

Globally Optimal Least-Squares ARMA Model Identification Is an Eigenvalue Problem

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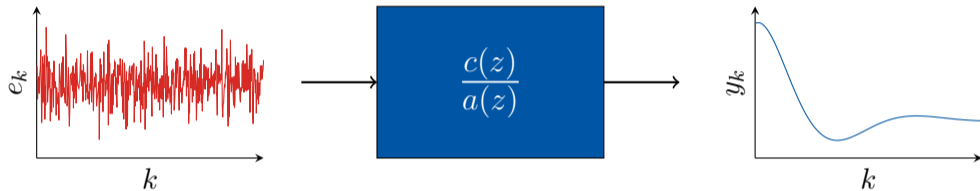
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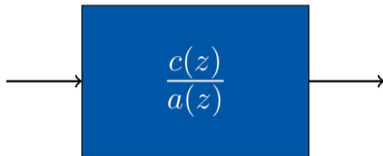
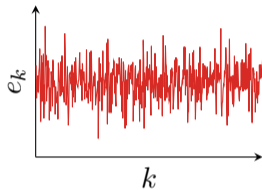
Introduction



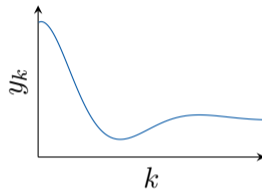
autoregressive moving-average (ARMA) model

Introduction

unknown latent input



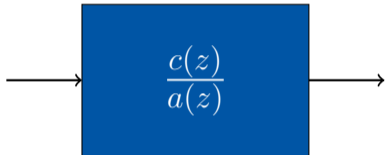
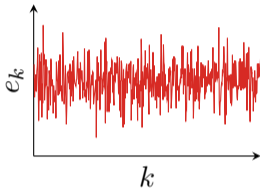
observed output



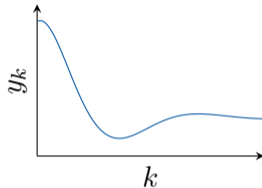
autoregressive moving-average (ARMA) model

Introduction

unknown latent input



observed output



autoregressive moving-average (ARMA) model

globally optimal least-squares ARMA model identification is an eigenvalue problem

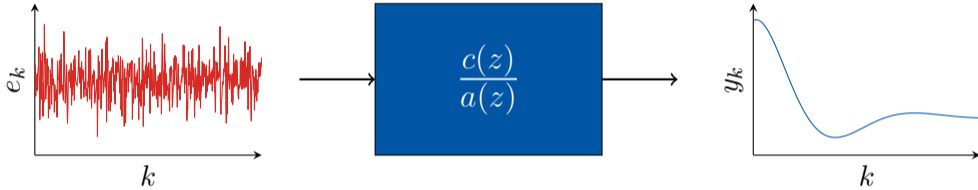
Outline

- 1 | Introduction
- 2 | Autoregressive moving-average model
- 3 | Multiparameter eigenvalue problem
- 4 | Block Macaulay matrix
- 5 | Conclusion and future work

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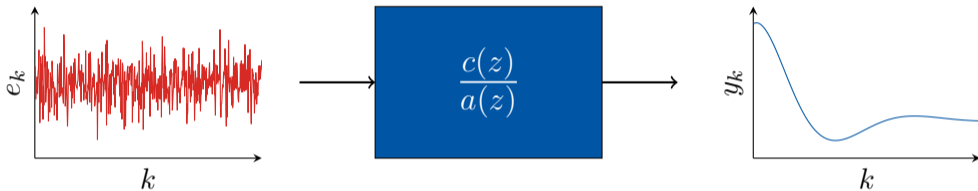
Autoregressive moving-average model



$$a(z)y_k = c(z)e_k$$
$$\sum_{i=0}^{n_a} \alpha_i y_{k-i} = \sum_{j=0}^{n_c} \gamma_j e_{k-j}$$

