

# A Parareal Algorithm for Optimal Control Problems

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Joint work with M.J. Gander (Geneva) and J. Salomon  
(Paris-Dauphine)

Gene Golub Memorial Day  
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# Outline

Parareal

Parareal for Control

Numerical Experiments

Conclusion

# Outline

Parareal

Parareal for Control

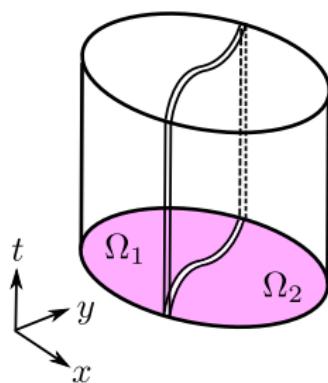
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Conclusion

# Parallel Solvers for Numerical PDEs

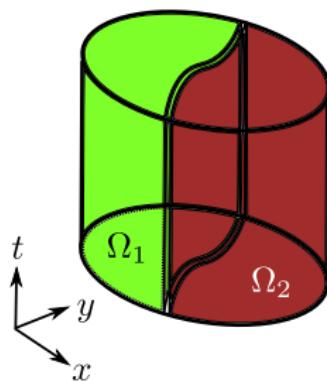
- ▶ **Goal:** Solve large, sparse (non)linear systems arising from discretized PDEs
- ▶ Exploit parallel architectures
- ▶ Use iterative methods/preconditioners in which each step has components that can be done in parallel

# Domain Decomposition in Space



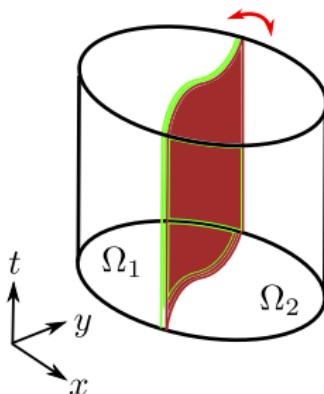
- ▶ Decompose domain into subdomains

# Domain Decomposition in Space



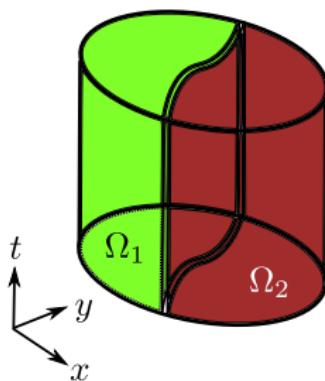
- ▶ Decompose domain into subdomains
- ▶ Iterate until convergence:
  1. Solve problem in each subdomain in parallel

# Domain Decomposition in Space



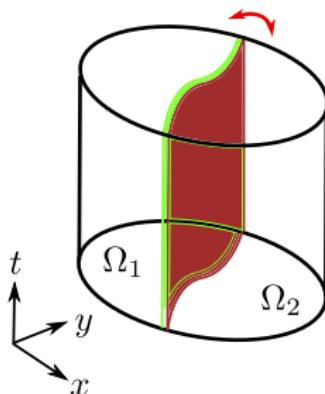
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# Domain Decomposition in Space



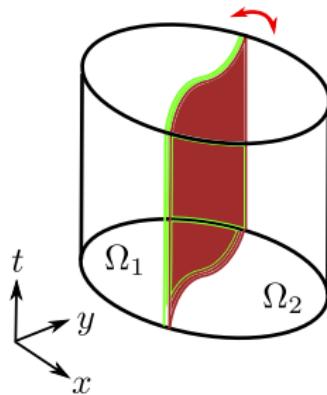
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# Domain Decomposition in Space



- ▶ Decompose domain into subdomains
- ▶ Iterate until convergence:
  1. Solve problem in each subdomain in parallel
  2. Exchange interface data
- ▶ Essentially a block Jacobi method/preconditioner

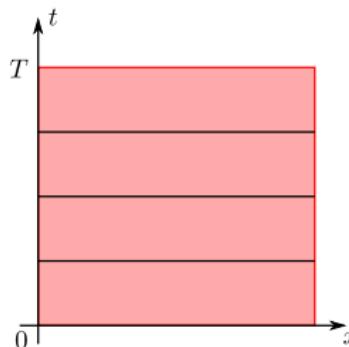
# Parallelization in Time?

- Solve systems of ODEs ( $\mathbf{y}' = f(t, \mathbf{y})$ ) or discretized PDEs

$$\left( \frac{\partial \mathbf{y}}{\partial t} = \mathcal{L}\mathbf{y} + \mathbf{f} \right)$$

- Block triangular system

$$\begin{bmatrix} A & & & \\ -I & A & & \\ & \ddots & \ddots & \\ & & -I & A \end{bmatrix} \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{pmatrix} = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{pmatrix}$$



- Is it possible to do useful computation at future time steps, before earlier time steps are known?

# Parareal for IVP (Lions, Maday & Turinici 2001)

C. R. Acad. Sci. Paris, t. 332, Série I, p. 661–668, 2001  
Analyse numérique/Numerical Analysis

## Résolution d'EDP par un schéma en temps «pararéel»

Jacques-Louis LIONS<sup>a</sup>, Yvon MADAY<sup>b</sup>, Gabriel TURINICI<sup>b,c</sup>

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### Résumé.

On propose dans cette Note un schéma permettant de profiter d'une architecture parallèle pour la discréttisation en temps d'une équation d'évolution aux dérivées partielles. Cette méthode, basée sur un schéma d'Euler, combine des résolutions grossières et des résolutions fines et indépendantes en temps en s'inspirant de ce qui est classique en espace. La parallélisation qui en résulte se fait dans la direction temporelle ce qui est en revanche non classique. Elle a pour principale motivation les problèmes en temps réel, d'où la terminologie proposée de «pararéel». © 2001 Académie des sciences/Éditions scientifiques et médicales Elsevier SAS

### A “parareal” in time discretization of PDE’s

### Abstract.

The purpose of this Note is to propose a time discretization of a partial differential evolution equation that allows for parallel implementations. The method, based on an Euler scheme, combines coarse resolutions and independent fine resolutions in time in the same spirit as standard spacial approximations. The resulting parallel implementation is done in the non standard time direction. Its main goal concerns real time problems, hence the proposed terminology of “parareal” algorithm. © 2001 Académie des sciences/Éditions scientifiques et médicales Elsevier SAS

# Parareal for IVP (Lions, Maday & Turinici 2001)

- ▶ Unknowns:  $Y_n \approx y(t_n)$
- ▶ Fine/coarse propagators:  $P^{\delta t}(t_{n+1}; t_n, y_n)$ ,  $P^{\Delta t}(t_{n+1}; t_n, y_n)$
- ▶ For  $k = 1, 2, \dots$ :
  1. Solve **fine** problems **in parallel**:

$$y_{n+1}^k(t_{n+1}) = P^{\delta t}(t_{n+1}; t_n, Y_n^k)$$

2. Correct initial conditions using **coarse propagator**:

$$Y_{n+1}^{k+1} = y_{n+1}^k(t_{n+1}) + P^{\Delta t}(t_{n+1}; t_n, Y_n^{k+1}) - P^{\Delta t}(t_{n+1}; t_n, Y_n^k)$$

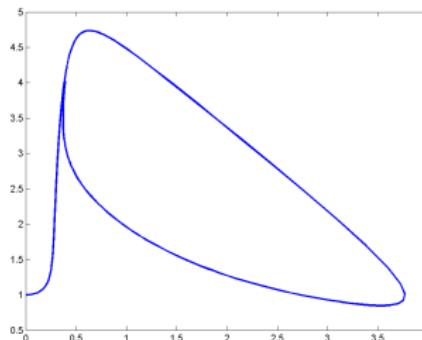
- ▶ Initial guesses for  $Y_n^0$  obtained by coarse propagation

# Example: Brusselator

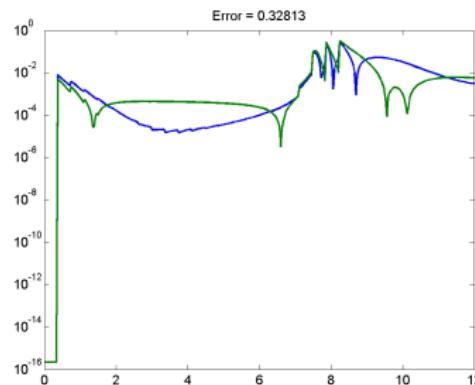
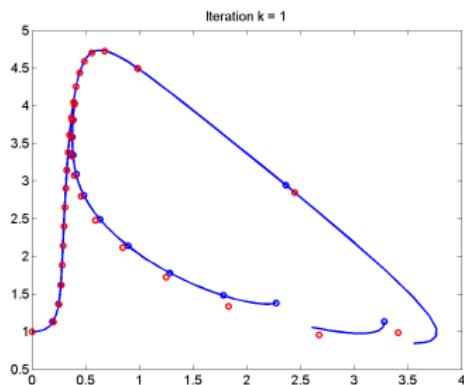
- ▶ Model equation:

$$\begin{aligned}\frac{dx}{dt} &= A + x^2y - (B + 1)x \\ \frac{dy}{dt} &= Bx - x^2y\end{aligned}$$

