

Math 574
class #02
8/21/2025

Cea's Lemma, the Stiffness Matrix, and Hilbert Spaces

Proposition (FGO): Suppose that $u \in V$ solves (1.6) and $u_h \in V_h \subseteq V$ solves (1.9).
Then

$$(2.1) \quad a(u - u_h, v) = 0 \quad \forall v \in V_h.$$

The identity in (2.1) is called the fundamental Galerkin orthogonality (FGO).

Proof: Because u solves (1.6),

$$a(u, v) \stackrel{(1.6)}{=} F(v), \quad \forall v \in V.$$

As $V_h \subseteq V$,

$$a(u, v) = F(v), \quad \forall v \in V_h.$$

Because u_h solves (1.9)

$$a(u_h, v) = F(v), \quad \forall v \in V_h.$$

Let $v \in V_h$ be arbitrary, using the linearity of a in its first argument,

$$a(u - u_h, v) = F(v) - F(v) = 0. \quad //$$

Remark: We have not yet proven that solutions to (1.6) and (1.9) can be found!

Theorem (Cea's Lemma): Suppose $u \in V$ solves (1.6) and $u_n \in V$ solves (1.9). Then

$$(2.2) \quad \|u - u_n\|_E = \inf_{v \in V_n} \|u - v\|_E$$

Proof: let $v \in V_n$ be arbitrary. Then

$$\begin{aligned} \|u - u_n\|_E^2 &= a(u - u_n, u - u_n) \\ &= a(u - u_n, u - u_n - v + v) \\ &\stackrel{\text{lin.}}{=} a(u - u_n, u - v) + a(u - u_n, \underbrace{v - u_n}_{\in V_n}) \\ &\stackrel{\text{FGO}}{=} a(u - u_n, u - v) \\ &\stackrel{\text{C.S.}}{\leq} \|u - u_n\|_E \|u - v\|_E. \end{aligned}$$

Assume that $u \neq u_n$. Then,

$$\|u - u_n\|_E \leq \|u - v\|_E, \quad \forall v \in V_n.$$

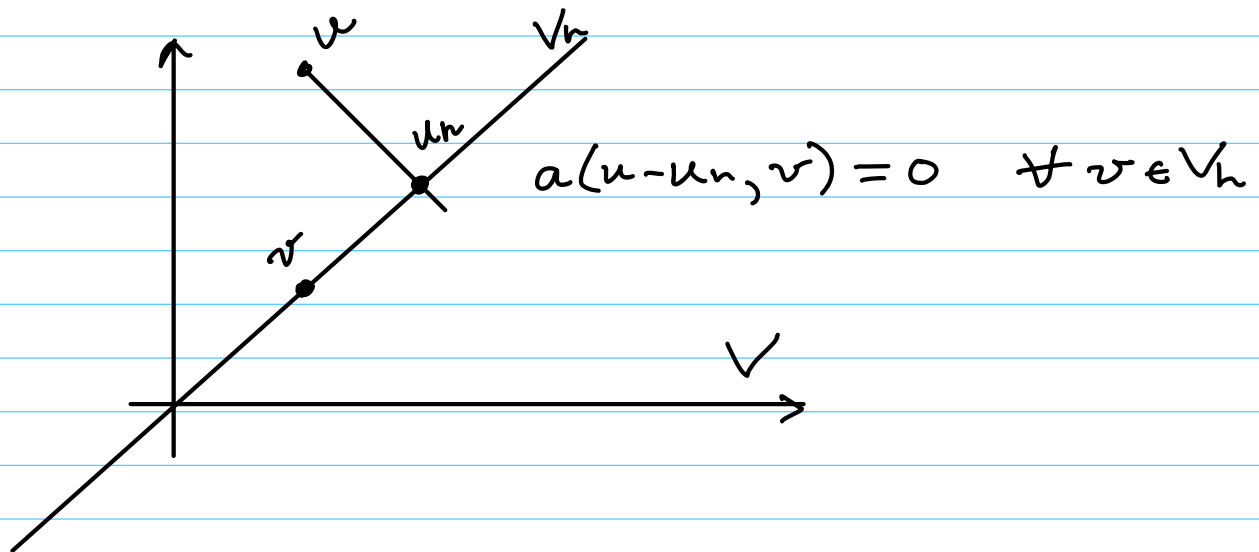
Then,

$$\begin{aligned} \|u - u_n\|_E &\leq \inf_{v \in V_n} \|u - v\|_E \\ &\leq \|u - u_n\|_E \end{aligned}$$

The only way this can happen is that

$$\|u - u_n\|_E = \inf_{v \in V_n} \|u - v\|_E //$$

Fundamental Galerkin Orthogonality



Is the Galerkin approx computable?