Autoregressive moving-average model

no assumptions (contrary to PEM)



$$a(z)y_k = c(z)e_k$$

$$\sum_{i=0}^{n_a} \alpha_i y_{k-i} = \sum_{j=0}^{n_c} \gamma_j e_{k-j}$$

Autoregressive moving-average model

$$\sum_{i=0}^{n_a} \alpha_i y_{k-i} = \sum_{j=0}^{n_c} \gamma_j e_{k-j} \quad k = 1, \dots, N$$

⇓

$$\begin{bmatrix} \alpha_{n_a} & \cdots & \alpha_1 & 1 & & & & \\ & \alpha_{n_a} & \cdots & \alpha_1 & 1 & & & \\ & & \ddots & & \ddots & \ddots & & \\ & & & \alpha_{n_a} & \cdots & \alpha_1 & 1 & \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} \gamma_{n_c} & \cdots & \gamma_1 & 1 & & & & \\ & \gamma_{n_c} & \cdots & \gamma_1 & 1 & & & \\ & & \ddots & & \ddots & \ddots & & \\ & & & \gamma_{n_c} & \cdots & \gamma_1 & 1 & \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_M \end{bmatrix}$$

⇓

$$T_a y = T_c e$$

Autoregressive moving-average model

$$\sum_{i=0}^{n_a} \alpha_i y_{k-i} = \sum_{j=0}^{n_c} \gamma_j e_{k-j} \quad \mathbf{k} = 1, \dots, \mathbf{N}$$

number of data points

⇓

$$\begin{bmatrix} \alpha_{n_a} & \cdots & \alpha_1 & 1 & & & & \\ & \alpha_{n_a} & \cdots & \alpha_1 & 1 & & & \\ & & \ddots & & \ddots & \ddots & & \\ & & & \alpha_{n_a} & \cdots & \alpha_1 & 1 & \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} \gamma_{n_c} & \cdots & \gamma_1 & 1 & & & & \\ & \gamma_{n_c} & \cdots & \gamma_1 & 1 & & & \\ & & \ddots & & \ddots & \ddots & & \\ & & & & \gamma_{n_c} & \cdots & \gamma_1 & 1 \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_M \end{bmatrix}$$

⇓

$$T_a y = T_c e$$

Identification problem

$$\min_{a,c,e} \|e\|_2^2$$

$$\text{subject to } T_a y = T_c e$$

Identification problem

optimality condition: minimize e , while $y = \hat{y}$


$$\min_{a,c,e} \|e\|_2^2$$

subject to $T_a y = T_c e$

Identification problem

optimality condition: minimize e , while $y = \hat{y}$


$$\min_{a,c,e} \|e\|_2^2$$

subject to $T_a y = T_c e$



model condition: $y = T_a^\dagger T_c e = \hat{y}$

First order optimality conditions

$$\sigma^2 = \|e\|_2^2 = y^T T_a^T (T_c T_c^T)^{-1} T_a y$$

First order optimality conditions

$$\begin{aligned}\sigma^2 &= \|e\|_2^2 = y^T T_a^T (\mathbf{T}_c \mathbf{T}_c^T)^{-1} T_a y \\ &= y^T T_a^T \mathbf{D}_c^{-1} T_a y\end{aligned}$$

First order optimality conditions

$$\begin{aligned}\sigma^2 &= \|e\|_2^2 = y^T T_a^T (T_c T_c^T)^{-1} T_a y \\ &= y^T T_a^T \mathbf{D}_c^{-1} \mathbf{T}_a y \\ &= y^T T_a^T \mathbf{f}\end{aligned}$$

