

Multigrid Methods

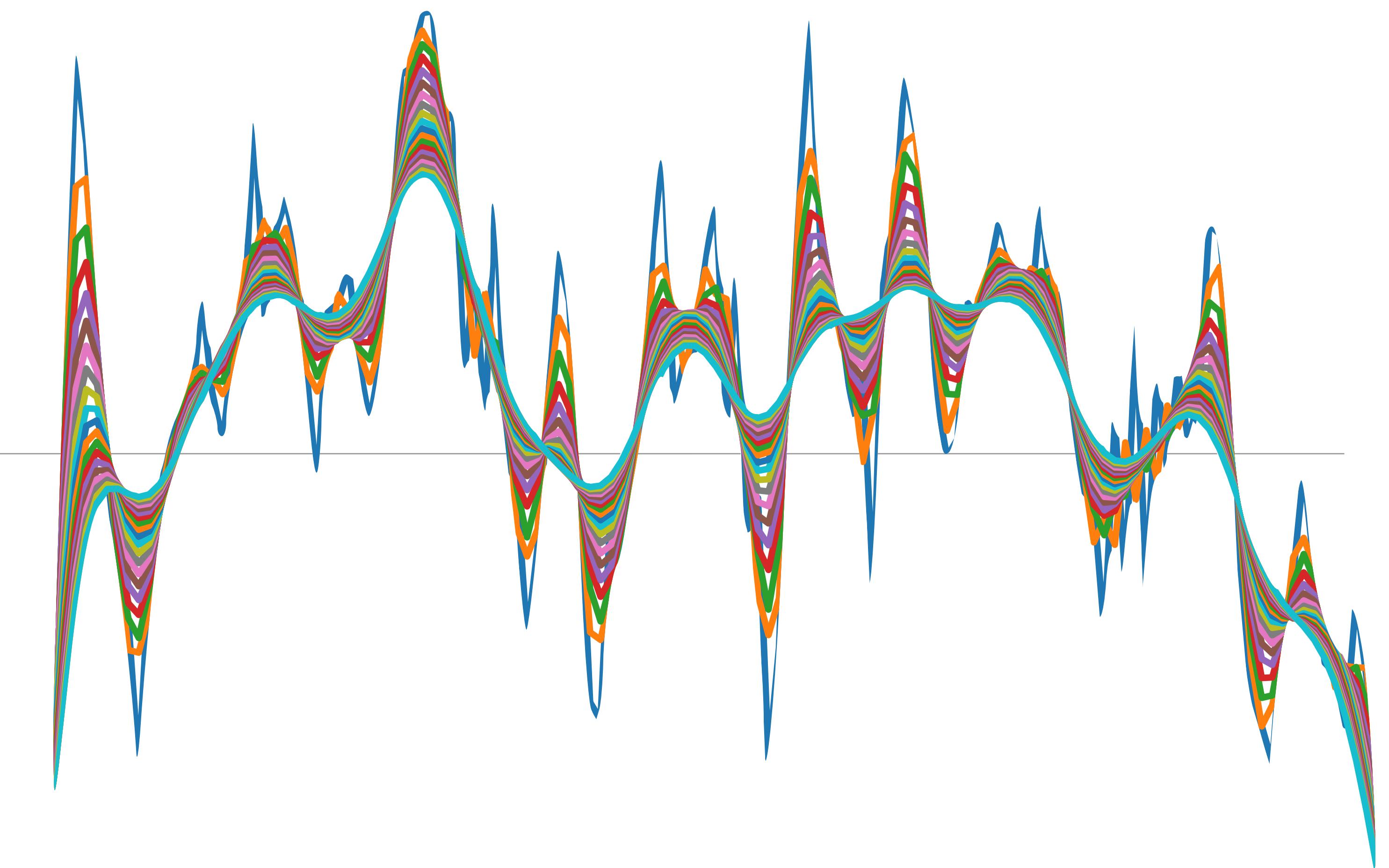
The Basics

2023 Copper Multigrid Conference
April 16, 2023

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(slides by Luke Olson, Department of Computer Science, University of Illinois at Urbana-Champaign)

+ Notebooks 6, 7, 8, 9 , slides



What are we trying to do...

$$A \in \mathbb{R}^{n \times n}$$

- Solve problems of the form

$$Ax = b$$

$$GE : w = O(n^3)$$

- Solve this problem **iteratively**:

$$x_1 \leftarrow x_0 + v$$

$$MG : w = O(n)$$

- Solve this problem **inexpensively**:

- The update should be “good” *(small number of iterations)*
- Finding the update should be “cheap”

Objectives – high level

- Construct a multigrid method for **your** problem
- Interpret the effectiveness of a multigrid method
- Identify *why* a method works — or — *why* a method does not
- Recognize different forms of multigrid, their pitfalls and their uses

Objectives – this session

- **Create** a two level multigrid method
- **Illustrate** the main components of a multigrid method
- **Calculate** the effectiveness of a multigrid method
- **Highlight** some limitations of multigrid
- **Outline** some approaches to fixing multigrid (and why)
- **Identify** key pieces in moving to unstructured problems

A cautionary example

(see slide 9)

Guess and look for
and update

$$x_1 = x_0 + \text{update}$$

Updating with the
error would be **ideal**

Or in another form

$$x_1 = x_0 + e_0 = x_0 + (x^* - x_0) = x^*$$

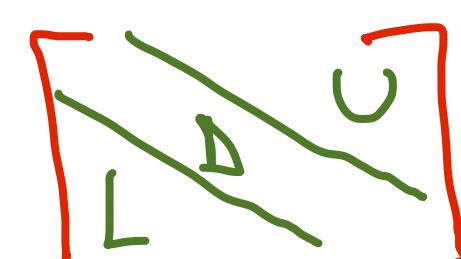
Not practical so...

$$x_1 = x_0 + A^{-1}r_0 = x^*$$

1 iteration

$$x_1 = x_0 + D^{-1}r_0$$

note: $A = D + L + U$



Jacobi ~ 1 SpMV

$(\omega = O(n) \text{ per iteration})$

x^* solution to $Ax = b$

$$e_0 = x^* - x_0$$

error

$$r_0 = b - Ax_0$$

residual

$$= Ae_0 = A(x^* - x_0)$$

$$Ae_0 = r_0$$

error equation

Jacobi Iteration:

$$A \vec{x} = \vec{b}$$

eq. b: $\sum_j a_{kj} x_j = b_j$

Jacobi: $x_a^{\text{new}} = \frac{1}{a_{Bk}} (b_B - \sum_{j \neq i} a_{kj} x_j^{\text{old}})$

$$\vec{x}_1 = D^{-1} (\vec{b} - (L+U) \vec{x}_0)$$

$$\vec{x}_1 = \underline{\vec{x}_0} + \underline{D^{-1} (\vec{b} - (D+L+U) \underline{\vec{x}_0})}$$

$$\vec{x}_1 = \vec{x}_0 + D^{-1} (\vec{b} - A \vec{x}_0)$$

$$\vec{x}_1 = \vec{x}_0 + D^{-1} \vec{r}_0$$

bz

A reminder – projection methods

- Take a guess

- Look for an update that is the “best”:

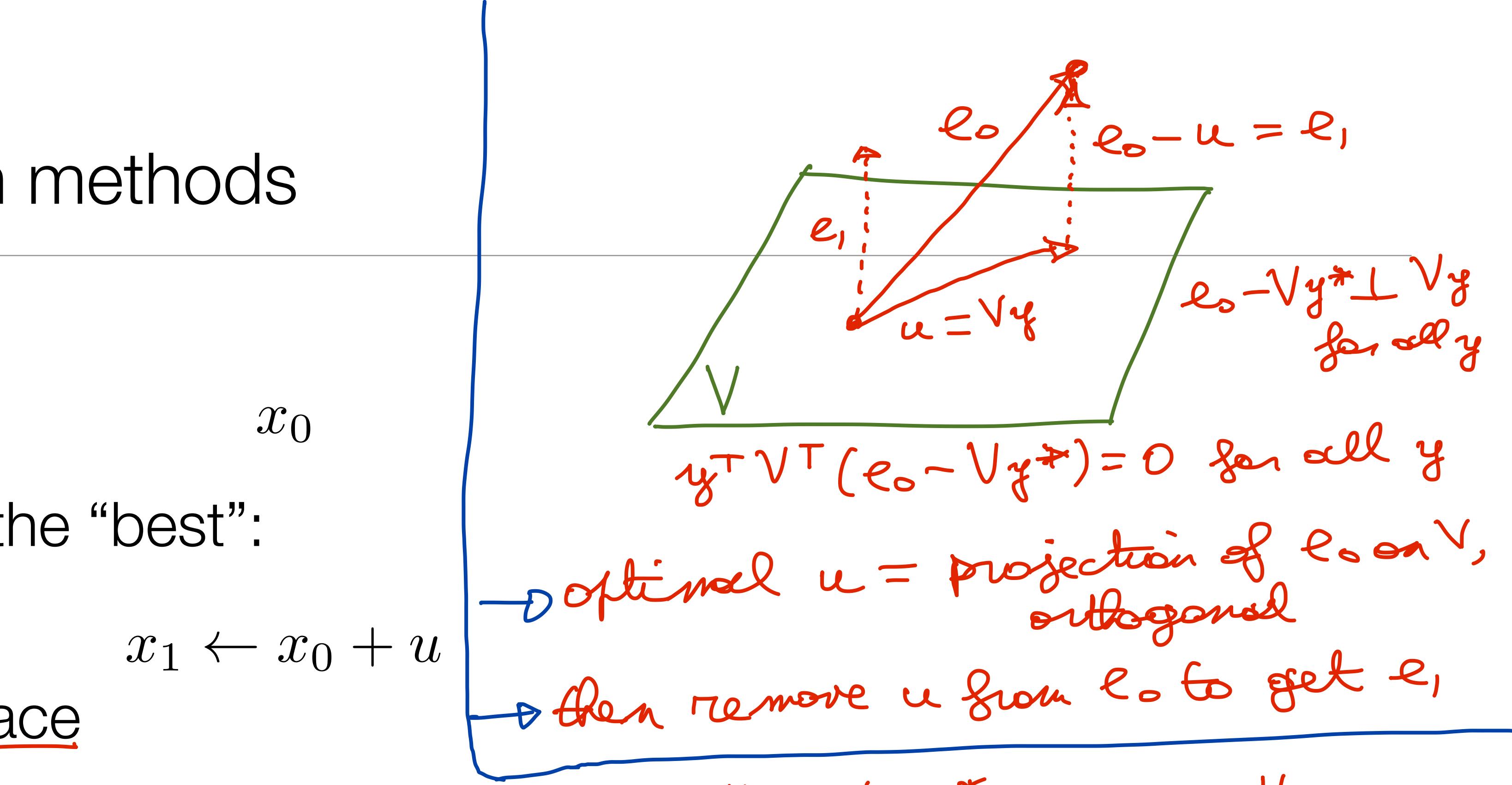
- Minimize over a smaller space

- Then $u = Vy$

- So the update looks like

$$x_1 = x_0 + V \underbrace{(V^T V)^{-1} V^T e_0}_y$$

(coarse grid correction)



$$x_1 \leftarrow x_0 + u$$

$$\min_{u \in \text{span}\{V\}} \|x^* - x_1\| = \|e_1\| = \|\underbrace{x^* - x_0 - u}_{e_0 - u}\| = \|e_0 - Vy\|$$

$$V^T V y = V^T e_0$$

normal equations

A reminder – projection methods

- Instead, look at the A-norm (A s.p.d.):

$$\min_{u \in \text{span}\{V\}} \|x^* - x_1\|_A$$

- Then $u = Vy$

$$V^T AVy = V^T Ae_0$$

$$V^T AVy = V^T r_0$$

- So that

optimal coarse-grid operator

$$x_1 = x_0 + V \underbrace{(V^T AV)^{-1} V^T}_{V^T A V} r_0$$

A-optimal coarse-grid correction

A-orthogonal projection:

$$\min_u \|x^* - x_1\|_A = \|x^* - x_0 - u\|_A$$

$$= \|x^* - x_0 - Vy\|_A$$

$$= \|e_0 - Vy\|_A$$

$$\min_y (e_0 - Vy)^T A (e_0 - Vy)$$

$$= e_0^T A e_0 + (Vy)^T A Vy$$

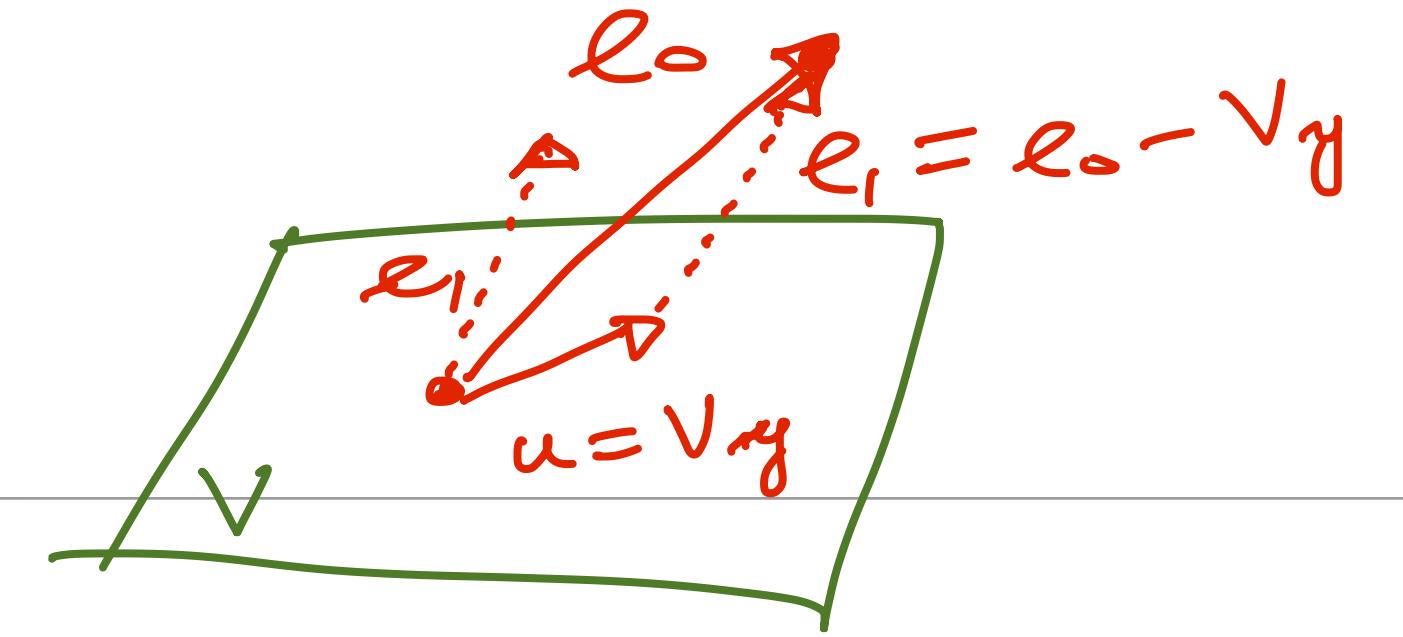
$$- 2 e_0^T A Vy$$

$$\Rightarrow V^T A V y = V^T A e_0$$

A-orthogonal projection of e_0

residual is cheaply computable ($O(n)$)

A reminder – projection methods



$$x_1 = x_0 + u$$

$$e_1 = e_0 - Vg^* \perp_A Vg$$

for all g

$$x_1 = x_0 + V(V^T AV)^{-1}V^T r_0$$

- What about the error

$$x^* - x_1 = x^* - x_0 - V(V^T AV)^{-1}V^T r_0$$

$$e_1 = e_0 - V(V^T AV)^{-1}V^T Ae_0$$

$$= (I - V(V^T AV)^{-1}V^T A) e_0$$

A-orthogonal
projection onto the
range of V

(optimal
coarse-grid
correction,
given V)

Model Problem

- A model problem

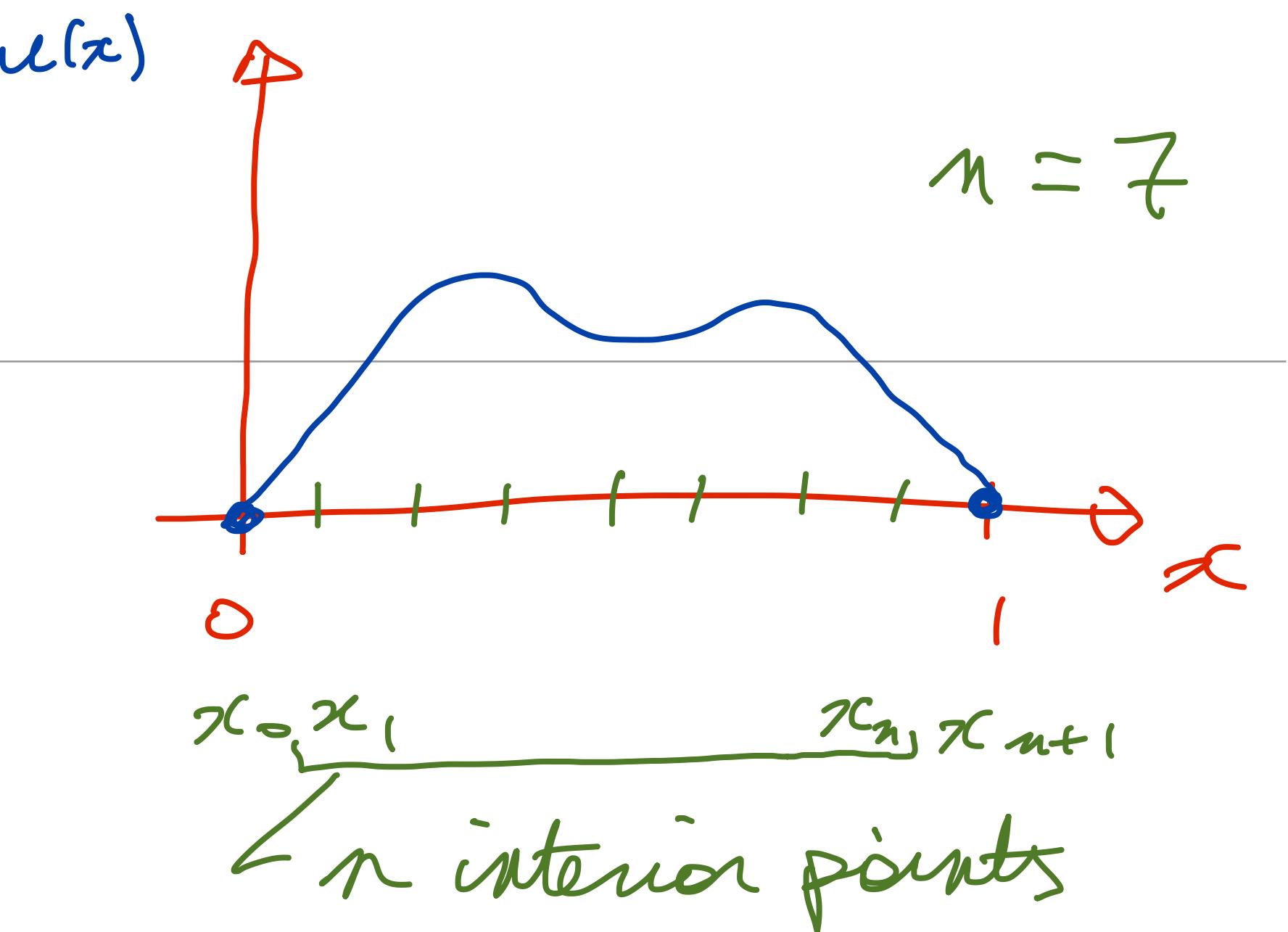
$$\begin{aligned}-u_{xx} &= f \\ u(0) &= u(1) = 0\end{aligned}$$

- Finite differences

$$\frac{-u_{i-1} + 2u_i - u_{i+1}}{h^2} = f_i \quad i = 1, \dots, n \quad u_0 = u_{n+1} = 0$$

- A model matrix problem

$$A = \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & \\ -1 & \ddots & & \\ & \ddots & \ddots & \\ & & \ddots & \ddots \end{bmatrix}$$



$$h = \frac{1}{n+1} = \frac{1}{8}$$

$A \in \mathbb{R}^{n \times n}$, sparse

$\text{nnz}(A) \approx 3n = O(n)$

$$A \in \mathbb{R}^{n \times n}$$

$$R = \frac{1}{n+1}$$

Model Problem

- A special matrix:

$$A = \begin{bmatrix} 2 & -1 & & \\ -1 & 2 & -1 & \\ & -1 & 2 & -1 \\ & & \ddots & \\ & & & -1 & 2 \end{bmatrix}$$

smoothest component = small λ_k ($\propto R^2$)

The eigenvalues

range from (0,4]

(or from $c h^2$ to ~ 4)

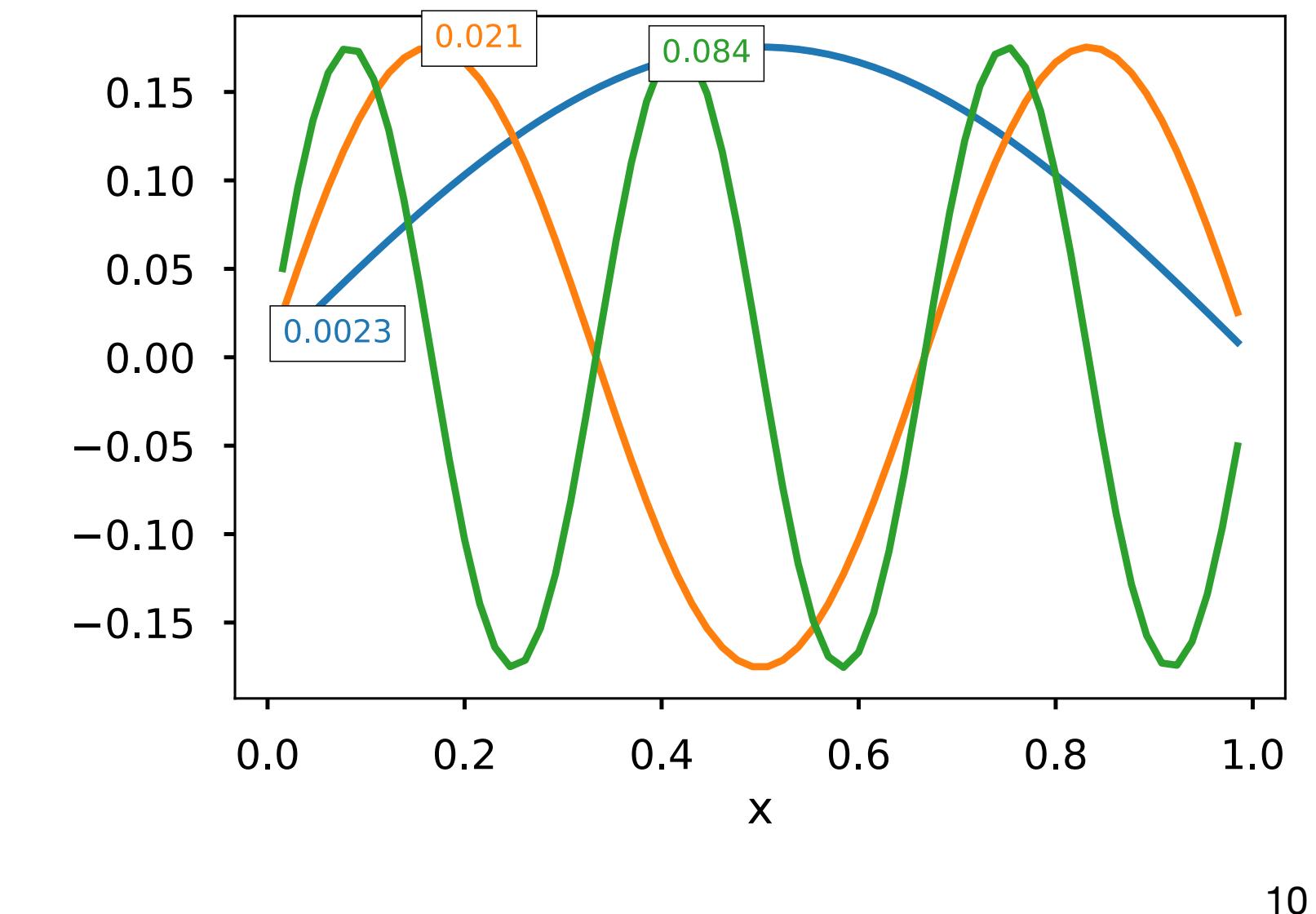
The eigenvectors are Fourier modes:

$$\lambda_1 = 4 \sin^2 \left(\frac{\pi}{2(n+1)} \right) \approx 4 \frac{\pi^2 h^2}{4}$$

$$\lambda_k = 4 \sin^2 \left(\frac{k\pi}{2(n+1)} \right)$$

$$k = 1, \dots, n$$

$$(v_k)_j = \sin \left(\frac{(j+1)*k\pi}{n+1} \right)$$



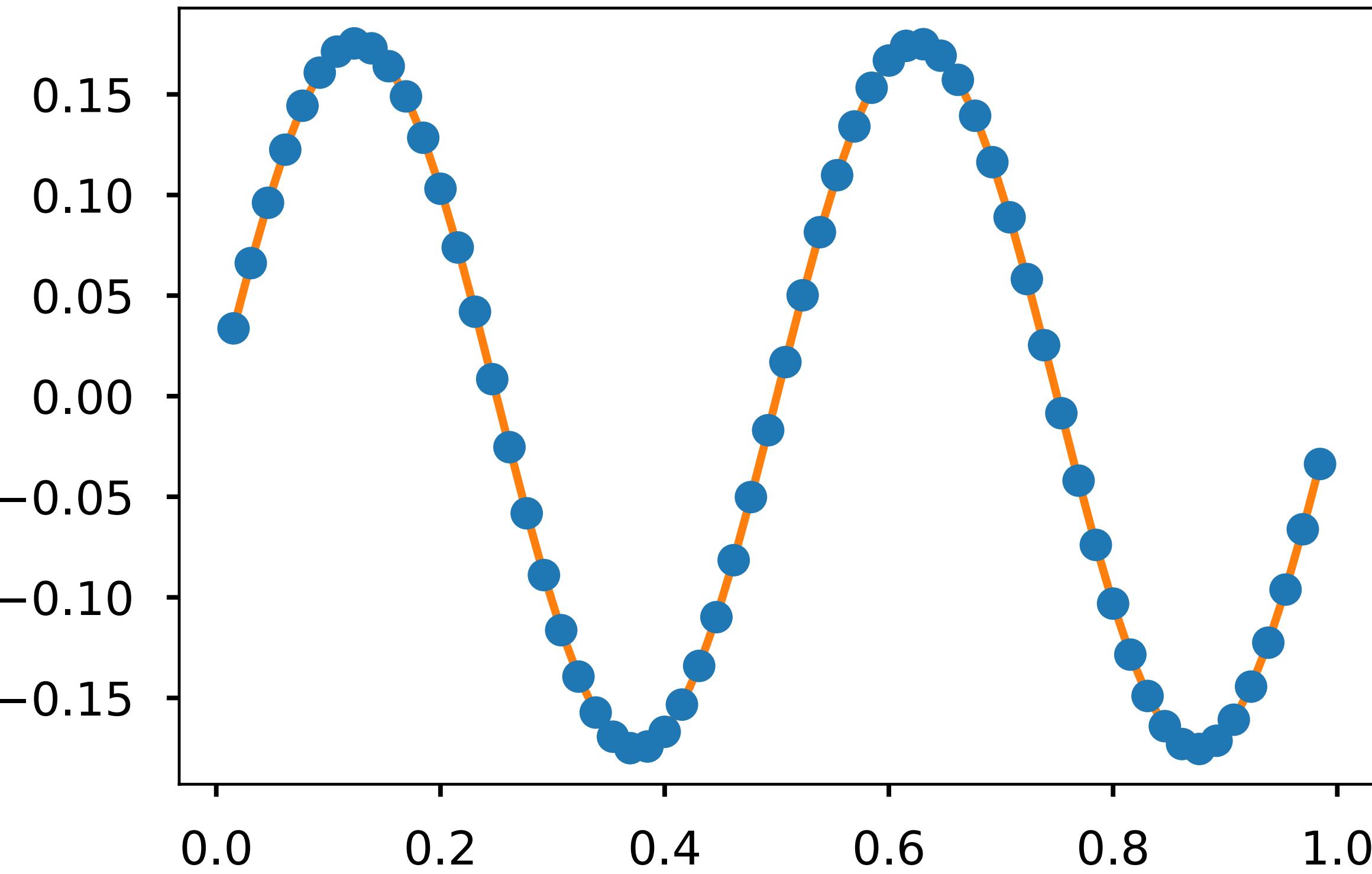
multigrid: (A) relaxation on the fine grid Take a look: 01-model-problem.ipynb

(B) coarse-grid correction

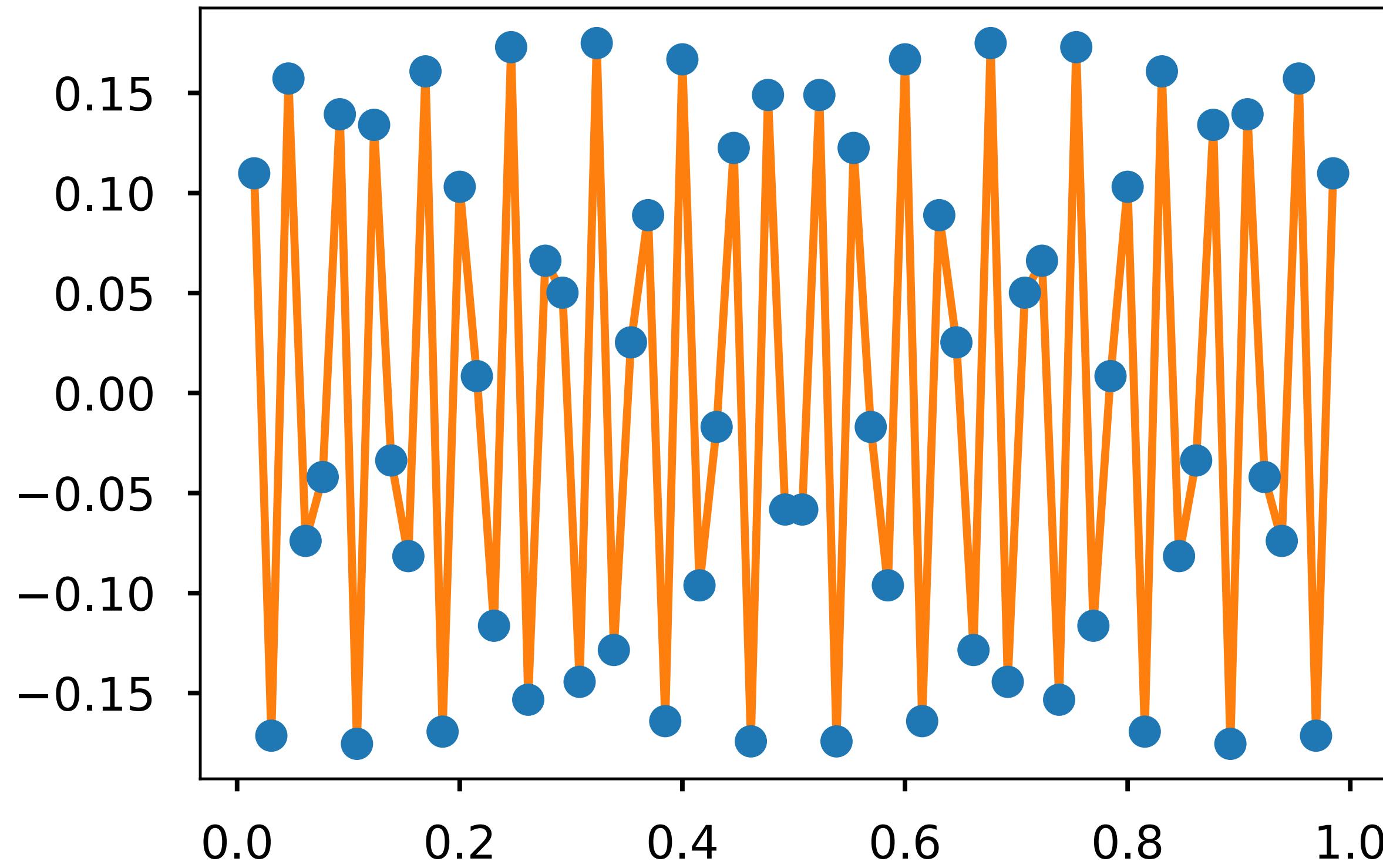
Smooth Mode ~ low Fourier Modes

(for ingredient (A))

- We will talk a lot about “smoothness” – how much variation there is **per** grid point.



small k



large $k \approx n$

First relaxation scheme: Jacobi

- The discretization at point i:

$$-u_{i-1} + \cancel{2u_i}^{\alpha_{ii}} - u_{i+1} = h^2 f_i$$

- Solving for the variable at this point (eliminating the residual):

$$u_i \leftarrow \frac{1}{2} \left(u_{i-1} + u_{i+1} + h^2 f_i \right) \quad / \alpha_{ii}$$

- In matrix form:

$$u \leftarrow (I - D^{-1}A)u + h^2 D^{-1}f$$

$$u \leftarrow u + D^{-1}r$$

- And the error:

$$e \leftarrow Ge$$

$$G = I - D^{-1}A$$

$$Au = f \quad (\alpha^2 \text{ in it})$$

$$\begin{aligned} u^* - u &\leftarrow u^* - u - D^{-1} A e \\ e &\leftarrow \underbrace{(I - D^{-1} A)}_G e \end{aligned}$$

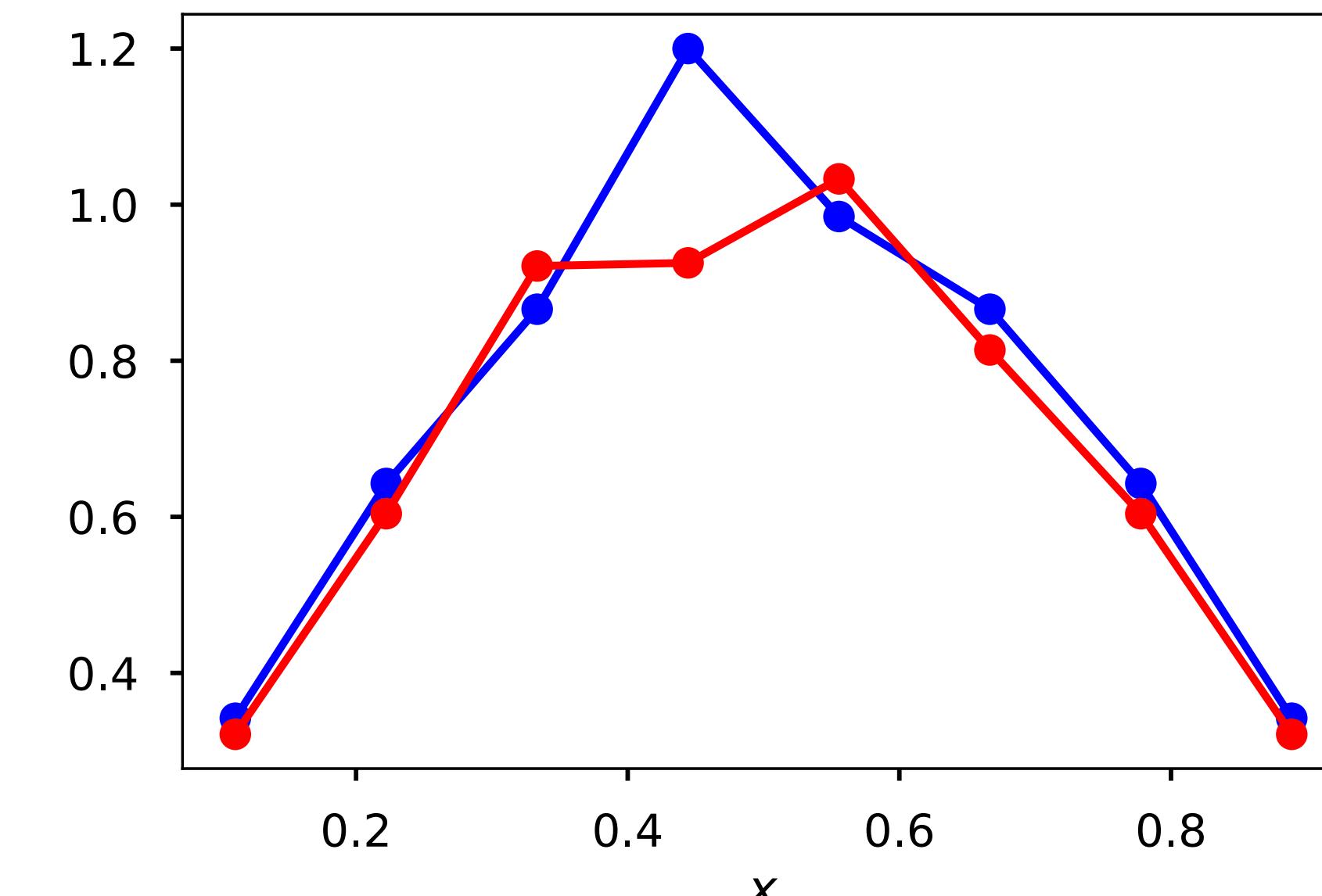
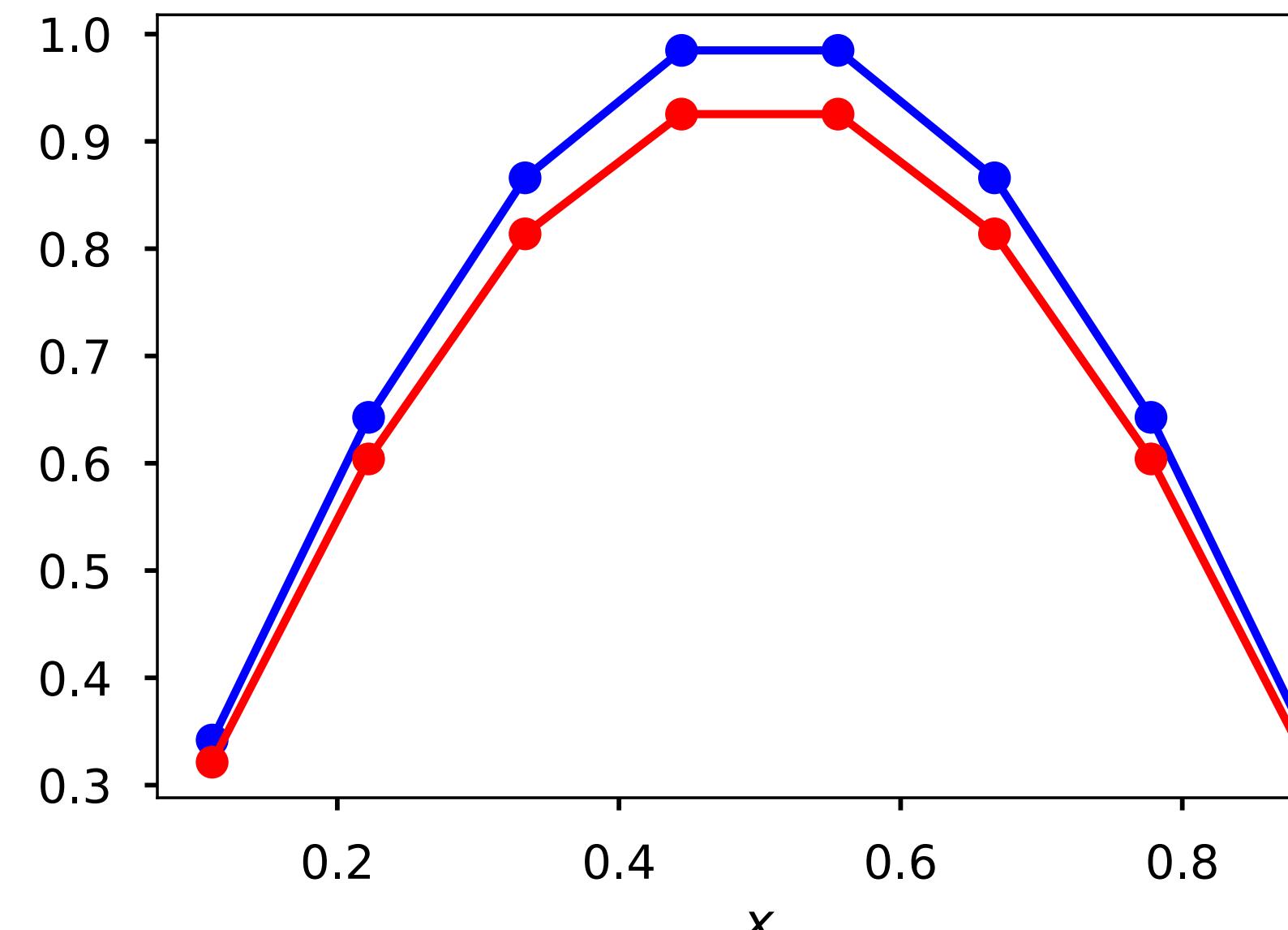
The “error propagation operator”

What does Jacobi do to error?