- ▶ Parameters:  $A = 1$ ,  $B = 3$ ,  
 $x(0) = 0$ ,  $y(0) = 1$
- ▶ Use 4th order Runge-Kutta with 32 coarse steps and 320 fine steps

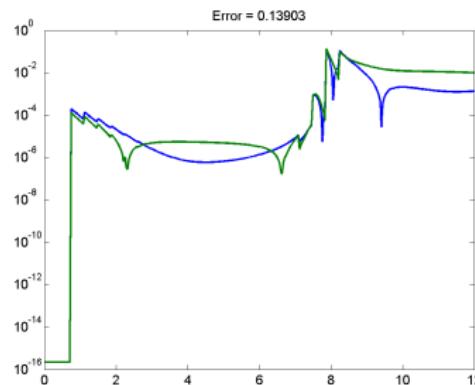
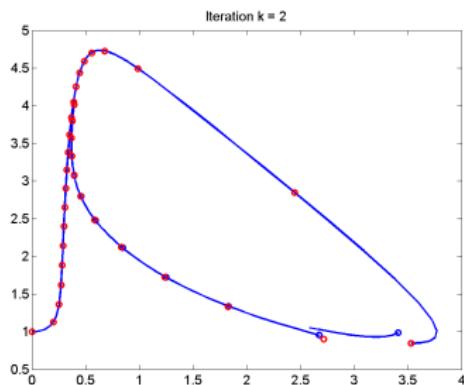


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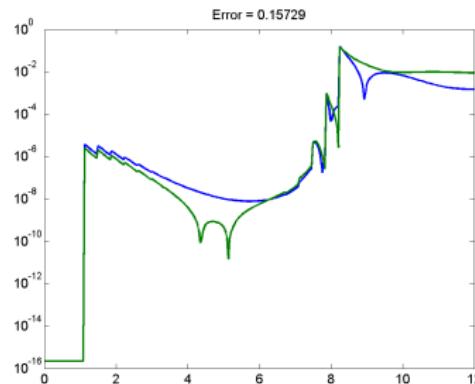
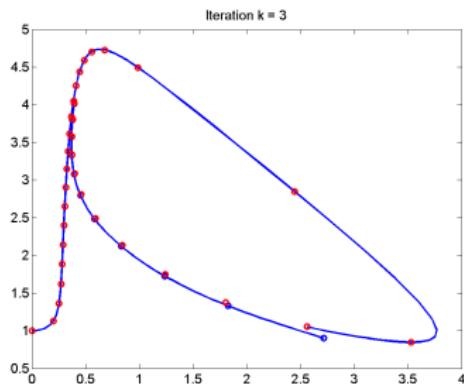
- Method is exact in the first  $k$  intervals after  $k$  iterations
- Parallel speedup  $\leq N/K$ , where  $K = \#$ iters to convergence

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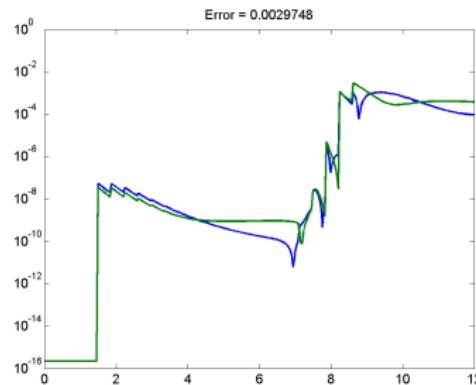
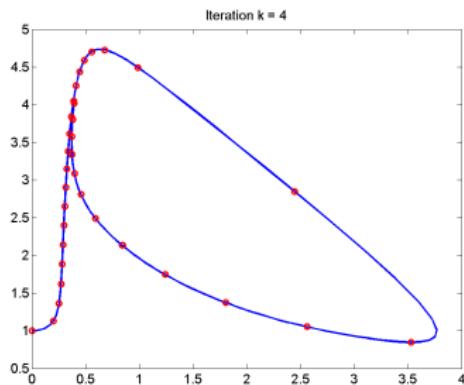
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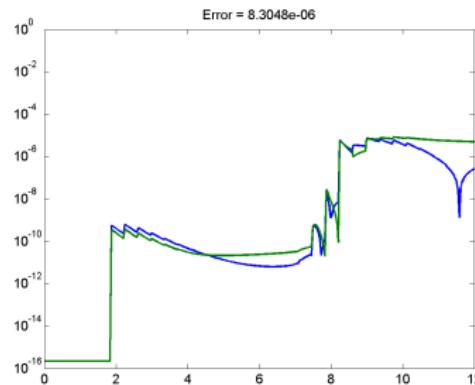
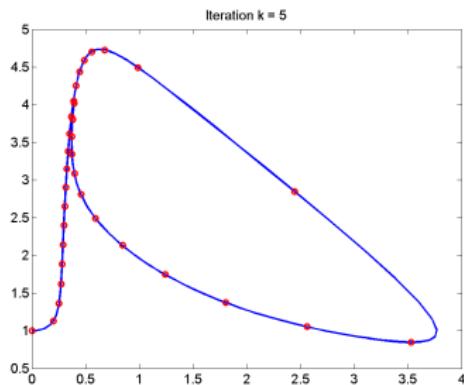
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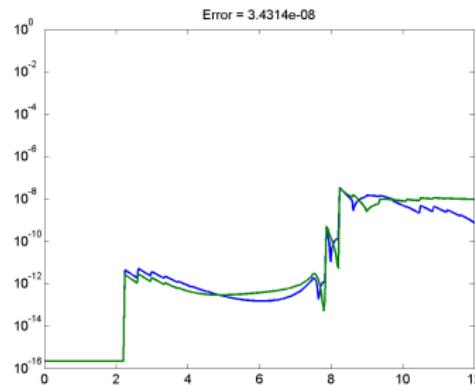
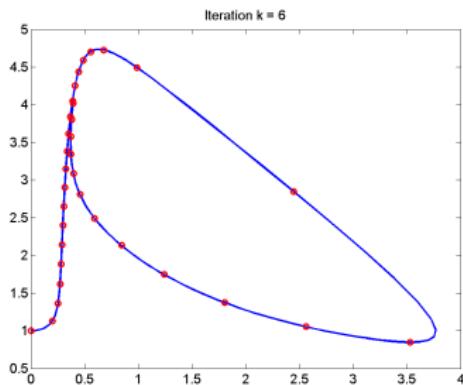
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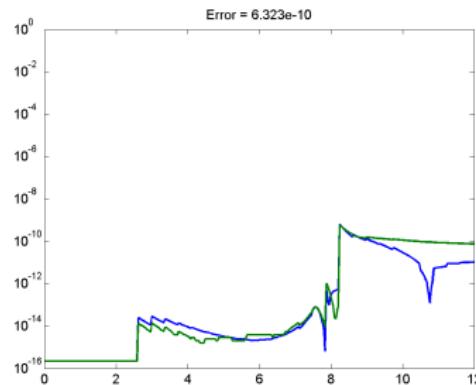
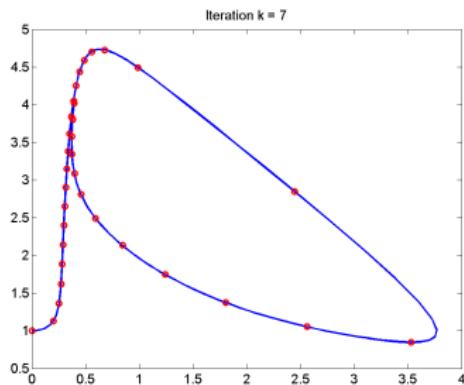
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# Parareal = Inexact Newton (Gander & Vandewalle 2003)

- ▶ Define the **residual function**

$$F(Y) = \begin{pmatrix} Y_0 - y_{\text{init}} \\ Y_1 - P^{\delta t}(t_1; t_0, Y_0) \\ \vdots \\ Y_N - P^{\delta t}(t_N; t_{N-1}, Y_{N-1}) \end{pmatrix} = 0.$$

- ▶ Newton's method reads (for  $n \geq 1$ )

$$Y_n^{k+1} = P^{\delta t}(t_n; t_{n-1}, Y_n^k) + \frac{\partial P^{\delta t}}{\partial Y}(t_n; t_{n-1}, Y_{n-1}^k)(Y_n^{k+1} - Y_n^k).$$

- ▶ Parareal replaces the derivative with a finite difference:

$$\frac{\partial P^{\delta t}}{\partial Y}(\cdot)(Y_n^{k+1} - Y_n^k) \approx P^{\Delta t}(t_{n+1}; t_n, Y_n^{k+1}) - P^{\Delta t}(t_{n+1}; t_n, Y_n^k)$$

# Derivative Parareal (Gander & Hairer 2014)

- ▶ Newton's method:

$$Y_n^{k+1} = P^{\delta t}(t_n; t_{n-1}, Y_n^k) + \frac{\partial P^{\delta t}}{\partial Y}(t_n; t_{n-1}, Y_{n-1}^k)(Y_n^{k+1} - Y_n^k).$$

