



# Model Reduction for Dynamical Systems

— Lecture 6 —

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[www.mpi-magdeburg.mpg.de/research/groups/csc/lehre/2012\\_SS\\_MOR/](http://www.mpi-magdeburg.mpg.de/research/groups/csc/lehre/2012_SS_MOR/)

# Outline

- 1 Introduction
  - Model Reduction for Dynamical Systems
  - Application Areas
  - Motivating Examples
- 2 Mathematical Basics
  - Numerical Linear Algebra
  - Systems and Control Theory
  - Qualitative and Quantitative Study of the Approximation Error
- 3 Model Reduction by Projection
  - Projection and Interpolation
  - Modal Truncation

# Model Reduction by Projection

## Goals

- Automatic generation of compact models.
- Satisfy desired error tolerance for all admissible input signals, i.e., want

$$\|y - \hat{y}\| < \text{tolerance} \cdot \|u\| \quad \forall u \in L_2(\mathbb{R}, \mathbb{R}^m).$$

⇒ Need computable error bound/estimate!

- Preserve physical properties:
  - stability (poles of  $G$  in  $\mathbb{C}^-$ ),
  - minimum phase (zeroes of  $G$  in  $\mathbb{C}^-$ ),
  - passivity

$$\int_{-\infty}^t u(\tau)^T y(\tau) d\tau \geq 0 \quad \forall t \in \mathbb{R}, \quad \forall u \in L_2(\mathbb{R}, \mathbb{R}^m).$$

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# Model Reduction by Projection

## Projection Basics

### Definition 3.1 (Projector)

A projector is a matrix  $P \in \mathbb{R}^{n \times n}$  with  $P^2 = P$ . Let  $\mathcal{V} = \text{range}(P)$ , then  $P$  is projector onto  $\mathcal{V}$ . On the other hand, if  $\{v_1, \dots, v_r\}$  is a basis of  $\mathcal{V}$  and  $V = [v_1, \dots, v_r]$ , then  $P = V(V^T V)^{-1} V^T$  is a projector onto  $\mathcal{V}$ .

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### Lemma 3.2: Projector Properties

- If  $P = P^T$ , then  $P$  is an **orthogonal projector** (aka: **Galerkin projection**), otherwise an **oblique projector** (aka: **Petrov-Galerkin projection**).
- $P$  is the identity operator on  $\mathcal{V}$ , i.e.,  $Pv = v \quad \forall v \in \mathcal{V}$ .
- $I - P$  is the complementary projector onto  $\ker P$ .
- If  $\mathcal{V}$  is an  $A$ -invariant subspace corresponding to a subset of  $A$ 's spectrum, then we call  $P$  a **spectral projector**.
- Let  $\mathcal{W} \subset \mathbb{R}^n$  be another  $r$ -dimensional subspace and  $W = [w_1, \dots, w_r]$  be a basis matrix for  $\mathcal{W}$ , then  $P = V(W^T V)^{-1} W^T$  is an **oblique projector onto  $\mathcal{V}$  along  $\mathcal{W}$** .

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# Model Reduction by Projection

subsecname

## Methods:

- 1 Modal Truncation
- 2 Rational Interpolation (Padé-Approximation and (rational) Krylov Subspace Methods)
- 3 Balanced Truncation
- 4 many more. . .

**Joint feature of these methods:**

**computation of reduced-order model (ROM) by projection!**

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subseaname

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Assume trajectory  $x(t; u)$  is contained in low-dimensional subspace  $\mathcal{V}$ . Thus, use Galerkin or Petrov-Galerkin-type projection of state-space onto  $\mathcal{V}$  along complementary subspace  $\mathcal{W}$ :  $x \approx VW^T x =: \tilde{x}$ , where

$$\text{range}(V) = \mathcal{V}, \quad \text{range}(W) = \mathcal{W}, \quad W^T V = I_r.$$

Then, with  $\hat{x} = W^T x$ , we obtain  $x \approx V\hat{x}$  so that

$$\|x - \tilde{x}\| = \|x - V\hat{x}\|,$$

and the reduced-order model is

$$\hat{A} := W^T A V, \quad \hat{B} := W^T B, \quad \hat{C} := C V, \quad (\hat{D} := D).$$



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Important observations:

