

SAND2015-9973PE

Nonlinear model reduction: discrete optimality and time parallelism

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Collaborators

2014–2015 M. Barone
Sandia National Laboratories

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George Mason University

2015 L. Brencher, B. Haasdonk
University of Stuttgart

2010–2011 C. Farhat, C. Bou-Mosleh, J. Cortial, D. Amsallem
Stanford University

Computational barrier

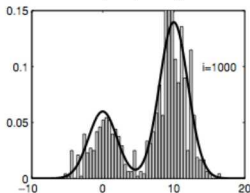
High-fidelity simulation

- + An indispensable tool
- Very high computational cost

Barrier

Time-critical applications

Many query



[Andrieu et al., 2003]

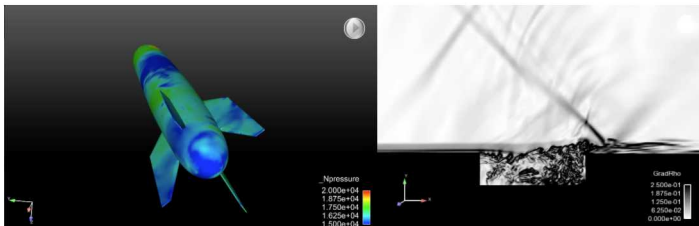
Real time



[pow,]

Objective: break barrier

Computational barrier at Sandia



- CFD model
 - 100 million cells
 - 200,000 time steps
- High simulation costs
 - 6 weeks, 5000 cores
 - 6 runs **maxes out Cielo**

Barrier

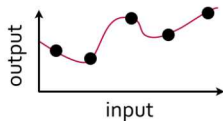
- Fast-turnaround design
- Uncertainty quantification (UQ)

Surrogate modeling

inputs $\mu \rightarrow$ **full-order model** \rightarrow outputs y

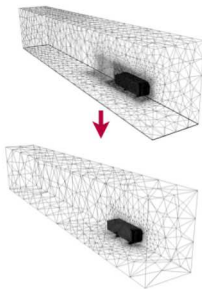
inputs $\mu \rightarrow$ **surrogate model** \rightarrow outputs y

1) Data fits



- Not physics based
- + High speedups

2) Coarsened physics



- + Physics based
- Low speedups

3) Reduced-order models (ROMs)

- + Physics based
- + High speedups
- + Preserve structure
- + Rigorous error analysis
- **Unproven for nonlinear dynamical systems**

ROM = data science + modeling and simulation

Goal: exploit simulation data to drastically reduce simulation costs

ROM: state of the art [Benner et al., 2015]

- Linear time-invariant systems: **mature** [Antoulas, 2005]
 - Balanced truncation [Moore, 1981]
 - Empirical balanced truncation [Willcox and Peraire, 2002, Rowley, 2005]
 - Moment matching
 - [Bai, 2002, Freund, 2003, Gallivan et al., 2004, Baur et al., 2011]
 - Loewner framework [Lefteriu and Antoulas, 2010, Ionita and Antoulas, 2014]
 - + *Reliable*: guaranteed stability, *a priori* error bounds
 - + *Certified*: sharp, computable *a posteriori* error bounds
- Elliptic/parabolic PDEs (FEM): **mature** [Rozza et al., 2008]
 - Reduced-basis method
 - [Prud'Homme et al., 2001, Veroy et al., 2003, Barrault et al., 2004]
 - Subsystem-based reduced-basis method
 - [Maday and Rønquist, 2002, Phuong Huynh et al., 2013, Eftang and Patera, 2013]
 - + *Reliable*: *a priori* error bounds
 - + *Certified*: sharp, computable *a posteriori* error bounds
- Nonlinear dynamical systems: **unproven**
 - Proper orthogonal decomposition (POD)–Galerkin
 - *Not reliable*: Stability and accuracy not guaranteed
 - *Not certified*: error bounds not sharp

Our research goal

Nonlinear model-reduction methods that are accurate, low cost, certified, and reliable.

+ Accuracy

- Improve projection technique [?, C. et al., 2015a]
- Preserve problem structure [C. et al., 2012, C. et al., 2015c]

+ Low cost

- Sample-mesh approach [C. et al., 2011, C. et al., 2013]
- Leverage time-domain data [C. et al., 2015b]

+ Certification

- Error bounds [C. et al., 2015a]
- Statistical error modeling [Drohmann and C., 2015]

+ Reliability

- *A posteriori* h -refinement [C., 2015]

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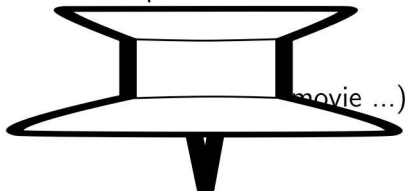
+ Reliability

- *A posteriori* h -refinement [C., 2015]

POD–Galerkin: offline data collection

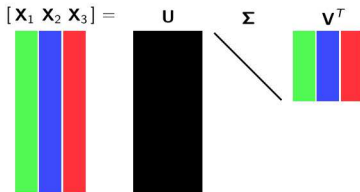
$$\frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x}; t, \boldsymbol{\mu}); \quad \mathbf{x}(0, \boldsymbol{\mu}) = \mathbf{x}^0(\boldsymbol{\mu}), \quad t \in [0, T], \quad \boldsymbol{\mu} \in \mathcal{D}$$

- 1 Collect ‘snapshots’ of the state



- 2 Data compression

- Compute SVD:

$$[\mathbf{x}_1 \ \mathbf{x}_2 \ \mathbf{x}_3] = \mathbf{U} \boldsymbol{\Sigma} \mathbf{V}^T$$


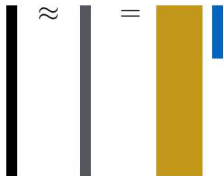
- Truncate: $\boldsymbol{\Phi} = [\mathbf{u}_1 \ \cdots \ \mathbf{u}_p]$

POD–Galerkin: online projection

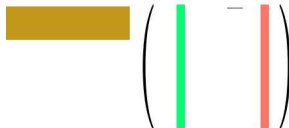
Full-order model:

$$\frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x}; t, \mu), \quad \mathbf{x}(0, \mu) = \mathbf{x}^0(\mu)$$

1 $\mathbf{x}(t) \approx \tilde{\mathbf{x}}(t) = \Phi \hat{\mathbf{x}}(t)$



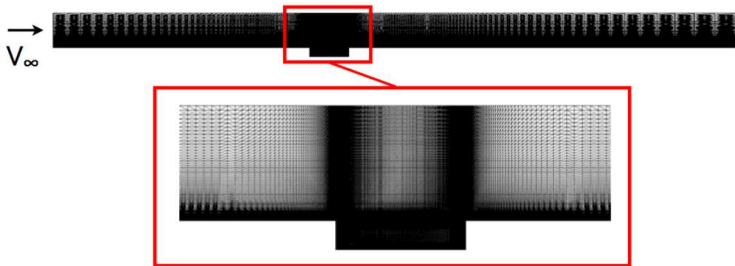
2 $\Phi^T \left(\mathbf{f}(\tilde{\mathbf{x}}, t) - \frac{d\tilde{\mathbf{x}}}{dt} \right) = 0$



