# ENRICHING CONTINUOUS LAGRANGE FINITE ELEMENT APPROXIMATION SPACES USING NEURAL NETWORKS





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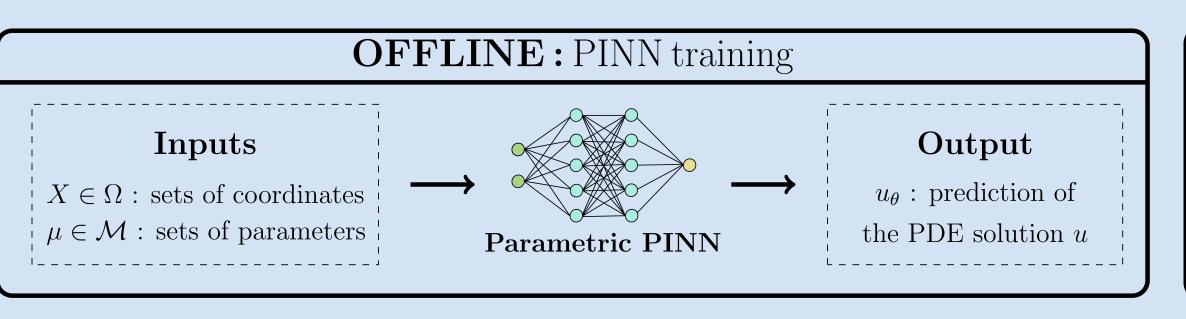
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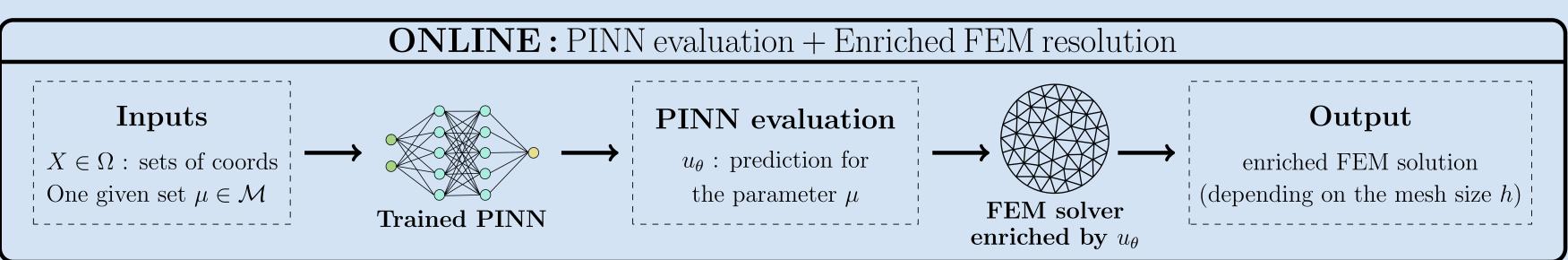
Motivations

Current Objective: Develop hybrid finite element / neural network methods.

accurate quick + parameterized

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





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

### How improve PINN prediction? - Using enriched FEM

### Additive approach

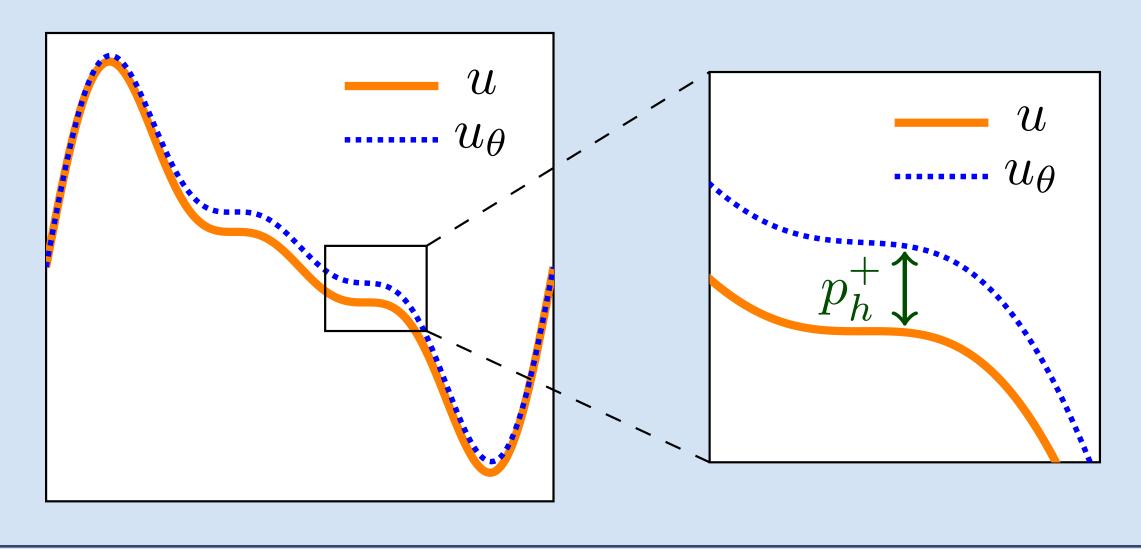
The enriched approximation space is defined by