- The state equation residual satisfies  $\dot{\tilde{x}} - A\tilde{x} - Bu \perp \mathcal{W}$ , since

$$W^T \left( \dot{\tilde{x}} - A\tilde{x} - Bu \right) = W^T \left( VW^T \dot{x} - AVW^T x - Bu \right)$$

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Given the ROM

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the error transfer function can be written as

$$G(s) - \hat{G}(s) = \left( C(sI_n - A)^{-1} B + D \right) - \left( \hat{C}(sI_r - \hat{A})^{-1} \hat{B} + \hat{D} \right)$$

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If  $s_* \in \mathbb{C} \setminus (\Lambda(A) \cup \Lambda(\hat{A}))$ , then  $P(s)$  is a projector onto  $\mathcal{V}$ :

$\text{range}(P(s)) \subset \text{range}(V)$ , all matrices have full rank  $\Rightarrow$  "=", and

$$P(s)^2 = V(sI_r - \hat{A})^{-1} W^T (sI_n - A) V(sI_r - \hat{A})^{-1} W^T (sI_n - A)$$

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$$\begin{aligned} P(s)^2 &= V(sI_r - \hat{A})^{-1} W^T (sI_n - A) V(sI_r - \hat{A})^{-1} W^T (sI_n - A) \\ &= V(sI_r - \hat{A})^{-1} \underbrace{(sI_r - \hat{A})(sI_r - \hat{A})^{-1}}_{=: I_r} W^T (sI_n - A) = P(s). \end{aligned}$$



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If  $s_* \in \mathbb{C} \setminus (\Lambda(A) \cup \Lambda(\hat{A}))$ , then  $P(s)$  is a projector onto  $\mathcal{V} \implies$

if  $(s_* I_n - A)^{-1} B \in \mathcal{V}$ , then  $(I_n - P(s_*))(s_* I_n - A)^{-1} B = 0$ ,

hence

$$G(s_*) - \hat{G}(s_*) = 0 \implies G(s_*) = \hat{G}(s_*), \text{ i.e., } \hat{G} \text{ interpolates } G \text{ in } s_*!$$

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$$\text{Analogously, } = C(sI_n - A)^{-1} \underbrace{\left( I_n - (sI_n - A) V(sI_r - \hat{A})^{-1} W^T \right)}_{=: Q(s)} B.$$

If  $s_* \in \mathbb{C} \setminus (\Lambda(A) \cup \Lambda(\hat{A}))$ , then  $Q(s)_*$  is a projector onto  $\mathcal{W} \implies$

$$\text{if } (s_* I_n - A)^{-*} C^T \in \mathcal{W}, \text{ then } C(s_* I_n - A)^{-1} (I_n - Q(s_*)) = 0,$$

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## Theorem 3.3

[GRIMME '97, VILLEMAGNE/SKELTON '87]

Given the ROM

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and  $s_* \in \mathbb{C} \setminus (\Lambda(A) \cup \Lambda(\hat{A}))$ , if either

- $(s_* I_n - A)^{-1} B \in \text{range}(V)$ , or
- $(s_* I_n - A)^{-*} C^T \in \text{range}(W)$ ,

then the interpolation condition

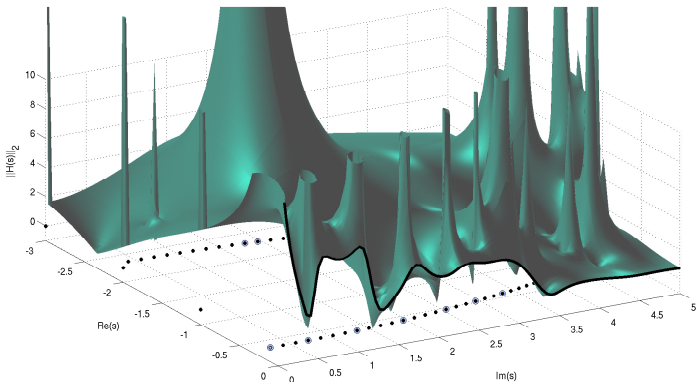
$$G(s_*) = \hat{G}(s_*).$$

in  $s_*$  holds.

Note: extension to Hermite interpolation conditions later!

# Modal Truncation

## Transfer Functions in $\mathbb{C}$



# Modal Truncation Example

