

Lecture 2

System Identification and Canonical Forms

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Overview

- Fast recap on systems and identification
- Isometric, co-isometric and unitary inner
- Numerics: RQ-factorization
- External canonical forms
- Outer-inner factorization
- A "simple" numerical example
- What shall be next?

Dynamical System Theory: a definition?

The theory that describes the evolution of a system as time progresses

Key notion #1: the STATE of the system: "what the system remembers from its past"

Key notion #2: the EVOLUTION of the state (i.e. its dynamics)

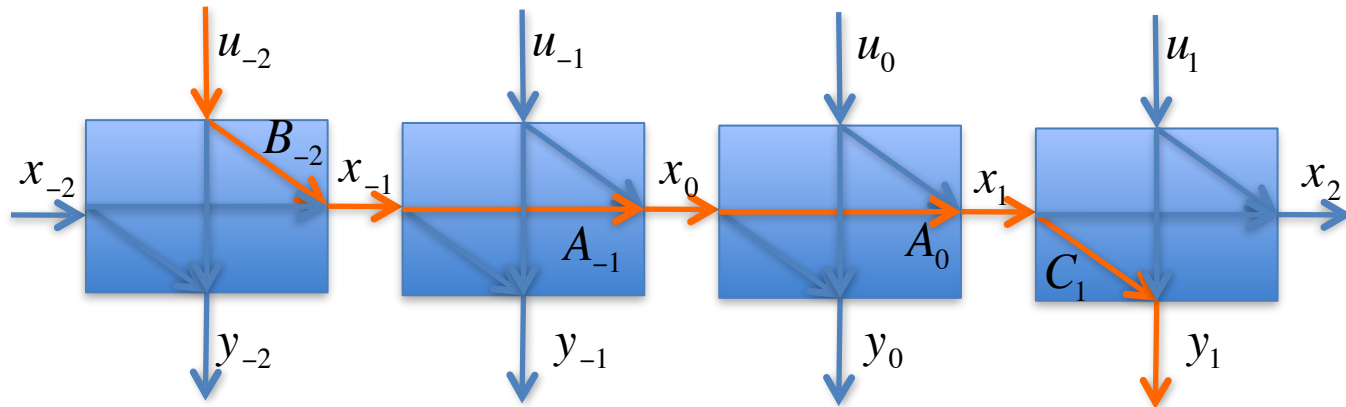
Key notion #3: the BEHAVIOR of the system (i.e. how the system looks from the outside)



Basic notions

- the STATE: a time dependent vector
- the EVOLUTION of the state: a difference equation
- REACHABILITY: how a state can be reached by past inputs (important for control)
- OBSERVABILITY: how one can estimate the state of a system by observing it (important for estimation)
- MINIMALITY: no superfluous states!

the input-output operator (causal)

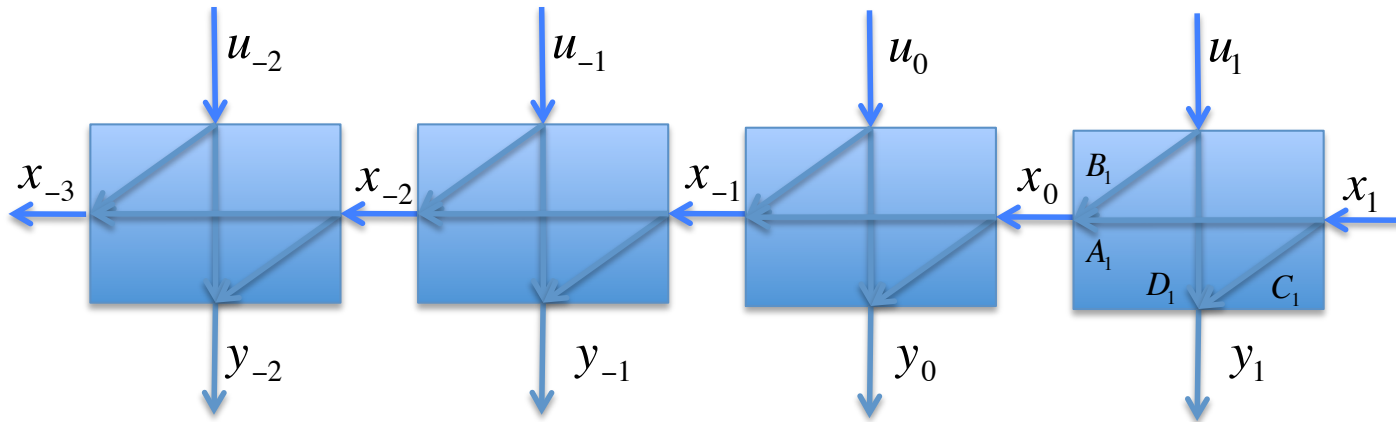


$$\begin{bmatrix} \vdots \\ y_{-2} \\ y_{-1} \\ \boxed{y_0} \\ \textcircled{y_1} \\ \vdots \end{bmatrix} = \begin{bmatrix} \ddots & & & & \\ & \ddots & & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & \ddots \end{bmatrix} \begin{bmatrix} \vdots \\ \textcircled{u_{-2}} \\ u_{-1} \\ \boxed{u_0} \\ u_1 \\ \vdots \end{bmatrix}$$

