

DYSCO course on low-rank approximation and its applications

Exercises

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Outline

Introduction

Computational tools

Behavioral approach

Approximate identification

Exact identification

Line fitting

problem: give a condition on the data

$$\mathcal{D} = \{d_1, \dots, d_N\} \subset \mathbb{R}^2$$

that is equivalent to the condition that

the points d_1, \dots, d_N are on a line in \mathbb{R}^2

Solution

the points $d_i = (a_i, b_i)$, $i = 1, \dots, N$ lie on a line



there is $(R_1, R_2, R_3) \neq 0$, such that
 $R_1 a_i + R_2 b_i + R_3 = 0$, for $i = 1, \dots, N$



there is $(R_1, R_2, R_3) \neq 0$, such that

$$\begin{bmatrix} R_1 & R_2 & R_3 \end{bmatrix} \begin{bmatrix} a_1 & \cdots & a_N \\ b_1 & \cdots & b_N \\ 1 & \cdots & 1 \end{bmatrix} = 0$$



$$\text{rank} \left(\begin{bmatrix} a_1 & \cdots & a_N \\ b_1 & \cdots & b_N \\ 1 & \cdots & 1 \end{bmatrix} \right) \leq 2$$

Note

- ▶ $\mathcal{B} = \{d \mid Rd = 0\}$ — linear static model
- ▶ $\mathcal{B} = \{d \mid R \begin{bmatrix} d \\ 1 \end{bmatrix} = 0\}$ — affine static model
- ▶ in exact modeling

affine fitting



data centering + linear modeling

- ▶ **HW:** is the same true in approximate modeling?

Conic section fitting

- ▶ conic section (with parameters $S = S^\top$, u , v)

$$\mathcal{B}(S, u, v) = \{d \in \mathbb{R}^2 \mid d^\top S d + u^\top d + v = 0\}$$

1. give a condition on the data

$$\mathcal{D} = \{d_1, \dots, d_N\} \subset \mathbb{R}^2$$

that is equivalent to the condition that

d_1, \dots, d_N are lying on a conic section

2. find a conic section fitting the points

$$d_1 = \begin{bmatrix} -1 \\ -1 \end{bmatrix}, \quad d_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}, \quad d_3 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad d_4 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

Solution

the points $d_i = (a_i, b_i)$, $i = 1, \dots, N$ lie on a conic section



$\exists S = S^T$, u , v , at least one of them nonzero, such that
 $d_i^T S d_i + u^T d_i + v = 0$, for $i = 1, \dots, N$



there is $(s_{11}, s_{12}, s_{22}, u_1, u_2, v) \neq 0$, such that

$$\begin{bmatrix} s_{11} & 2s_{12} & u_1 & s_{22} & u_2 & v \end{bmatrix} \begin{bmatrix} a_1^2 & \cdots & a_N^2 \\ a_1 b_1 & \cdots & a_N b_N \\ a_1 & \cdots & a_N \\ b_1^2 & \cdots & b_N^2 \\ b_1 & \cdots & b_N \\ 1 & \cdots & 1 \end{bmatrix} = 0$$

Solution (continued)

the points $d_i = (a_i, b_i)$, $i = 1, \dots, N$ lie on a conic section

\Leftrightarrow

$$\text{rank} \begin{pmatrix} \begin{bmatrix} a_1^2 & \cdots & a_N^2 \\ a_1 b_1 & \cdots & a_N b_N \\ a_1 & \cdots & a_N \\ b_1^2 & \cdots & b_N^2 \\ b_1 & \cdots & b_N \\ 1 & \cdots & 1 \end{bmatrix} \end{pmatrix} \leq 5$$

```
f = @(a, b) [a.^2; a.*b; a; b.^2; b; ones(size(a))];
```


Solution (continued)

- ▶ finding exact models

```
R = null(f(d(1, :), d(2, :)))';
```

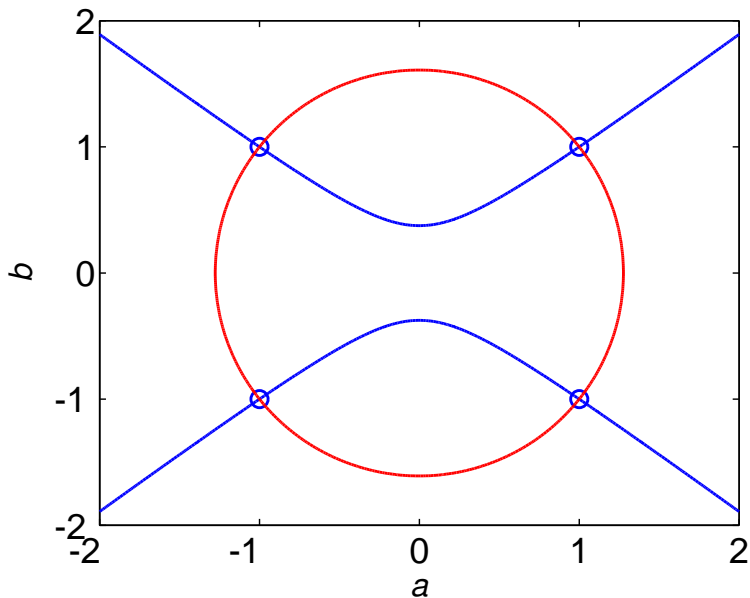
- ▶ plotting a model

```
function H = plot_model(th, f, ax, c)
H = ezplot(@(a, b) th * f(a, b), ax);
for h = H', set(h, 'color', c, 'linewidth',
```