- ▶ Approximate derivatives cheaply using coarse propagator:

$$Y_n^{k+1} = P^{\delta t}(t_n; t_{n-1}, Y_n^k) + \frac{\partial P^{\Delta t}}{\partial Y}(t_n; t_{n-1}, Y_{n-1}^k)(Y_n^{k+1} - Y_n^k).$$

- ▶ Compare with Parareal:

$$Y_{n+1}^{k+1} = P^{\delta t}(t_n; t_{n-1}, Y_n^k) + P^{\Delta t}(t_{n+1}; t_n, Y_n^{k+1}) - P^{\Delta t}(t_{n+1}; t_n, Y_n^k)$$

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# Optimal Control Problem

- ▶ Optimal control problem: minimize

$$J[y, u] = \frac{1}{2} \|y(T) - y_{\text{target}}\|^2 + \frac{\alpha}{2} \int_0^T \|u(t)\|^2 dt$$

subject to the (non)-linear ODE constraint

$$\dot{y}(t) = f(y(t)) + u(t), \quad t \in (0, T).$$

- ▶ Assumptions:
  1. No state or control constraints
  2. Distributed control entering additively
- ▶ Includes cases where  $f$  is the discretization of a partial differential operator

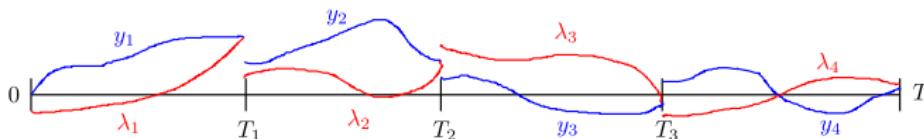
# Optimality System

- ▶ Using Lagrange multipliers, we deduce the optimality conditions to be

$$\begin{cases} \dot{y}(t) = f(y(t)) - \frac{1}{\alpha} \lambda(t), \\ y(0) = y_{\text{init}}, \end{cases} \quad \begin{cases} \dot{\lambda}(t) = -(f'(y(t)))^T \lambda(t), \\ \lambda(T) = y(T) - y_{\text{target}}. \end{cases}$$

- ▶ Coupled forward-backward problem!

# Time-domain decomposition for control



- ▶ Divide time horizon  $(0, T)$  into “subdomains”  $I_i = (T_{i-1}, T_i)$
- ▶ Subdomain problem on  $I_i$  well defined when  $y(T_{i-1})$  and  $\lambda(T_i)$  are given
- ▶ Multiple shooting: solve for intermediate states  $Y_i = y(T_i)$  and  $\Lambda_i = \lambda(T_i)$

# Parareal for Control

- ▶ Unknowns: state  $Y_n \approx y(t_n)$  and adjoint  $\Lambda_n \approx \lambda(t_n)$
- ▶ Fine/coarse propagators:

$$\begin{aligned} P^{\delta t}, P^{\Delta t} : & (Y_n, \Lambda_{n+1}) \mapsto y(t_{n+1}), \\ Q^{\delta t}, Q^{\Delta t} : & (Y_n, \Lambda_{n+1}) \mapsto \lambda(t_n) \end{aligned}$$

- ▶ Residual function:

$$F(Y, \Lambda) = \begin{pmatrix} Y_0 - y_{\text{init}} \\ Y_1 - P^{\delta t}(t_1; t_0, Y_0, \Lambda_1) \\ \vdots \\ Y_N - P^{\delta t}(t_N; t_{N-1}, Y_{N-1}, \Lambda_N) \\ \Lambda_1 - Q^{\delta t}(t_1; t_2, Y_1, \Lambda_2) \\ \vdots \\ \Lambda_{N-1} - Q^{\delta t}(t_{N-1}; t_N, Y_{N-1}, \Lambda_N) \\ \Lambda_N - y_N + y_{\text{target}} \end{pmatrix} = 0$$

# Parareal for Control

- ▶ Newton's method:

$$Y_n^{k+1} = P^{\delta t}(t_n; t_{n-1}, Y_{n-1}^k, \Lambda_n^k) + \frac{\partial P^{\delta t}}{\partial Y}(Y_{n-1}^{k+1} - Y_{n-1}^k) + \frac{\partial P^{\delta t}}{\partial \Lambda}(\Lambda_n^{k+1} - \Lambda_n^k)$$
$$\Lambda_n^{k+1} = Q^{\delta t}(t_n; t_{n+1}, Y_n^k, \Lambda_{n+1}^k) + \frac{\partial Q^{\delta t}}{\partial Y}(Y_n^{k+1} - Y_n^k) + \frac{\partial Q^{\delta t}}{\partial \Lambda}(\Lambda_{n+1}^{k+1} - \Lambda_{n+1}^k)$$

- ▶ Derivatives expensive to evaluate
- ▶ Use parareal approximation

# Parareal for Control

- ▶ Derivative Parareal:

$$Y_n^{k+1} = P^{\delta t}(t_n; t_{n-1}, Y_{n-1}^k, \Lambda_n^k) + \frac{\partial P^{\Delta t}}{\partial Y}(Y_{n-1}^{k+1} - Y_{n-1}^k) + \frac{\partial P^{\Delta t}}{\partial \Lambda}(\Lambda_n^{k+1} - \Lambda_n^k)$$

$$\Lambda_n^{k+1} = Q^{\delta t}(t_n; t_{n+1}, Y_n^k, \Lambda_{n+1}^k) + \frac{\partial Q^{\Delta t}}{\partial Y}(Y_n^{k+1} - Y_n^k) + \frac{\partial Q^{\Delta t}}{\partial \Lambda}(\Lambda_{n+1}^{k+1} - \Lambda_{n+1}^k)$$

- ▶ Still coupled, must solve

$$\tilde{F}'(Y^k, \Lambda^k) \begin{pmatrix} Y^{k+1} - Y^k \\ \Lambda^{k+1} - \Lambda^k \end{pmatrix} = -F(Y^k, \Lambda^k)$$

- using an iterative method, e.g., preconditioned GMRES
- ▶  $\tilde{F}'$  = approximation of Jacobian matrix

# Parareal for Control: Algorithm

- ▶ Unknowns:  $Y_n \approx y(t_n)$ ,  $\Lambda_n \approx \lambda(t_n)$
- ▶ For  $k = 1, 2, \dots$ :
  1. Solve fine subdomain problems **in parallel**:

$$y_n(t_{n+1}) = P^{\delta t}(Y_n^k, \Lambda_{n+1}^k), \quad \lambda_n(t_n) = Q^{\delta t}(Y_n^k, \Lambda_{n+1}^k)$$

2. Solve  $\tilde{F}'(Y^k, \Lambda^k) \begin{pmatrix} \Delta Y \\ \Delta \Lambda \end{pmatrix} = -F(Y^k, \Lambda^k)$  by GMRES:
  - ▶ Calculate  $P_Y, P_\Lambda, Q_Y, Q_\Lambda$  with coarse propagator on **each subdomain**
  - ▶ Matrix multiplication = **in parallel**
  - ▶ Preconditioning = backward/forward sweep
3. Update:  $Y^{k+1} = Y^k + \Delta Y$ ,  $\Lambda^{k+1} = \Lambda^k + \Delta \Lambda$

# Parallel Speedup

- ▶ Assume cost of solving problem  $\propto$  # time steps
- ▶ Global fine problem (no parareal):  $C_1 T / \delta t$
- ▶ Parareal with  $N$  subdomains:
  - ▶ Fine propagation:  $C_1 T / (N\delta t)$  (parallel)
  - ▶ Coarse propagation:  $C_1 T / (N\Delta t)$  (parallel)
  - ▶ Preconditioning:  $2T / \Delta t$  (sequential)
- ▶ If  $K$  parareal iterations are needed for convergence, then

$$\text{Speedup} = \frac{C_1 T / \delta t}{K(C_1 T / (N\delta t) + C_1 T / (N\Delta t) + 2T / \Delta t)}$$

# Parallel Speedup

- ▶ Assume cost of solving problem  $\propto$  # time steps
- ▶ Global fine problem (no parareal):  $C_1 T / \delta t$
- ▶ Parareal with  $N$  subdomains:
  - ▶ Fine propagation:  $C_1 T / (N\delta t)$  (parallel)
  - ▶ Coarse propagation:  $C_1 T / (N\Delta t)$  (parallel)
  - ▶ Preconditioning:  $2T/\Delta t$  (sequential)
- ▶ If  $K$  parareal iterations are needed for convergence, then

$$\text{Speedup} = \frac{N}{K} \left( 1 + \frac{\delta t}{\Delta t} (1 + 2N/C_1) \right)^{-1}$$

# Convergence of Parareal for Control

- ▶ Method works for linear as well as nonlinear problems
- ▶ Convergence results for linear problems via eigenvalue analysis
- ▶ Results for implicit Euler:
  - ▶ Contraction factor:  $\rho \leq C(\Delta t - \delta t)$
  - ▶ For dissipative problems,  $C$  can be chosen independent of  $\sigma$
  - ▶ For very large  $\alpha$  (heavy penalization against large control values),  $C$  can grow like  $\log(\alpha)$  when the number of subdomains becomes large