Galerkin ROM:

$$\frac{d\hat{\mathbf{x}}}{dt} = \Phi^T \mathbf{f}(\Phi \hat{\mathbf{x}}; t, \mu), \quad \hat{\mathbf{x}}(0, \mu) = \Phi^T \mathbf{x}^0(\mu)$$

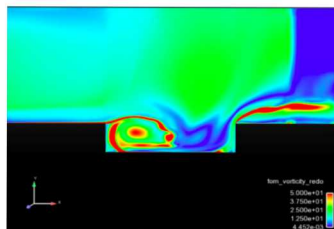
Cavity-flow problem. Collaborator: M. Barone (SNL)



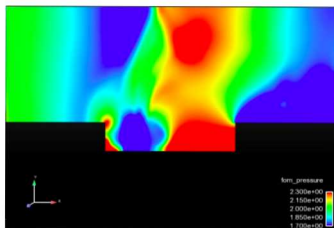
- Unsteady Navier–Stokes
- DES turbulence model
- 1.2 million degrees of freedom

- $Re = 6.3 \times 10^6$
 - $M_\infty = 0.6$
 - CFD code: AERO-F
- [Farhat et al., 2003]

FOM responses

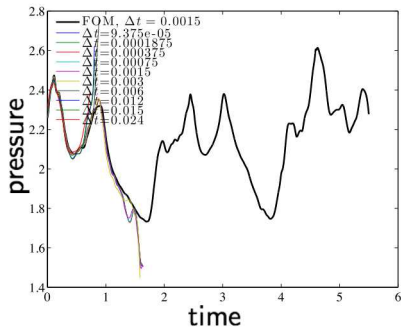


vorticity field



pressure field

POD–Galerkin failure



- Galerkin ROMs unstable

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+ Certification

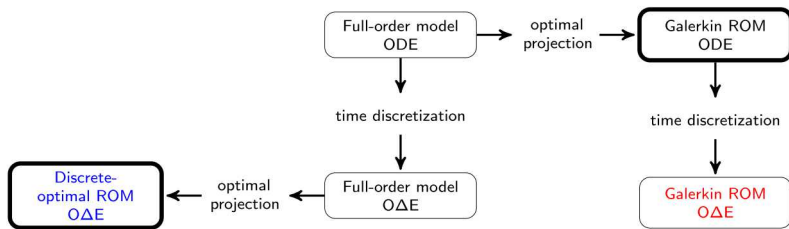
- Error bounds [C. et al., 2015a]
- Statistical error modeling [Drohmann and C., 2015]

+ Reliability

- *A posteriori* h -refinement [C., 2015]

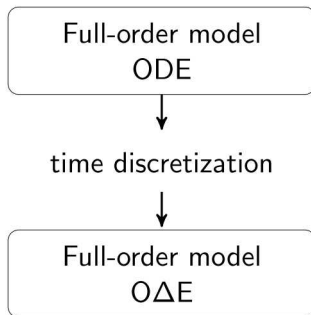
How to construct a ROM for nonlinear dynamical systems?

- Optimize then discretize? (Galerkin)
- Discretize then optimize? (discrete optimal)



■ Outstanding questions:

- 1 Time-continuous and time-discrete representations?
- 2 Are the two techniques ever equivalent?
- 3 Discrete-time error bounds?



Full-order model (FOM)

- ODE: time continuous

$$\frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x}, t), \quad \mathbf{x}(0) = \mathbf{x}^0, \quad t \in [0, T]$$

- OΔE, linear multistep schemes: $\boxed{\mathbf{r}^n(\mathbf{x}^n) = 0}$, $n = 1, \dots, N$

$$\mathbf{r}^n(\mathbf{x}) := \alpha_0 \mathbf{x} - \delta t \beta_0 \mathbf{f}(\mathbf{x}, t^n) + \sum_{j=1}^k \alpha_j \mathbf{x}^{n-j} - \delta t \sum_{j=1}^k \beta_j \mathbf{f}(\mathbf{x}^{n-j}, t^{n-j})$$

$$\mathbf{x}^n = \mathbf{x}^n \text{ (explicit state update)}$$

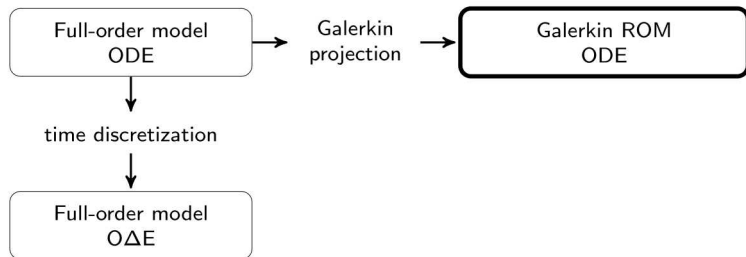
- OΔE, Runge–Kutta: $\boxed{\mathbf{r}_i^n(\mathbf{x}_1^n, \dots, \mathbf{x}_s^n) = 0}$, $i = 1, \dots, s$

$$\mathbf{r}_i^n(\mathbf{x}_1, \dots, \mathbf{x}_s) := \mathbf{x}_i - \mathbf{f}(\mathbf{x}^{n-1} + \delta t \sum_{j=1}^s a_{ij} \mathbf{x}_j, t^{n-1} + c_i \delta t)$$

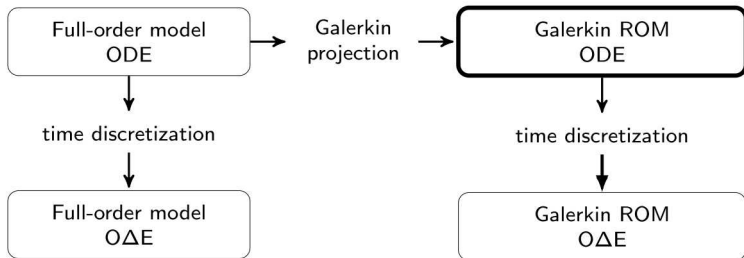
$$\mathbf{x}^n = \mathbf{x}^{n-1} + \delta t \sum_{i=1}^s b_i \mathbf{x}_i^n \text{ (explicit state update)}$$

This talk focuses on linear multistep schemes.

