Enriching continuous Lagrange finite element approximation spaces using neural networks

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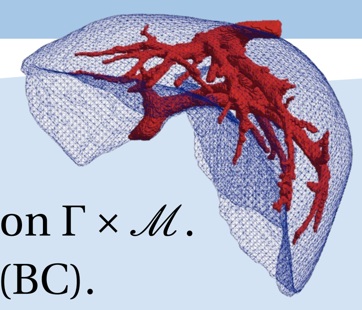
Motivations



Current Objective : Develop hybrid **finite element** / **neural network** methods.
accurate **quick + parameterized**

Problem considered : $-\Delta u(X,\mu) = f(X,\mu) \quad \text{in } \Omega \times \mathcal{M}, \quad u(x,\mu) = 0 \quad \text{on } \Gamma \times \mathcal{M}.$
Poisson problem with homogeneous Dirichlet boundary conditions (BC).

OFFLINE : PINN training

Inputs: $X \in \Omega$: sets of coordinates, $\mu \in \mathcal{M}$: sets of parameters → Parametric PINN → Output: u_θ : prediction of the PDE solution u

ONLINE : PINN evaluation + Enriched FEM resolution

Inputs: $X \in \Omega$: sets of coords, One given set $\mu \in \mathcal{M}$ → Trained PINN → PINN evaluation: u_θ : prediction for the parameter μ → FEM solver enriched by u_θ → Output: enriched FEM solution (depending on the mesh size h)

Long term objective : Create real-time digital twins of an organ (e.g. liver).

How improve PINN prediction ? - Using enriched FEM

Additive approach

The enriched approximation space is defined by

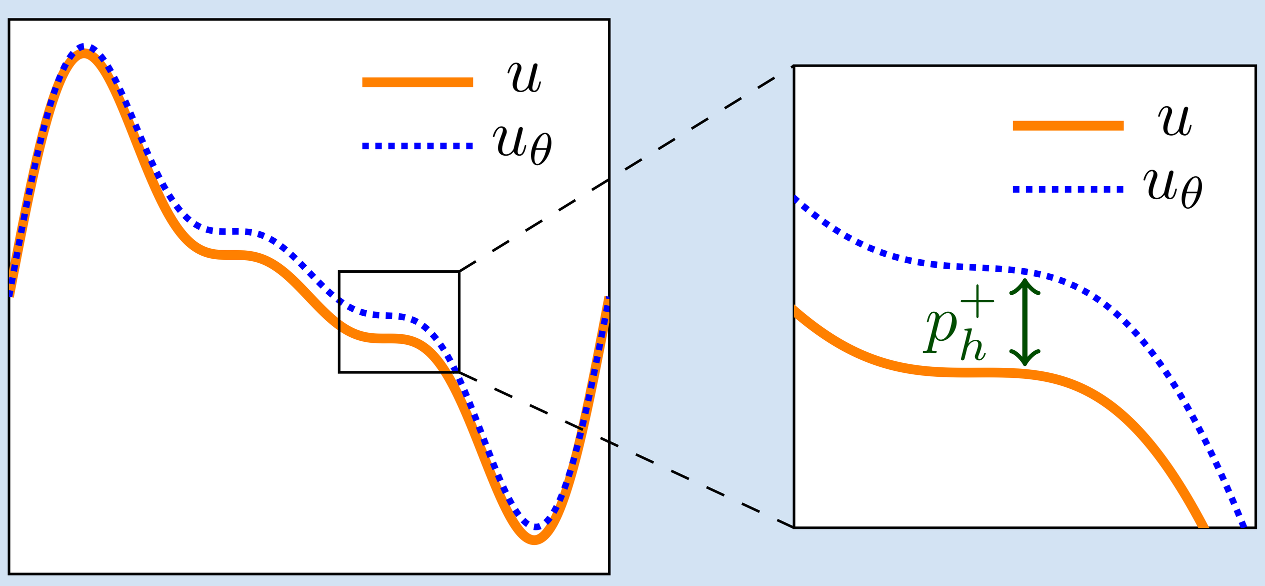
$$V_h^+ = \{u_h^+ = u_\theta + p_h^+ ,\ p_h^+ \in V_h^0\}$$

with V_h^0 the standard continuous Lagrange FE space and the weak problem becomes

$$\text{Find } p_h^+ \in V_h^0,\ \forall v_h \in V_h^0,\ a(p_h^+, v_h) = l(v_h) - a(u_\theta, v_h), \qquad (\mathcal{P}_h^+)$$

with modified boundary conditions and

$$a(u,v) = \int_\Omega \nabla u \cdot \nabla v, \quad l(v) = \int_\Omega f\, v.$$



Convergence analysis

u : solution of the Poisson problem. u_θ : prediction of the PINN [RPK19].

