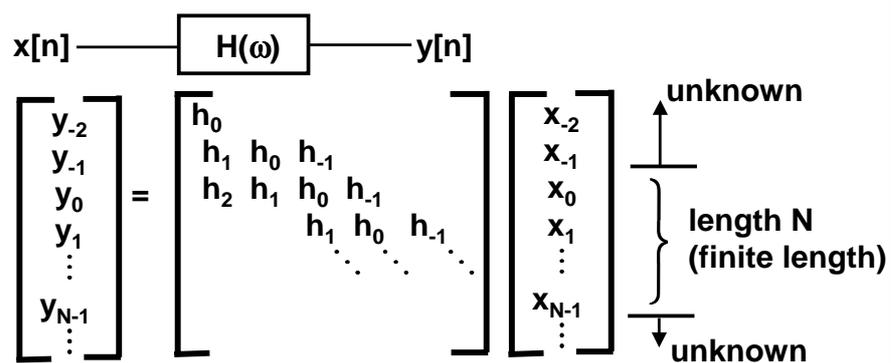


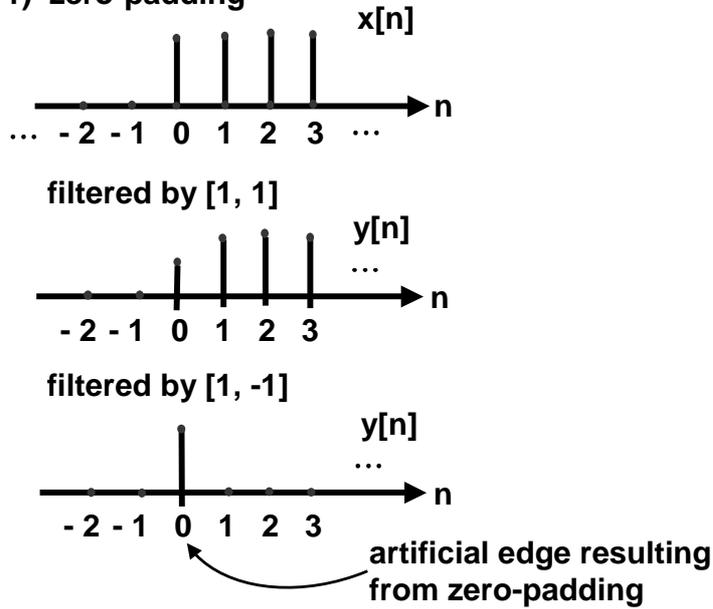
Course 18.327 and 1.130 Wavelets and Filter Banks

Signal and Image Processing: finite length signals; boundary filters and boundary wavelets; wavelet compression algorithms.

Finite-Length Signals

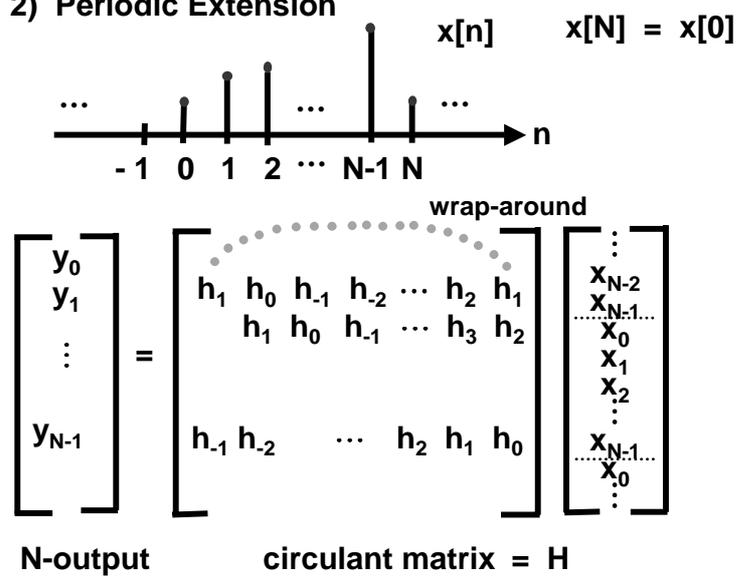


1) zero-padding



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2) Periodic Extension



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What is the eigenvector for the circulant matrix?

