

# Composing Nonlinear Solvers

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Numerical Methods for  
Large-Scale Nonlinear Problems and Their Applications  
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# Programming with Options

## ex55: Allen-Cahn problem in 2D

- constant mobility
- triangular elements

## Geometric multigrid method for saddle point variational inequalities:

```
./ex55 -ksp_type fgmres -pc_type mg -mg_levels_ksp_type fgmres  
-mg_levels_pc_type fieldsplit -mg_levels_pc_fieldsplit_detect_saddle_point  
-mg_levels_pc_fieldsplit_type schur -da_grid_x 65 -da_grid_y 65  
-mg_levels_pc_fieldsplit_factorization_type full  
-mg_levels_pc_fieldsplit_schur_precondition user  
-mg_levels_fieldsplit_1_ksp_type gmres -mg_coarse_ksp_type preonly  
-mg_levels_fieldsplit_1_pc_type none -mg_coarse_pc_type svd  
-mg_levels_fieldsplit_0_ksp_type preonly  
-mg_levels_fieldsplit_0_pc_type sor -pc_mg_levels 5  
-mg_levels_fieldsplit_0_pc_sor_forward -pc_mg_galerkin  
-snes_vi_monitor -ksp_monitor_true_residual -snes_atol 1.e-11  
-mg_levels_ksp_monitor -mg_levels_fieldsplit_ksp_monitor  
-mg_levels_ksp_max_it 2 -mg_levels_fieldsplit_ksp_max_it 5
```

# Programming with Options

## ex55: Allen-Cahn problem in 2D

Run flexible GMRES with 5 levels of multigrid as the preconditioner

```
./ex55 -ksp_type fgmres -pc_type mg -pc_mg_levels 5  
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```

Use the Galerkin process to compute the coarse grid operators

```
-pc_mg_galerkin
```

Use SVD as the coarse grid saddle point solver

```
-mg_coarse_ksp_type preonly -mg_coarse_pc_type svd
```

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# Programming with Options

## ex55: Allen-Cahn problem in 2D

Smoother: Flexible GMRES (2 iterates) with a Schur complement PC

```
-mg_levels_ksp_type fgmres -mg_levels_pc_fieldsplit_detect_saddle_point  
-mg_levels_ksp_max_it 2 -mg_levels_pc_type fieldsplit  
-mg_levels_pc_fieldsplit_type schur  
-mg_levels_pc_fieldsplit_factorization_type full  
-mg_levels_pc_fieldsplit_schur_precondition diag
```

Schur complement solver: GMRES (5 iterates) with no preconditioner

```
-mg_levels_fieldsplit_1_ksp_type gmres  
-mg_levels_fieldsplit_1_pc_type none -mg_levels_fieldsplit_ksp_max_it 5
```

Schur complement action: Use only the lower diagonal part of A00

```
-mg_levels_fieldsplit_0_ksp_type preonly  
-mg_levels_fieldsplit_0_pc_type sor  
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# Programming with Options

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```

# Magma FAS Options

## Top level

```
-snes_monitor -snes_converged_reason
-snes_type fas -snes_fas_type full -snes_fas_levels 4
-fas_levels_3_snes_monitor -fas_levels_3_snes_converged_reason
-fas_levels_3_snes_atol 1.0e-9 -fas_levels_3_snes_max_it 2
-fas_levels_3_snes_type newtonls -fas_levels_3_snes_linesearch_type bt
-fas_levels_3_snes_fd_color -fas_levels_3_snes_fd_color_use_mat
-fas_levels_3_ksp_rtol 1.0e-10 -mat_coloring_type greedy
-fas_levels_3_ksp_gmres_restart 50 -fas_levels_3_ksp_max_it 200
-fas_levels_3_pc_type fieldsplit
-fas_levels_3_pc_fieldsplit_0_fields 0,2
-fas_levels_3_pc_fieldsplit_1_fields 1
-fas_levels_3_pc_fieldsplit_type schur
-fas_levels_3_pc_fieldsplit_schur_precondition selfp
-fas_levels_3_pc_fieldsplit_schur_factorization_type full
-fas_levels_3_fieldsplit_0_pc_type lu
-fas_levels_3_fieldsplit_pressure_ksp_rtol 1.0e-9
-fas_levels_3_fieldsplit_pressure_pc_type gamg
-fas_levels_3_fieldsplit_pressure_ksp_gmres_restart 100
-fas_levels_3_fieldsplit_pressure_ksp_max_it 200
```

# Magma FAS Options

## 2nd level

```
-fas_levels_2_snes_monitor -fas_levels_2_snes_converged_reason
-fas_levels_2_snes_atol 1.0e-9 -fas_levels_2_snes_max_it 2
-fas_levels_2_snes_type newtonls -fas_levels_2_snes_linesearch_type bt
-fas_levels_2_snes_fd_color -fas_levels_2_snes_fd_color_use_mat
-fas_levels_2_ksp_rtol 1.0e-10 -fas_levels_2_ksp_gmres_restart 50
-fas_levels_2_pc_type fieldsplit
-fas_levels_2_pc_fieldsplit_0_fields 0,2
-fas_levels_2_pc_fieldsplit_1_fields 1
-fas_levels_2_pc_fieldsplit_type schur
-fas_levels_2_pc_fieldsplit_schur_precondition selfp
-fas_levels_2_pc_fieldsplit_schur_factorization_type full
-fas_levels_2_fieldsplit_0_pc_type lu
-fas_levels_2_fieldsplit_pressure_ksp_rtol 1.0e-9
-fas_levels_2_fieldsplit_pressure_pc_type gamg
-fas_levels_2_fieldsplit_pressure_ksp_gmres_restart 100
-fas_levels_2_fieldsplit_pressure_ksp_max_it 200
```