First order optimality conditions

$$\sigma^2 = y^T T_a^T D_c^{-1} T_a y = y^T T_a^T f$$


partial derivatives: $\frac{\partial \cdot}{\partial \alpha_i} = 0, \frac{\partial \cdot}{\partial \gamma_j} = 0$

$$\left\{ \begin{array}{ll} y^T T_a^T f^{\alpha_i} + y^T T_a^{\alpha_i T} f = 0 & \forall i = 1, \dots, n_a \\ y^T T_a^T f^{\gamma_j} = 0 & \forall j = 1, \dots, n_c \\ D_c f^{\alpha_i} - T_a^{\alpha_i} y = 0 & \forall i = 1, \dots, n_a \\ D_c^{\gamma_j} f + D_c f^{\gamma_j} = 0 & \forall j = 1, \dots, n_c \\ D_c f - T_a y = 0 & \end{array} \right.$$

Multiparameter eigenvalue problem

$$\begin{bmatrix} I \otimes y^T T_a^T & 0 & \{y^T T_a^{\alpha_i T}\}_i & 0 \\ 0 & I \otimes y^T T_a^T & 0 & 0 \\ I \otimes D_c & 0 & 0 & \{T_a^{\alpha_i} y\}_i \\ 0 & I \otimes D_c & \{D_c^{\gamma_j}\}_j & 0 \\ 0 & 0 & D_c & T_a y \end{bmatrix} \begin{bmatrix} \{f^{\alpha_i}\}_i \\ \{f^{\gamma_j}\}_j \\ f \\ -1 \end{bmatrix} = 0$$

Multiparameter eigenvalue problem

$$\begin{bmatrix}
 I \otimes y^T T_a^T & 0 & \{y^T T_a^{\alpha_i T}\}_i & 0 \\
 0 & I \otimes y^T T_a^T & 0 & 0 \\
 I \otimes D_c & 0 & 0 & \{T_a^{\alpha_i} y\}_i \\
 0 & I \otimes D_c & \{D_c^{\gamma_j}\}_j & 0 \\
 0 & 0 & D_c & T_a y
 \end{bmatrix}
 \begin{bmatrix}
 \{f^{\alpha_i}\}_i \\
 \{f^{\gamma_j}\}_j \\
 f \\
 -1
 \end{bmatrix}
 = 0$$


Kronecker product:

$$A \otimes B = \begin{bmatrix}
 a_{11}B & \cdots & a_{1n}B \\
 \vdots & \ddots & \vdots \\
 a_{m1}B & \cdots & a_{mn}B
 \end{bmatrix}$$

Multiparameter eigenvalue problem

$$\begin{bmatrix} I \otimes y^T T_a^T & 0 \\ 0 & I \otimes y^T T_a^T \\ I \otimes D_c & 0 \\ 0 & I \otimes D_c \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \{y^T T_a^{\alpha_i T}\}_i \\ 0 \\ 0 \\ \{D_c^{\gamma_j}\}_j \\ D_c \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ \{T_a^{\alpha_i} y\}_i \\ 0 \\ T_a y \end{bmatrix} \begin{bmatrix} \{f^{\alpha_i}\}_i \\ \{f^{\gamma_j}\}_j \\ f \\ -1 \end{bmatrix} = 0$$

Kronecker product:

$$A \otimes B = \begin{bmatrix} a_{11}B & \cdots & a_{1n}B \\ \vdots & \ddots & \vdots \\ a_{m1}B & \cdots & a_{mn}B \end{bmatrix}$$

matrix stack:

$$\{M_i\}_i = \begin{bmatrix} M_1 \\ \vdots \\ M_m \end{bmatrix}$$

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Multiparameter eigenvalue problem

Multiparameter eigenvalue problem:

$$\left(\sum_{\omega} A_{\omega} \omega \right) z = 0, \quad z \neq 0$$

- $\omega(\lambda_1, \dots, \lambda_n) = \lambda_1^{k_1} \cdots \lambda_n^{k_n}$ is a monomial function of the eigenvalues
- A_{ω} is the corresponding matrix of coefficients

