

PART B: The Rayleigh quotient.

* The main and only difference with ERN/GIERHARD is that we consider a generic $m: X \times X \rightarrow \mathbb{R}$.

In this section we will work under the assumption that $a: X \times X \rightarrow \mathbb{R}$ and $m: X \times X \rightarrow \mathbb{R}$ are SYMMETRIC POSITIVE DEFINITE bilinear forms, i.e. it $\exists \alpha > 0$ and $\mu > 0$ such that

$$\mu \leq m(u, u) \quad \text{and} \quad \alpha \leq a(u, u) \quad \forall u \in X,$$

and $a: X \times X \rightarrow \mathbb{R}$ and $m: X \times X \rightarrow \mathbb{R}$ is bounded.

We consider the usual variational eigenvalue problem

$$\text{Find } (\lambda, u) \in \mathbb{C} \times X \text{ such that } a(u, v) = \lambda m(u, v) \quad \forall v \in X \quad (\text{EQ 1})$$

In the previous part we characterised u as the reciprocal eigenvalues of a compact self adjoint operator when $m: X \times X \rightarrow \mathbb{R}$ was the L^2 scalar product. We notice that the same characterisation also hold for any $m: X \times X \rightarrow \mathbb{R}^2$ that is symmetric, in fact the operator

$$T: X \longrightarrow X$$

$$f \mapsto T_f \text{ s.t. } a(T_f, v) = m(f, v) \quad \forall v \in X,$$

by virtue of the LAX-MISERAN Lemma and the fact that both $m: X \times X \rightarrow \mathbb{R}$ and $a: X \times X \rightarrow \mathbb{R}$ induce a scalar product.

REMARK You should not be worried about the operator m , because it appears every time we actually assemble the load-vector for the FEM method and it disassembles it takes care of passing from nodal value to the load vector i.e. an element of the dual of X .

One theorem that we didn't mention before is the HILBERT BASIS theorem, i.e.

THEOREM Let $T: X \rightarrow X$ be a compact self-adjoint operator, then the eigenfunctions of T , form a basis for the space X , provided that X is a separable Hilbert space. In particular such basis is orthogonal wrt $m: X \times X \rightarrow \mathbb{R}$.

DEFINITION The Rayleigh quotient of a function $v \in X$, relative to the bilinear forms $a: X \times X \rightarrow \mathbb{R}$ and $m: X \times X \rightarrow \mathbb{R}$ is defined as, $R(v) := \frac{a(v, v)}{m(v, v)}$, where m is a POSITIVE-DEFINITE bilinear form.

Armed with the notion of a Rayleigh quotient we can characterise the problem of solving the eigenvalue problem, (EQ 1) as a CALCULUS OF VARIATION PROBLEM.

PROPOSITION Let λ_1 be the smallest eigenvalue of (EQ 3) and u_1 be the corresponding eigen-vector, then:

$$\lambda_1 = R(u_1) = \min_{u \in X} R(u).$$

where

$$u \in X$$

PROOF Notice that if u_1 is the first eigenfunction of (EQ 1) then

$$a(u_1, u_1) = \lambda m(u_1, u_1) \Rightarrow \lambda_1 = \frac{a(u_1, u_1)}{m(u_1, u_1)} = R(u_1).$$

Obviously we have for free that $\lambda_1 \geq \inf_{u \in X} R(u)$ we need to prove the converse.

We begin expanding a vector $v \in X$ in the Hilbert basis generated by the eigenvalue

$$v = \sum_{n=1}^{\infty} v^{(n)} u_n, \text{ substituting this in the Rayleigh quotient we get that:}$$

$$R(v) = \frac{a(v,v)}{m(v,v)} = \frac{\sum_{k=1}^{\infty} v^{(k)} a(u_k, u_k)}{\sum_{k=1}^{\infty} v^{(k)} m(u_k, u_k)} \geq \frac{v^{(1)} a(u_1, u_1)}{v^{(1)} m(u_1, u_1)} = \lambda_1 \quad \square$$

Notice that this characterisation doesn't only hold for the first eigenvalue but choosing appropriately the space over which we are minimizing we can characterize all eigenvalues as a min/max problem.