# Magma FAS Options

## 1st level

```
-fas_levels_1_snes_monitor -fas_levels_1_snes_converged_reason
-fas_levels_1_snes_atol 1.0e-9
-fas_levels_1_snes_type newtonls -fas_levels_1_snes_linesearch_type bt
-fas_levels_1_snes_fd_color -fas_levels_1_snes_fd_color_use_mat
-fas_levels_1_ksp_rtol 1.0e-10 -fas_levels_1_ksp_gmres_restart 50
-fas_levels_1_pc_type fieldsplit
-fas_levels_1_pc_fieldsplit_0_fields 0,2
-fas_levels_1_pc_fieldsplit_1_fields 1
-fas_levels_1_pc_fieldsplit_type schur
-fas_levels_1_pc_fieldsplit_schur_precondition selfp
-fas_levels_1_pc_fieldsplit_schur_factorization_type full
-fas_levels_1_fieldsplit_0_pc_type lu
-fas_levels_1_fieldsplit_pressure_ksp_rtol 1.0e-9
-fas_levels_1_fieldsplit_pressure_pc_type gamg
```

## Coarse level

```
-fas_coarse_snes_monitor -fas_coarse_snes_converged_reason
-fas_coarse_snes_atol 1.0e-9
-fas_coarse_snes_type newtonls -fas_coarse_snes_linesearch_type bt
-fas_coarse_snes_fd_color -fas_coarse_snes_fd_color_use_mat
-fas_coarse_ksp_rtol 1.0e-10 -fas_coarse_ksp_gmres_restart 50
-fas_coarse_pc_type fieldsplit
-fas_coarse_pc_fieldsplit_0_fields 0,2
-fas_coarse_pc_fieldsplit_1_fields 1
-fas_coarse_pc_fieldsplit_type schur
-fas_coarse_pc_fieldsplit_schur_precondition selfp
-fas_coarse_pc_fieldsplit_schur_factorization_type full
-fas_coarse_fieldsplit_0_pc_type lu
-fas_coarse_fieldsplit_pressure_ksp_rtol 1.0e-9
-fas_coarse_fieldsplit_pressure_pc_type gamg
```

# Outline

- 1 Composition Strategies
- 2 Algebra
- 3 Solvers
- 4 Examples
- 5 Convergence
- 6 Further Questions

# Abstract System

Our prototypical nonlinear equation is:

$$\mathbf{F}(\mathbf{x}) = \mathbf{b}$$

and we define the residual as

$$\mathbf{r}(\mathbf{x}) = \mathbf{F}(\mathbf{x}) - \mathbf{b}$$



# Abstract System

Our prototypical nonlinear equation is:

$$\mathbf{F}(\mathbf{x}) = \mathbf{b}$$

and we define the (linear) residual as

$$\mathbf{r}(\mathbf{x}) = \mathbf{Ax} - \mathbf{b}$$

# Linear Left Preconditioning

The modified equation becomes

$$P^{-1} (A\mathbf{x} - \mathbf{b}) = 0 \quad (1)$$

# Linear Left Preconditioning

The modified defect correction equation becomes

$$P^{-1} (A\mathbf{x}_i - \mathbf{b}) = \mathbf{x}_{i+1} - \mathbf{x}_i \quad (2)$$

# Additive Combination

The linear iteration

$$\mathbf{x}_{i+1} = \mathbf{x}_i - (\alpha P^{-1} + \beta Q^{-1})(A\mathbf{x}_i - \mathbf{b}) \quad (3)$$

becomes the nonlinear iteration

# Additive Combination

The linear iteration

$$\mathbf{x}_{i+1} = \mathbf{x}_i - (\alpha \mathbf{P}^{-1} + \beta \mathbf{Q}^{-1}) \mathbf{r}_i \quad (4)$$

becomes the nonlinear iteration

# Additive Combination

The linear iteration

$$\mathbf{x}_{i+1} = \mathbf{x}_i - (\alpha \mathbf{P}^{-1} + \beta \mathbf{Q}^{-1}) \mathbf{r}_i \quad (4)$$

becomes the nonlinear iteration

$$\mathbf{x}_{i+1} = \mathbf{x}_i + \alpha(\mathcal{N}(\mathbf{F}, \mathbf{x}_i, \mathbf{b}) - \mathbf{x}_i) + \beta(\mathcal{M}(\mathbf{F}, \mathbf{x}_i, \mathbf{b}) - \mathbf{x}_i) \quad (5)$$

# Nonlinear Left Preconditioning

From the additive combination, we have

$$P^{-1}\mathbf{r} \implies \mathbf{x}_j - \mathcal{N}(\mathbf{F}, \mathbf{x}_j, \mathbf{b}) \quad (6)$$

so we define the preconditioning operation as

$$\mathbf{r}_L \equiv \mathbf{x} - \mathcal{N}(\mathbf{F}, \mathbf{x}, \mathbf{b}) \quad (7)$$

# Multiplicative Combination

The linear iteration

$$\mathbf{x}_{i+1} = \mathbf{x}_i - (P^{-1} + Q^{-1} - Q^{-1}AP^{-1})\mathbf{r}_i \quad (8)$$

becomes the nonlinear iteration



# Multiplicative Combination

The linear iteration

$$\mathbf{x}_{i+1/2} = \mathbf{x}_i - P^{-1} \mathbf{r}_i \quad (9)$$

$$\mathbf{x}_i = \mathbf{x}_{i+1/2} - Q^{-1} \mathbf{r}_{i+1/2} \quad (10)$$

becomes the nonlinear iteration

# Multiplicative Combination

The linear iteration

$$\mathbf{x}_{i+1/2} = \mathbf{x}_i - P^{-1} \mathbf{r}_i \quad (9)$$

$$\mathbf{x}_i = \mathbf{x}_{i+1/2} - Q^{-1} \mathbf{r}_{i+1/2} \quad (10)$$

becomes the nonlinear iteration

$$\mathbf{x}_{i+1} = \mathcal{M}(\mathbf{F}, \mathcal{N}(\mathbf{F}, \mathbf{x}_i, \mathbf{b}), \mathbf{b}) \quad (11)$$

