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# On Generalizing the *AMG* Framework

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# Outline

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- ***AMG / AMGe* framework background**
- **New Measures and Convergence Theory**
- **Building Interpolation**
- **Compatible Relaxation**
- **Examples**
  
- **Conclusions and future directions**

# AMG / AMGe Framework

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- **AMGe heuristic is based on multigrid theory:**  
*interpolation must reproduce a mode up to the same accuracy as the size of the associated eigenvalue*
- **Bound a measure (weak approximation property):**

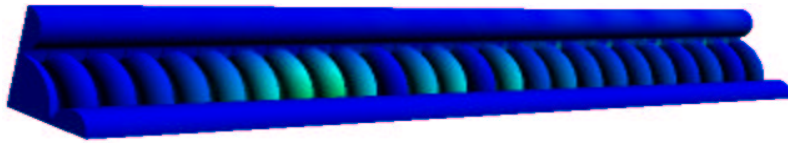
$$\|A\| \frac{\langle (I-Q)e, (I-Q)e \rangle}{\langle Ae, e \rangle}; \quad Q = P \begin{bmatrix} 0 & I \end{bmatrix}$$

- **Localize the measure to build AMGe components**
- **Several variants developed: *E-Free, Spectral***
- **Based on pointwise relaxation**
- **Assumes coarse grid is a subset of fine grid**

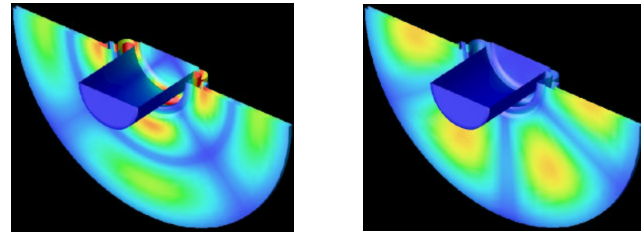
# We are generalizing our *AMG* framework to address new problem classes

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- Maxwell and Helmholtz problems have huge near null spaces and require more than pointwise smoothing to achieve optimality in multigrid



*Model of a section of the Next Linear Collider structure*



*Resonant frequencies in a Helmholtz Application*

- Our new theory allows for **any type of smoother**, and also works for a **variety of coarsening approaches** (e.g., vertex-based, cell-based, agglomeration)
- A paper is in the works

# Preliminaries...

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- Consider solving the **linear system**

$$Au = f$$

- Consider **smoothers** of the form

$$u_{k+1} = u_k + M^{-1}r_k$$

where we assume that  $(M+M^T-A)$  is **SPD** (sufficient condition for convergence)

- **Note:**  $M$  may be symmetric or nonsymmetric
- Smoother **error propagation**

$$e_{k+1} = (I - M^{-1}A) e_k$$

# Preliminaries continued...

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- Let  $P : \mathcal{R}^{n_c} \rightarrow \mathcal{R}^n$  be **interpolation** (prolongation)
- Let  $R : \mathcal{R}^n \rightarrow \mathcal{R}^{n_c}$  be some “**restriction**” operator
  - Note that  $R$  is not the MG restriction operator
  - The form of  $R$  will be important later
- Define  $Q : \mathcal{R}^n \rightarrow \mathcal{R}^n$  to be a **projection** onto  $\text{range}(P)$ ; hence  $Q=PR$  such that  $RP=I$

# Two new measures

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- **First measure:**

$$\mu(Q, e) = \frac{\langle M^T (M + M^T - A)^{-1} M (I - Q) e, (I - Q) e \rangle}{\langle A e, e \rangle}$$

- **Second measure:** Define  $\sigma(M) \equiv 1/2(M + M^T)$ , then

$$\mu_\sigma(Q, e) = \frac{\langle \sigma(M) (I - Q) e, (I - Q) e \rangle}{\langle A e, e \rangle}$$