PROPOSITION For all $m \geq 1$ we have that and denoting (λ_i, u_i) the eigenvalue and eigenfunctions of (EG 1) we have that,

$$\lambda_m = \max_{E_m \subseteq X} \min_{v \in E_m^\perp} R(v), \text{ where } E_m \text{ denotes the subspace of dimension } m$$

and $E_m^\perp$ its orthogonal w.r.t to $m: X \times X \rightarrow \mathbb{R}$. Clearly the eigenfunction $u_m \in \{u_1, \dots, u_m\}$ hence we have:

$$\min_{E_m} \max_{v \in E_m} R(v) \leq \max_{v \in \{u_1, \dots, u_m\}} R(v) = \lambda_m \text{ since } R(u_i) = \lambda_i.$$

Now let us pick any $E_m \subseteq X$ with $\dim(E_m) = m-1$, let us now consider the orthogonal projection of E_m onto $\{u_1, \dots, u_{m-1}\}$ by the RANK NULLITY THEOREM there is a non zero element in the kernel of the projection, we call it w and observe $w \in W_{m-1}^\perp$ hence we have $w = \sum_{n=m}^{\infty} w^{(n)} u_n$ it is simple to show that

$$R(w) = \frac{\sum_{n=m}^{\infty} w^{(n)} a(u_n, u_n)}{\sum_{n=m}^{\infty} w^{(n)} m(u_n, u_n)} \geq \lambda_m$$

$$\min_{E_m} \max_{v \in E_m} R(v) \geq \lambda_m \text{ so we can conclude.}$$

We now introduce the discrete projection operator as we have done for the continuous solution operator, i.e.

$$T_h: X \rightarrow X_h \subseteq X \\ f \mapsto T_h f \text{ s.t. } a(T_h f, v_h) = a(f, v_h) \quad \forall v_h \in X_h$$

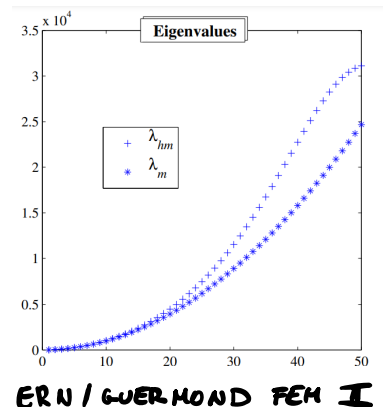
which once again we know it's well posed by CONFORMITY, i.e. $X_h \subseteq X$ and LAX-MISERAN LEMMA. We also define the quantity, $\sigma_h^{(m)} = \min_{\substack{v \in \{u_1, \dots, u_m\} \\ v \neq 0}} \frac{m(T_h v, T_h v)}{\sqrt{m(v, v)}}$ we now consider the discrete variational eigenvalue problem:

$$\text{Find } u_h \in X_h \text{ such that } a(u_h, v_h) = \lambda_h^m m(u_h, v_h) \quad \forall v_h \in V_h. \quad (\text{EG } 2)$$

Notice now that by the conformity of the approximation, i.e. $X_h \subseteq X$ and the min/max characterisation of the eigenvalue problem, then we know that the discrete eigenvalues λ_h^m will be approximating the continuous eigenvalue from above, i.e.

$$\lambda_i \leq \lambda_i^h \quad i = 1, \dots, m \quad \text{where } m \ll \dim(V_h)^*$$

* This is not a functional analysis accuracy I'll have many more basis function. we want to approximate the first 10 eigenvalues to a discrete degree of



PROPOSITION Let $\sigma_n^{(m)}$ be non-zero then we have, $\lambda_m \leq \lambda_m^h \leq (\sigma_n^{(m)})^{-2} \lambda_m$

PROOF We have already discussed one of the estimates.