# Nonlinear Right Preconditioning

For the linear case, we have

$$AP^{-1}\mathbf{y} = \mathbf{b} \quad (12)$$

$$\mathbf{x} = P^{-1}\mathbf{y} \quad (13)$$

so we define the preconditioning operation as

$$\mathbf{y} = \mathcal{M}(\mathbf{F}(\mathcal{N}(\mathcal{F}, \cdot, \mathbf{b})), \mathbf{x}_i, \mathbf{b}) \quad (14)$$

$$\mathbf{x} = \mathcal{N}(\mathbf{F}, \mathbf{y}, \mathbf{b}) \quad (15)$$

# Nonlinear Preconditioning

Type	Sym	Statement	Abbreviation
Additive	+	$\mathbf{x} + \alpha(\mathcal{M}(\mathbf{F}, \mathbf{x}, \mathbf{b}) - \mathbf{x})$ $+ \beta(\mathcal{N}(\mathbf{F}, \mathbf{x}, \mathbf{b}) - \mathbf{x})$	$\mathcal{M} + \mathcal{N}$
Multiplicative	*	$\mathcal{M}(\mathbf{F}, \mathcal{N}(\mathbf{F}, \mathbf{x}, \mathbf{b}), \mathbf{b})$	$\mathcal{M} * \mathcal{N}$
Left Prec.	$-_L$	$\mathcal{M}(\mathbf{x} - \mathcal{N}(\mathbf{F}, \mathbf{x}, \mathbf{b}), \mathbf{x}, \mathbf{b})$	$\mathcal{M} -_L \mathcal{N}$
Right Prec.	$-_R$	$\mathcal{M}(\mathbf{F}(\mathcal{N}(\mathbf{F}, \mathbf{x}, \mathbf{b})), \mathbf{x}, \mathbf{b})$	$\mathcal{M} -_R \mathcal{N}$
Inner Lin. Inv.	\	$\mathbf{y} = \mathbf{J}(\mathbf{x})^{-1} \mathbf{r}(\mathbf{x}) = \mathbf{K}(\mathbf{J}(\mathbf{x}), \mathbf{y}_0, \mathbf{b})$	$\mathcal{N} \setminus \mathbf{K}$

Composing Scalable Nonlinear Algebraic Solvers (Brune et al. 2015)

# Outline

- 1 Composition Strategies
- 2 Algebra**
- 3 Solvers
- 4 Examples
- 5 Convergence
- 6 Further Questions

# Additive Composition

We can represent the additive update rule

$$\vec{x}_{i+1} = \vec{x}_i + \alpha(\mathcal{M}(\mathcal{F}, \vec{x}_i, ) - \vec{x}_i) + \beta(\mathcal{N}(\mathcal{F}, \vec{x}_i, ) - \vec{x}_i)$$

as

$$\vec{x}_{i+1} = (\mathcal{M} + \mathcal{N})(\mathcal{F}, \vec{x}_i, )$$

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as

$$\vec{x}_{i+1} = (\mathcal{M} + \mathcal{N})(\mathcal{F}, \vec{x}_i, )$$

# Additive Composition

If  $\alpha = \beta = 1$ , this has an identity operation  $0$  (the identity map),

$$\begin{aligned}\vec{x}_{i+1} &= \vec{x}_i + \alpha(\mathcal{M}(\mathcal{F}, \vec{x}_i, ) - \vec{x}_i) + \beta(\mathbf{0}(\mathcal{F}, \vec{x}_i, ) - \vec{x}_i) \\ &= \vec{x}_i + (\mathcal{M}(\mathcal{F}, \vec{x}_i, ) - \vec{x}_i) + (\vec{x}_i - \vec{x}_i) \\ &= \mathcal{M}(\mathcal{F}, \vec{x}_i, )\end{aligned}$$

so that  $(\mathcal{M}, +)$  is an abelian group.



# Multiplicative Composition

We can represent the multiplicative update rule

$$\vec{x}_{i+1} = \mathcal{M}(\mathcal{F}, \mathcal{N}(\mathcal{F}, \vec{x}_i), )$$

as

$$\vec{x}_{i+1} = (\mathcal{M} * \mathcal{N})(\mathcal{F}, \vec{x}_i, )$$

which is clearly associative.

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which is clearly associative.

# Algebraic Structure

If we look at the distributive case,

$$\vec{x}_{i+1} = ((\mathcal{M} + \mathcal{N}) * \mathcal{Q})(\mathcal{F}, \vec{x}_i, )$$

we get the update rule

$$\begin{aligned} \vec{x}_{i+1} = \vec{x}_i &+ \alpha(\mathcal{M}(\mathcal{F}, \mathcal{Q}(\mathcal{F}, \vec{x}_i, ), ) - \vec{x}_i) \\ &+ \beta(\mathcal{N}(\mathcal{F}, \mathcal{Q}(\mathcal{F}, \vec{x}_i, ), ) - \vec{x}_i) \end{aligned}$$

# Algebraic Structure

If we look at the distributive case,

$$\vec{x}_{i+1} = ((\mathcal{M} + \mathcal{N}) * \mathcal{Q})(\mathcal{F}, \vec{x}_i,)$$

which we can write as

$$\vec{x}_{i+1} = (\mathcal{M} * \mathcal{Q} + \mathcal{N} * \mathcal{Q})(\mathcal{F}, \vec{x}_i,)$$

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Note however that

$$\mathcal{Q} * (\mathcal{M} + \mathcal{N}) \neq \mathcal{Q} * \mathcal{M} + \mathcal{Q} * \mathcal{N}$$

which means  $(\mathcal{M}, +, *)$  is a **near ring**.

# Algebraic Structure

If we combine it using our left NPC operation

$$\vec{x}_{i+1} = ((\mathcal{M} + \mathcal{N}) -_L \mathcal{Q})(\mathcal{F}, \vec{x}_i, )$$

we get the update rule

$$\begin{aligned} \vec{x}_{i+1} = \vec{x}_i + & \alpha(\mathcal{M}(\vec{x} - \mathcal{Q}(\mathcal{F}, \vec{x}_i, ), \vec{x}_i, ) - \vec{x}_i) \\ & + \beta(\mathcal{N}(\vec{x} - \mathcal{Q}(\mathcal{F}, \vec{x}_i, ), \vec{x}_i, ) - \vec{x}_i) \end{aligned}$$

# Algebraic Structure

If we combine it using our left NPC operation

$$\vec{x}_{i+1} = ((\mathcal{M} + \mathcal{N}) -_L \mathcal{Q})(\mathcal{F}, \vec{x}_i, )$$

which we can write as

$$\vec{x}_{i+1} = (\mathcal{M} -_L \mathcal{Q} + \mathcal{N} -_L \mathcal{Q})(\mathcal{F}, \vec{x}_i, )$$

we we again have a near ring.