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# Scalar example

- ▶ Minimize

$$J[y, u] = \frac{1}{2}|y(1) - y_{\text{target}}|^2 + \frac{1}{2} \int_0^1 u^2(t) dt$$

with  $y_{\text{target}} = 1$ , subject to

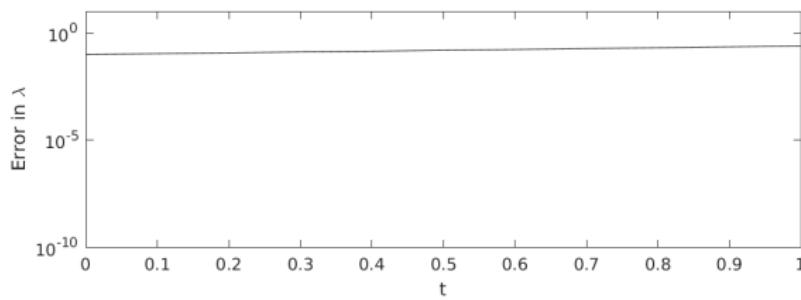
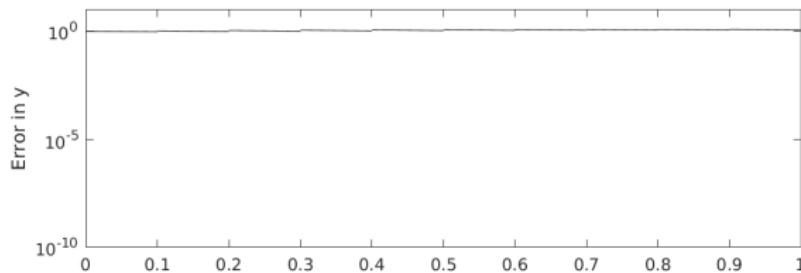
$$\frac{\partial y}{\partial t} = \sin(y) + u, \quad t \in (0, 1)$$

$$y(0) = 1$$

- ▶ Backward Euler,  $\delta t = 10^{-6}$

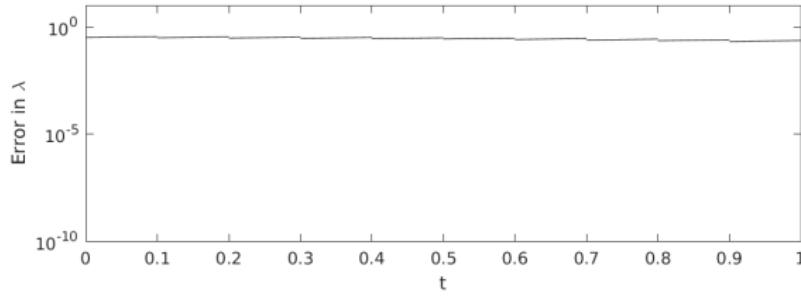
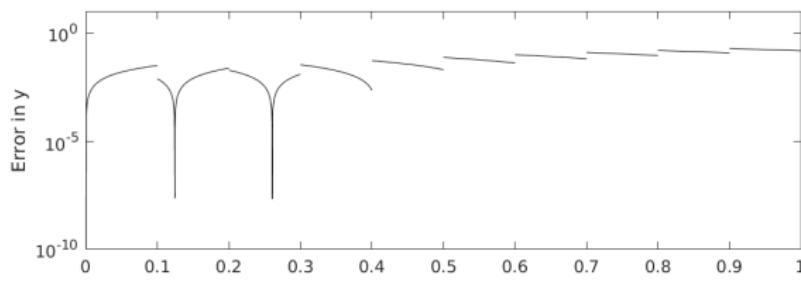
# Scalar example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #1



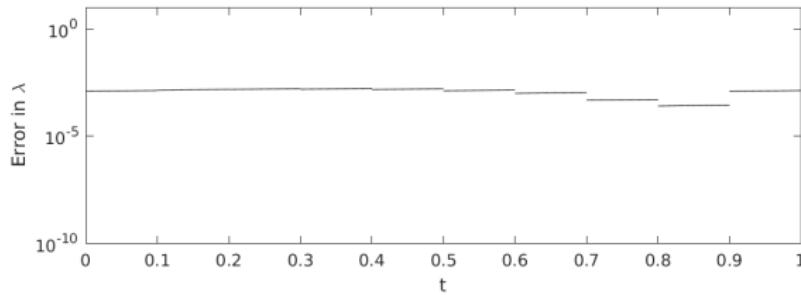
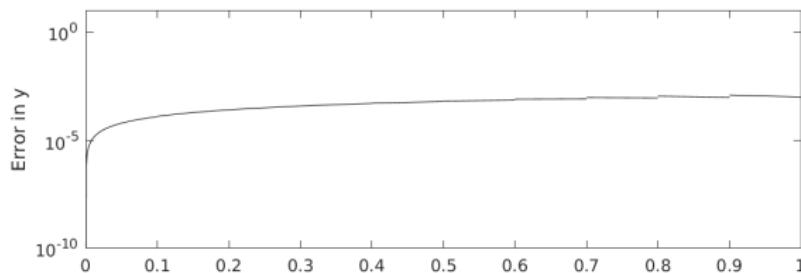
# Scalar example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #2



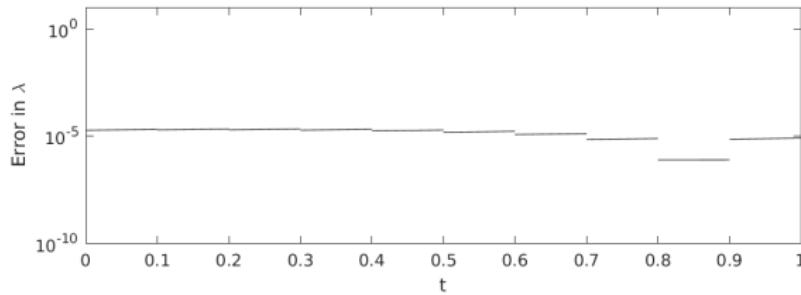
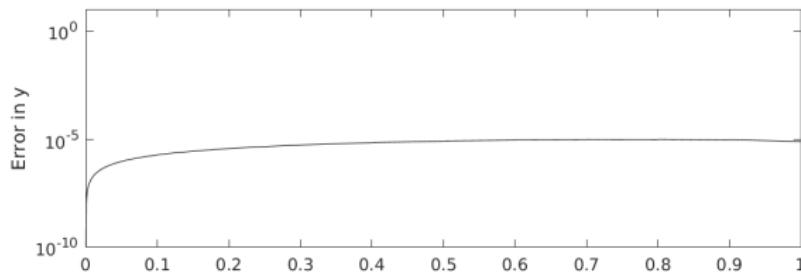
# Scalar example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #3



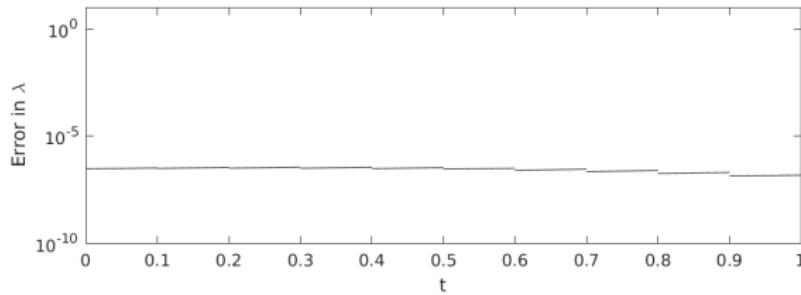
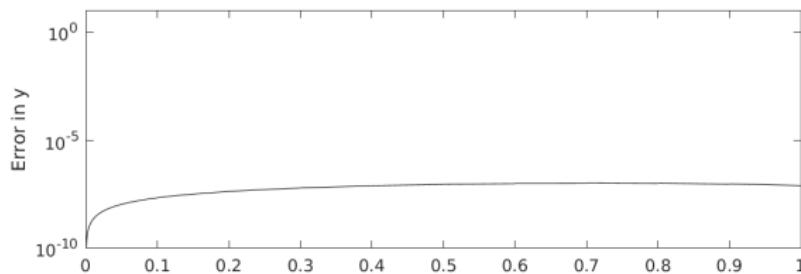
# Scalar example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #4



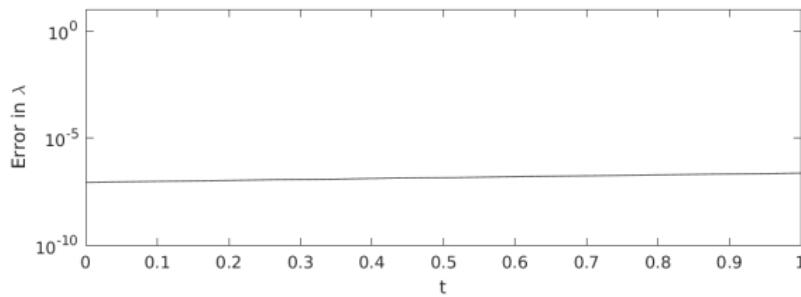
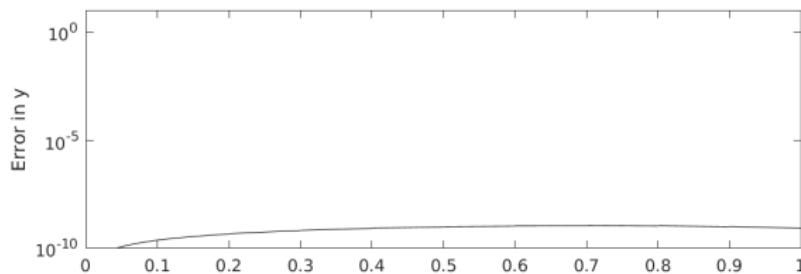
# Scalar example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #5