Multiparameter eigenvalue problem

comparison

**standard eigenvalue
problem**

$$Az = \lambda z$$

$$(A - I\lambda)z = 0$$

one eigenvalue

**multiparameter eigenvalue
problem**

$$A_1 z = \sum_{\omega \neq 1} A_\omega \omega z$$

$$(\sum_{\omega} A_\omega \omega) z = 0$$

multiple eigenvalues

Multiparameter eigenvalue problem

examples

standard eigenvalue problem: $(A - I\lambda)z = 0$

generalized eigenvalue problem: $(A - B\lambda)z = 0$

linear two-parameter eigenvalue problem: $(A_1 + A_\alpha\alpha + A_\gamma\gamma)z = 0$

multiparameter eigenvalue problem: $\left(A_1 + A_{\lambda_1^2}\lambda_1^2 + A_{\lambda_2\lambda_3^3}\lambda_2\lambda_3^3\right)z = 0$

Multiparameter eigenvalue problem

autoregressive moving-average model

$$\underbrace{\begin{bmatrix} I \otimes y^T T_a^T & 0 & \{y^T T_a^{\alpha_i T}\}_i & 0 \\ 0 & I \otimes y^T T_a^T & 0 & 0 \\ I \otimes D_c & 0 & 0 & \{T_a^{\alpha_i} y\}_i \\ 0 & I \otimes D_c & \{D_c^{\gamma_j}\}_j & 0 \\ 0 & 0 & D_c & T_a y \end{bmatrix}}_{A(\alpha_i, \gamma_j)} \underbrace{\begin{bmatrix} \{f^{\alpha_i}\}_i \\ \{f^{\gamma_j}\}_j \\ f \\ -1 \end{bmatrix}}_z = 0$$

Multiparameter eigenvalue problem

autoregressive moving-average model

$$\underbrace{\begin{bmatrix} I \otimes y^T T_a^T & 0 & \{y^T T_a^{\alpha_i T}\}_i & 0 \\ 0 & I \otimes y^T T_a^T & 0 & 0 \\ I \otimes D_c & 0 & 0 & \{T_a^{\alpha_i} y\}_i \\ 0 & I \otimes D_c & \{D_c^{\gamma_j}\}_j & 0 \\ 0 & 0 & D_c & T_a y \end{bmatrix}}_{A(\alpha_i, \gamma_j)} \underbrace{\begin{bmatrix} \{f^{\alpha_i}\}_i \\ \{f^{\gamma_j}\}_j \\ f \\ -1 \end{bmatrix}}_z = 0$$

$$\left(\sum_{\omega} A_{\omega} \omega \right) z = 0$$

Multiparameter eigenvalue problem

autoregressive moving-average model

$$\underbrace{\begin{bmatrix} I \otimes y^T T_a^T & 0 & \{y^T T_a^{\alpha_i T}\}_i & 0 \\ 0 & I \otimes y^T T_a^T & 0 & 0 \\ I \otimes D_c & 0 & 0 & \{T_a^{\alpha_i} y\}_i \\ 0 & I \otimes D_c & \{D_c^{\gamma_j}\}_j & 0 \\ 0 & 0 & D_c & T_a y \end{bmatrix}}_{A(\alpha_i, \gamma_j)} \underbrace{\begin{bmatrix} \{f^{\alpha_i}\}_i \\ \{f^{\gamma_j}\}_j \\ f \\ -1 \end{bmatrix}}_z = 0$$

$$\left(\sum_{\omega} A_{\omega} \omega \right) z = 0$$

eigenvector (z) and $(n_a + n_c)$ -tuple of eigenvalues (α_i and γ_j)

Multiparameter eigenvalue problem

example: first order ARMA(1,1) model

$$\begin{bmatrix} y^T T_a^T & 0 & y^T T_a^{\alpha_1 T} & 0 \\ 0 & y^T T_a^T & 0 & 0 \\ D_c & 0 & 0 & T_a^{\alpha_1} y \\ 0 & D_c & D_c^{\gamma_1} & 0 \\ 0 & 0 & D_c & T_a y \end{bmatrix} \begin{bmatrix} f^{\alpha_1} \\ f^{\gamma_1} \\ f \\ -1 \end{bmatrix} = 0$$