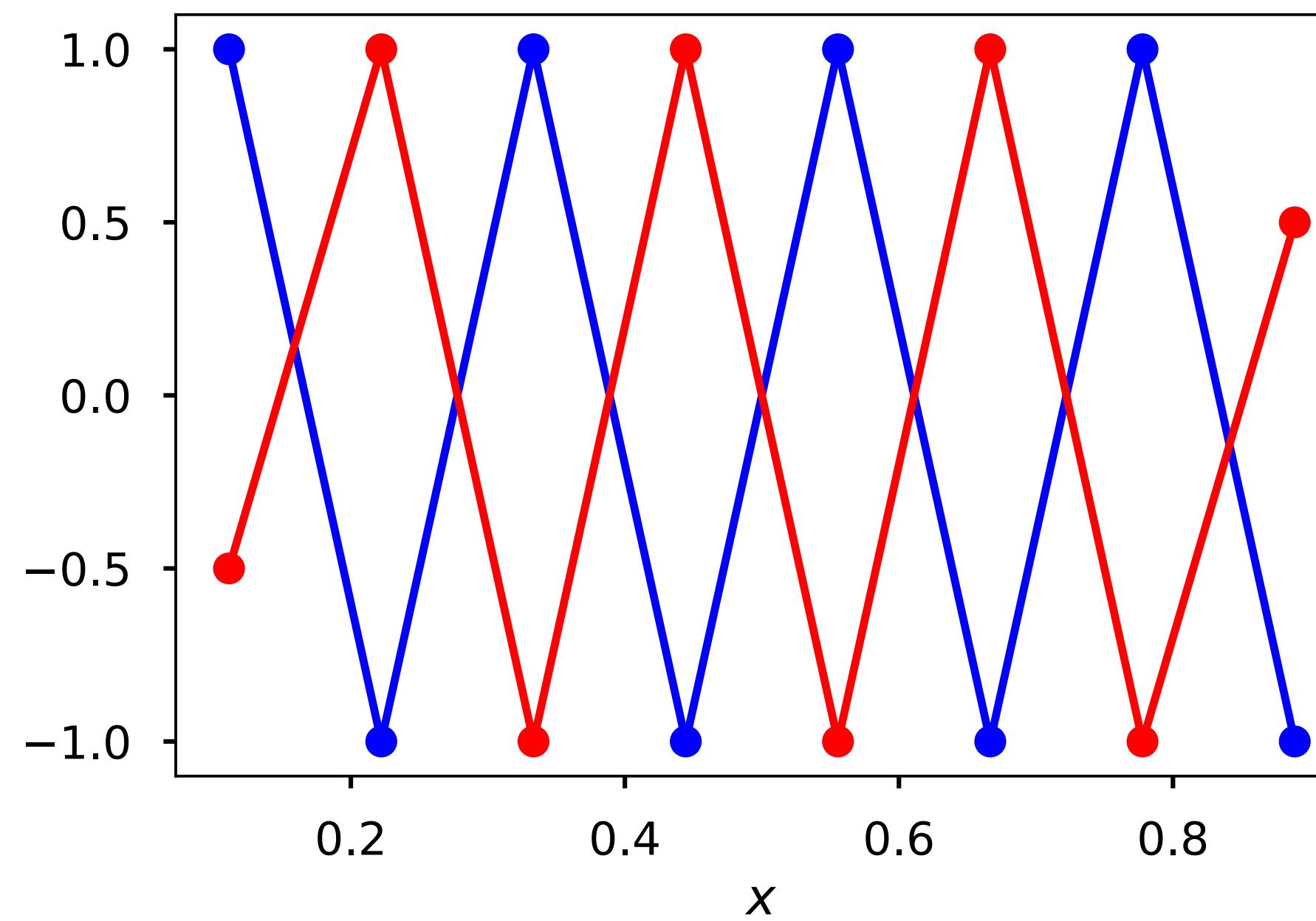
$$e^{new} \leftarrow (I - D^{-1}A)e^{old}$$

$$e_i^{new} \leftarrow \frac{1}{2} (e_{i-1}^{old} + e_{i+1}^{old})$$

- It averages...
- Consider smooth and oscillatory error:



But...

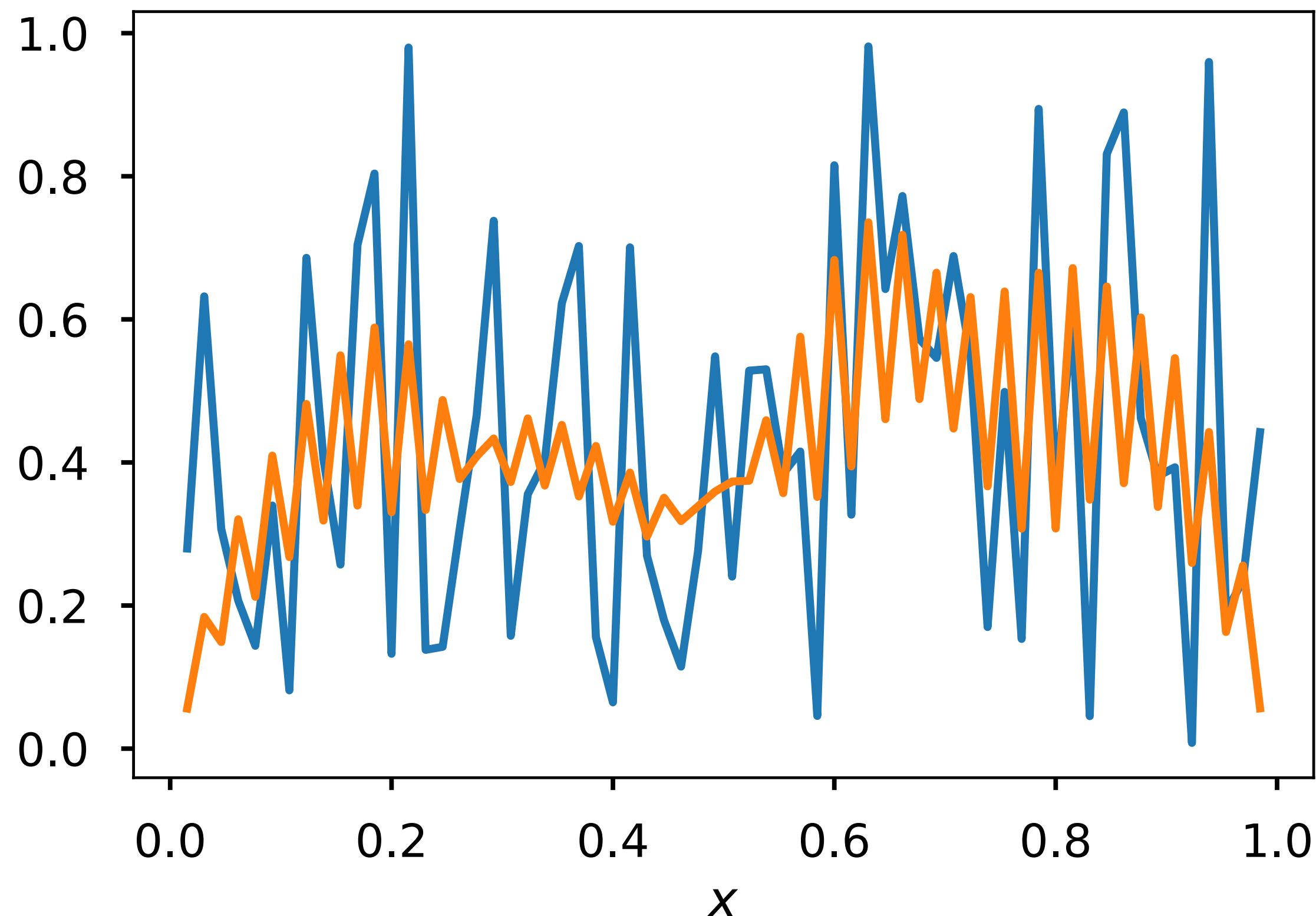


- Jacobi “averages out” certain error very quickly.
- But stagnates on very smooth error or very oscillatory error

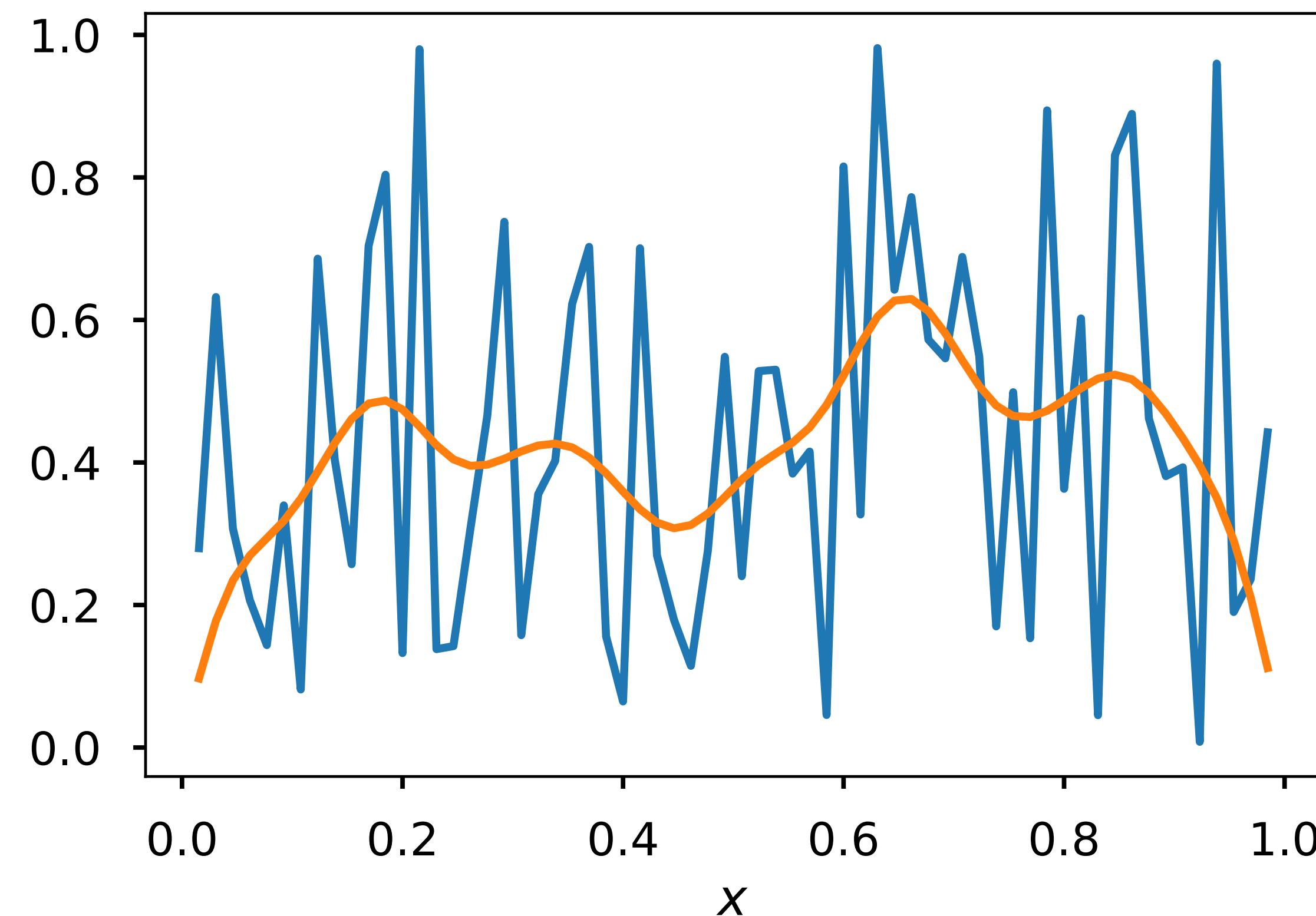
From Jacobi to weighted-Jacobi

- Random initial guess (random error):

$$u \leftarrow u + D^{-1}r$$



$$u \leftarrow u + (2/3)D^{-1}r$$



Weighted Jacobi

- Weighted Jacobi

$$u \leftarrow u + (2/3)D^{-1}r = \frac{1}{3}u + \frac{2}{3}(u + D^{-1}r)$$
$$= (1-\omega)u + \omega(u + D^{-1}r)$$

- What does this do to other modes?

- Are smooth modes damped slowly?
- What about oscillatory modes?

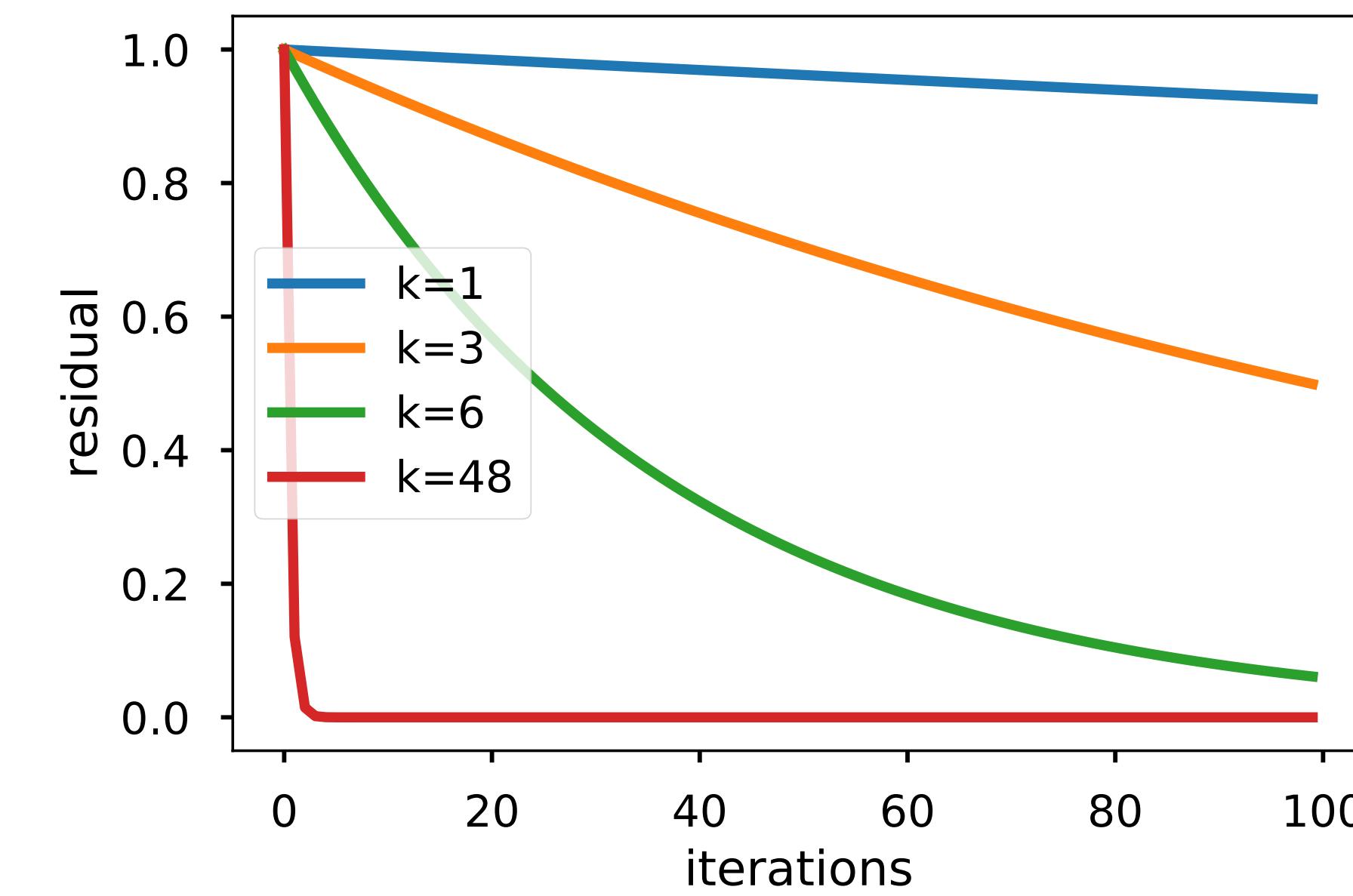
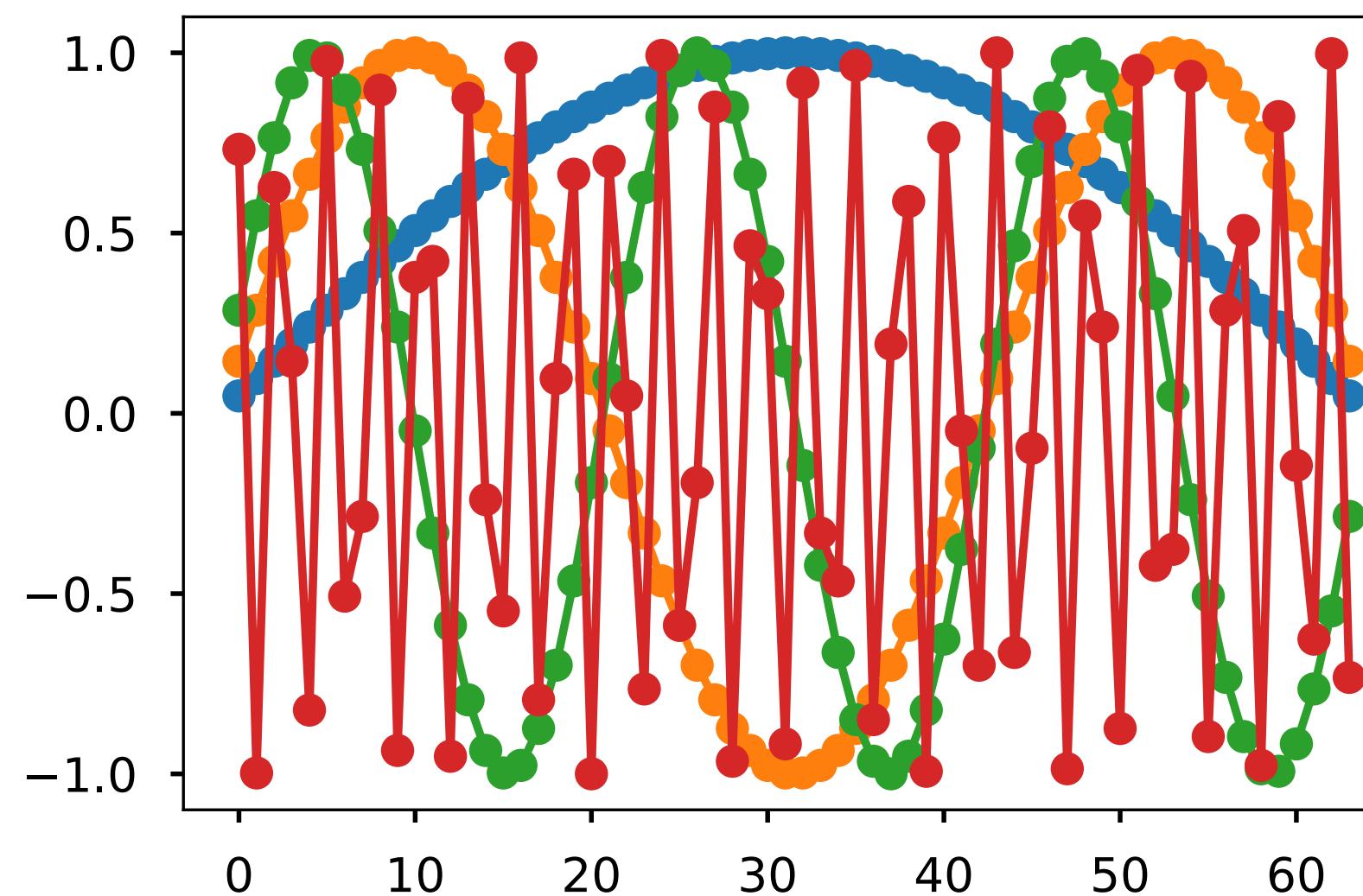
- Why did we pick 2/3 – that seemed like a lucky guess?!

Weighted Jacobi

$$n = 64$$

- If we picked 4 modes, 1, 3, 6, and 48 (out of 64)
- Then smooth modes still dampen less quickly than higher ones

$$\lambda = \frac{1}{65}$$



Error Propagation

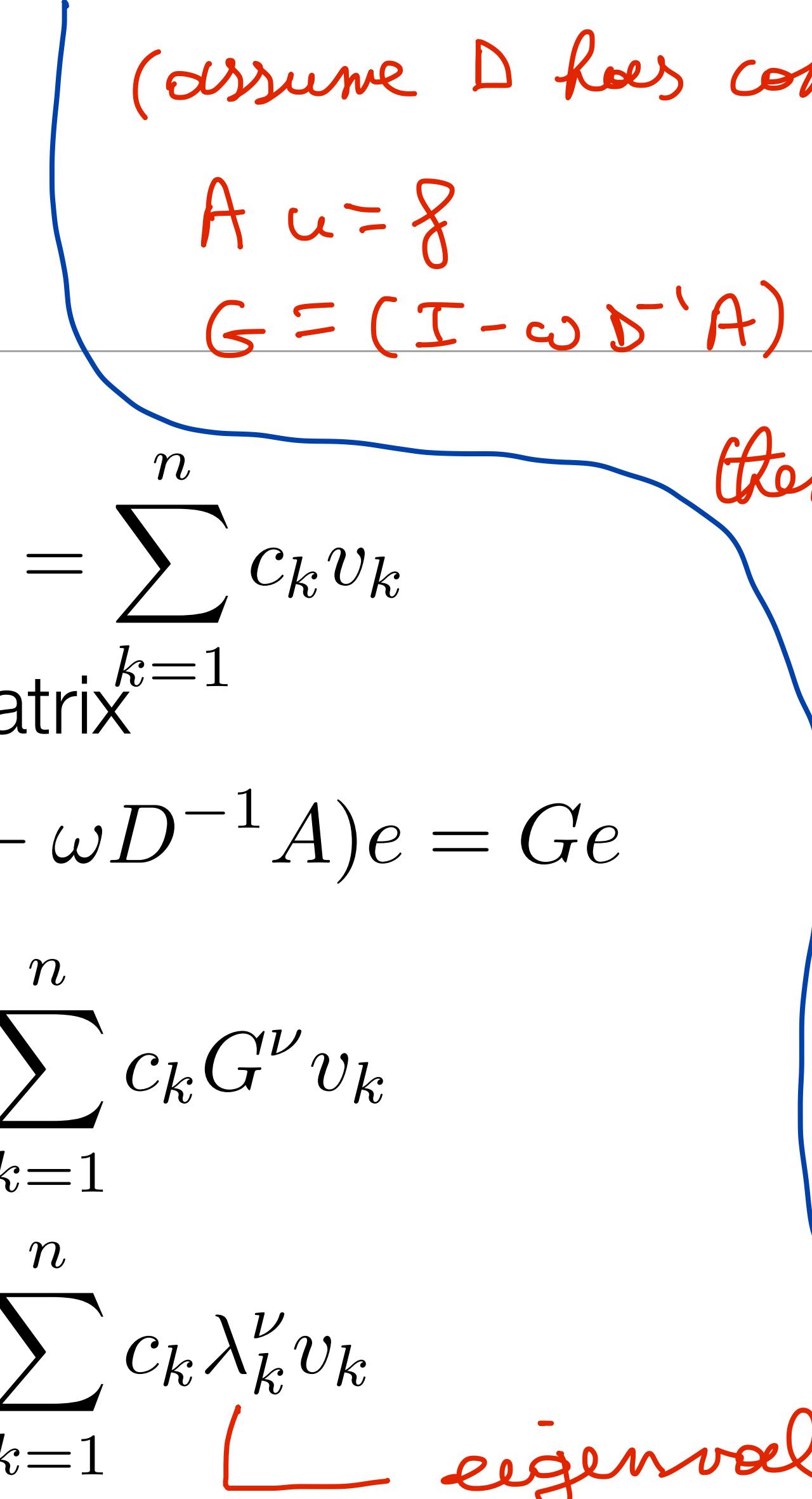
- Let's consider an initial error

- And the weighted Jacobi iteration matrix

$$e \leftarrow (I - \omega D^{-1} A)e = Ge$$

- From ν iterations we have

$$\begin{aligned} G^\nu e_0 &= \sum_{k=1}^n c_k G^\nu v_k \\ &= \sum_{k=1}^n c_k \lambda_k^\nu v_k \end{aligned}$$

 eigenvalues of G

- As a result, mode k is reduced by the magnitude of λ_k in every pass

(assume D has constant diagonal)

$$A u = f$$

$$G = (I - \omega D^{-1} A)$$

$$A \hat{u} = \hat{\lambda} \hat{u}$$

then

$$(I - \omega D^{-1} A) \hat{u}$$

$$= u - \omega D^{-1} A \hat{\lambda} \hat{u}$$

$$= (1 - \omega \frac{1}{\lambda} \hat{\lambda}) \hat{u}$$

so $\lambda = 1 - \frac{\omega}{\lambda} \hat{\lambda}$, $u = \hat{u}$

$\Omega = 1$: $\hat{\lambda}_i = O(\epsilon^2)$

$\lambda_i = O(1)$

Fundamental Theorem of Iteration

$$G = I - M^{-1}A$$

- Convergent ($G^n \rightarrow 0$) if and only if $\rho(G) < 1$

if $G = G^\top$,
 $\|G\| = \rho(G)$

$$\frac{\|e_n\|}{\|e_0\|} \leq \|G^n\| \leq \|G\|^n \approx 10^{-d}$$

$$\hookrightarrow n \log_{10}(\rho(G)) \approx -d$$

- How many iterations do we need to guarantee the reduction of the error by d digits?

$$n \approx -\frac{d}{\log_{10} \rho(G)}$$

Relaxation

- Convergence **factor** $\|G\|$ or $\rho(G)$
- Convergence **rate** $-\log_{10} \rho(G)$ *(digits per iteration)*

- For Jacobi:

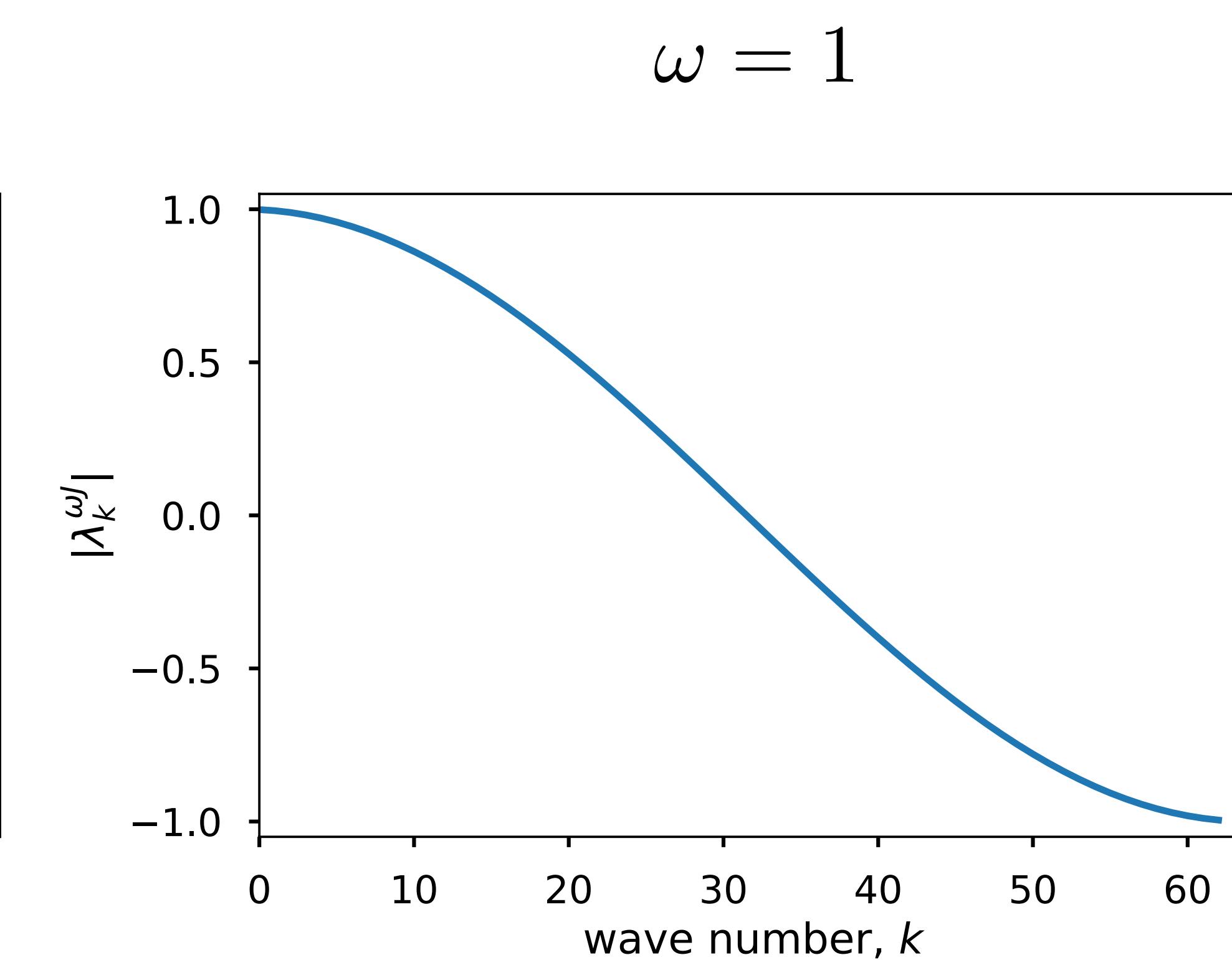
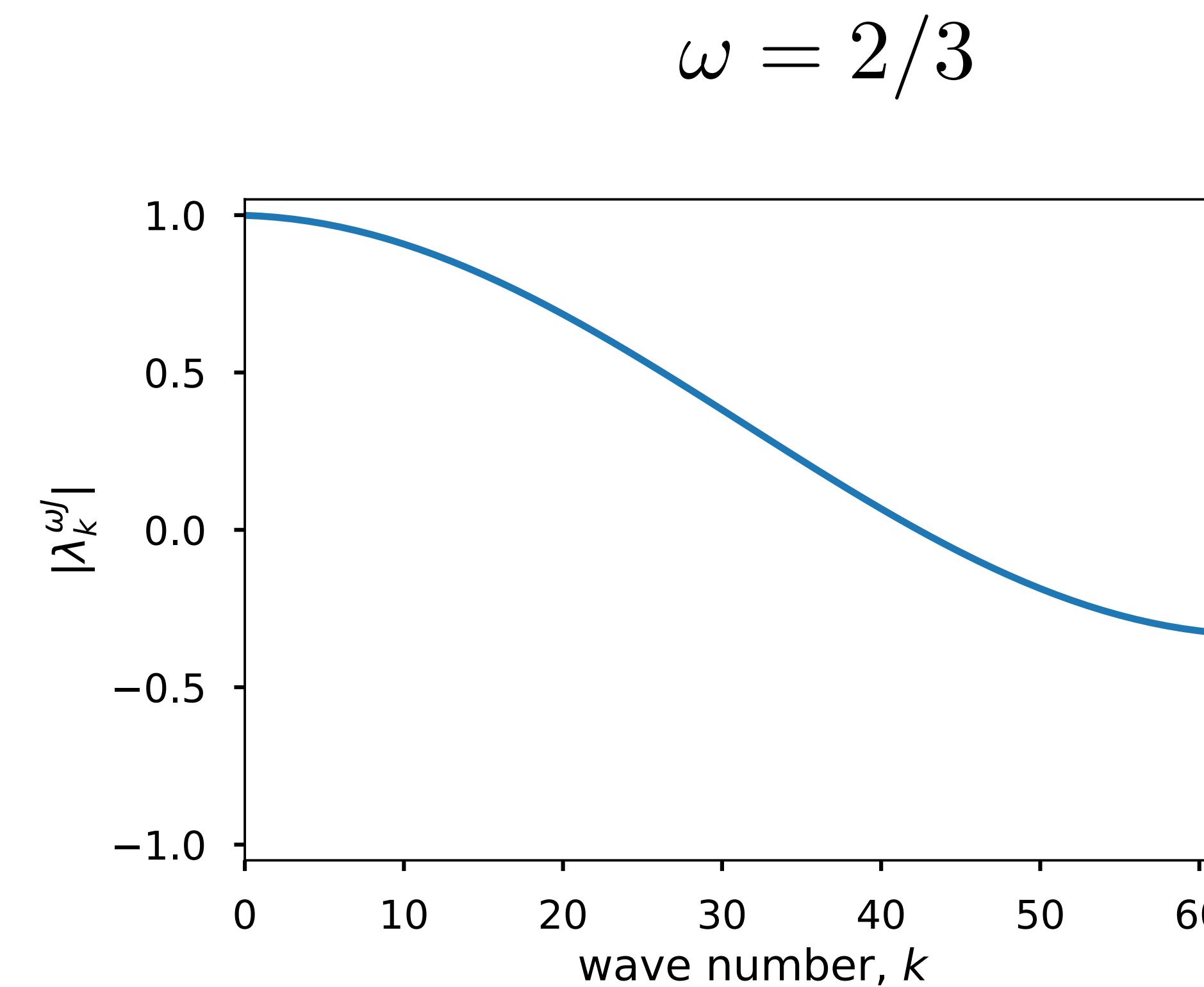
$$G = I - D^{-1}A \longrightarrow \lambda_k = 1 - \frac{1}{2} \cdot 4 \cdot \sin^2 \left(\frac{k\pi}{2(n+1)} \right)$$

$$G = I - (2/3)D^{-1}A \longrightarrow \lambda_k = 1 - \frac{2}{3} \cdot \frac{1}{2} \cdot 4 \cdot \sin^2 \left(\frac{k\pi}{2(n+1)} \right)$$

The spectral radius is almost the same, but...