Galerkin ROM: first optimize



Galerkin: first optimize, then discretize



Galerkin ROM

■ ODE

$$\frac{d\hat{\mathbf{x}}}{dt} = \mathbf{\Phi}^T \mathbf{f}(\mathbf{\Phi} \hat{\mathbf{x}}, t), \quad \hat{\mathbf{x}}(0) = \mathbf{\Phi}^T \mathbf{x}^0, \quad t \in [0, T]$$

+ Continuous velocity $\frac{d\hat{\mathbf{x}}}{dt}$ is **optimal**

Theorem (Galerkin ROM: continuous optimality)

The Galerkin ROM velocity minimizes the time-continuous FOM residual:

$$\frac{d\tilde{\mathbf{x}}}{dt}(\mathbf{x}, t) = \arg \min_{\mathbf{v} \in \text{range}(\mathbf{\Phi})} \|\mathbf{v} - \mathbf{f}(\mathbf{x}, t)\|_2^2$$

■ OΔE

$$\hat{\mathbf{r}}^n(\hat{\mathbf{x}}^n) = 0, \quad n = 1, \dots, N$$

$$\hat{\mathbf{r}}^n(\hat{\mathbf{x}}) := \alpha_0 \hat{\mathbf{x}} - \delta t \beta_0 \mathbf{\Phi}^T \mathbf{f}(\mathbf{\Phi} \hat{\mathbf{x}}, t^n) + \sum_{j=1}^k \alpha_j \hat{\mathbf{x}}^{n-j} - \delta t \sum_{j=1}^k \beta_j \mathbf{\Phi}^T \mathbf{f}(\mathbf{\Phi} \hat{\mathbf{x}}^{n-j}, t^{n-j})$$

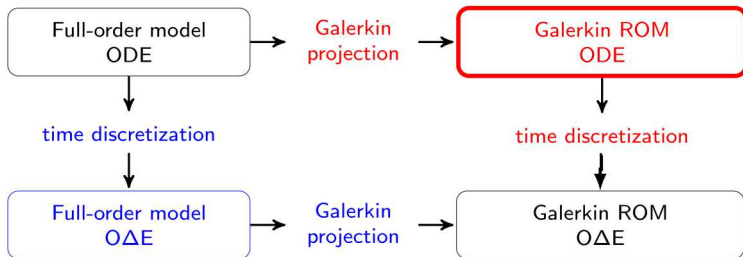
- Discrete state $\hat{\mathbf{x}}^n$ is **not generally optimal**

Galerkin ROM: Commutativity

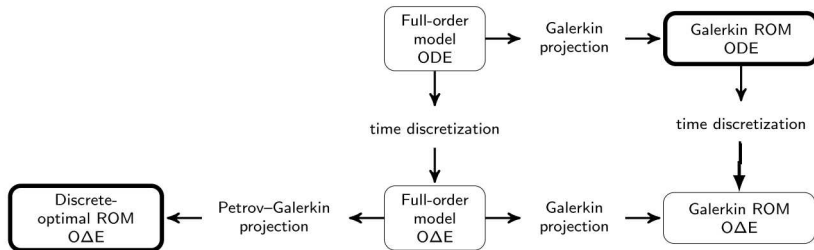
Theorem

Projection and time discretization are commutative for Galerkin ROMs:

$$\hat{r}^n(\hat{x}) = \Phi^T r^n(\Phi \hat{x})$$



Discrete-optimal ROM: first discretize, then optimize



Discrete-optimal ROM

- FOM OΔE

$$\mathbf{r}^n(\mathbf{x}^n) = 0, \quad n = 1, \dots, N$$

- Discrete-optimal ROM OΔE:

$$\hat{\mathbf{x}}^n = \arg \min_{\hat{\mathbf{z}} \in \mathbb{R}^p} \|\mathbf{A} \mathbf{r}^n(\Phi \hat{\mathbf{z}})\|_2^2.$$



$$\Psi^n(\hat{\mathbf{x}}^n)^T \mathbf{r}^n(\Phi \hat{\mathbf{x}}^n) = 0, \quad \Psi^n(\hat{\mathbf{x}}) := \mathbf{A}^T \mathbf{A} \frac{\partial \mathbf{r}^n}{\partial \mathbf{x}}(\Phi \hat{\mathbf{x}})$$

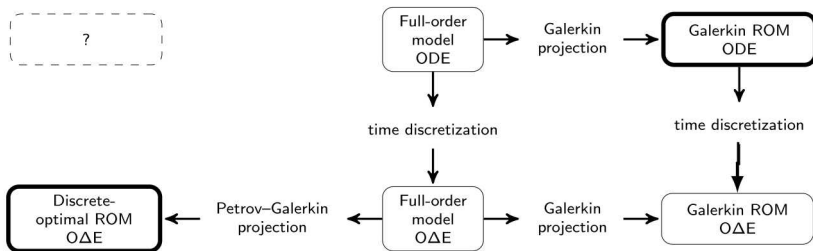
- $\mathbf{A} = \mathbf{I}$: Least-squares Petrov–Galerkin

[LeGresley, 2006, Bui-Thanh et al., 2008, ?]

- Alternative norm: ℓ^1 [Abgrall and Amsallem, 2015]

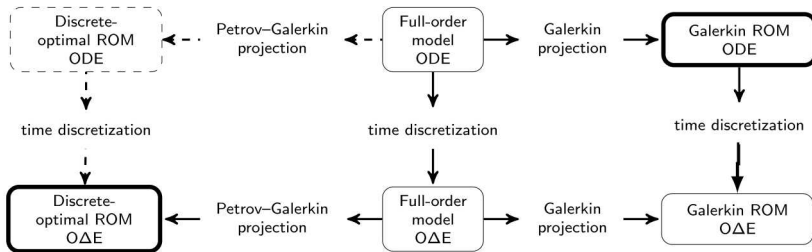
+ Discrete solution is optimal

Does the discrete-optimal ROM have a time-continuous representation?



Does the discrete-optimal ROM have a time-continuous representation?

Sometimes.



Discrete-optimal ROM: continuous representation

Theorem

The discrete-optimal ROM is equivalent to applying a Petrov–Galerkin projection to the FOM ODE with test basis

$$\Psi(\hat{\mathbf{x}}, t) = \mathbf{A}^T \mathbf{A} \left(\alpha_0 \mathbf{I} - \Delta t \beta_0 \frac{\partial \mathbf{f}}{\partial \mathbf{x}}(\mathbf{x}^0 + \Phi \hat{\mathbf{x}}, t) \right) \Phi$$

if

- 1 $\beta_j = 0, j \geq 1$ (e.g., a single-step method),
- 2 the velocity \mathbf{f} is linear in the state, or
- 3 $\beta_0 = 0$ (i.e., explicit schemes).

*Time-continuous test basis depends on
time-discretization parameters!*

Are the two approaches ever equivalent?

- Galerkin: $\Phi^T r^n(\Phi \hat{x}^n) = 0$
- Discrete-optimal: $\Psi^n(\hat{x}^n)^T r^n(\Phi \hat{x}^n) = 0$

Does $\Psi^n(\hat{x}^n) = \Phi$ ever?