Theorem 1: Convergence analysis of the standard FEM [EG]

We denote $u_h \in V_h^0$ the discrete solution of standard FEM with V_h^0 a $\mathbb{P}_k$ Lagrange space. Thus,

$$|u - u_h|_{H^1} \le C_{H^1} h^k |u|_{H^{k+1}},$$
$$\|u - u_h\|_{L^2} \le C_{L^2} h^{k+1} |u|_{H^{k+1}}.$$

Theorem 2: Convergence analysis of the enriched FEM [F L+25]

We denote $u_h^+ \in V_h^+$ the discrete solution of $(\mathcal{P}_h^+)$ with V_h^+ a $\mathbb{P}_k$ Lagrange space. Thus

$$|u - u_h^+|_{H^1} \le \frac{|u-u_\theta|_{H^{k+1}}}{|u|_{H^{k+1}}} \left(C_{H^1} h^k |u|_{H^{k+1}}\right),$$

and

$$\|u - u_h^+\|_{L^2} \le \frac{|u-u_\theta|_{H^{k+1}}}{|u|_{H^{k+1}}} \left(C_{L^2} h^{k+1} |u|_{H^{k+1}}\right).$$

Theoretical gain of the additive approach.

Numerical results - Considered problem

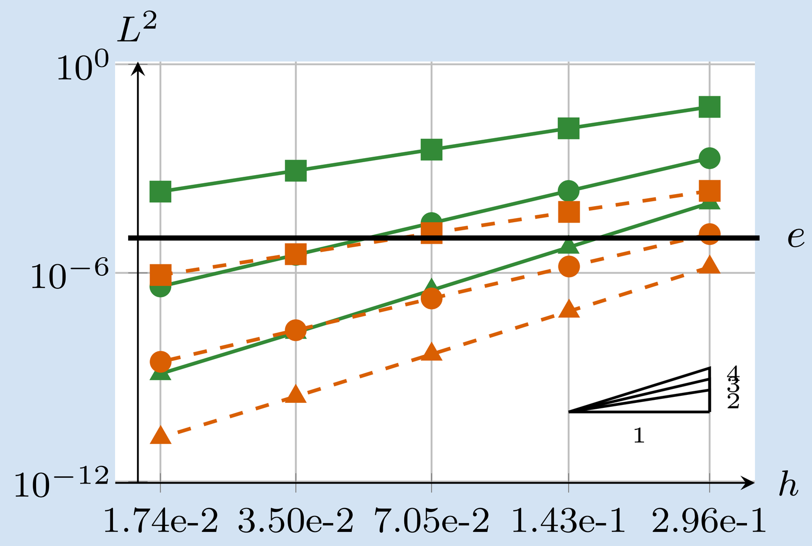
→ Spatial domain : $\Omega = [-0.5\pi, 0.5\pi]^2$
→ Parametric domain : $\mathcal{M} = [-0.5, 0.5]^2$
→ Analytical solution :

$$u_{ex}((x,y),\mu) = \exp\left(-\frac{(x-\mu_1)^2 + (y-\mu_2)^2}{2}\right) \sin(2x)\sin(2y)$$

with $\mu = (\mu_1, \mu_2) \in \mathcal{M}$ (**parametric**) and the associated source term f.

Numerical results - Improve errors

Error estimates : $\mu = (0.05, 0.22)$.



Gains achieved : 50 sets of parameters.

$$S = \{\mu^{(1)}, \dots, \mu^{(50)}\}$$

Gains in L^2 rel error of our method w.r.t. FEM

k	min	max	mean
1	134.32	377.36	269.39
2	67.02	164.65	134.85
3	39.52	72.65	61.55

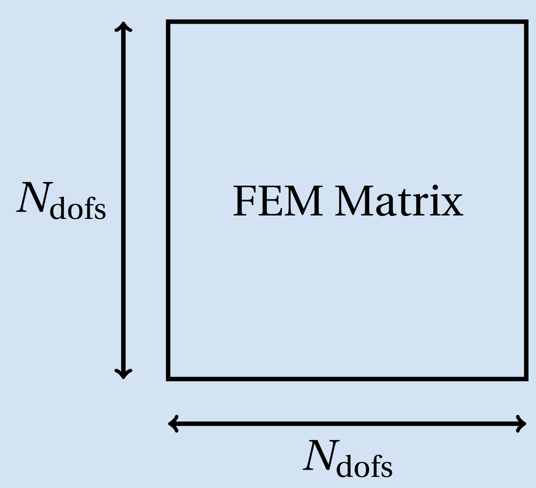
Gain : $\|u - u_h\|_{L^2} / \|u - u_h^+\|_{L^2}$

Cartesian mesh : 20^2 nodes.