Multiparameter eigenvalue problem

example: first order ARMA(1,1) model

$$\begin{bmatrix} y^T T_a^T & 0 & y^T T_a^{\alpha_1 T} & 0 \\ 0 & y^T T_a^T & 0 & 0 \\ D_c & 0 & 0 & T_a^{\alpha_1} y \\ 0 & D_c & D_c^{\gamma_1} & 0 \\ 0 & 0 & D_c & T_a y \end{bmatrix} \begin{bmatrix} f^{\alpha_1} \\ f^{\gamma_1} \\ f \\ -1 \end{bmatrix} = 0$$

$$(A_1 + A_\alpha \alpha + A_\gamma \gamma + A_{\alpha^2} \alpha^2 + A_{\alpha\gamma} \alpha\gamma + A_{\gamma^2} \gamma^2) z = 0$$

Multiparameter eigenvalue problem

example: first order ARMA(1,1) model

$$\begin{bmatrix} y^T T_a^T & 0 & y^T T_a^{\alpha_1 T} & 0 \\ 0 & y^T T_a^T & 0 & 0 \\ D_c & 0 & 0 & T_a^{\alpha_1} y \\ 0 & D_c & D_c^{\gamma_1} & 0 \\ 0 & 0 & D_c & T_a y \end{bmatrix} \begin{bmatrix} f^{\alpha_1} \\ f^{\gamma_1} \\ f \\ -1 \end{bmatrix} = 0$$

$$(A_1 + A_\alpha \alpha + A_\gamma \gamma + A_{\alpha^2} \alpha^2 + A_{\alpha\gamma} \alpha\gamma + A_{\gamma^2} \gamma^2) z = 0$$

eigenvector (z) and 2-tuple of eigenvalues (α and γ)

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Quadratic two-parameter eigenvalue problem

for example, a **first order ARMA(1,1) model** with parameters α and γ :

$$(A_1 + A_\alpha\alpha + A_\gamma\gamma + A_{\alpha^2}\alpha^2 + A_{\alpha\gamma}\alpha\gamma + A_{\gamma^2}\gamma^2) z = 0$$

Block Macaulay matrix

$$(A_1 + A_\alpha \alpha + A_\gamma \gamma + A_{\alpha^2} \alpha^2 + A_{\alpha\gamma} \alpha\gamma + A_{\gamma^2} \gamma^2) z = 0$$

Block Macaulay matrix

$$(A_1 + A_\alpha \alpha + A_\gamma \gamma + A_{\alpha^2} \alpha^2 + A_{\alpha\gamma} \alpha\gamma + A_{\gamma^2} \gamma^2) z = 0$$

↳ “shift” with the eigenvalues α and γ

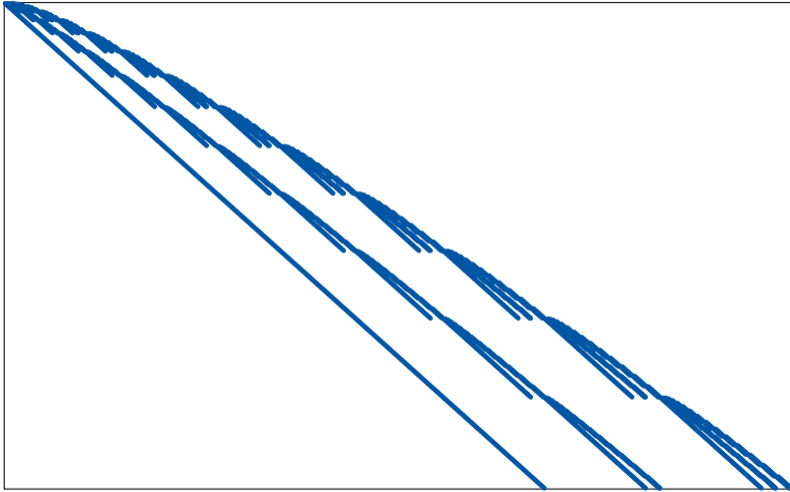
$$\alpha(A_1 + A_\alpha \alpha + A_\gamma \gamma + A_{\alpha^2} \alpha^2 + A_{\alpha\gamma} \alpha\gamma + A_{\gamma^2} \gamma^2) z = 0$$

