

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

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

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

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

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

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

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

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

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Computational tools

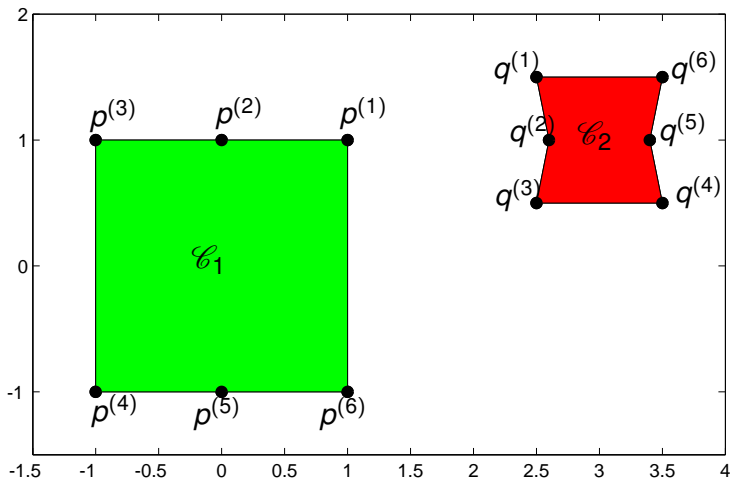
Behavioral approach

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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 $R(z) = [1 \ -1] + [-1 \ 1]z$

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

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. $\mathcal{B} + w_p = \{w \mid (0.5 + \sigma)w = 1\}$

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

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?

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);
```

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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}

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}

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)

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

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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

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 $\text{leftker}(\mathcal{H}_{\ell+2}(w))$ (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 $\text{leftker}(\mathcal{H}_{\ell+2}(w))$?

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

Impulse response estimation

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