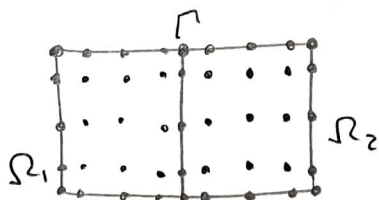


Last time:



$$\begin{aligned}\nabla^2 u &= f \text{ in } \Omega \\ u &= 0 \text{ on } \partial\Omega\end{aligned}$$

① Solve $A_{11} u_1^{\text{source}} = f_1$
 $A_{22} u_2^{\text{source}} = f_2$ ← zero Dirichlet BCs

② Solve $\sum u_p = f_p - A_{p1} u_1^{\text{source}} - A_{p2} u_2^{\text{source}}$

③ Solve $A_{11} u_1^{\text{harmonic}} = 0$
 $A_{22} u_2^{\text{harmonic}} = 0$ ← u_p Dirichlet BCs

④ Update: $u_1 = u_1^{\text{source}} + u_1^{\text{harmonic}}$
 $u_2 = u_2^{\text{source}} + u_2^{\text{harmonic}}$

Σ has fast mat-vec:

$$\begin{aligned}\Sigma x &= (A_{111} - A_{11} A_{11}^{-1} A_{11} - A_{12} A_{22}^{-1} A_{21}) x \\ &= \underbrace{A_{111} x}_{O(n^2)} - \underbrace{DZ N_1(x)}_{O(n^2 \log n)} - \underbrace{DZ N_2(x)}_{O(n^2 \log n)}\end{aligned}$$

$DZ N_i(x) =$ • Solve $A_{ii} v_i = 0$ with x Dirichlet BC

• Evaluate normal derivative of v_i on Γ

Need good preconditioner for Σ .

Suppose* we have a fast spectrally accurate subdomain solver $O(n^2 \log n)$. Then the remaining piece is to solve ② fast.

Traditional approaches attempt to solve $\Sigma u_\Gamma = z_\Gamma$ using a preconditioned iterative method such as CG, since Σ has a fast matrix-vector multiply:

$$\begin{aligned} \Sigma x &= (A_{\Gamma\Gamma} - \underbrace{A_{\Gamma 1} A_{11}^{-1} A_{1\Gamma}}_{D2N_1} - \underbrace{A_{\Gamma 2} A_{22}^{-1} A_{2\Gamma}}_{D2N_2}) x \\ &= A_{\Gamma\Gamma} x - D2N_1(x) - D2N_2(x) \end{aligned}$$

where $D2N_i(x) =$

- Solve $A_{ii} v_i = 0$ with x Dirichlet BC
- Evaluate normal derivative of v_i on Γ .

$D2N_i(x)$ takes $O(n^2 \log n)$ & $A_{\Gamma\Gamma} x$ takes $O(n^2)$.

We would need a good preconditioner for Σ to get optimal complexity. (This is what is done currently: solve for u_Γ exactly, then u_1 & u_2 .)

Instead: Design a preconditioner \tilde{A} for the global problem based on approximate subdomain solves $A_{ii}^\dagger \approx A_{ii}^{-1}$ and approximate interface solve $\Sigma^\dagger \approx \Sigma^{-1}$.

("DD-PCG")

For K elements, $\tilde{u} = A^+ f$ is

```
for  $i = 1, \dots, K$ 
  • Solve  $\tilde{u}_i^{\text{source}} = A_{ii}^+ f_i$  with zero BCs
  • Compute normal derivative  $S_i = -A_{\Gamma i} \tilde{u}_i^{\text{source}}$ 
end
• Compute  $z_\Gamma = f_\Gamma + S_1 + \dots + S_K$ 
• Solve  $\tilde{u}_\Gamma = \Sigma^+ z_\Gamma$ 
for  $i = 1, \dots, K$ 
  • Solve  $\tilde{u}_i^{\text{harmonic}} = A_{ii}^+ 0$  with  $\tilde{u}_\Gamma$  BCs
  • Compute  $\tilde{u}_i = \tilde{u}_i^{\text{source}} + \tilde{u}_i^{\text{harmonic}}$ 
end
```

It remains to specify A_{ii}^+ and Σ^+ .

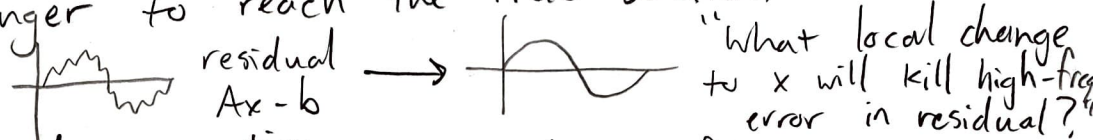
A_{ii}^+ is "easy" = "approximate fast Poisson solve"

If we assume discretization is SPD (such as Legendre-Galerkin), can use multigrid method.

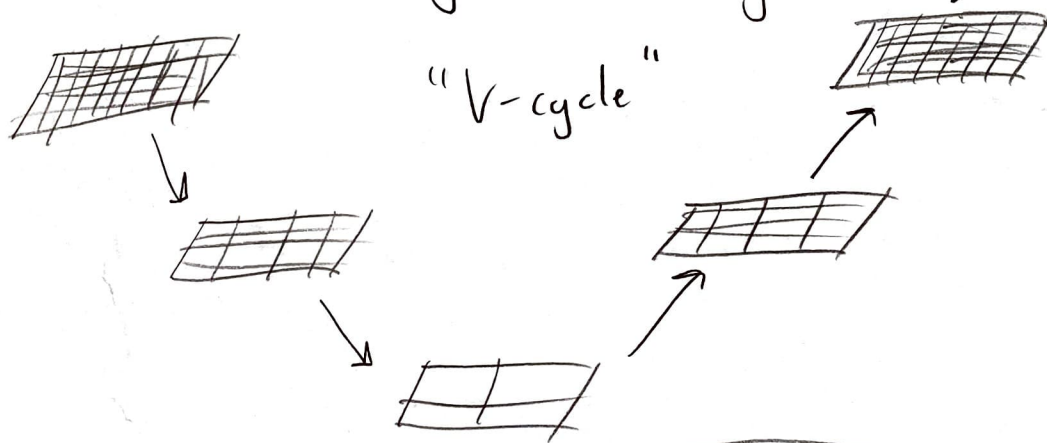
A multigrid solver for the interface

Multigrid methods rely on two ingredients:
smoothing & coarse-grid correction.