$$[1 \ e^{i\omega} \ e^{i2\omega} \ \dots \ e^{i(N-1)\omega}]^T$$

We need

$$e^{iN\omega} = 1 = e^{i0\omega}$$

$$\therefore N\omega = 2\pi k \quad ,$$

$$\omega = \frac{2\pi k}{N}$$

discrete set of ω 's

For the 0th row,

$$H[k] = \sum_{n=0}^{N-1} h[n] e^{-i\frac{2\pi k}{N}n}$$

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$$[H] \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & w & w^2 & & w^{N-1} \\ 1 & w^2 & w^4 & & w^{2(N-1)} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & w^{N-1} & & & \end{bmatrix} = [F] \begin{bmatrix} H[0] \\ H[1] \\ \vdots \\ H[N-1] \end{bmatrix}$$

$\underbrace{\quad\quad\quad}_{F} \quad w = e^{i\frac{2\pi}{N}}$

$k=0 \quad k=1 \quad \quad \quad k=N-1$

$HF = F\Lambda$ Λ contains the Fourier coefficients

$$H[k] = \sum_n h[n] e^{-i\frac{2\pi k}{N}n}$$

$$\sum_n \sum_\ell h[n-\ell] x[\ell] e^{-i\frac{2\pi k}{N}n} = H[k] X[k]$$

$$\text{If } x[\ell] = e^{i\frac{2\pi k_0}{N}\ell} \Rightarrow X[k] = \delta[k - k_0]$$

$$\Rightarrow H[k] X[k] = H[k_0] X[k]$$

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3) Symmetric Extension

1) Whole point symmetry – when filter is whole point symmetric.

2) Half point symmetry – when filter is half point symmetric.

e.g. Whole point symmetry: filter and signal

$$\begin{bmatrix} h_1x_2 + h_0x_1 + h_1x_0 \\ h_1x_1 + h_0x_0 + h_1x_1 \\ h_1x_0 + h_0x_1 + h_1x_2 \end{bmatrix} = \begin{bmatrix} h_0 & h_1 & & \\ & h_1 & h_0 & h_1 \\ & & h_1 & h_0 & h_1 \\ & & & \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} x_2 \\ x_1 \\ x_0 \\ x_1 \\ x_2 \end{bmatrix}$$

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e.g. whole point symmetry – filter,
half-point symmetry - signal

$$\begin{bmatrix} h_1x_2 + h_0x_1 + h_1x_0 \\ h_1x_1 + h_0x_0 + h_1x_0 \\ \hline h_1x_0 + h_0x_0 + h_1x_1 \\ h_1x_0 + h_0x_1 + h_1x_2 \end{bmatrix} = \begin{bmatrix} h_1 & h_0 & h_1 & & \\ & h_1 & h_0 & h_1 & \\ & & h_1 & h_0 & h_1 \\ & & & \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} x_2 \\ x_1 \\ x_0 \\ \dots \\ x_0 \\ x_1 \\ x_2 \end{bmatrix}$$

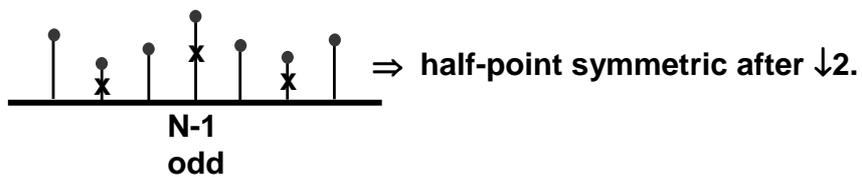
Half point symmetry Whole point symmetry

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Downsampling a whole-point symmetric signal with even length N at the left boundary:



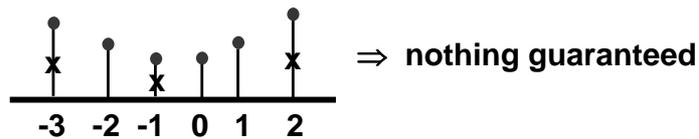
at the right boundary:



E.g. 9/7 filter: whole-point symmetric
use the above extension for signal $\Rightarrow N \begin{cases} N/2 \\ N/2 \end{cases}$ exactly

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Downsample a half-point symmetric signal