# Algebraic Structure

In the same way, we can combine it with our right NPC operation

$$\vec{x}_{i+1} = ((\mathcal{M} + \mathcal{N}) -_R \mathcal{Q})(\mathcal{F}, \vec{x}_i, )$$

and get the update rule

$$\begin{aligned} \vec{x}_{i+1} = \vec{x}_i + & \alpha(\mathcal{M}(\mathcal{F}(\mathcal{Q}(\mathcal{F}, \vec{x}_i, )), \vec{x}_i, ) - \vec{x}_i) \\ & + \beta(\mathcal{N}(\mathcal{F}(\mathcal{Q}(\mathcal{F}, \vec{x}_i, )), \vec{x}_i, ) - \vec{x}_i) \end{aligned}$$



# Algebraic Structure

In the same way, we can combine it with our right NPC operation

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which we can write as

$$\vec{x}_{i+1} = (\mathcal{M} -_R \mathcal{Q} + \mathcal{N} -_R \mathcal{Q})(\mathcal{F}, \vec{x}_i, )$$

we we again have a near ring.

# Polynomial solution through decomposition

Let us solve

$$x^8 - 4x^6 - 11x^4 + 30x^2 + 56 = 0$$

which can be decomposed

$$(x^4 - 4x^3 - 11x^2 + 30x + 56) \circ x^2 = 0$$

$$(x^2 - 15x + 56) \circ (x^2 - 2x) \circ x^2 = 0.$$

# Polynomial solution through decomposition

Let us solve

$$x^8 - 4x^6 - 11x^4 + 30x^2 + 56 = 0$$

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$$(x^4 - 4x^3 - 11x^2 + 30x + 56) \circ x^2 = 0$$

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# Polynomial solution through decomposition

Let us solve

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which can be decomposed

$$\begin{aligned}(x^4 - 4x^3 - 11x^2 + 30x + 56) \circ x^2 &= 0 \\ (x^2 - 15x + 56) \circ (x^2 - 2x) \circ x^2 &= 0.\end{aligned}$$

We solve the first equation, to get

$$x_{00} = 7 \quad x_{01} = 8,$$

# Polynomial solution through decomposition

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$$x^8 - 4x^6 - 11x^4 + 30x^2 + 56 = 0$$

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and then solve

$$x^2 - 2x = 7 \text{ or } 8,$$

to get

$$x_{10} = 1 + 2\sqrt{2} \quad x_{11} = 1 - 2\sqrt{2} \quad x_{12} = 4 \quad x_{13} = -2.$$

# Polynomial solution through decomposition

Let us solve

$$x^8 - 4x^6 - 11x^4 + 30x^2 + 56 = 0$$

which can be decomposed

$$\begin{aligned} (x^4 - 4x^3 - 11x^2 + 30x + 56) \circ x^2 &= 0 \\ (x^2 - 15x + 56) \circ (x^2 - 2x) \circ x^2 &= 0. \end{aligned}$$

At the end, we have  $x^2 = x_{1j}$ , so that

$$\begin{aligned} x_{0,1,2,3} &= \pm \sqrt{1 \pm 2\sqrt{2}} \\ x_{5,6} &= \pm 2 \\ x_{7,8} &= \pm i\sqrt{2}. \end{aligned}$$

There is an  $\mathcal{O}(d \ln d)$  algorithm for finding the unique decomposition.

# Outline

1 Composition Strategies

2 Algebra

**3 Solvers**

- Richardson
- Newton
- Generalized Broyden

4 Examples

5 Convergence

6 Further Questions

# Outline

## 3 Solvers

- Richardson
- Newton
- Generalized Broyden



# Nonlinear Richardson

1: **procedure** NRICH( $\mathbf{F}, \mathbf{x}_i, \mathbf{b}$ )

$\mathbf{d} := -\mathbf{r}(\mathbf{x}_i)$

3:  $\mathbf{x}_{i+1} = \mathbf{x}_i + \lambda \mathbf{d}$

▷  $\lambda$  determined by line search

4: **end procedure**

5: **return**  $\mathbf{x}_{i+1}$

L Adds line search to  $\mathcal{N}$

R Uses  $\mathcal{N}$  to improve search direction

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# Line Search

Equivalent to NRICH  ${}_L \mathcal{N}$ :

NRICH  ${}_L \mathcal{N}$

# Line Search

Equivalent to NRICH  $_{-L} \mathcal{N}$ :

NRICH  $_{-L} \mathcal{N}$

NRICH(**x** -  $\mathcal{N}(\mathbf{F}, \mathbf{x}, \mathbf{b})$ , **x**, **b**)

# Line Search

Equivalent to NRICH  $_{-L} \mathcal{N}$ :

NRICH  $_{-L} \mathcal{N}$

NRICH( $\mathbf{x} - \mathcal{N}(\mathbf{F}, \mathbf{x}, \mathbf{b}), \mathbf{x}, \mathbf{b}$ )

$$\mathbf{x}_{i+1} = \mathbf{x}_i - \lambda \mathbf{r}_L$$

# Line Search

Equivalent to NRICH  $_{-L} \mathcal{N}$ :

NRICH  $_{-L} \mathcal{N}$

NRICH( $\mathbf{x} - \mathcal{N}(\mathbf{F}, \mathbf{x}, \mathbf{b}), \mathbf{x}, \mathbf{b}$ )

$$\mathbf{x}_{i+1} = \mathbf{x}_i - \lambda \mathbf{r}_L$$

$$\mathbf{x}_{i+1} = \mathbf{x}_i + \lambda(\mathcal{N}(\mathbf{F}, \mathbf{x}_i, \mathbf{b}) - \mathbf{x}_i)$$

# Line Search

Equivalent to NRICH  $_{-L} \mathcal{N}$ :

$$\begin{aligned} & \text{NRICH }_{-L} \mathcal{N} \\ & \text{NRICH}(\mathbf{x} - \mathcal{N}(\mathbf{F}, \mathbf{x}, \mathbf{b}), \mathbf{x}, \mathbf{b}) \\ & \mathbf{x}_{i+1} = \mathbf{x}_i - \lambda \mathbf{r}_L \\ & \mathbf{x}_{i+1} = \mathbf{x}_i + \lambda(\mathcal{N}(\mathbf{F}, \mathbf{x}_i, \mathbf{b}) - \mathbf{x}_i) \end{aligned}$$

Let  $R_1$  be Richardson iteration with a unit step scaling (no damping). Then we have

$$\mathcal{M} \text{ }_{-L} \mathbb{R}_1 = \mathcal{M} \quad \mathbb{R}_1 \text{ }_{-L} \mathcal{M} = \mathcal{M} \quad (16)$$

so that  $\mathbb{R}_1$  is the identity operation for left preconditioning, whereas for right preconditioning this is just the identity map.