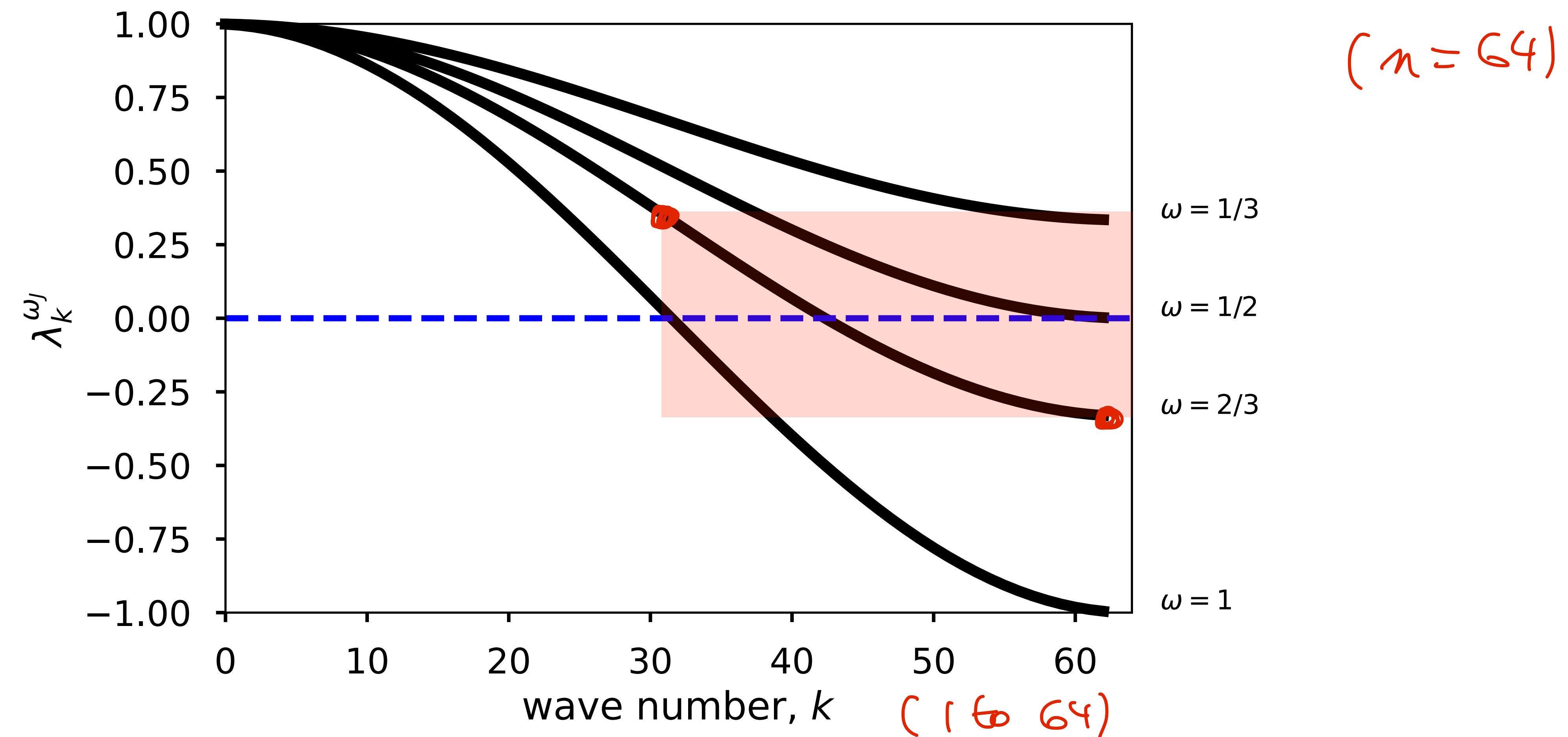
Weighted Jacobi

- If we look at the spectrum:
 - Weighted Jacobi dampens modes that are highly oscillatory



Weighted Jacobi

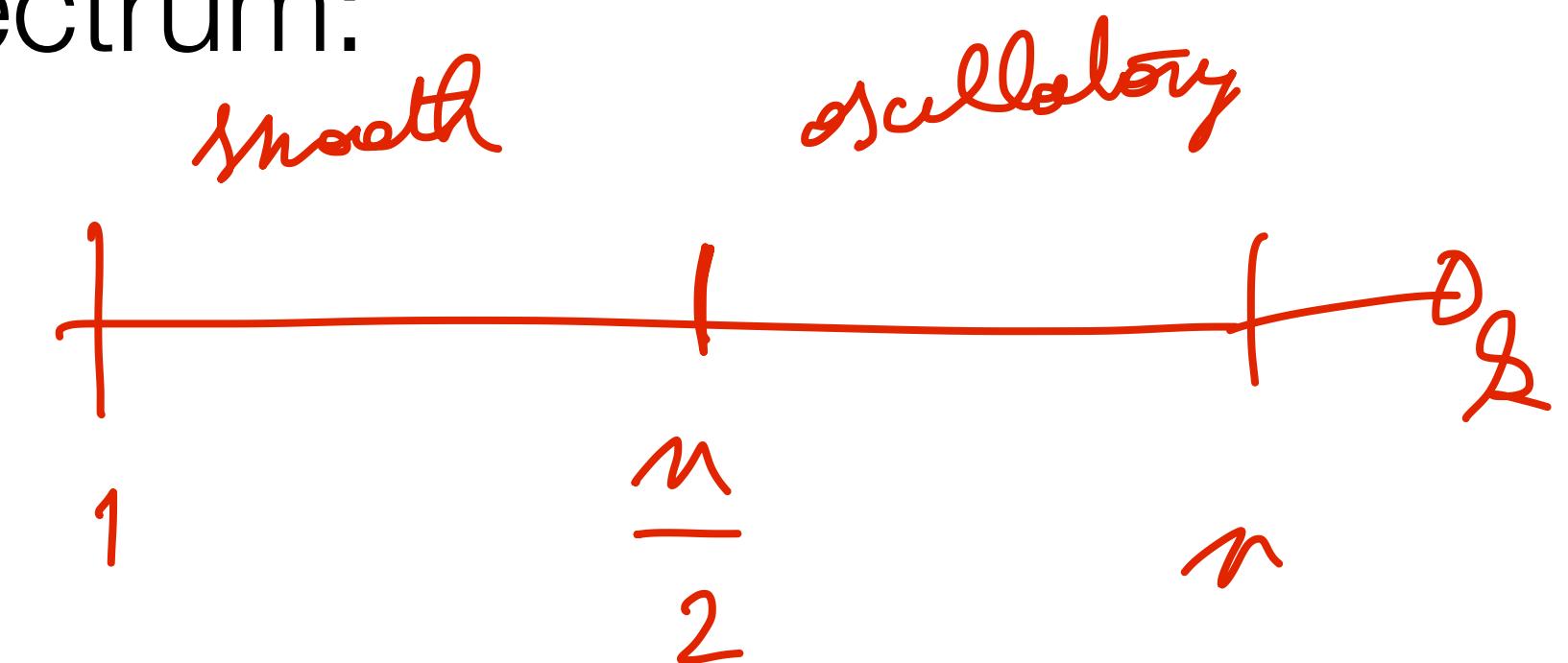
- Selecting 2/3 balances the reduction in error in the **high** modes



The multigrid smoothing factor

- The **smoothing factor** of relaxation method G is the maximum magnitude of the upper half of the spectrum:

$$\max_{k \in [n/2, n]} |\lambda_k^G|$$



- A desired feature for relaxation:

Oscillatory modes are quick to converge
Smooth modes are slow to converge

Multigrid Step #1: pick a smoother

(A) relaxation on the fine grid

- For $\omega = 2/3$

$$|\lambda_{n/2}| = |\lambda_n| = 1/3$$

- For $\omega = 1$

$$|\lambda_{\cancel{n/2}}| = |\lambda_n| = 1$$

$$|\lambda_{\frac{n}{2}}| \approx 0$$

- Jacobi is not a smoother (weighted *is*)

An important observation on “smoothness”

- So far, we've mainly looked at

$$Au = 0$$

- In general we need to consider

$$Au = f$$

- If we **smooth** with

$$u \leftarrow u + \omega D^{-1}r$$

$$\epsilon_1 = G \epsilon_0$$

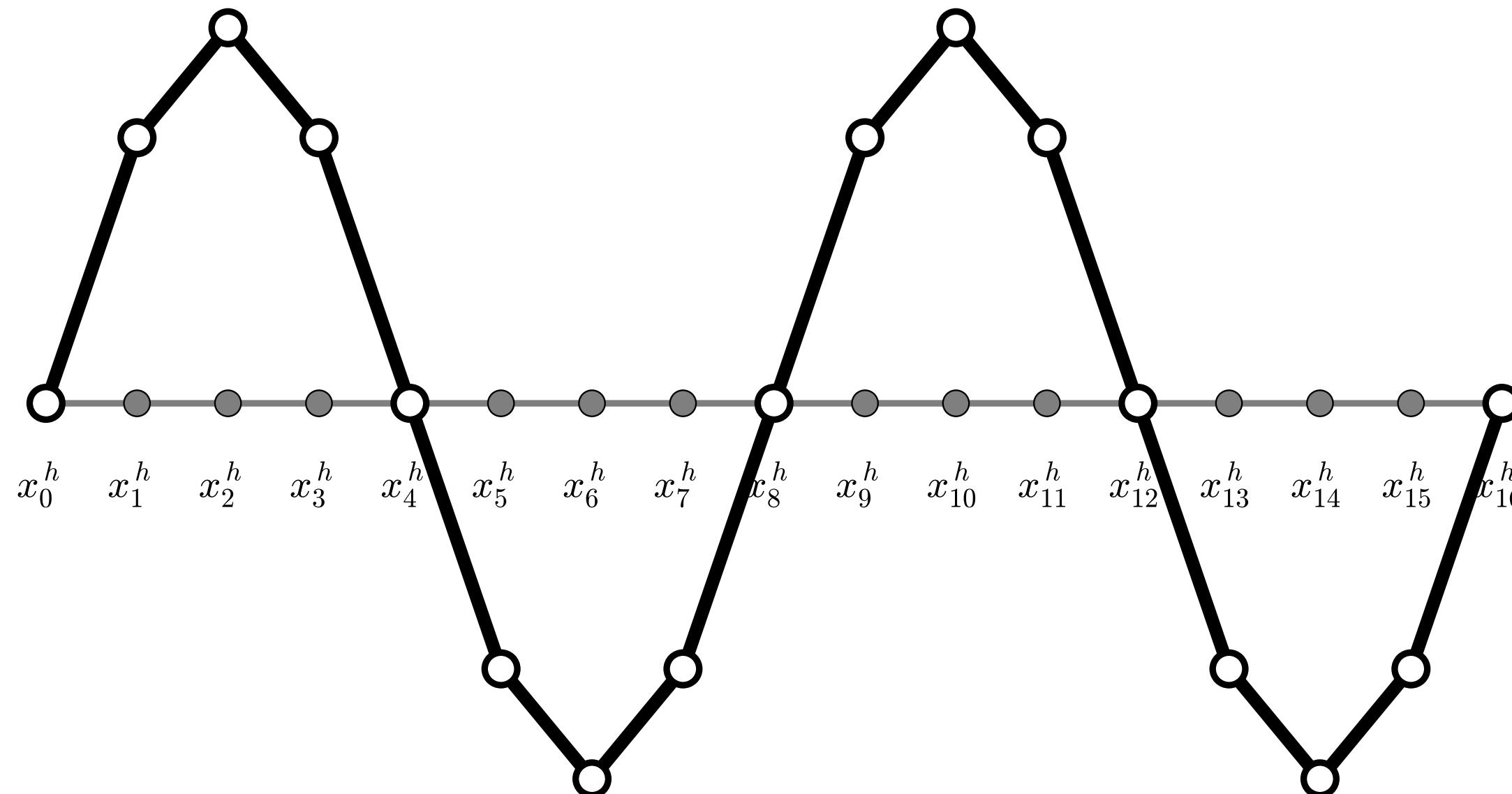
then the **error** is smooth, not (necessarily the solution).

Coarse Grids

(B)

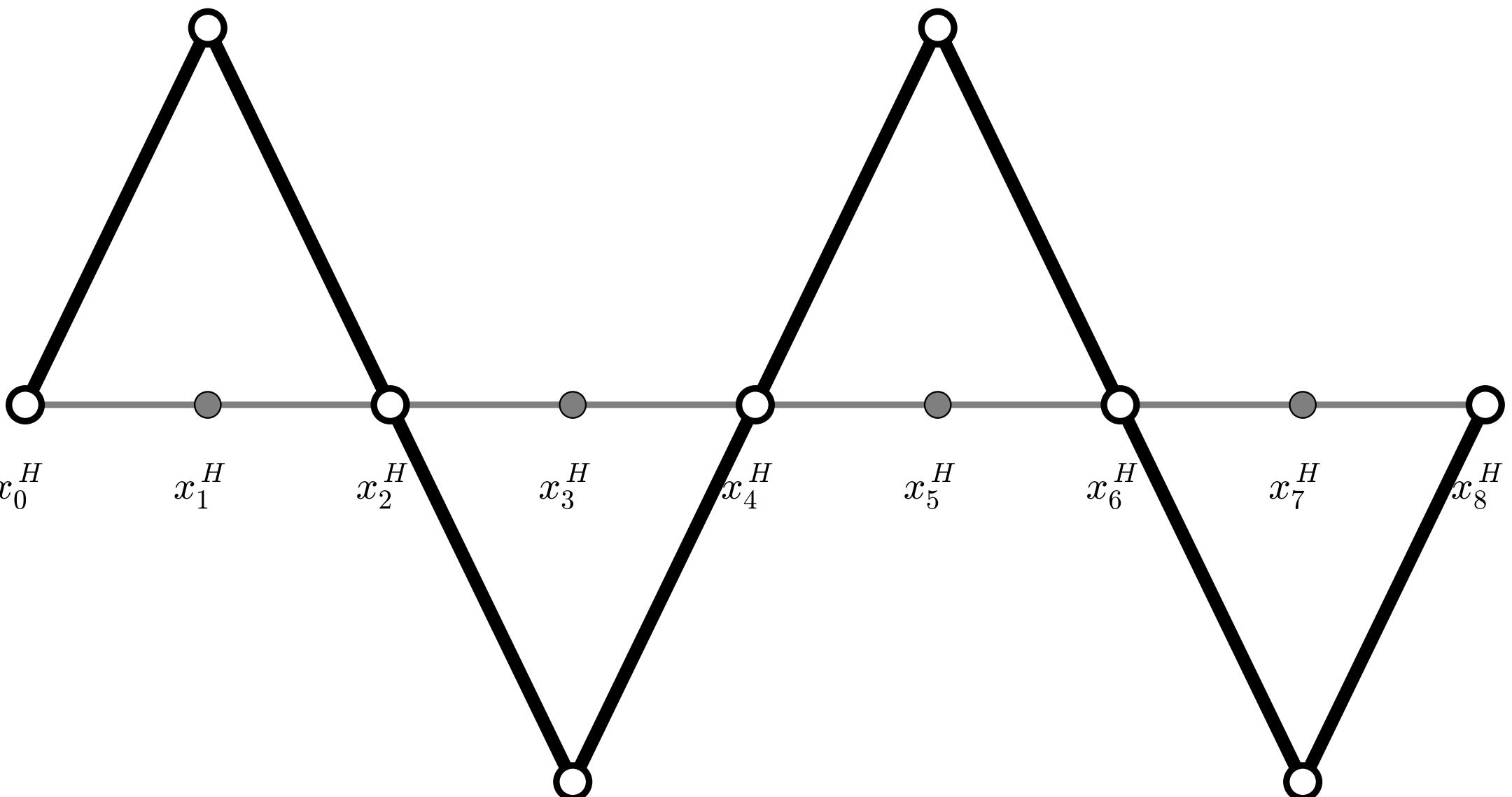
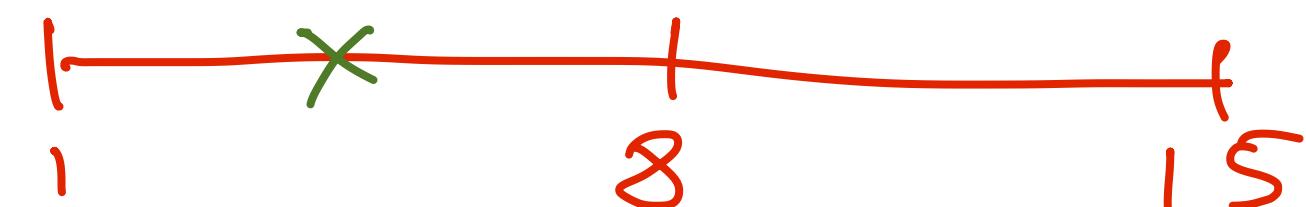
use coarse-grid correction to remove smooth fine-level error modes

- Smooth modes look like oscillatory modes when sampled on a coarse grid
- 4-mode of 15 **versus** 4-mode of 7 → use relaxation on coarse grid



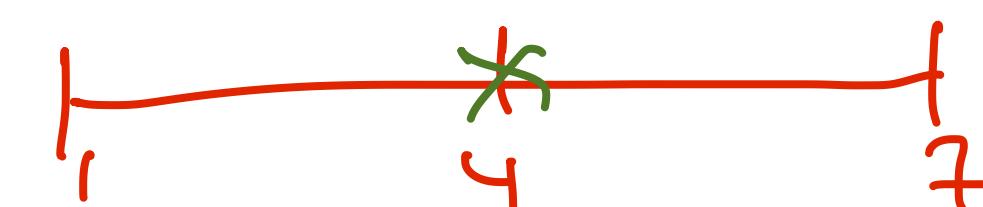
$$k=4, n=15$$

This looks like a “smooth” mode



$$k=4, n=7$$

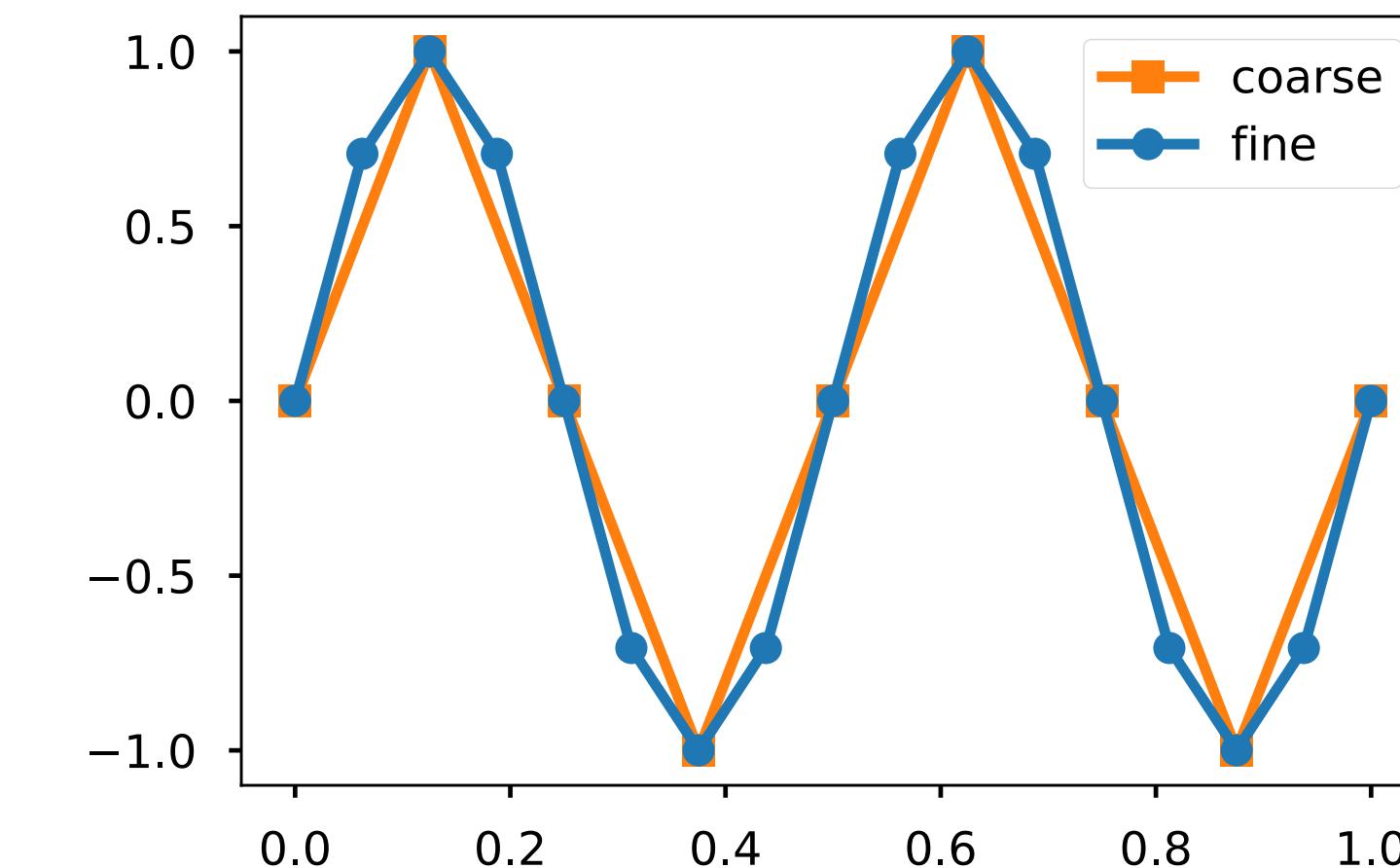
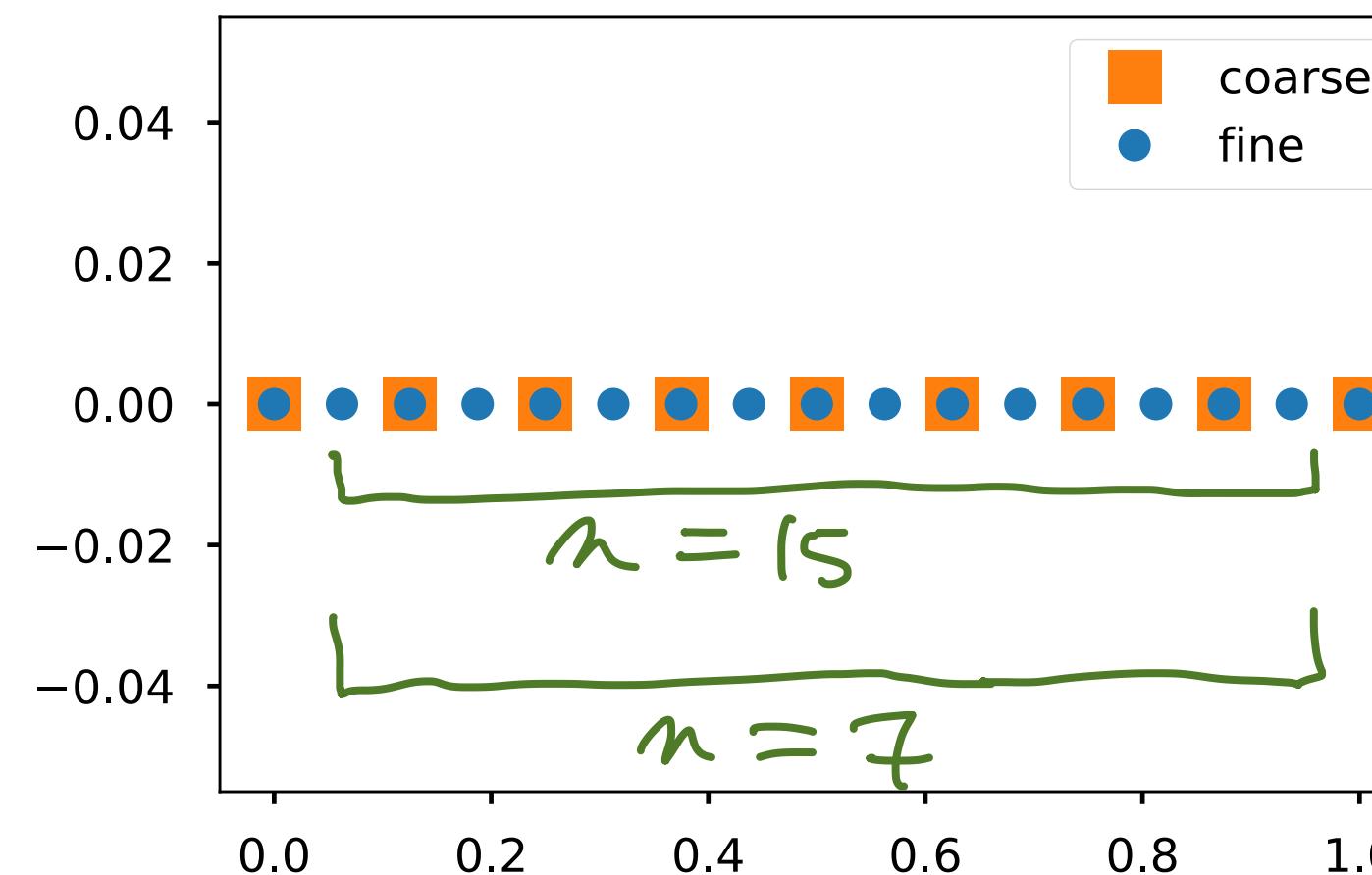
This looks like an “oscillatory” mode



Coarse modes

$$(k \in [1, \frac{n-1}{2}])$$

$$R = \frac{1}{n+1}$$



4 fine
4 coarse
mode 4 of 15

$$(v_k)_j = \sin \frac{jk\pi}{n+1}$$

Fine mode

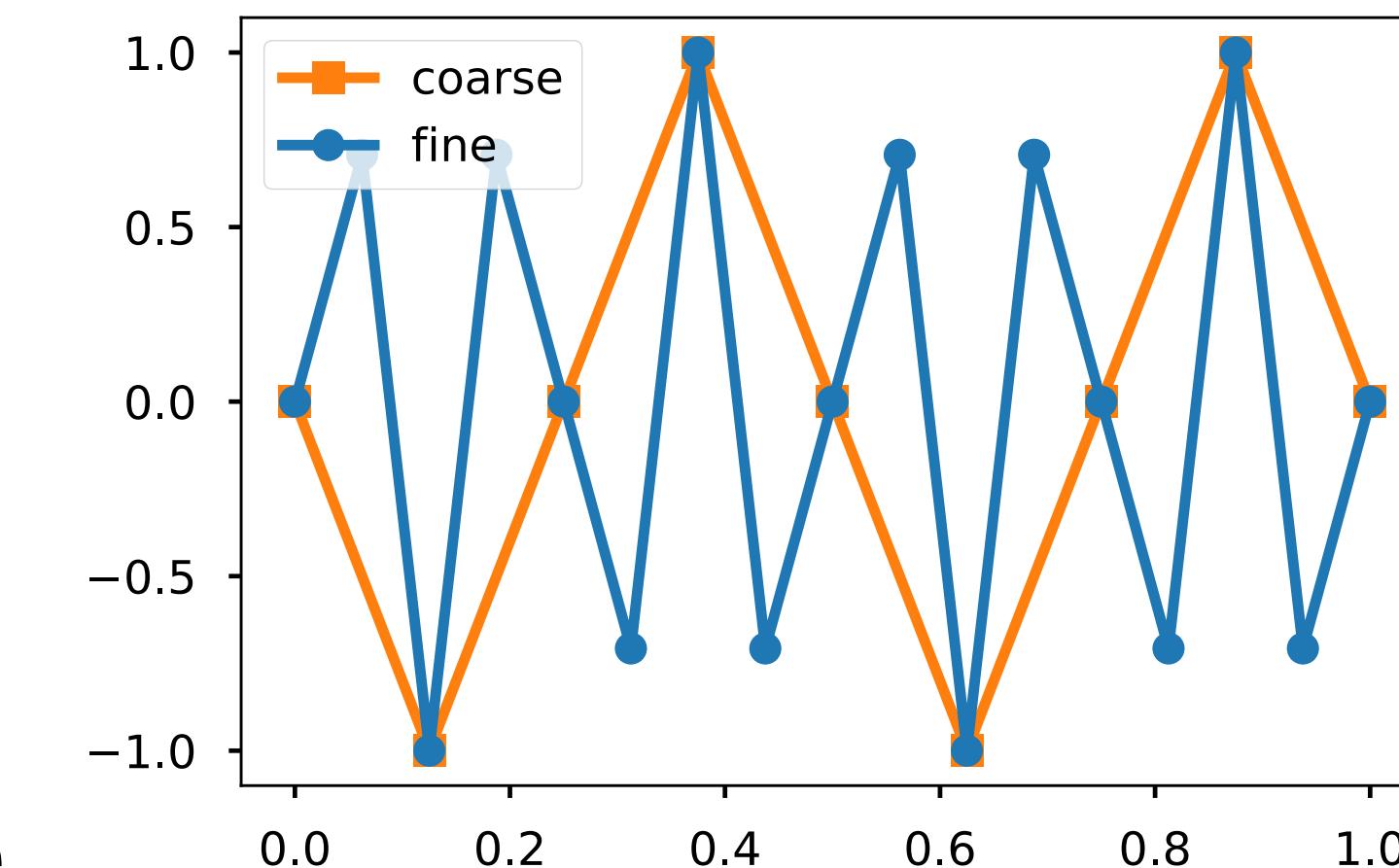
$$(v_k)_{2j} = \sin \frac{2jk\pi}{n+1}$$

Fine mode
(every other)

$$= \sin \frac{jk\pi}{(n+1)/2}$$

Coarse mode

$$= (\hat{v}_k)_j$$

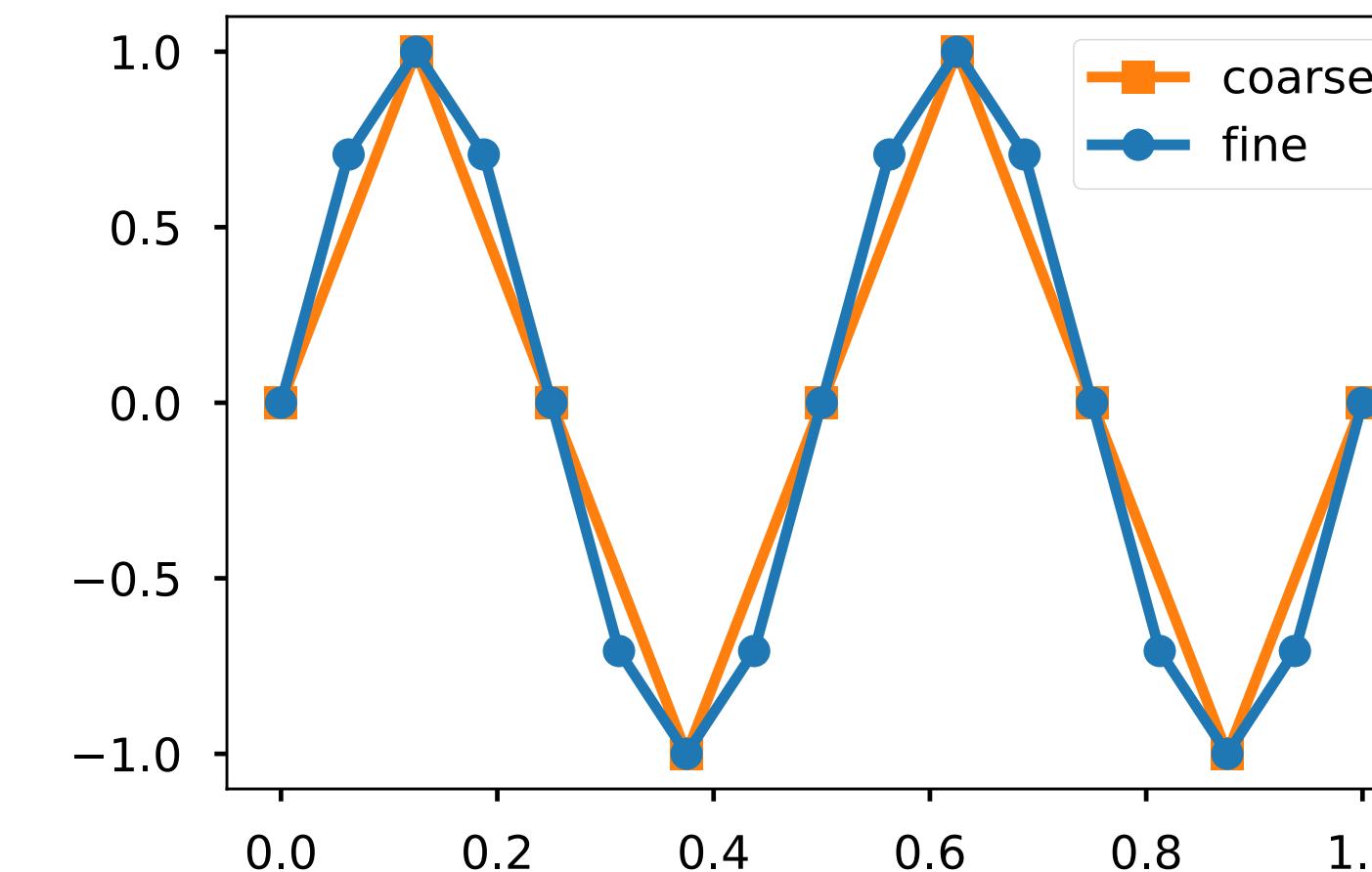
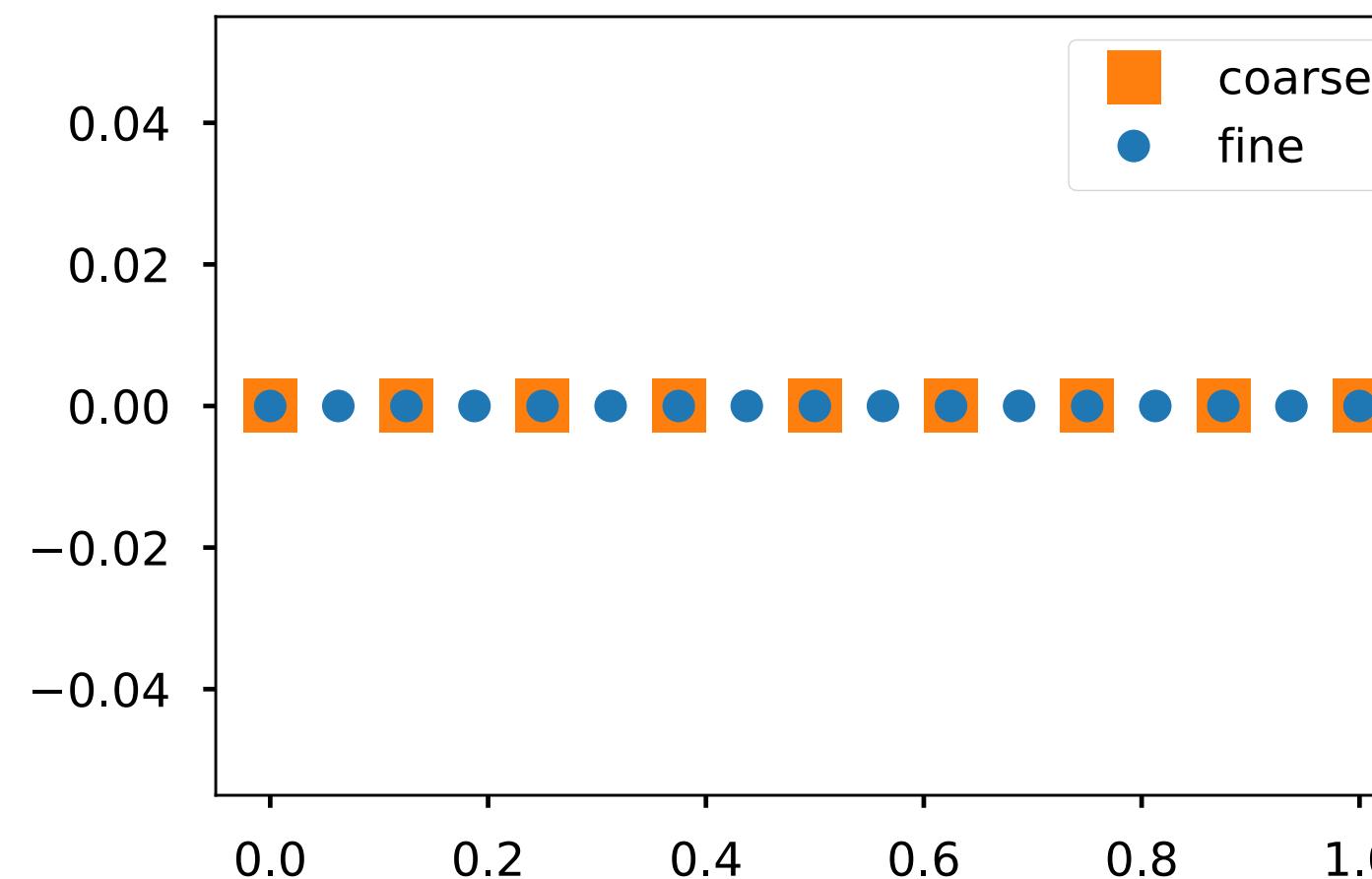