- **Measure  $\mu_\sigma$  is the analogue to the *AMGe* measure**

# First measure and *MG* convergence

- **Theorem:** Assume that the following holds for some constant  $K$ :

$$\mu(Q, e) \leq K \quad \forall e \in \mathbb{R}^n \setminus \{0\}$$

Then, 2-level *MG* converges uniformly:

$$\left\| (I - M^{-1}A) (I - Q_A) e \right\|_A \leq \left(1 - \frac{1}{K}\right)^{1/2} \|e\|_A$$

Here,  $Q_A = P(P^TAP)^{-1}P^TA$  is the  $A$ -orthogonal projector onto  $\text{range}(P)$

- **As in *AMGe*, we could try to directly localize this new measure to help us build *AMG* algorithms**
- **But, we will take a different approach**



# Second measure and MG convergence

- **Bounding  $\mu_\sigma$  also implies uniform convergence...**
- **Lemma:** Assume that  $(M+M^T-A)$  is SPD. Then,

$$\mu(Q, e) \leq \frac{\Delta^2}{2-\omega} \mu_\sigma(Q, e)$$

where  $\Delta \geq 1$  measures the deviation of  $M$  from  $\sigma(M)$

$$\langle Mv, w \rangle \leq \Delta \langle \sigma(M)v, v \rangle^{1/2} \langle \sigma(M)w, w \rangle^{1/2}$$

and where  $0 < \omega \equiv \lambda_{\max}(\sigma(M)^{-1}A) < 2$ .

- **Must insure “good” constants**
  - in particular,  $\omega \ll 2$

# General notions of C-pts & F-pts

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- Recall the projection  $Q=PR$ , with  $RP=I$
- We now fix  $R$  so that it does not depend on  $P$ 
  - Defines the coarse-grid variables,  $u_c = Ru$
  - Recall that  $R=[0, I]$  ( $P^T=[W^T, I]^T$ ) for AMGe; i.e., the coarse-grid variables were a subset of the fine grid
  - C-pt analogue
- Define  $S : \mathcal{R}^{n_s} \rightarrow \mathcal{R}^n$  s.t.  $n_s = n - n_c$  and  $RS = 0$ 
  - Think of  $\text{range}(S)$  as the “smoother space”, i.e., the space on which the smoother must be effective
  - Note that  $S$  is not unique
  - F-pt analogue
- $S$  and  $R^T$  define an orthogonal decomposition of  $\mathcal{R}^n$ ; any vector  $e$  can be written as  $e = Se_s + R^T e_c$

# The new theory separates construction of coarse-grid correction into two parts

- The following measures the ability of a given coarse grid  $\Omega_c$  to represent algebraically smooth error:

$$\mu^* \equiv \min_P \max_{e \neq 0} \mu(PR, e)$$

- **Theorem:** (1) Assume that  $\mu^* \leq K$  for some constant  $K$ .  
(2) Assume that any one of the following holds for  $\eta \geq 1$ :

$$\langle A Qe, Qe \rangle \leq \eta \langle Ae, e \rangle, \quad \forall e$$

$$\langle A(I-Q)e, (I-Q)e \rangle \leq \eta \langle Ae, e \rangle, \quad \forall e$$

$$\langle APe_c, Se_s \rangle^2 \leq (1 - \eta^{-1}) \langle APe_c, Pe_c \rangle \langle ASe_s, Se_s \rangle, \quad \forall e_c, e_s$$

Then,  $\mu(PR, e) \leq \eta K, \forall e$ .

- **(1) insures coarse grid quality** – use  $CR$
- **(2) insures interpolation quality** – necessary condition!