# Outline

## 3 Solvers

- Richardson
- **Newton**
- Generalized Broyden



# Newton-Krylov

```
1: procedure  $\mathcal{N}\backslash\mathcal{K}(\mathbf{F}, \mathbf{x}_i, \mathbf{b})$   
2:    $\mathbf{d} = \mathbf{J}(\mathbf{x}_i)^{-1} \mathbf{r}(\mathbf{x}_i, \mathbf{b})$   
3:    $\mathbf{x}_{i+1} = \mathbf{x}_i + \lambda \mathbf{d}$   
4: end procedure  
5: return  $\mathbf{x}_{i+1}$ 
```

- ▷ solve by Krylov method
- ▷  $\lambda$  determined by line search

# Left Preconditioned Newton-Krylov

- 1: **procedure**  $\mathcal{N}\backslash\mathcal{K}(\mathbf{x} - \mathcal{M}(\mathbf{F}, \mathbf{x}, \mathbf{b}), \mathbf{x}_i, 0)$
- 2:      $\mathbf{d} = \frac{\partial(\mathbf{x}_i - \mathcal{M}(\mathbf{F}, \mathbf{x}_i, \mathbf{b}))}{\partial \mathbf{x}_i}^{-1} (\mathbf{x}_i - \mathcal{M}(\mathbf{F}, \mathbf{x}_i, \mathbf{b}))$
- 3:      $\mathbf{x}_{i+1} = \mathbf{x}_i + \lambda \mathbf{d}$
- 4: **end procedure**
- 5: **return**  $\mathbf{x}_{i+1}$

# Jacobian Computation

$$\frac{\partial(\mathbf{x} - \mathcal{M}(\mathbf{F}, \mathbf{x}_i, \mathbf{b}))}{\mathbf{x}_i} = I - \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{x}_i, \mathbf{b})}{\partial \mathbf{x}_i},$$

Direct differencing would require

- one inner nonlinear iteration per **Krylov** iteration.

# Jacobian Computation

$$\frac{\partial(\mathbf{x} - \mathcal{M}(\mathbf{F}, \mathbf{x}_i, \mathbf{b}))}{\mathbf{x}_i} = I - \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{x}_i, \mathbf{b})}{\partial \mathbf{x}_i},$$

Direct differencing would require

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# Jacobian Computation

**Impractical!**

$$\frac{\partial(\mathbf{x} - \mathcal{M}(\mathbf{F}, \mathbf{x}_i, \mathbf{b}))}{\mathbf{x}_i} = I - \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{x}_i, \mathbf{b})}{\partial \mathbf{x}_i},$$

Direct differencing would require

- one inner nonlinear iteration per **Krylov** iteration.

# Jacobian Computation

## Approximation for NASM

$$\frac{\partial(\mathbf{x} - \mathcal{M}(\mathbf{F}, \mathbf{x}, \mathbf{b}))}{\partial \mathbf{x}} = \frac{\partial(\mathbf{x} - (\mathbf{x} - \sum_b \mathbf{J}_b(\mathbf{x}_b)^{-1} \mathbf{F}_b(\mathbf{x}_b)))}{\partial \mathbf{x}}$$

$$\approx \sum_b \mathbf{J}_b(\mathbf{x}_{b^*})^{-1} \mathbf{J}(\mathbf{x})$$

This would require

- one inner nonlinear iteration
- small number of block solves

per **outer nonlinear** iteration.

Nonlinearly preconditioned inexact Newton algorithms (X.-C. Cai and Keyes 2002)

# Right Preconditioned Newton-Krylov

```
1: procedure NK( $\mathbf{F}(\mathcal{M}(\mathbf{F}, \cdot, \mathbf{b}))$ ,  $\mathbf{y}_i$ ,  $\mathbf{b}$ )  
2:    $\mathbf{x}_i = \mathcal{M}(\mathbf{F}, \mathbf{y}_i, \mathbf{b})$   
3:    $\mathbf{d} = J(\mathbf{x})^{-1} \mathbf{r}(\mathbf{x}_i)$   
4:    $\mathbf{x}_{i+1} = \mathbf{x}_i + \lambda \mathbf{d}$   
5: end procedure  
6: return  $\mathbf{x}_{i+1}$ 
```

▷  $\lambda$  determined by line search

# Jacobian Computation

## First-Order Approximation

Only the action of the original Jacobian is needed at first order:

$$\mathbf{y}_{i+1} = \mathbf{y}_i - \lambda \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{y}_i)^{-1}}{\partial \mathbf{y}_i} J(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))^{-1} \mathbf{F}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))$$

$$\mathcal{M}(\mathbf{F}, \mathbf{y}_{i+1}) = \mathcal{M}(\mathbf{F}, \mathbf{y}_i - \lambda \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{y}_i)^{-1}}{\partial \mathbf{y}_i} J(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))^{-1} \mathbf{F}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i)))$$

$$\approx \mathcal{M}(\mathbf{F}, \mathbf{y}_i)$$

$$- \lambda \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{y}_i)}{\partial \mathbf{y}_i} \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{y}_i)^{-1}}{\partial \mathbf{y}_i} J(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))^{-1} \mathbf{F}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))$$

$$= \mathcal{M}(\mathbf{F}, \mathbf{y}_i) - \lambda J(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))^{-1} \mathbf{F}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))$$

$$\mathbf{x}_{i+1} = \mathbf{x}_i - \lambda J(\mathbf{x}_i)^{-1} \mathbf{F}(\mathbf{x}_i)$$