12 fine becomes
- 4 coarse
mode 12 of 15

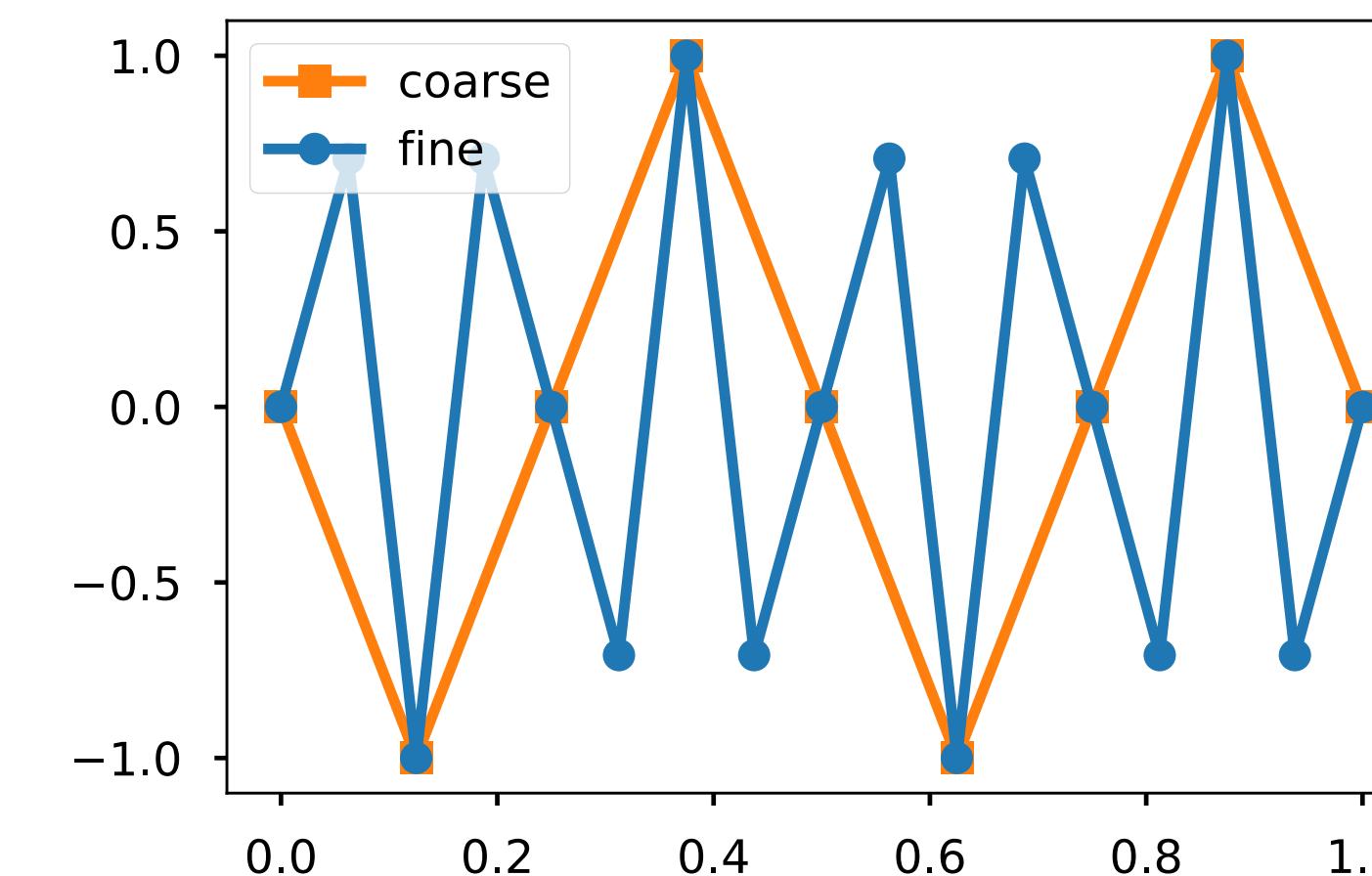
For low modes, k-modes are preserved

Coarse modes

$$(k \in \left[\frac{n+1}{2}, n \right])$$



mode 4 of 15



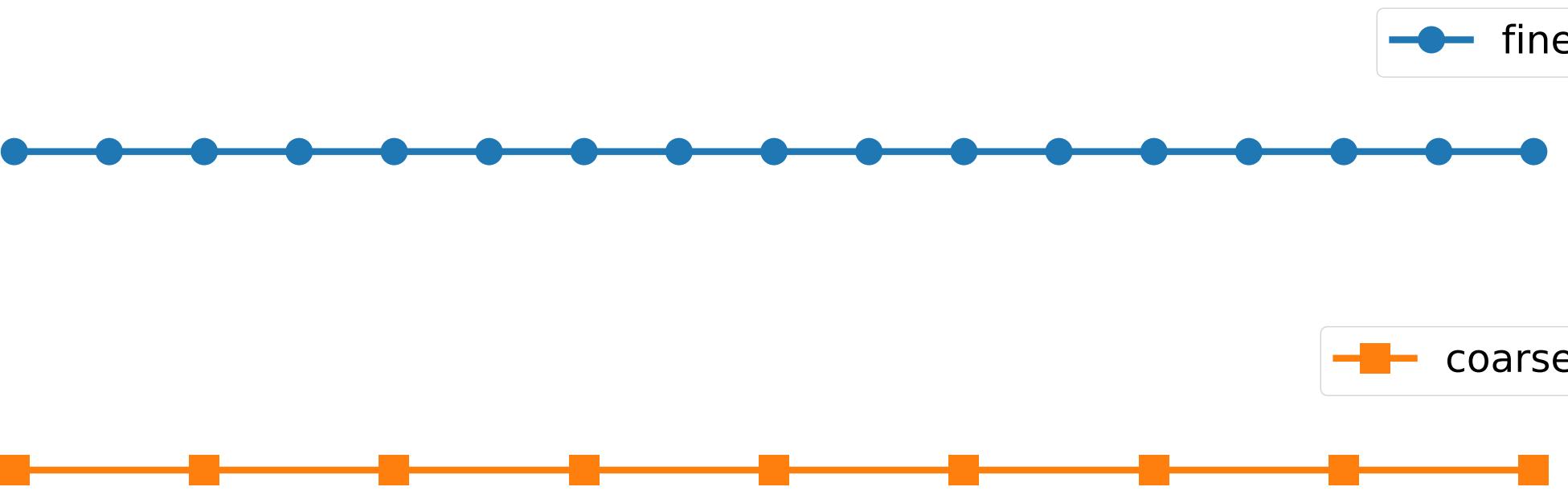
12 fine becomes
- 4 coarse
mode 12 of 15

$$\begin{aligned}
 (v_k)_{2j} &= \sin \frac{2jk\pi}{n+1} \\
 &= -\sin \frac{2j(n-k)\pi}{n+1} \quad \text{Fine mode} \\
 &= -\sin \frac{j(n-k)\pi}{(n+1)/2} \quad \text{(every other)} \\
 &= -(\hat{v}_{n-k})_j
 \end{aligned}$$

Fine mode
(every other)
Coarse mode

For high modes, k-modes are aliased

Questions to resolve...



- How to transfer between **fine** and **coarse**? *(we want to use relaxation on coarse grid to correct fine grid)*
- What do we do to “solve” on a coarse grid? *(relax to efficiently remove slow-to-converge fine-grid error)*

What to use to transfer...

- Return to our projection problem: *(optimal coarse-grid correction)*

$$x_1 = x_0 + V \underbrace{(V^T A V)^{-1} V^T}_{\substack{15 \times 7 \\ 7 \times 7}} r_0$$

15 × 1
7 × 15

- If we have a smoothing property, then smoothing a few times will leave smooth error.
- coarse-grid correction: project e_0 onto range of V , and subtract the projection
- Let's construct V from say continuous piecewise linears

after five relaxation

Interpolation P: from coarse to fine

- Consider coarse grid

$$\Omega^{2h}$$

- and fine grid

$$\Omega^h$$

- Construct an operator

$$P : \Omega^{2h} \rightarrow \Omega^h$$

- Such that

$$Pv^{2h}$$

is continuous and piecewise linear

$$P = \begin{bmatrix} & \\ & \\ & \\ & \\ & \\ & \end{bmatrix} \quad (\text{P} = \nabla)$$

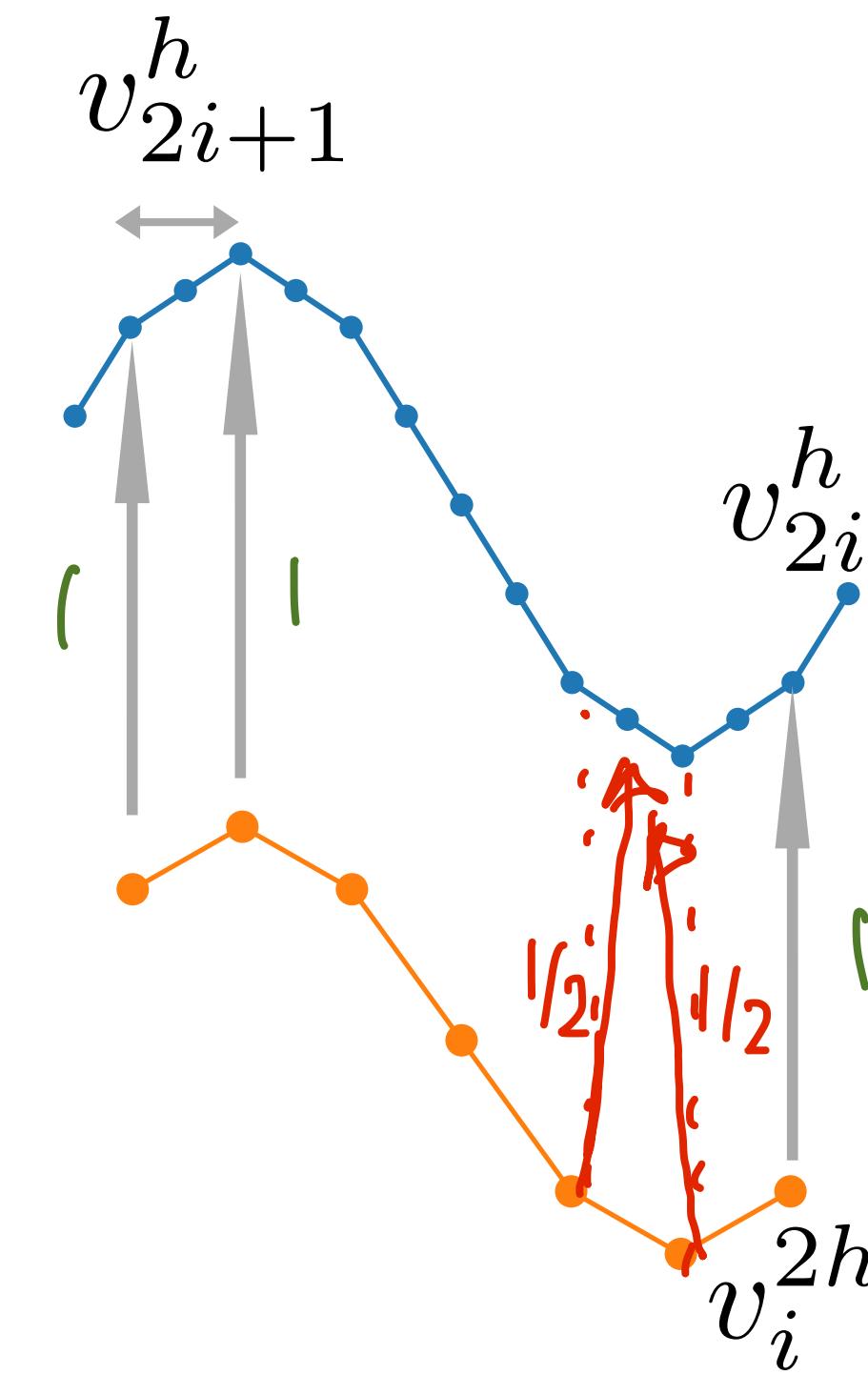
Interpolation *P: from coarse to fine*

$$v_{2i}^h = v_i^{2h}$$

$$v_{2i+1}^h = \frac{1}{2}(v_i^{2h} + v_{i+1}^{2h})$$

Injection

Average
(linear interp)

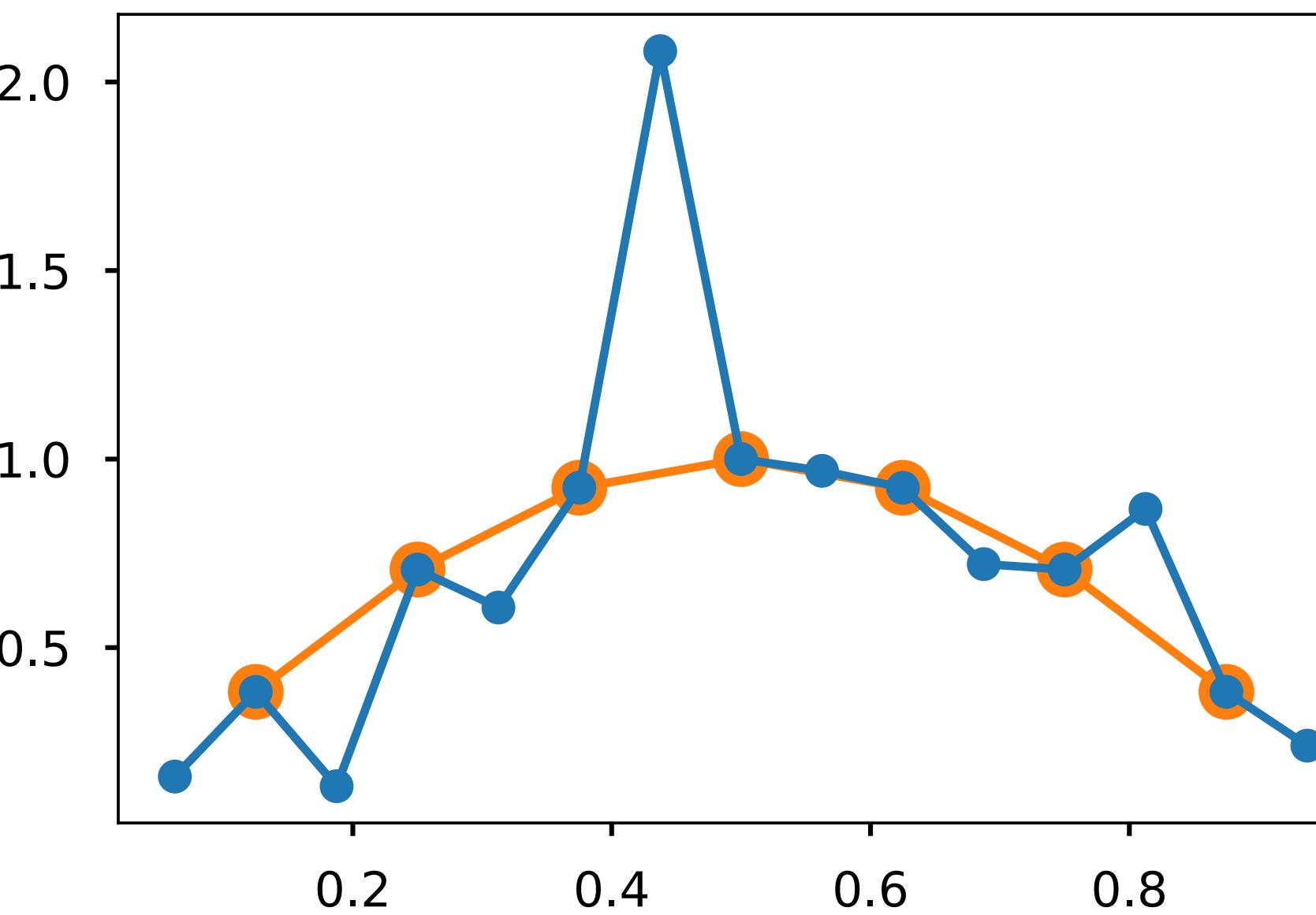
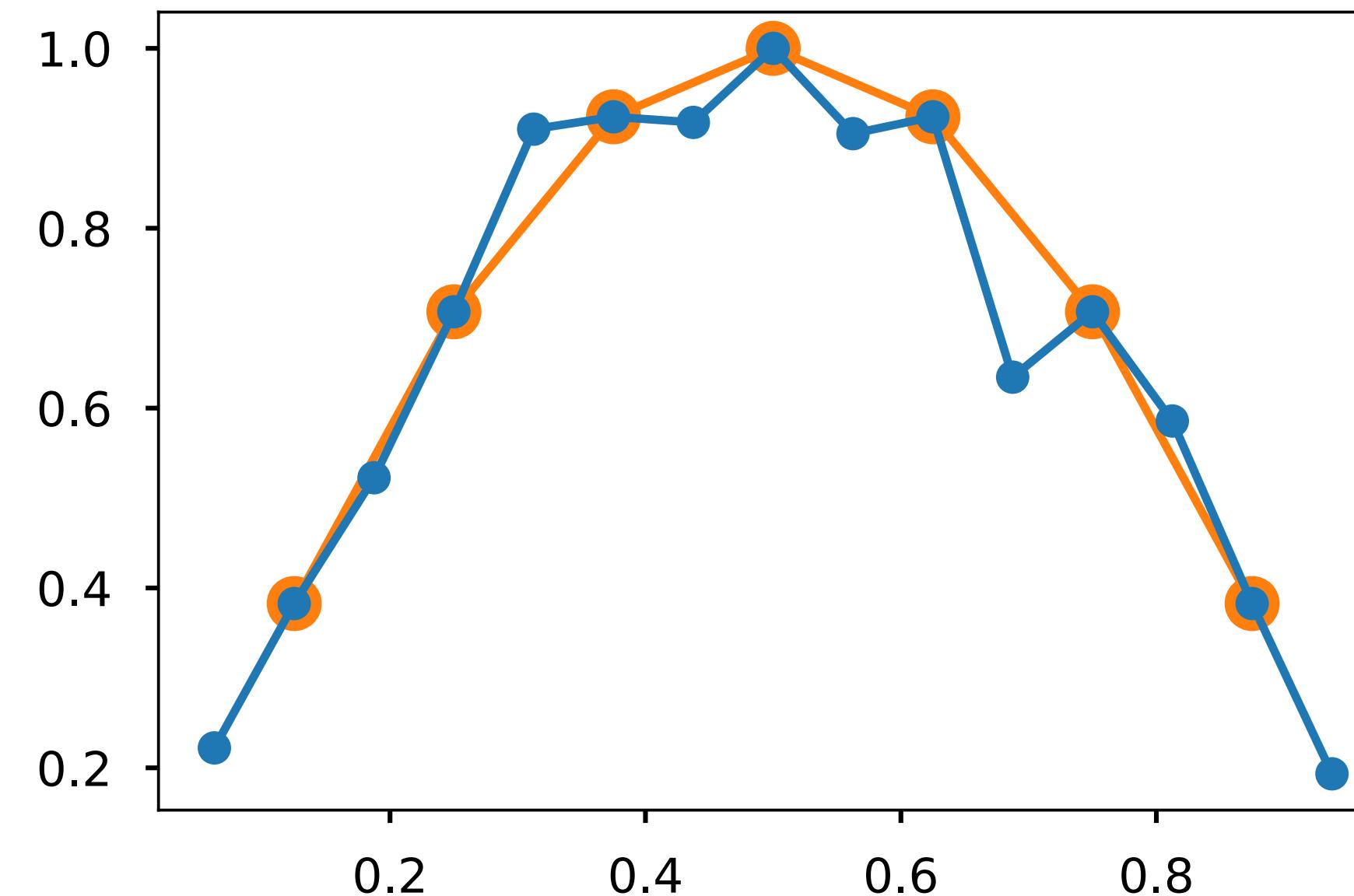


- Values at points common to both grids are reused (injected)

Interpolation

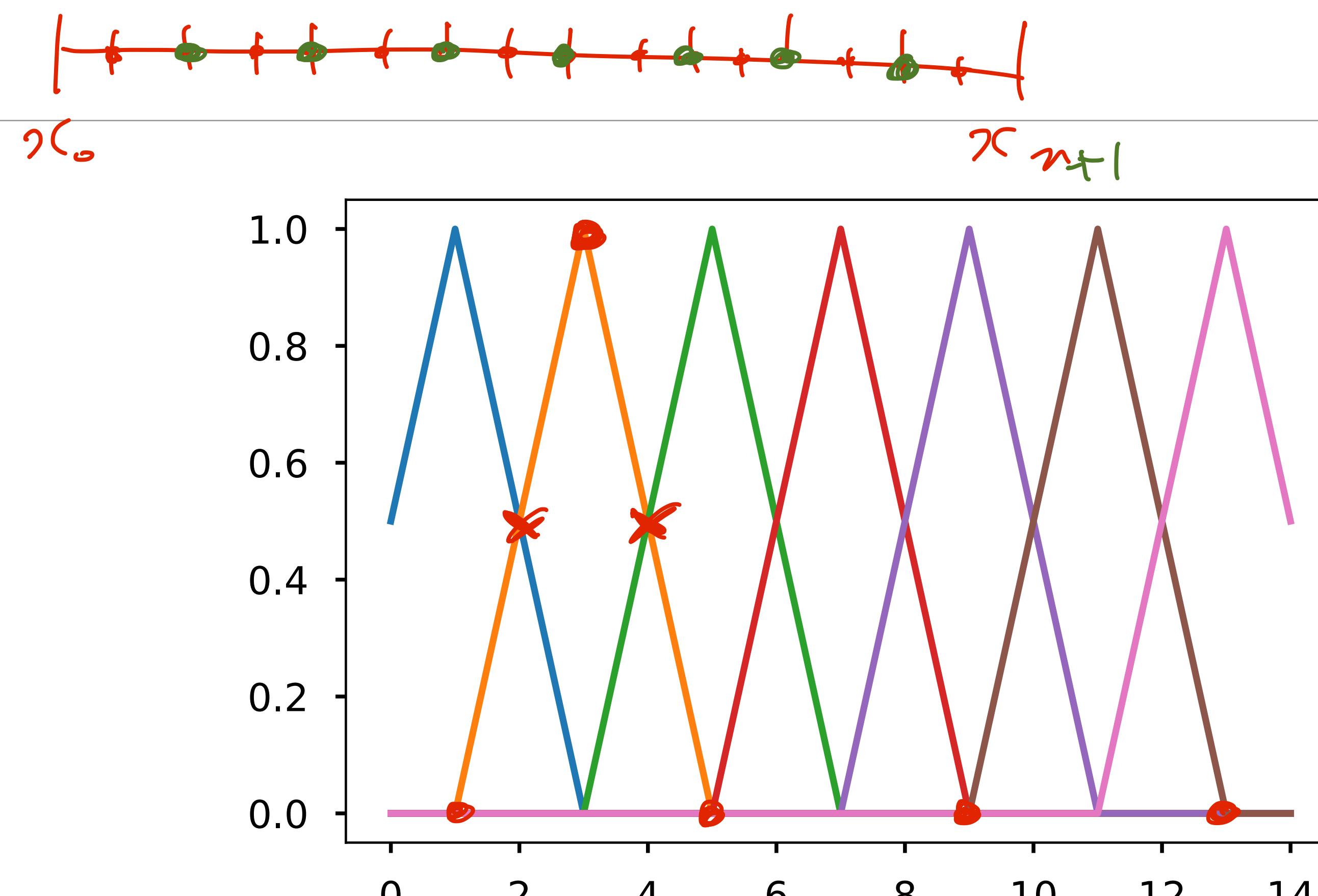
- interpolation gives smooth result

(we want to correct
smooth error on the fine grid)

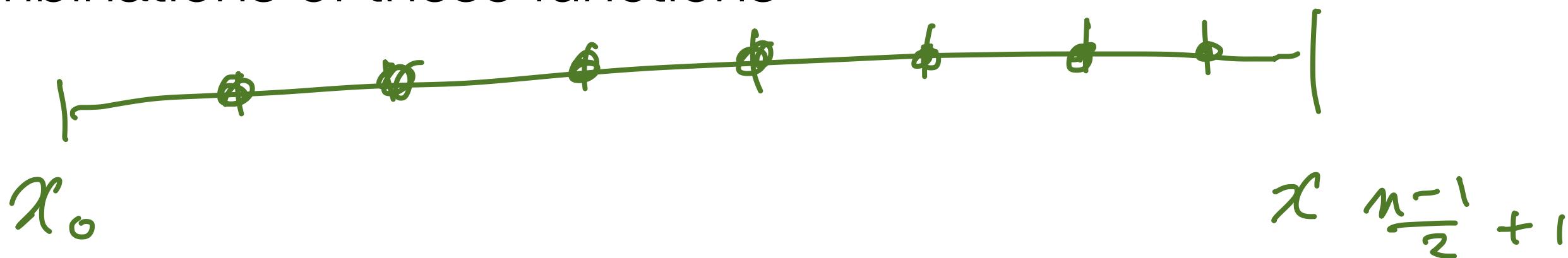


In matrix form

$$P = \frac{1}{2} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 \\ 1 & 1 & 2 & 1 & 1 & 2 & 1 & 1 & 2 & 1 & 1 & 2 \\ 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 \\ 1 & 1 & 2 & 1 & 1 & 2 & 1 & 1 & 2 & 1 & 1 & 2 \\ 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 \\ 1 & 1 & 2 & 1 & 1 & 2 & 1 & 1 & 2 & 1 & 1 & 2 \\ 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 \\ 1 & 1 & 2 & 1 & 1 & 2 & 1 & 1 & 2 & 1 & 1 & 2 \\ 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 \\ 1 & 1 & 2 & 1 & 1 & 2 & 1 & 1 & 2 & 1 & 1 & 2 \\ 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 \end{bmatrix}$$



- The columns of P are basis functions (right)
- The fine grid vectors, Pv, are linear combinations of these functions
- Notice: P is full rank!



The coarse grid operator

$$x_1 = x_0 + V(V^T A V)^{-1} V^T r_0$$

(sub)space defined by P

$$x_1 = x_0 + P(P^T A P)^{-1} P^T r_0$$

- If V is defined by $\text{span}\{P\}$ — or just P ,
- Then V^T defines **restriction** as P^T
- And the **coarse level operator** is defined by $P^T A P$

L optional coarse-grid correction, given V
(minimizes $\|e_1\|_A$)

Two level method

$$x_1 = x_0 + V(V^T A V)^{-1} V^T r_0$$

$$x_1 = x_0 + P(P^T A P)^{-1} P^T r_0$$

$$x_0 \leftarrow x_0 + \hat{e}_c$$

$$x_0 \leftarrow x_0 + \omega D^{-1} A r_0$$

$$r_0 = b - A x_0$$

$$P^T r_0$$

$$P^T A P \hat{e}_c = P^T r_0$$

$$A_c \hat{e}_c = r_c$$

- Given
- Smooth a few times

• Form residual

• Restrict the residual

• Solve the coarse problem

• Interpolate the approx error

• Correct the initial guess

• What should this be?

• How many times

• What does this mean?

• What are we interpolating?

• Are we done?

$$x_0 + P \hat{e}_0$$

$$x_1 = x_0 + e_{CGC}$$

find "good" e_{CGC} (to remove smooth fine-level error)

note $A e_0 = r_0$ (e_0 is smooth after fine-level relaxation)
($x^* = x_0 + e_0$)

find coarse approximation of current e_0

$$P^T A e_0 = P^T r_0 \quad \text{let } e_0 \approx \hat{P} \hat{e}_c$$

solve
$$\boxed{P^T A \hat{P} \hat{e}_c = P^T r_0}$$

(choose P such that its range contains smooth fine-level errors)

correct $x_1 \leftarrow x_0 + \hat{P} \hat{e}_c$

$$A_c = P^T A P \quad \text{or:} \quad A_c = A_{2R}$$

Notes on variants

- An alternative to restriction, is injection
- Or a weighted transpose of linear interpolation (to restrict constants exactly)
- An alternative to $A_c = P^T A_h P$ is to rediscretize $A_c = A_{2h}$

$$\begin{bmatrix} 0 & 1 & 0 & & & \\ & 0 & 1 & 0 & & \\ & & 0 & 1 & 0 & \\ & & & 0 & 1 & 0 \\ & & & & 0 & 1 & 0 \\ & & & & & 0 & 1 & 0 \\ & & & & & & 0 & 1 & 0 \\ & & & & & & & 0 & 1 \\ \end{bmatrix}$$
$$\frac{1}{4} \begin{bmatrix} 1 & 2 & 1 & & & \\ & 1 & 2 & 1 & & \\ & & 1 & 2 & 1 & \\ & & & 1 & 2 & 1 \\ & & & & 1 & 2 & 1 \\ & & & & & 1 & 2 & 1 \\ & & & & & & 1 & 2 & 1 \\ & & & & & & & 1 & 2 \\ \end{bmatrix}$$

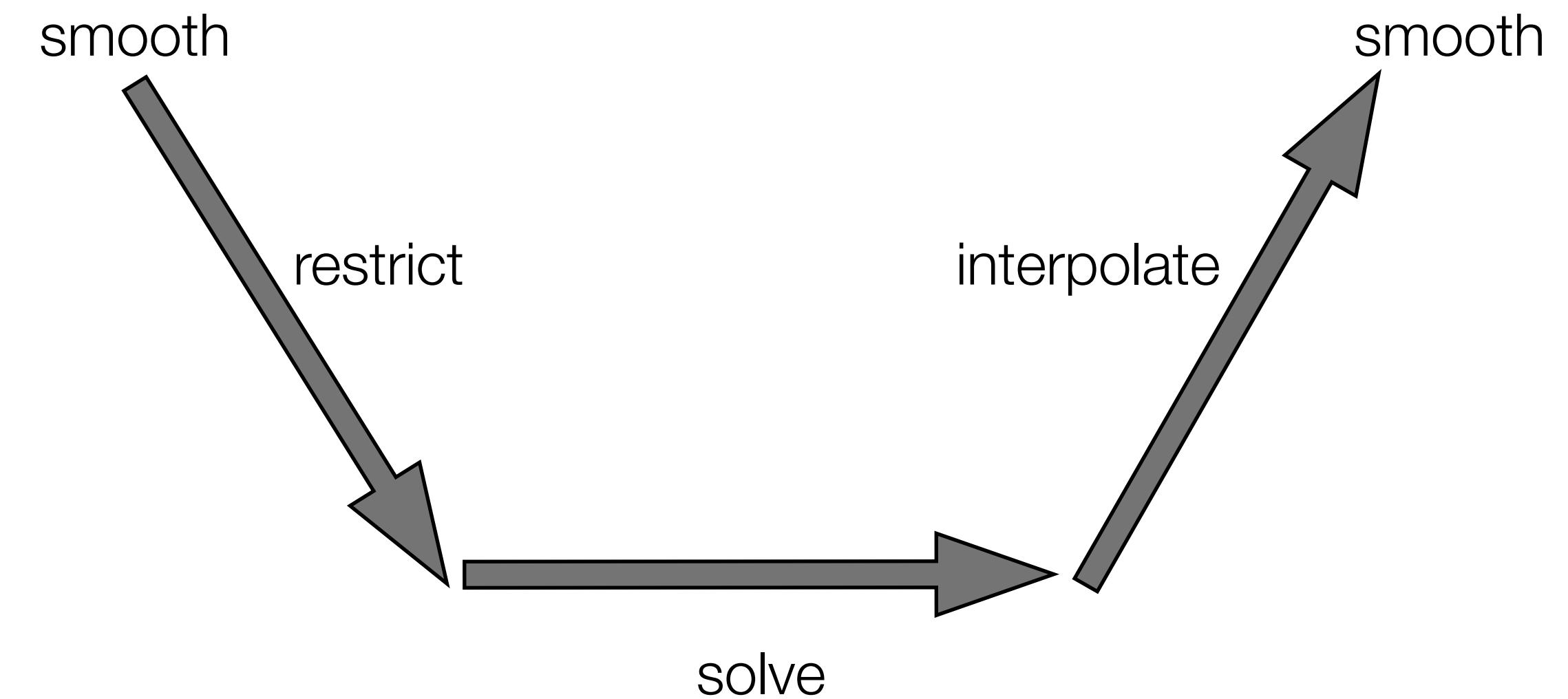
$$x_1 \leftarrow x_0 + P A_{2h}^{-1} R r_0$$

Algorithm: two-level multigrid

Input: initial guess

$$P^T = R$$

1. Smooth ν_{pre} times on $Au = f$
2. Compute $r = f - Au$
3. Compute $r_c = Rr$
4. Solve $A_c e_c = r_c$
5. Interpolate $\hat{e} = Pe_c$
6. Correct $u \leftarrow u + \hat{e}$
7. Smooth ν_{post} times on $Au = f$



A two-level “V” cycle

How Accurate is Multigrid?

- Consider the exact solution to the PDE u^*

$$-u'' = f$$

- The exact solution to the **discrete** problem u_h^*

$$Au = b$$

- The approximate **discrete** solution $u_h \approx u_h^*$

- Define

$$u^* - u_h^* \quad \text{Discretization error}$$

$$u_h^* - u_h \quad \text{Algebraic error}$$

How Accurate should Multigrid aim to be?