Numerical results - Improve numerical costs

N_{dofs} required to reach the same error e : $\mu = (0.05, 0.22)$.

k	e	N_{dofs} FEM	N_{dofs} Add
1	$1 \cdot 10^{-3}$	14,161	64
	$1 \cdot 10^{-4}$	143,641	576
2	$1 \cdot 10^{-4}$	6,889	225
	$1 \cdot 10^{-5}$	31,329	1,089
3	$1 \cdot 10^{-5}$	6,724	784
	$1 \cdot 10^{-6}$	20,164	2,704

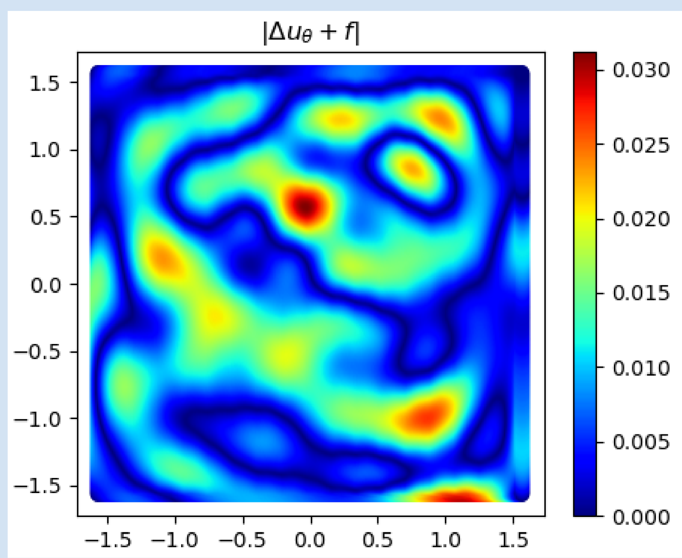


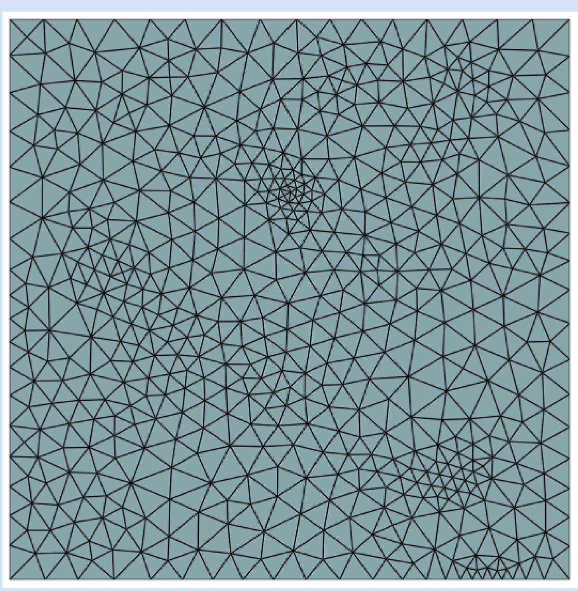
Less degrees of freedom ⇒ Lower numerical cost, Faster simulation

Perspectives

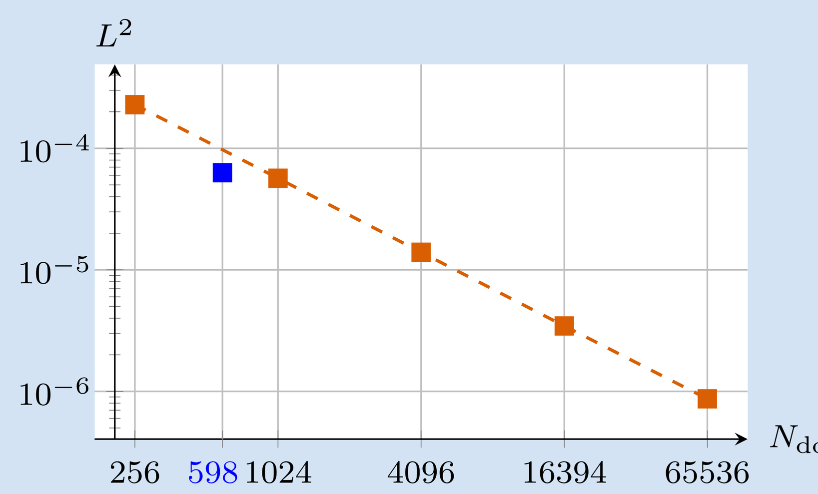
Mesh adaptation

Construction of the mesh: $N_{\text{dofs}} = 598$.

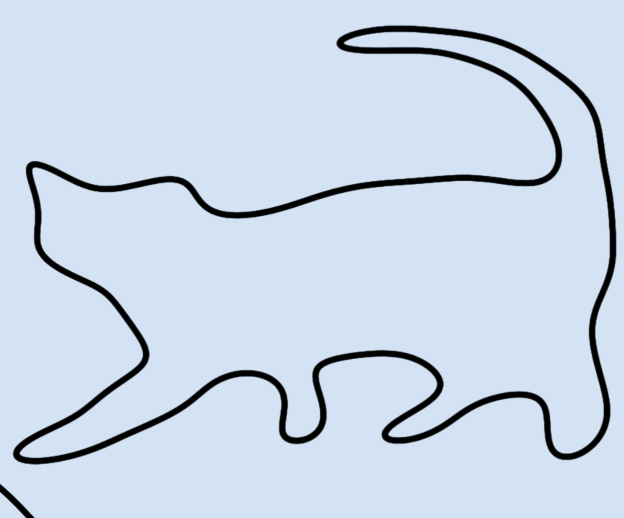




Apply enriched FEM:



More complex geometries



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