Proposition: $u_h \in V_h$ is the Galerkin approx

$$(2.3) \quad a(u_h, v) = (f, v)_{L^2} =: \int_{\Omega} f v \, dx \quad \forall v \in V_h$$

iff u_h solves

$$(2.4) \quad a(u_h, \phi_i) = (f, \phi_i)_{L^2} \quad i=1, \dots, M,$$

where

$$B = \{\phi_i\}_{i=1}^M$$

is a basis for V_h .

Proof: (\Rightarrow): Suppose that u_h solves (2.3). Then it must clearly solve (2.4). (Why?) //

(\Leftarrow): Suppose that u_n solves (2.4). Let $v \in V_n$ be arbitrary. Then, $\exists! c_i \in \mathbb{R}$, $i=1, \dots, M$, such that

$$v = \sum_{i=1}^M c_i \phi_i \quad (\text{unique basis expansion})$$

But

$$\begin{aligned} a(u_n, v) &= a(u_n, \sum_{i=1}^M c_i \phi_i) \\ &= \sum_{i=1}^M c_i a(u_n, \phi_i) \\ &\stackrel{(2.4)}{=} \sum_{i=1}^M c_i (f, \phi_i)_{L^2} \\ &= (f, \sum_{i=1}^M c_i \phi_i)_{L^2} \\ &= (f, v)_{L^2} \quad // \end{aligned}$$

Defn: Suppose that $B = \{\phi_i\}_{i=1}^M$ is a basis for V_n . The matrix $A = [a_{ij}]_{i,j=1}^M \in \mathbb{R}^{M \times M}$ whose entries are

$$(2.5) \quad a_{ij} = a(\phi_j, \phi_i), \quad i, j = 1, \dots, M$$

is called the stiffness matrix. The vector $\vec{f} \in \mathbb{R}^M$ whose entries are

$$(2.6) \quad f_i = (f, \phi_i)_{L^2}, \quad i = 1, \dots, M$$

is called the load vector.

Remark: Clearly A is symmetric.

Proposition: Let $B = \{\phi_i\}_{i=1}^M$ be a basis for V_h and suppose that A and \vec{f} are assembled as above. Then $u_h \in V_h$ satisfies the Galerkin approx (2.3) iff $\vec{u} \in \mathbb{R}^M$ solves

$$A\vec{u} = \vec{f}$$

where $\vec{u} = [u_i]_{i=1}^M$ is the vector whose components are the coefficients in the basis expansion for $u_h \in V_h$, i.e.,

$$u_h = \sum_{i=1}^M u_i \phi_i = \sum_{i=1}^M [\vec{u}]_i \phi_i \quad ([\vec{u}]_i = u_i)$$

Proof: (\Rightarrow): Suppose u_h solves (2.3). Then

$$a(u_h, \phi_i) = (f, \phi_i)_{L^2} \quad i=1, \dots, M.$$

Since $u_h \in V_h$ and B is a basis, there are unique coefficients $u_j \in \mathbb{R}$, $j=1, \dots, M$, such that

$$u_h = \sum_{j=1}^M u_j \phi_j$$

Set

$$\vec{u} = [u_j]_{j=1}^M \in \mathbb{R}^M$$

Then

$$\begin{aligned} [A\vec{u}]_i &= \sum_{j=1}^M a_{ij} u_j \\ &= \sum_{j=1}^M a(\phi_j, \phi_i) u_j \end{aligned}$$

$$= a\left(\sum_{j=1}^M u_j \phi_j, \phi_i\right)$$

$$= a(u_n, \phi_i)$$

$$= (f, \phi_i)_{L^2}$$

$$= f_i \quad //$$

(\Leftarrow): Now suppose that $\vec{u} \in \mathbb{R}^M$ solves

$$A\vec{u} = \vec{f}.$$

Set

$$u_n = \sum_{j=1}^M u_j \phi_j$$

$$= \sum_{j=1}^M [\vec{u}]_j \phi_j.$$

Run the last argument in reverse. ///

Proposition: The stiffness matrix $A \in \mathbb{R}^{M \times M}$, computed as above, is SPD.