- ▶ show results

```
plot(d(1, :), d(2, :), 'o', 'markersize', 12)
ax = 2 * axis;
for i = 1:size(R, 1)
    hold on, plot_model(R(i, :), f, ax, c(i));
end
```

Solution (continued)



Subspace clustering

- ▶ union of two lines (with parameters $R^1, R^2 \in \mathbb{R}^{1 \times 2}$)

$$\mathcal{B}(R^1, R^2) = \{d \in \mathbb{R}^2 \mid (R^1 d)(R^2 d) = 0\}$$

1. give a condition on the data

$$\mathcal{D} = \{d_1, \dots, d_N\} \subset \mathbb{R}^2$$

that is equivalent to the condition that

d_1, \dots, d_N are lying on a union of two lines

2. find a union of two lines model fitting the points

$$d_1 = \begin{bmatrix} -1 \\ -1 \end{bmatrix}, \quad d_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}, \quad d_3 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad d_4 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

Solution

the points $d_i \in \mathbb{R}^2$, $i = 1, \dots, N$ lie on a union of two lines



there are $R^1 \neq 0$ and $R^2 \neq 0$, v , such that
 $(R^1 d_i)(R^2 d_i) = 0$, for $i = 1, \dots, N$



there are $[R_1^1 \ R_2^1] \neq 0$ and $[R_1^2 \ R_2^2] \neq 0$, such that

$$[R_1^1 R_1^2 \quad R_1^1 R_2^2 + R_2^1 R_1^2 \quad R_2^1 R_2^2] \begin{bmatrix} a_1^2 & \dots & a_N^2 \\ a_1 b_1 & \dots & a_N b_N \\ b_1^2 & \dots & b_N^2 \end{bmatrix} = 0$$

Solution (continued)

- ▶ if $d_i \in \mathbb{R}^2$, $i = 1, \dots, N$ lie on a union of two lines, then

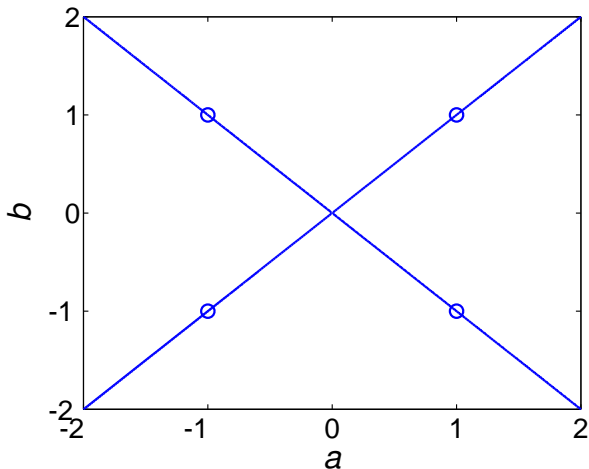
$$\text{rank} \left(\begin{bmatrix} a_1^2 & \cdots & a_N^2 \\ a_1 b_1 & \cdots & a_N b_N \\ b_1^2 & \cdots & b_N^2 \end{bmatrix} \right) \leq 2$$

- ▶ in this case, the rank condition is only necessary
- ▶ in addition, a basis for the left kernel is

$$[1 \quad \alpha + \beta \quad \alpha\beta], \quad \text{for some } \alpha \text{ and } \beta$$

- ▶ union of two lines fitting is a special case of the **Generalized principal component analysis**

Solution (continued)



- ▶ **HW:** how to "extract" R^1 and R^2 from $\ker(D)$

Recursive sequences

- ▶ $w = (w(1), \dots, w(T))$ is recursive of order ℓ if

$$R_0 w(t) + R_1 w(t+1) + \dots + R_\ell w(t+\ell) = 0,$$

for $t = 1, \dots, T - \ell$ and some $R_0, R_1, \dots, R_\ell \in \mathbb{R}$

1. give a condition on w that is equivalent to w is a recursive of order ℓ
2. find the minimal recursive order of

$$(1, 2, 4, 7, 13, 24, 44, 81)$$

Solution

$$\begin{aligned} w \text{ is recursive} & \\ \text{of order } \ell & \iff \exists R \in \mathbb{R}^{1 \times (\ell+1)} \text{ s.t. } R\mathcal{H}_{\ell+1}(w) = 0 \\ & \implies \text{rank}(\mathcal{H}_{\ell+1}(w)) \leq \ell \end{aligned}$$

where

$$\mathcal{H}_{\ell+1}(w) := \begin{bmatrix} w(1) & w(2) & \dots & w(T-\ell) \\ w(2) & w(3) & \dots & w(T-\ell+1) \\ \vdots & \vdots & & \vdots \\ w(\ell+1) & w(\ell+2) & \dots & w(T) \end{bmatrix}$$