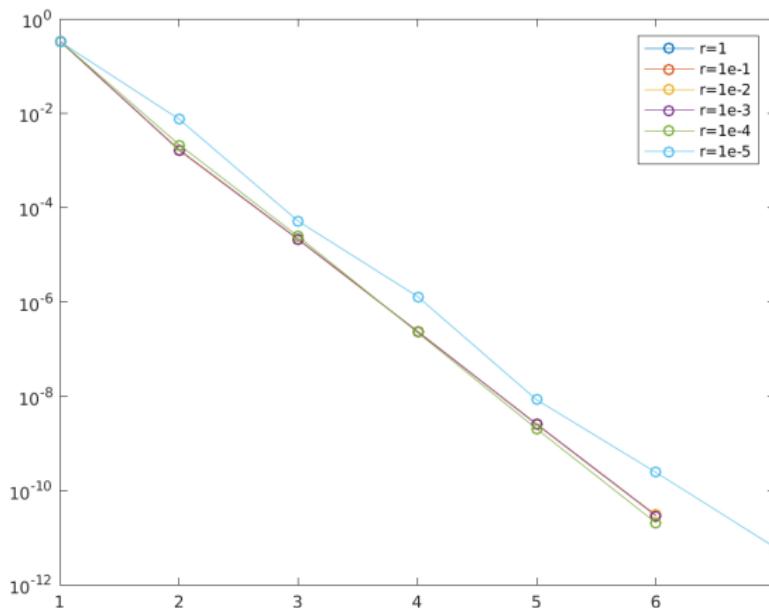
# Scalar example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #6



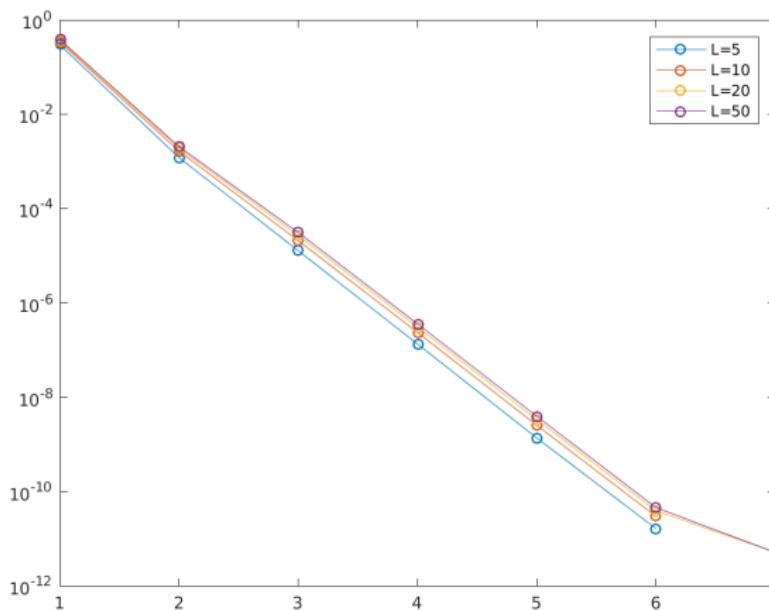
# Scalar example

$N = 10$  subdomains, varying  $r = \delta t / \Delta t$



# Scalar example

$\delta t/\Delta t = 0.01$ , varying # subdomains



# Vector example

- ▶ Minimize

$$J[y, u] = \frac{1}{2}|y(1) - y_{\text{target}}|^2 + \frac{1}{2} \int_0^1 |u(t)|^2 dt$$

with  $y_{\text{target}} = (100, 20)^T$ , subject to the Lotka-Volterra equation

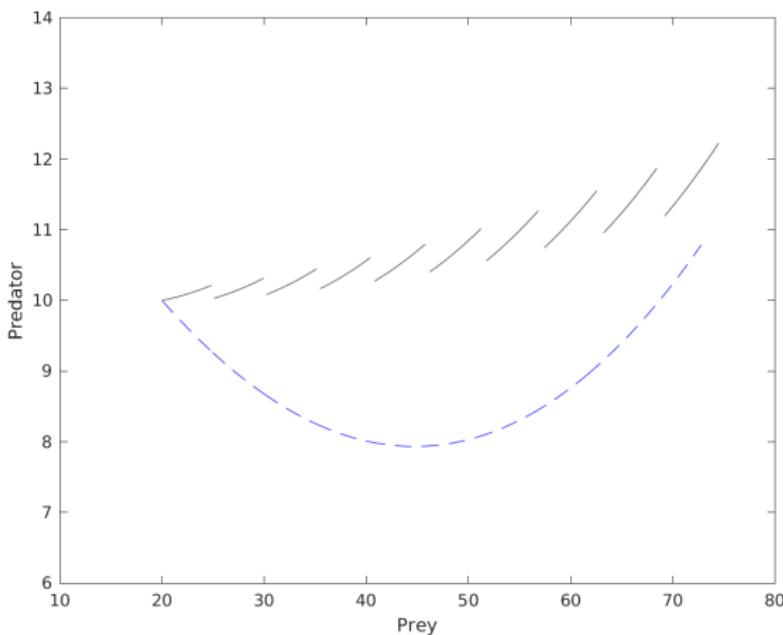
$$\dot{y}_1 = ay_1 - by_1y_2, \quad \dot{y}_2 = cy_1y_2 - dy_2$$

with initial conditions  $y(0) = (20, 10)^T$

- ▶ Backward Euler,  $\delta t = 10^{-5}$

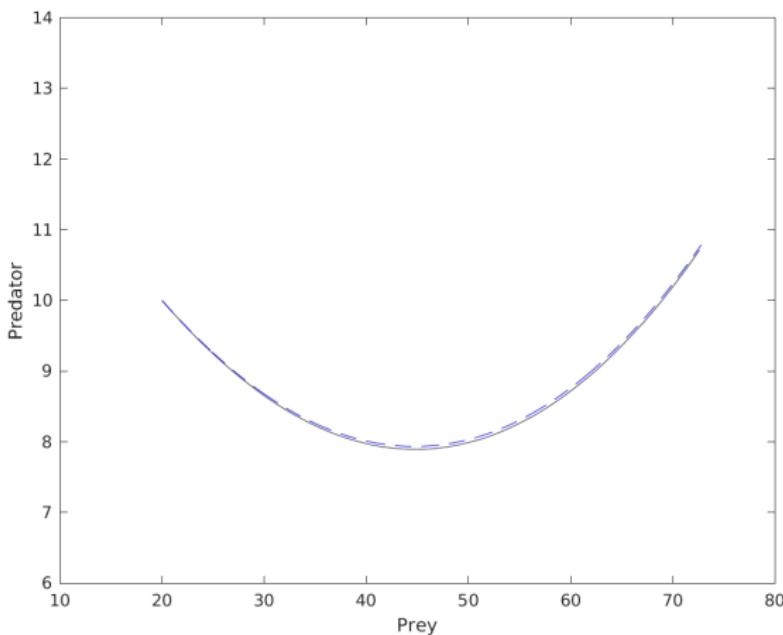
# Vector example - $N = 10, r = \delta t / \Delta t = 0.01$

Iteration #1



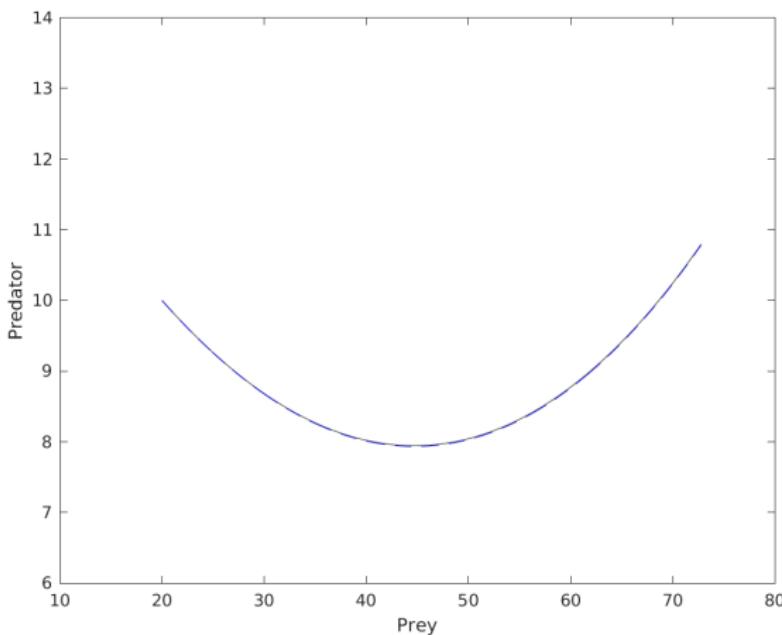
# Vector example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #2