Now we notice that $\ker(T_h) \cap \{u_1, \dots, u_m\} = \{0\}$ or else $\sigma_n^{(m)}$ is null. We then apply the RANK NULLITY THEOREM to see that $\text{rk}(T_h|_{E_m}) = m$

Once again we consider the ℓ^2 projection from $T_h(E_m)$ onto $\{u_{h,1}, \dots, u_{h,m}\}$ and observe that the RANK NULLITY THEOREM implies $\{u_{h,1}, \dots, u_{h,m}\}^\perp \cap T_h(E_m)$ is non-trivial, we call v_h such element and observe $v_h = \sum_{i=1}^m v_i u_{h,i}$, hence as discussed above $R(v_h) \geq \lambda_m^h$.

$$\lambda_{h,m} \leq R(v_h) \leq \max_{u_h \in T_h(E_m)} \frac{a(u_h, u_h)}{m(u_h, u_h)} = \max_{v \in \{u_1, \dots, u_m\}} \frac{a(T_h v, T_h v)}{m(T_h v, T_h v)}$$

notice now that $a(T_h(v), T_h(v)) = a(v, T_h(v)) \leq a(v, v)^{1/2} a(T_h v, T_h v)^{1/2}$ hence we have:

$a(T_h(v), T_h(v)) \leq a(v, v)$, notice that here was important that a was POSITIVE DEFINITE.

$$\lambda_m^h \leq \max_{v \in E_m} \frac{a(v, v)}{\|T_h(v)\|^2} \leq \max_{v \in E_m} \frac{m(v, v)}{\|T_h(v)\|^2} \max_{v \in E_m} R(v) = (\sigma_n^{(m)})^{-2} \lambda_m.$$

to prove that
 $\max_{v \in E_m} R(v) = \lambda_m$ we used min/max characterisation.

LEMMA In the hypothesis of the previous proposition we have that:

$$\sigma_{h,m}^2 \geq 1 - 2\sqrt{m} \frac{\|a\|}{\lambda_1} \max_{\substack{v \in E_m \\ m(v,v)=1}} \|v - T_h(v)\|_X$$

PROOF We begin observing that

$$\|T_h v\|_m^2 = \|v\|_m^2 - 2m(v, v - T_h v) + \|v - T_h v\|_m^2 \geq \|v\|_m^2 - 2m(v, v - T_h v)$$

$$\begin{aligned} \text{We now compute, } m(v, v - T_h v) &= \sum_{i=1}^m v_i m(u_i, v - T_h v) = \sum_{i=1}^m \lambda_i^{-1} v_i a(u_i, v - T_h v) \\ &= \sum_{i=1}^m \lambda_i^{-1} v_i a(u_i - T_h u_i, v - T_h v) \\ &\quad \uparrow \text{GAUSSIAN ORTHOGONALITY} \end{aligned}$$

hence we have,

$$\begin{aligned} m(v, v - T_h v) &\leq \frac{\|a\|}{\lambda_1} \|v - T_h v\|_X \sum_{i=1}^m |v_i| \underbrace{\|u_i - T_h u_i\|_X}_{\text{This is bounded by estimates on } H^1 \text{ projection.}} \\ &\quad \uparrow \lambda_1 \leq \lambda_i \quad \sum_{i=1}^m |v_i|^2 \leq 1 \Rightarrow \sum_{i=1}^m |v_i| \leq \sqrt{m} \\ &\leq \frac{\|a\|}{\lambda_1} \|v - T_h v\|_X \sqrt{m} \end{aligned}$$

THEOREM Let $m \in \mathbb{N} \setminus \{0\}$ then there exist h_0 such that $\forall h \leq h_0$,

$$0 \leq \lambda_m^h - \lambda_m \leq C \max_{\substack{v \in E_m \\ m(v,v)=1}} \min_{u \in X_h} \|v - u\|_X^2$$

PROOF

From the previous lemma we know that:

$$\lambda_{nm}^h - \lambda_{nm} \leq [(\sigma_h^{(m)})^{-2} - 1] \lambda_{nm} \leq 2\sqrt{m} \frac{\|a\|}{\lambda_1} \max_{\substack{v \in E_m \\ m(v,v)=1}} \|v - T_h v\|_X^2 \text{ by Cea's lemma we conclude.}$$

Can we provide an a priori error bound also on the eigenfunction?