$\textcircled{y_1} \xleftarrow{C_1 A_0 A_{-1} B_{-2}} \textcircled{u_{-2}}$
 \uparrow
 -2

$$y = Tu$$

input-output anti-causal



$$T = \begin{bmatrix} \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\ & D_{-1} & C_{-1}B_0 & C_{-1}A_0B_1 & \ddots & \ddots \\ & & \boxed{D_0} & C_0B_1 & \ddots & \ddots \\ 0 & & & D_1 & \ddots & \ddots \\ & & & & \ddots & \ddots \end{bmatrix}$$



Representations

Linear Time-Invariant:

$$\begin{cases} U(z) = \cdots + u_{-1}z^{-1} + u_0 + u_1z + \cdots \\ Y(z) = \cdots + y_{-1}z^{-1} + y_0 + y_1z + \cdots \\ T(z) = D + C(I - zA)^{-1}zB \end{cases}$$

Time-variant: define *block diagonal operators*

instantaneous:

$$A = \begin{bmatrix} \ddots & & & \\ & A_{-1} & & \\ & & \boxed{A_0} & \\ & & & A_1 \\ & & & & \ddots \end{bmatrix}, B = \begin{bmatrix} \ddots & & & \\ & B_{-1} & & \\ & & \boxed{B_0} & \\ & & & B_1 \\ & & & & \ddots \end{bmatrix} \text{ etc...}$$

shifts, causal:

$$Z = \begin{bmatrix} \ddots & & & \\ & \ddots & & \\ & & 0 & \\ & & I & \boxed{0} \\ & & & I & 0 \\ & & & & \ddots & \ddots \end{bmatrix}$$

anti-causal:

$$Z' = \begin{bmatrix} \ddots & & & & \\ & \ddots & & & \\ & & \ddots & & \\ & & & 0 & I \\ & & & I & 0 \\ & & & & \ddots & \ddots \end{bmatrix}$$

Resulting transfer operators:

$$T = D + C(I - ZA)^{-1}ZB$$

$$T = D + C(I - Z'A)^{-1}Z'B$$

Stability?

The state evolves as:

$$(I - ZA)^{-1} = I + ZA + ZAZA + \dots$$

Define diagonal shifts:

$$A^{\langle +1 \rangle} = ZAZ' \quad \begin{array}{c} \nearrow \\ \downarrow \end{array} \quad (\text{forward})$$

$$A^{\langle -1 \rangle} = Z'AZ \quad \begin{array}{c} \nwarrow \\ \uparrow \end{array} \quad (\text{backward})$$

$$(I - ZA)^{-1} = I + ZA + Z^2 A^{\langle -1 \rangle} A + Z^3 A^{\langle -2 \rangle} A^{\langle -1 \rangle} A + \dots$$

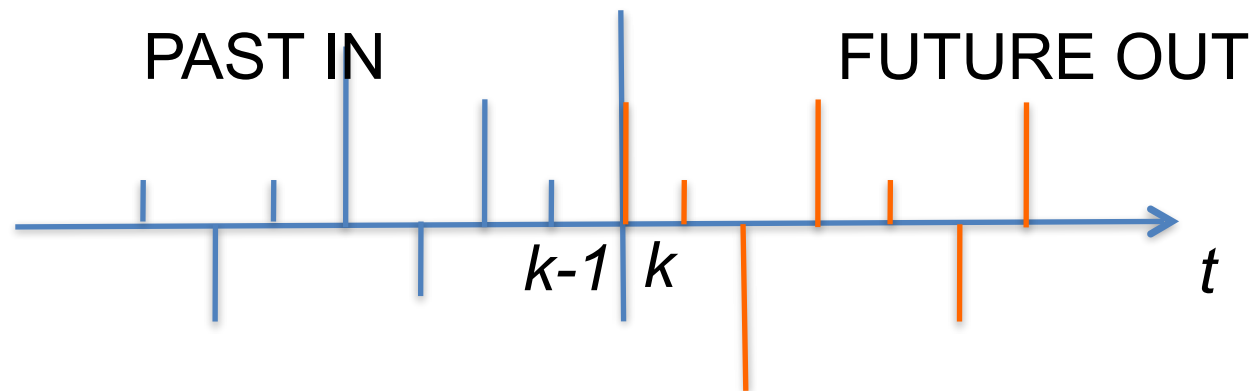
continuous product should decrease exponentially
(called "u.e.s."= uniform exponentially stable)

example of unstable:

$$\begin{bmatrix} 1 & & & & \\ -2 & 1 & & & \\ & -2 & 1 & & \\ & & -2 & 1 & \\ & & & -2 & 1 \end{bmatrix}^{-1} = \begin{bmatrix} 1 & & & & \\ 2 & 1 & & & \\ 4 & 2 & 1 & & \\ 8 & 4 & 2 & 1 & \\ 16 & 8 & 4 & 2 & 1 \end{bmatrix}$$