$$\gamma(A_1 + A_\alpha \alpha + A_\gamma \gamma + A_{\alpha^2} \alpha^2 + A_{\alpha\gamma} \alpha\gamma + A_{\gamma^2} \gamma^2) z = 0$$

$$\alpha^2(A_1 + A_\alpha \alpha + A_\gamma \gamma + A_{\alpha^2} \alpha^2 + A_{\alpha\gamma} \alpha\gamma + A_{\gamma^2} \gamma^2) z = 0$$

⋮

Block Macaulay matrix



Block Macaulay matrix

rewrite the MEP and its shifts using the block Macaulay matrix

$$\begin{array}{cccccccc}
 & z & z\alpha & z\gamma & z\alpha^2 & z\alpha\gamma & z\gamma^2 & z\alpha^3 & & \\
 \left[\begin{array}{cccccccc}
 A_1 & A_\alpha & A_\gamma & A_{\alpha^2} & A_{\alpha\gamma} & A_{\gamma^2} & 0 & \dots \\
 0 & A_1 & 0 & A_\alpha & A_\gamma & 0 & A_{\alpha^2} & \dots \\
 0 & 0 & A_1 & 0 & A_\alpha & A_\gamma & 0 & \dots \\
 0 & 0 & 0 & A_1 & 0 & 0 & A_\alpha & \dots \\
 \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots
 \end{array} \right]
 \begin{array}{c}
 \left[\begin{array}{c}
 z \\
 z\alpha \\
 z\gamma \\
 z\alpha^2 \\
 z\alpha\gamma \\
 z\gamma^2 \\
 z\alpha^3 \\
 \vdots
 \end{array} \right]
 \end{array}
 = 0
 \end{array}$$

Block multi-shift-invariant null space

- Solutions generate vectors in the null space of M

$$MK = 0$$

- Nullity corresponds to the number of solutions m_b

$$m_b = \prod_{i=1}^n d_i$$

- Null space has a **block multi-shift-invariant** structure

block multivariate
Vandermonde basis K

$$K = \begin{bmatrix} z & \cdots & z \\ z\alpha & \cdots & z\alpha \\ z\gamma & \cdots & z\gamma \\ z\alpha^2 & \cdots & z\alpha^2 \\ z\alpha\gamma & \cdots & z\alpha\gamma \\ z\gamma^2 & \cdots & z\gamma^2 \\ z\alpha^3 & \cdots & z\alpha^3 \\ \vdots & \vdots & \vdots \end{bmatrix}$$

Multidimensional realization theory

for one solution

$$\begin{bmatrix} z \\ z\alpha \\ z\gamma \\ z\alpha^2 \\ z\alpha\gamma \\ z\gamma^2 \\ z\alpha^3 \\ \vdots \end{bmatrix} \xrightarrow{\alpha} \begin{bmatrix} z \\ z\alpha \\ z\gamma \\ z\alpha^2 \\ z\alpha\gamma \\ z\gamma^2 \\ z\alpha^3 \\ \vdots \end{bmatrix}$$