# **CR is an efficient method for measuring the quality of the set of coarse variables**

- **CR (Brandt, 2000) is a modified relaxation scheme that keeps the coarse-level variables,  $Ru$ , invariant**
- **We have defined several variants of CR, and shown that fast converging CR implies a good coarse grid:**

$$\mu^* \leq \left( \frac{\Delta^2}{2 - \omega} \right) \frac{1}{1 - \rho_{cr}}$$

- **Hence, CR can be used as a tool to efficiently measure the quality of a coarse grid!**
- **General idea:** *If CR is slow to converge, either increase the size of the coarse grid or modify relaxation*
- **F-relaxation is a specific instance of CR**

# CR based on matrix splittings

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$$e_{k+1} = (I - M_s^{-1}A_s) e_k; \quad M_s = S^T M S; \quad A_s = S^T A S$$

- **Theorem:** Assume that  $(M + M^T - A)$  is SPD. Then,

$$\mu^* \leq \left( \frac{\Delta^2}{2 - \omega} \right) \frac{1}{1 - \rho_s}$$

where  $\Delta$  and  $\omega$  are as before, and  $\rho_s = \|(I - M_s^{-1}A_s)\|_{A_s}$ .

- **Fast converging CR implies good coarse grid**
- **If relaxation is based on a splitting  $A = M - N$ , then  $M$  is explicitly available, and CR is probably feasible**

# CR based on additive subspace methods

- Consider the following additive method:

$$I - M^{-1}A; \quad M^{-1} = \sum_i I_i (I_i^T A I_i)^{-1} I_i^T$$

where  $I_i : \mathfrak{R}^{n_i} \rightarrow \mathfrak{R}^n$  and  $\mathfrak{R}^n = \cup_i \text{range}(I_i)$ .

- Define full rank normalized operators  $S_i$  and  $R_i^T$  s.t.  $\text{range}(S_i) = \text{range}(I_i^T A)$  and  $\text{range}(R_i^T) = \text{range}(I_i^T)$
- The  $I_i$  must be chosen so that  $R_i S_i = 0$
- Then an additive CR is given by

$$I - M_{cr}^{-1}A_s; \quad M_{cr}^{-1} = \sum_i S_i^T I_{s,i} (I_{s,i}^T A I_{s,i})^{-1} I_{s,i}^T; \quad I_{s,i} = I_i S_i$$

- The theoretical result is the same as before
- Additive Schwarz is straightforward when  $R = [0, I]$

# More general form of **CR**

$$e_{k+1} = (I - (S^T M^{-1} S) A_s) e_k; A_s = S^T A S$$

- Here,  $S$  must be normalized so that  $S^T S = I$
- This variant of **CR** is always computable
- Theoretical result currently requires **SPD smoother**,  $M$ , and involves an additional constant:

$$\mu^* \leq \left( \frac{1}{2-\omega} \right) \left( \frac{1}{1-\gamma^2} \right) \frac{1}{1-\rho_s}$$

where  $\gamma \in [0, 1)$  satisfies

$$\langle MSv_s, R^T v_c \rangle \leq \gamma \langle MSv_s, Sv_s \rangle^{1/2} \langle MR^T v_c, R^T v_c \rangle^{1/2}; \quad \forall v_s, v_c$$

# We can use **CR** to choose the coarse grid

- To check convergence of **CR**, relax on the equation

$$A_{ff} x = 0$$

and monitor pointwise convergence to 0

- **CR** coarsening algorithm:

Initialize  $U = \Omega$ ;  $C = \emptyset$ ;  $F = \Omega - C$

While  $U \neq \emptyset$

Do  $\nu$  compatible relaxation sweeps

$$U = \{i : x_i^y / x_i^{y-1} > \theta\}$$

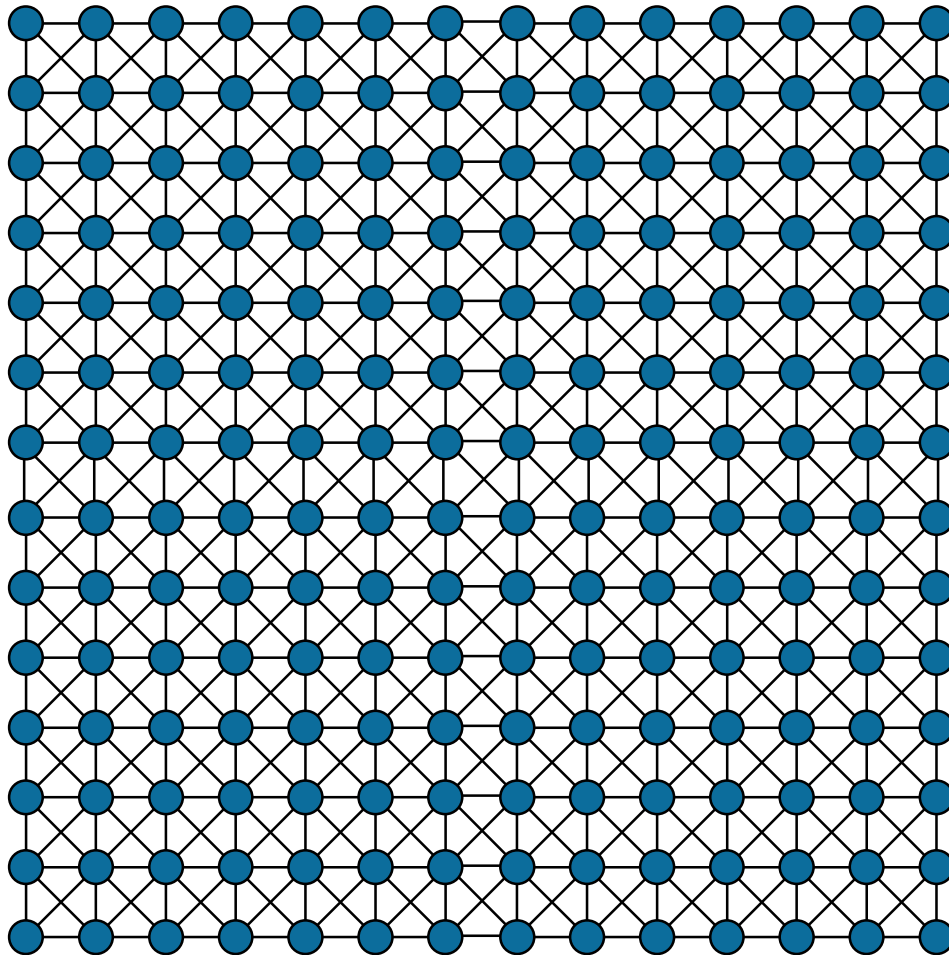
$$C = C \cup \{\text{independent set of } U\}; F = \Omega - C$$



# Using *CR* to choose the coarse grid

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→ Initialize U-pts

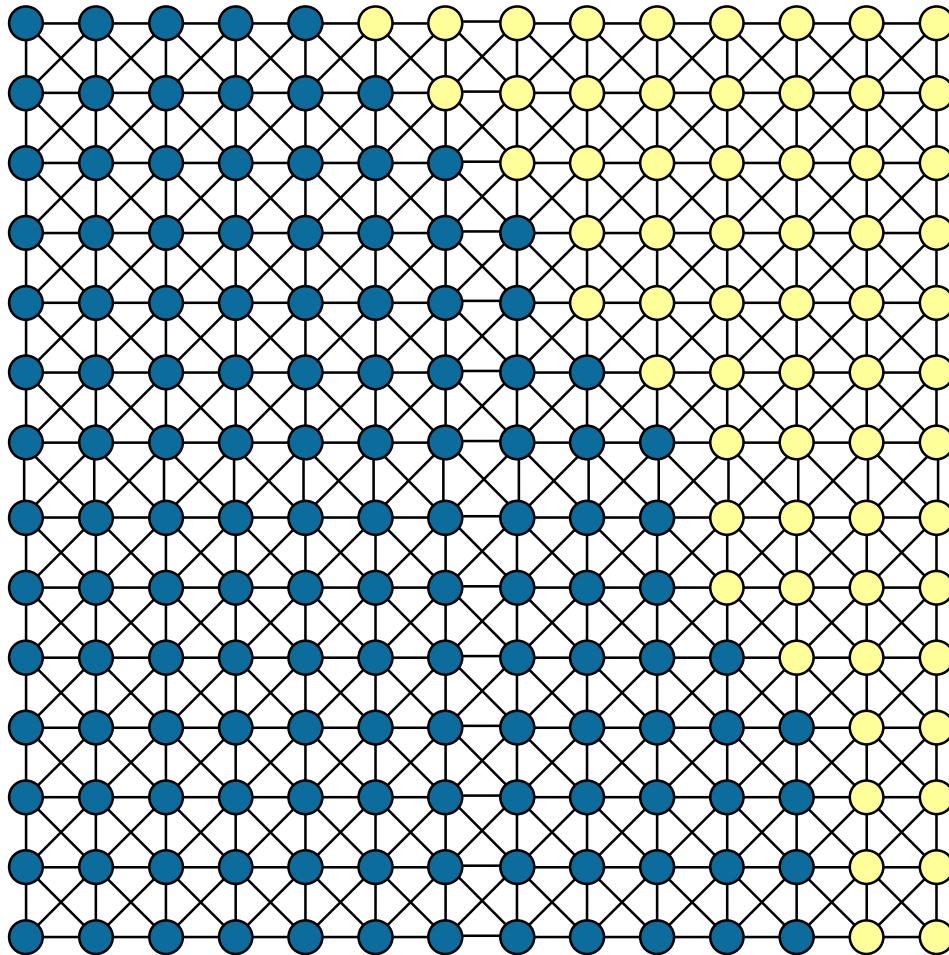
→ Do CR and redefine U-pts as points slow to converge

