





# Scientific Machine Learning (SciML) and Data-Driven Model Reduction for Reservoir Simulation

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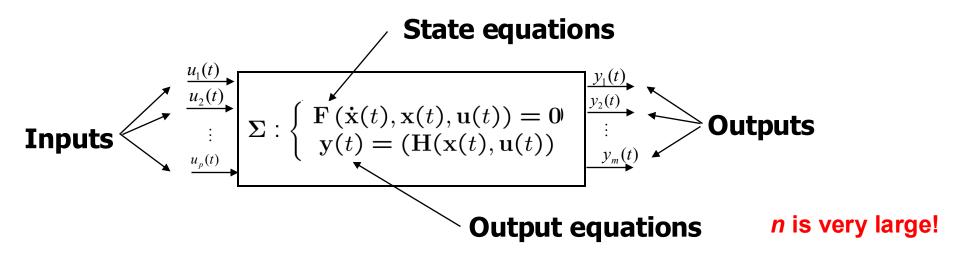


# Intro Dynamical Systems

### MODEL REDUCTION PROBLEM







•linear time-invariant (LTI):

$$\Sigma : \left\{ \begin{array}{l} \dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \\ \mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t) \end{array} \right. \Leftrightarrow \Sigma = \left[ \begin{array}{c|c} \mathbf{A} & \mathbf{B} \\ \hline \mathbf{C} & \mathbf{D} \end{array} \right] \in \mathbb{R}^{(n+p)\times(n+m)}$$



### Linear, Time-Invariant (LTI) Systems

$$\begin{array}{lcl} E\dot{x} & = & f(t,x,u) & = & Ax+Bu, & E,A\in\mathbb{R}^{n\times n}, & B\in\mathbb{R}^{n\times m},\\ y & = & g(t,x,u) & = & Cx+Du, & C\in\mathbb{R}^{q\times n}, & D\in\mathbb{R}^{q\times m}. \end{array}$$

### Linear, Time-Invariant Parametric Systems

$$E(p)\dot{x}(t;p) = A(p)x(t;p) + B(p)u(t),$$
  
$$y(t;p) = C(p)x(t;p) + D(p)u(t),$$

where  $A(p), E(p) \in \mathbb{R}^{n \times n}, B(p) \in \mathbb{R}^{n \times m}, C(p) \in \mathbb{R}^{q \times n}, D(p) \in \mathbb{R}^{q \times m}$ .

### **Model Reduction**



#### Original System

$$\Sigma: \begin{cases} \dot{x}(t) = f(t, x(t), u(t)), \\ y(t) = g(t, x(t), u(t)). \end{cases}$$

- states  $x(t) \in \mathbb{R}^n$ ,
- inputs  $u(t) \in \mathbb{R}^m$ ,
- outputs  $y(t) \in \mathbb{R}^q$ .



#### Reduced-Order Model (ROM)

$$\widehat{\Sigma}: \begin{cases} \dot{\widehat{x}}(t) = \widehat{f}(t, \widehat{x}(t), u(t)), \\ \hat{y}(t) = \widehat{g}(t, \widehat{x}(t), u(t)). \end{cases}$$

- states  $\hat{x}(t) \in \mathbb{R}^r$ ,  $r \ll n$
- inputs  $u(t) \in \mathbb{R}^m$ ,
- outputs  $\hat{y}(t) \in \mathbb{R}^q$ .



#### Goal:

 $||y - \hat{y}|| < \text{tolerance} \cdot ||u||$  for all admissible input signals.

Secondary goal: reconstruct approximation of x from  $\hat{x}$ .

# **Projection-Based MOR**



Approximate the states by a linear combination of basis

vectors

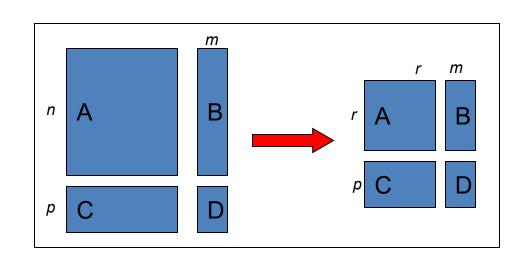
$$\mathbf{x} \approx \sum_{i=1}^{\Gamma} \mathbf{V}_i x_{r_i}$$

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$$\mathbf{\Sigma}_r : \begin{cases} \dot{\mathbf{x}}_r(t) = \underbrace{\mathbf{W}^T \mathbf{A} \mathbf{V}}_T \mathbf{x}_r(t) + \underbrace{\mathbf{W}^T \mathbf{B}}_T \mathbf{u}(t) \\ \vdots = \mathbf{A}_r \\ \mathbf{y}_r(t) = \underbrace{\mathbf{C} \mathbf{V}}_T \mathbf{x}_r(t) + \underbrace{\mathbf{D}}_T \mathbf{u}(t) \\ \vdots = \mathbf{C}_r \\ \vdots = \mathbf{D}_r \end{cases}$$

## **Project**

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### Some definitions

#### Definition

The Laplace transform of a time domain function  $f \in L_{1,loc}$  with  $dom(f) = \mathbb{R}_0^+$  is

$$\mathcal{L}: f(t) \mapsto f(s) := \mathcal{L}\{f(t)\}(s) := \int_0^\infty e^{-st} f(t) dt, \quad s \in \mathbb{C}.$$

F is a function in the (Laplace or) frequency domain.

