(0) = u(1) = 0$$

Numerically we can solve this by discretizing:

$$x_j = j \Delta x \quad u_j \approx u(x_j)$$

$$f(x_j) = \partial_x r \partial_x u(x_j) \approx \left(r(\frac{x_{j+1}}{\epsilon}) \frac{u_{j+1} - u_j}{\Delta x} - r(\frac{x_j}{\epsilon}) \frac{u_j - u_{j-1}}{\Delta x} \right) / \Delta x$$

$$= \frac{u_{j+1} - R_j u_j + u_{j-1}}{\Delta x^2} \quad R_j^\epsilon = r(\frac{x_{j+1}}{\epsilon}) + r(\frac{x_j}{\epsilon})$$

$$\Rightarrow \underbrace{\begin{pmatrix} -R_1^\epsilon & 1 & & & \\ 1 & -R_2^\epsilon & & & \\ & & \ddots & & \\ & & & 1 & -R_N^\epsilon \end{pmatrix}}_{L^\epsilon \in \mathbb{R}^{N \times N}} \begin{pmatrix} u_1^\epsilon \\ \vdots \\ u_N^\epsilon \end{pmatrix} = \Delta x^2 \begin{pmatrix} f_1 \\ \vdots \\ f_N \end{pmatrix} \quad f_j = f(x_j)$$

$N = 1/\Delta x$

Need $\Delta x \sim \epsilon$ to get accurate result, $\Rightarrow N = O(1/\epsilon)$

Solving system cost $O(N)$ (normally $O(N^3)$ but here sparse can be solved faster) = $O(1/\epsilon)$

We know from homogenization theory that

$$u^\epsilon - \bar{u} = O(\epsilon) \quad \text{where } \bar{u} \text{ solves homogenized eq:}$$

$$(*) \quad \partial_x \bar{r} \partial_x \bar{u} = f \quad \bar{u}(0) = \bar{u}(1) = 0$$

We can decompose $L^\epsilon = \Delta_+ R \Delta_-$ where $\Delta_+ = \begin{pmatrix} 1 & & \\ & \ddots & \\ & & 1 \end{pmatrix}$ and $\Delta_- = \begin{pmatrix} 1 & & \\ & \ddots & \\ & & 1 \end{pmatrix}$ of

Discretizing in the same way:

$$\bar{L} \vec{U} = \Delta x^2 \vec{f}$$

where $\bar{L} \in \mathbb{R}^{N \times N}$ but $N = \mathcal{O}(1)$ indep. of ϵ .

Cost = $\mathcal{O}(1)$ \Rightarrow Much cheaper and almost as accurate when $\epsilon \ll 1$.

Numerical homogenization:

Compute \bar{L} (a matrix) directly from original eq. or from L^ϵ (another, bigger matrix) (without having to know explicitly about $(*)$).

Remark: Both L^ϵ & \bar{L} are sparse, banded, matrices. This is natural since they approximate local differential operators. We would like the numerically homogenized operator to have these properties too.

Taking $N = 2^{j+1}$ we can think of the vectors \vec{U}, \vec{f} as coefficient vectors for some functions in V_{j+1} and L^ϵ as a linear operator $V_{j+1} \rightarrow V_{j+1}$.