Yes.

$$\Psi^n(\hat{x}) := A^T A \frac{\partial r^n}{\partial x}(\Phi \hat{x}) = A^T A \left(\alpha_0 I - \delta t \beta_0 \frac{\partial f}{\partial x}(\Phi \hat{x}, t^n) \right) \Phi$$

Theorem

The two approaches are equivalent ($\Psi^n(\hat{x}) = \Phi$)

- 1 *in the limit of $\delta t \rightarrow 0$ with $A = 1/\sqrt{\alpha_0}I$,*
- 2 *if the scheme is explicit ($\beta_0 = 0$) with $A = 1/\sqrt{\alpha_0}I$, or*
- 3 *if $\frac{\partial r^n}{\partial x}$ is positive definite with $[\frac{\partial r^n}{\partial x}]^{-1} = A^T A$.*

Discrete-time error bound

Theorem

If the following conditions hold:

- 1 $\mathbf{f}(\cdot, t)$ is Lipschitz continuous with Lipschitz constant κ , and
- 2 δt is such that $0 < h := |\alpha_0| - |\beta_0|\kappa\delta t$,

then

$$\|\delta \mathbf{x}_G^n\| \leq \frac{\delta t}{h} \sum_{\ell=0}^k |\beta_\ell| \|(\mathbf{I} - \mathbb{V}) \mathbf{f}(\mathbf{x}_0 + \Phi \hat{\mathbf{x}}_G^{n-\ell})\| + \frac{1}{h} \sum_{\ell=1}^k (|\beta_\ell|\kappa\delta t + |\alpha_\ell|) \|\delta \mathbf{x}_G^{n-\ell}\|$$
$$\|\delta \mathbf{x}_D^n\| \leq \frac{\delta t}{h} \sum_{\ell=0}^k |\beta_\ell| \|(\mathbf{I} - \mathbb{P}^n) \mathbf{f}(\mathbf{x}_0 + \Phi \hat{\mathbf{x}}_D^{n-\ell})\| + \frac{1}{h} \sum_{\ell=1}^k (|\beta_\ell|\kappa\delta t + |\alpha_\ell|) \|\delta \mathbf{x}_D^{n-\ell}\|,$$

with

- $\delta \mathbf{x}_G^n := \mathbf{x}_\star^n - \Phi \hat{\mathbf{x}}_G^n.$
- $\mathbb{V} := \Phi \Phi^T$
- $\delta \mathbf{x}_D^n := \mathbf{x}_\star^n - \Phi \hat{\mathbf{x}}_D^n$
- $\mathbb{P}^n := \Phi ((\Psi^n)^T \Phi)^{-1} (\Psi^n)^T$

Discrete-optimal ROM yields a smaller error bound

Theorem (Backward Euler)

If conditions (1) and (2) hold, then

$$\|\delta \mathbf{x}_G^n\| \leq \delta t \sum_{j=0}^{n-1} \frac{1}{(h)^{j+1}} \underbrace{\|(\mathbf{I} - \mathbb{V}) \mathbf{f}(\mathbf{x}_0 + \Phi \hat{\mathbf{x}}_G^{n-j})\|}_{\varepsilon_G^{n-j}}$$

$$\|\delta \mathbf{x}_D^n\| \leq \delta t \sum_{j=0}^{n-1} \frac{1}{(h)^{j+1}} \underbrace{\|(\mathbf{I} - \mathbb{P}^{n-j}) \mathbf{f}(\mathbf{x}_0 + \Phi \hat{\mathbf{x}}_D^{n-j})\|}_{\varepsilon_D^{n-j}}$$

$$\varepsilon_G^k = \|\Phi \hat{\mathbf{x}}_G^k - \delta t \mathbf{f}(\mathbf{x}_0 + \Phi \hat{\mathbf{x}}_G^k) - \Phi \hat{\mathbf{x}}_G^{k-1}\|$$

$$\varepsilon_D^k = \|\Phi \hat{\mathbf{x}}_D^k - \delta t \mathbf{f}(\mathbf{x}_0 + \Phi \hat{\mathbf{x}}_D^k) - \Phi \hat{\mathbf{x}}_D^{k-1}\| = \min_{\mathbf{y}} \|\Phi \mathbf{y} - \delta t \mathbf{f}(\mathbf{x}_0 + \Phi \mathbf{y}) - \Phi \hat{\mathbf{x}}_D^{k-1}\|$$

Corollary (Discrete-optimal smaller error bound)

If $\hat{\mathbf{x}}_D^{k-1} = \hat{\mathbf{x}}_G^{k-1}$, then $\varepsilon_D^k \leq \varepsilon_G^k$.

Discrete-optimal ROM has an interesting time-step dependence

Corollary (Backward Euler)

Define

- $\Delta \hat{\mathbf{x}}_D^j := \hat{\mathbf{x}}_D^j - \hat{\mathbf{x}}_D^{j-1}$ and
- $\Delta \bar{\mathbf{x}}^j$: full-space solution increment from $\hat{\mathbf{x}}_D^{j-1}$.

Then, the discrete-optimal error can also be bounded as

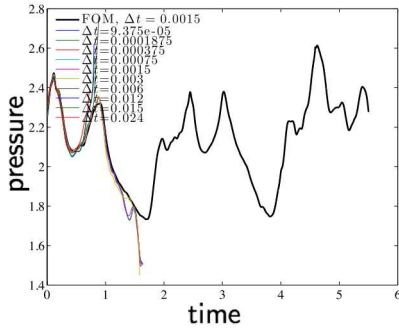
$$\|\delta \mathbf{x}_D^n\| \leq \delta t (1 + \kappa \delta t) \sum_{j=0}^{n-1} \frac{\mu^{n-j}}{(h)^{j+1}} \|\mathbf{f}(\hat{\mathbf{x}}_D^{j-1} + \Delta \bar{\mathbf{x}}^{n-j})\|$$

with $\mu^j := \|\Phi \Delta \hat{\mathbf{x}}_D^j - \Delta \bar{\mathbf{x}}^j\| / \Delta \bar{\mathbf{x}}^j$.