Past-present-future: the Hankel operator

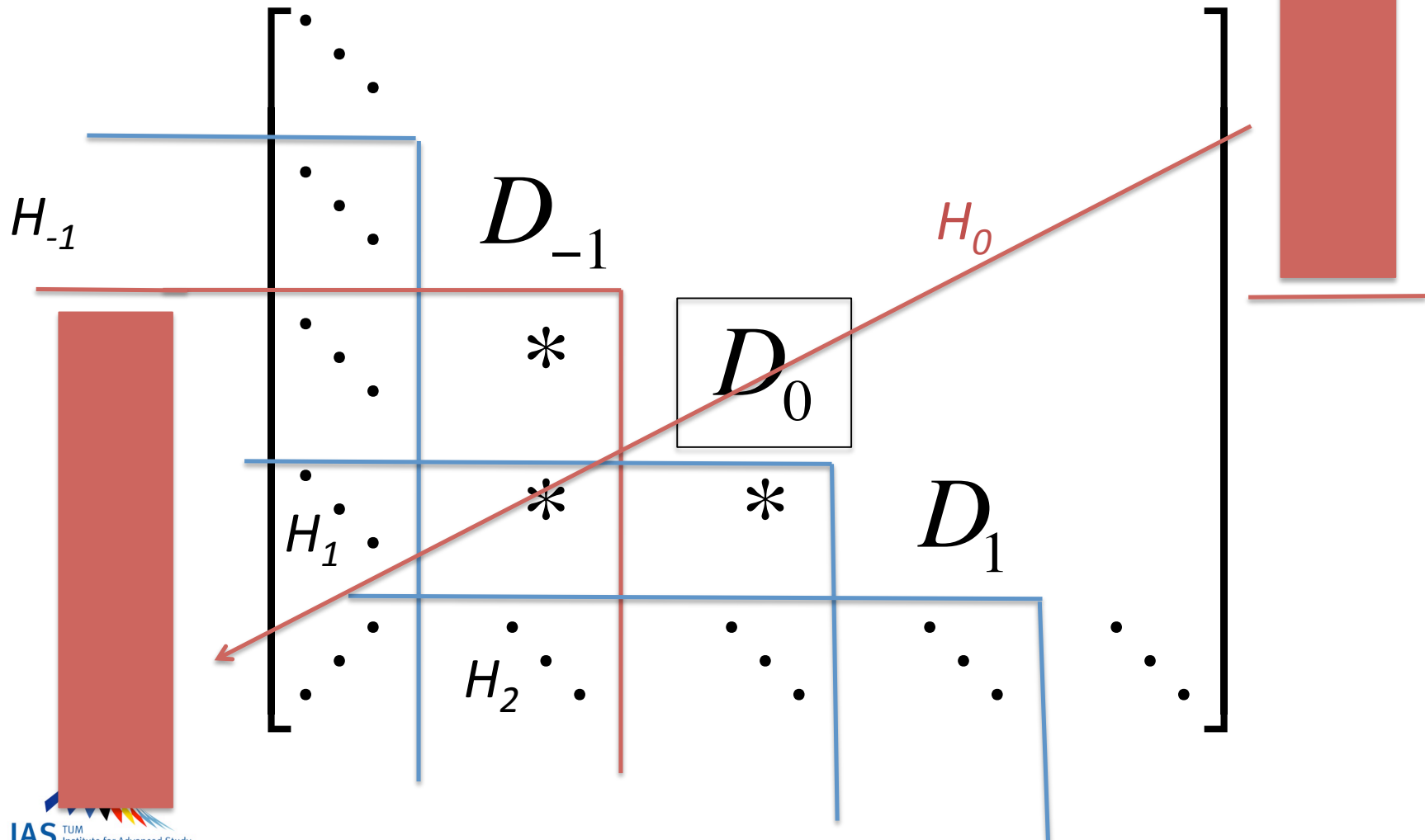
the causal case: H_k maps past inputs up to $k-1$ to future outputs from k on:



$$\begin{bmatrix} \vdots & & \\ \dots & C_k A_{k-1} B_{k-2} & C_k B_{k-1} & D_k & \vdots \\ \dots & C_{k+1} A_k A_{k-1} B_{k-2} & C_{k+1} A_k B_{k-1} & & \ddots \\ \dots & C_{k+2} A_{k+1} A_k A_{k-1} B_{k-2} & C_{k+2} A_{k+1} A_k B_{k-1} & & \\ \vdots & \vdots & \vdots & & \end{bmatrix}$$

$$H_k = \begin{bmatrix} T_{k,k-1} & T_{k,k-2} & \dots \\ T_{k+1,k-1} & T_{k+1,k-2} & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