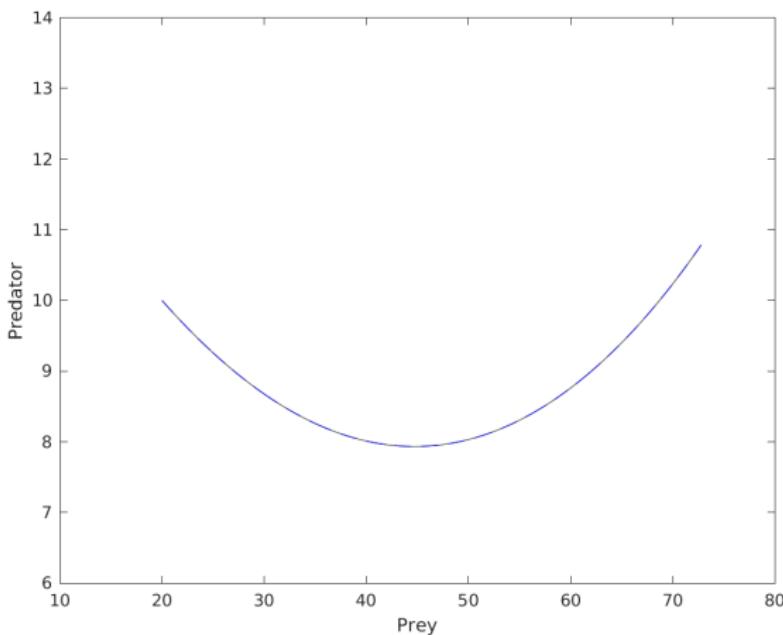
# Vector example - $N = 10, r = \delta t / \Delta t = 0.01$

Iteration #3



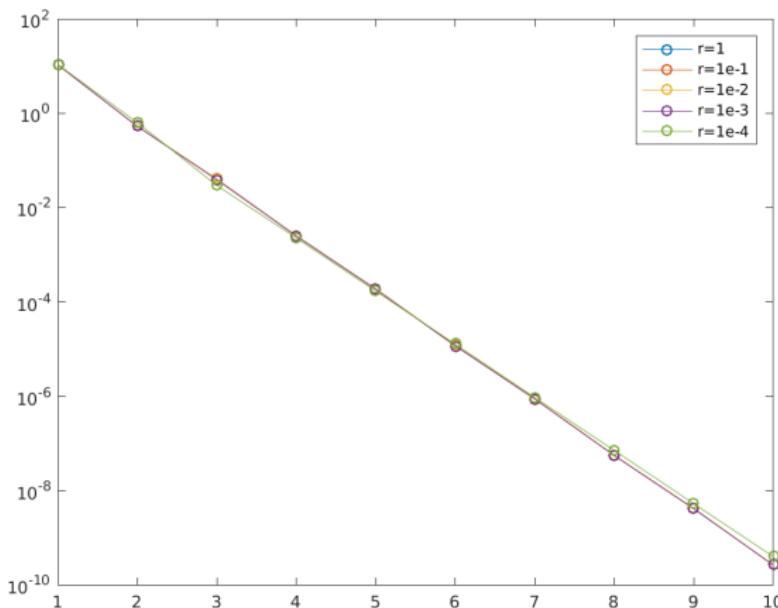
# Vector example - $N = 10, r = \delta t / \Delta t = 0.01$

Iteration #4



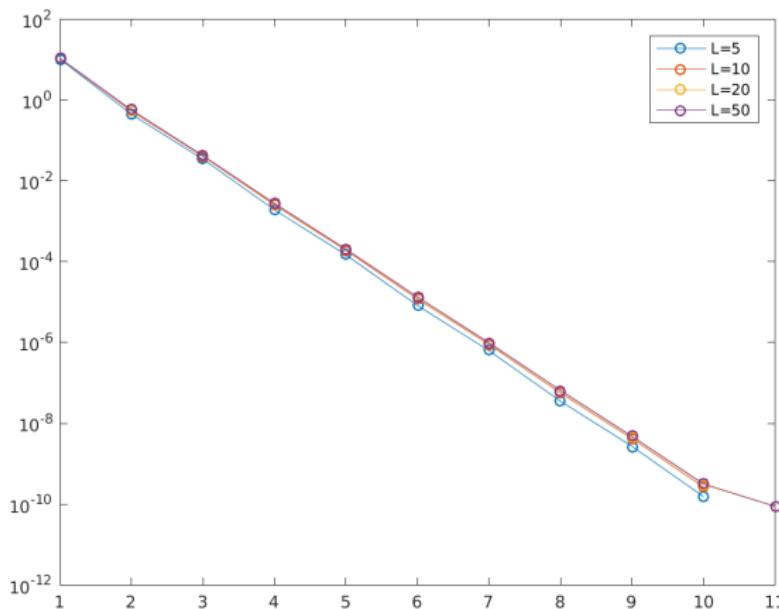
# Vector example

$N = 10$  subdomains, varying  $r = \delta t / \Delta t$



# Vector example

$\delta t/\Delta t = 0.01$ , varying # subdomains



# Vector example

- ▶ Minimize

$$J[y, u] = \frac{1}{2} |y(20) - y_{\text{target}}|^2 + \frac{1}{2} \int_0^{20} |u(t)|^2 dt$$

with  $y_{\text{target}} = (100, 20)^T$ , subject to the Lotka-Volterra equation

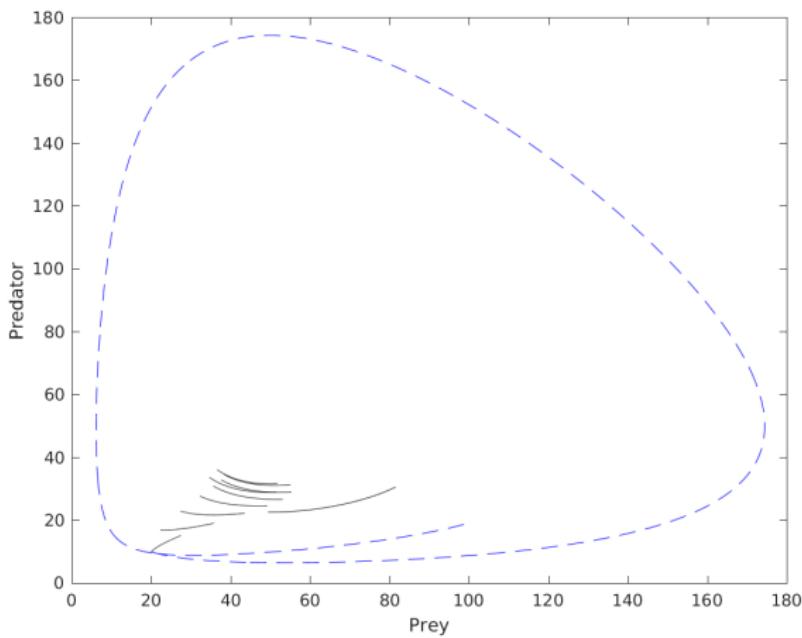
$$\dot{y}_1 = ay_1 - by_1y_2, \quad \dot{y}_2 = cy_1y_2 - dy_2$$

with initial conditions  $y(0) = (20, 10)^T$

- ▶ Backward Euler,  $\delta t = 20 \cdot 10^{-5}$

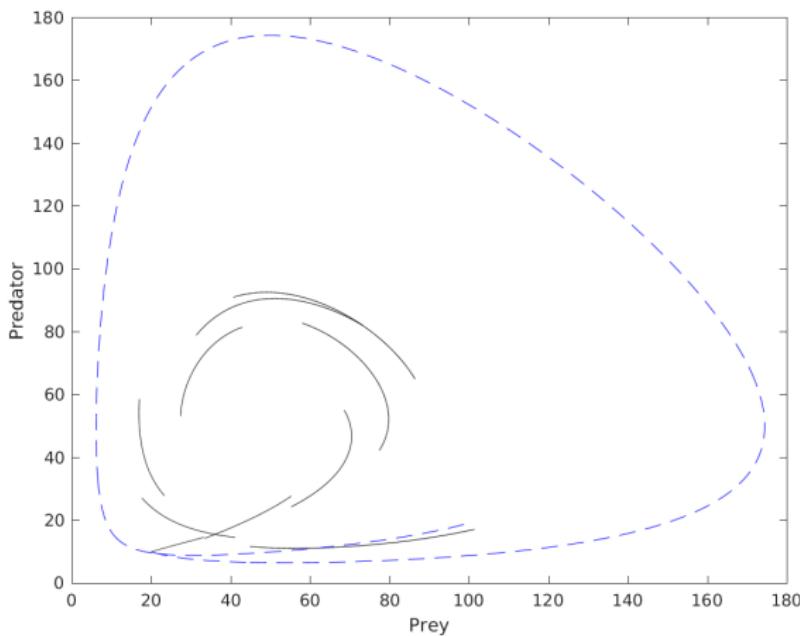
# Vector example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #1



