

Numerical Methods for Computational Science and Engineering

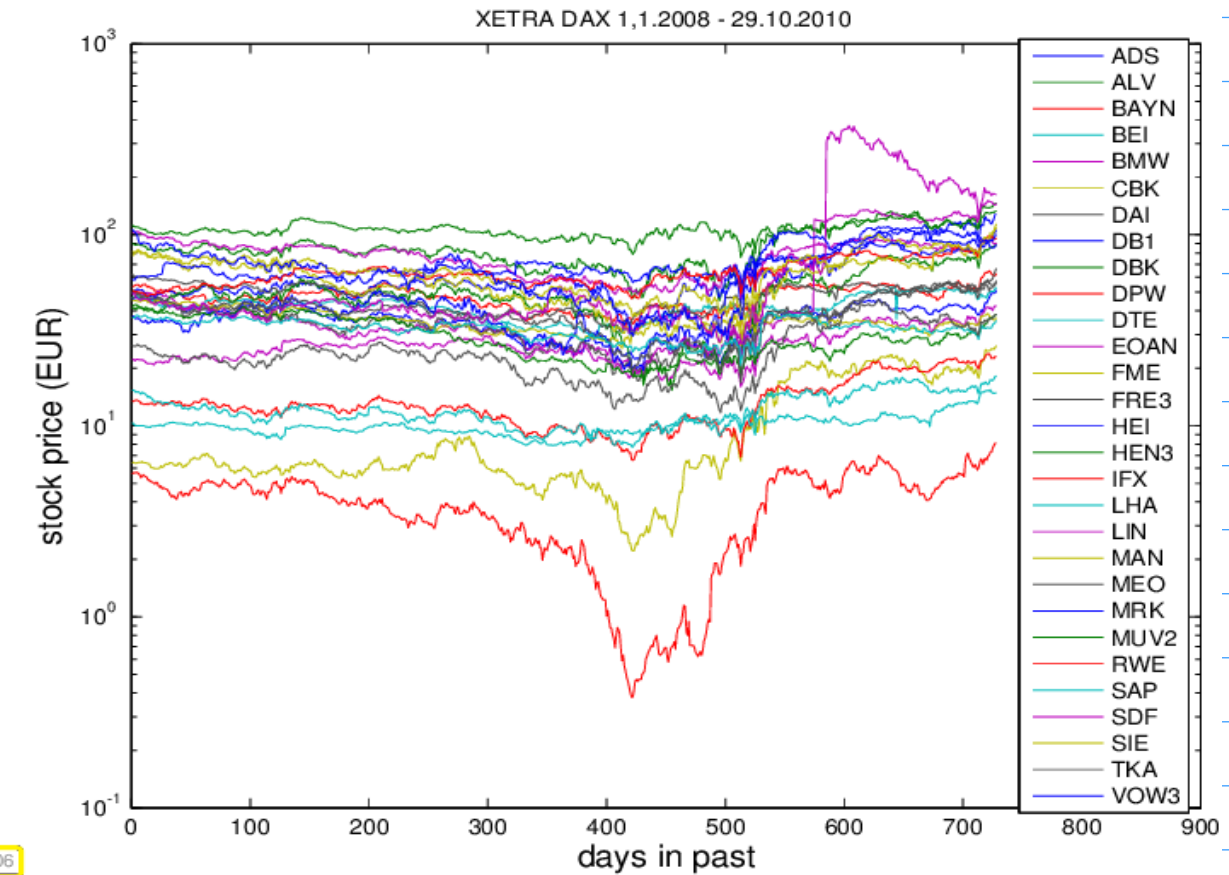
Autumun Semester 2018, Week 5

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Principle Component Analysis (PCA)

- Important for :
- dimensionality reduction
 - trend analysis
 - data classification

Example :



Is there an underlying trend in the price development?

Each stock price as a vector $a_j \in \mathbb{R}^m$

$j = 1, \dots, n$ (n stocks)

$$A = [a_1 \ a_2 \ \dots \ a_n] \in \mathbb{R}^{m,n}$$

Trend $\hat{=}$ There are a few vectors $\tilde{u}_1, \dots, \tilde{u}_p$, $p \ll n$,
 (strict sense) s.t. $a_j \in \text{span}\{\tilde{u}_1, \dots, \tilde{u}_p\}$
 for all $j \in \{1, \dots, n\}$
 (and $\tilde{u}_1, \dots, \tilde{u}_p$ orthonormal)

This would mean: $\mathcal{R}(A) \subseteq \text{span}\{\tilde{u}_1, \dots, \tilde{u}_p\}$

$$\Rightarrow \text{rank}(A) = p$$

unrealistic scenario

Stock prices for example: small random fluctuations
 in the stock prices

More realistic scenario instead:

Can we find orthonormal vectors $\tilde{u}_1, \dots, \tilde{u}_p$ s.t.

$\forall j \in \{1, \dots, n\}: a_j \in \text{span}\{\tilde{u}_1, \dots, \tilde{u}_p\} + \text{"small perturbation"}$

This means: Stock prices approximately follow a trend

Find an (approximate) trend by exploiting the SVD of A .

$$A = U \Sigma V^T$$

$$\begin{bmatrix} \uparrow \\ \vdots \\ a_j \\ \vdots \\ \uparrow \end{bmatrix} A = \sigma_1 \begin{bmatrix} \vdots \\ u_1 \\ \vdots \end{bmatrix} \left[\begin{array}{c} \bullet \\ \uparrow \\ v_1^T \\ \vdots \\ (v_1)_j \\ \vdots \end{array} \right] + \dots + \sigma_n \begin{bmatrix} \vdots \\ u_n \\ \vdots \end{bmatrix} \left[\begin{array}{c} \bullet \\ \uparrow \\ v_n^T \\ \vdots \\ (v_n)_j \\ \vdots \end{array} \right]$$

Each a_j is a linear combination of u_1, \dots, u_n

[Recall: $\{u_1, \dots, u_n\}$ ONB for column space of A]

Vectors v_i carry weights of this linear combination:

$$a_j = (\sigma_1 (v_1)_j) u_1 + (\sigma_2 (v_2)_j) u_2 + \dots + (\sigma_n (v_n)_j) u_n$$

In the unrealistic scenario of $\text{rank}(A) = p \ll n$:

SVD: $A = U \Sigma V^H$ satisfies $\sigma_1 \geq \sigma_2 \geq \dots \sigma_p > \sigma_{p+1} = \dots = \sigma_{\min\{m,n\}} = 0$,
orthonormal trend vectors $(U)_{:,1}, \dots, (U)_{:,p}$.
last non-zero sing. value

More realistic scenario:

SVD: $A = U \Sigma V^H$ satisfies $\sigma_1 \geq \sigma_2 \geq \dots \sigma_p \gg \sigma_{p+1} \approx \dots \approx \sigma_{\min\{m,n\}} \approx 0$,
orthonormal trend vectors $(U)_{:,1}, \dots, (U)_{:,p}$.
last significant sing. val.
pronounced gap