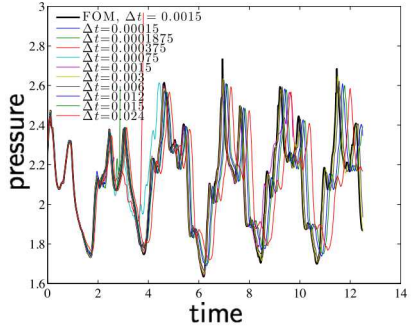
Effect of decreasing δt :

- + The terms $\delta t(1 + \kappa \delta t)$ and $1/(h)^{j+1}$ decrease
- The number of total time instances n increases
- ? The term μ^{n-j} may **increase** or **decrease**, depending on the spectral content of the basis Φ

Galerkin and discrete-optimal responses for basis dimension $p = 204$



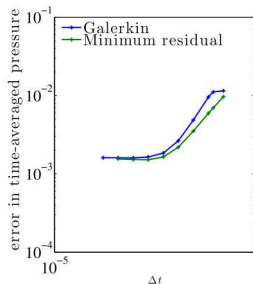
(a) Galerkin



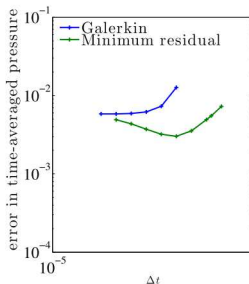
(b) Discrete optimal

- Galerkin ROMs unstable for long time intervals
(consistent with previous results [C. et al., 2013, ?, C., 2011])
- + Discrete-optimal ROMs accurate and stable (most time steps)

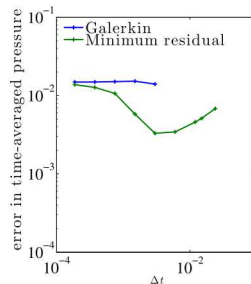
Discrete-optimal ROM: superior performance



(c) $0 \leq t \leq 0.55$



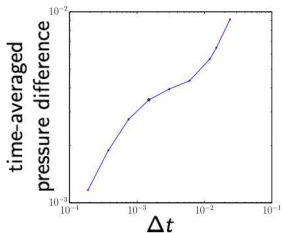
(d) $0 \leq t \leq 1.1$



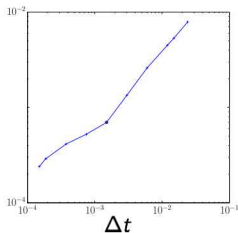
(e) $0 \leq t \leq 1.54$

- ✓ Discrete-optimal ROM yields a **smaller error** for all time intervals and time steps.

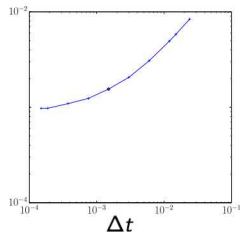
Limiting equivalence



(f) $p = 204$



(g) $p = 368$

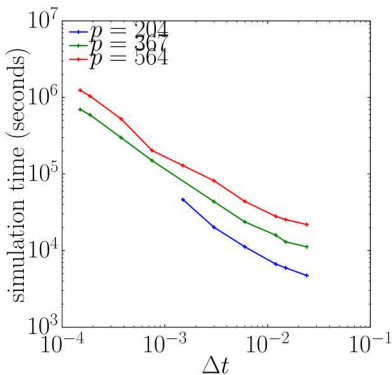
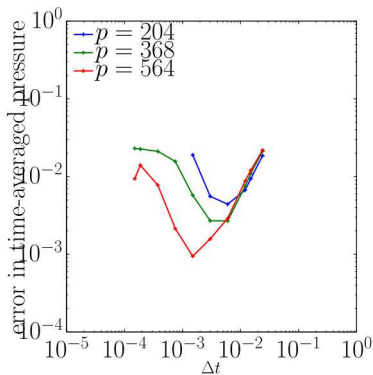


(h) $p = 564$

Galerkin/discrete-optimal difference in the stable Galerkin interval
 $0 \leq t \leq 1.1$.

✓ The discrete-optimal ROM converges to Galerkin as $\delta t \rightarrow 0$.

Discrete-optimal performance in $0 \leq t \leq 2.5$



✓ An intermediate δt produces the lowest error and better speedup.

$p = 564$ case:

- $\delta t = 1.875 \times 10^{-4}$ sec: relative error = 1.40%, time = 289 hrs
- $\delta t = 1.5 \times 10^{-3}$ sec: relative error = 0.095%, time = 35.8 hrs

KTC: Still slow!!!

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+ Low cost

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+ Certification

- Error bounds [C. et al., 2015a]
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+ Reliability

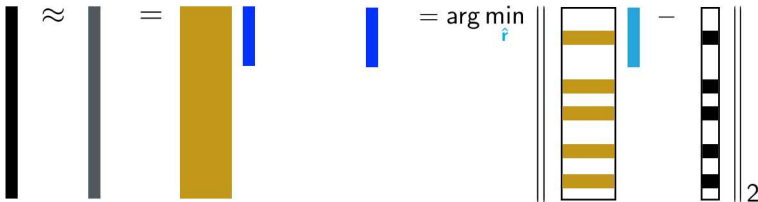
- *A posteriori* h -refinement [C., 2015]

Hyper-reduction via Gappy POD [Everson and Sirovich, 1995]

$$\hat{\mathbf{x}}^n = \arg \min_{\hat{\mathbf{z}} \in \mathbb{R}^p} \|\mathbf{A} \mathbf{r}^n(\Phi \hat{\mathbf{z}})\|_2^2.$$

Can we select \mathbf{A} to make this inexpensive?

$$1. \mathbf{r}^n(\mathbf{x}) \approx \tilde{\mathbf{r}}^n(\mathbf{x}) = \Phi_R \hat{\mathbf{r}}^n(\mathbf{x}) \quad 2. \hat{\mathbf{r}}^n(\mathbf{x}) = \arg \min_{\hat{\mathbf{r}}} \|\mathbf{P} \Phi_R \hat{\mathbf{r}} - \mathbf{P} \mathbf{r}^n(\mathbf{x})\|_2$$



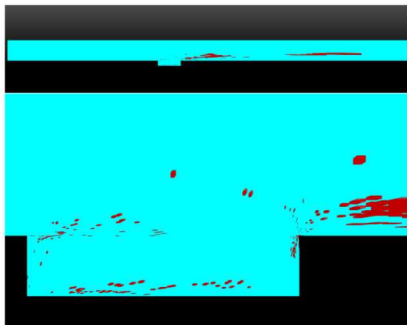
$$\begin{aligned} \hat{\mathbf{x}}^n &= \arg \min_{\hat{\mathbf{z}} \in \mathbb{R}^p} \|\tilde{\mathbf{r}}^n(\Phi \hat{\mathbf{z}})\|_2^2 = \arg \min_{\hat{\mathbf{z}} \in \mathbb{R}^p} \|\Phi_R \hat{\mathbf{r}}^n(\Phi \hat{\mathbf{z}})\|_2^2 = \arg \min_{\hat{\mathbf{z}} \in \mathbb{R}^p} \|\hat{\mathbf{r}}^n(\Phi \hat{\mathbf{z}})\|_2^2 \\ &= \arg \min_{\hat{\mathbf{z}} \in \mathbb{R}^p} \underbrace{\|(\mathbf{P} \Phi_R)^+ \mathbf{P} \mathbf{r}^n(\Phi \hat{\mathbf{z}})\|_2^2}_{\mathbf{A}}. \end{aligned}$$

+ $\mathbf{A} = (\mathbf{P} \Phi_R)^+ \mathbf{P}$ leads to low-cost

■ Offline: Construct Φ_R (POD) and \mathbf{P} (greedy method)