THEOREM Let $m \in \mathbb{N}/\{0\}$ and assume that λ_m is a SIMPLE eigenvalue, furthermore let us consider as in the previous proposition $h \in (0, h_0]$. Then we have the following a priori error estimate on the eigenfunctions,

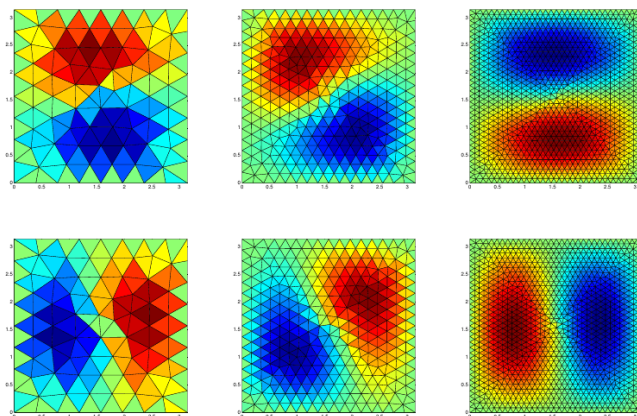
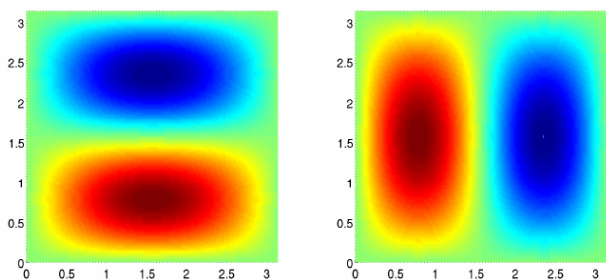
$$\|u_m - u_m^h\|_X \leq C \max_{\substack{v \in E_m \\ m(v,v)=1}} \min_{v_h \in X_h} \|v - v_h\|_X \quad (\text{THEM I})$$

PROOF We begin using the coercivity of $a: X \times X \rightarrow \mathbb{R}$,

$$\alpha \|u_m - u_m^h\|_X^2 \leq \alpha a(u_m - u_m^h, u_m - u_m^h)$$

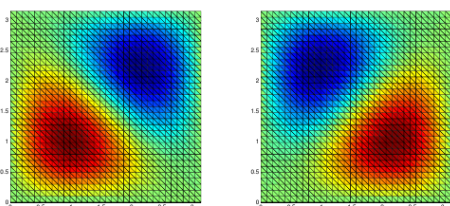
$$\begin{aligned} &= \lambda_{u_m} + \lambda_m - 2\lambda_m m(u_m, u_m^h) \\ \text{we are using } m(u,u) &= 1 \quad \uparrow \\ &= \lambda_{u_m} + \lambda_m - \lambda_m [m(u_m, u_m) - m(u_m - u_m^h, u_m - u_m^h) + m(u_m^h, u_m^h)] \\ &= \lambda_{u_m} + \lambda_m - 2\lambda_m + \lambda_m \|u_m - u_m^h\|_{m}^2 \\ &= \lambda_{u_m} - \lambda_m + \lambda_m \|u_m - u_m^h\|_{m}^2 \\ &\leq C \max_{\substack{v \in E_m \\ \|v\|=1}} \min_{v \in E_m} \|v - v_h\|_X^2 + \lambda_m \|m\| \|u_m - u_m^h\|_X^2 \\ &\leq C \max_{\substack{v \in E_m \\ m(v,v)=1}} \min_{v \in E_m} \|v - v_h\|_X^2 + \lambda_m \|m\| \|u_m - T_h u_m\|_X \\ &\leq C(\|a\|, \|m\|) \max_{\substack{v \in E_m \\ m(v,v)=1}} \min_{v \in E_m} \|v - v_h\|_X \\ &\quad \uparrow \text{ APPLYING CEA'S LEMMA} \end{aligned}$$