A smoother (e.g. Jacobi, Gauss-Seidel) is an iterative scheme that locally satisfies a linear system. Thus, it kills high-freq. error quickly, but takes longer to reach the true solution.



Coarse-grid correction notes that if we run the smoother on a coarser "grid", then the local action of the smoother now has a more global effect, and the low frequency modes of error that were a problem on the fine grid are "higher" frequency here.



Jacobi: $A = D + L + U$, $Ax = b$ "Matrix splitting"
Iterate $x^{(i+1)} = D^{-1}(b - (L+U)x^{(i)})$

G-S: $A = D + L + U$, $Ax = b$
Iterate $x^{(i+1)} = (D+L)^{-1}(b - Ux^{(i)})$

To use either of these on Σ , need to have formed Σ explicitly, which is not optimal complexity due to A_{ii}^{-1} !

Trick: If Σ is SPD, can prove the following
(fixed pt) iteration will always converge:

$$\left(\Sigma = A_{\Gamma\Gamma} - \sum_{i=1}^K A_{\Gamma i} A_{ii}^{-1} A_{i\Gamma} \right)$$

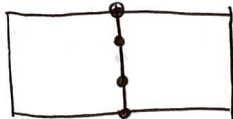
$$A_{\Gamma\Gamma} u_{\Gamma}^{(j+1)} = f_{\Gamma} + \sum_{i=1}^K A_{\Gamma i} A_{ii}^{-1} A_{i\Gamma} u_{\Gamma}^{(j)} \quad (\text{Assembly-free!})$$

Need to invert $A_{\Gamma\Gamma}$. (Fast?) (c.f. $\Sigma = D - L - U$ Jacobi
 $D u_{\Gamma}^{(j+1)} = f_{\Gamma} + (L+U) u_{\Gamma}^{(j)}$)

Then, what are the coarse grids for the interface problem?



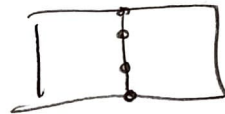
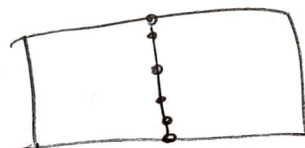
L^2 projection



(coeffs or values)

"p-multigrid"

$$\Sigma^{2h} = A_{\Gamma\Gamma}^{2h} - \sum_{i=1}^K A_{\Gamma i}^{2h} (A_{ii}^{2h})^{-1} A_{i\Gamma}^{2h}$$



So, $\Sigma^T =$ "approximate interface solve"
= run a few V-cycles of multigrid.

Proof: $\underbrace{A_{rr}}_{S_1} u_r^{(j+1)} = f_r + \underbrace{\sum_{i=1}^K A_{ri} A_{ii}^{-1} A_{ir}}_{S_2} u_r^{(j)}$

$$\Rightarrow S_1 u_r^{(j+1)} = f_r + S_2 u_r^{(j)} \quad (1)$$

Let u_r^* be the fixed point, so

$$S_1 u_r^* = f_r + S_2 u_r^* \quad (2)$$

Then the error $e^{(j)} = u_r^{(j)} - u_r^*$ is given by (1) - (2):

$$S_1 e^{(j+1)} = S_2 e^{(j)}$$

$$\Rightarrow e^{(j+1)} = S_1^{-1} S_2 e^{(j)}$$

$\nearrow \lambda_{\max}$

This will converge iff $\rho(S_1^{-1} S_2) < 1$.

Note • $\Sigma = S_1 - S_2 \Rightarrow S_1 = \Sigma + S_2$

• $S_1^{-1} S_2 \sim S_2^{1/2} (S_1^{-1} S_2) S_2^{-1/2} = S_2^{1/2} S_1^{-1} S_2^{1/2}$

($S_2^{1/2}$ exists since S_2 is real symmetric)

$$\begin{aligned} \text{So } \rho(S_1^{-1} S_2) &= \rho(S_2^{1/2} S_1^{-1} S_2^{1/2}) = \rho((S_2^{-1/2} S_1 S_2^{-1/2})^{-1}) \\ &= \rho((S_2^{-1/2} (\Sigma + S_2) S_2^{-1/2})^{-1}) \end{aligned}$$

Since Σ is SPD and $S_2^{-1/2}$ is symmetric, $S_2^{-1/2} \Sigma S_2^{-1/2}$ is SPD, so:

$$\lambda_{\min}(S_2^{-1/2} \Sigma S_2^{-1/2}) > 0.$$

Thus, $\rho(S_1^{-1} S_2) < 1$.

$$\begin{aligned} &= \rho((S_2^{-1/2} \Sigma S_2^{-1/2} + I)^{-1}) \\ &= \frac{1}{\lambda_{\min}(S_2^{-1/2} \Sigma S_2^{-1/2} + I)} \\ &= \frac{1}{\lambda_{\min}(S_2^{-1/2} \Sigma S_2^{-1/2}) + 1} \end{aligned}$$