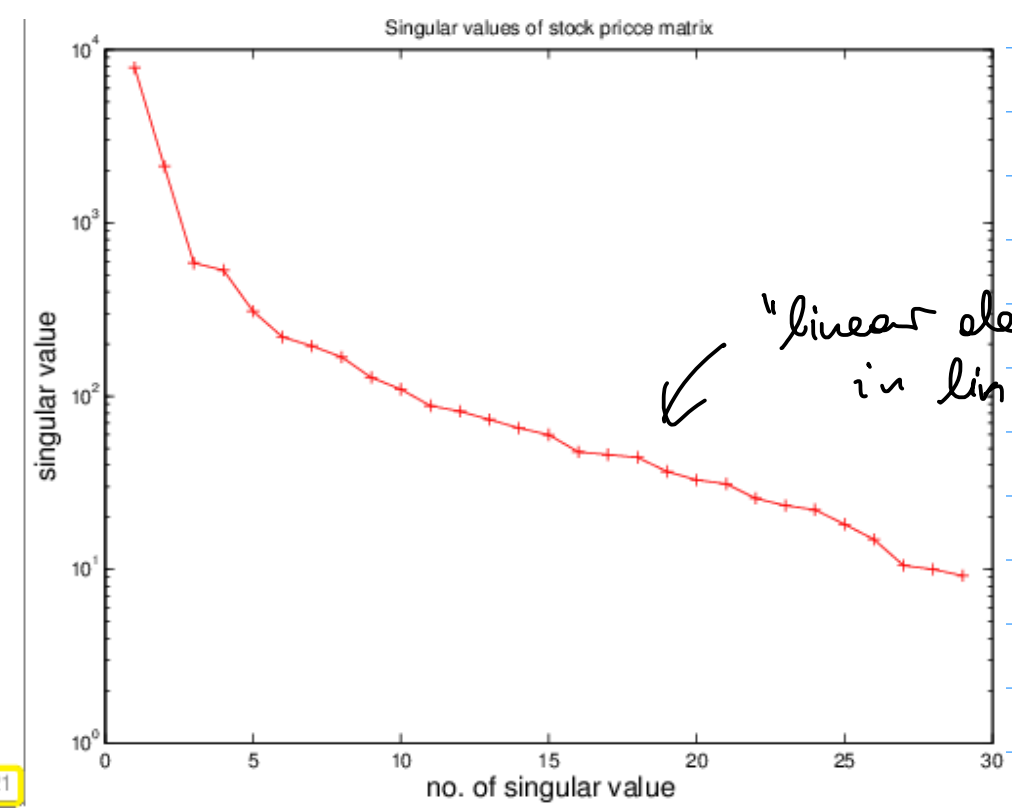
This means: " $\mathcal{R}(A)$ is almost p -dimensional"

$$A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_p u_p v_p^T$$

$$+ \sigma_{p+1} u_{p+1} v_{p+1}^T + \dots + \sigma_n u_n v_n^T$$

comparably small

log scale



lin-log plot

"linear decay" in lin-log-scale

exponential decay (in lin-lin-scale)

linear scale

Common criterion:

$$p = \min \left\{ q : \sum_{j=1}^q \sigma_j^2 \geq (1-\tau) \sum_{j=1}^n \sigma_j^2 \right\} \quad \tau \ll 1$$

→ the sum of the first p σ_j^2 's is almost as large as the sum over all σ_j^2 's.

Example: Classification of measured data

measured data: voltage -vs.- current in diodes

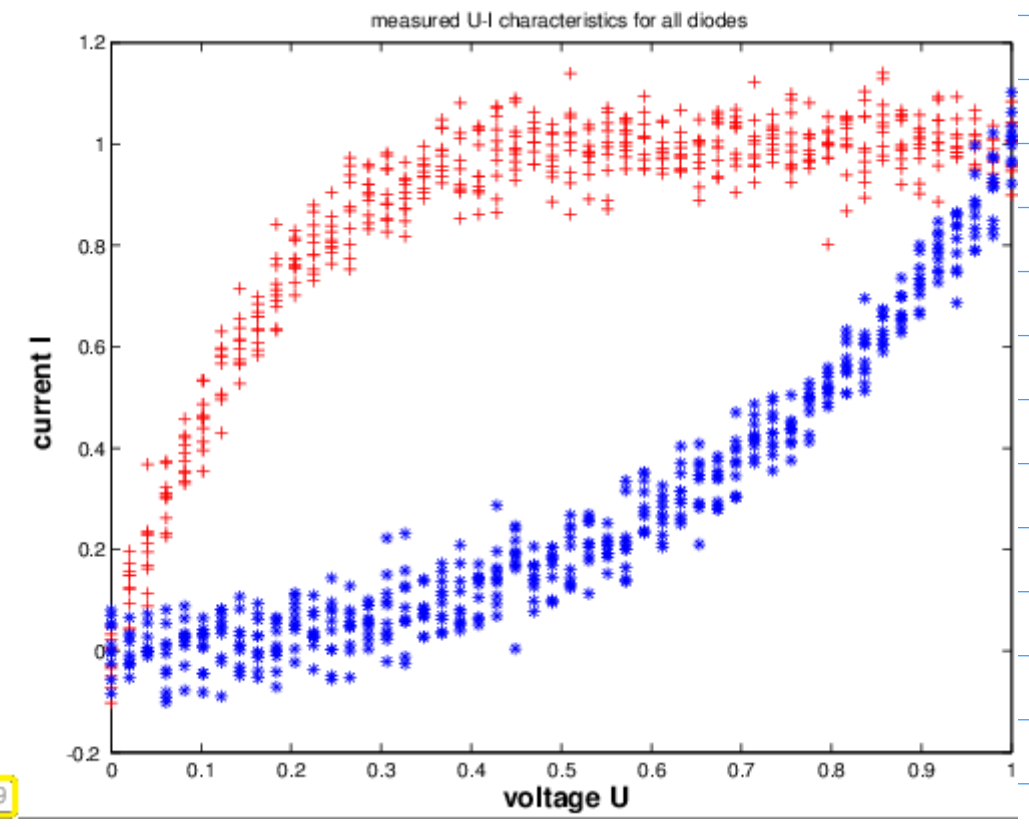


Fig. 109

How many types of diodes → consider SVD

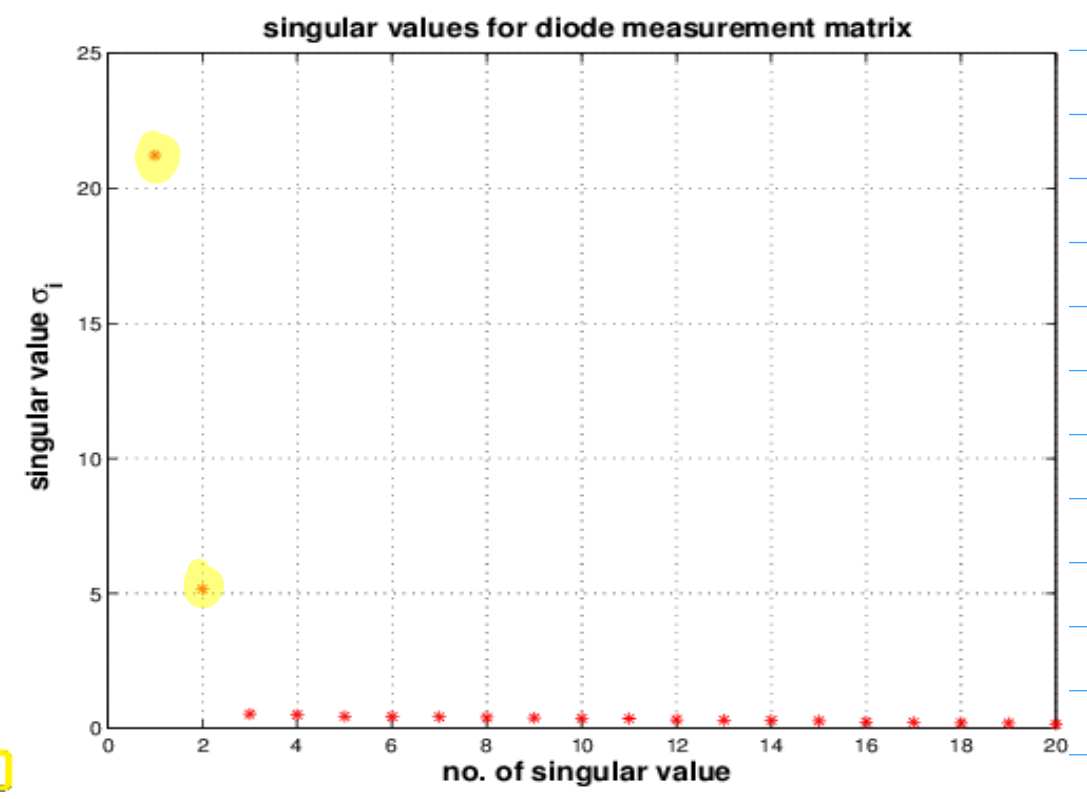


Fig. 113

2 dominant sing values
 → 2 groups in voltage-vs-current behavior
 → this suggest: 2 types of diodes