- ▶ for $\ell = 1, 2, \dots$, if $\text{rank}(\mathcal{H}_{\ell+1}(w)) = \ell$, stop
- ▶ $\ell_{\min} = 3$ and $R = [1 \quad 1 \quad 1 \quad -1]$

Polynomial common divisor

- ▶ the polynomials

$$p(z) = p_0 + p_1 z + \cdots + p_{\ell_p} z^{\ell_p}$$

$$q(z) = q_0 + q_1 z + \cdots + q_{\ell_q} z^{\ell_q}$$

have a common divisor

$$c(z) = c_0 + c_1 z + \cdots + c_{\ell_c} z^{\ell_c}$$

iff $p = ca$ and $q = cb$ for some polynomials a and b

- ▶ give a condition on p, q that is equivalent to
 p, q have a common divisor of degree ℓ_c

Solution

$$c(z) = a(z)b(z) \iff \begin{bmatrix} c_0 \\ c_1 \\ \vdots \\ c_{l_c} \end{bmatrix} = \begin{bmatrix} a_0 & & & & & \\ a_1 & a_0 & & & & \\ \vdots & a_1 & \ddots & & & \\ a_{l_a} & \vdots & \ddots & & a_0 & \\ & a_{l_a} & & & a_1 & \\ & & & \ddots & \vdots & \\ & & & & & a_{l_a} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_{l_b} \end{bmatrix}$$

$$\iff : c = S_{l_b}(a)b \iff c = S_{l_a}(b)a$$

Solution (continued)

$p \in \mathbb{R}[z]$ and $q \in \mathbb{R}[z]$
have common divisor $c \in \mathbb{R}[z]$, $\deg(c) = l_c$ \iff $\exists a \in \mathbb{R}[z]$, $\deg(a) = l_p - l_c$
 $\exists b \in \mathbb{R}[z]$, $\deg(b) = l_q - l_c$
such that $p = ca$ and $q = cb$

$$\iff qa - pb = 0$$

$$\iff \begin{bmatrix} S_{l_a}(q) & S_{l_b}(p) \end{bmatrix} \begin{bmatrix} a \\ -b \end{bmatrix} = 0$$

$$\iff \begin{bmatrix} S_{l_a}(q) & S_{l_b}(p) \end{bmatrix} \text{ is rank deficient}$$

Outline

Introduction

Computational tools

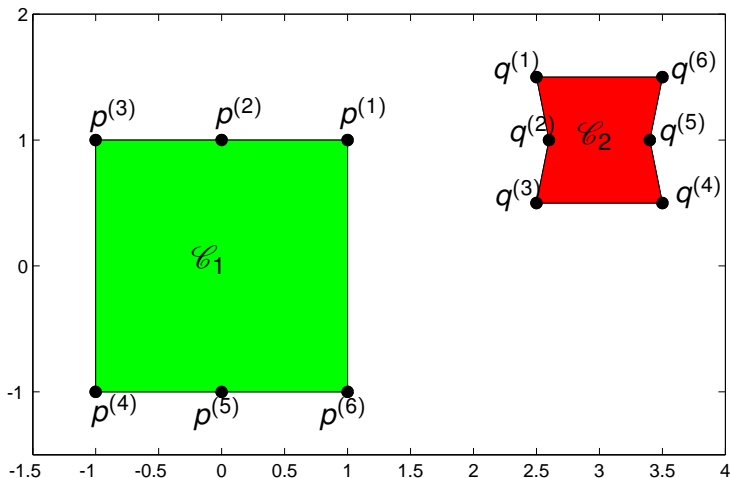
Behavioral approach

Approximate identification

Exact identification

Least squares contour alignment

given contours $\mathcal{C}_1, \mathcal{C}_2$, specified by matching points $p^{(i)} \leftrightarrow q^{(i)}$



Problem

- ▶ find a transformation (rotation + scaling + translation)

$$\mathcal{A}_{a,\theta,s}(p) = s \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} p + a$$

that minimizes the LS distance between

$$\min_{a \in \mathbb{R}^2, \theta \in [0, 2\pi), s \in \mathbb{R}_+} \sum_{i=1}^N \|p^{(i)} - \mathcal{A}_{a,\theta,s}(q^{(i)})\|_2^2$$