Linear-phase filters

$$H(\omega) = A(\omega)e^{-i\omega\alpha}$$

1) half-point symmetric, $\alpha = \text{fraction}$

2) whole-point symmetric, $\alpha = \text{integer}$

Symmetric extension of finite-length signal

$$X(\omega) = B(\omega)e^{-i\omega\beta}$$

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The output:

$$Y(\omega) = H(\omega)X(\omega)$$

W	W	W
W	H	H
H	H	W
H	W	H

W = whole-point symmetry

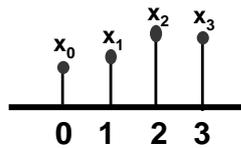
H = half-point symmetry

The above extensions ensure the continuity of function values at boundaries, but not the continuity of derivatives at boundaries.

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4) Polynomial Extrapolation (not useful in image processing)

- Useful for PDE with boundary conditions.



4 coefficients \Rightarrow fits up to 3rd order polynomials.

$$a + bn + cn^2 + dn^3 = x(n)$$

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 1 & 2 & 2^2 & 2^3 \\ 1 & 3 & 3^2 & 3^3 \end{bmatrix}}_A \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

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Then,

$$\mathbf{x}_{-1} = [1 \ -1 \ 1 \ -1] \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = [1 \ -1 \ 1 \ -1] \mathbf{A}^{-1} \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

PDE

$$f(x) = \sum_k c_k \phi(x - k)$$

Assume $f(x)$ has polynomial behavior near boundaries

$$\sum_{i=0}^{p-1} \alpha_i x^i = f(x) = \sum_k c_k \phi(x - k)$$

$\{\phi(\bullet - k)\}$ orthonormal

$$\Rightarrow \sum_{i=0}^{p-1} \alpha_i \underbrace{\int \phi(x - k) x^i dx}_{\mu_k^i} = c_k$$

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$$\begin{bmatrix} \mu_0^0 & \mu_0^1 & \dots & \mu_0^{p-1} \\ \mu_1^0 & \mu_1^1 & \mu_1^2 & \dots \\ \vdots & & & \end{bmatrix} \begin{bmatrix} \alpha_0 \\ \alpha_1 \\ \vdots \\ \alpha_{p-1} \end{bmatrix} = \begin{bmatrix} c_0 \\ c_1 \\ \vdots \\ c_{p-1} \end{bmatrix}$$

Using the computed α_i 's, we can extrapolate,

e.g. $c_{-1} = [\mu_{-1}^0 \ \mu_{-1}^1 \ \dots \ \mu_{-1}^{p-1}] \begin{bmatrix} \alpha_0 \\ \vdots \\ \alpha_{p-1} \end{bmatrix}$

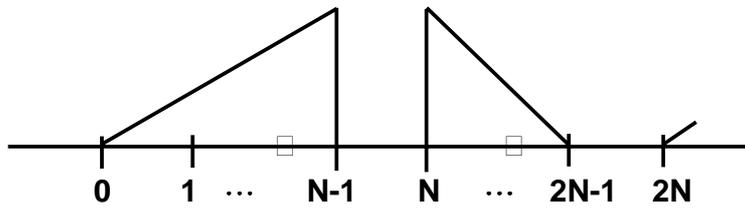
DCT idea of symmetric extension

cf. DFT $X[k] = \sum_n x[n] e^{-i \frac{2\pi k n}{N}}$

complex-valued

Want real-valued results.

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DFT of this extended signal:

$$\sum_{n=0}^{N-1} x[n]e^{-i\frac{2\pi k}{2N}n} + \underbrace{\sum_{n=N}^{2N-1} x[2N-1-n]e^{-i\frac{2\pi k}{2N}n}}$$

$$\sum_{m=0}^{N-1} x[m]e^{-i\frac{2\pi k}{2N}(2N-1-m)}$$

$$= \sum_{n=0}^{N-1} x[n] \{e^{-i\frac{2\pi k}{2N}n} + e^{-i\frac{2\pi k}{2N}(2N-1-n)}\}$$

$$X(k) = c_k \sum_{n=0}^{N-1} \frac{1}{N} x[n] \cos \frac{\pi k}{N} (n + \frac{1}{2}) \dots \text{DCT - II used in JPEG}$$

$$c_k = \begin{cases} 1/\sqrt{2} & k = 0 \\ 1 & k = 1, 2, \dots, N-1 \end{cases}$$

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