$$S_1 k \alpha = S_\alpha k$$

Multidimensional realization theory

for all solutions

$$\begin{bmatrix} z & \cdots & z \\ z\alpha & \cdots & z\alpha \\ z\gamma & \cdots & z\gamma \\ z\alpha^2 & \cdots & z\alpha^2 \\ z\alpha\gamma & \cdots & z\alpha\gamma \\ z\gamma^2 & \cdots & z\gamma^2 \\ z\alpha^3 & \cdots & z\alpha^3 \\ \vdots & \vdots & \vdots \end{bmatrix} \xrightarrow{\alpha} \begin{bmatrix} z & \cdots & z \\ z\alpha & \cdots & z\alpha \\ z\gamma & \cdots & z\gamma \\ z\alpha^2 & \cdots & z\alpha^2 \\ z\alpha\gamma & \cdots & z\alpha\gamma \\ z\gamma^2 & \cdots & z\gamma^2 \\ z\alpha^3 & \cdots & z\alpha^3 \\ \vdots & \vdots & \vdots \end{bmatrix}$$

$$S_1 K D_\alpha = S_\alpha K$$

Multidimensional realization theory

consider m_α affine and simple solutions

Realization theory for an unknown α :

$$S_1 K D_\alpha = S_\alpha K,$$

where S_1 and S_α select blocks from K

Multidimensional realization theory

numerical basis for the null space

$$S_1 K D_\alpha = S_\alpha K$$

Multidimensional realization theory

numerical basis for the null space

$$S_1 K D_\alpha = S_\alpha K$$

- The solutions are not known in advance
- Consider a **numerical basis for the null space** Z

$$K = ZT$$

- This results in

$$(S_1 Z) T D_\alpha = (S_\alpha Z) T$$

Multidimensional realization theory

numerical basis for the null space

$$S_1 K D_\alpha = S_\alpha K$$

for example, calculated via the SVD

- The solutions are not known in advance
- Consider a **numerical basis for the null space** Z

$$K = ZT$$

- This results in

$$(S_1 Z) T D_\alpha = (S_\alpha Z) T$$

Multidimensional realization theory

numerical basis for the null space

$$S_1 K D_\alpha = S_\alpha K$$

for example, calculated via the SVD

- The solutions are not known in advance
- Consider a **numerical basis for the null space** Z

$$K = ZT$$

non-singular matrix T

- This results in

$$(S_1 Z) T D_\alpha = (S_\alpha Z) T$$

Multidimensional realization theory

standard eigenvalue problem

Realization theory for an unknown α :

$$(S_1 Z) T D_\alpha = (S_\alpha Z) T,$$

where S_1 and S_α select blocks from Z

- Generalized eigenvalue problem, with T the matrix of eigenvectors
- We can rewrite this as a **standard eigenvalue problem**

$$T D_\alpha T^{-1} = (S_1 Z)^\dagger (S_\alpha Z)$$

Multidimensional realization theory

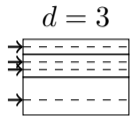
Other shift functions

- It is **possible to shift with any polynomial** in the eigenvalues – for example with γ

$$(S_1 Z) T D_\gamma = (S_\gamma Z) T$$

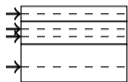
- This leads to the same eigenvectors T

Solutions at infinity

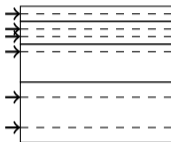


Solutions at infinity

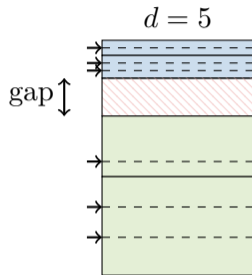
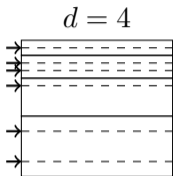
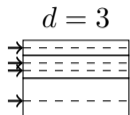
$d = 3$



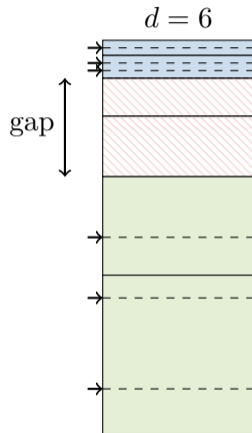
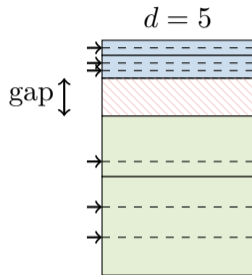
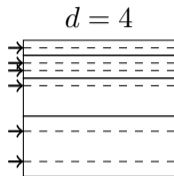
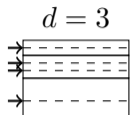
$d = 4$