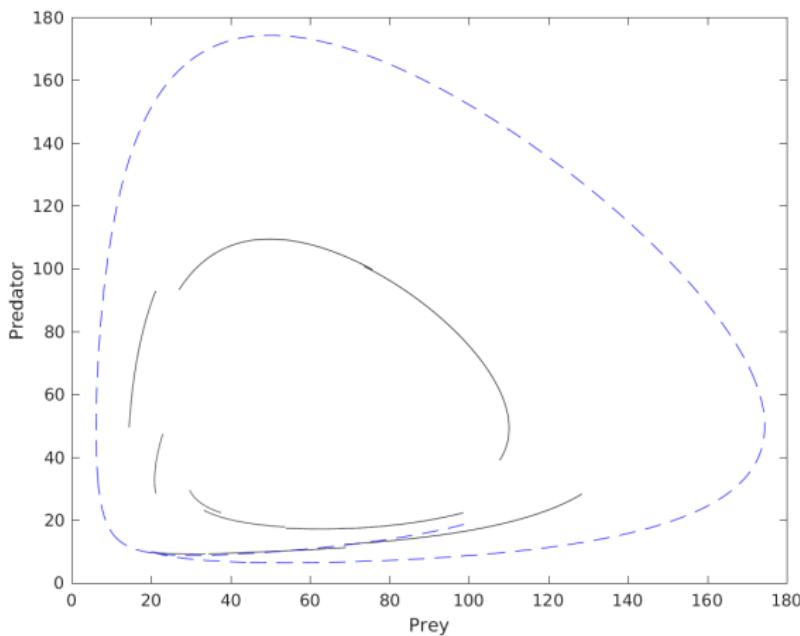
# Vector example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #2



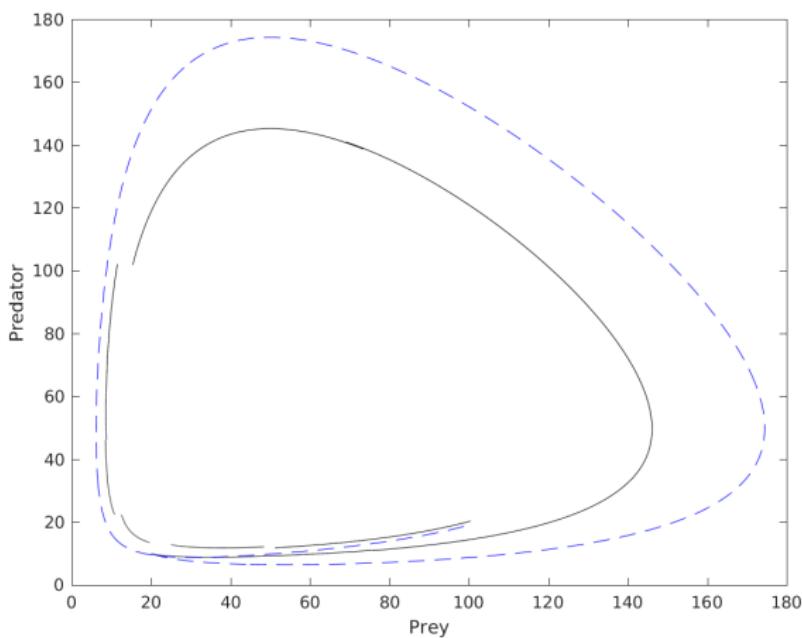
# Vector example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #3



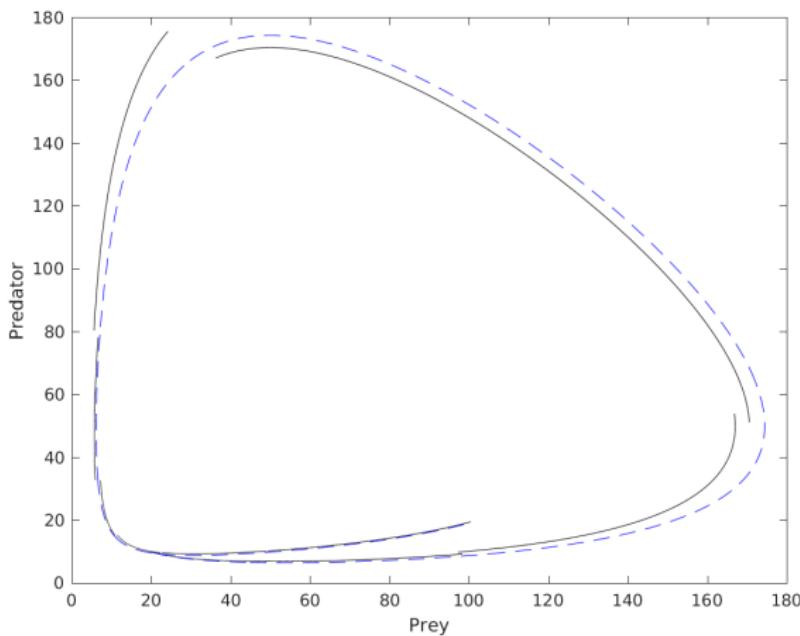
# Vector example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #4



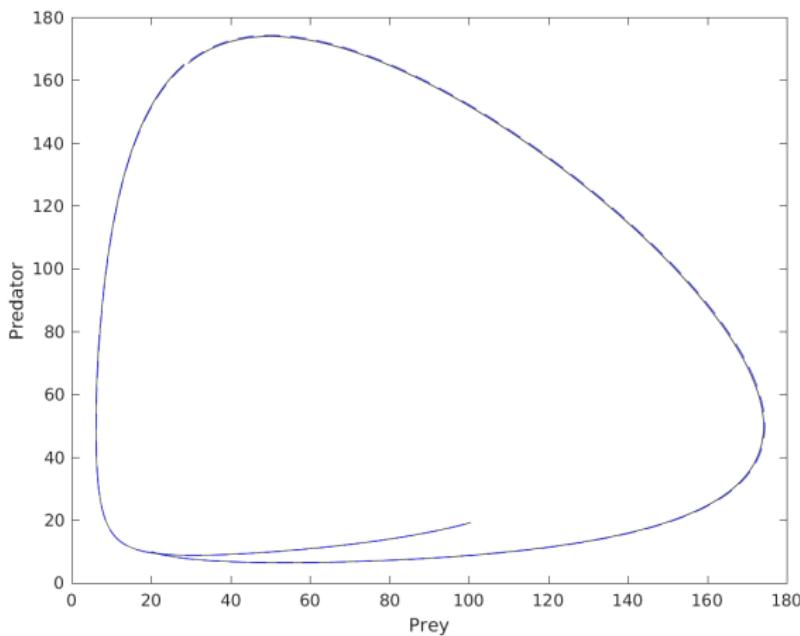
# Vector example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #5



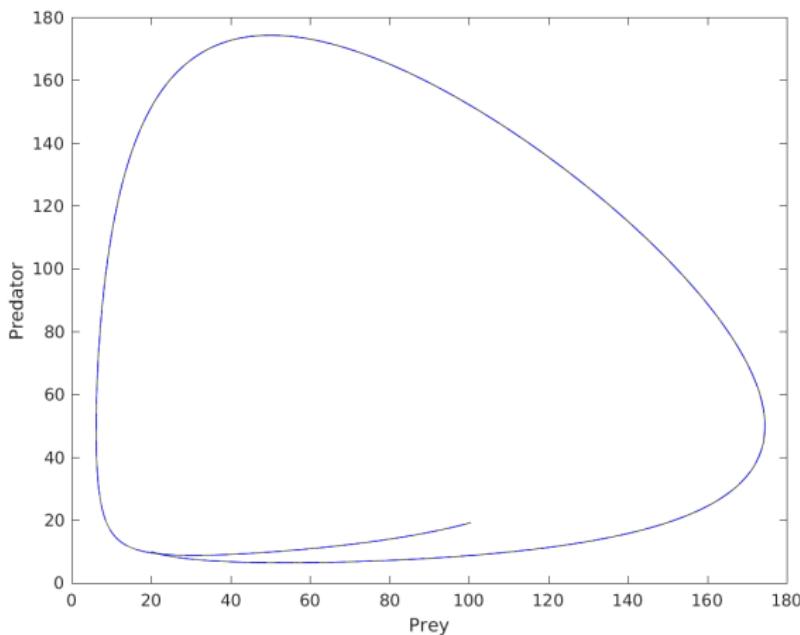
# Vector example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #6



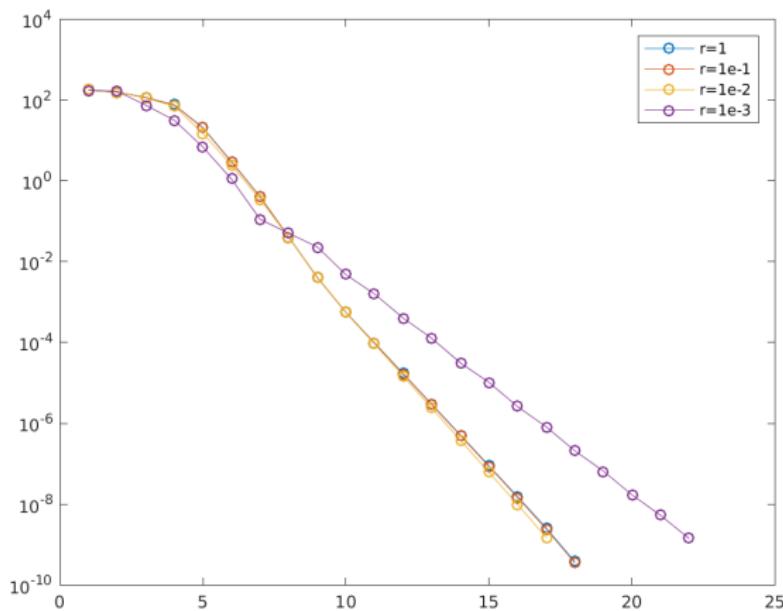
# Vector example - $N = 10$ , $r = \delta t / \Delta t = 0.01$