$\mathcal{N} \setminus K -_R \vec{M}$  is equivalent to  $\mathcal{N} \setminus K * \vec{M}$  at first order

A parallel adaptive nonlinear elimination preconditioned inexact Newton method for transonic full



# Jacobian Computation

## First-Order Approximation

Only the action of the original Jacobian is needed at first order:

$$\mathbf{y}_{i+1} = \mathbf{y}_i - \lambda \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{y}_i)^{-1}}{\partial \mathbf{y}_i} \mathbf{J}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))^{-1} \mathbf{F}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))$$

$$\mathcal{M}(\mathbf{F}, \mathbf{y}_{i+1}) = \mathcal{M}(\mathbf{F}, \mathbf{y}_i - \lambda \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{y}_i)^{-1}}{\partial \mathbf{y}_i} \mathbf{J}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))^{-1} \mathbf{F}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i)))$$

$$\approx \mathcal{M}(\mathbf{F}, \mathbf{y}_i)$$

$$- \lambda \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{y}_i)}{\partial \mathbf{y}_i} \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{y}_i)^{-1}}{\partial \mathbf{y}_i} \mathbf{J}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))^{-1} \mathbf{F}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))$$

$$= \mathcal{M}(\mathbf{F}, \mathbf{y}_i) - \lambda \mathbf{J}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))^{-1} \mathbf{F}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i))$$

$$\mathbf{x}_{i+1} = \mathbf{x}_i - \lambda \mathbf{J}(\mathbf{x}_i)^{-1} \mathbf{F}(\mathbf{x}_i)$$

$\mathcal{N} \setminus \mathbf{K} -_R \vec{M}$  is equivalent to  $\mathcal{N} \setminus \mathbf{K} * \vec{M}$  at first order

A parallel adaptive nonlinear elimination preconditioned inexact Newton method for transonic full

# Jacobian Computation

## Direct Approximation

$$\begin{aligned}\mathbf{F}(\mathcal{M}(\mathbf{F}, \mathbf{y}_i, \mathbf{b})) &= J(\mathcal{M}(\mathbf{F}, \mathbf{y}_i, \mathbf{b})) \frac{\partial \mathcal{M}(\mathbf{F}, \mathbf{y}_i, \mathbf{b})}{\partial \mathbf{y}_i} (\mathbf{y}_{i+1} - \mathbf{y}_i) \\ &\approx J(\mathcal{M}(\mathbf{F}, \mathbf{y}_i, \mathbf{b})) (\mathcal{M}(\mathbf{F}, \mathbf{y}_i + \mathbf{d}, \mathbf{b}) - \mathbf{x}_i)\end{aligned}$$

- Solve for  $\mathbf{d}$
- Requires inner nonlinear solve for each Krylov iterate
- Needs FGMRES

On nonlinear preconditioners in Newton-Krylov methods for unsteady flows (Birken and Jameson 2010)

# Outline

## 3 Solvers

- Richardson
- Newton
- Generalized Broyden

# Anderson

- 1: **procedure** ANDERSON( $\mathbf{F}$ ,  $\mathbf{x}_i$ ,  $\mathbf{b}$ )
- 2:      $\gamma_i = (\mathbf{F}_i^T \mathbf{F}_i)^{-1} \mathbf{F}_i^T \mathbf{r}(\mathbf{x}_i, \mathbf{b})$
- 3:      $\mathbf{x}_{i+1} = \mathbf{x}_i + \beta \mathbf{r}(\mathbf{x}_i, \mathbf{b}) - (\mathbf{x}_k + \beta \mathbf{F}_k) \gamma_k$
- 4: **end procedure**
- 5: **return**  $\mathbf{x}_{i+1}$

▷ solve LS by SVD

Iterative procedures for nonlinear integral equations (Anderson 1965)

# Generalized Broyden

- 1: **procedure** GB( $\mathbf{F}$ ,  $\mathbf{x}_i$ ,  $\mathbf{b}$ )
- 2:      $\gamma_i = (\mathbf{F}_i^T \mathbf{F}_i)^{-1} \mathbf{F}_i^T \mathbf{r}(\mathbf{x}_i, \mathbf{b})$  ▷ solve LS by SVD
- 3:      $\mathbf{x}_{i+1} = \mathbf{x}_i - \mathbf{G}_0 \mathbf{r}(\mathbf{x}_i, \mathbf{b}) - (\mathbb{X}_k - \mathbf{G}_0 \mathbf{F}_k) \gamma_k$
- 4: **end procedure**
- 5: **return**  $\mathbf{x}_{i+1}$

Two classes of multisequant methods for nonlinear acceleration (Fang and Saad 2009)

# Left Preconditioned Generalized Broyden

- 1: **procedure** GB( $\mathbf{x} - \vec{M}(\mathbf{F}, \mathbf{x}, \mathbf{b}), \mathbf{x}_i, \mathbf{b}$ )
- 2:      $\gamma_i = (\mathbf{F}_i^T \mathbf{F}_i)^{-1} \mathbf{F}_i^T (\mathbf{x} - \vec{M}(\mathbf{F}, \mathbf{x}, \mathbf{b}))$      ▷ solve LS by SVD
- 3:      $\mathbf{x}_{i+1} = \mathbf{x}_i - \mathbf{G}_0 (\mathbf{x} - \vec{M}(\mathbf{F}, \mathbf{x}, \mathbf{b})) - (\mathbb{X}_k - \mathbf{G}_0 \mathbf{F}_k) \gamma_k$
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We change the minimization problem,  
since we minimize over different residuals.