	Computed eigenvalue (rate)				
	$N = 4$	$N = 8$	$N = 16$	$N = 32$	$N = 64$
2	2.2468	2.0463 (2.4)	2.0106 (2.1)	2.0025 (2.1)	2.0006 (2.0)
5	6.5866	5.2732 (2.5)	5.0638 (2.1)	5.0154 (2.0)	5.0038 (2.0)
5	6.6230	5.2859 (2.5)	5.0643 (2.2)	5.0156 (2.0)	5.0038 (2.0)
8	10.2738	8.7064 (1.7)	8.1686 (2.1)	8.0402 (2.1)	8.0099 (2.0)
10	12.7165	11.0903 (1.3)	10.2550 (2.1)	10.0610 (2.1)	10.0152 (2.0)
10	14.3630	11.1308 (1.9)	10.2595 (2.1)	10.0622 (2.1)	10.0153 (2.0)
13	19.7789	14.8941 (1.8)	13.4370 (2.1)	13.1046 (2.1)	13.0258 (2.0)
13	24.2262	14.9689 (2.5)	13.4435 (2.2)	13.1053 (2.1)	13.0258 (2.0)
17	34.0569	20.1284 (2.4)	17.7468 (2.1)	17.1771 (2.1)	17.0440 (2.0)
17		20.2113	17.7528 (2.1)	17.1798 (2.1)	17.0443 (2.0)
#	9	56	257	1106	4573

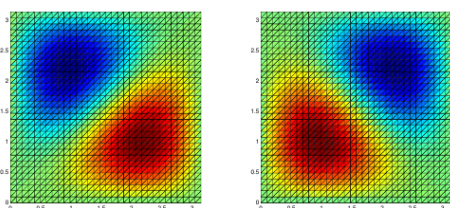


Uniform mesh

These are Type I meshes.



Uniform mesh (reversed)



REMARK What happens when we don't have a SIMPLE eigenvalue? We need to use BABUSKA-OSBORN theory, because we see phenomenon that looks like the one in the pictures.

FIGURES You can find this figures in BOFFI ACTA NUMERICA 2010.

REMARK The Poincaré inequality can be evaluated looking at it as our Ray quotient, i.e.

$$C_P = \inf_{v \in X} \frac{\|\nabla v\|}{\|v\|} = \inf_{v \in X} \frac{a(v,v)}{(v,v)} = \lambda_1 \quad \text{where } \lambda_1 \text{ is the first eigenvalue of the LAPLACIAN.}$$

EXAMPLE (Stokes eigenvalue problem) We can discretize the Stokes eigenvalue problem using divergence free element, i.e. we choose $X_h \subseteq \{v \in H_0^1 : \nabla \cdot v = 0\}$. The Stokes problem in this setting looks like:

$$\text{Find } u_h \in X_h : (E(u_h), E(v_h))_{L^2} = \lambda (u_h, v_h)_{L^2} \quad \forall v_h \in X_h$$

* This is the primal formulation of STOKES.

hence we end up with the estimate,

$$0 \leq \lambda_m^h - \lambda_m \leq C \max_{\substack{v \in E_m \\ \|v\|=1}} \min_{v_h \in X_h} \|v - v_h\|_X^2$$

Type I meshes



LEMMA Let $w \in H^s(\Omega)$ with $s \geq 2$, and assume that $\nabla \cdot w = 0$, then on type I mesh:

$$\inf_{w_h \in P_p(\mathcal{T}_h)} \|w - w_h\|_{H^1(\Omega)} \leq C \|w\|_{H^s} \begin{cases} h^{\min(p-1, s-1)} & p \in \{2, 3\} \\ h^{\min(p, s-1)} & p \geq 4 \end{cases}$$

For this result check Charlie's "UNLOCK THE SECRETS OF LOCKING"

Scott-Vogelius element with approximate eigenvalues from above and converge with optimal rate on smooth domains and $p \geq 4$.