Proof: A is clearly symmetric. Let $\vec{v} \in \mathbb{R}^M$ be arbitrary but $\vec{v} \neq \vec{0}$. Then

$$\vec{v}^T A \vec{v} = \sum_{i=1}^M \sum_{j=1}^M v_i a_{ij} v_j$$

$$= a\left(\sum_{j=1}^M v_j \phi_j, \sum_{i=1}^M v_i \phi_i\right)$$

where $= a(v, v)$

$$v = \sum_{i=1}^M v_i \phi_i \in V_h$$

Thus

$$\vec{v}^T A \vec{v} = \|v\|_E^2$$

Since $v \neq 0 \in V_h$, $\|v\|_E^2 > 0$. Hence A is SPD. //

Corollary: Problem (2.3) has a unique solution.

Proof: This follows since A is SPD. //

Hilbert Spaces

Let us talk about some Functional Analysis.

Defn: Let V be a linear (vector) space over \mathbb{R} . An inner product

$$(\cdot, \cdot) : V \times V \rightarrow \mathbb{R}$$

is a function with the properties

1) Positivity: For all $v \in V$,

$$(v, v) \geq 0$$

and

$$(v, v) = 0 \quad \text{iff} \quad v = 0 \in V$$

2) Symmetry: For all $u, v \in V$

$$(u, v) = (v, u)$$

3) Linearity: For all $u, v, w \in V$ and $\alpha, \beta \in \mathbb{R}$,

$$(\alpha u + \beta v, w) = \alpha(u, w) + \beta(v, w)$$

Defn: Let V be a linear space over \mathbb{R} .
A norm, $\|\cdot\|: V \rightarrow \mathbb{R}$, is a function with the properties

1) Positivity: For all $v \in V$

$$\|v\| \geq 0$$

and

$$\|v\| = 0 \text{ iff } v = 0.$$

2) Non-Negative Homogeneity:

$$\|\alpha v\| = |\alpha| \cdot \|v\|$$

for all $\alpha \in \mathbb{R}$ and all $v \in V$.

3) Triangularity: For all $u, v \in V$,

$$\|u + v\| \leq \|u\| + \|v\|.$$

A linear space V with an inner product is called an inner product space. One with a norm is called a normed linear space.

Theorem: (Cauchy-Schwarz) let $(V, (\cdot, \cdot))$ be an inner product space. Then, for all $u, v \in V$

$$|(u, v)| \leq \sqrt{(u, u)} \sqrt{(v, v)}$$

Equality holds iff u and v are linearly dependent.

Proof: Similar to that of the last lecture. ///

Theorem: let V be an inner product space. Then

$$\|v\| = \sqrt{(v, v)}, \quad v \in V$$

defines a norm. Thus $(V, \|\cdot\|)$ is a normed linear space.

Proof: Exercise. Use C-S ineq. ///

Defn: let $(V, \|\cdot\|)$ be a normed linear space. A sequence $\{v_n\}_{n=1}^{\infty} \subset V$ converges in V iff there is a point $v \in V$ such that, for every $\varepsilon > 0$, there is an $N \in \mathbb{N}$, such that if $n \geq N$

$$\|v_n - v\| \leq \varepsilon$$

We write $v_n \xrightarrow[n \rightarrow \infty]{v} v$, $\|v_n - v\| \xrightarrow{n \rightarrow \infty} 0$.

$\{v_n\}_{n=1}^{\infty} \subset V$ is called Cauchy iff for every $\varepsilon > 0$ there is an $N \in \mathbb{N}$ such that when $n, m \geq N$

$$\|v_n - v_m\| \leq \varepsilon$$

A sequence $\{v_n\}_{n=1}^{\infty} \subset V$ is bounded iff there is an $M \in [0, \infty)$ such that for all $n \in \mathbb{N}$

$$\|v_n\| \leq M.$$

Theorem: Let $(V, \|\cdot\|)$ be a normed linear space. Let $\{v_n\}_{n=1}^{\infty} \subset V$ be a convergent sequence. Then, $\{v_n\}$ is bounded. If

$$v_n \rightarrow v \text{ and } v_n \rightarrow w$$

it follows that $v = w$, i.e., limits are unique. Finally, $\{v_n\}$ is Cauchy.

Proof: Exercise !!!

Defn: A linear space for which every Cauchy sequence is convergent is called complete. A complete normed linear space is called a Banach space. A complete inner product space is called a Hilbert space.