Iteration #7



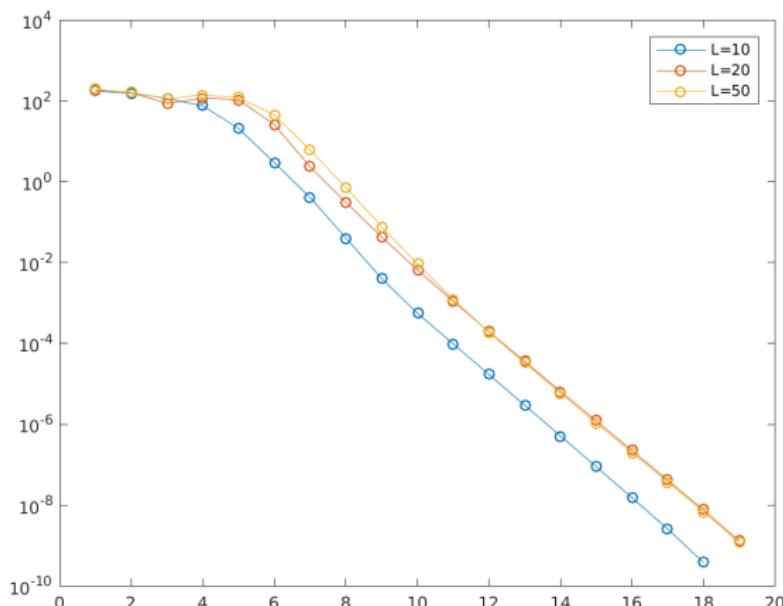
# Vector example

$N = 10$  subdomains, varying  $r = \delta t / \Delta t$



# Vector example

$\delta t / \Delta t = 0.01$ , varying # subdomains



# PDE example

- Minimize

$$J[y, u] = \frac{1}{2} \|y(x, 1) - y_{\text{target}}(x)\|^2 + \frac{0.1}{2} \int_0^1 u^2(t) dt$$

with  $y_{\text{target}}(x) = x(1 - x)$ , subject to the minimal surface PDE

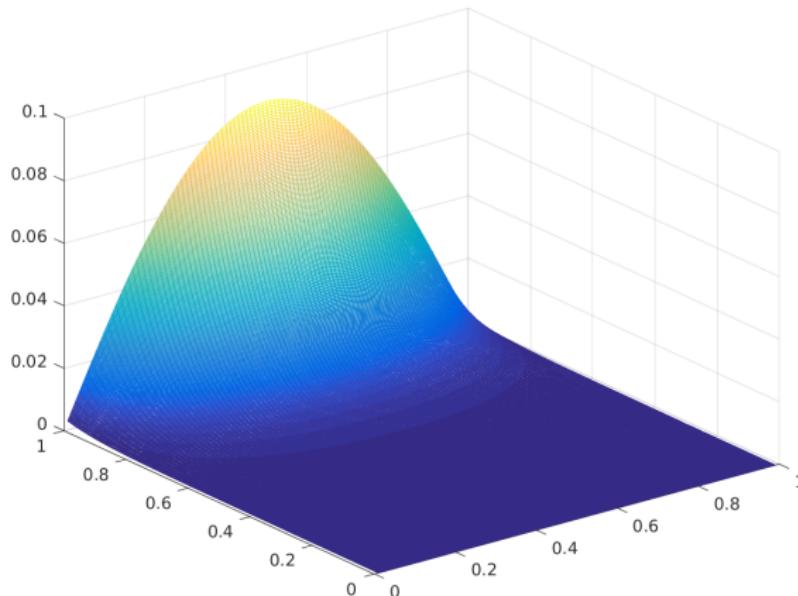
$$\frac{\partial y}{\partial t} = \frac{\partial}{\partial x} \left( \frac{y_x}{\sqrt{1 + |y_x|^2}} \right) + u, \quad (x, t) \in (0, 1)^2$$

$$y(x, 0) = 0, \quad y(0, t) = y(1, t) = 0$$

- Centered difference in space with  $h = 1/100$
- Backward Euler,  $\delta t = 10^{-4}$

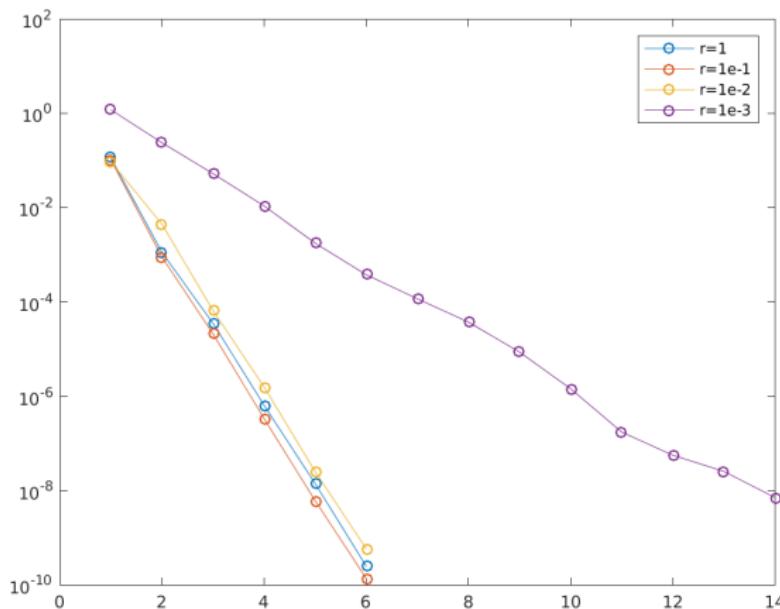
# PDE example

Optimal  $y(x, t)$



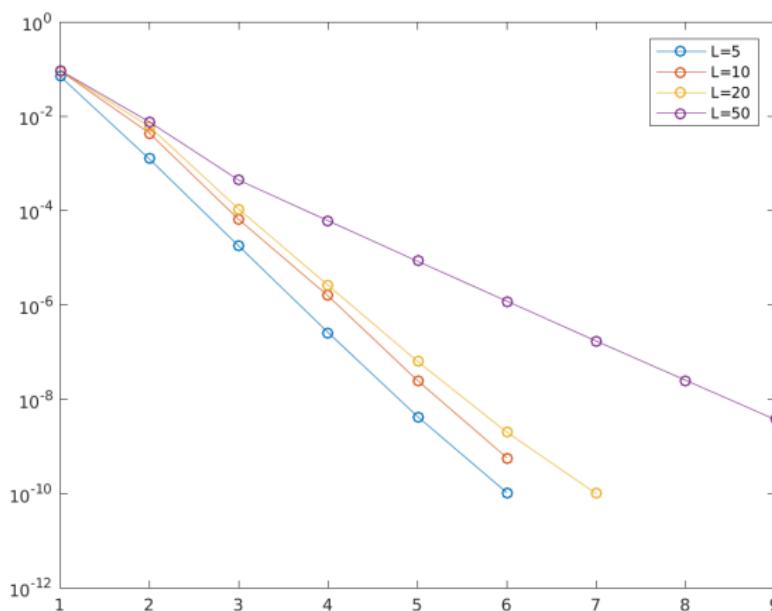
# PDE example

$N = 10$  subdomains, varying  $r = \delta t / \Delta t$



# PDE example

$\delta t/\Delta t = 0.01$ , varying # subdomains



# Outline

Parareal

Parareal for Control

Numerical Experiments

Conclusion

# Conclusion

- ▶ Parareal for control problems involving nonlinear ODE/PDEs
- ▶ Derivatives easier to approximate than finite difference  
     $\implies$  derivative parareal variant
- ▶ Contraction factor proportional to coarse step sizes
- ▶ Ongoing work:
  - ▶ Control entering nonlinearly, or only over part of the domain
  - ▶ Spatial coarsening in the PDE case
  - ▶ Control constraints

# Other approaches

DD on control problem:

- ▶ Heinkenschloss (JCAM 2005): block symmetric Gauss-Seidel preconditioning
- ▶ Maday, Salomon and Turinici (SINUM 2007): Quantum control, method of intermediate targets
- ▶ Maday, Riahi & Salomon (2013): Intermediate targets for parabolic problems
- ▶ Barker & Stoll (2015), Gander & Kwok (2016): Schwarz methods in time

Related:

- ▶ Apply parareal to forward and backward solves in shooting method (Mathew, Sarkis & Shaerer 2010, Ulbrich 2015)
- ▶ Multigrid methods (Hackbusch 1984, Borzì 2003)

# Thank you!