- Would like the total error bounded

$$\|u^* - u_h\| \leq \underbrace{\|u^* - u_h^*\|}_{\text{disc.}} + \underbrace{\|u_h^* - u^h\|}_{\text{alg.}}$$
$$\leq \varepsilon$$

- To achieve this,

- force the discretization (grid space) so that

$$\|u^* - u_h^*\| \leq ch^2 \leq \frac{\varepsilon}{2}$$

- and the algebraic error (convergence) up to the discretization error

$$\|u_h^* - u^h\| \leq \frac{\varepsilon}{2}$$

Multigrid convergence

- Convergence factor of a cycle – the factor by which the error (residual) is reduced (in some norm) in each iteration

γ

$$\gamma^m = c n^{-2}$$

...assume this is independent of n

$$m \log \gamma = \log c - 2 \log n$$

- Wish to have m cycles such that

$$\gamma^m \sim \mathcal{O}(n^{-2}) \leq \frac{\epsilon}{2}$$

- Then we need

cycles

$$m \sim \mathcal{O}(\log n)$$

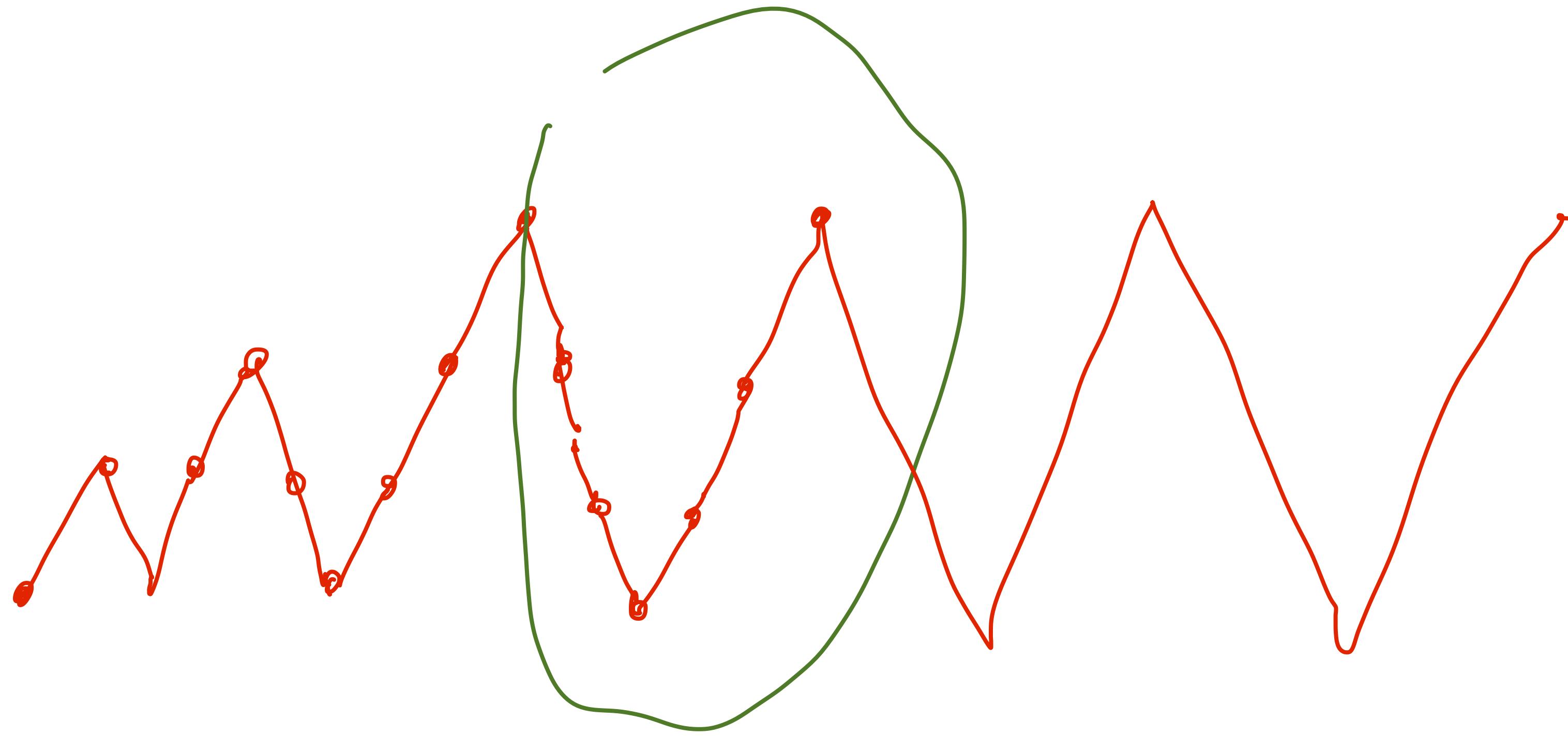
$$W = \Theta(n \log n)$$

want

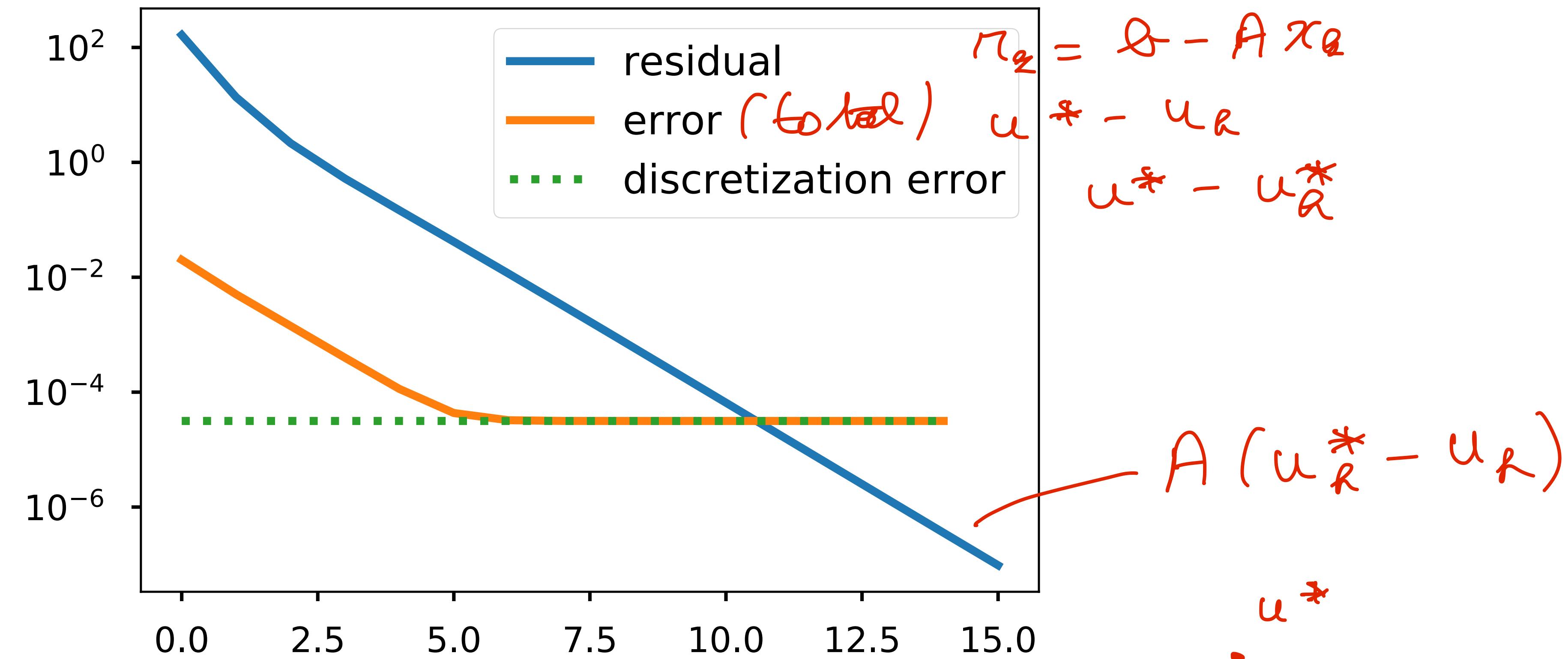
$$W = \Theta(n)$$

Full Multigrid (FMG)

$$w = \mathcal{O}(n)$$



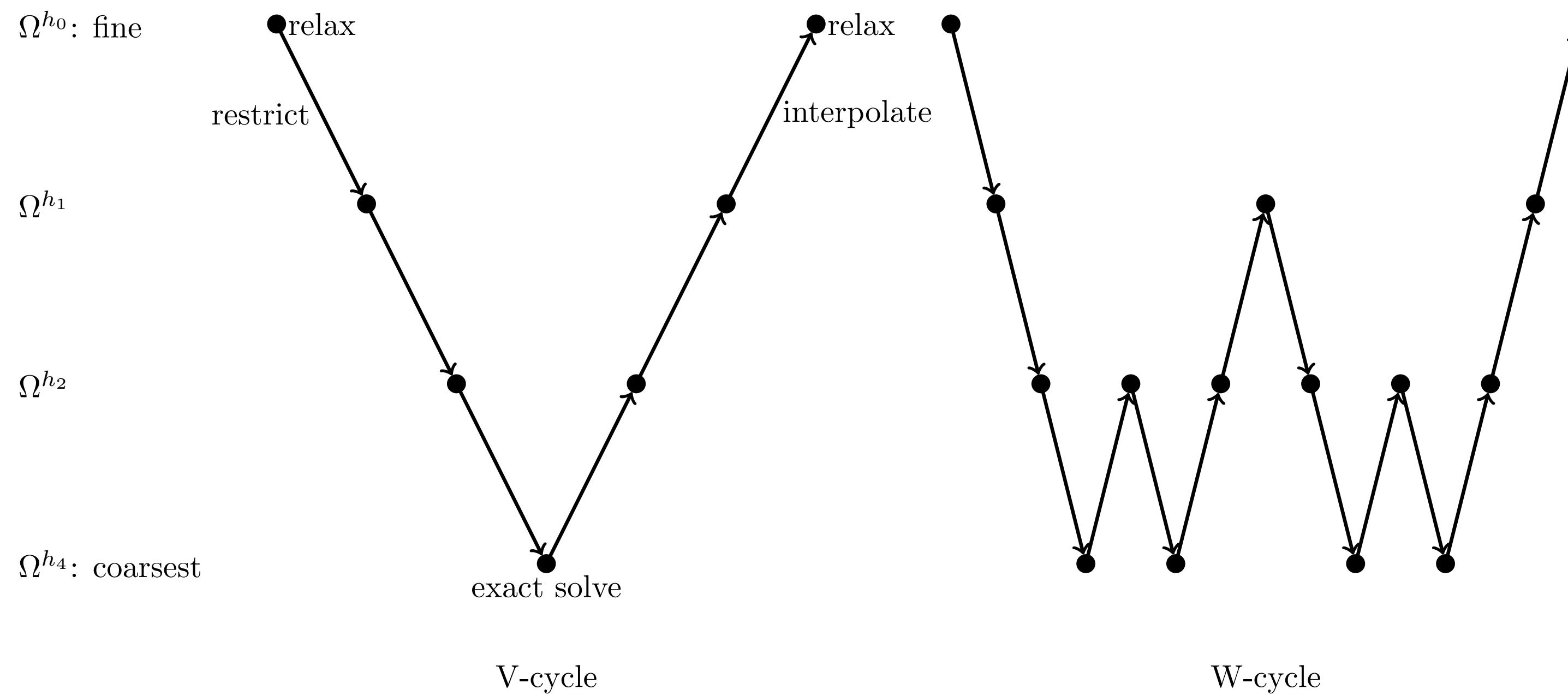
Algebraic error



- The total error is limited by the discretization error

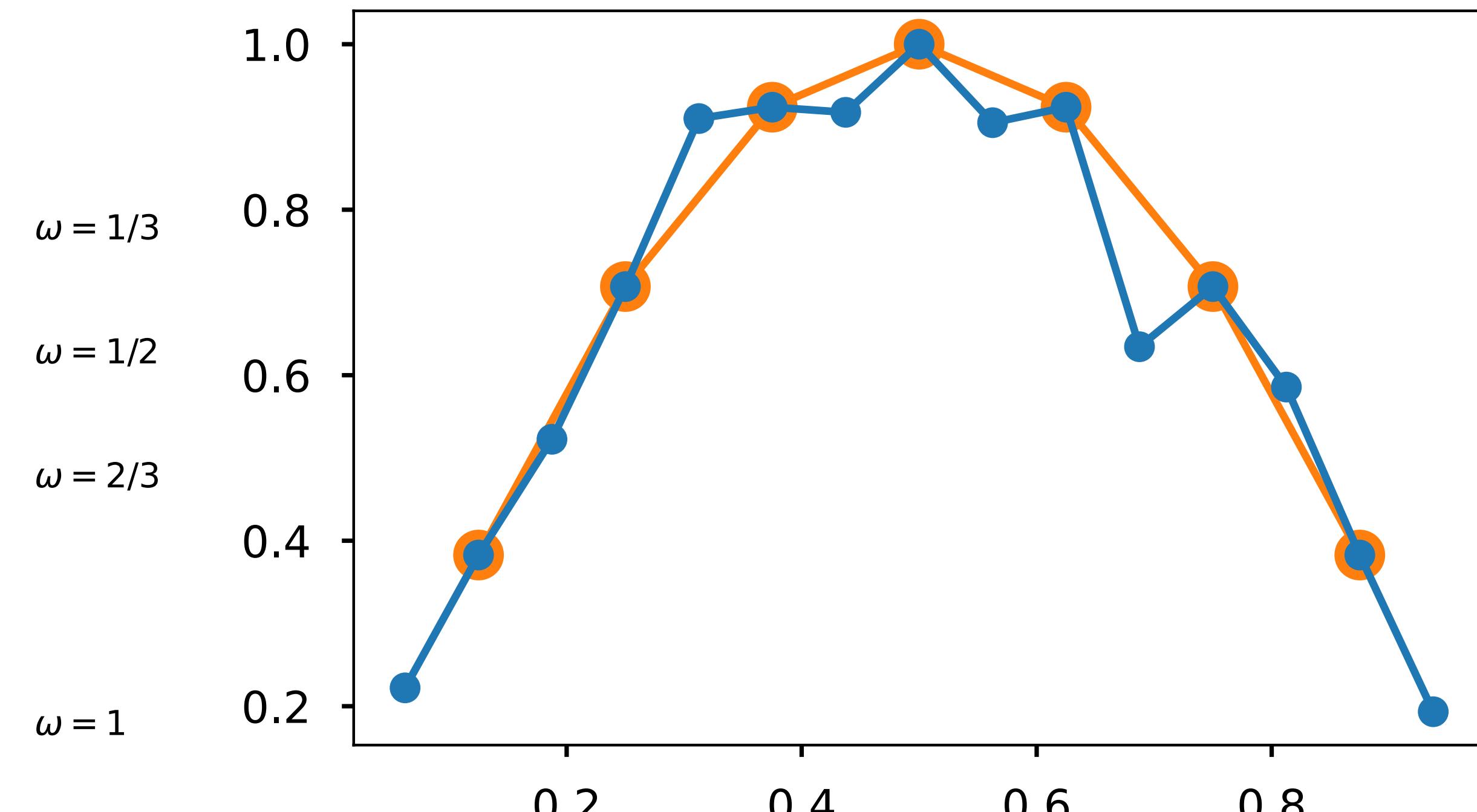
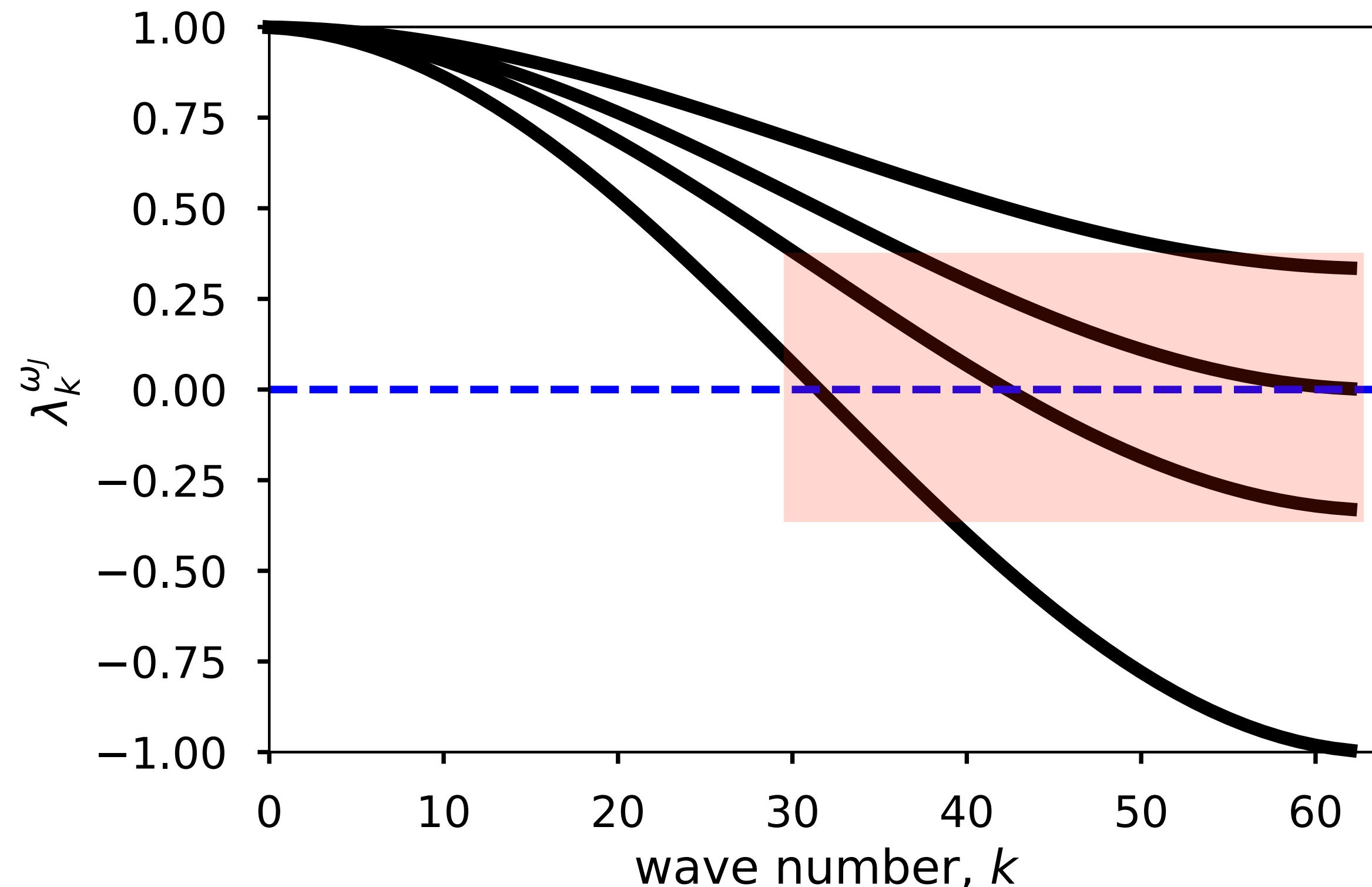
u^*
 u_Q^*
 u_R

The Multigrid V-Cycle and W-Cycle



- W-Cycle can account for inadequate coarse level solves

Recap...

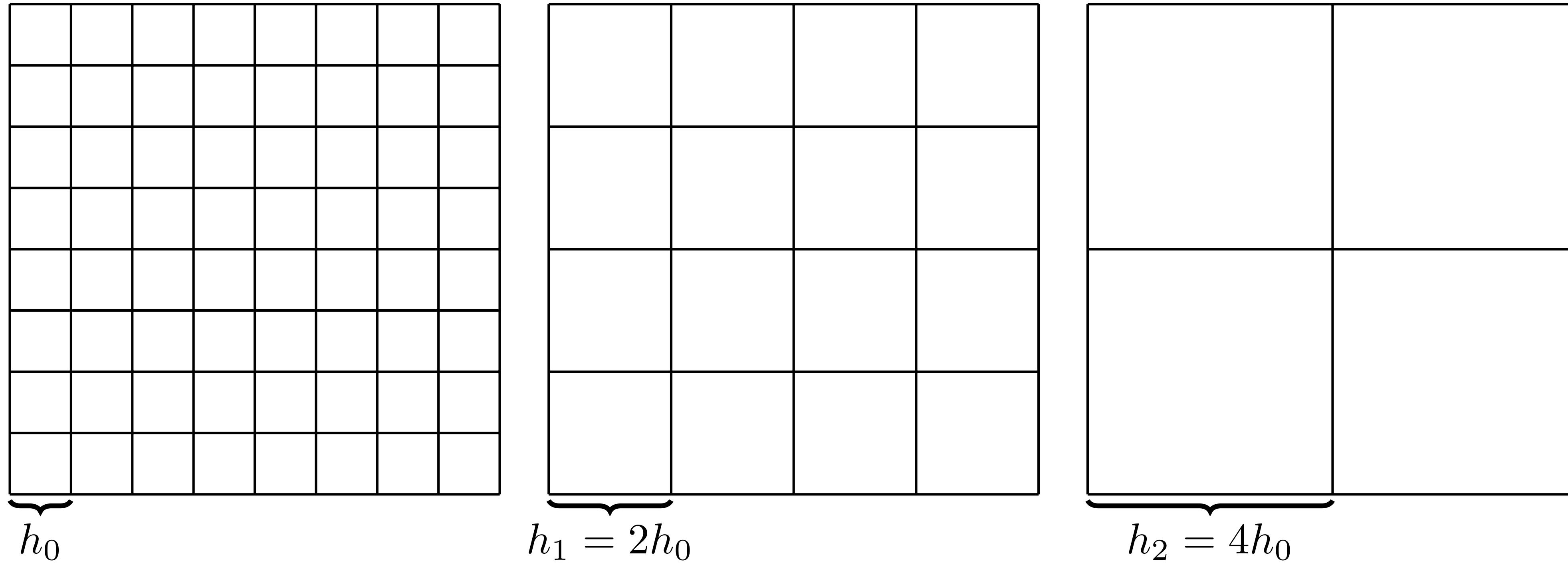


- Smoothing:
Reduce high frequency error

$$e_1 = e_0 - P(P^T A P)^{-1} P^T A G \underbrace{e_0}_{\tilde{e}_0}$$

- Coarse-grid correction:
Reduce smooth-ish things in the range of interpolation

Multigrid in 2D



- Again, assume we have a sequence of uniform grids
- Relaxation remains the same (what is ω ?)

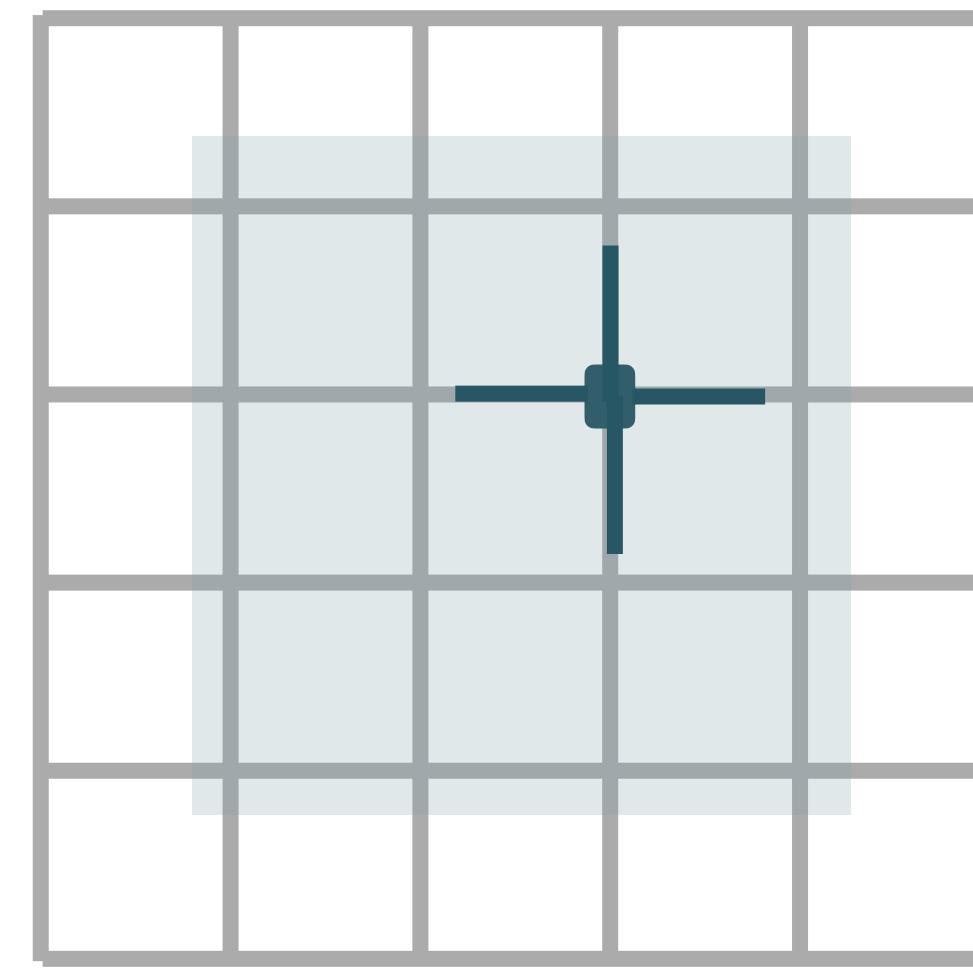
Multigrid in 2D

- Model problem

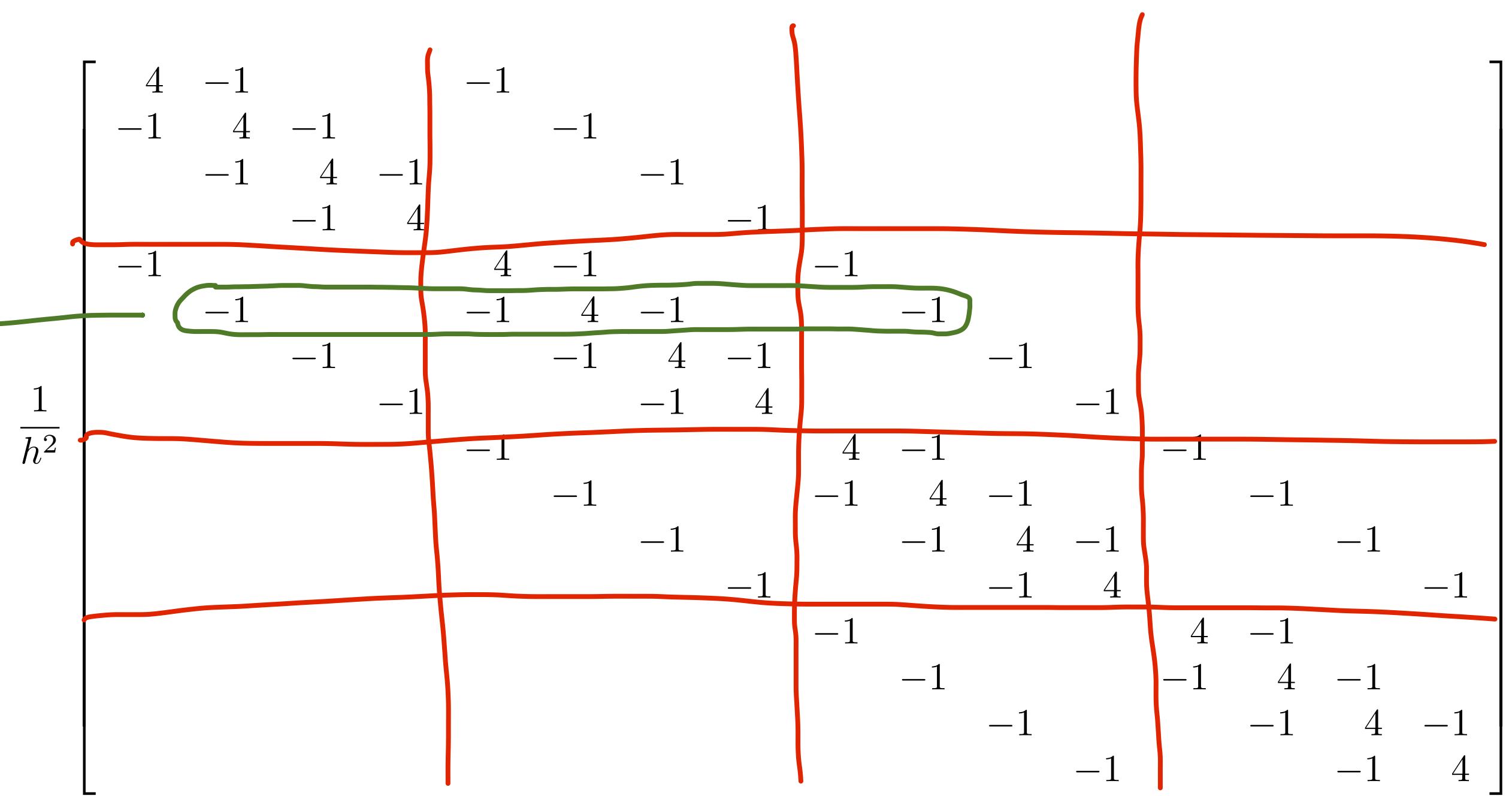
$$\begin{aligned} -u_{xx} - u_{yy} &= f \\ u &= 0 \quad \text{on boundary} \end{aligned}$$

$$nnz \approx 5n$$

- Results in the stencil / matrix



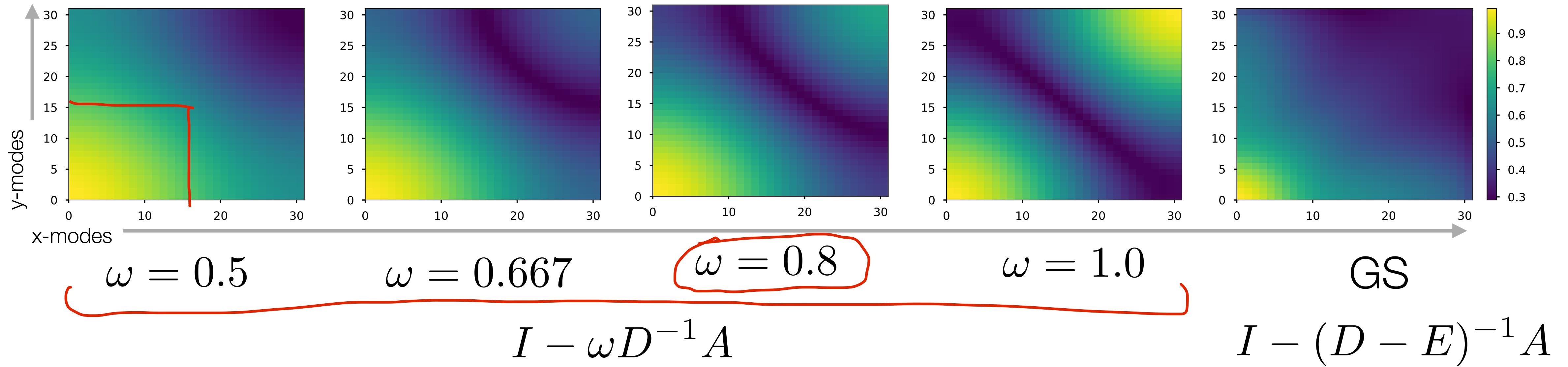
$$\begin{bmatrix} -1 & -1 \\ -1 & 4 & -1 \\ -1 & -1 \end{bmatrix} \rightarrow \frac{1}{h^2}$$



Relaxation in 2D

$$\sin\left(\frac{k_x i \pi}{n+1}\right) \sin\left(\frac{k_y j \pi}{n+1}\right)$$

Convergence factor
over 10 sweeps



- weighted Jacobi: Same issue – need to select a parameter
- Gauss-Seidel improved
- Red-Black Gauss-Seidel and other schemes even more effective

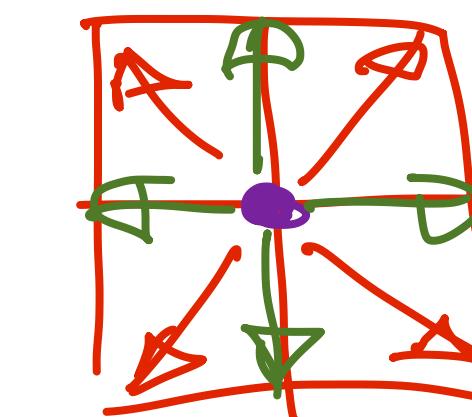
Interpolation in 2D

- Bilinear interpolation, tensor product of 1D interpolation

$$\frac{1}{2} \begin{bmatrix} 1 & 2 & 1 \end{bmatrix}$$

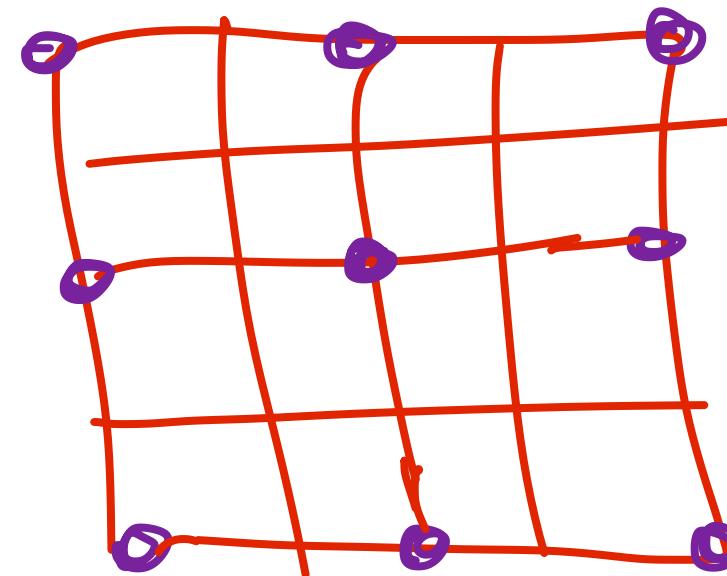


$$\frac{1}{4} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$



• is coarse

- Example $3 \times 3 \rightarrow 7 \times 7$



$$\begin{bmatrix} 0.5 & & \\ & 1 & \\ 0.5 & & \end{bmatrix}$$

$$\otimes$$

$$\begin{bmatrix} 0.5 & & \\ & 1 & \\ 0.5 & & \end{bmatrix} \otimes \begin{bmatrix} 0.5 & & \\ & 1 & \\ 0.5 & & \end{bmatrix}$$



$$\begin{bmatrix} 1 & 2 & 1 & 1 & 2 & 1 & 1 \\ 2 & 4 & 2 & 2 & 4 & 2 & 2 \\ 1 & 2 & 1 & 1 & 2 & 1 & 1 \\ 1 & 2 & 1 & 1 & 2 & 1 & 1 \\ 2 & 4 & 2 & 2 & 4 & 2 & 2 \\ 1 & 2 & 1 & 1 & 2 & 1 & 1 \\ 1 & 2 & 1 & 1 & 2 & 1 & 1 \end{bmatrix}$$

A few observations so far: **One**

- Let's consider a V(1,1) cycle – weighted Jacobi, etc.

- The **error** propagation for this looks like

$$e_1 = \underbrace{G(I - P(P^T A P)^{-1} P^T A) G e_0}_M$$

$G = I - \omega D^{-1} A$

smooth *smooth*

CGC

before smoothing

$M e_k \not\rightarrow 0?$

- One thing we can do, is consider bounds on each operation.

