



# Model Reduction for Dynamical Systems

— Lecture 12 —

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# Interpolatory Model Reduction

## Padé Approximation

### Theorem (moment matching) [GRIMME '97, VILLEMAGNE/SKELTON '87]

For LTI system given by  $A \in \mathbb{R}^{n \times n}$ ,  $B \in \mathbb{R}^{n \times m}$ ,  $C \in \mathbb{R}^{p \times n}$  and  $s_1, \dots, s_k \notin \Lambda(A)$ , let

$$A^{(i)} := (s_i I_n - A)^{-1}, \quad B^{(i)} := (s_i I_n - A)^{-1} B, \quad C^{(i)} := C (s_i I_n - A)^{-1}, \quad i = 1, \dots, k,$$

and

$$\begin{aligned} \mathcal{K}_{K_1} \left( A^{(1)}, B^{(1)} \right) \cup \dots \cup \mathcal{K}_{K_k} \left( A^{(k)}, B^{(k)} \right) &\subset \text{range}(V), \\ \mathcal{K}_{K_1} \left\{ (A^{(1)})^T, (C^{(1)})^T \right\} \cup \dots \cup \mathcal{K}_{K_k} \left\{ (A^{(k)})^T, (C^{(k)})^T \right\} &\subset \text{range}(W). \end{aligned}$$

Then

$$\frac{d^j}{ds^j} G(s_i) = \frac{d^j}{ds^j} \hat{G}(s_i), \quad \text{for } i = 1, \dots, k, \quad j = 0, \dots, \ell_i - 1,$$

where  $\ell_i \geq \lfloor \frac{K_i}{m} \rfloor + \lfloor \frac{K_i}{p} \rfloor$ .

**Note:** for  $m \neq p$ , must extend  $\mathcal{V}$  (for  $m < p$ ) or  $\mathcal{W}$  (for  $m > p$ ) by arbitrary vectors yielding an orthogonal bases of the respective subspace so that  $\mathcal{V}$  and  $\mathcal{W}$  have the same dimension.

Also need to take care of deflation (linear dependencies in the Krylov spaces)!

# $\mathcal{H}_2$ -Optimal Model Reduction

Best  $\mathcal{H}_2$ -norm approximation problem

$$\text{Find } \arg \min_{\hat{G} \in \mathcal{H}_2 \text{ of order } \leq r} \|G - \hat{G}\|_2.$$

# $\mathcal{H}_2$ -Optimal Model Reduction

## Best $\mathcal{H}_2$ -norm approximation problem

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$\rightsquigarrow$  First-order necessary  $\mathcal{H}_2$ -optimality conditions:

For SISO systems

$$\begin{aligned} G(-\mu_i) &= \hat{G}(-\mu_i), \\ G'(-\mu_i) &= \hat{G}'(-\mu_i), \end{aligned}$$

where  $\mu_i$  are the poles of the reduced transfer function  $\hat{G}$ .

# $\mathcal{H}_2$ -Optimal Model Reduction

## Best $\mathcal{H}_2$ -norm approximation problem

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↪ First-order necessary  $\mathcal{H}_2$ -optimality conditions:

For MIMO systems

$$\begin{aligned} G(-\mu_i)\tilde{B}_i &= \hat{G}(-\mu_i)\tilde{B}_i, & \text{for } i = 1, \dots, r, \\ \tilde{C}_i^T G(-\mu_i) &= \tilde{C}_i^T \hat{G}(-\mu_i), & \text{for } i = 1, \dots, r, \\ \tilde{C}_i^T G'(-\mu_i)\tilde{B}_i &= \tilde{C}_i^T \hat{G}'(-\mu_i)\tilde{B}_i, & \text{for } i = 1, \dots, r, \end{aligned}$$

where  $T^{-1}\hat{A}T = \text{diag}\{\mu_1, \dots, \mu_r\} = \text{spectral decomposition}$  and

$$\tilde{B} = \hat{B}^T T^{-T}, \quad \tilde{C} = \hat{C}T.$$

↪ **tangential interpolation conditions.**

# Interpolatory Model Reduction

## Interpolation of the Transfer Function by Projection

Construct reduced transfer function by **Petrov-Galerkin** projection

$\mathcal{P} = VW^T$ , i.e.

$$\hat{G}(s) = CV (sI - W^T AV)^{-1} W^T B,$$

where  $V$  and  $W$  are given as the **rational Krylov subspaces**

$$V = [(-\mu_1 I - A)^{-1} B, \dots, (-\mu_r I - A)^{-1} B],$$

$$W = [(-\mu_1 I - A^T)^{-1} C^T, \dots, (-\mu_r I - A^T)^{-1} C^T].$$

Then

$$G(-\mu_i) = \hat{G}(-\mu_i) \quad \text{and} \quad G'(-\mu_i) = \hat{G}'(-\mu_i),$$

for  $i = 1, \dots, r$  as desired.

↪ iterative algorithms (IRKA/MIRIAM) that yield  $\mathcal{H}_2$ -optimal models.

[GUGERCIN ET AL. '06], [BUNSE-GERSTNER ET AL. '07],  
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# $\mathcal{H}_2$ -Optimal Model Reduction

## The basic IRKA Algorithm

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### Algorithm 1 IRKA

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**Input:**  $A$  stable,  $B, C, \hat{A}$  stable,  $\hat{B}, \hat{C}, \delta > 0$ .

**Output:**  $A^{opt}, B^{opt}, C^{opt}$

- 1: **while**  $(\max_{j=1, \dots, r} \left\{ \frac{|\mu_j - \mu_j^{old}|}{|\mu_j|} \right\} > \delta)$  **do**
  - 2:  $\text{diag} \{ \mu_1, \dots, \mu_r \} := T^{-1} \hat{A} T = \text{spectral decomposition,}$   
 $\tilde{B} = \hat{B}^* T^{-*}, \tilde{C} = \hat{C} T.$
  - 3:  $V = \left[ (-\mu_1 I - A)^{-1} B \tilde{B}_1, \dots, (-\mu_r I - A)^{-1} B \tilde{B}_r \right]$
  - 4:  $W = \left[ (-\mu_1 I - A^T)^{-1} C^T \tilde{C}_1, \dots, (-\mu_r I - A^T)^{-1} C^T \tilde{C}_r \right]$
  - 5:  $V = \text{orth}(V), W = \text{orth}(W)$
  - 6:  $W = (W^* V)^{-1} W$
  - 7:  $\hat{A} = W^* A V, \hat{B} = W^* B, \hat{C} = C V$
  - 8: **end while**
  - 9:  $A^{opt} = \hat{A}, B^{opt} = \hat{B}, C^{opt} = \hat{C}$
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