4. Filtering Algorithms

↓
 applying an operation ("filter") to a signal,
 an image, etc. to analyze / transmit the signal.

signal processing: time-discrete signals as
 sequences

$$(\dots, 0, 0, x_0, x_1, x_2, \dots, x_{n-1}, 0, 0, \dots)$$

(sampling time-continuous signals)

time-cont. signal: $X(t) \quad t \in [0, T]$

time-discrete signal: $x_j = X(j \cdot \Delta t)$

$$x = [x_0, x_1, \dots, x_{n-1}]^T \in \mathbb{R}^n$$

$n \cdot \Delta t \leq T$

spacing between 2 samples

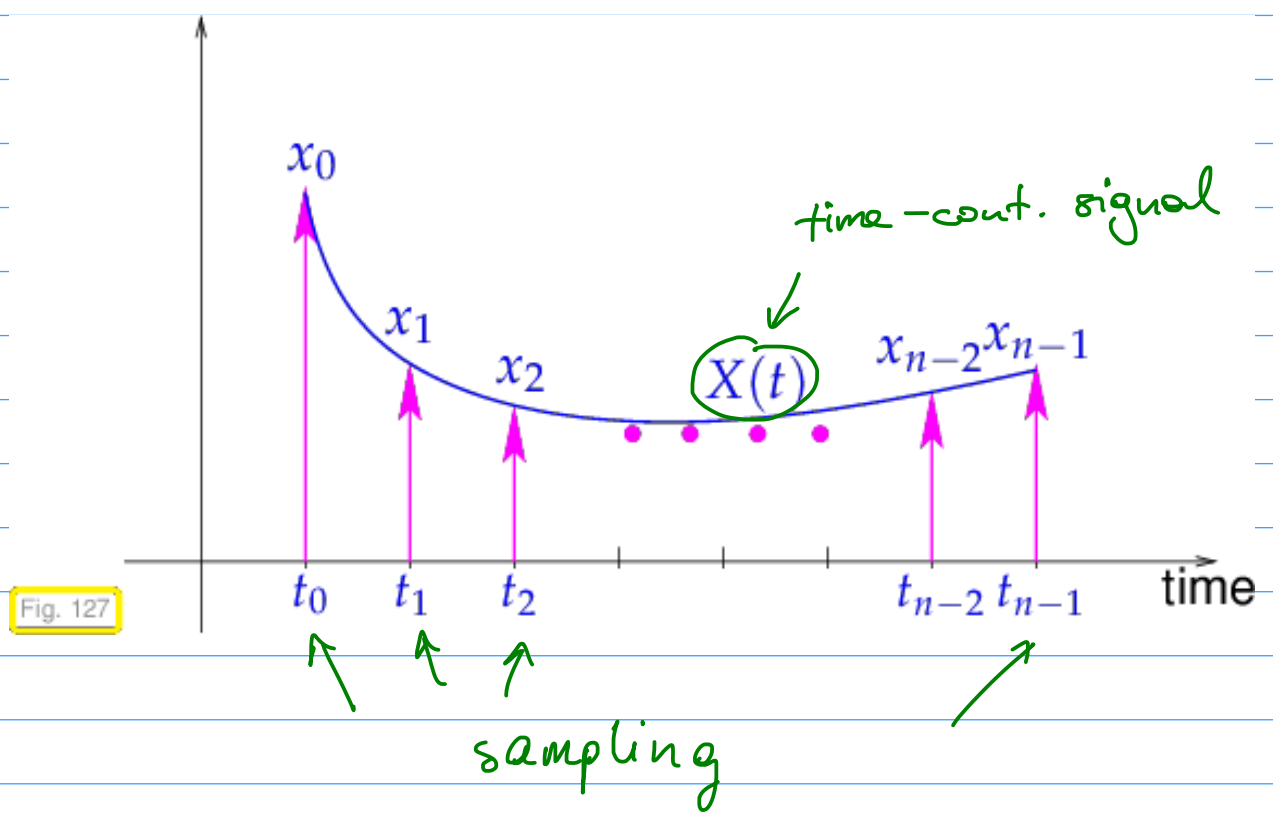
4.1 Discrete convolutions (→ operating on sequences)

Filters or channels (as in wireless communication)

LT-FIR filters:

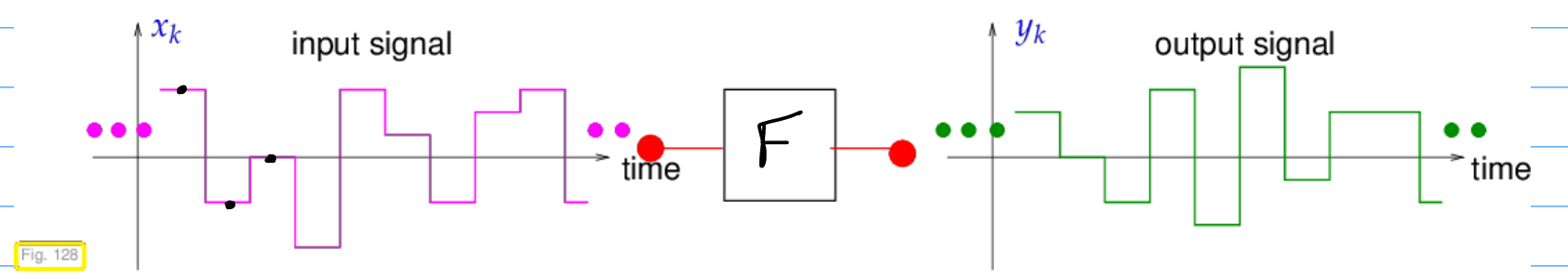
Channel / filter: mapping $F: l^\infty(\mathbb{Z}) \rightarrow l^\infty(\mathbb{Z})$

$$F((x_j)_{j \in \mathbb{Z}}) = (y_j)_{j \in \mathbb{Z}}$$



In general: signal $\hat{=}$ bounded sequence

$$l^\infty(\mathbb{Z}) = \left\{ \underbrace{(x_j)_{j \in \mathbb{Z}}}_{\text{sequence}} : \sup_{j \in \mathbb{Z}} |x_j| < \infty \right\}$$



Properties of F?