**Note:** for frequency domain evaluations ("frequency response analysis"), one takes re s=0 and im  $s\geq 0$ . Then  $\omega:=\operatorname{im} s$  takes the role of a frequency (in [rad/s], i.e.,  $\omega=2\pi v$  with v measured in [Hz]).

#### Lemma

$$\mathcal{L}\{\dot{f}(t)\}(s)=sF(s).$$

#### Linear Systems in Frequency Domain

Application of Laplace transform  $(x(t) \mapsto x(s), \dot{x}(t) \mapsto sx(s))$  to linear system

$$E\dot{x}(t) = Ax(t) + Bu(t), \quad y(t) = Cx(t) + Du(t)$$

with x(0) = 0 yields:

$$sEx(s) = Ax(s) + Bu(s), \quad y(s) = Cx(s) + Du(s),$$

 $\implies$  I/O-relation in frequency domain:

$$y(s) = \left(\underbrace{C(sE - A)^{-1}B + D}_{=:G(s)}\right)u(s).$$

G(s) is the transfer function of  $\Sigma$ .

#### Formulating model reduction in frequency domain

Approximate the dynamical system

$$E\dot{x} = Ax + Bu, \qquad E, A \in \mathbb{R}^{n \times n}, \ B \in \mathbb{R}^{n \times m},$$
  
 $y = Cx + Du, \qquad C \in \mathbb{R}^{q \times n}, \ D \in \mathbb{R}^{q \times m},$ 

by reduced-order system

$$\hat{E}\dot{\hat{x}} = \hat{A}\hat{x} + \hat{B}u, \quad \hat{E}, \hat{A} \in \mathbb{R}^{r \times r}, \ \hat{B} \in \mathbb{R}^{r \times m}, 
\hat{y} = \hat{C}\hat{x} + \hat{D}u, \quad \hat{C} \in \mathbb{R}^{q \times r}, \ \hat{D} \in \mathbb{R}^{q \times m}$$

of order  $r \ll n$ , such that

$$||y - \hat{y}|| = ||Gu - \hat{G}u|| \le ||G - \hat{G}|| \cdot ||u|| < \text{tolerance} \cdot ||u||.$$

 $\implies$  Approximation problem:  $\min_{\text{order } (\hat{G}) \leq r} ||G - \hat{G}||$ .



### Output errors in time-domain

$$||y - \hat{y}||_2 \le ||G - \hat{G}||_{\infty} ||u||_2 \implies ||G - \hat{G}||_{\infty} < \text{tol}$$
  
 $||y - \hat{y}||_{\infty} \le ||G - \hat{G}||_2 ||u||_2 \implies ||G - \hat{G}||_2 < \text{tol}$ 

$\mathcal{H}_{\infty}$ -norm	best approximation problem for given reduced order $r$ in
	general open; balanced truncation yields suboptimal solu-
	tion with computable $\mathcal{H}_{\infty}$ -norm bound.
$\mathcal{H}_2$ -norm	necessary conditions for best approximation known; (local)
	optimizer computable with iterative rational Krylov algo-
	rithm (IRKA)
Hankel-norm	optimal Hankel norm approximation (AAK theory).
$\ G\ _H := \sigma_{max}$	

# **Similarity Transformations**

#### Definition

For a linear (time-invariant) system

$$\Sigma: \begin{cases} \dot{x}(t) = Ax(t) + Bu(t), & \text{with transfer function} \\ y(t) = Cx(t) + Du(t), & G(s) = C(sI - A)^{-1}B + D, \end{cases}$$

the quadruple  $(A, B, C, D) \in \mathbb{R}^{n \times n} \times \mathbb{R}^{n \times m} \times \mathbb{R}^{q \times n} \times \mathbb{R}^{q \times m}$  is called a realization of  $\Sigma$ .

#### Realizations are not unique!

Transfer function is invariant under state-space transformations,

$$\mathcal{T}: \left\{ \begin{array}{ccc} X & \rightarrow & TX, \\ (A,B,C,D) & \rightarrow & (TAT^{-1},TB,CT^{-1},D), \end{array} \right.$$

#### Realizations are not unique!

Hence,

$$(A, B, C, D), \qquad \left( \begin{bmatrix} A & 0 \\ 0 & A_1 \end{bmatrix}, \begin{bmatrix} B \\ B_1 \end{bmatrix}, \begin{bmatrix} C & 0 \end{bmatrix}, D \right),$$

$$(TAT^{-1}, TB, CT^{-1}, D), \qquad \left( \begin{bmatrix} A & 0 \\ 0 & A_2 \end{bmatrix}, \begin{bmatrix} B \\ 0 \end{bmatrix}, \begin{bmatrix} C & C_2 \end{bmatrix}, D \right),$$

are all realizations of  $\Sigma$ !

## **Projection Framework**

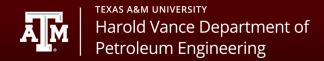


### Projection

### 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  $\{v_1, \ldots, v_r\}$  is a basis of  $\mathcal{V}$  and  $V = [v_1, \ldots, v_r]$ , then  $P = V(V^T V)^{-1} V^T$  is a projector onto  $\mathcal{V}$ .

# **Projection Properties**



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

# Example