\mathcal{C}_1 and $\mathcal{A}_{a,\theta,s}(\mathcal{C}_2)$

- ▶ apply the solution on the data in the example

Data in the example

```
p = [1      0      -1      -1      0      1  
     1      1      1      -1     -1     -1];
```

```
q = [2.5     2.6     2.5     3.5     3.4     3.5  
     1.5     1.0     0.5     0.5     1.0     1.5];
```

Hint

- ▶ use the change of variables

$$\begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = s \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} \theta \\ s \end{bmatrix} = \begin{bmatrix} \sin^{-1}(b_2 / \sqrt{b_1^2 + b_2^2}) \\ \sqrt{b_1^2 + b_2^2} \end{bmatrix}$$

- ▶ to obtain an equivalent problem

$$\min_{(a_1, a_2, b_1, b_2) \in \mathbb{R}^4} \left\| \begin{bmatrix} p_1^{(1)} \\ p_2^{(1)} \\ \vdots \\ p_1^{(N)} \\ p_2^{(N)} \end{bmatrix} - \begin{bmatrix} 1 & 0 & q_1^{(1)} & -q_2^{(1)} \\ 0 & 1 & q_2^{(1)} & q_1^{(1)} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & q_1^{(N)} & -q_2^{(N)} \\ 0 & 1 & q_2^{(N)} & q_1^{(N)} \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ b_1 \\ b_2 \end{bmatrix} \right\|_2$$

Orthogonal Procrustes problem

- ▶ **HW:** alignment by reflection + scaling + translation
- ▶ rigid transformation =
rotation + reflection + scaling + translation
- ▶ contour alignment by rigid transformation is related to the orthogonal Procrustes problem:
 - ▶ given $m \times n$ real matrices C_1 and C_2
minimize over Q $\|C_1 - QC_2\|_F$ subject to $Q^T Q = I$
 - ▶ solution: $Q = UV^T$, where $U\Sigma V^T$ is the SVD of $C_1^T C_2$

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Check whether $w \stackrel{?}{\in} \mathcal{B}$

► $w = (u_d, y_d) = ((0, 1), (0, 1), (0, 1), (0, 1))$

$$w = [0 \ 0 \ 0 \ 0; 1 \ 1 \ 1 \ 1];$$

► $\mathcal{B} = \ker(R(\sigma))$, where $R(z) = [1 \ -1] + [-1 \ 1]z$

$$R = [1 \ -1 \ -1 \ 1]; \text{ e11} = 1;$$

$$w \stackrel{?}{\in} \ker(R(\sigma))$$

$$\iff R(\sigma)w = 0$$

$$\iff R_0 w(t) + R_1 w(t+1) + \dots + R_\ell w(t+\ell) = 0$$

for $t = 1, \dots, T - \ell$

$$\iff \underbrace{\begin{bmatrix} R_0 & R_1 & \dots & R_\ell & & & \\ & R_0 & R_1 & \dots & R_\ell & & \\ & & \ddots & \ddots & & \ddots & \\ & & & R_0 & R_1 & \dots & R_\ell \end{bmatrix}}_{\mathcal{M}_T(R) \in \mathbb{R}^{(T-\ell) \times qT}} \underbrace{\begin{bmatrix} w(1) \\ w(2) \\ \vdots \\ w(T) \end{bmatrix}}_{\text{vec}(w)} = 0$$

$$w \stackrel{?}{\in} \ker (R(\sigma))$$

$$\iff \mathcal{M}_T(R) \text{vec}(w) = 0$$

$$\iff R\mathcal{H}_{\ell+1}(w) = 0$$

where

$$\underbrace{\begin{bmatrix} R_0 & R_1 & \dots & R_\ell \end{bmatrix}}_R \underbrace{\begin{bmatrix} w(1) & w(2) & \dots & w(T-\ell) \\ w(2) & w(3) & \dots & \\ \vdots & \vdots & & \vdots \\ w(\ell+1) & w(\ell+2) & \dots & w(T) \end{bmatrix}}_{\mathcal{H}_{\ell+1}(w) \in \mathbb{R}^{q(\ell+1) \times (T-\ell)}} = 0$$

- ▶ compute $e = \|R\mathcal{H}_{\ell+1}(w)\|$ and check if $e < \varepsilon$

```
w = [0 0 0 0; 1 1 1 1];  
R = [1 -1 -1 1]; ell = 1;  
norm(R * blkhank(w, ell + 1))
```

- ▶ blkhank constructs a block-Hankel matrix $\mathcal{H}_L(w)$

```
function H = blkhank(w, i, j)  
[q, T] = size(w);  
if T < q, w = w'; [q, T] = size(w); end  
if nargin < 3, j = T - i + 1; end  
H = zeros(i * q, j);  
for ii = 1:i  
    H((ii - 1) * q + 1):(ii * q), :) ...  
        = w(:, ii:(ii + j - 1));  
end
```

