

# Lecture 5 Numerical Analysis 13/02

Basic Result = Cea's Lemma

- $a: H \times H \rightarrow \mathbb{R}$  bilinear form.
- $a(u, v) \leq C \|u\| \|v\|$  continuity
- $a(u, u) \geq k \|u\|^2$  coercivity.

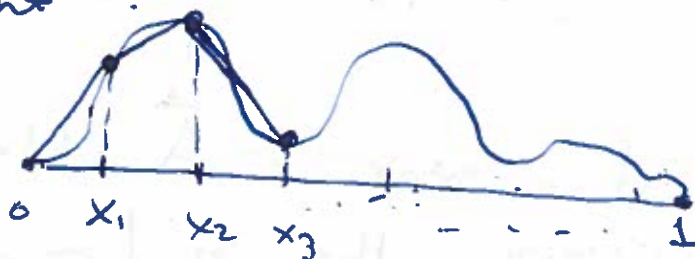
Choose  $H_h \subseteq H$ , F.E:  $a(u_h, v_h) = f(v_h)$ ,  $\forall v_h \in H_h$   
P.D.E:  $a(u, v) = f(v)$ ,  $\forall v \in H$ .

$$\|u - u_h\| \leq \frac{C}{k} \inf_{v_h \in H_h} \|u - v_h\|$$

$H_h = \{ \text{p.w. linear functions, associated to a mesh} \}$   
 $= \{ \text{p.w. polynomials of degree } p \text{ associated to a mesh} \}$   
 $= \{ \sin, \cos, \text{etc.} \dots \}$

P.w. linear functions: determined by their values in the nodes  $x_j$ .

A polynomial of degree 2 is uniquely determined by the values in the end points + (p-1) interior (auxiliary) point.



$\dim H_h = \# \text{ auxiliary nodes} + \# \text{ of the } x_j \text{'s}$ .

Solve  $A\vec{c} = \vec{F}$  ( $A = A^T, A > 0$ )

Consider  $E(\vec{c}) = \frac{1}{2} \vec{c}^T A \vec{c} - \vec{F} \cdot \vec{c} = \frac{1}{2} \vec{c} \cdot (A\vec{c}) - \vec{F} \cdot \vec{c}$

By the gradient test  $\frac{\partial E}{\partial c_j} = 0$  for all  $j$ .

$A\vec{c} = \vec{F}$



The Equation we are trying to solve  $\Leftrightarrow$  Finding a minimum

Idea = Flow along  $-\vec{\nabla} E(\vec{c})$

Algorithm = Choose  $\vec{c}_0 \in \mathbb{R}^d$  (initial guess)

- Determine direction  $\vec{d}_k = -\vec{\nabla}_{\vec{c}} E(\vec{c}_k)$

- Line search: Determine the minimum of  $E(\vec{c})$

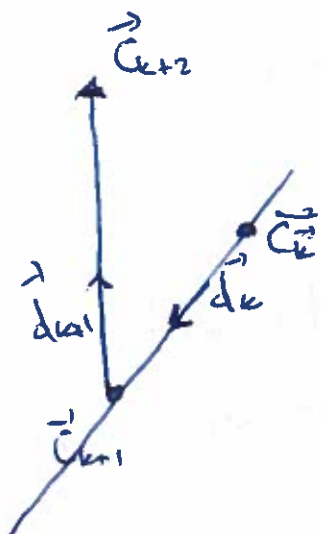
Some explicit formulas =  $E = \frac{1}{2} \vec{c}^T A \vec{c} - \vec{F} \cdot \vec{c}$

$\vec{d}_k = \vec{F} - A\vec{c}_k$

$\vec{c}_{k+1} = \vec{c}_k + \frac{\vec{d}_k \cdot \vec{d}_k}{\vec{d}_k \cdot (A\vec{d}_k)} \vec{d}_k$

$\vec{d}_k = -\vec{\nabla}_{\vec{c}_k} E(\vec{c}_k)$

$\vec{c}_{k+1}$  = the minimizer in this direction  $\vec{d}_k$ .



Condition number of  $A$ :  $k(A) = \frac{\lambda_{max}}{\lambda_{min}}$   
and determines the speed of convergence.

example:  $A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \Rightarrow k(A) = 1000$ .

As a measure of the error, we use energy norm

$$\|x\|_A := \left( \begin{matrix} \vec{x}^T A \vec{x} \\ \geq 0 \end{matrix} \right)^{1/2} > 0, \text{ if } \vec{x} \neq 0 \text{ (because } A > 0)$$

if  $\vec{c}^*$  is the exact solution  $(A\vec{c}^* = \vec{f} \Leftrightarrow E(\vec{c}) = E(\vec{c}^*))$

$$\Rightarrow E(\vec{c}) = E(\vec{c}^*) + \frac{1}{2} \|\vec{c} - \vec{c}^*\|_A^2$$

$$E(\vec{c}_{k+1}) = E\left(\vec{c}_k + \frac{\vec{d}_k \cdot \vec{d}_k}{\vec{d}_k^T A \vec{d}_k} \vec{d}_k\right) = E(\vec{c}_k + \alpha_k \vec{d}_k)$$

$$= \frac{1}{2} (\vec{c}_k + \alpha_k \vec{d}_k)^T A (\vec{c}_k + \alpha_k \vec{d}_k) - \vec{f} \cdot (\vec{c}_k + \alpha_k \vec{d}_k)$$

$$= E(\vec{c}_k) + \alpha_k \vec{d}_k^T (A\vec{c}_k - \vec{f}) + \frac{1}{2} \alpha_k^2 \vec{d}_k^T A \vec{d}_k$$

$$= E(\vec{c}_k) - \frac{1}{2} \frac{(\vec{d}_k \cdot \vec{d}_k)^2}{\vec{d}_k^T A \vec{d}_k}$$

\* Kantorovich Inequality  
 $\frac{(\vec{x}^T A \vec{x})(\vec{x}^T A^{-1} \vec{x})}{(\vec{x}^T \vec{x})^2} \leq \left( \frac{1}{2} \sqrt{\kappa(A)} + \frac{1}{2} \sqrt{\kappa(A)} \right)$

$$\vec{d}_k := \vec{f} - A\vec{c}_k = -A(\vec{c}_k - \vec{c}^*)$$

$$\|\vec{c}_k - \vec{c}^*\|_A^2 = (\vec{c}_k - \vec{c}^*)^T A (\vec{c}_k - \vec{c}^*) = -\vec{d}_k^T \vec{d}_k$$

$$= (\vec{d}_k^T A^{-1} \vec{d}_k)$$

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$$\Rightarrow \|\vec{c}_{k+1} - \vec{c}^*\|_A^2 = \|\vec{c}_k - \vec{c}^*\|_A^2 \left[ 1 - \frac{(\vec{d}_k \cdot \vec{d}_k)^2}{(\vec{d}_k^T A \vec{d}_k)(\vec{d}_k^T A^{-1} \vec{d}_k)} \right]$$

finer after  $k$ -steps.

else \*  $\vec{x} = \vec{d}_k$   $\|\vec{c}_{k+1} - \vec{c}^*\|_A \leq \|\vec{c}_k - \vec{c}^*\|_A \left( 1 - \frac{4}{\kappa(A) + 1} \right)$

Theorem: The error of the gradient method, after  $k$ -steps is  $\|\vec{c}_k - \vec{c}_*\|_A \leq \frac{(k-1)^k}{(k+1)^k} \|\vec{c} - \vec{c}_*\|_A$