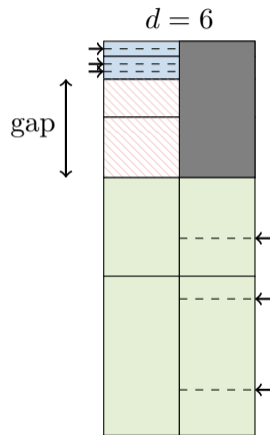
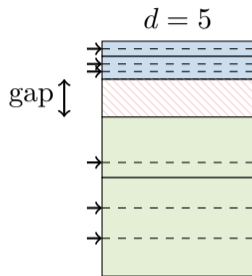
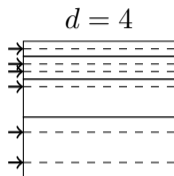
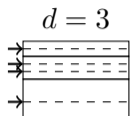
Solutions at infinity



Solutions at infinity

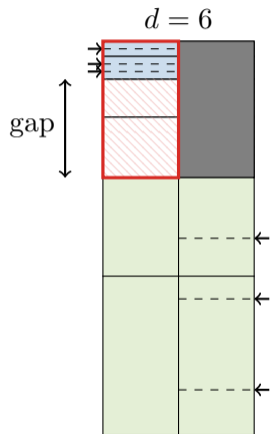
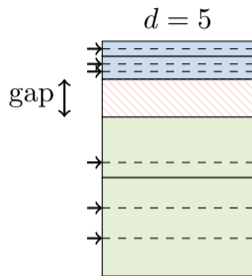
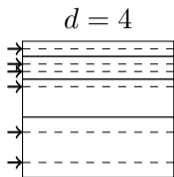
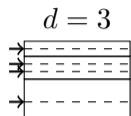


Solutions at infinity



column compression

Solutions at infinity



column compression

Multiplicity higher than one

simple roots

$$\left[\begin{array}{c|c|c} k^{(1)} & k^{(2)} & \dots \end{array} \right]$$

multiple roots

$$\left[\begin{array}{c|c|c} k^{(1)} & \partial k^{(1)} & \dots \end{array} \right]$$

System theoretic interpretations

- Corresponds to a **multidimensional observability matrix**

$$H = [\Gamma_R \quad \Gamma_S]$$

- Generated by a multidimensional descriptor system
- Contains the block multi-shift-invariance

$$S_\alpha H A_\gamma = S_{\alpha\gamma} H,$$

$$A_\gamma = (S_\alpha H)^\dagger (S_{\alpha\gamma} H)$$

block column echelon basis H

$$H = \begin{bmatrix} C_R & 0 \\ C_R A_\alpha & 0 \\ C_R A_\gamma & 0 \\ C_R A_\alpha^2 & 0 \\ C_R A_\alpha A_\gamma & 0 \\ C_R A_\alpha^2 & 0 \\ \vdots & \vdots \\ C_R A_\alpha^n & 0 \\ \vdots & \vdots \\ \times & C_S E_\alpha^{m-1} \\ \vdots & \vdots \end{bmatrix}$$

Outline

- 1 | Introduction
- 2 | Autoregressive moving-average model
- 3 | Multiparameter eigenvalue problem
- 4 | Block Macaulay matrix
- 5 | Conclusion and future work

Conclusion

- Identification of ARMA models is an MEP
- MEP can be solved via the block Macaulay matrix
- Null space of block Macaulay matrix yields an SEP

Future work

- Investigate rigorous properties of block Macaulay matrix
- Extend to other model classes
- Restrict the calculations to the optimizing solution only
- Solve large real-life problems