→ Select new C-pts as indep. set over U

# Using *CR* to choose the coarse grid

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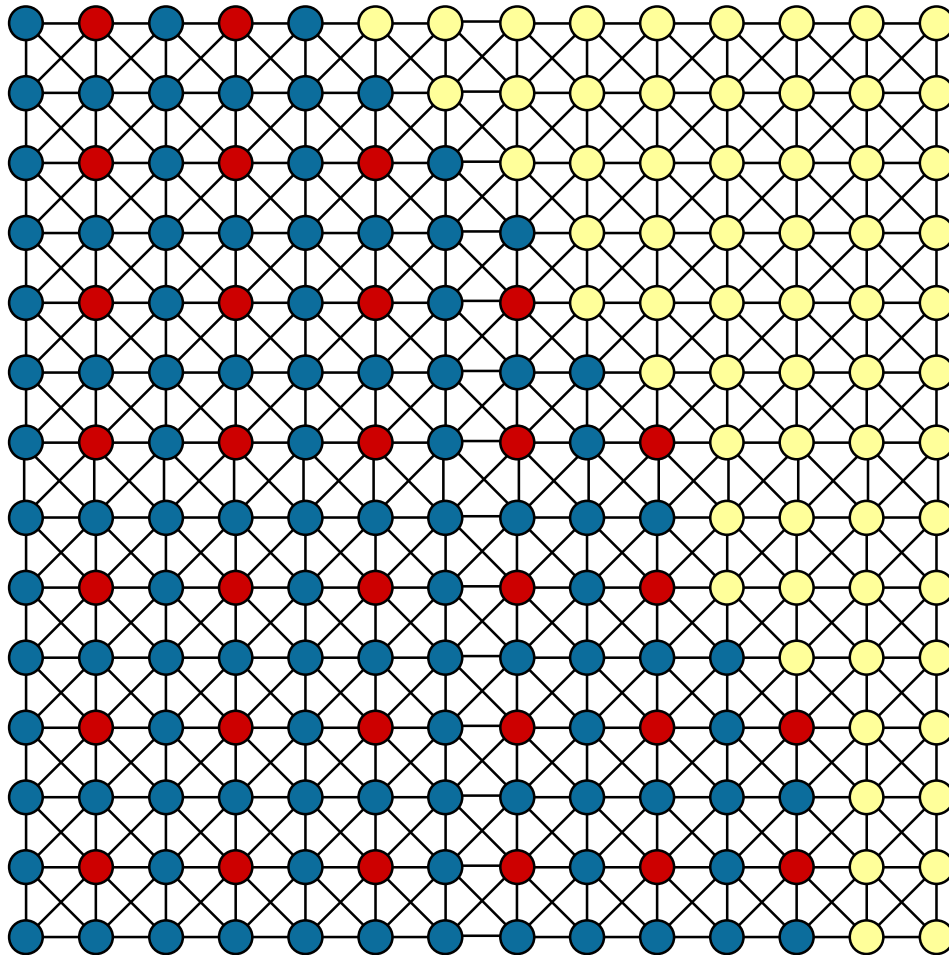
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