Homework

- ▶ use image representation to check

$$w \stackrel{?}{\in} \text{image}(P(\sigma))$$

- ▶ use state space representation to check

$$w \stackrel{?}{\in} \mathcal{B}(A, B, C, D)$$

Affine time-invariant system

- ▶ an LTI system $\mathcal{B} \in \mathcal{L}_{m,\ell}$ admits a kernel repr.

$$\mathcal{B} = \ker(R(\sigma)) := \{w \mid R(\sigma)w = 0\}$$

for some $R(z) = R_0z^0 + R_1z^1 + \dots + R_\ell z^\ell$

- ▶ show that

$$\mathcal{B}_c := \{w \mid R(\sigma)w = c\}$$

is an affine time-invariant system, *i.e.*, $\mathcal{B}_c = \mathcal{B} + w_p$
for LTI model $\mathcal{B} \in \mathcal{L}_{m,\ell}$ and trajectory w_p

- ▶ find \mathcal{B} and w_p , s.t. $\mathcal{B} + w_p = \{w \mid (0.5 + \sigma)w = 1\}$

- ▶ using the matrix representation of $R(\sigma)$

$$\begin{aligned}
 w \in \mathcal{B}_c &\iff \mathcal{M}_T(R)w = \mathbf{1}_{T-\ell} \otimes \mathbf{c} =: \mathbf{c} \\
 &\iff \mathcal{M}_T(R)(w - w_p) = 0 \\
 &\iff w - w_p \in \ker(R(\sigma)) = \mathcal{B}
 \end{aligned}$$

- ▶ therefore, $\mathcal{B}_c = \mathcal{B} + w_p$, where $\mathcal{B} \in \mathcal{L}_{m,\ell}$ and

$$\mathcal{M}_T(R)w_p = \mathbf{c}$$

- ▶ e.g., the least-norm solution

$$w_p = \mathcal{M}_T^\top(R) (\mathcal{M}_T(R) \mathcal{M}_T^\top(R))^{-1} \mathbf{c}$$

- ▶ **HW:** find input/state/output representation of \mathcal{B}_c

- ▶ in the case of $\{ w \mid (0.5 + \sigma)w = 1 \}$
- ▶ `sylv(R, T)` constructs the matrix $\mathcal{M}_T(R)$

```
function S = sylv(R, T)
nR = length(R); q = 2;
n = (nR / q) - 1;
S = zeros(T - n, q * T);
for i = 1:T - n
    S(i, (1:nR) + (i - 1) * q) = R;
end
```

Transfer function \mapsto kernel representation

- ▶ what model $\mathcal{B}_{\text{tf}}(H)$ is specified by a transfer function

$$H(z) = \frac{q(z)}{p(z)} = \frac{q_0 + q_1 z^1 + \dots + q_\ell z^\ell}{p_0 + p_1 z^1 + \dots + p_\ell z^\ell}$$

- ▶ find R , such that

$$\mathcal{B}_{\text{tf}}(H) = \ker(R)$$

- ▶ write a function `tf2ker` converting H (tf object) to R

▶ $H(z) = q(z)/p(z) \stackrel{?}{\leftrightarrow} R(z)$

▶ $y(z) = H(z)u(z) \leftrightarrow p(\sigma)y = q(\sigma)u$

$$\underbrace{\begin{bmatrix} q(\sigma) & -p(\sigma) \end{bmatrix}}_{R(\sigma)} \begin{bmatrix} u \\ y \end{bmatrix} = 0$$

▶ note: z may correspond to σ^{-1} as well as σ

▶ does $\mathcal{B}_{\text{tf}}(H)$ assume zero initial conditions?

▶ if so,

$$\mathcal{B}_{\text{tf}}(H) = \{w \mid R(\sigma)(0 \wedge w) = 0\}$$

▶ otherwise,

$$\mathcal{B}_{\text{tf}}(H) = \ker(R(\sigma))$$

- ▶ note: MATLAB uses descending order of coefficients

```
function R = tf2ker(H)
[Q P] = tfdata(tf(H), 'v');
R = vec(flip1r([Q; -P]))';
```

Specification of initial conditions

- ▶ initial conditions are explicitly specified in I/S/O repr.
- ▶ in MATLAB
LSIM(SYS,U,T,X0) specifies the initial state vector X0 at time T(1)
(for state-space models only).
- ▶ in transfer function representation initial conditions are often set to 0
- ▶ explain how to specify initial conditions in a representation free manner
- ▶ what is the link to $x_{ini} = x(1)$ in I/S/O repr?