- finite: Every finite-length signal $(x_j)_{j \in \mathbb{Z}}$ has a finite-length output $F((x_j)_{j \in \mathbb{Z}})$

• time-invariant:

time-shift of the input & then filter applied

= apply filter & then time-shift output

time-shift operator $S_k: l^\infty(\mathbb{Z}) \rightarrow l^\infty(\mathbb{Z})$

$$S_k((x_j)_{j \in \mathbb{Z}}) = (x_{j-k})_{j \in \mathbb{Z}}$$

time-invariant:

$$F(S_k((x_j)_{j \in \mathbb{Z}})) = S_k(F((x_j)_{j \in \mathbb{Z}}))$$

• linear:

$$F(\underbrace{\alpha \cdot (x_j)_{j \in \mathbb{Z}} + \beta \cdot (y_j)_{j \in \mathbb{Z}}}_{\text{linear comb. of 2 seq.}}) = \alpha \cdot F((x_j)_{j \in \mathbb{Z}}) + \beta \cdot F((y_j)_{j \in \mathbb{Z}})$$

• causal: output only depends on past & present inputs, not future:

$$\text{If } x_j = 0 \quad \forall j \leq M \Rightarrow F((x_j)_{j \in \mathbb{Z}})_k = 0 \quad \forall k \leq M$$

At index k : output only takes into account x_1, \dots, x_k

Impulse response:

Analogue: Matrix $\hat{=}$ describing action of a linear map $\mathbb{R}^n \rightarrow \mathbb{R}^m$ through its action on unit vectors e_j

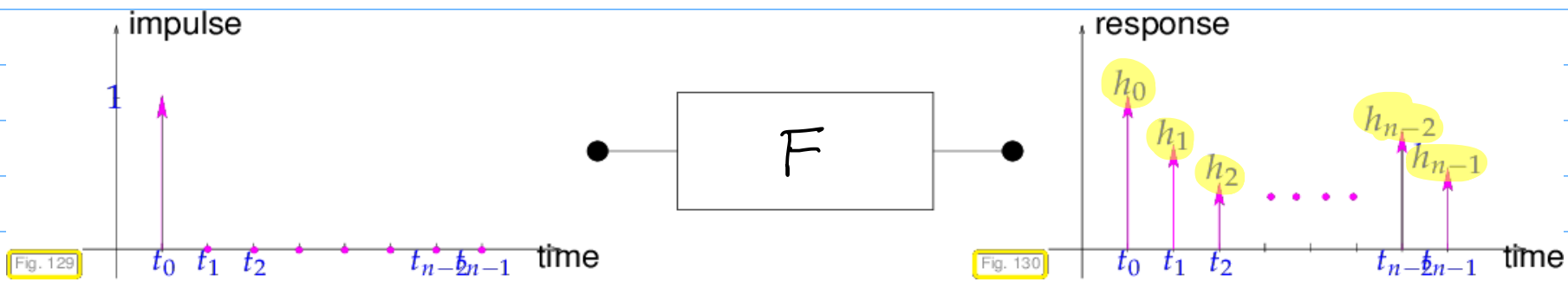
$$Ae_1 = (A)_{:,1} \quad Ae_j = (A)_{:,j}$$

Now in the same spirit:

describe filters through their action on "impulses"
 $\hat{=}$ "unit sequences"

How does F respond to the input signal

$(\dots, 0, 0, 1, 0, 0, 0, \dots)$ "unit impulse"
 \uparrow
 0-th entry



We can write $(\dots, 0, 0, 1, 0, 0, 0, \dots)$

$$= (\delta_{j,0})_{j \in \mathbb{Z}}$$

$$\delta_{j,l} = \begin{cases} 1 & j=l \\ 0 & \text{otherwise} \end{cases}$$

$$h_k := F((\delta_{j,0})_{j \in \mathbb{Z}})_k$$

Impulse response $\hat{=}$ "building block"

\rightarrow can build response $F((x_i)_{i \in \mathbb{Z}})$
 out of these building blocks

Impulse response $(\dots, 0, 0, h_0, h_1, \dots, h_{m-1}, 0, 0, \dots)$

m : length of the filter

order of the filter

$$F((\delta_{j,0})_{j \in \mathbb{Z}}) = (\dots, 0, 0, \underset{\substack{\uparrow \\ \text{0-th index}}}{h_0}, h_1, \dots, h_{m-1}, 0, 0, \dots)$$

$$F((\delta_{j,k})_{j \in \mathbb{Z}}) = (\dots, 0, 0, \underset{\substack{\uparrow \\ \text{k-th index}}}{h_0}, h_1, \dots, h_{m-1}, 0, 0, \dots)$$

\uparrow
 shifted unit impulse
 (shifted by k)

How to use impulse response?

Any finite signal $(x_j)_{j \in \mathbb{Z}} = (\dots, 0, x_0, x_1, \dots, x_{n-1}, 0, \dots)$ is a linear combination of shifted impulses:

$$(x_j)_{j \in \mathbb{Z}} = \sum_{k=0}^{n-1} x_k \cdot (\delta_{j,k})_{j \in \mathbb{Z}} \quad \leftarrow \text{just a basis!}$$

$$= \sum_{k=0}^{n-1} x_k \cdot S_k((\delta_{j,0})_{j \in \mathbb{Z}})$$

↑
time-shift by k

Response of $(x_j)_{j \in \mathbb{Z}}$?

$$F((x_j)_{j \in \mathbb{Z}}) = F\left(\sum_{k=0}^{n-1} x_k \cdot S_k((\delta_{j,0})_{j \in \mathbb{Z}})\right)$$

$$\stackrel{\text{linearity}}{\rightarrow} \sum_{k=0}^{n-1} x_k \cdot F(S_k((\delta_{j,0})_{j \in \mathbb{Z}}))$$

$$= \sum_{k=0}^{n-1} x_k S_k \left(\underbrace{F((\delta_{j,0})_{j \in \mathbb{Z}})}_{\text{impulse response}} \right)$$

↑
time-invariance

$$(\dots, 0, h_0, \dots, h_{m-1}, 0, \dots)$$

$$(y_j)_{j \in \mathbb{Z}} = F((x_j)_{j \in \mathbb{Z}})$$

$$\begin{bmatrix} y_0 \\ y_1 \\ \vdots \\ y_{n+m-2} \end{bmatrix} = x_0 \begin{bmatrix} h_0 \\ h_1 \\ \vdots \\ h_{m-1} \\ 0 \\ \vdots \\ 0 \end{bmatrix} + x_1 \begin{bmatrix} 0 \\ h_0 \\ h_1 \\ \vdots \\ h_{m-1} \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \dots + x_{n-1} \begin{bmatrix} 0 \\ \vdots \\ 0 \\ h_0 \\ \vdots \\ \vdots \\ h_{m-1} \end{bmatrix}$$

$$\Rightarrow F((x_j)_{j \in \mathbb{Z}})_k = y_k = \sum_{j=0}^{n-1} x_j h_{k-j}$$

$k = 0, \dots, m+n-2$ $h_j = 0$ for $j < 0, j \geq m$

Output is a linear combination of
 / shifted impulse responses

Maximal duration of output:

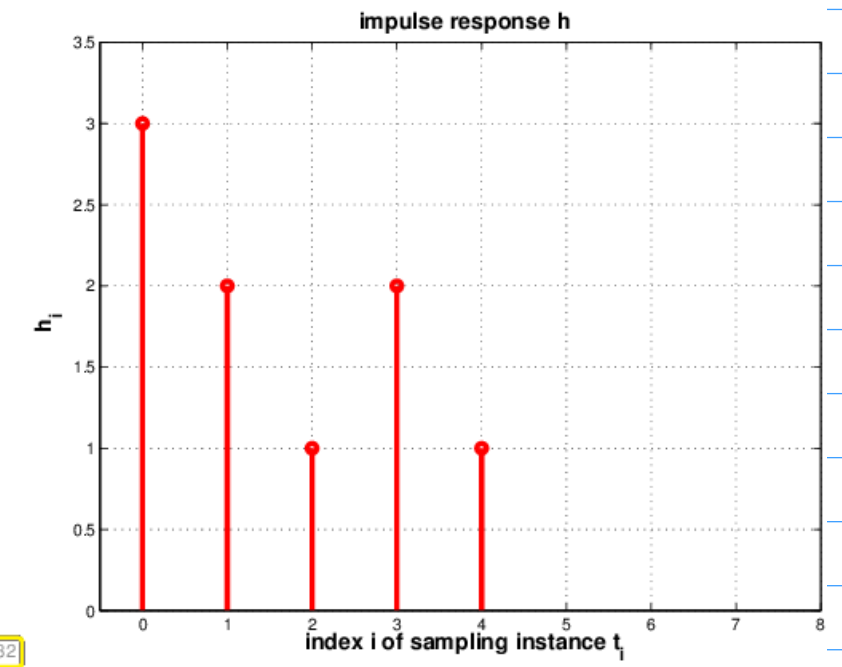
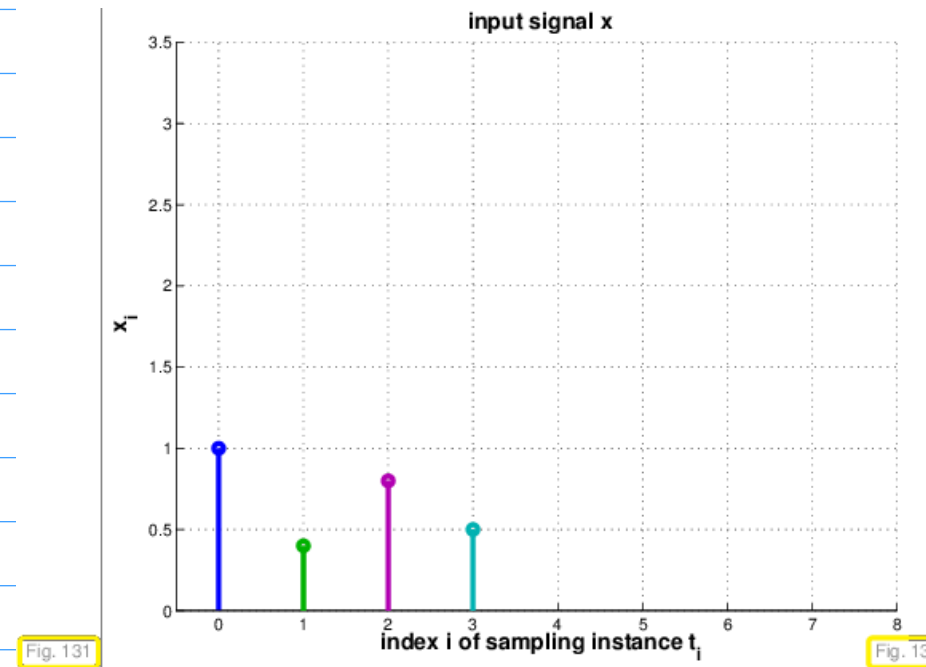
$n + m - 1$
 ↑ ↑
 length of signal length of filter

Example:

signal: $(x_i)_{i \in \mathbb{Z}} = (\dots, 0, 0, 3, 1, 2, 4, 0, 0, \dots)$ $n = 4$

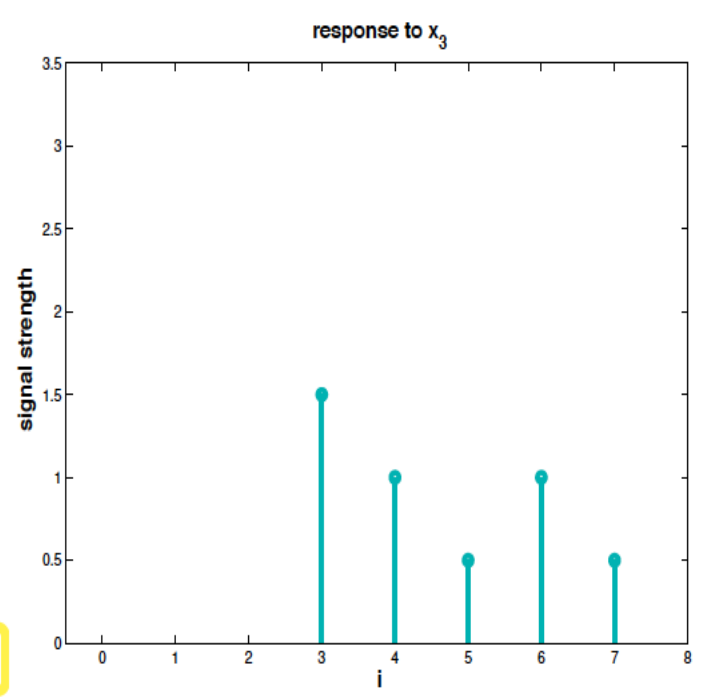
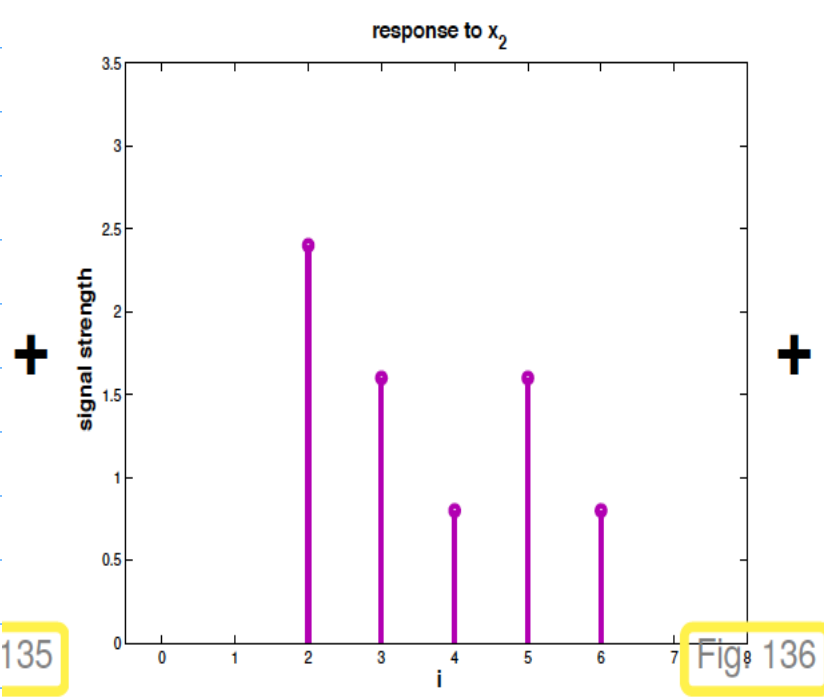
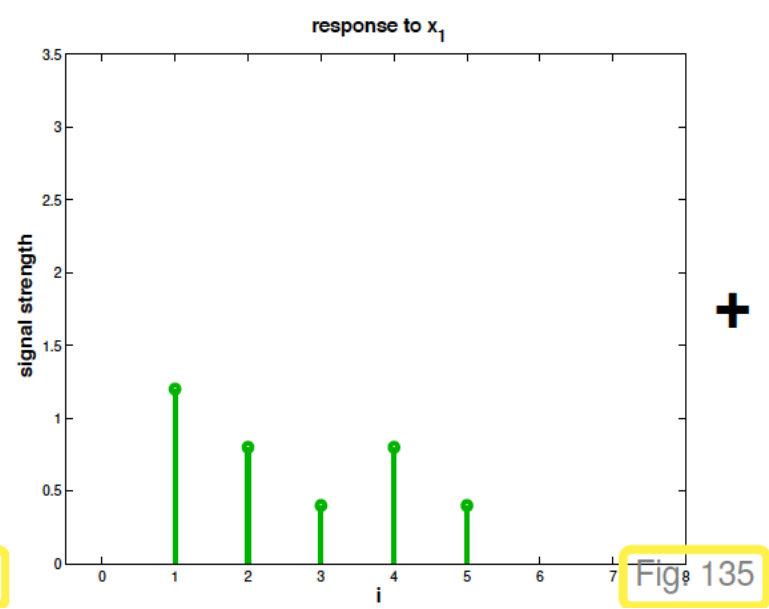
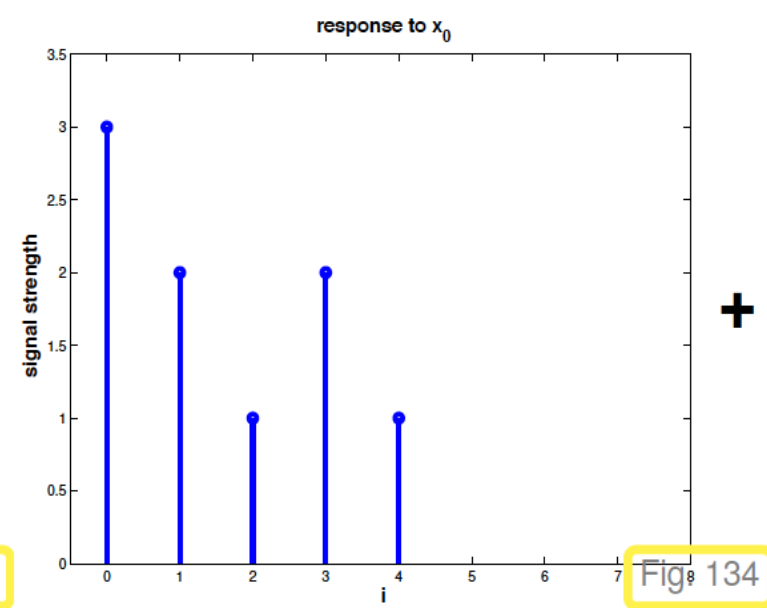
filter: $(\dots, 0, 0, 1, 1, 2, 3, 1, 0, 0, \dots)$ $m = 5$
 (impulse response)

