

# Low-rank approximation and its applications

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## Exact line fitting

the points  $w_i = (x_i, y_i)$ ,  $i = 1, \dots, N$  lie on a line (\*)



there is  $(a, b, c) \neq 0$ , such that  $ax_i + by_i + c = 0$ , for  $i = 1, \dots, N$



there is  $(a, b, c) \neq 0$ , such that 
$$\begin{bmatrix} a & b & c \end{bmatrix} \begin{bmatrix} x_1 & \cdots & x_N \\ y_1 & \cdots & y_N \\ 1 & \cdots & 1 \end{bmatrix} = 0$$



$$\text{rank} \left( \begin{bmatrix} x_1 & \cdots & x_N \\ y_1 & \cdots & y_N \\ 1 & \cdots & 1 \end{bmatrix} \right) \leq 2 \quad (**)$$

- restatement of problem (\*) as an equivalent problem (\*\*)
- however, (\*\*) is a standard problem
- the solution generalizes to
  1. multivariable data (points in  $\mathbb{R}^q$ ) fitting by an affine set
  2. time-series fitting by linear time-invariant dynamical models
  3. data fitting by nonlinear models

## Exact conic section fitting

the points  $w_i = (x_i, y_i)$ ,  $i = 1, \dots, N$  lie on a conic section



there are  $A = A^\top$ ,  $b$ ,  $c$ , at least one of them nonzero, such that

$$w_i^\top A w_i + b^\top w_i + c = 0, \text{ for } i = 1, \dots, N$$



there is  $(a_{11}, a_{12}, a_{22}, b_1, b_2, c) \neq 0$ , such that

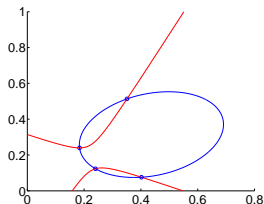
$$\begin{bmatrix} a_{11} & 2a_{12} & b_1 & a_{22} & b_2 & c \end{bmatrix} \begin{bmatrix} x_1^2 & \cdots & x_N^2 \\ x_1 y_1 & \cdots & x_N y_N \\ x_1 & \cdots & x_N \\ y_1^2 & \cdots & y_N^2 \\ y_1 & \cdots & y_N \\ 1 & \cdots & 1 \end{bmatrix} = 0$$

the points  $w_i = (x_i, y_i)$ ,  $i = 1, \dots, N$  lie on a conic section

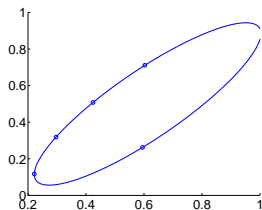


$$\text{rank} \begin{pmatrix} \begin{bmatrix} x_1^2 & \cdots & x_N^2 \\ x_1 y_1 & \cdots & x_N y_N \\ x_1 & \cdots & x_N \\ y_1^2 & \cdots & y_N^2 \\ y_1 & \cdots & y_N \\ 1 & \cdots & 1 \end{bmatrix} \end{pmatrix} \leq 5$$

- $N < 4 \rightsquigarrow$  nonunique fit



- $N = 4$  (different points)  $\rightsquigarrow$  unique fit



- $N > 4 \rightsquigarrow$  generically no conic section fits the data exactly

## Exact fitting by linear homogeneous recurrence relations with constant coefficients

the sequence  $w = (w_1, \dots, w_T)$  is generated by linear recurrence relations with lag  $\leq \ell$



there is  $a = (a_0, a_1, \dots, a_\ell) \neq 0$ , such that

$$a_0 w_i + a_1 w_{i+1} + \dots + a_\ell w_{i+\ell} = 0, \text{ for } i = 1, \dots, T - \ell$$



there is  $a = (a_0, a_1, \dots, a_\ell) \neq 0$ , such that

$$a^\top \begin{bmatrix} w_1 & w_2 & \cdots & w_{T-\ell} \\ w_2 & w_3 & \cdots & w_{T-\ell+1} \\ \vdots & \vdots & & \vdots \\ w_{\ell+1} & w_{\ell+2} & \cdots & w_T \end{bmatrix} = a^\top \mathcal{H}_\ell(w) = 0$$

the sequence  $w = (w_1, \dots, w_T)$  is a linear recursion with lag  $\leq \ell$



$$\text{rank} \left( \begin{bmatrix} w_1 & w_2 & \cdots & w_{T-\ell} \\ w_2 & w_3 & \cdots & w_{T-\ell+1} \\ \vdots & \vdots & & \vdots \\ w_{\ell+1} & w_{\ell+2} & \cdots & w_T \end{bmatrix} \right) \leq \ell$$

- $T \leq 2\ell \rightsquigarrow$  there is exact fit (independent of  $w$ )
- $T > 2\ell \rightsquigarrow$  generically there is no exact fit



## Existence of greatest common divisor

the polynomials  $p$  and  $q$  have a GCD of degree  $\geq \ell$



...



$$\text{rank}(\text{Sylvester matrix of } p \text{ and } q) \leq m + n - \ell$$

## Data, model, and model class

	line fitting	conic section fitting	linear recurrence with lag $\leq \ell$	GCD
data	points (in $\mathbb{R}^2$ )	points (in $\mathbb{R}^2$ )	sequence	pair of polynomials
model	line (in $\mathbb{R}^2$ )	conic section	autonomous LTI system	polynomials with nontrivial GCD
model class	{ lines (in $\mathbb{R}^2$ ) }	{ conic sections }	class of LTI systems	?