- ▶ assuming that \mathcal{B} is controllable
- ▶ initial conditions can be specified by prefix trajectory

$$w_{\text{ini}} = (w_{\text{ini}}(1), \dots, w_{\text{ini}}(T_{\text{ini}}))$$

i.e., by $w_{\text{ini}} \wedge w \in \mathcal{B}$

- ▶ the link between w_{ini} and x_{ini} is given by

$$y_{\text{ini}} = \mathcal{O}_l(A, C)A^{-l}x_{\text{ini}} + \mathcal{T}_l(A, B, C, D)u_{\text{ini}}$$

```
function x0 = inistate(w, sys)
l = size(sys, 'order');
x0 = obsv(sys) \ (w(1:l, 2) ...
                  - lsim(sys, w(1:l, 1)));
```

Output matching

- ▶ given y_f and \mathcal{B}
- ▶ find u_f , such that $(u_f, y_f) \in \mathcal{B}$

Setup

- ▶ random SISO unstable system \mathcal{B}

```
clear all, n = 3;  
Br = drss(n); [Qr, Pr] = tfdata(Br, 'v');  
B = ss(tf(fliplr(Qr), fliplr(Pr), -1));
```

- ▶ reference output

```
T = 100; yf = ones(T, 1);
```


▶ $\mathcal{M}_T(R)w = 0 \implies \mathcal{M}_T(P)u = \mathcal{M}_T(P)y$

```
R = tf2ker(B); M = sylv(R, T);
```

```
Mu = M(:, 1:2:end); My = - M(:, 2:2:end);
```

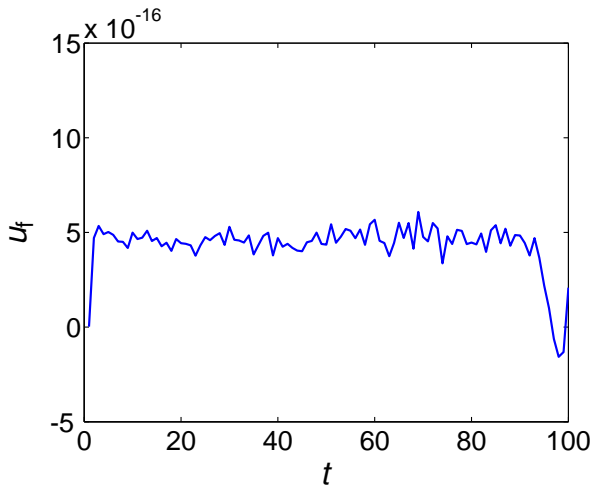
▶ many solutions (why?); compute a particular one

```
uf = pinv(Mu) * My * yf;
```

- ▶ $(u_f, y_f) \stackrel{?}{\in} \ker(R(\sigma))$
- ▶ $(u_f, y_f) \stackrel{?}{\in} \text{image}(P(\sigma))$
- ▶ $(u_f, y_f) \stackrel{?}{\in} \mathcal{B}(A, B, C, D)$
- ▶ where is the problem?

- ▶ the system is anti-stable
- ▶ the test $w \in \mathcal{B}(A, B, C, D)$ is ill-conditioned
- ▶ do backwards in time simulation

- ▶ particular (least squares) input



- ▶ **HW:** find all inputs

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Exact identification

Misfit computation using image repr.

- ▶ given
 - ▶ data $w = (w(1), \dots, w(T))$ and
 - ▶ LTI system $\mathcal{B} = \text{image}(P(\sigma))$
- ▶ derive a method for computing

$$\text{misfit}(w, \mathcal{B}) := \min_{\hat{w} \in \mathcal{B}} \|w - \hat{w}\|_2$$

- ▶ *i.e.*, find the orthogonal projection of w on \mathcal{B}

$w \stackrel{?}{\in} \text{image}(P(\sigma))$

\iff there is v , such that $w = P(\sigma)v$

\iff there is v , such that for $t = 1, \dots, T$
 $w(t) = P_0 v(t) + P_1 v(t+1) + \dots + P_\ell v(t+\ell)$

\iff there is solution v of the system

$$\begin{bmatrix} w(1) \\ w(2) \\ \vdots \\ w(T) \end{bmatrix} = \underbrace{\begin{bmatrix} P_0 & P_1 & \cdots & P_\ell & & & \\ & P_0 & P_1 & \cdots & P_\ell & & \\ & & \ddots & \ddots & & \ddots & \\ & & & P_0 & P_1 & \cdots & P_\ell \end{bmatrix}}_{\mathcal{M}_{T+\ell}(P)} \begin{bmatrix} v(1) \\ v(2) \\ \vdots \\ v(T+\ell) \end{bmatrix}$$

Solution

- ▶ we showed that

$$\hat{w} \in \ker(R(\sigma)) \iff \hat{w} = \mathcal{M}_T(P)v, \text{ for some } v$$

- ▶ then the misfit computation problem

$$\text{misfit}(w, \mathcal{B}) := \min_{\hat{w} \in \mathcal{B}} \|w - \hat{w}\|$$

becomes

$$\text{minimize over } v \quad \|w - \mathcal{M}_T(P)v\|$$

- ▶ this is a standard least-norm problem
- ▶ projector on $\mathcal{B} = \text{image}(P)$

$$\Pi_{\text{image}(P)} := \mathcal{M}_T(P) (\mathcal{M}_T^\top(P) \mathcal{M}_T(P))^{-1} \mathcal{M}_T^\top(P)$$

- ▶ misfit

$$\text{misfit}(\mathbf{w}, \mathcal{B}) := \sqrt{\mathbf{w}^\top (I - \Pi_{\text{image}(P)}) \mathbf{w}}$$

and optimal approximation

$$\hat{\mathbf{w}} = \Pi_{\text{image}(P)} \mathbf{w}$$

- ▶ **HW:** misfit computation with $\mathcal{B} = \ker(R(\sigma))$

Misfit computation using I/S/O repr.