Output $F((x_i)_{i \in \mathbb{Z}})$?

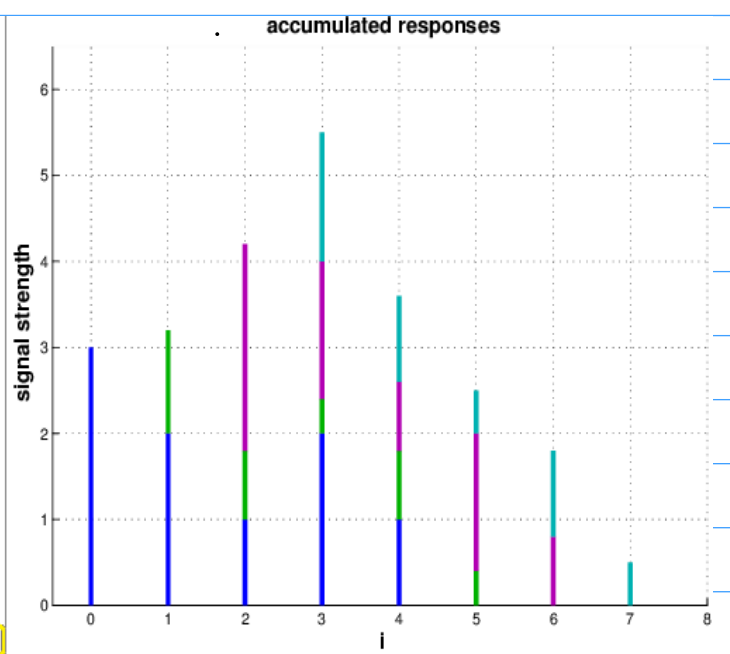
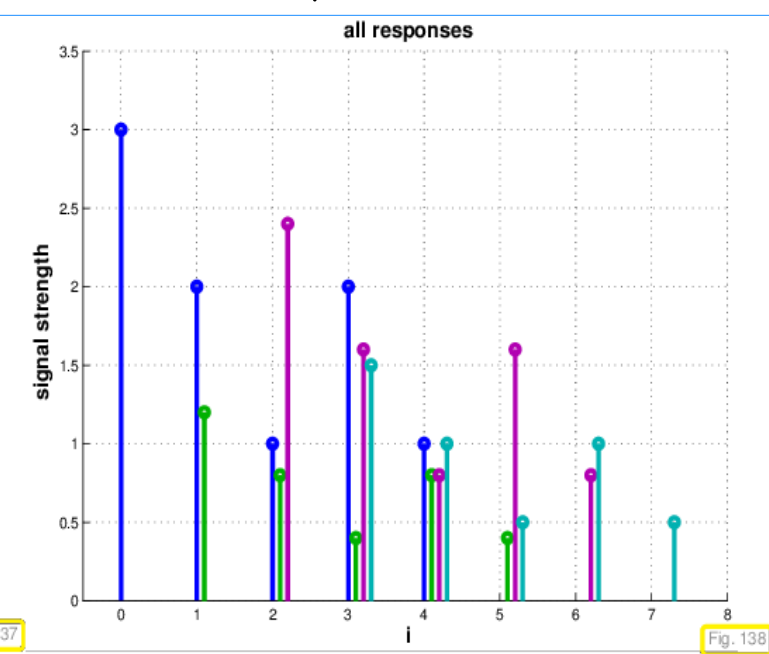


$$x = (\dots, 0, x_0, \dots, x_3, 0, \dots) \quad n = 4$$

$$h = (\dots, 0, h_0, \dots, h_4, 0, \dots) \quad m = 5$$



Add up all the responses:



For finite length signals:

- Represent $x = (\dots, 0, x_0, \dots, x_{n-1}, 0, \dots)$ by a vector $\underline{x} = [x_0, \dots, x_{n-1}]^T \in \mathbb{R}^n$
- Represent filter as a linear mapping $F: \mathbb{R}^n \rightarrow \mathbb{R}^{m+n-1}$

Here: filter of length m

$$\begin{bmatrix} y_0 \\ \vdots \\ y_{m+n-2} \end{bmatrix} = \begin{bmatrix} h_0 & 0 & \dots & 0 \\ h_1 & h_0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ h_{m-1} & \vdots & \vdots & \vdots & 0 \\ 0 & \vdots & \vdots & h_0 & \vdots \\ \vdots & \vdots & \vdots & h_1 & \vdots \\ 0 & \dots & 0 & h_{m-1} & \vdots \end{bmatrix} \begin{bmatrix} x_0 \\ \vdots \\ x_{n-1} \end{bmatrix}$$

⇒ Representation of an LT-FIR filter as a matrix.

Can we exploit the special matrix structure?

Recall: $F((x_j)_{j \in \mathbb{Z}})_k = \sum_{j \in \mathbb{Z}} x_j h_{k-j}$

This operation is called (linear) discrete convolution

of $x = (\dots, 0, x_0, \dots, x_{n-1}, 0, \dots)$

with $h = (\dots, 0, h_0, \dots, h_{m-1}, 0, \dots)$

Definition (discrete convolution):

For 2 finite sequences $f, g \in l^\infty(\mathbb{Z})$

their discrete convolution

$$u := f * g (= g * f) \in l^\infty(\mathbb{Z})$$

is defined by

$$u_k := \sum_{j \in \mathbb{Z}} f_j g_{k-j} = \sum_{j \in \mathbb{Z}} f_{k-j} g_j$$

Filtering: output $y = x * h$ finite & in $l^\infty(\mathbb{Z})$

In the same way:

discrete convolution for vectors:

$$\underline{y} := \underline{x} * \underline{h}$$

↑
 $\in \mathbb{R}^{m+n-1}$

$$y_k = \sum_{j=0}^{n-1} x_j h_{k-j}$$

where $h_j = 0$ for $j \notin \{0, \dots, m-1\}$
(convention)

y_k is the inner product of x and
time-shifted (by k) and reversed h .