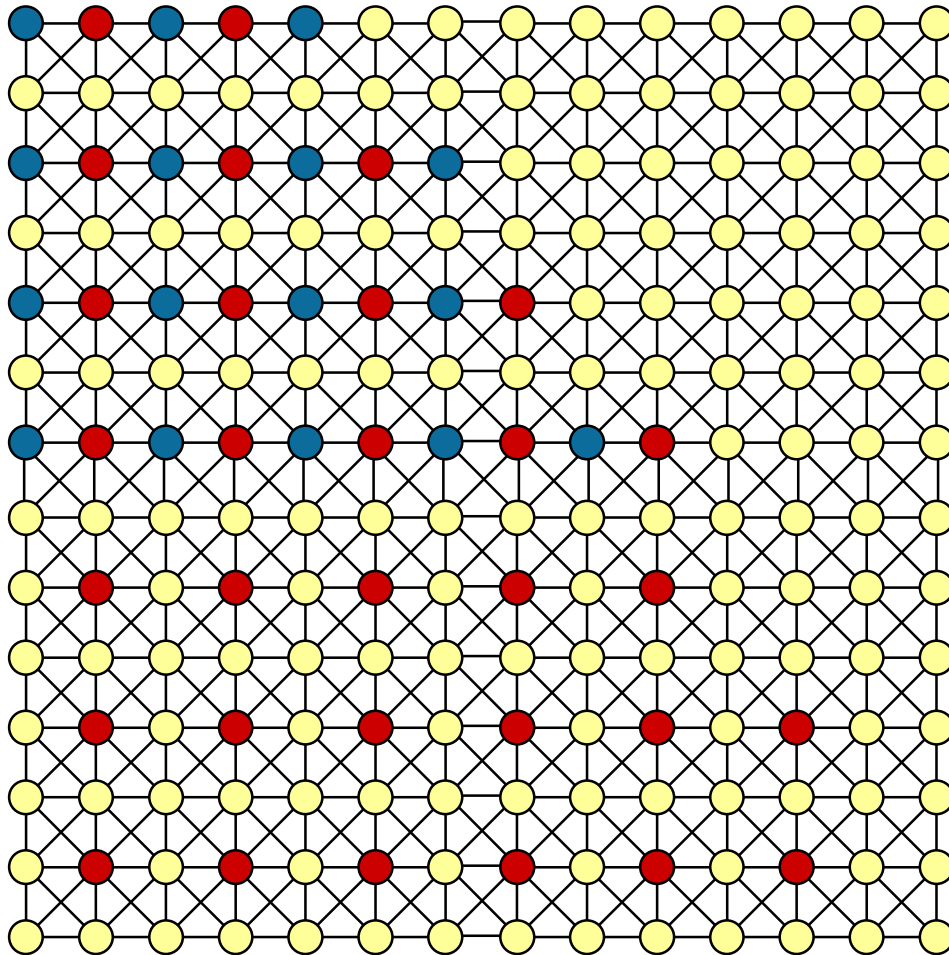
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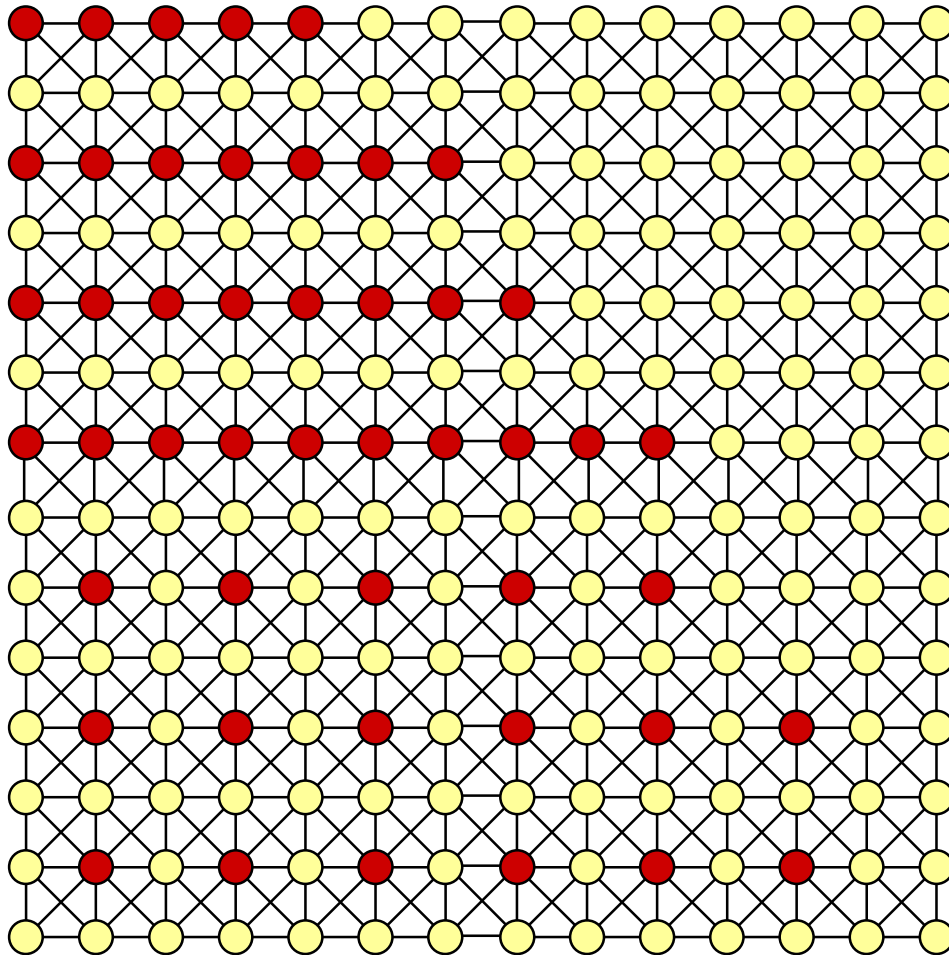
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# Using *CR* to choose the coarse grid