Anderson acceleration for fixed-point iterations (Walker and Ni 2011)

# Left Preconditioned Generalized Broyden

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- 4: **end procedure**
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# Right Preconditioned Generalized Broyden

- 1: **procedure** GB( $\mathbf{F}(\mathcal{M}(\mathbf{F}, \cdot, \mathbf{b})), \mathbf{x}_i, \mathbf{b}$ )
- 2:      $\gamma_i = (\mathbf{F}_i^T \mathbf{F}_i)^{-1} \mathbf{F}_i^T \mathbf{r}(\mathcal{M}(\mathbf{x}_i), \mathbf{b})$  ▷ solve LS by SVD
- 3:      $\mathbf{x}_{i+1} = \mathbf{x}_i - \mathbf{G}_0 \mathbf{r}(\mathcal{M}(\mathbf{x}_i), \mathbf{b}) - (\mathbb{X}_k - \mathbf{G}_0 \mathbf{F}_k) \gamma_k$
- 4: **end procedure**
- 5: **return**  $\mathbf{x}_{i+1}$

We change the minimization problem,  
since we use candidate solutions from the inner solver.

Krylov Subspace Acceleration for Nonlinear Multigrid Schemes with Application to Recirculating  
Flow (Washio and Oosterlee 2000)



# Right Preconditioned Generalized Broyden

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# Outline

- 1 Composition Strategies
- 2 Algebra
- 3 Solvers
- 4 Examples**
- 5 Convergence
- 6 Further Questions

I ran NPC on some problem  
and it worked.

# Outline

- 1 Composition Strategies
- 2 Algebra
- 3 Solvers
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# Rate of Convergence

What should be a Rate of Convergence? [Ptak, 1977]:

- 1 It should relate quantities which may be measured or estimated during the actual process
- 2 It should describe accurately in particular the initial stage of the process, not only its asymptotic behavior . . .

$$\|x_{n+1} - x^*\| \leq c \|x_n - x^*\|^q$$

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# Rate of Convergence

What should be a Rate of Convergence? [Ptak, 1977]:

- 1 It should relate quantities which may be measured or estimated during the actual process
- 2 It should describe accurately in particular the initial stage of the process, not only its asymptotic behavior ...

$$\|x_{n+1} - x_n\| \leq \omega(\|x_n - x_{n-1}\|)$$

where we have for all  $r \in (0, R]$

$$\sigma(r) = \sum_{n=0}^{\infty} \omega^{(n)}(r) < \infty$$

# Nondiscrete Induction

Define an approximate set  $Z(r)$ , where  $x^* \in Z(0)$  implies  $f(x^*) = 0$ .



# Nondiscrete Induction

Define an approximate set  $Z(r)$ , where  $x^* \in Z(0)$  implies  $f(x^*) = 0$ .

For Newton's method, we use

$$Z(r) = \left\{ x \mid \|f'(x)^{-1}f(x)\| \leq r, d(f'(x)) \geq h(r), \|x - x_0\| \leq g(r) \right\},$$

where

$$d(A) = \inf_{\|x\| \geq 1} \|Ax\|,$$

and  $h(r)$  and  $g(r)$  are positive functions.

# Nondiscrete Induction

Define an approximate set  $Z(r)$ , where  $x^* \in Z(0)$  implies  $f(x^*) = 0$ .

For  $r \in (0, R]$ ,

$$Z(r) \subset U(Z(\omega(r)), r)$$

implies

$$Z(r) \subset U(Z(0), \sigma(r)).$$

# Nondiscrete Induction

For the fixed point iteration

$$x_{n+1} = Gx_n,$$

if I have

$$x_0 \in Z(r_0)$$

and for  $x \in Z(r)$ ,

$$\begin{aligned}\|Gx - x\| &\leq r \\ Gx &\in Z(\omega(r))\end{aligned}$$

then

# Nondiscrete Induction

For the fixed point iteration

$$x_{n+1} = Gx_n,$$

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and for  $x \in Z(r)$ ,

$$\begin{aligned} \|Gx - x\| &\leq r \\ Gx &\in Z(\omega(r)) \end{aligned}$$

then

$$\begin{aligned} x^* &\in Z(0) \\ x_n &\in Z(\omega^{(n)}(r_0)) \end{aligned}$$

# Nondiscrete Induction

For the fixed point iteration

$$x_{n+1} = Gx_n,$$

if I have

$$x_0 \in Z(r_0)$$

and for  $x \in Z(r)$ ,

$$\begin{aligned}\|Gx - x\| &\leq r \\ Gx &\in Z(\omega(r))\end{aligned}$$

then

$$\begin{aligned}\|x_{n+1} - x_n\| &\leq \omega^{(n)}(r_0) \\ \|x_n - x^*\| &\leq \sigma(\omega^{(n)}(r_0))\end{aligned}$$

# Nondiscrete Induction

For the fixed point iteration

$$x_{n+1} = Gx_n,$$

if I have

$$x_0 \in Z(r_0)$$

and for  $x \in Z(r)$ ,

$$\begin{aligned} \|Gx - x\| &\leq r \\ Gx &\in Z(\omega(r)) \end{aligned}$$

then

$$\begin{aligned} \|x_n - x^*\| &\leq \sigma(\omega(\|x_n - x_{n-1}\|)) \\ &= \sigma(\|x_n - x_{n-1}\|) - \|x_n - x_{n-1}\| \end{aligned}$$

# Newton's Method

$$\omega_{\mathcal{N}}(r) = cr^2$$

# Newton's Method

$$\omega_{\mathcal{N}}(r) = \frac{r^2}{2\sqrt{r^2 + a^2}}$$
$$\sigma_{\mathcal{N}}(r) = r + \sqrt{r^2 + a^2} - a$$

where

$$a = \frac{1}{k_0} \sqrt{1 - 2k_0 r_0},$$

$k_0$  is the (scaled) Lipschitz constant for  $f'$ , and  $r_0$  is the (scaled) initial residual.



# Newton's Method

$$\omega_{\mathcal{N}}(r) = \frac{r^2}{2\sqrt{r^2 + a^2}}$$
$$\sigma_{\mathcal{N}}(r) = r + \sqrt{r^2 + a^2} - a$$

This estimate is *tight* in that the bounds hold with equality for some function  $f$ ,

$$f(x) = x^2 - a^2$$

using initial guess

$$x_0 = \frac{1}{k_0}.$$

Also, if equality is attained for some  $n_0$ , this holds for all  $n \geq n_0$ .