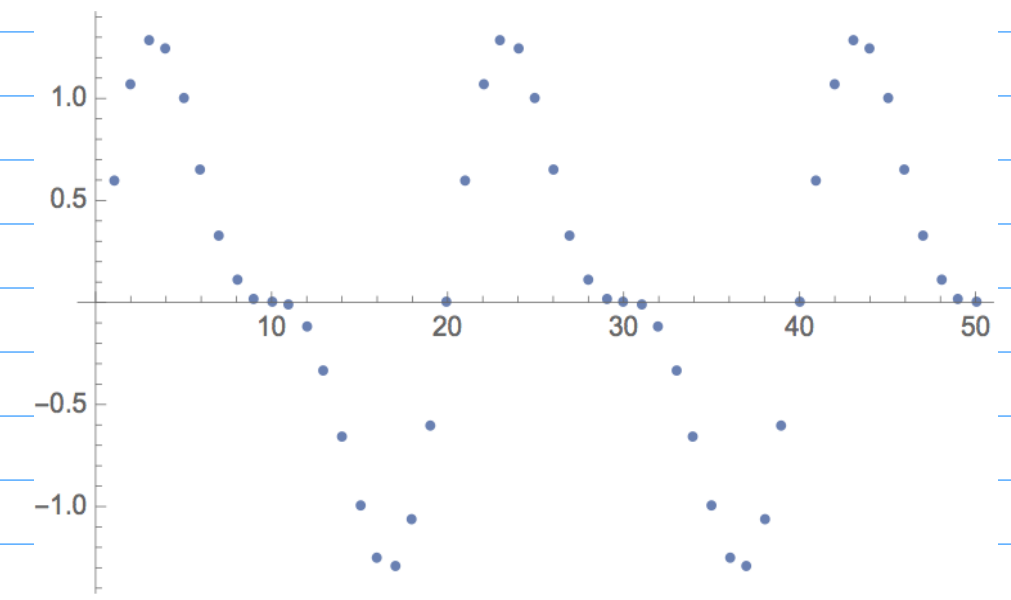
Circular / periodic convolution:

Goal: It turns out that periodic convolution
is "easier" (\leadsto convolution theorem)

So ultimately: describe linear convolution
from before as periodic convolution

Filtering of periodic signal

$$x_j = x_{j+n} \quad \forall j \in \mathbb{Z} \quad (\text{period of length } n)$$



$$\begin{aligned}
y_k &= \sum_{j \in \mathbb{Z}} x_j h_{k-j} \\
&= \sum_{j \in \mathbb{Z}} x_{k-j} h_j \quad (\text{then: } y \text{ is also } n\text{-periodic}) \\
&= \sum_{j=0}^{n-1} \underbrace{\left(\sum_{l \in \mathbb{Z}} h_{j+ln} \right)}_{\text{periodic summation}} x_{k-j}
\end{aligned}$$

$$p_j^n := \sum_{l \in \mathbb{Z}} h_{j+ln}$$

where $h = (\dots, 0, h_0, \dots, h_{m-1}, 0, \dots)$

Note:

$$\parallel \sum_{l \in \mathbb{Z}} h_{j+(l+1)n}$$

$$p_{j+n} = \sum_{l \in \mathbb{Z}} h_{j+n+ln} = \sum_{l \in \mathbb{Z}} h_{j+ln} = p_j$$

More generally: $p_{j+kn} = p_j \quad \forall k \in \mathbb{Z}$

$\Rightarrow p^{(n)}$ is n -periodic as well

$$y_k = \sum_{j=0}^{n-1} p_j^n x_{k-j} = \sum_{j=0}^{n-1} p_{k-j} x_j \quad k \in \mathbb{Z}$$

Definition 4.1.7 (Discrete periodic convolution). The *discrete periodic convolution* of two n -periodic sequences $(p_k)_{k \in \mathbb{Z}}, (x_k)_{k \in \mathbb{Z}}$ yields the n -periodic sequence:

$$(y_k) := (p_k) *_{n} (x_k) \quad , \quad y_k := \sum_{j=0}^{n-1} p_{k-j} x_j = \sum_{j=0}^{n-1} x_{k-j} p_j, \quad k \in \mathbb{Z}.$$

$$y_0 = p_0 x_0 + p_{-1} x_1 + \dots + p_{-(n-1)} x_{n-1}$$

$$= p_0 x_0 + p_{n-1} x_1 + \dots + p_1 x_{n-1}$$

$$y_1 = p_1 x_0 + p_0 x_1 + \dots + p_{-(n-2)} x_{n-1}$$

$$= p_1 x_0 + p_0 x_1 + \dots + p_2 x_{n-1}$$

$$\begin{bmatrix} y_0 \\ \vdots \\ y_{n-1} \end{bmatrix} = \begin{bmatrix} p_0 & p_{n-1} & p_{n-2} & \cdots & \cdots & p_1 \\ p_1 & p_0 & p_{n-1} & & & \vdots \\ p_2 & p_1 & p_0 & \ddots & & \\ \vdots & \vdots & \ddots & \ddots & \ddots & \\ \vdots & \vdots & & \ddots & \ddots & p_{n-1} \\ p_{n-1} & p_{n-2} & & & p_1 & p_0 \end{bmatrix} \begin{bmatrix} x_0 \\ \vdots \\ x_{n-1} \end{bmatrix}$$

↑
=:P

very special structure
Circulant matrix

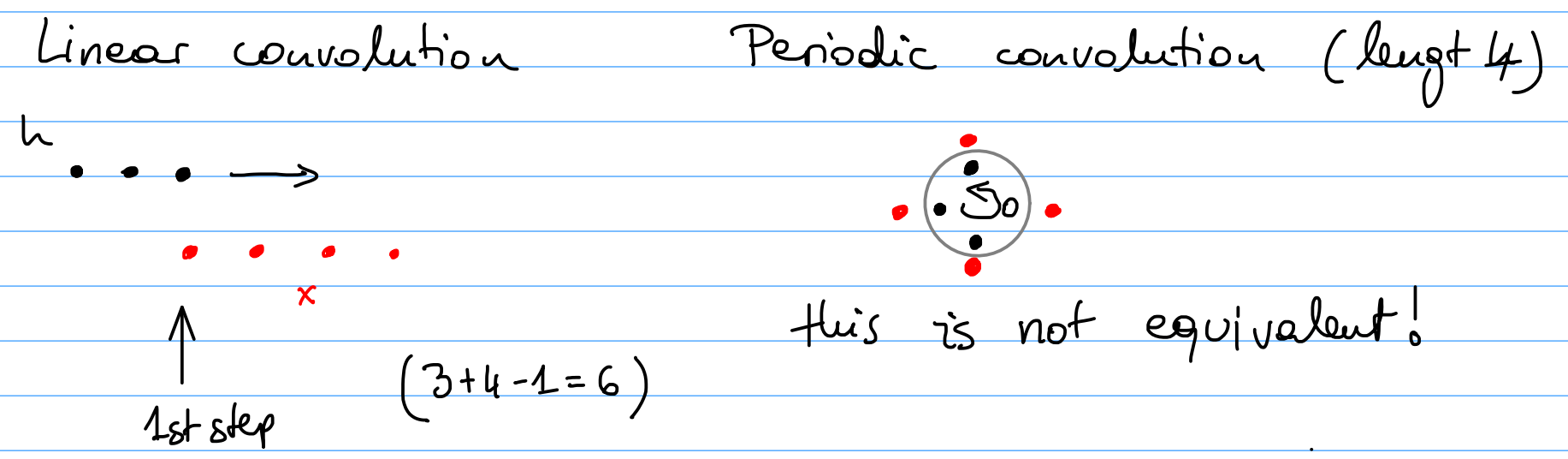
Definition 4.1.8 (Circulant matrix). A matrix $C = [c_{ij}]_{i,j=0}^{n-1} \in \mathbb{K}^{n,n}$ is *circulant* if and only if there exists an n -periodic sequence $(p_k)_{k \in \mathbb{Z}}$ such that:

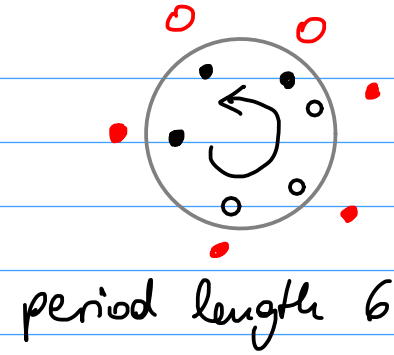
$$c_{ij} = p_{j-i}, \quad 0 \leq i, j \leq n-1$$

Circulant matrix: Diagonal & all subdiagonals are constant
 \hookrightarrow determined by $\underline{p} = [p_0, \dots, p_{n-1}]^T$

Later: We will exploit the nice property of circulant matrices (i.e. their relation to the Fourier matrix)

But first: Can we interpret linear convolution as periodic convolution multiplication by a circulant matrix





this is the periodic convolution equivalent to the linear conv.

⇒ Discrete linear convolution of

$$\underline{x} = [x_0, \dots, x_{n-1}]^T \quad \text{and}$$

$$\underline{h} = [h_0, \dots, h_{m-1}]^T$$

$$y_k = (\underline{x} * \underline{h})_k = \sum_{j=0}^{n-1} x_j h_{k-j} \quad k=0, \dots, m+n-2$$

y has length $m+n-1$

↳ to "fit" this in a periodic setting requires period of length $L := m+n-1$

zero-pad \underline{x} to length L

$$\underline{x}^L = [x_0, \dots, x_{n-1}, 0, \dots, 0]^T \in \mathbb{R}^L$$

\underline{x}^L periodic extension of \underline{x}^L
↓
sequence

$$h = (\dots, 0, h_0, \dots, h_{m-1}, 0, \dots) \quad \text{s.t.}$$

$$\hookrightarrow p_j = \sum_{l \in \mathbb{Z}} h_{j+lL} = h_{j+kL} \quad \leftarrow \in \{0, \dots, m-1\}$$

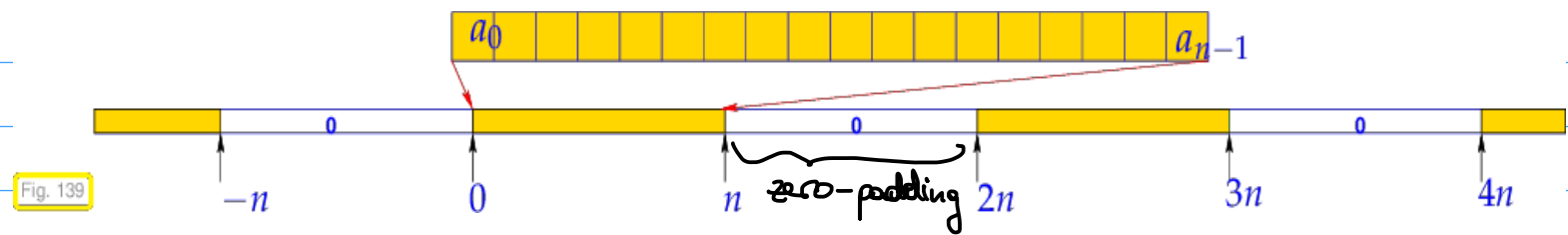
L is large enough

$$\underline{h}^L = [h_0, \dots, h_{m-1}, 0, \dots, 0]^T$$

p is periodic extension of \underline{h}^L

$$y^L = x^L *_L p$$

k -th entry of $y^L = k$ -th entry of y



a is a signal of length n
 zero-padded to length $2n$
 and then periodized

$$\begin{bmatrix} Y_0 \\ \vdots \\ Y_{L-1} \end{bmatrix} = \begin{bmatrix} p_0 & p_{L-1} & \dots & p_1 \\ p_1 & p_0 & & \vdots \\ \vdots & p_1 & & \vdots \\ \vdots & \vdots & & \vdots \\ p_{L-1} & p_{L-2} & & p_0 \end{bmatrix} \begin{bmatrix} x_0 \\ \vdots \\ x_{n-1} \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$L = m + n - 1$
 ↑ ↙
 length of h length of x

In terms of h :

$$\begin{bmatrix} Y_0 \\ \vdots \\ Y_{L-1} \end{bmatrix} = \underbrace{\begin{bmatrix} h_0 & 0 & \dots & h_{m-1} & h_{m-2} & \dots & h_1 \\ h_1 & h_0 & & 0 & h_{m-1} & & \vdots \\ \vdots & h_1 & & \vdots & 0 & & \vdots \\ \vdots & \vdots & & 0 & \vdots & & h_{m-1} \\ h_{m-1} & \vdots & & h_0 & 0 & & 0 \\ 0 & h_{m-1} & & \vdots & h_0 & & 0 \\ \vdots & 0 & & \vdots & \vdots & & \vdots \\ \vdots & \vdots & & \vdots & \vdots & & 0 \\ 0 & 0 & & h_{m-2} & h_{m-3} & \dots & h_0 \end{bmatrix}}_{\substack{\in \mathbb{R}^{L \times L} \\ \text{circulant matrix}}} \begin{bmatrix} x_0 \\ \vdots \\ x_{n-1} \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Example:

$$\text{Signal: } \underline{x} = [2, 1, 3, 2]^T$$

$$\text{Filter: } \underline{h} = [1, 1, 2]^T$$

1. 4-periodic convolution?

2. 6-periodic convolution?

$$1. \quad y^4 = x^4 *_{4} p^4$$

$$x^4 = (\dots, 2, 1, 3, 2, 2, 1, 3, 2, 2, 1, 3, 2, \dots)$$

$$p^4 = (\dots, 1, 1, 2, 0, 1, 1, 2, 0, 1, 1, 2, 0, \dots)$$

Exercise: Compute y^4

2. 6-periodic convolution

$$y^6 = x^6 *_{6} p^6$$

$$x^6 = (\dots, 2, 1, 3, 2, 0, 0, 2, 1, 3, 2, 0, 0, 2, \dots)$$

$$p^6 = (\dots, 1, 1, 2, 0, 0, 0, 1, 1, 2, 0, 0, 0, 1, \dots)$$

Exercise: Compute y^6

Consider the case in which the period is

shorter than the length of h :

$$\underline{x} = [2, 1]^T \quad x = (\dots, 2, 1, 2, 1, 2, 1, \dots)$$

$$\underline{h} = [1, 1, 2]^T$$

$$y^2 = x^2 *_{2} p^2$$

$$p = (\dots, 3, 1, 3, 1, 3, 1, \dots)$$