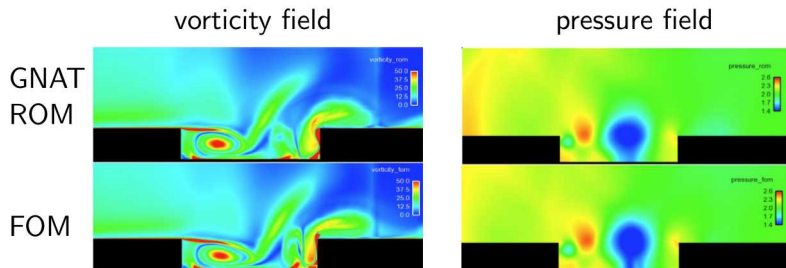
Cavity-flow problem: GNAT

$$\hat{\mathbf{x}}^n = \arg \min_{\hat{\mathbf{z}} \in \mathbb{R}^p} \| (\mathbf{P}\Phi_R)^+ \mathbf{P}\mathbf{r}^n(\Phi\hat{\mathbf{z}}) \|_2^2$$



- Sample mesh: 4.1% nodes, 3.0% cells
- + Small problem size: can run on many fewer cores

GNAT performance



+ $< 1\%$ error in time-averaged drag

- FOM: 5 hour x 48 CPU

- GNAT ROM: 32 min x 2 CPU

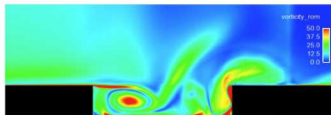
+ 229x CPU-hour savings

GNAT performance

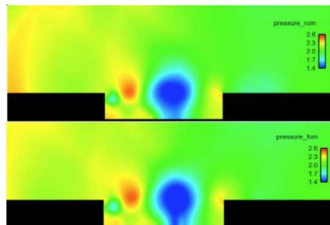
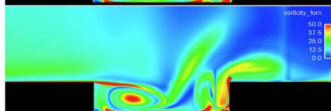
vorticity field

pressure field

GNAT
ROM



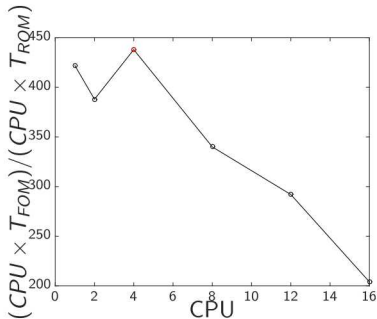
FOM



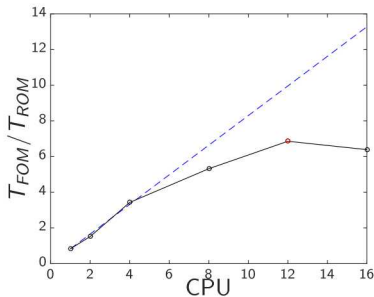
- + $< 1\%$ error in time-averaged drag
 - FOM: 5 hour \times 48 CPU
 - GNAT ROM: 32 min \times 2 CPU
- + 229x CPU-hour savings. Good for many query.
- 9.4x walltime savings. Bad for real time.

Why?

GNAT: strong scaling (Ahmed body) [C., 2011]



(c) CPU-hour savings



(d) Walltime savings

- + Significant CPU-hour savings (max: 438 for 4 CPU)
- Modest walltime savings (max: 7 for 12 CPU)

Spatial parallelism is quickly saturated!

Our research goal

Nonlinear model-reduction methods that are accurate, low cost, certified, and reliable.

+ Accuracy

- Improve projection technique [?, C. et al., 2015a]
- Preserve problem structure [C. et al., 2012, C. et al., 2015c]

+ Low cost

- Sample-mesh approach [C. et al., 2011, C. et al., 2013]
- Leverage time-domain data [C. et al., 2015b]

+ Certification

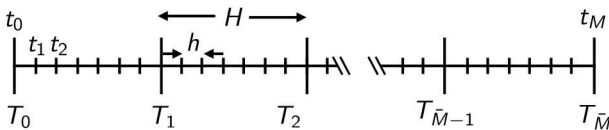
- Error bounds [C. et al., 2015a]
- Statistical error modeling [Drohmann and C., 2015]

+ Reliability

- *A posteriori* h -refinement [C., 2015]

Time-parallel algorithms [Lions et al., 2001a, Farhat and Chandesris, 2003]

Goal: expose more parallelism to reduce walltime



- Fine propagator: time step h

$$\mathcal{F}(\mathbf{x}; \tau_1, \tau_2)$$

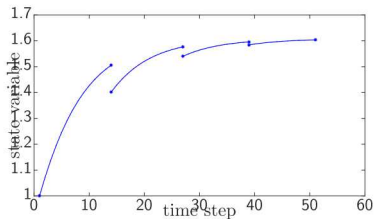
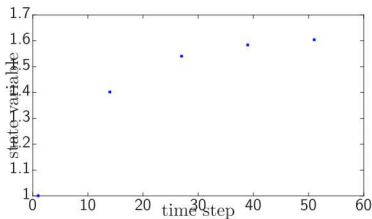
- Coarse propagator: time step H

$$\mathcal{G}(\mathbf{x}; \tau_1, \tau_2)$$

- Parareal iteration k (sequential and parallel steps):

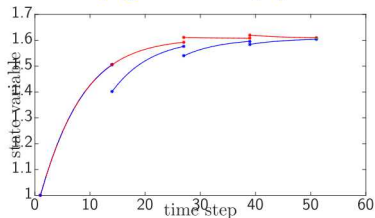
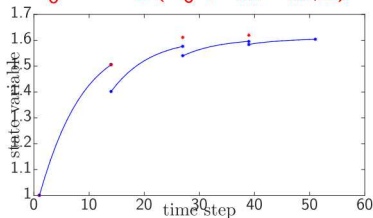
$$\mathbf{x}_{k+1}^{m+1} = \mathcal{G}(\mathbf{x}_{k+1}^m; T_m, T_{m+1}) + \mathcal{F}(\mathbf{x}_k^m; T_m, T_{m+1}) - \mathcal{G}(\mathbf{x}_k^m; T_m, T_{m+1})$$

Illustration: sequential and parallel steps



$$\mathbf{x}_0^{m+1} = \mathcal{G}(\mathbf{x}_0^m; T_m, T_{m+1})$$

$$\mathcal{F}(\mathbf{x}_0^m; T_m, T_{m+1})$$



$$\mathbf{x}_1^{m+1} = \mathcal{F}(\mathbf{x}_0^m; T_m, T_{m+1}) + \mathcal{G}(\mathbf{x}_1^m; T_m, T_{m+1}) - \mathcal{G}(\mathbf{x}_0^m; T_m, T_{m+1})$$

$$\mathcal{F}(\mathbf{x}_1^m; T_m, T_{m+1})$$

Coarse propagator

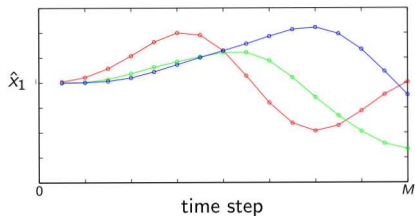
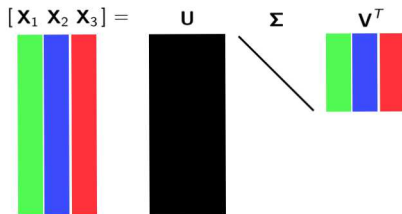
Critical: coarse propagator should be **fast, accurate, stable**