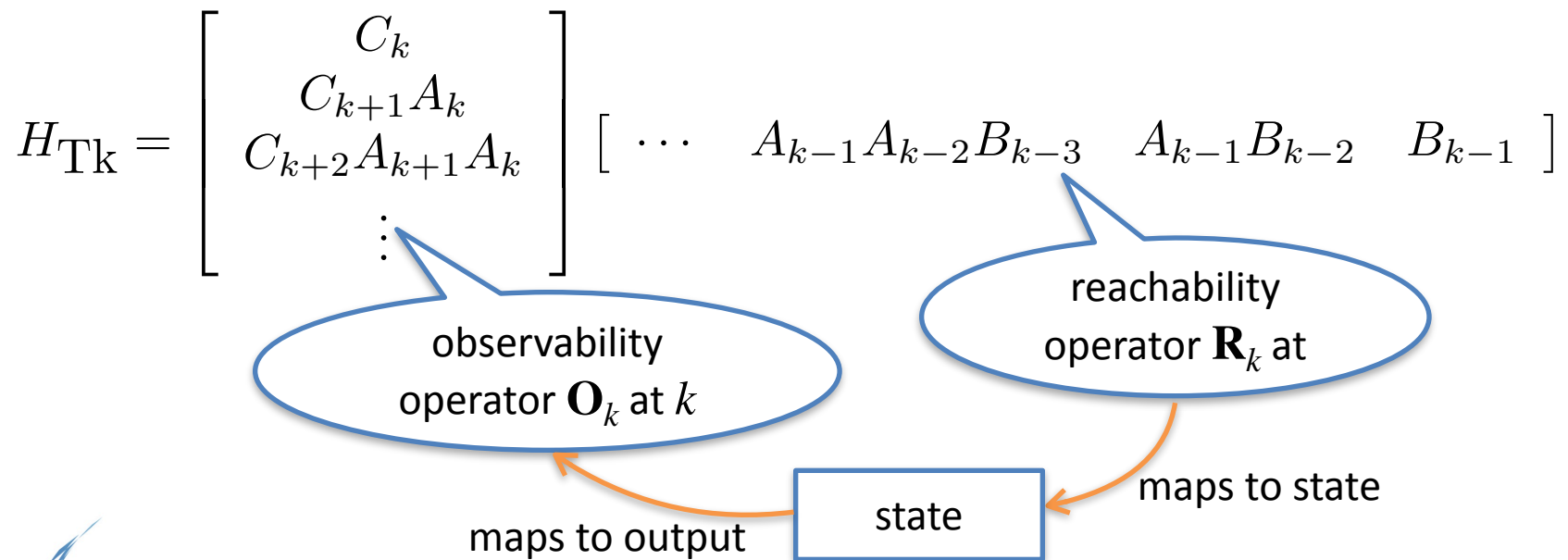
the (causal) Hankel operator:
maps “past” to “future”



System identification: factoring the Hankel operator

Given T , what is a minimal realization $\{A, B, C, D\}$?

The answer: it is given by a minimal factorization of **each** Hankel operator H_{Tk} :
(generalized Kronecker theorem)



minimal factorization \equiv choosing complementary bases

Identification (2) and normal forms

Remark: $\mathbf{O}_k = \begin{bmatrix} C_k \\ \mathbf{O}_{k+1} A_k \end{bmatrix}$, $\mathbf{R}_k = \begin{bmatrix} A_{k-1} \mathbf{R}_{k-1} & B_{k-1} \end{bmatrix}$

hence: $C_k = [\mathbf{O}_k]_k$, $B_k = [\mathbf{R}_{k+1}]_k$, $A_k = \mathbf{O}_{k+1}^+ [\mathbf{O}_k]_{k+1:\infty}$

Input normal form: choose an orthonormal basis for all \mathbf{R}_k

then $\begin{bmatrix} A_k & B_k \end{bmatrix}$ is co-isometric: $A_k A_k' + B_k B_k' = I$

Output normal form: choose an orthonormal basis for all \mathbf{O}_k

then $\begin{bmatrix} A_k \\ C_k \end{bmatrix}$ will be isometric: $A_k' A_k + C_k' C_k = I$

Change of basis (causal case -- notice: R_k is **very** different from \mathbf{R}_k !):

$$x_k = R_k \hat{x}_k \Rightarrow \begin{bmatrix} A_k & B_k \\ C_k & D_k \end{bmatrix} \mapsto \begin{bmatrix} R_{k+1}^{-1} A_k R_k & R_{k+1}^{-1} B_k \\ C_k R_k & D_k \end{bmatrix}$$