## Continue the sequences

( 1, 2, 3, 5, 8, 13, ? )

( -5, 5, 0, 5, 5, 10, ? )

( 1, 0, -1, -1, 0, 1, ? )

## An algorithm for continuation of a sequence

**Input:**  $w = (w_1, \dots, w_T)$

1:  $\ell := 1$

2: **while**  $\text{rank}(\mathcal{H}_\ell(w)) = \ell + 1$  **do**

3:    $\ell := \ell + 1$

4: **end while**

5: compute nonzero vector  $a$  in the left null space of  $\mathcal{H}_\ell(w)$

**Output:**  $w_{T+1} = -\frac{1}{a_\ell}(a_0 w_{T-\ell+1} + a_1 w_{T-\ell+2} + \dots + a_{\ell-1} w_T)$

# Abstract setting for data modeling

- data space  $\mathcal{U}$

examples:  $\mathbb{R}^q$ ,  $(\mathbb{R}^q)^T$ ,  $\mathbb{R}[\mathbf{z}] \times \mathbb{R}[\mathbf{z}]$ ,  $\{\text{true}, \text{false}\}$

- data  $\mathcal{D} = \{\mathcal{D}_1, \dots, \mathcal{D}_N\} \subset \mathcal{U}$

$\mathcal{D}_i \in \mathcal{U}$  — observation, realization, or outcome

- model  $\mathcal{B} \subset \mathcal{U}$

an exclusion rule, declares what outcomes are possible

- model class  $\mathcal{M} \subset 2^{\mathcal{U}}$

## Exact vs approximate models

- $\mathcal{B}$  is an exact model for  $\mathcal{D}$  if  $\mathcal{D} \subset \mathcal{B}$   
otherwise  $\mathcal{B}$  is an approximate model for  $\mathcal{D}$
- $\mathcal{B} = \mathcal{U}$  is a (trivial) exact model for any  $\mathcal{D} \subset \mathcal{U}$   
     $\rightsquigarrow$  we want nontrivial model  
     $\rightsquigarrow$  notion of model complexity
- any model is approximate model for any data set  
     $\rightsquigarrow$  we need to quantify the approximation accuracy  
     $\rightsquigarrow$  notion of model accuracy (w.r.t. the data)

# Model complexity

- the “smaller” a model is the more powerful/useful it is
- the “bigger” a model is the more complex it is
- we prefer simple models over complex ones
- exact modeling problem:  
find the least complex model that fits the data exactly

## Linear model complexity

- a linear model  $\mathcal{B}$  is a subspace of  $\mathcal{U}$  ( $\mathcal{U}$  is a vector space)
- the complexity of  $\mathcal{B}$  is defined as its dimension
- in the linear case

$$\mathcal{D} \subset \mathcal{B} \quad \implies \quad \text{span}(\mathcal{D}) \subset \mathcal{B}$$

and the rank of the data matrix is  $\leq \dim(\mathcal{B})$

- $\text{span}(\mathcal{D})$  — the smallest linear model, consistent with  $\mathcal{D}$



# Model accuracy

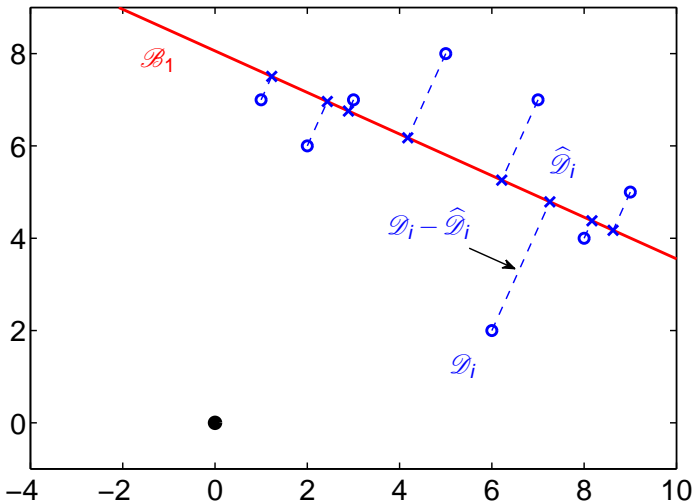
- let  $\mathcal{U}$  be a normed vector space with norm  $\|\cdot\|$
- the distance between the data  $\mathcal{D}$  and a model  $\mathcal{B}$  is