- ▶ given
 - ▶ data $w = (w(1), \dots, w(T))$ and
 - ▶ LTI system $\mathcal{B} = \mathcal{B}(A, B, C, D)$
- ▶ derive a method for computing

$$\text{misfit}(w, \mathcal{B}) := \min_{\hat{w} \in \mathcal{B}} \|w - \hat{w}\|_2$$

- ▶ *i.e.*, find the orthogonal projection of w on \mathcal{B}

$$w \stackrel{?}{\in} \mathcal{B}(A, B, C, D)$$

$$\mathcal{B}(A, B, C, D) = \{(u, y) \mid \sigma x = Ax + Bu, y = Cx + Du\}$$

$$(u_d, y_d) \in \mathcal{B}(A, B, C, D) \iff \exists x_{ini} \in \mathbb{R}^n, \text{ such that}$$

$$y = \underbrace{\begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{T-1} \end{bmatrix}}_{\mathcal{O}_T(A, C)} x_{ini} + \begin{bmatrix} D & & & & \\ CB & D & & & \\ CAB & CB & D & & \\ \vdots & \ddots & \ddots & \ddots & \\ CA^{T-1}B & \dots & CAB & CB & D \end{bmatrix} u$$

Solution

- ▶ we showed that

$$\hat{w} \in \mathcal{B}(A, B, C, D) \iff \hat{y} = \mathcal{O}_T(A, C)\hat{x}_{\text{ini}} + \mathcal{I}_T(H)\hat{u}$$

- ▶ then the misfit computation problem

$$\min_{\hat{x}_{\text{ini}}, \hat{u}} \left\| \begin{bmatrix} u_d \\ y_d \end{bmatrix} - \begin{bmatrix} 0 & I \\ \mathcal{O}_T(A, C) & \mathcal{I}_T(H) \end{bmatrix} \begin{bmatrix} \hat{x}_{\text{ini}} \\ \hat{u} \end{bmatrix} \right\|$$

- ▶ exploiting the structure in the problem
 \leadsto EIV Kalman filter

Latency computation

- ▶ given
 - ▶ data w and
 - ▶ LTI system $\mathcal{B}_{\text{ext}} = \ker(R(\sigma))$ $(w_{\text{ext}} := \begin{bmatrix} \hat{e} \\ w \end{bmatrix})$
- ▶ find an algorithm for computing
minimize over e $\|\hat{e}\|$ subject to $(\hat{e}, w) \in \mathcal{B}_{\text{ext}}$
- ▶ **HW:** latency computation with $\mathcal{B}_{\text{ext}} = \mathcal{B}(A, B, C, D)$
(this is the ordinary Kalman filter)

Solution

- ▶ partition $R = [R_e \ R_w]$ conformably with $w_{\text{ext}} = \begin{bmatrix} e \\ w \end{bmatrix}$
- ▶ by analogy with the derivation on page 47, we have

$$\begin{bmatrix} e \\ w \end{bmatrix} \in \ker(R(\sigma)) \iff [\mathcal{M}_T(R_e) \ \mathcal{M}_T(R_w)] \begin{bmatrix} e \\ w \end{bmatrix} = 0$$

- ▶ the latency computation problem is

$$\min_e \|e\|_2 \quad \text{subject to} \quad \mathcal{M}_T(R_e)e = -\mathcal{M}_T(R_w)w$$

- ▶ the solution is given by

$$\hat{e} = - \underbrace{(\mathcal{M}_T(R_e)^\top \mathcal{M}_T(R_e))^{-1} \mathcal{M}_T(R_e)^\top}_{\mathcal{M}_T(R_e)^+} \mathcal{M}_T(R_w)w$$

Software

- ▶ mosaic-Hankel low-rank approximation

<http://slra.github.io/software.html>

- ▶ `[sysh, info, wh] = ident(w, m, ell, opt)`
 - ▶ `sysh` — I/S/O representation of the identified model
 - ▶ `opt.sys0` — I/S/O repr. of initial approximation
 - ▶ `opt.wini` — initial conditions
 - ▶ `opt.exct` — exact variables
 - ▶ `info.Rh` — parameter R of kernel repr.
 - ▶ `info.M` — misfit