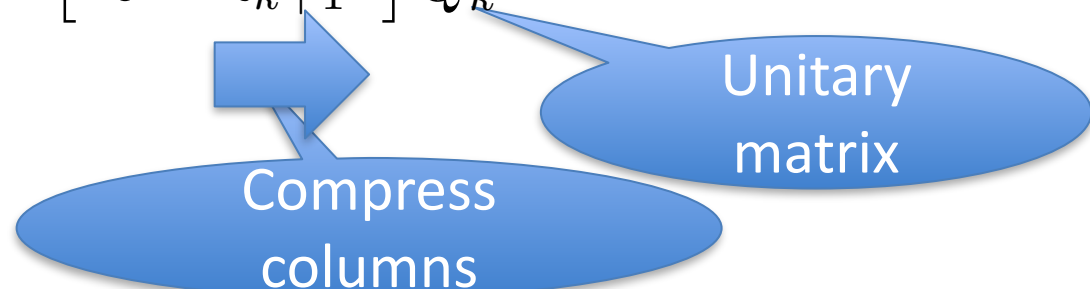
How to obtain a normalized form from any minimal factorization?

Solve an RQ factorization for the base transformation to obtain the Output Normal Form -- this is called a *Lyapunov-Stein equation*:

$$R_{k+1}R'_{k+1} = A_k R_k R'_k A'_k + B_k B'_k \quad (\text{a forward recursion})$$

Best method: R-Q factorization (square root algorithm):

$$\begin{bmatrix} A_k R_k & B_k \end{bmatrix} = \begin{bmatrix} 0 & R_{k+1} \end{bmatrix} Q_k$$



example:
$$\begin{bmatrix} \sqrt{2} & 1 & 3 \\ 0 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 0 & -2 & 2\sqrt{2} \\ 0 & 0 & \sqrt{2} \end{bmatrix} \begin{bmatrix} 1/\sqrt{2} & 1/2 & -1/2 \\ -1/\sqrt{2} & 1/2 & -1/2 \\ 0 & 1/\sqrt{2} & 1/\sqrt{2} \end{bmatrix}$$

An algebraic approach to canonical forms

The start: isometric, co-isometric and unitary operators
(an alternative theory works with polynomials, see later)

T is isometric if $T'T = I$ (some care needed with infinite matrices!)
We consider quasi-separable T 's (i.e., having realizations.)

Central property: an isometric T has a u.e.s. isometric realization and conversely

$$\begin{bmatrix} A'_k & C'_k \\ B'_k & D'_k \end{bmatrix} \begin{bmatrix} A_k & B_k \\ C_k & D_k \end{bmatrix} = I$$

Caution: "u.e.s." is essential in the statement in case of infinitely indexed systems (u.e.s. = uniformly exponentially

isometries (ctn'd)

An isometric realization of an isometry is in *Output Normal Form ONF*)

a co-isometric realization of a co-isometry is in *Input Normal Form (INF)*

a *unitary* quasi-separable operator has a *unitary realization* that is also u.e.s and conversely,

however:

unitary realizations may not correspond to unitary operators!

Example, when e.g. for large $k > 0$:

$$\begin{bmatrix} A_k & B_k \\ C_k & D_k \end{bmatrix} = \begin{bmatrix} \sqrt{1 - \frac{1}{k^2}} & \frac{1}{k} \\ -\frac{1}{k} & \sqrt{1 - \frac{1}{k^2}} \end{bmatrix}$$

*energy disappears
at infinity!*

the basic ingredient: R-Q factorization

The situation: suppose a matrix $T : \mathcal{U} \rightarrow \mathcal{Y}_1 \oplus \mathcal{Y}_2$

$$T = \begin{bmatrix} T_1 \\ T_2 \end{bmatrix}$$

and we wish a basis for the range (columns) of T_2 *first*, and then generate a full basis for T :

$$T = \begin{bmatrix} 0 & R_{11} & R_{12} \\ 0 & 0 & R_{22} \end{bmatrix} \cdot \begin{bmatrix} Q_1 \\ Q_2 \\ Q_3 \end{bmatrix}$$