A few observations so far: **One**

- Take the operator

$$M = G(I - P(P^T A P)^{-1} P^T A)G$$

- And makes some bounds

$$\|I - P(P^T A P)^{-1} P^T A\| \|G\|^2$$

approximation property smoothing property

- General $\|G\| \leq 1$

1D over $[n/2, n]$:

$$\|G\| \leq \frac{1}{3}$$

2D over $[n/2, n]$:

$$\|G\| \leq \frac{3}{5}$$

"Multigrid tutorial"

A few observations so far: **One**

$$\|I - P(P^T A P)^{-1} P^T A\| \|G\|^2$$

approximation property smoothing property

- General $\|G\| \leq 1$

$$1D \text{ over } [n/2, n]: \quad \|G\| \leq \frac{1}{3}$$

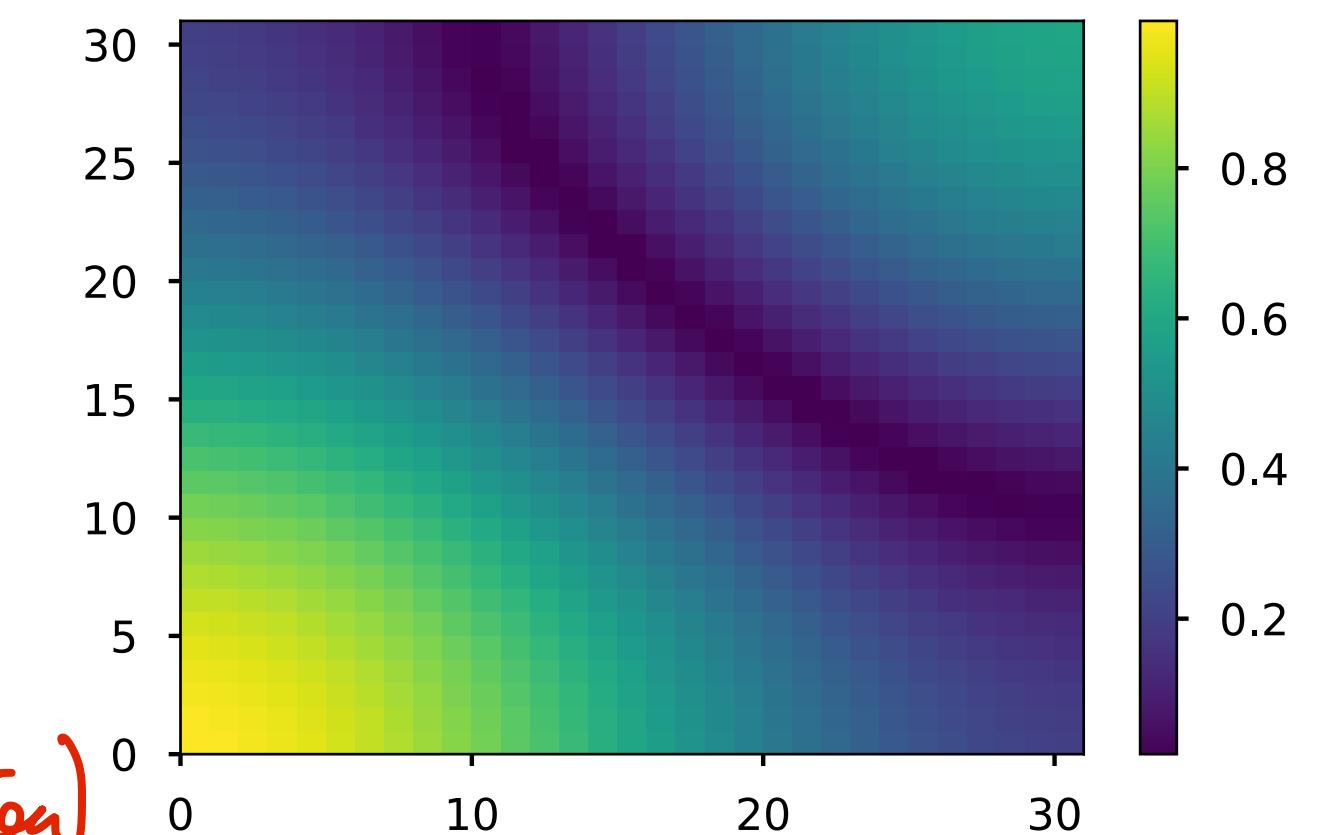
$$2D \text{ over } [n/2, n]: \quad \|G\| \leq \frac{3}{5}$$

- Also, if w s.t. $Aw \in \mathcal{N}(P^T)$ *(null space of restriction)*

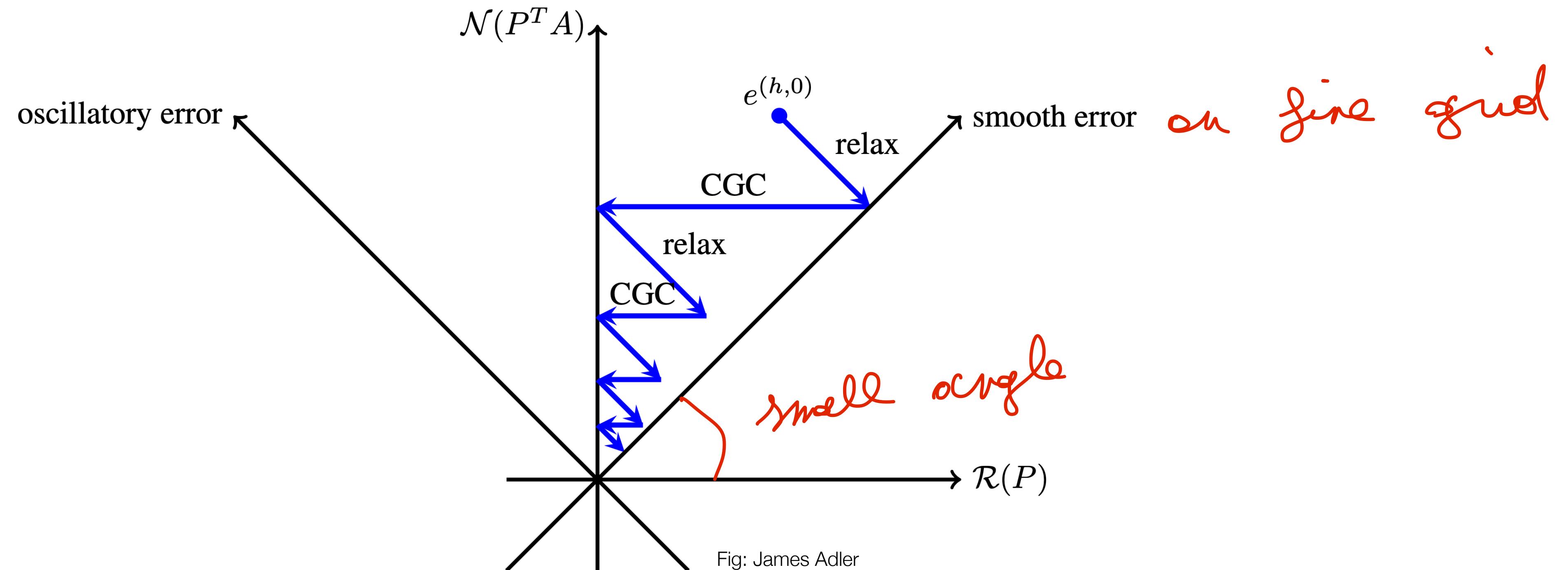
then $(I - P(P^T A P)^{-1} P^T A)w = w$

$$\|\cdot\| \geq 1$$

L error



A few observations so far: **Two**



- Complementary processes:
 - **relaxation:** targets (Fourier) smoothing
 - **coarse grid correction:** targets things in the range of interpolation

A few observations so far: **Three**

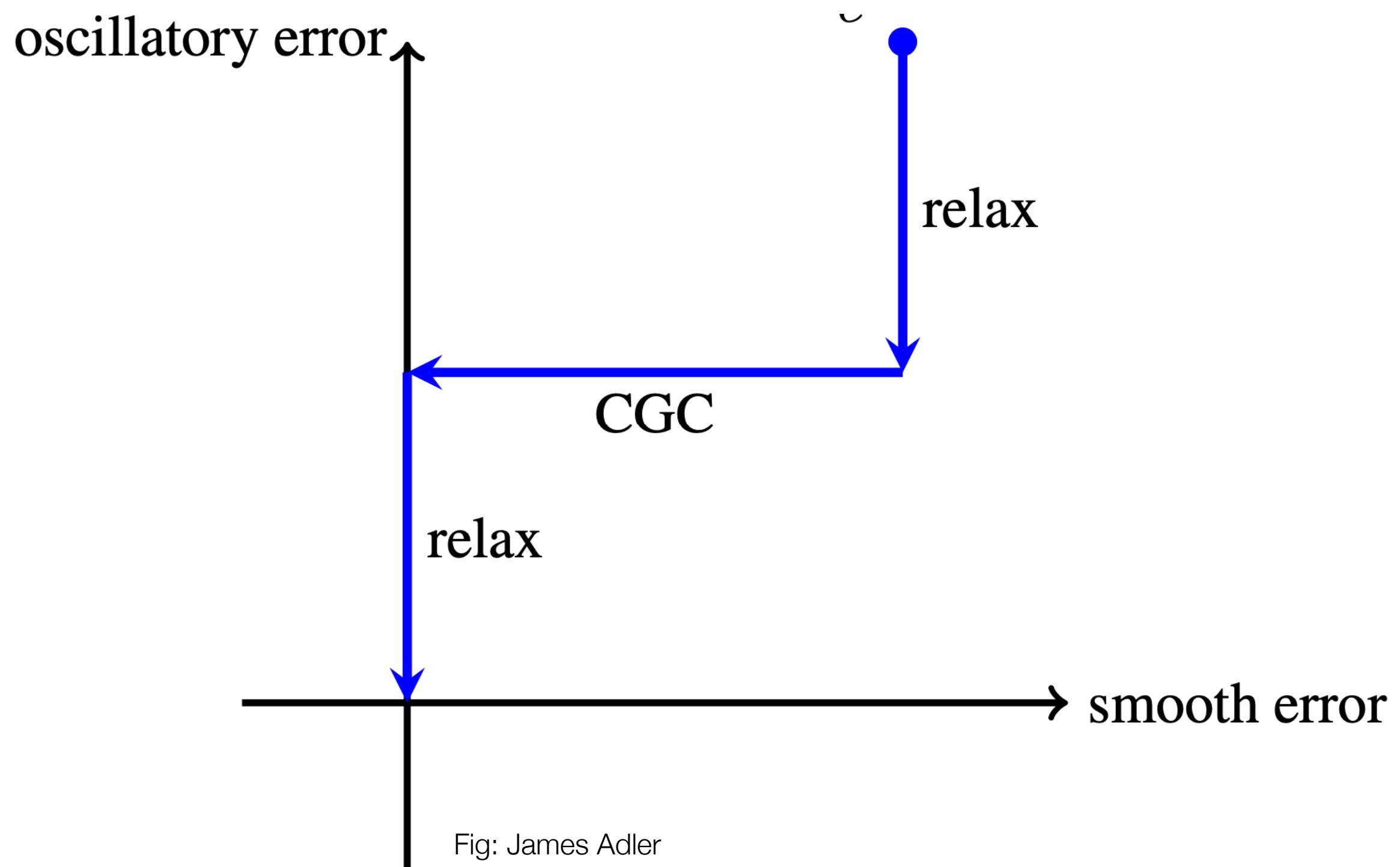


Fig: James Adler

$$e_1 \leftarrow (I - P(P^T A P)^{-1} P^T A) G e_0$$

$$G e_0 \in \mathcal{R}(P) \Rightarrow e_1 = 0$$

interpolation should capture what relaxation misses

What can go wrong?!

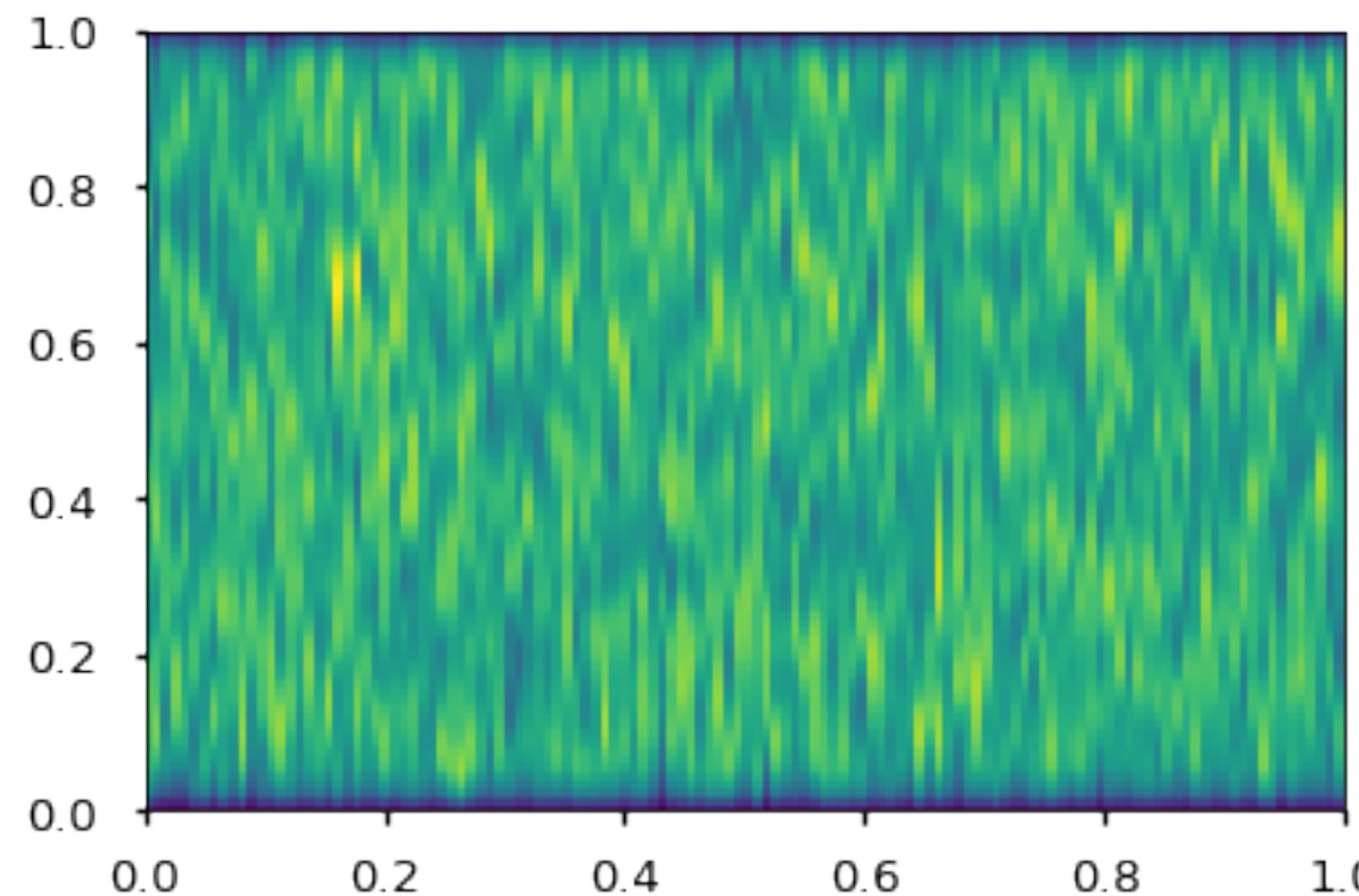
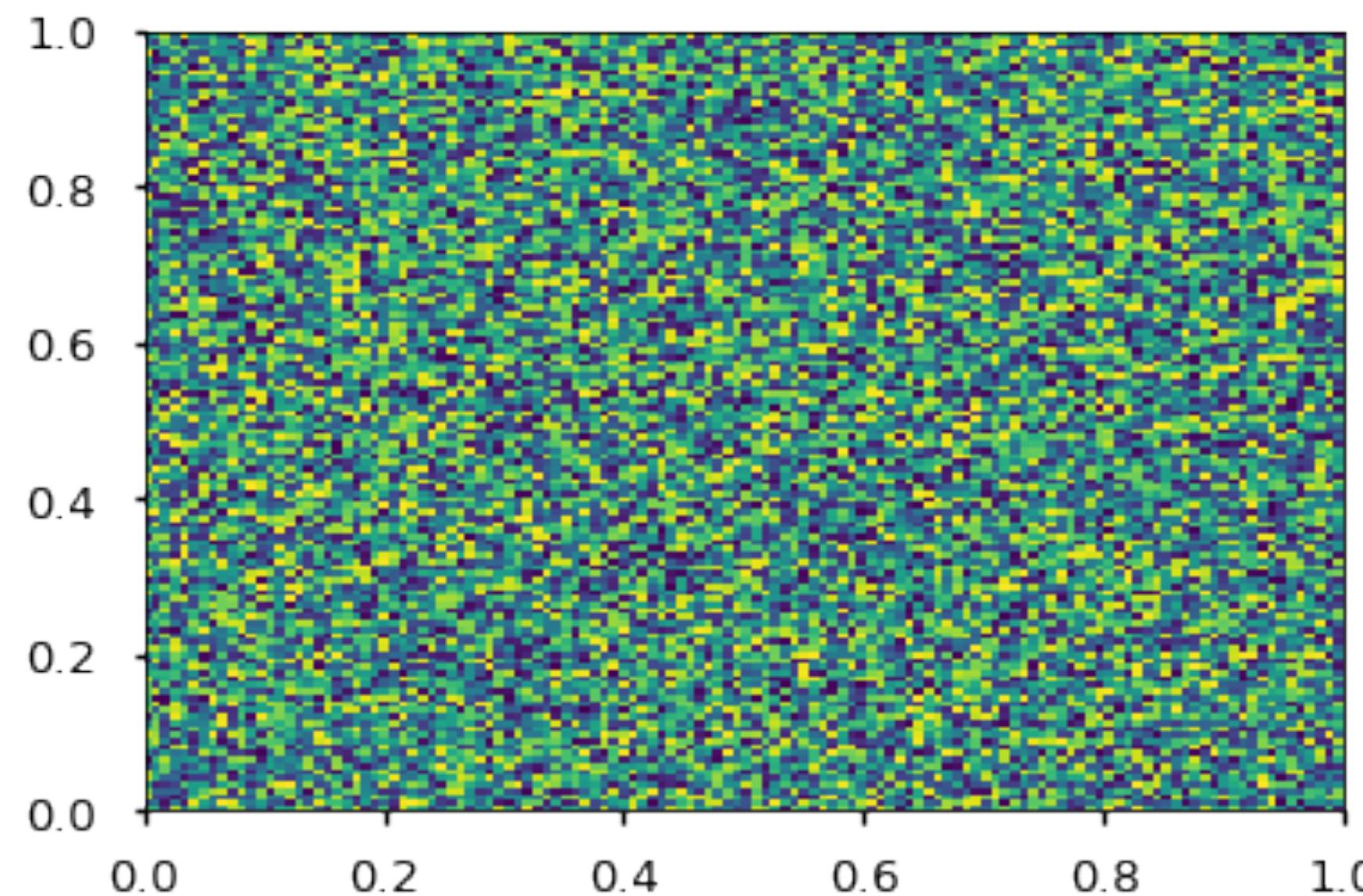
- Consider an *anisotropic problem*

$$-\varepsilon u_{xx} - u_{yy} = f$$

$u = 0$ on boundary

after relaxation: smooth in y ,
not in x

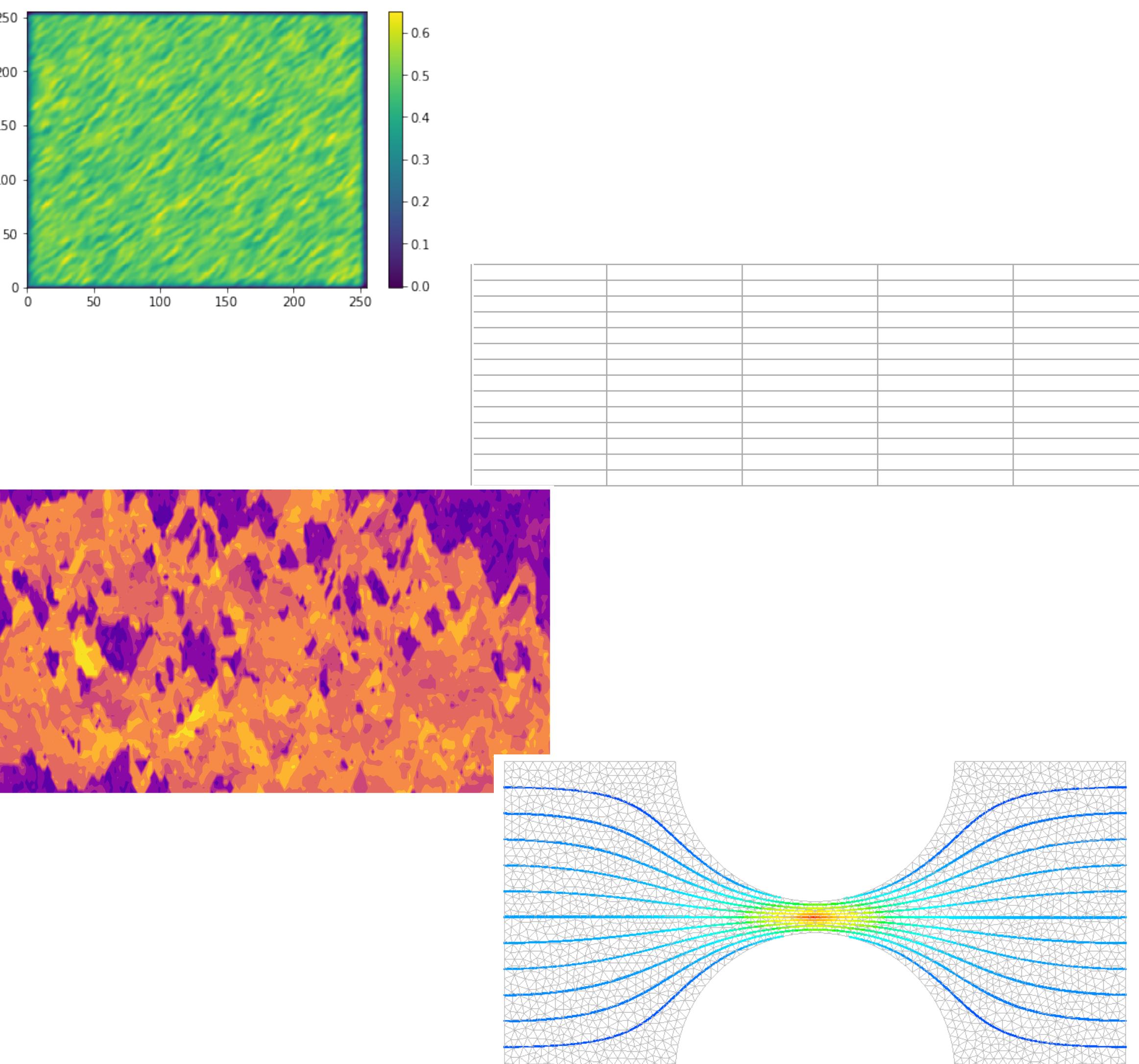
$$\begin{bmatrix} & & -1 \\ -\varepsilon & 2 + 2\varepsilon & -\varepsilon \\ & -1 & \end{bmatrix}$$



we cannot coarsen in x !

What can go wrong?!

- Anisotropy
- Mesh stretching
- Jumping coefficients
- Non-elliptic

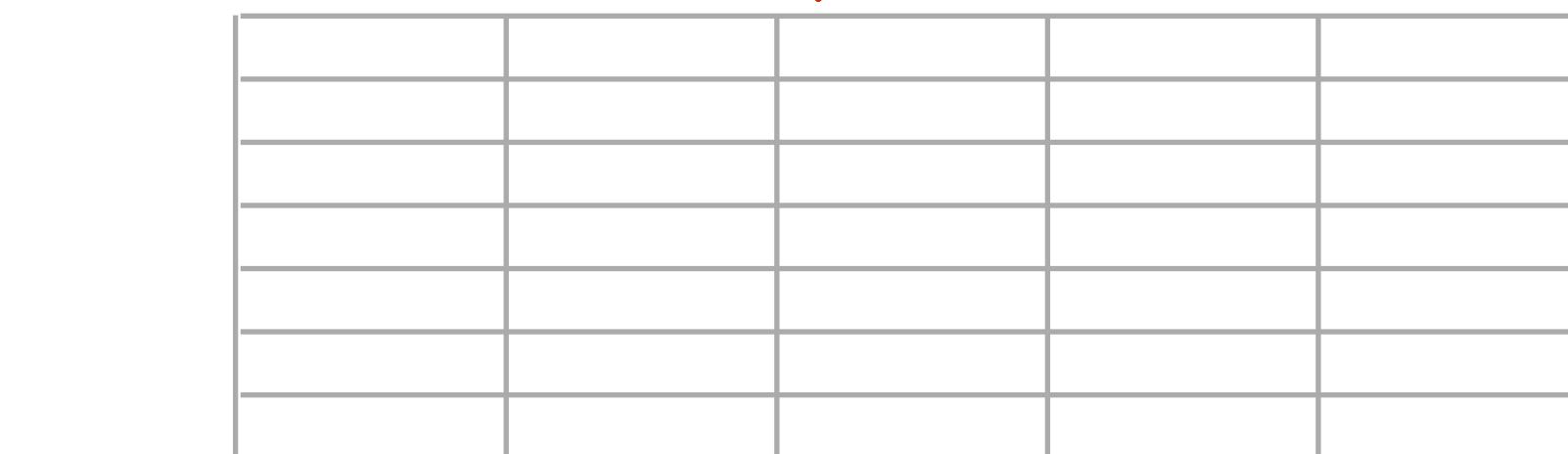
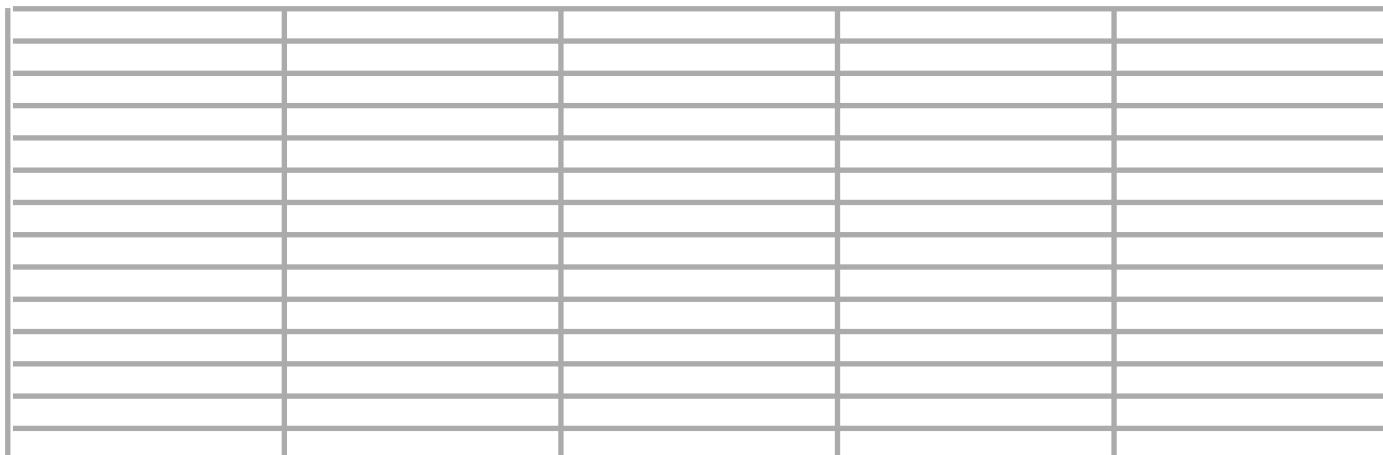
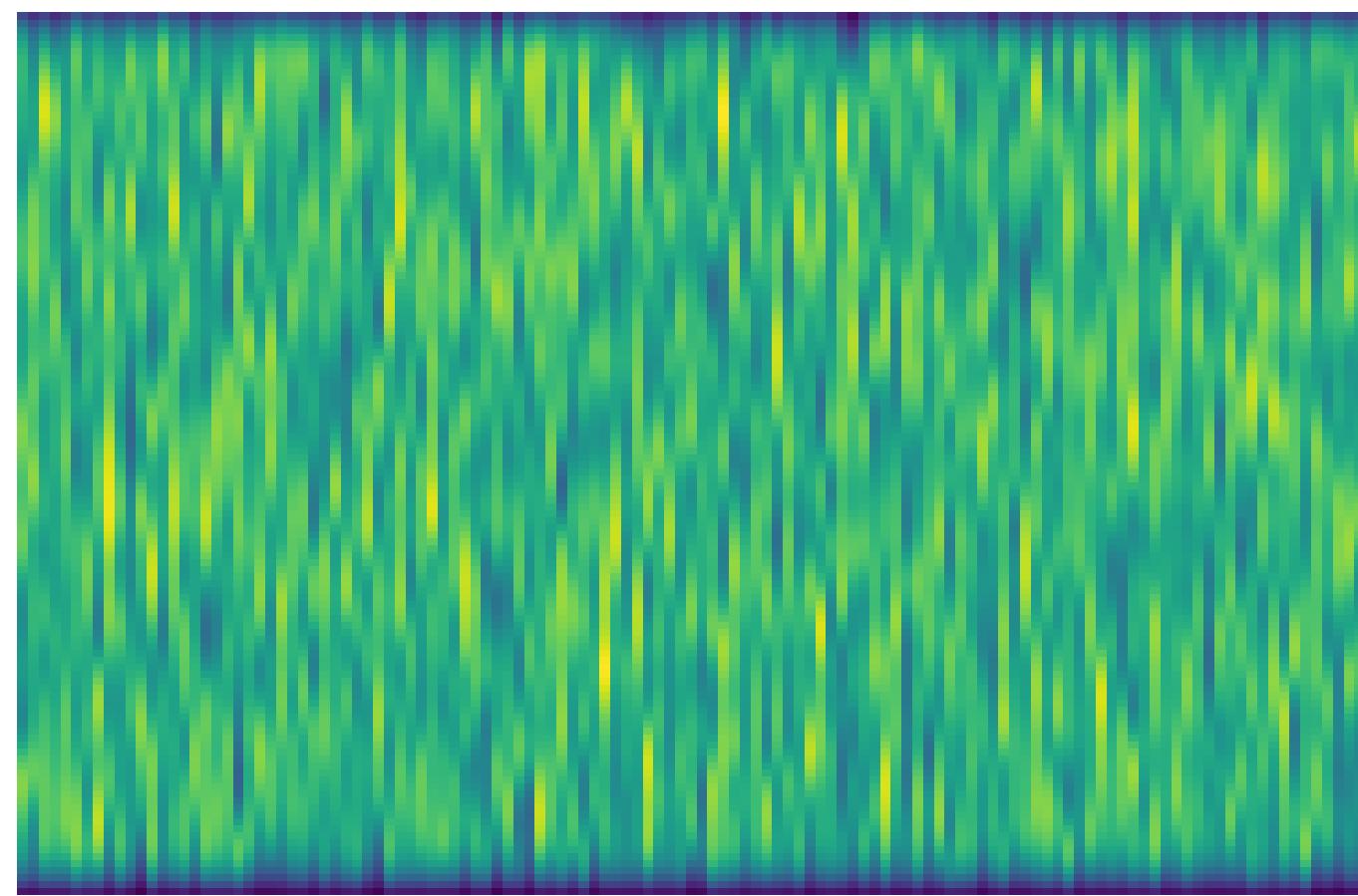


$$-\epsilon u_{xx} - u_{yy} = f$$

Options for more robust Multigrid

- **Semicoarsening:** Coarsen in the direction of smoothness

(charge coarsening)



don't coarsen in x

only coarsen in y

(then CGC will be OK)
(on special coarse grid)

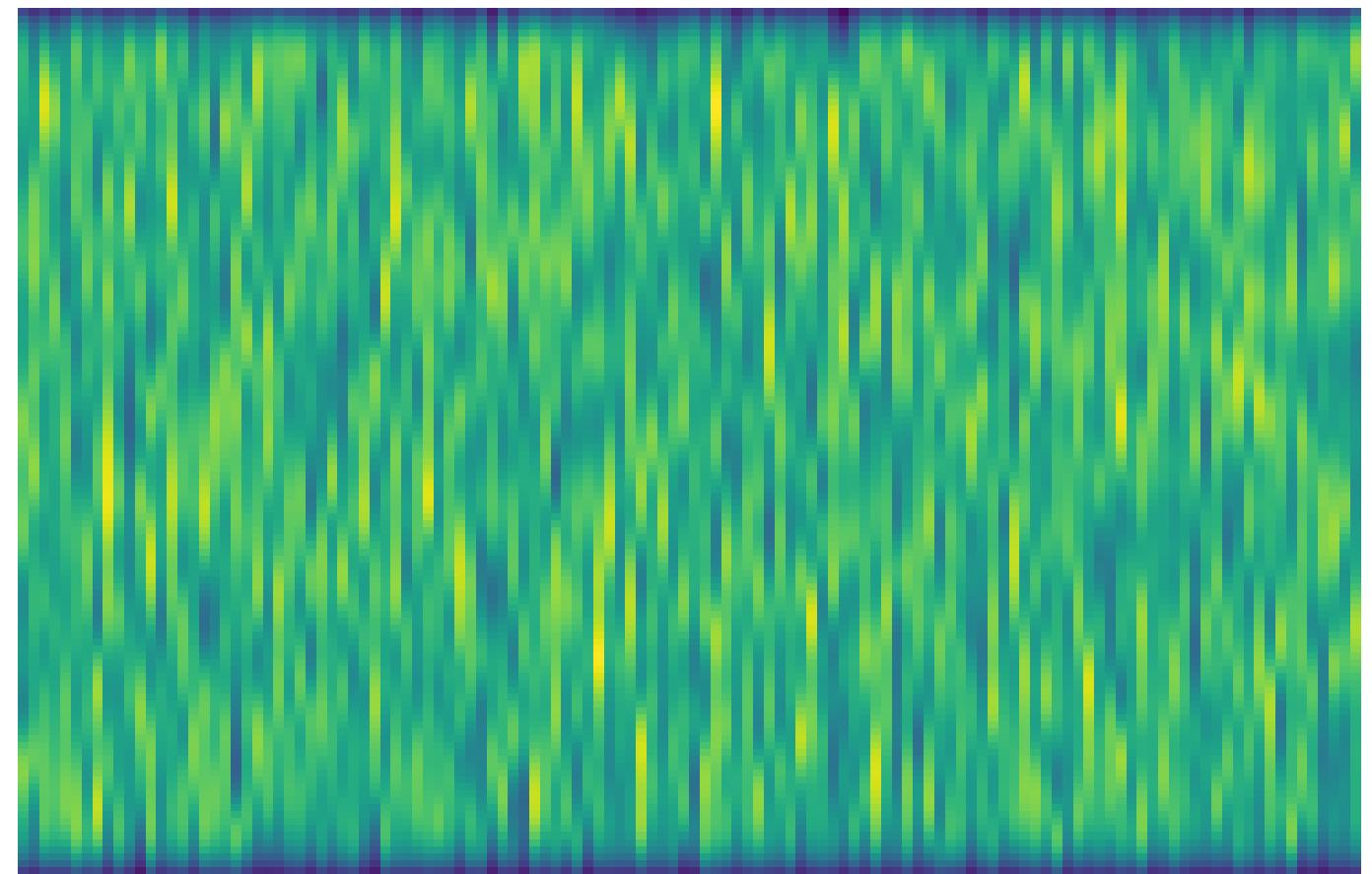
- Downside: if anisotropy varies in another direction, we need a different grid

$$-\epsilon u_{xx} + u_{yy} = f$$

Options for more robust Multigrid

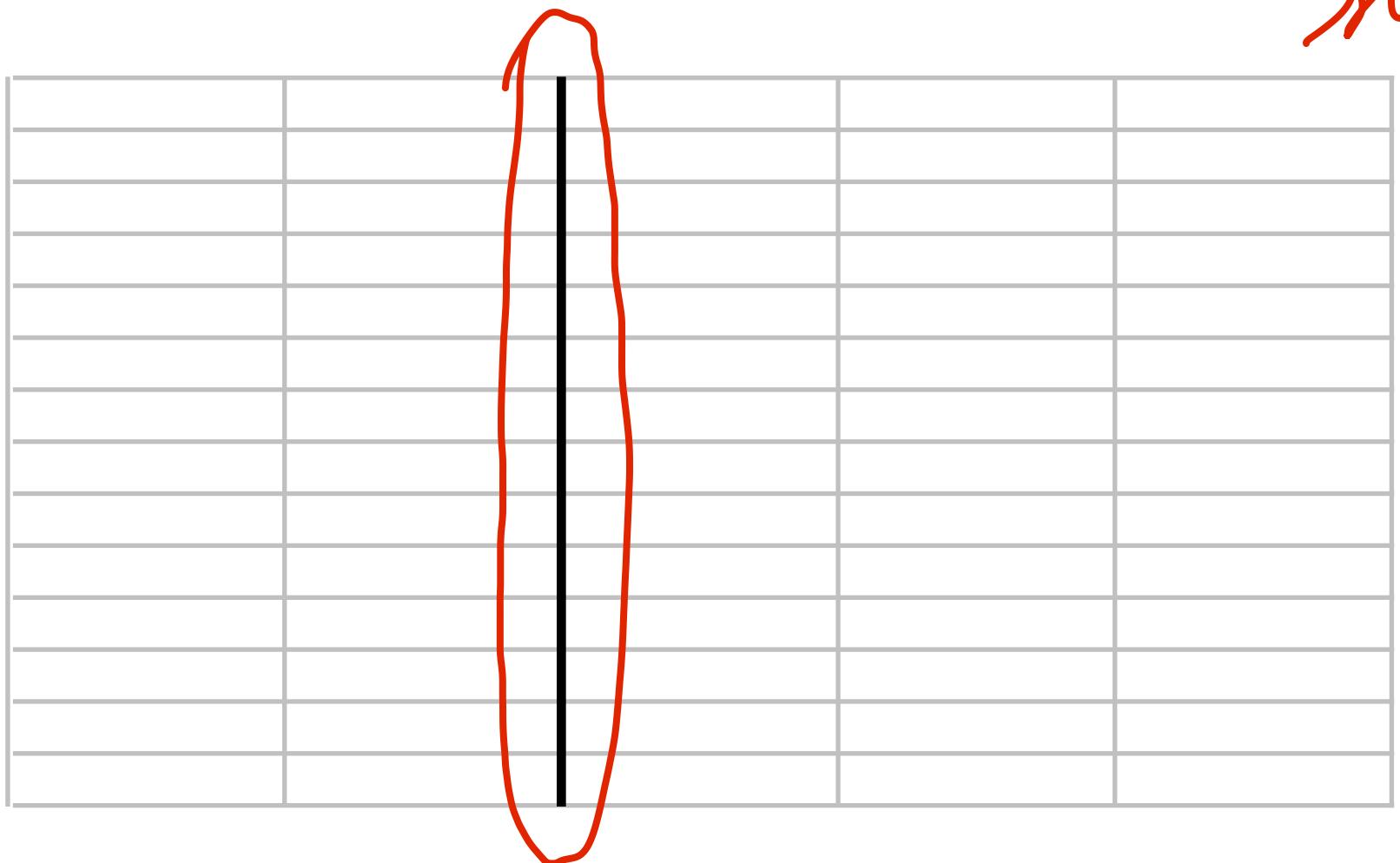
- **Line/plane relaxation**

Perform relaxation in groups (in a line)



(or: charge relaxation)

smooth these together
(direction of strong connections)



- Example:

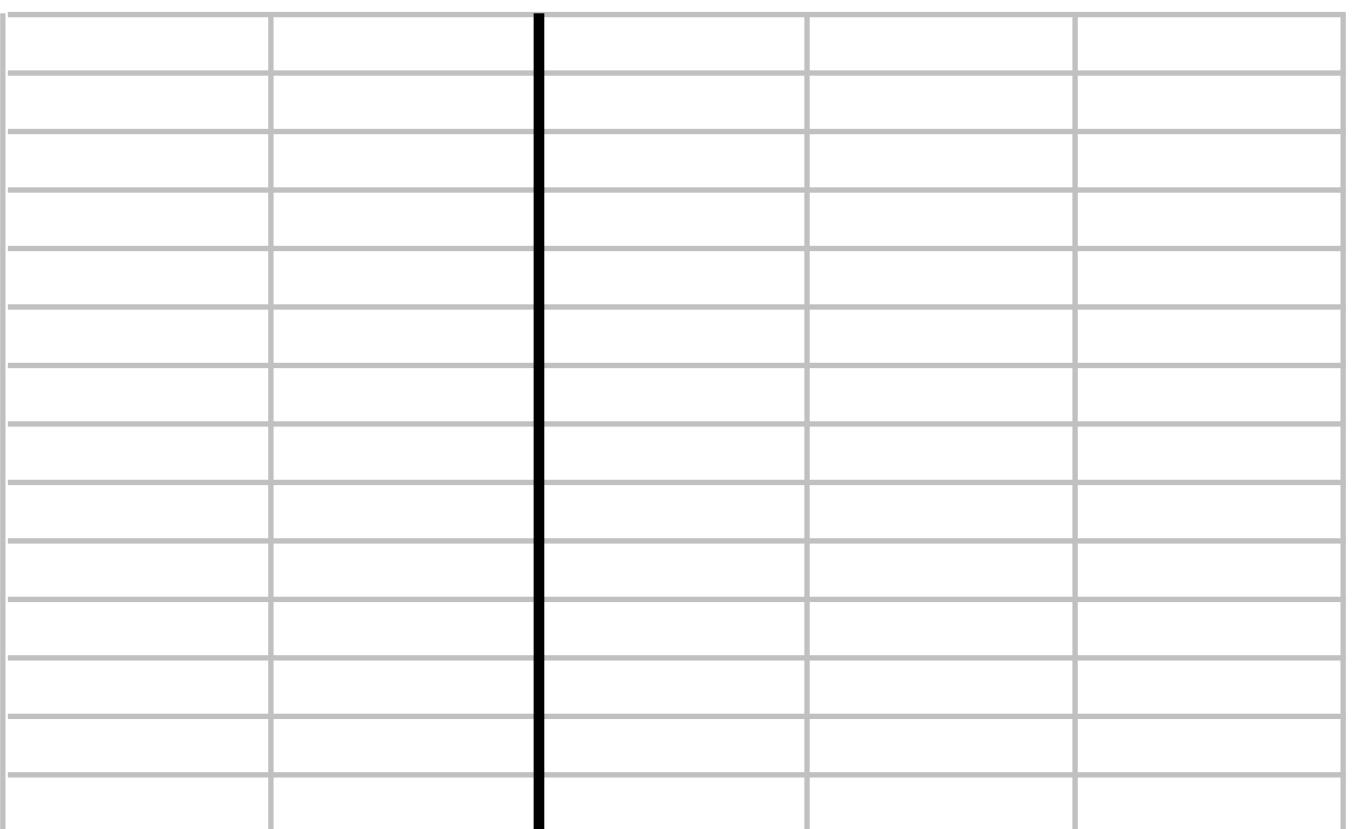
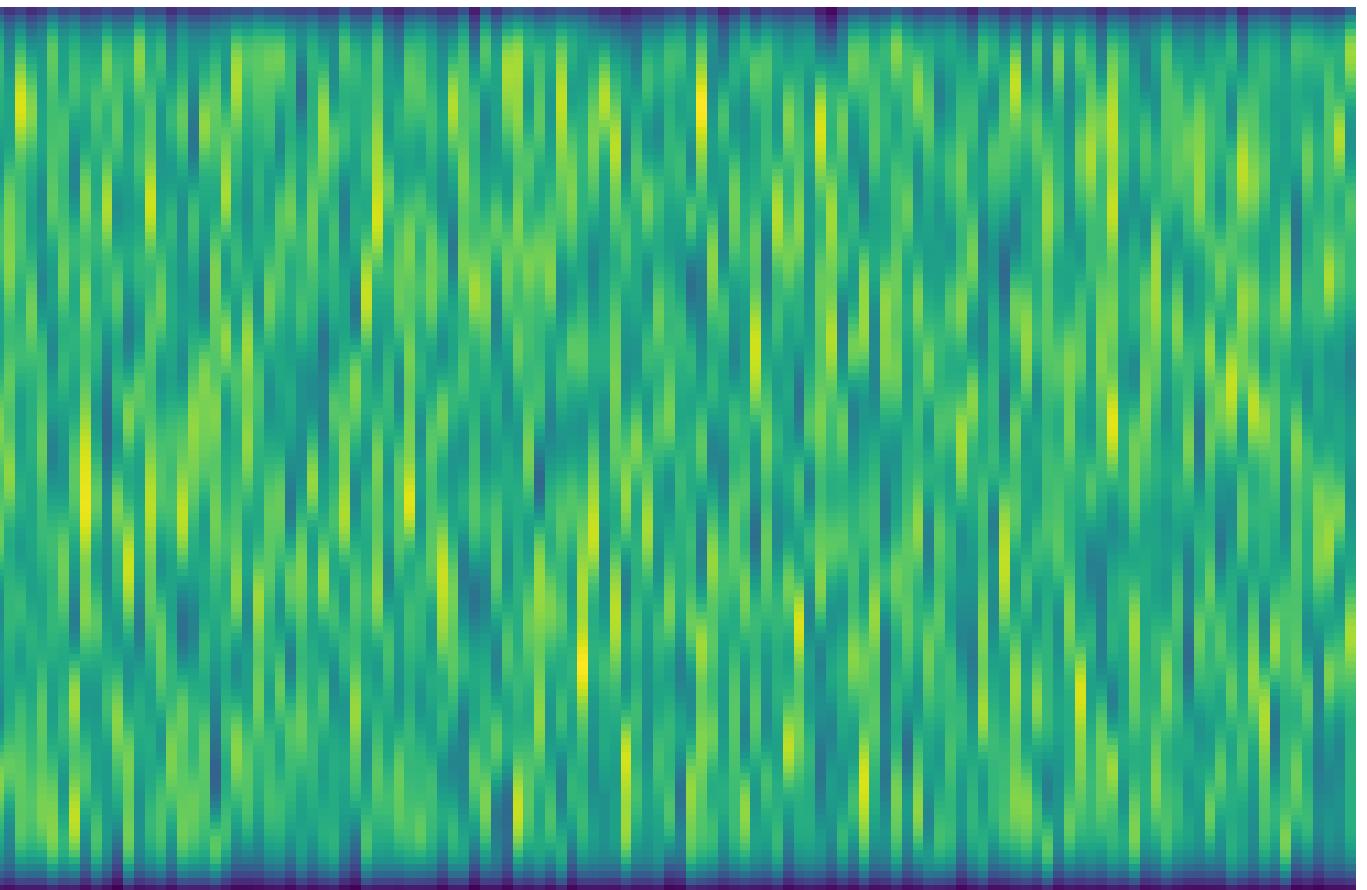
- relax error in block in the y-direction (constant x-lines)
- no (block) smoothing in the x-direction (constant y-lines)

(then CGC
will be
OK)

on fully coarsened grid)⁵⁷

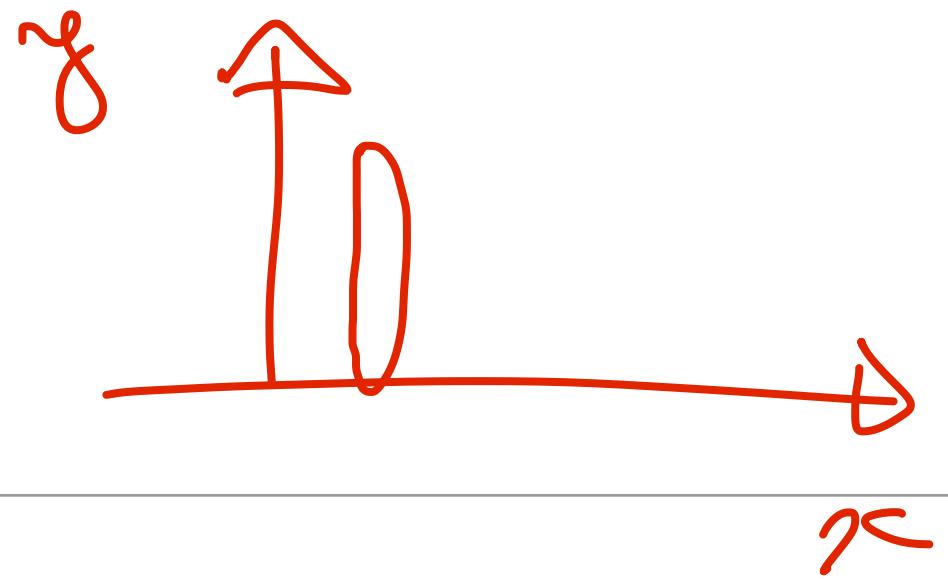
Options for more robust Multigrid

- **Line/plane relaxation**
- For each x-line (lines of strong anisotropy):
 - Eliminate the residual on the entire line
 - (Gauss-Seidel, by lines)



$$-\varepsilon u_{xx} + u_{yy} = f$$

Options for more robust Multigrid

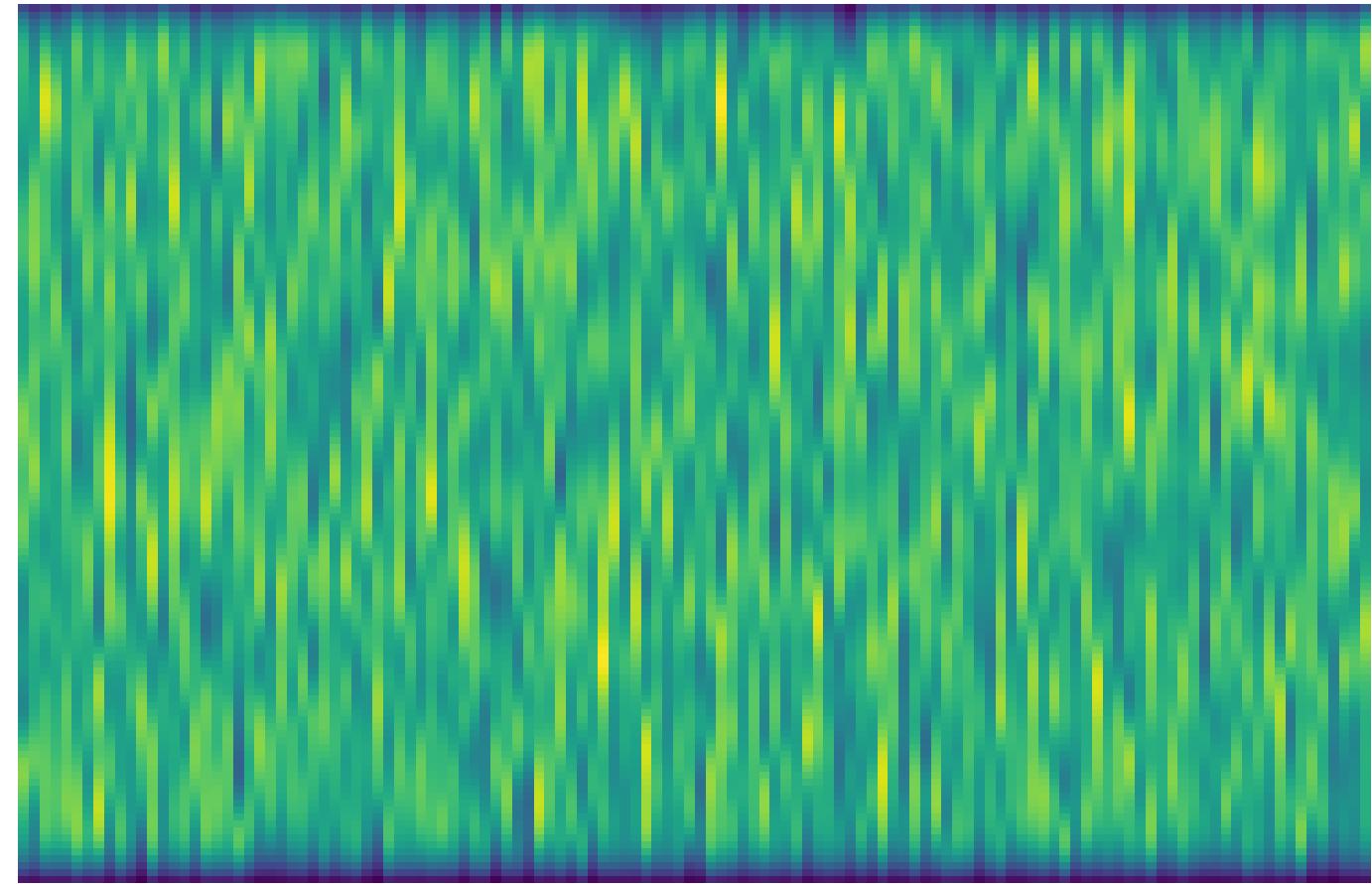


column -
lesiegraphie

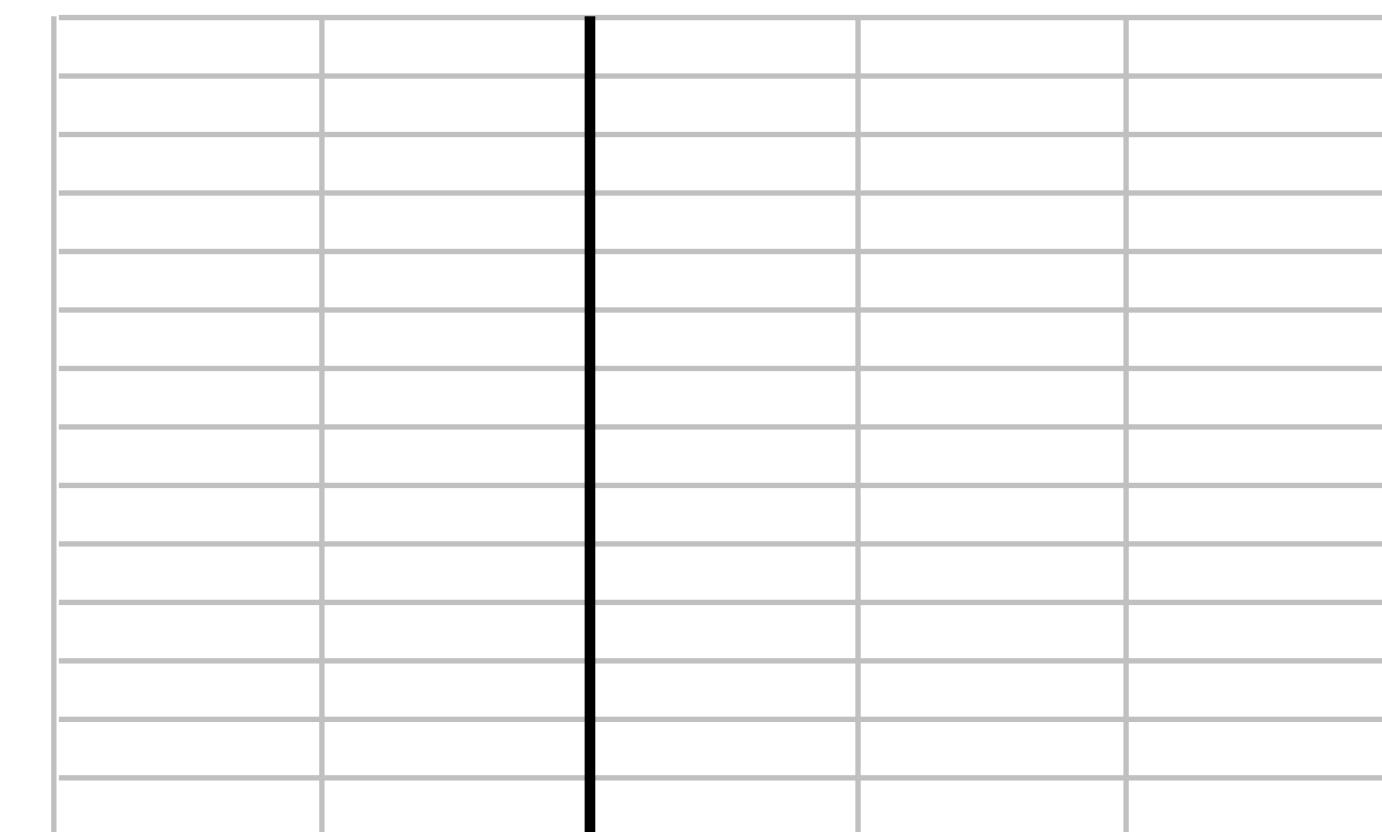
- **Line/plane relaxation**

-

$$A = \underbrace{(n+1)^2}_{\text{[]}} \begin{bmatrix} A_{1D} & -\varepsilon I \\ -\varepsilon I & A_{1D} & -\varepsilon I \\ & -\varepsilon I & A_{1D} & -\varepsilon I \\ & & \ddots & \\ & & & -\varepsilon I & A_{1D} \end{bmatrix}$$



$$A_{1D} = \underbrace{(n+1)^2}_{\text{[]}} \begin{bmatrix} 2 + 2\varepsilon & -1 & & \\ -1 & 2 + 2\varepsilon & -1 & \\ & \ddots & \ddots & \\ & & -1 & 2 + 2\varepsilon \end{bmatrix}$$



Options for more robust Multigrid

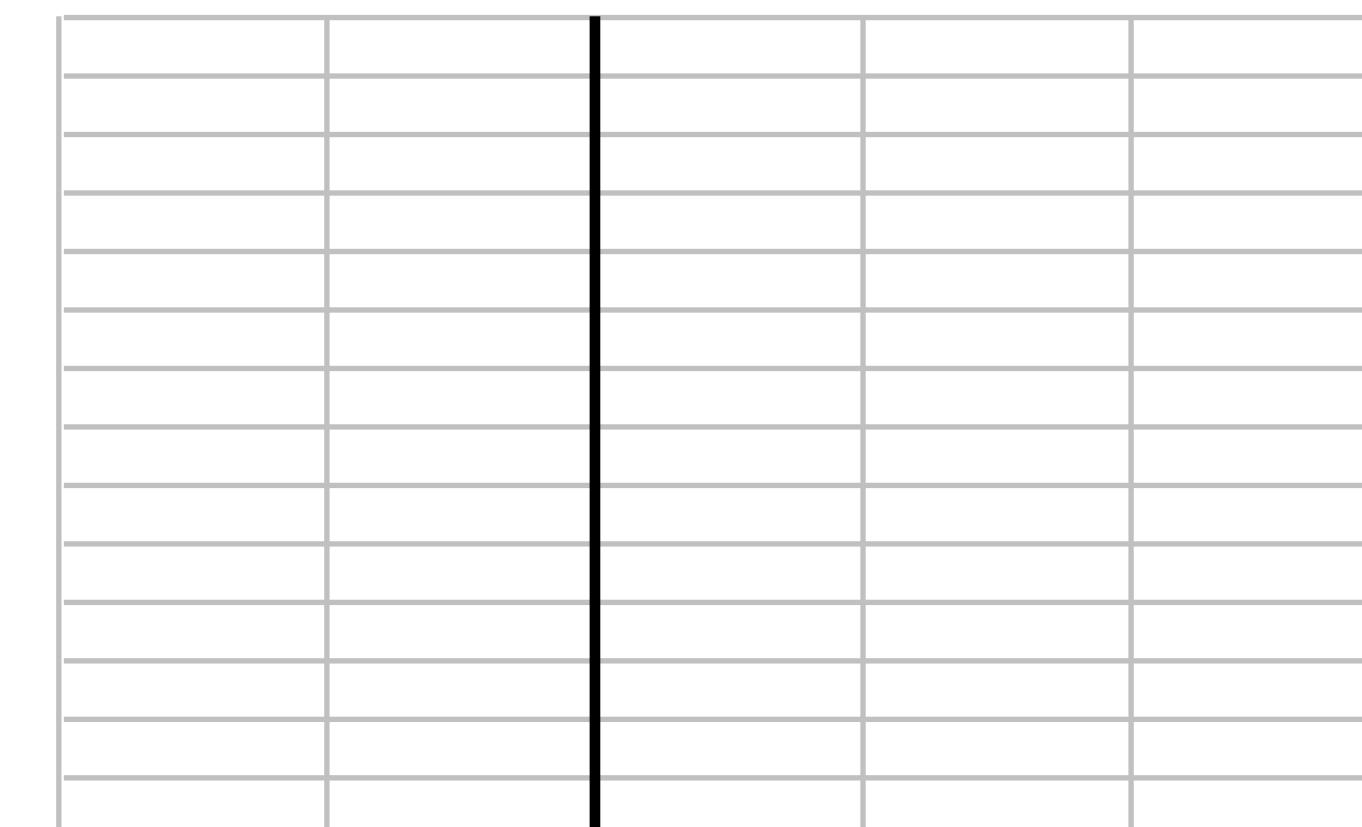
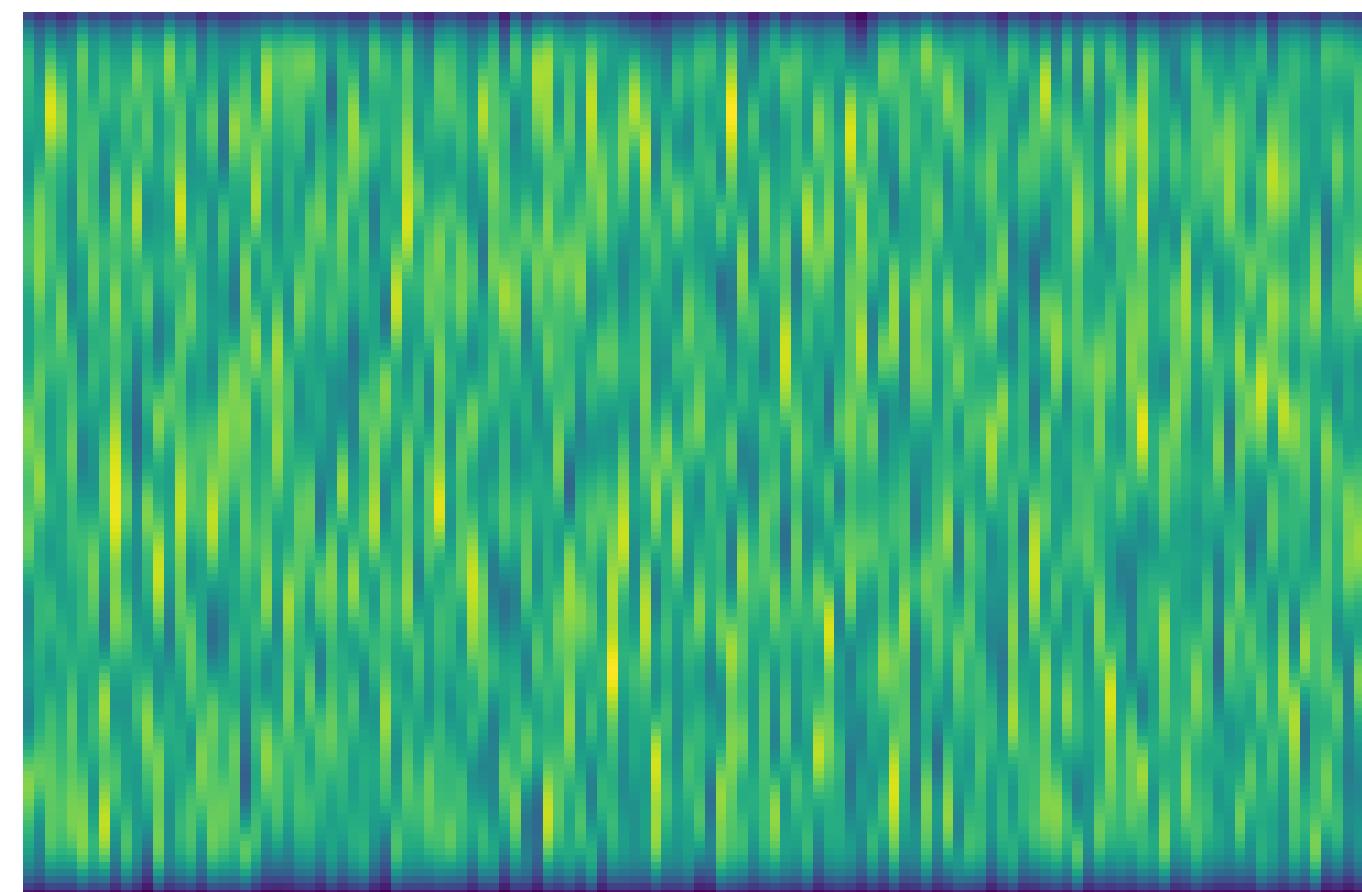
- **Line/plane relaxation**
- For each line, solve

$\mathcal{L}_{xc \text{ constant}}$

$$A_{1D}v_k = g_k$$

$$v_k = \begin{bmatrix} \vdots \\ v_{k,j-1} \\ v_{k,j} \\ v_{k,j+1} \\ \vdots \end{bmatrix} \quad g_k = \begin{bmatrix} \vdots \\ f_{k,j-1} + \varepsilon(v_{k-1,j-1} + v_{k+1,j-1}) \\ f_{k,j} + \varepsilon(v_{k-1,j} + v_{k+1,j}) \\ f_{k,j+1} + \varepsilon(v_{k-1,j+1} + v_{k+1,j+1}) \\ \vdots \end{bmatrix}$$

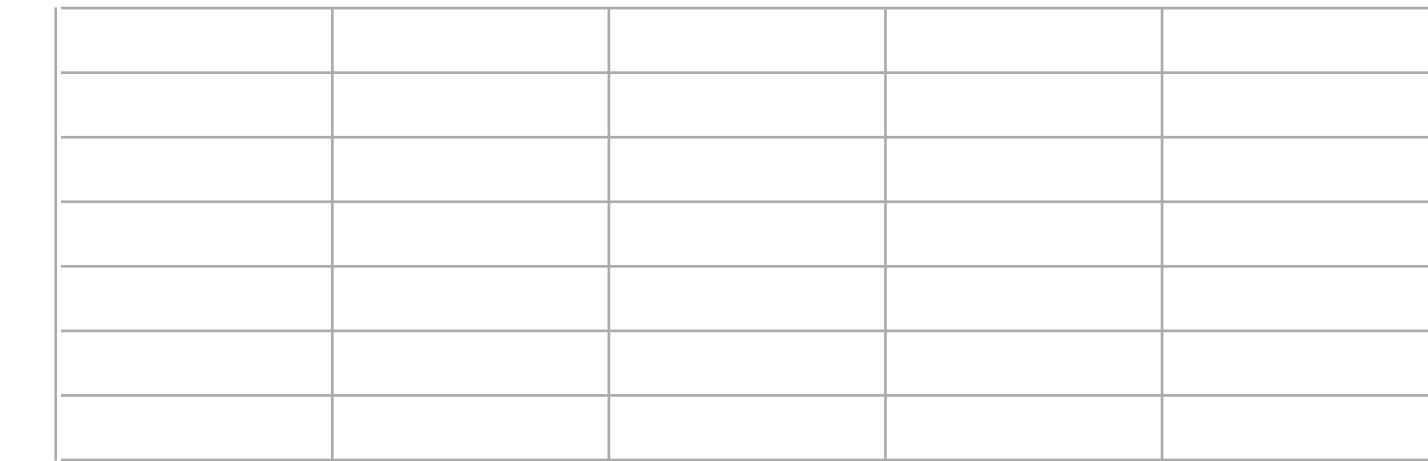
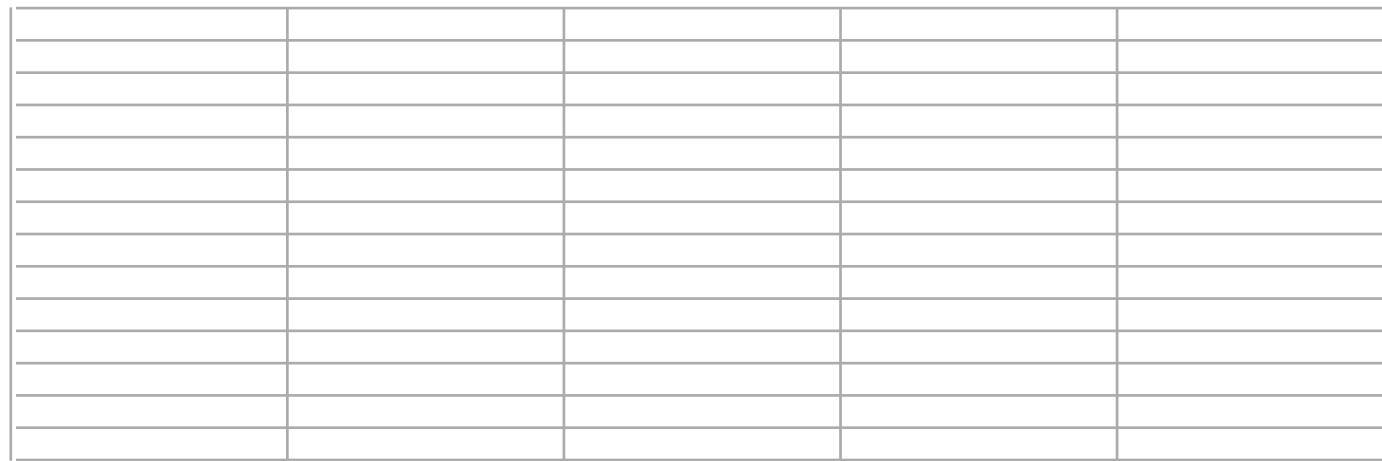
- In 3D, lines become planes...



Options for more robust Multigrid

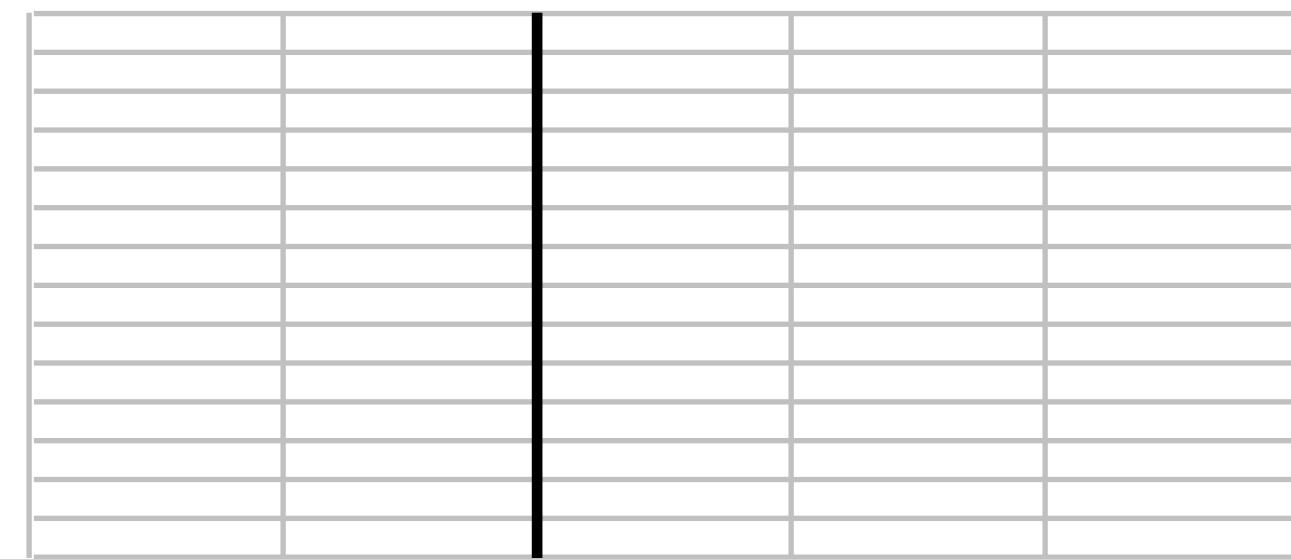
- **Semicoarsening**

Coarsen in the direction of smoothness



- **Line/plane relaxation**

Perform relaxation in groups (in a line)

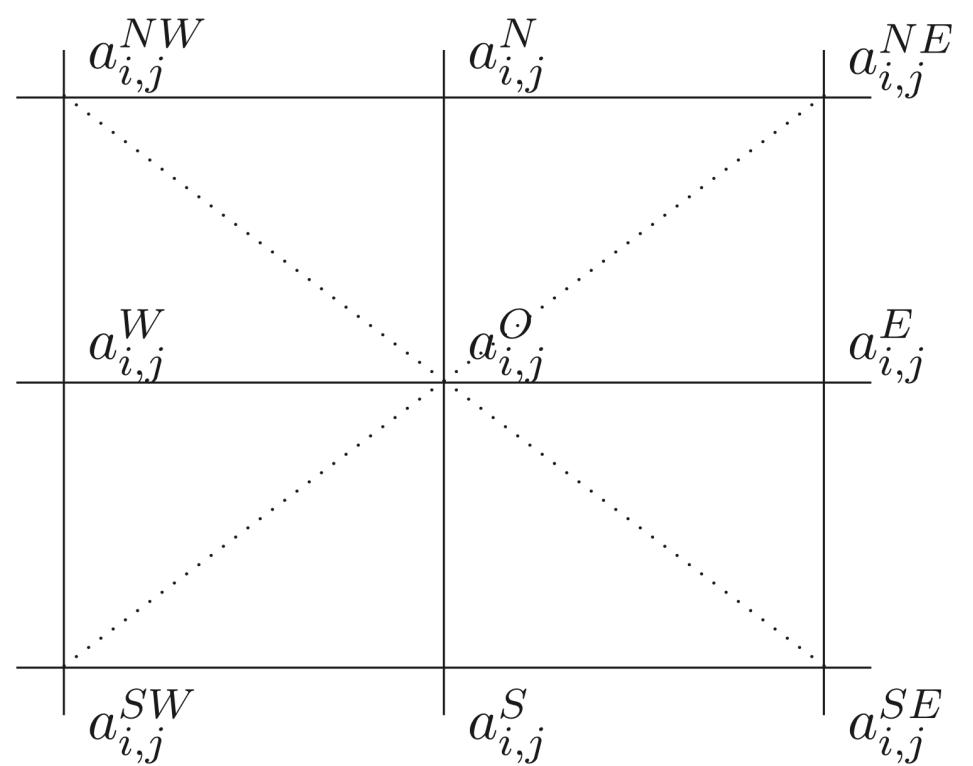


- **Operator based Interpolation** (e.g. BoxMG)
 $Ae = 0$

J. E. Dendy, Black box multigrid, J. Comput. Phys., 1982

J. E. Dendy and J. D. Moulton, Black box multigrid with coarsening by a factor of three, J. Numer. Lin. Alg. App., 2010

- Node (i,j) stencil:

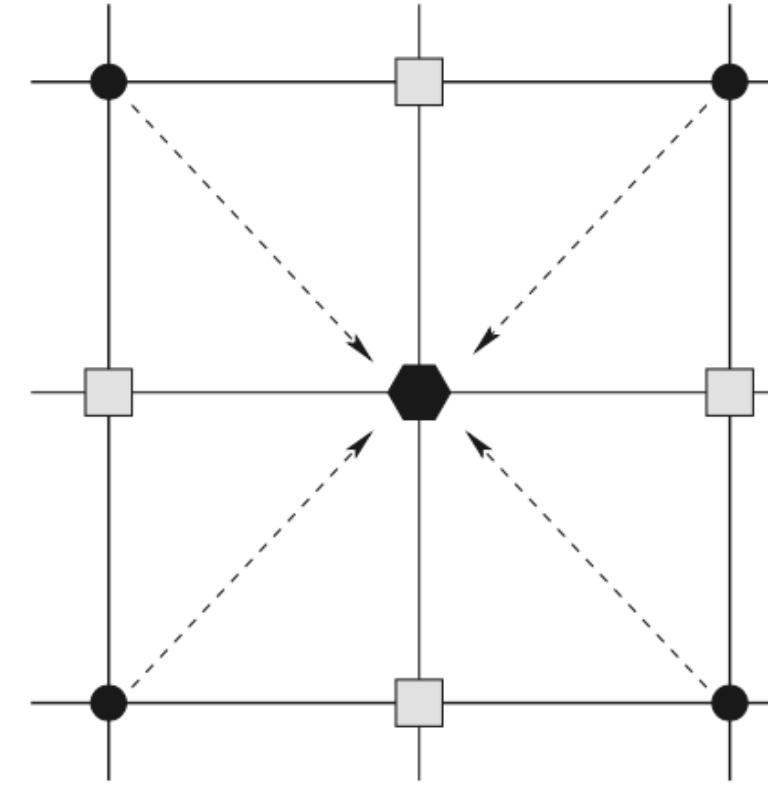
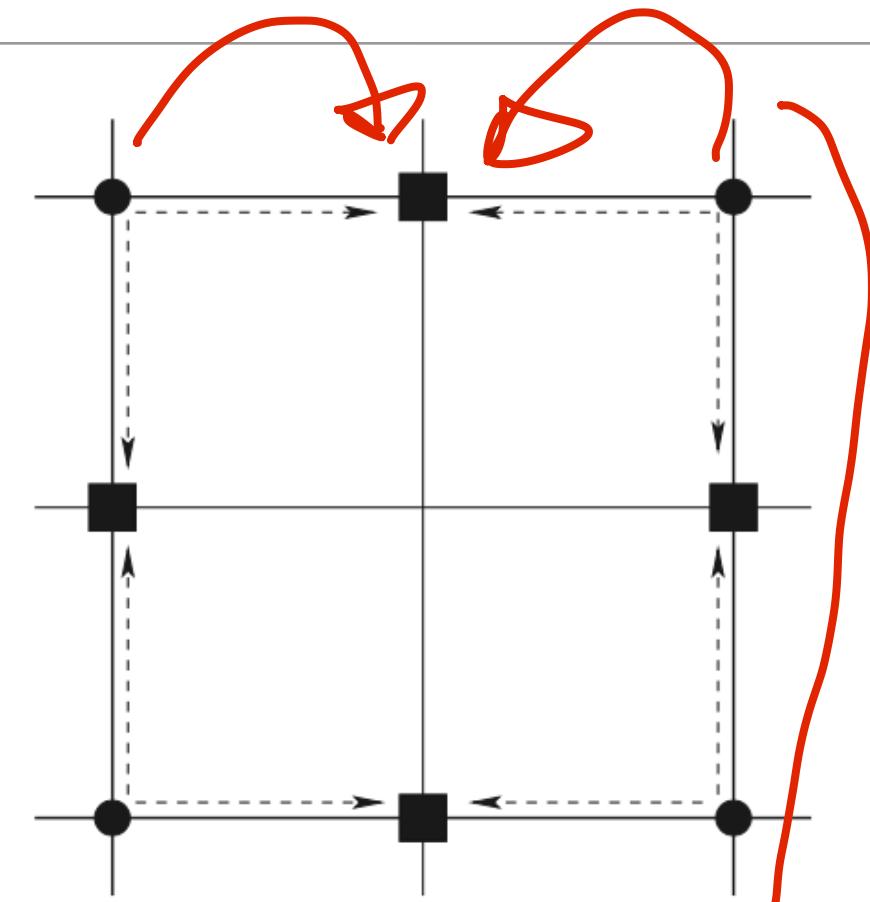
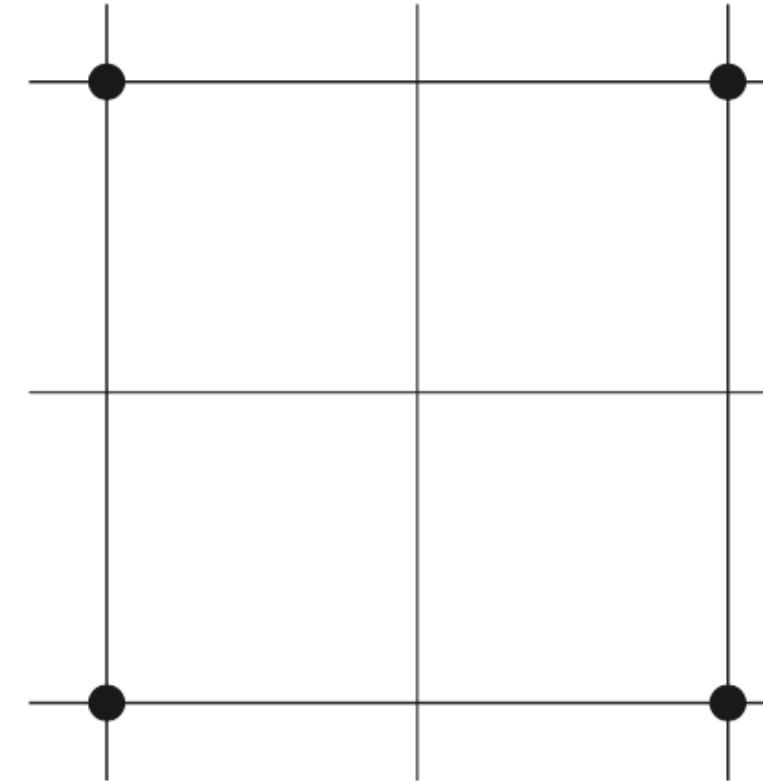


$$Ax = b$$

$$\begin{aligned}
 a_{i,j}^{SW} x_{i-1,j-1} + a_{i,j}^S x_{i,j-1} + a_{i,j}^{SE} x_{i+1,j-1} + a_{i,j}^W x_{i-1,j} + a_{i,j}^O x_{i,j} \\
 + a_{i,j}^E x_{i+1,j} + a_{i,j}^{NW} x_{i-1,j+1} + a_{i,j}^N x_{i,j+1} + a_{i,j}^{NE} x_{i+1,j+1} = b_{i,j}
 \end{aligned}$$

BoxMG

Math and figures from:
 Robust and adaptive multigrid methods: comparing structured and algebraic approaches, MacLachlan, Moulton, Chartier



1. Inject coarse points (left)
2. Assume the error is constant along x-lines (and y-lines)
3. Infer interpolation from the edges (right)

Example: Assuming $Ae=0$ and constant y-lines:

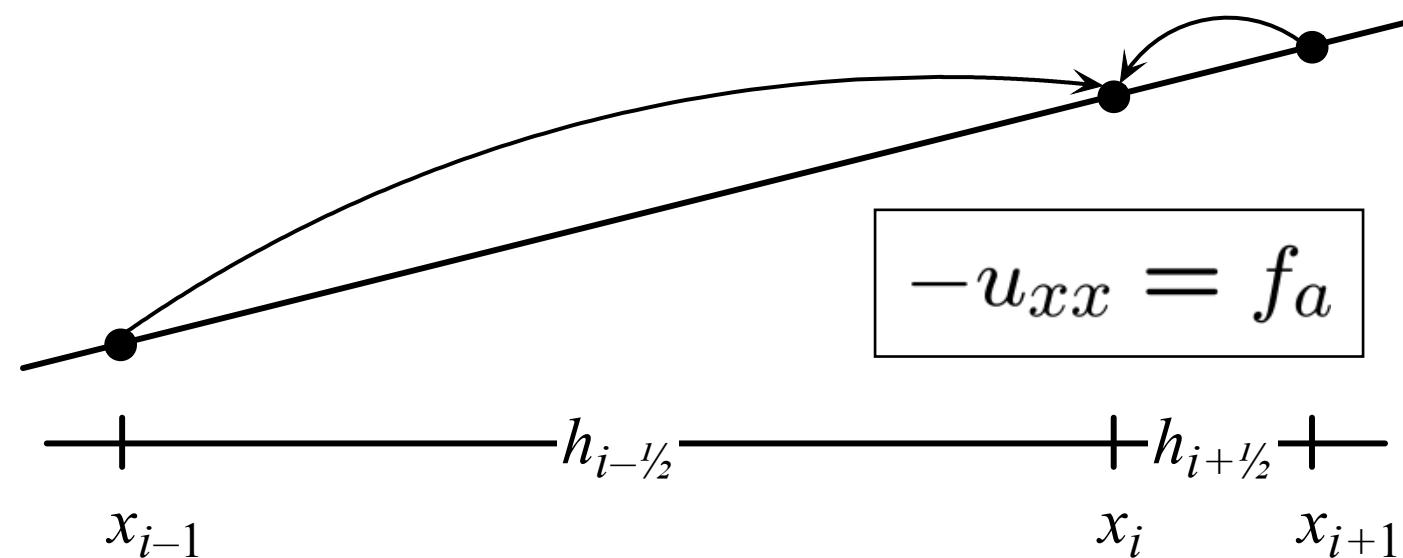
$$(a^S + a^O + a^N)e = -(a^{SW} + a^W + a^{NW})e_w^c - (a^{SE} + a^E + a^{NE})e_E^c$$

Interpolation based on entries in A

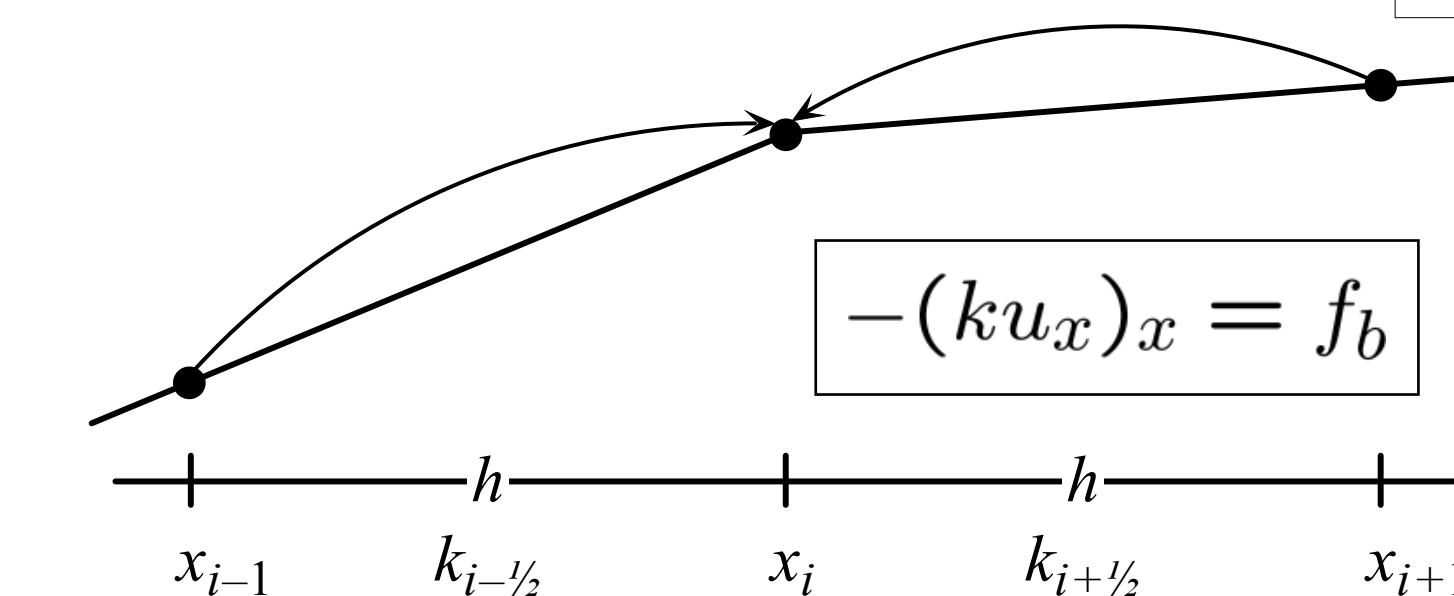
Algebraic Multigrid (AMG) uses matrix coefficients

- Geometric information alone is not sufficient

Linear Interpolation



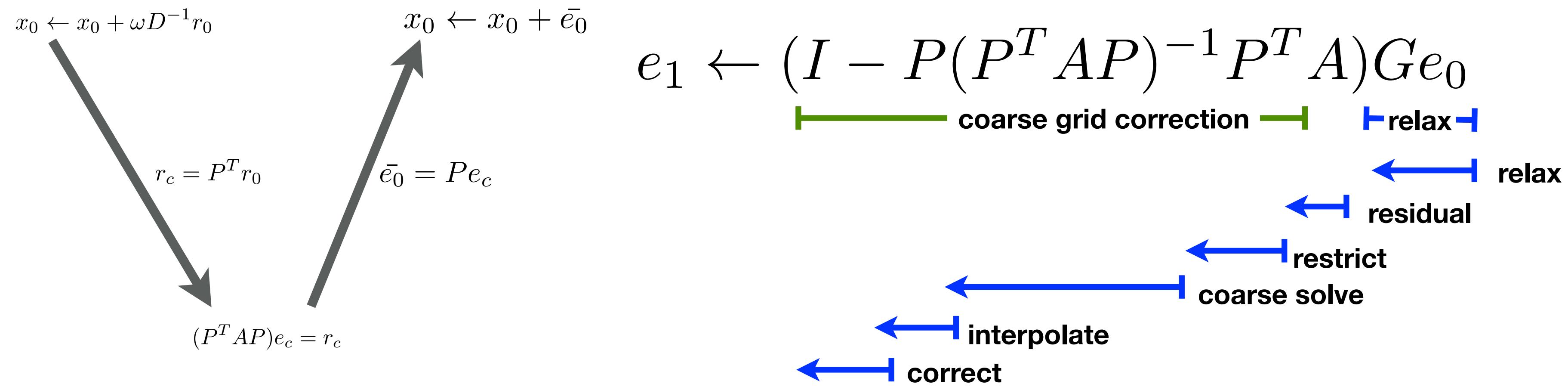
Operator-Dependent Interpolation



- AMG does not use geometric information, but captures both linear & operator-dep interpolation

$$(Au)_i = a_{i,i-1}u_{i-1} + a_{i,i}u_i + a_{i,i+1}u_{i+1} \quad \approx \circ \quad (\text{slow nodes are close to constant})$$
$$u_i = \left(-\frac{a_{i,i-1}}{a_{i,i}} \right) u_{i-1} + \left(-\frac{a_{i,i+1}}{a_{i,i}} \right) u_{i+1}$$

Algebraic Observation



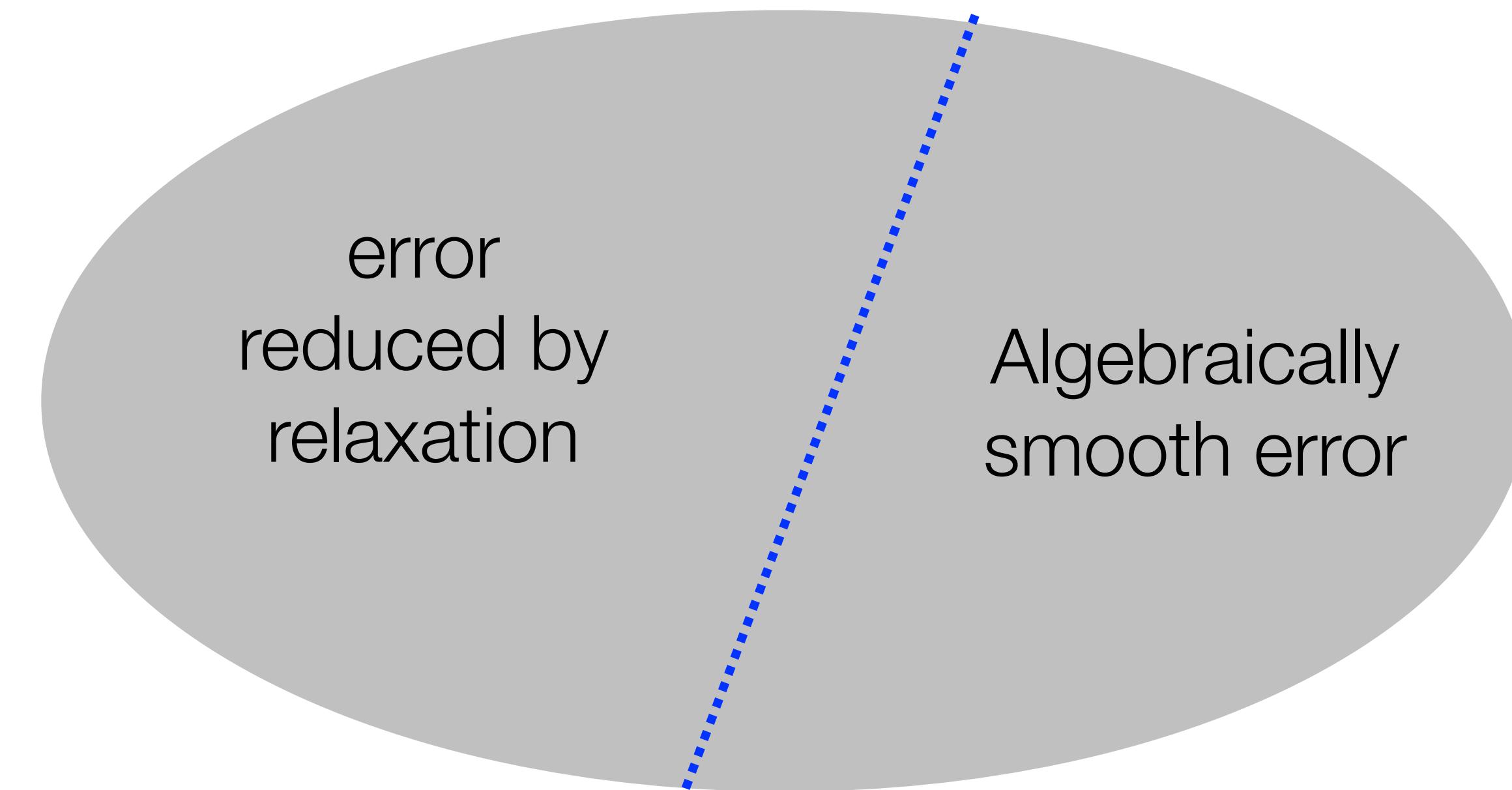
$$Ge_0 \in \mathcal{R}(P) \Rightarrow e_1 = 0$$

interpolation should capture what relaxation misses

determine coarse grid
and interpolation
based on A

Algebraically Smooth Error

- “Algebraically smooth” error may not be geometrically smooth

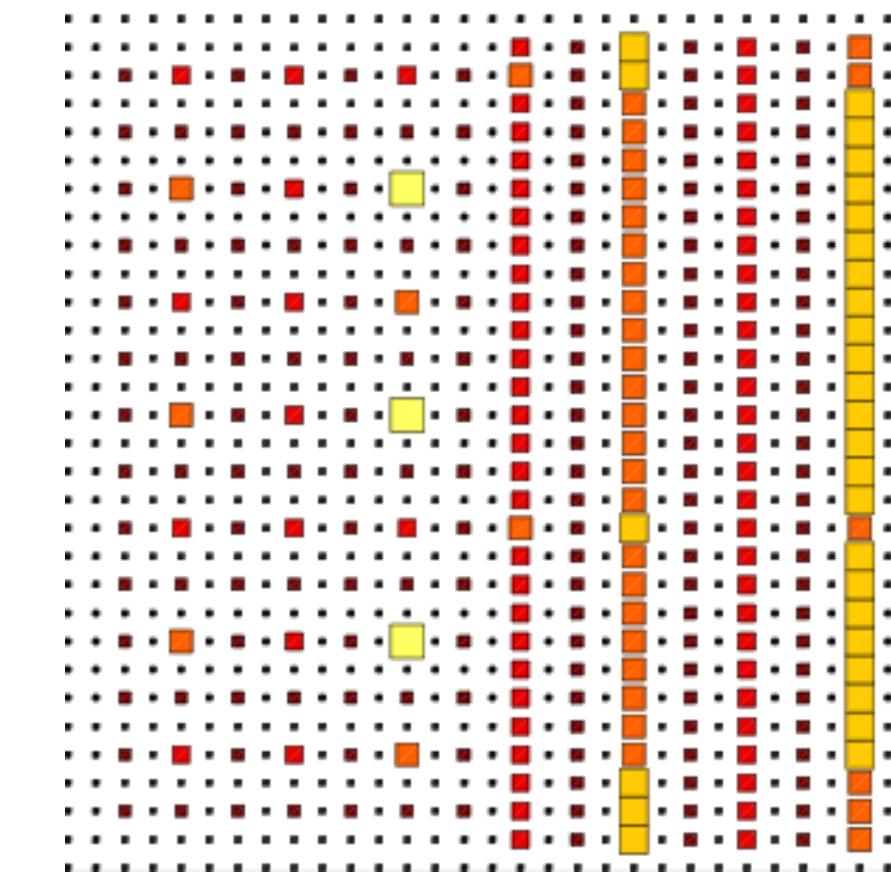
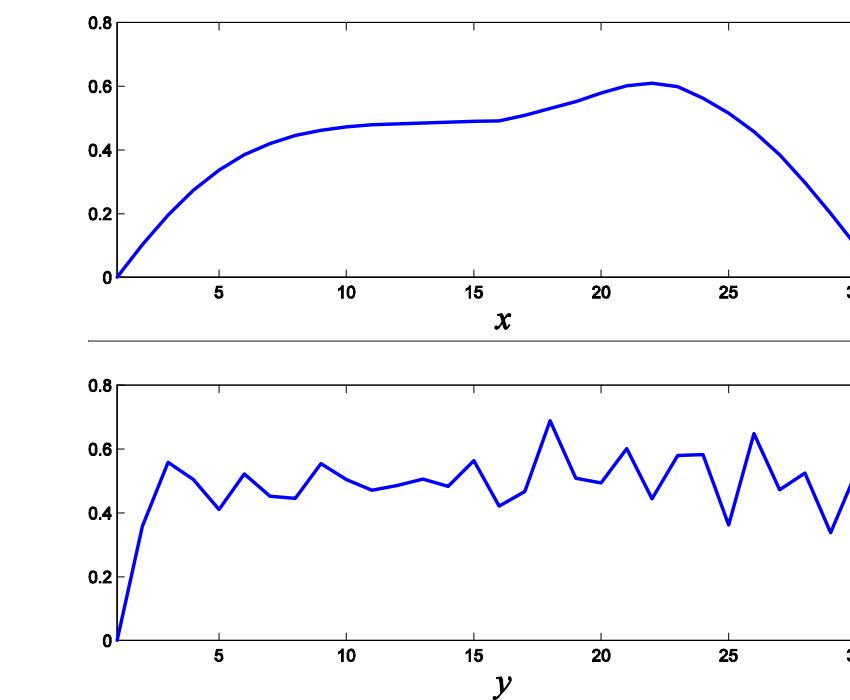
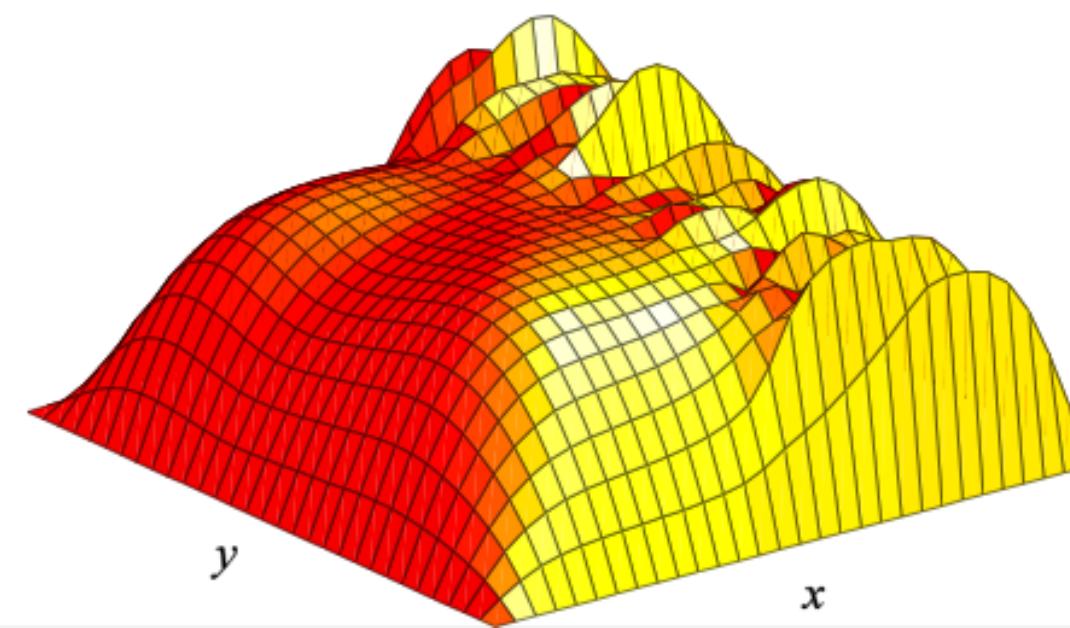


Error left by relaxation can be geometrically oscillatory

- 7 GS sweeps on

$$-au_{xx} - bu_{yy} = f$$

$$\begin{array}{|c|c|} \hline a & b \\ \hline a \gg b & \\ \hline \end{array}$$



don't coarsen
in y , because
 b is very
small, error
is oscillatory
in y

Slide credit: R. Falgout, 2/1/2016

- Caution: this example
 - targets geometric smoothness
 - uses pointwise smoothers

AMG coarsens grids in the direction
of geometric smoothness

“coarsen in the direction of strong corrections”

Main idea: Algebraically smooth error

- Take a relaxation scheme such as w-Jacobi

$$e \leftarrow (I - M^{-1}A)e$$

- If relaxation stagnates, then the remaining error exhibits poor convergence, so

- Formally (characterized by small eigenvalues)

$$(I - M^{-1}A)e \approx e \Rightarrow M^{-1}Ae \approx 0 \Rightarrow r \approx 0$$

(small residual)

$$\langle Ae, e \rangle \ll 1$$

(small eigenvalues of A)
(if $\|e\|=1$)

Main idea: Algebraically smooth error

- We then have

$$\begin{aligned}\langle Ae, e \rangle &= \sum_i e_i (A_{ii}e_i + \sum_{j \neq i} A_{ij}e_j) \\ &= \sum_i e_i \left(\sum_{j \neq i} -A_{ij}(e_i - e_j) \right) \\ &= \sum_{i < j} -A_{ij} \cdot e_i \cdot (e_i - e_j) + \sum_{i > j} -A_{ij} \cdot e_i \cdot (e_i - e_j) \\ &= \sum_{i < j} -A_{ij} \cdot e_i \cdot (e_i - e_j) - \sum_{i < j} -A_{ij} \cdot e_j \cdot (e_i - e_j) \\ &= \sum_{i < j} -A_{ij} \cdot (e_i - e_j)^2\end{aligned}$$

$$A\tilde{e}_i = -\sum_{j \neq i} A_{ij}e_j$$

assume zero row sum

swap i, j

$$\lceil A_{j|i}$$

- Ok, so smooth error varies **slowly** in the direction of large matrix coefficients

\lceil when A_{ij} is large,
 $e_i \approx e_j$ after relaxation

Briggs, William L. and Henson, Van Emden and
McCormick, Steve F., A Multigrid Tutorial (2Nd Ed.,
2000)

Main idea: Algebraically smooth error

- We have assumed **geometric** smoothness to show

$$\mathbf{e}^T A \mathbf{e} = \sum_{i < j} (-a_{ij})(e_i - e_j)^2 \ll 1$$

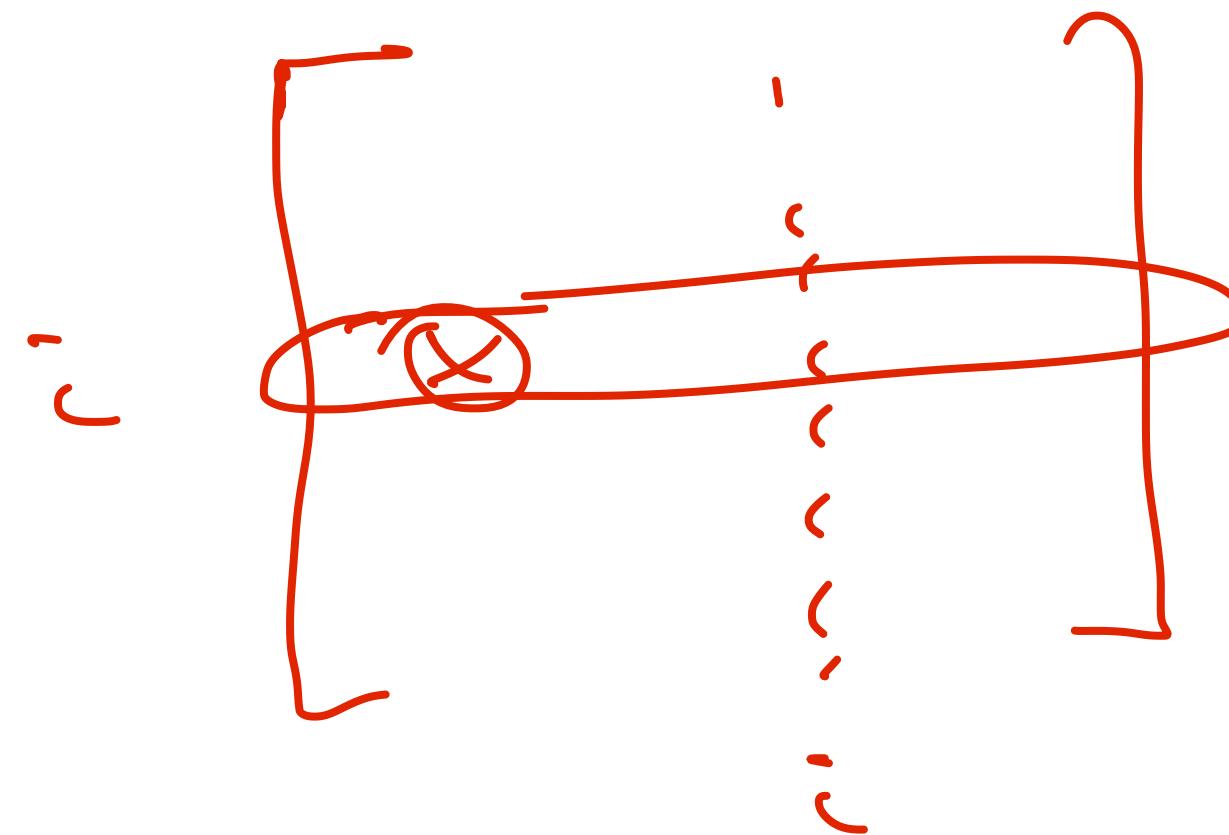
*assume $a_{ij} < 0$
 $\forall i \neq j$*

- CF AMG:** Smooth error varies slowly in the direction of “large” matrix coefficients
- Strength of connection:** Given a threshold $0 < \theta \leq 1$, we say that variable u_i strongly depends on variable u_j if

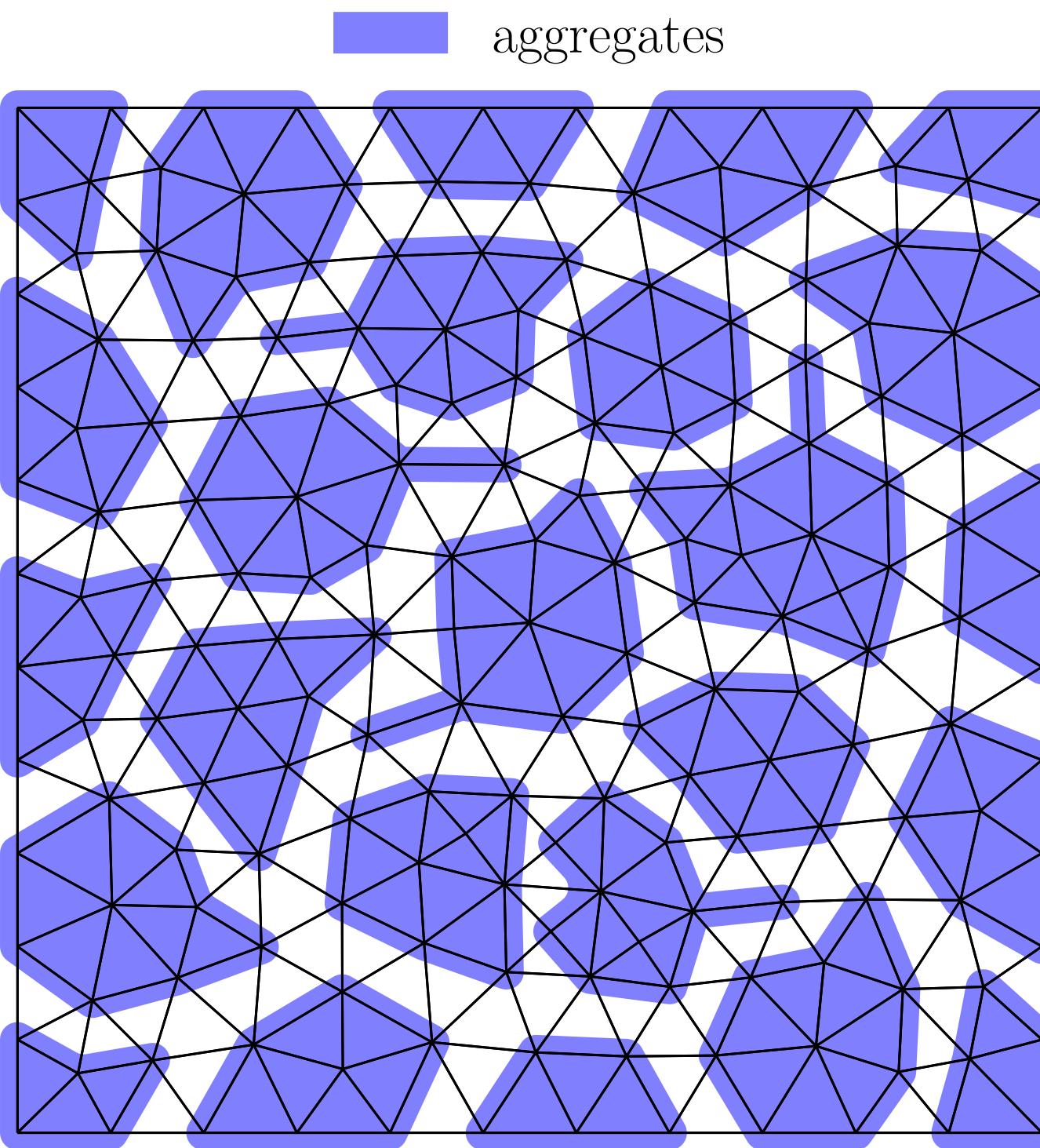
$$-a_{ij} \geq \theta \max_{k \neq i} \{-a_{ik}\}$$

in row i

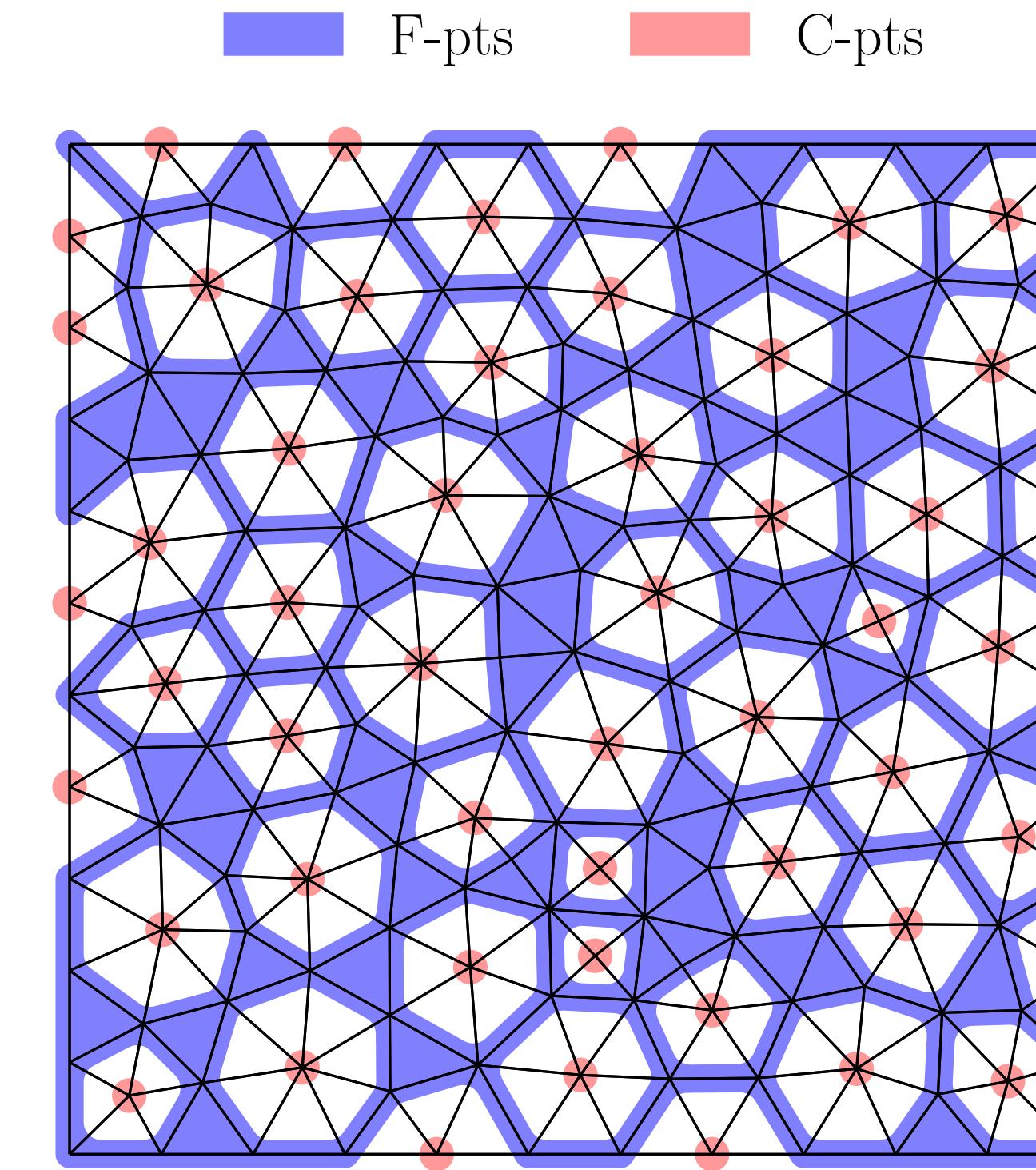
- Often positive off-diagonals are treated as **weak**
- This definition of strength of connection is not symmetric



Two (general) forms of AMG



- Smoothed Aggregation AMG (SA-AMG)
- Interpolation constructed from candidate vectors
- Clear approach to *optimize* interpolation



- Coarse-Fine AMG (CF-AMG) or Ruge-Stüben
- Coarse grid points are a subset of the fine grid points
- Edge-wise construction of interpolation, allowing straightforward control of sparsity
- Incorporating near-nullspace is not straightforward