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

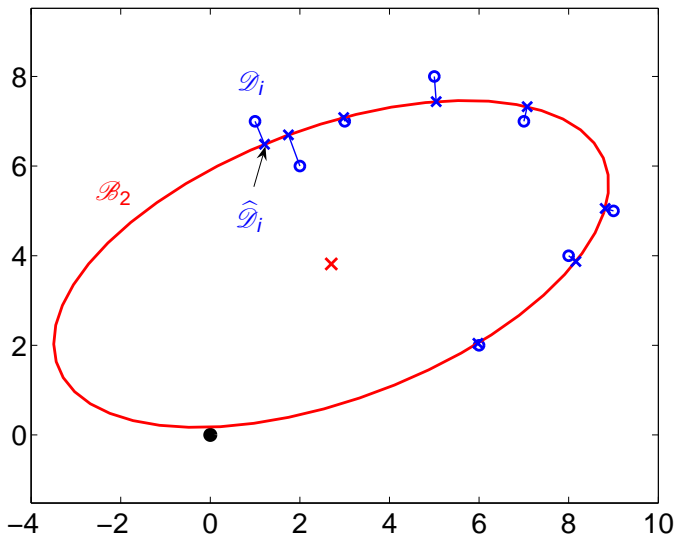
- approximate modeling problem:

$$\text{minimize over } \mathcal{B} \in \mathcal{M} \quad \text{dist}(\mathcal{D}, \mathcal{B})$$

Example:  $\mathcal{U} = \mathbb{R}^2$ , Euclidean norm,  $\mathcal{M} = \{\text{lines}\}$



Example:  $\mathcal{U} = \mathbb{R}^2$ , Euclidean norm,  $\mathcal{M} = \{\text{ellipses}\}$



# Approximate modeling $\iff$ Low-rank approximation

minimize over  $\mathcal{B} \in \mathcal{M}$   $\text{dist}(\mathcal{D}, \mathcal{B})$

$\iff$

minimize over  $\hat{\mathcal{D}} \subset \mathcal{B} \in \mathcal{M}$   $\|\mathcal{D} - \hat{\mathcal{D}}\|$

$\iff$

minimize over  $\hat{\mathcal{D}}$   $\|\mathcal{D} - \hat{\mathcal{D}}\|$  subject to  
 $\text{rank}(\text{matrix constructed of } \hat{\mathcal{D}}) \leq \text{complexity of } \mathcal{M}$

- in general, nonconvex optimization problem
- different matrix structures occur in the applications

## Approximate line fitting in $\mathbb{R}^2$

$$\text{minimize over } \mathcal{B} \in \{\text{lines}\} \quad \text{dist}(\mathcal{D}, \mathcal{B})$$

$$\Updownarrow$$

$$\text{minimize over } \hat{x}_i, \hat{y}_i, i = 1, \dots, N \quad \sum_{i=1}^N \left\| \begin{bmatrix} x_i \\ y_i \end{bmatrix} - \begin{bmatrix} \hat{x}_i \\ \hat{y}_i \end{bmatrix} \right\|_2^2$$

$$\text{subject to} \quad \text{rank} \left( \begin{bmatrix} \hat{x}_1 & \cdots & \hat{x}_N \\ \hat{y}_1 & \cdots & \hat{y}_N \\ 1 & \cdots & 1 \end{bmatrix} \right) \leq 2$$

can be solved using the singular value decomposition

## Approximate conic section fitting in $\mathbb{R}^2$

minimize over  $\mathcal{B} \in \{\text{conic sections}\}$   $\text{dist}(\mathcal{D}, \mathcal{B})$

$\Updownarrow$

minimize over  $\hat{x}_i, \hat{y}_i, i = 1, \dots, N$   $\sum_{i=1}^N \left\| \begin{bmatrix} x_i \\ y_i \end{bmatrix} - \begin{bmatrix} \hat{x}_i \\ \hat{y}_i \end{bmatrix} \right\|_2^2$

subject to  $\text{rank} \begin{pmatrix} \begin{bmatrix} \hat{x}_1^2 & \dots & \hat{x}_N^2 \\ \hat{x}_1 \hat{y}_1 & \dots & \hat{x}_N \hat{y}_N \\ \hat{x}_1 & \dots & \hat{x}_N \\ \hat{y}_1^2 & \dots & \hat{y}_N^2 \\ \hat{y}_1 & \dots & \hat{y}_N \\ 1 & \dots & 1 \end{bmatrix} \end{pmatrix} \leq 5$

requires iterative optimization methods and initial approx.

# Conclusions

- common pattern in data modeling

data is exact for a model of bounded complexity



matrix constructed from the data is rank deficient

- exact modeling  $\approx$  rank computation

- approximate modeling problem

*modify the data as little as possible in order to  
make it exact for a model in the given model class*

- the problem is equivalent to low-rank approximation

# Conclusions

- seemingly unrelated problems (line, ellipse, dynamic model fitting, GCD computation) are reduced to one problem
- theory, algorithms, and related software for the generic problem have impact on many applied problems
- postdoc position available from January 2011



Questions?