orthogonal

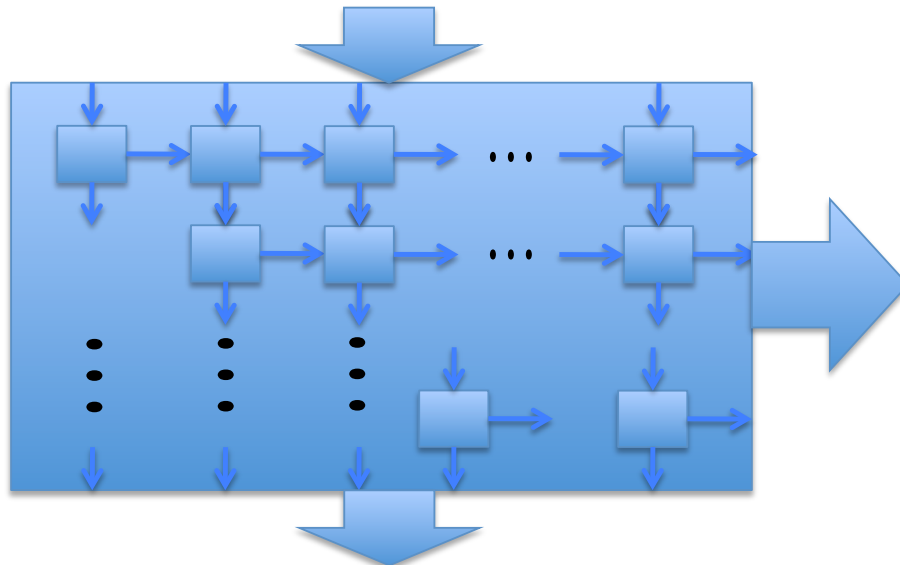
compress the
columns

an elementary algorithm

use Jacobi (Givens) rotations:

$$\begin{bmatrix} a & b \end{bmatrix} = \begin{bmatrix} 0 & \sqrt{|a|^2 + |b|^2} \end{bmatrix} \cdot \begin{bmatrix} \frac{b}{\sqrt{|a|^2 + |b|^2}} & \frac{a^*}{\sqrt{|a|^2 + |b|^2}} \\ \frac{-a}{\sqrt{|a|^2 + |b|^2}} & \frac{b^*}{\sqrt{|a|^2 + |b|^2}} \end{bmatrix}$$

and a Gentlemen-Kung array, processing the rows in sequence:



(and there are nice alternatives!)

External factorization (characterizes the dynamics - poles)

We start out with a realization in input normal form:

$$T \sim_c \begin{bmatrix} A & B \\ C & D \end{bmatrix} \text{ with } AA' + BB' = I$$

and assume the system to be u.e.s. as well. Let

$$V \sim_c \begin{bmatrix} A & B \\ C_V & D_V \end{bmatrix} \text{ be a unitary completion of } [A \ B]$$

consider $TV' = \Delta'$, then

Lemma: partial fraction decomposition

$$\begin{aligned}\Delta' &= [D + C(I - ZA)^{-1}ZB][D'_V + B'Z'(I - A'Z')^{-1}C'_V] \\ &= [DD'_V + CC'_V] + [DB' + CA']Z'(I - A'Z')^{-1}C'_V\end{aligned}$$

because

$$(I - ZA)^{-1}ZBB'Z'(I - A'Z')^{-1} = (I - ZA)^{-1}ZA + I + A'Z'(I - A'Z')^{-1}$$

External factorization (2)

hence a canonical factorization: $T = \Delta' V = \Delta' (V')^{-1}$

interpretation: V characterizes the dynamics of T (in the LTI-case, the poles)

LTI example: $\frac{z-2}{1-(1/3)z} = \frac{z-2}{z-3} \bullet \frac{z-3}{1-(1/3)z}$

State space formula: $\Delta =_c \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} I & C' \\ 0 & D' \end{bmatrix}$

This was a "right" factorization, there is of course also a "left" factorization, based on the observability data:

$$T = \Delta_r' V_r = V_\ell \Delta_\ell'$$

dynamics of the inverse system?

T^{-1} , even when it exists, is not necessarily causal
In first instance, we look at the anti-causal dynamics

The trick is: outer-inner factorization $T = T_o V$,
in which V is co-isometric and T_o *left* invertible

V' is the largest (anti-causal) isometry that can be applied
to T without destroying causality

Geometric interpretation: generalized "Beurling-Lax theorem"
to be discussed in a further lecture.

Let's determine V algebraically!

Outer-Inner by a square-root algorithm

We want TV' still causal, with V maximal (the bigger V , the more it pushes T back into the past). Let

$$V \sim_c \begin{bmatrix} A_V & B_V \\ C_V & D_V \end{bmatrix} \text{ be a co-isometric realization for } V$$

then

$$TV' = [D + C(I - ZA)^{-1}ZB][D'_V + B'_V Z'(I - A'_V Z')^{-1}C'_V]$$

causal terms: $DD'_V + C(I - ZA)^{-1}ZBD'_V$

mixed term: $C(I - ZA)^{-1}ZBB'_V Z'(I - A'_V Z')^{-1}C'_V$

anti-causal term: $DB'_V Z'(I - A'_V Z')^{-1}$

a partial fraction decomposition is needed!