- ▶ `[M, wh, xini] = misfit(w, sysh, opt)`

- ▶ demo file

Variable permutation

- ▶ verify that permutation of the variables doesn't change the optimal misfit

```
T = 100; n = 2; B0 = drss(n);  
u = randn(T, 1); y = lsim(B0, u) + 0.001 * randn(T, 1);  
[B1, info1] = ident([u y], 1, n); disp(info1.MSE)  
    2.9736e-05  
[B2, info2] = ident([y u], 1, n); disp(info2.MSE)  
    2.9736e-05  
disp(norm(B1 - inv(B2)))  
    5.8438e-12
```


Output error identification

- ▶ verify that the results of `oe` and `ident` coincide

```
T = 100; n = 2; B0 = drss(n);  
u = randn(T, 1); y = lsim(B0, u) + 0.001 * randn(T, 1);  
opt = oeOptions('InitialCondition', 'estimate');  
B1 = oe(iddata(y, u), [n + 1 n 0], opt);  
B2 = ident([u y], 1, n, struct('exct', 1));  
norm(B1 - B2) / norm(B1)
```

ans =

1.4760e-07

Outline

Introduction

Computational tools

Behavioral approach

Approximate identification

Exact identification

Identification without PE input

- ▶ given exact data $w = (u_d, y_d) \in \mathcal{B} \in \mathcal{L}_{1,\ell}^2$
- ▶ assuming controllability and PE of u_d of order $2\ell + 1$
- ▶ $\text{leftker}(\mathcal{H}_{\ell+1}(w))$ completely specifies \mathcal{B}
(the model is identifiable from the data)
- ▶ what "goes wrong" when u_d is not PE of order $\ell + 1$?
- ▶ verify it numerically

Solution

- ▶ u_d not PE $\implies \exists R_u \in \mathbb{R}^{1 \times (\ell+1)} \neq 0, R_u \mathcal{H}_{\ell+1}(u_d) = 0$
- ▶ then, leftker ($\mathcal{H}_{\ell+1}(w)$) contains R , $\ker(R) = \mathcal{B}$ and input annihilator $\begin{bmatrix} R_u & 0 \end{bmatrix}$
- ▶ **HW:** how to distinguish R from $\begin{bmatrix} R_u & 0 \end{bmatrix}$?

Spurious poles

- ▶ given exact data $w \in \mathcal{B} \in \mathcal{L}_{0,\ell}^p$ (autonomous system)
- ▶ assume that w is PE of maximal order, *i.e.*,
 $\text{rank}(\mathcal{H}_{\ell+1}(w)) = \ell$
- ▶ the roots of $P \neq 0, P\mathcal{H}_{\ell+1}(w) = 0$ are the poles of \mathcal{B}
- ▶ consider now leftker $(\mathcal{H}_{\ell+2}(w))$ (ℓ is over-specified)
- ▶ what are the roots of $P \neq 0, P\mathcal{H}_{\ell+2}(w) = 0$?
- ▶ how to recover \mathcal{B} from leftker $(\mathcal{H}_{\ell+2}(w))$?

Solution

- ▶ the roots of $P \in \mathbb{R}^{1 \times (\ell+2)}$ are the poles of \mathcal{B}
+ an additional pole (called spurious)
- ▶ $\dim(\text{left ker}(\mathcal{H}_{\ell+2}(w))) = 2 \rightsquigarrow$ two independent annihilators
- ▶ their common divisor is an annihilator of \mathcal{B}

Identification from short record(s)

- ▶ what is the minimum number T_{\min} of sequential samples needed for identification of a model in $\mathcal{L}_{m,\ell}^q$ from $N = 1$ trajectory?
- ▶ what is the minimum number T'_{\min} of sequential samples for identification of a model in $\mathcal{L}_{m,\ell}^q$ if $N' > 1$ trajectories with T'_{\min} samples can be used?

MPUM for noisy data

- ▶ consider "noisy data"

$$w = \bar{w} + \tilde{w}, \quad \text{where } \bar{w} \in \overline{\mathcal{B}} \in \mathcal{L}_{m,\ell}$$

and \tilde{w} is white noise

- ▶ under the usual assumptions $\mathcal{B}_{\text{mpum}}(\bar{w}) = \overline{\mathcal{B}}$
- ▶ what is $\mathcal{B}_{\text{mpum}}(w)$ for the noisy data?
- ▶ suggest modifications of exact identification methods that make them suitable for approximation

Solution

- ▶ a.s., there is no exact model of bounded complexity

$$\mathcal{B}_{\text{mpum}}(\mathbf{w})|_{\mathcal{T}} \stackrel{\text{a.s.}}{=} (\mathbb{R}^q)^T \quad (\text{a trivial model})$$

- ▶ the requirement that $\hat{\mathcal{B}}$ is unfalsified is too restrictive
- ▶ subspace identification methods: replace
 - ▶ "kernel" by "approx. kernel" obtained from the SVD
 - ▶ "rank revealing factorization" by "low-rank approx."
 - ▶ "solution (of a system)" by "LS approximation"

Impulse response estimation

- ▶ implement the method $w \rightarrow H$
- ▶ compare it with `impulseest`