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→ Initialize U-pts


→ Do CR and redefine U-pts as points slow to converge

→ **Select new C-pts as indep. set over U**

# Conclusions and Future Directions

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- **We have developed a more general theoretical framework for AMG methods**
  - Allows for **any type of smoother**
  - Allows for a **variety of coarsening approaches** (e.g., vertex-based, cell-based, agglomeration)
- **The theory separates construction of coarse-grid correction into two parts:**
  - Insuring the quality of the **coarse grid** via *CR*
  - Insuring the quality of **interpolation** for the given coarse grid (leverages earlier work)
- **We have defined several variants of *CR***
- **Will explore further the use of *CR* in practice**
- **Choosing / modifying smoothers automatically?**



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# Min-max

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- **Theorem:** Define

$$\mu_x^* \equiv \min_P \max_{e \neq 0} \mu_x(PR, e)$$

The *arg min* satisfies  $P^TAS=0$  and the minimum is

$$\mu_x^* = \lambda_{\min}^{-1} \left( (S^TXS)^{-1}(S^TAS) \right)$$

- **The solution above has the following general form:**

$$P = \begin{bmatrix} S & R^T \end{bmatrix} \begin{bmatrix} -(S^TAS)^{-1}(S^TAR^T) \\ I \end{bmatrix}$$

- **It can also be viewed as a “smoothed” prolongator**

$$P = (I - S(S^TAS)^{-1}S^TA) R^T$$