This is provided by a generalized partial fraction decomposition:

Lemma: partial fraction decomposition again

$$C(I - ZA)^{-1}ZBB'_VZ'(I - A'_VZ')^{-1}C'_V = \\ C(I - ZA)^{-1}ZAY + Y + YA'_VZ'(I - A'_VZ')^{-1}C'_V$$

in which the new Y satisfies the Lyapunov-Stein equation

$$Z'YZ = BB'_V + AY A'_V$$

i.e., $Y_{k+1} = [BB'_V + AY A'_V]_k$

a forward equation, which always has a unique solution provided A is u.e.s.

outer-inner sq.r. algorithm (2)

require the anti-causal terms to add up to zero:

$$CYA'_V + DB'_V = 0$$

and define the remainder:

$$T_o = [CYC'_V + DD'_V + CI_A Z)^{-1} [AYC'_V + BD'_V]$$

hence:

$$T_o \sim_c \begin{bmatrix} A & B_o \\ C & D_o \end{bmatrix} = \begin{bmatrix} A & BD'_V + AYC'_V \\ C & DD'_V + CYC'_V \end{bmatrix}$$

Putting the four equations together:

$$\begin{bmatrix} AY & B \\ CY & D \end{bmatrix}_k \begin{bmatrix} A'_V & C'_V \\ B'_V & D'_V \end{bmatrix}_k = \begin{bmatrix} Y_{k+1} & B_{ok} \\ 0 & D_{ok} \end{bmatrix}$$

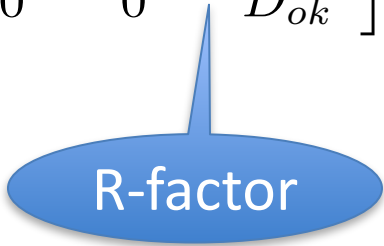
isometric

left
invertible

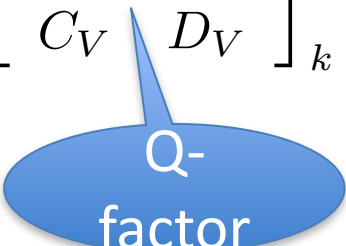
the square-root algorithm (3)

(complete RQ-factorization: embed the isometry)

$$\begin{bmatrix} AY & B \\ CY & D \end{bmatrix}_k = \begin{bmatrix} 0 & Y_{k+1} & B_{ok} \\ 0 & 0 & D_{ok} \end{bmatrix} \begin{bmatrix} C_n & D_n \\ A_V & B_V \\ C_V & D_V \end{bmatrix}_k$$



R-factor



Q-factor

interpretations: - V characterizes the anti-causal dynamics of T

- $W = D_n + C_n(I - ZA_V)^{-1}ZB_V$ defines the kernel of " T acting on causal signals"
- D_{ok} and Y_{k+1} are compressed to left invertible
- Y is the cross-correlation between the reachability ops. of T and V
- Proofs are based on ranges and kernels

some more remarks on O-I (4)

$$\begin{bmatrix} AY & B \\ CY & D \end{bmatrix}_k = \begin{bmatrix} 0 & Y_{k+1} & B_{ok} \\ 0 & 0 & D_{ok} \end{bmatrix} \begin{bmatrix} C_n & D_n \\ A_V & B_V \\ C_V & D_V \end{bmatrix}_k$$

- the outer factor T_o is causally left-invertible
- Y can disappear completely (when T is already outer)
the algorithm can be used to show whether a transfer function is indeed causally invertible
- T_o as obtained from the algorithm is not necessarily minimal (e.g. when T is already inner)

**this is the most important
algorithm in system theory**

Applications

In the following talks I shall show:

- how the Kalman estimation filter is nothing but an outer-inner factorization, and how this insight gives an easy and simple proof
- how outer-inner succeeds in providing a stable algorithm for LU or spectral factorization
- how outer-inner and inner-outer succeeds in computing the Moore-Penrose inverse of semi-separable systems
- how outer-inner or inner-outer can be used in control applications (aside from the Kalman filter)
- how the theory generalizes to non-linear, and which consequences that has

A simple example

Let's try to compute the Moore-Penrose inverse of

$$T = \begin{bmatrix} \boxed{1} & & & \\ -2 & 1 & & \\ 0 & -2 & 1 & \\ \vdots & \ddots & \ddots & \ddots \end{bmatrix}$$

T is not invertible, co-kernel: $\text{span}[1 \ 1/2 \ 1/4 \ \dots]$

it has a left inverse:

$$\begin{bmatrix} \boxed{0} & -1/2 & -1/4 & -1/8 & \dots \\ & 0 & -1/2 & -1/4 & \ddots \\ & & 0 & -1/2 & \ddots \\ & & & 0 & \ddots \\ & & & & \ddots \end{bmatrix}$$

but this is not the Moore-Penrose inverse.

Moore-Penrose inverse (2)

What is then the Moore-Penrose inverse?