- Existing coarse propagators

- Same integrator [Lions et al., 2001b, Bal and Maday, 2002]
- Coarse spatial discretization
[Fischer et al., 2005, Farhat et al., 2006, Cortial and Farhat, 2009]
- Simplified physics model [Baffico et al., 2002, Maday and Turinici, 2003, Blouza et al., 2011, Engblom, 2009, Maday, 2007]
- Relaxed solver tolerance [Guibert and Tromeur-Dervout, 2007]
- Reduced-order model (on the fly) [Farhat et al., 2006, Cortial and Farhat, 2009, Ruprecht and Krause, 2012, Chen et al., 2014]

Can we leverage offline data to improve the coarse propagator?

Revisit the SVD



First row of \mathbf{V}^T

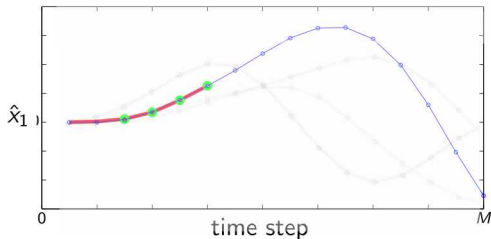
j th row of \mathbf{V}^T contains a basis for time evolution of \hat{x}_j

- Construct Ξ_j : basis for time evolution of \hat{x}_j

$$\Xi_j := \begin{bmatrix} \xi_j^1 & \cdots & \xi_j^{n_{\text{train}}} \end{bmatrix}, \quad \xi_j^i := [v_{M(i-1)+1,j} \cdots v_{Mi,j}]^T$$

Previous method [C. et al., 2015b]

- 1 compute forecast by gappy POD in time domain:



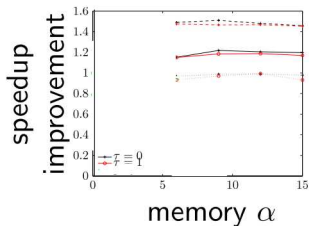
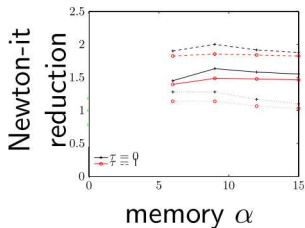
\hat{x}_1 so far; memory $\alpha = 4$; forecast; temporal basis

$$\mathbf{z}_j = \arg \min_{\mathbf{z} \in \mathbb{R}^{a_j}} \|\mathbf{Z}(m-1, \alpha) \Xi_j \mathbf{z} - \mathbf{Z}(m-1, \alpha) \mathbf{g}(\hat{x}_j)\|_2$$

- Time sampling: $\mathbf{Z}(k, \beta) := [\mathbf{e}_{k-\beta} \cdots \mathbf{e}_k]^T$
- Time unrolling: $\mathbf{g}(\hat{x}_j) : \hat{x}_j \mapsto [\hat{x}_j(t_0) \cdots \hat{x}_j(t_M)]^T$

- 2 use $\mathbf{e}_m^T \Xi_j \mathbf{z}_j$ as *initial guess* for $\hat{x}_j(t_m)$ in Newton solver

Previous results: structural dynamics [C. et al., 2015b]

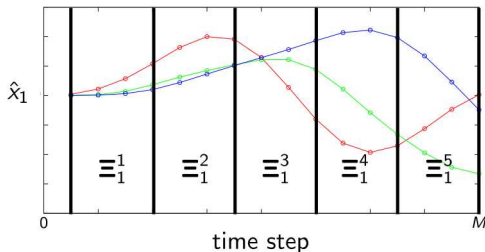


- + Newton iterations reduced by up to $\sim 2\times$
- + Speedup improved by up to $\sim 1.5\times$
- + No accuracy loss
- + Applicable to any nonlinear ROM
- Insufficient for real-time computation

Can we apply the same idea for the coarse propagator?

Coarse propagator for coordinate j and time interval m

- **Offline:** Construct time-evolution basis Ξ_j^m



- **Online:** Coarse propagator \mathcal{G}_j^m defined via forecasting:

- 1 Compute α time steps with fine propagator
- 2 Compute forecast via gappy POD
- 3 Select last timestep of forecast

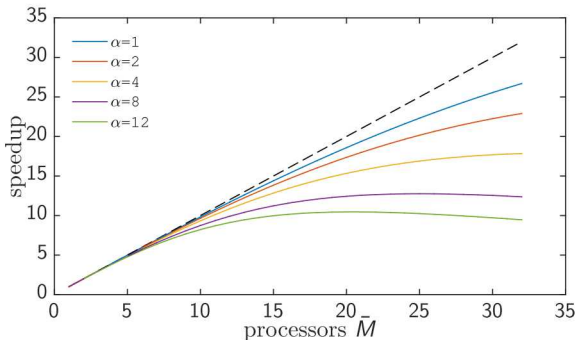
$$\mathcal{G}_j^m : (\hat{\mathbf{x}}_j; T_m, T_{m+1}) \mapsto \mathbf{e}_{H/h}^T \Xi_j^m [\mathbf{Z}(\alpha + 1, \alpha) \Xi_j^m]^+ \begin{bmatrix} \mathcal{F}(\hat{\mathbf{x}}_j; T_m, T_m + h) \\ \vdots \\ \mathcal{F}(\hat{\mathbf{x}}_j; T_m, T_m + h\alpha) \end{bmatrix}$$

Ideal-conditions speedup

Theorem

If $g(\hat{x}_j) \in \text{range}(\Xi_j)$, $j = 1, \dots, p$, then the proposed method converges in one parareal iteration and realizes a theoretical speedup of

$$\frac{\bar{M}}{\bar{M}(\bar{M} - 1)\alpha/M + 1}.$$



Ideal-conditions speedup for $M = 5000$

Ideal-conditions speedup with initial guesses

Corollary

If \mathbf{f} is nonlinear, $g(\hat{x}_j) \in \text{range}(\Xi_j)$, $j = 1, \dots, p$, and the forecasting method also provides Newton-solver initial guesses, then

- 1** *the method converges in **one parareal iteration**, and*
- 2** *only α nonlinear systems of algebraic equations are solved in each time interval.*