# Newton's Method

$$\omega_{\mathcal{N}}(r) = \frac{r^2}{2\sqrt{r^2 + a^2}}$$
$$\sigma_{\mathcal{N}}(r) = r + \sqrt{r^2 + a^2} - a$$

If  $r \gg a$ , meaning we have an inaccurate guess,

$$\omega_{\mathcal{N}}(r) \approx \frac{1}{2}r,$$

whereas if  $r \ll a$ , meaning we are close to the solution,

$$\omega_{\mathcal{N}}(r) \approx \frac{1}{2a}r^2.$$

# Left vs. Right

Left:

$$\mathcal{F}(x) \implies x - \mathcal{N}(\mathcal{F}, x, b)$$

Right:

$$x \implies y = \mathcal{N}(\mathcal{F}, x, b)$$

Heisenberg vs. Schrödinger Picture

# Left vs. Right

Left:

$$\mathcal{F}(x) \implies x - \mathcal{N}(\mathcal{F}, x, b)$$

Right:

$$x \implies y = \mathcal{N}(\mathcal{F}, x, b)$$

Heisenberg vs. Schrödinger Picture

$\mathcal{M} -_R \mathcal{N}$ 

We start with  $x \in Z(r)$ , apply  $\mathcal{N}$  so that

$$y \in Z(\omega_{\mathcal{N}}(r)),$$

and then apply  $\mathcal{M}$  so that

$$x' \in Z(\omega_{\mathcal{M}}(\omega_{\mathcal{N}}(r))).$$

Thus we have

$$\omega_{\mathcal{M}-_R\mathcal{N}} = \omega_{\mathcal{M}} \circ \omega_{\mathcal{N}}$$

## Non-Abelian

 $\mathcal{N} -_R \text{NRICH}$ 

$$\begin{aligned}
 \omega_{\mathcal{N}} \circ \omega_{\text{NRICH}} &= \frac{1}{2} \frac{r^2}{\sqrt{r^2 + a^2}} \circ cr, \\
 &= \frac{1}{2} \frac{c^2 r^2}{\sqrt{c^2 r^2 + a^2}}, \\
 &= \frac{1}{2} \frac{cr^2}{\sqrt{r^2 + (a/c)^2}}, \\
 &= \frac{1}{2} c \frac{r^2}{\sqrt{r^2 + \tilde{a}^2}},
 \end{aligned}$$

## Non-Abelian

$$\mathcal{N} \text{ --}_R \text{NRICH: } \frac{1}{2} \mathbf{c} \frac{r^2}{\sqrt{r^2 + \tilde{a}^2}}$$

$$\text{NRICH} \text{ --}_R \mathcal{N}$$

$$\begin{aligned} \omega_{\text{NRICH}} \circ \omega_{\mathcal{N}} &= \mathbf{c} r \circ \frac{1}{2} \frac{r^2}{\sqrt{r^2 + a^2}}, \\ &= \frac{1}{2} \mathbf{c} \frac{r^2}{\sqrt{r^2 + a^2}}, \\ &= \frac{1}{2} \mathbf{c} \frac{r^2}{\sqrt{r^2 + a^2}}. \end{aligned}$$

## Non-Abelian

$$\mathcal{N} -_R \text{NRICH}: \frac{1}{2} \mathbf{C} \frac{r^2}{\sqrt{r^2 + \tilde{a}^2}}$$

$$\text{NRICH} -_R \mathcal{N}: \frac{1}{2} \mathbf{C} \frac{r^2}{\sqrt{r^2 + a^2}}$$

The first method also changes the onset of second order convergence.

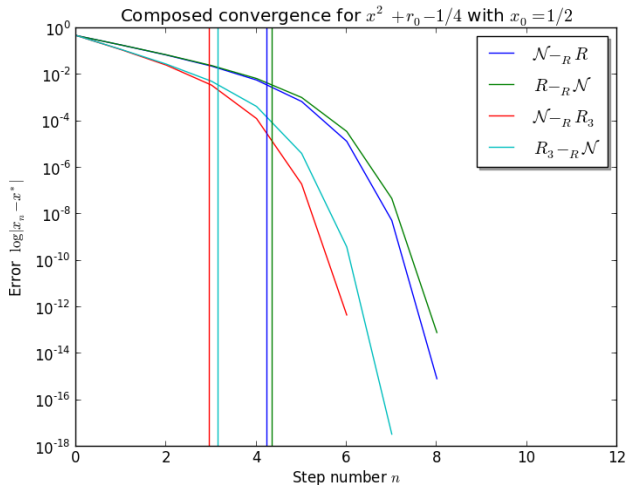


## Example

$$f(x) = x^2 + (0.0894427)^2$$

n	$\ x_{n+1} - x_n\ $	$\ x_{n+1} - x_n\  - w^{(n)}(r_0)$	$\ x_n - x^*\  - s(w^{(n)}(r_0))$
0	1.9990e+00	$< 10^{-16}$	$< 10^{-16}$
1	9.9850e-01	$< 10^{-16}$	$< 10^{-16}$
2	4.9726e-01	$< 10^{-16}$	$< 10^{-16}$
3	2.4470e-01	$< 10^{-16}$	$< 10^{-16}$
4	1.1492e-01	$< 10^{-16}$	$< 10^{-16}$
5	4.5342e-02	$< 10^{-16}$	$< 10^{-16}$
6	1.0251e-02	$< 10^{-16}$	$< 10^{-16}$
7	5.8360e-04	$< 10^{-16}$	$< 10^{-16}$
8	1.9039e-06	$< 10^{-16}$	$< 10^{-16}$
9	2.0264e-11	$< 10^{-16}$	$< 10^{-16}$
10	0.0000e+00	$< 10^{-16}$	$< 10^{-16}$

# Example



Matrix iterations also 1D scalar once you diagonalize

Pták's nondiscrete induction and its application to matrix iterations, Liesen, IMA J. Num. Anal., 2014.

# Outline

- 1 Composition Strategies
- 2 Algebra
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## Further Questions

- Can we say something general about left preconditioning?
- Can the composed iteration have a larger region of convergence?
- What should be a nonlinear smoother?
- Can we usefully predict the convergence of NPC solvers?