(definition: $T^\dagger y = \min\{\arg \min_v \|Tv - y\|_2\}$

typically used in principal component analysis)

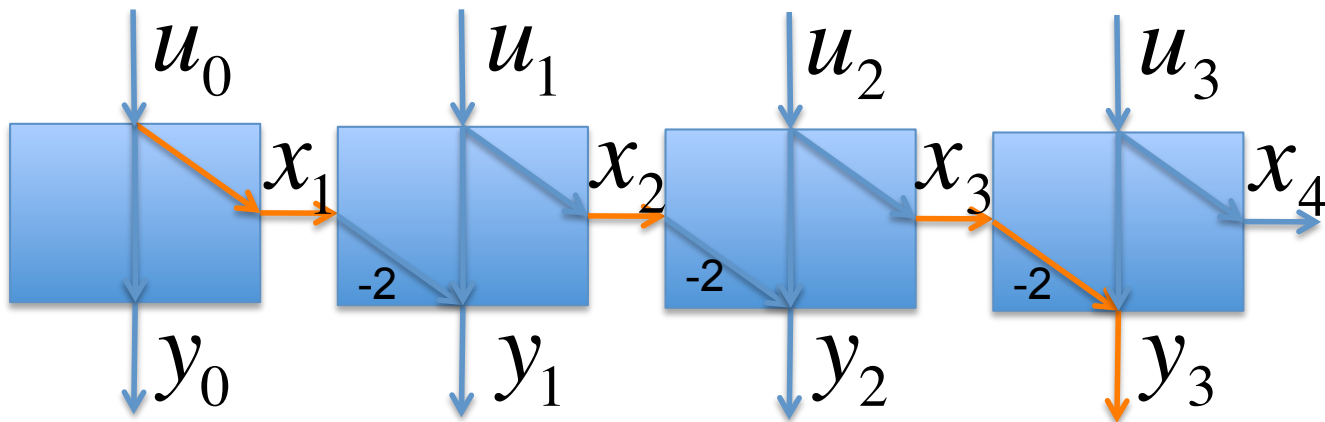
As T has a left inverse, it is already left outer. What about the right side? To convert T to fully outer, we need to find an inner-outer factorization: $T = UT_o$. The corresponding square root algorithm is:

$$\begin{bmatrix} Y_k A_k & Y_k B_k \\ C_k & D_k \end{bmatrix} = \begin{bmatrix} B_{ak} & A_{uk} & B_{uk} \\ D_{ak} & C_{uk} & D_{uk} \end{bmatrix} \begin{bmatrix} "0" & "0" \\ Y_{k-1} & 0 \\ C_{ok} & D_{ok} \end{bmatrix}$$

(it is a backward recursion now). As the system is LTI in the far future, this provides for a starting point of the recursion

Moore-Penrose inverse (3)

A realization for T is easily found (e.g. INF):



$$T \sim_c \text{diag} \left(\begin{bmatrix} \cdot & \cdot \\ \cdot & \cdot \end{bmatrix}, \boxed{\begin{bmatrix} | & 1 \\ | & 1 \end{bmatrix}}, \begin{bmatrix} 0 & 1 \\ -2 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ -2 & 1 \end{bmatrix}, \dots \right)$$

Moore-Penrose (4)

Running the square root algorithm produces:

$$\begin{array}{l}
 U \sim_c \text{diag} \left(\begin{bmatrix} | & | \\ \cdot & \cdot \end{bmatrix}, \begin{bmatrix} 1/2 & \sqrt{3}/2 \\ -\sqrt{3}/2 & 1/2 \end{bmatrix}, \begin{bmatrix} 1/2 & \sqrt{3}/2 \\ -\sqrt{3}/2 & 1/2 \end{bmatrix}, \dots \right) \\
 T_o \sim_c \text{diag} \left(\begin{bmatrix} \cdot & \cdot \\ \cdot & \cdot \end{bmatrix}, \begin{bmatrix} | & 1 \\ | & 2 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ -1 & 2 \end{bmatrix}, \dots \right)
 \end{array}$$

and finally

$$\begin{array}{l}
 U = \begin{bmatrix} 1/2 & & & \\ -3/4 & 1/2 & & \\ -3/8 & -3/4 & 1/2 & \\ \vdots & \ddots & \ddots & \ddots \end{bmatrix} \\
 T_o = \begin{bmatrix} 2 & & & \\ -1 & 2 & & \\ 0 & -1 & 2 & \\ \vdots & \ddots & \ddots & \ddots \end{bmatrix}
 \end{array}
 \quad T^\dagger = \frac{1}{4} \begin{bmatrix} 1 & -3/2 & -3/4 & -3/8 & \dots \\ 1/2 & 1/4 & -15/8 & -15/16 & \dots \\ 1/4 & 1/8 & 1/16 & -63/32 & \dots \\ 1/8 & 1/16 & 1/32 & 1/64 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

Envoy

**We are now going to use
our new knowledge on
stochastic state estimation
(Kalman filtering)!**