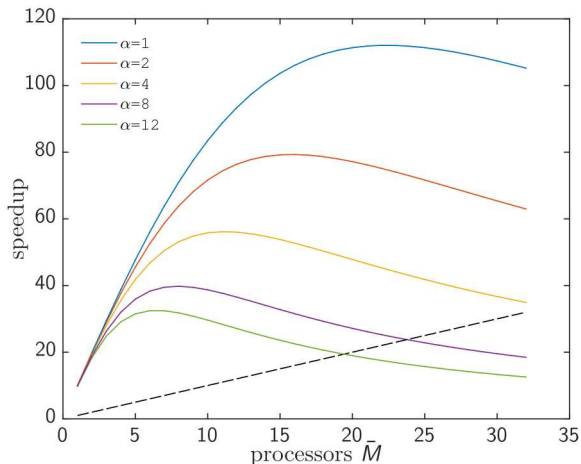
The method then realizes a theoretical speedup of

$$\frac{M}{(\bar{M}\alpha) + (M/\bar{M} - \alpha)\tau_r}$$

relative to the sequential algorithm without forecasting. Here,

$$\tau_r = \frac{\text{residual computation time}}{\text{nonlinear-system solution time}}.$$

Ideal-conditions speedup with initial-guesses



Ideal-condition speedup for $M = 5000$, $\tau_r = 1/10$

Significant speedups possible by leveraging time-domain data!

Theorem

If the fine propagator is stable, i.e.,

$$\|\mathcal{F}(\mathbf{x}; \tau_1, \tau_2)\| \leq (1 + C_{\mathcal{F}}H)\|\mathbf{x}\|,$$

then the proposed method is also stable, i.e.,

$$\|\hat{\mathbf{x}}_{k+1}^m\| \leq C_m \exp(C_F m H) \|\hat{\mathbf{x}}^0\|.$$

- $C_m := \sum_{k=1}^m \binom{k}{m} \beta_k \gamma^m \alpha^k (H/h)^{m-k}$
- $\beta_k := \exp(-C_{\mathcal{F}} k (H - h\alpha)) \leq 1$
- $\gamma := \max(\max_{m,j} 1/\|\mathbf{Z}(\alpha+1, \alpha)\Xi_j^m\|, 1/\sigma_{\min}(\mathbf{Z}(\alpha+1, \alpha)\Xi_j^m))$

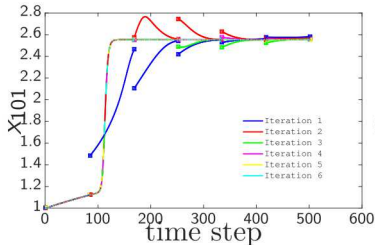
Example: inviscid Burgers equation [Rewiński, 2003]

$$\begin{aligned}\frac{\partial u(x, \tau)}{\partial \tau} + \frac{1}{2} \frac{\partial (u^2(x, \tau))}{\partial x} &= 0.02 e^{\mu_2 x} \\ u(0, \tau) &= \mu_1, \quad \forall \tau \in [0, 25] \\ u(x, 0) &= 1, \quad \forall x \in [0, 100],\end{aligned}$$

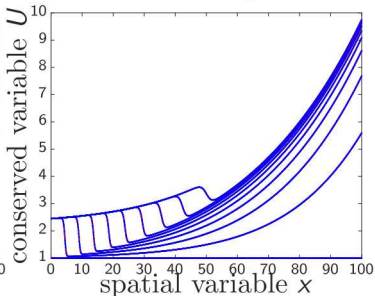
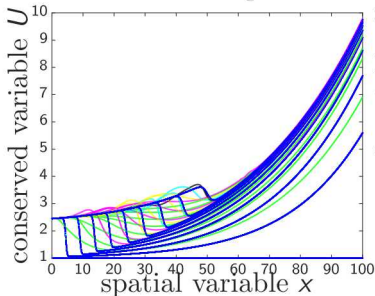
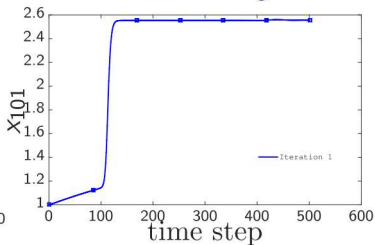
- Discretization: Godunov's scheme
- $(\mu_1, \mu_2) \in [2.5, 3.5] \times [0.02, 0.075]$
- $h = 0.1$, $M = 250$ fine time steps
- FOM: $N = 500$ degrees of freedom
- ROM: LSPG [?] with POD basis dimension $p = 100$
- $n_{\text{train}} = 4$ training points (LHS sampling); random online point
- Two coarse propagators: Backward Euler and forecasting

Forecasting outperforms backward Euler

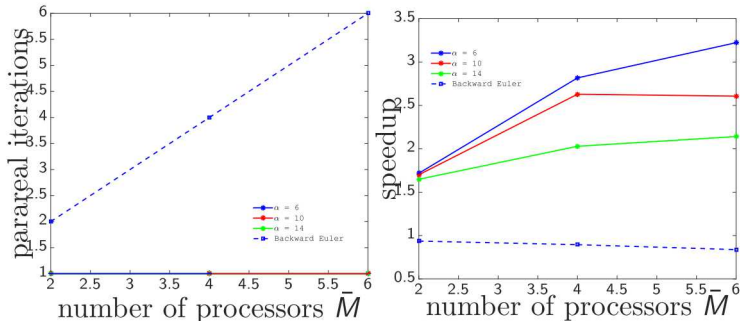
Backward Euler



Forecasting



Parareal performance



- + *Forecasting*: minimum possible iterations
- *Backward Euler*: maximum possible iterations

More parallelism successfully exposed!

Conclusions

Use temporal data to reduce ROM simulation time

- **offline:** time-evolution bases from right singular vectors
- **online:** use as coarse propagator

- 1 compute α time steps with fine propagator

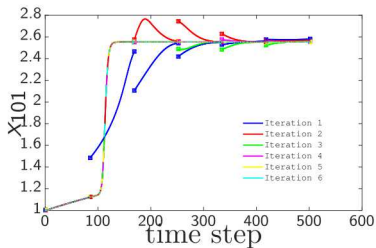
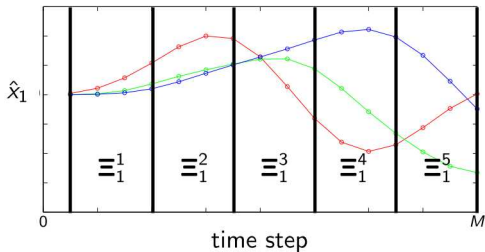
- 2 use gappy POD to forecast

- + theory: excellent speedup and stability
- + ideal parareal performance observed
- + significant improvement over Backward Euler
- + no additional error introduced
- + generally applicable

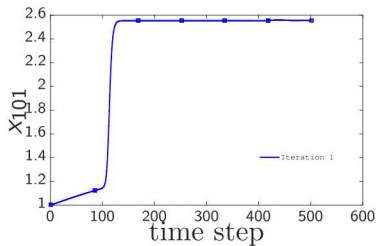
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Questions?








Backward Euler



Forecasting

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