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

with  $V_h^0$  the standard continuous Lagrange FE space and the weak problem becomes Find  $p_h^+ \in V_h^0$ ,  $\forall v_h \in V_h^0$ ,  $a(p_h^+, v_h) = l(v_h) - a(u_\theta, v_h)$ ,  $(\mathcal{P}_h^+)$ 

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.  $u_{\theta}$ : 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  $(\mathscr{P}_h^+)$  with  $V_h^+$  a  $\mathbb{P}_k$  Lagrange space. Thus

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

and

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

Theoretical gain of the additive approach.

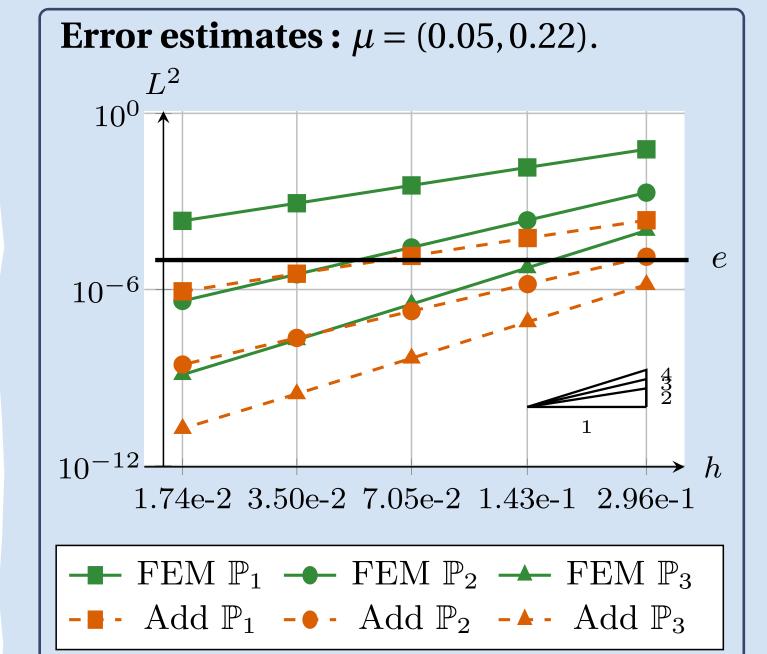
# Numerical results - Considered problem

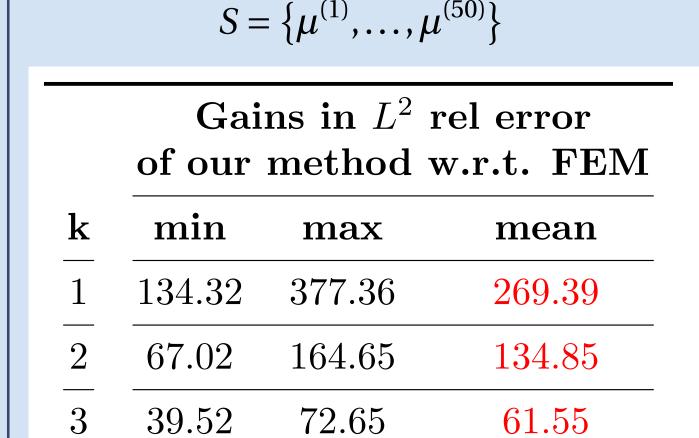
- → Spatial domain :  $\Omega = [-0.5\pi, 0.5\pi]^2$
- → Parametric domain :  $\mathcal{M} = [-0.5, 0.5]^2$
- → Analytical solution :

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

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

### Numerical results - Improve errors





**Gains achieved:** 50 sets of parameters.

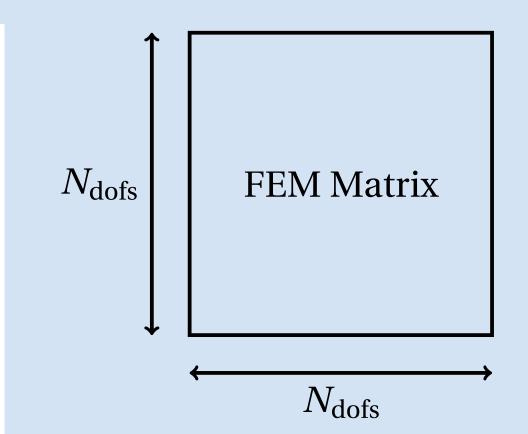
Gain:  $||u - u_h||_{L^2} / ||u - u_h^+||_{L^2}$ Cartesian mesh:  $20^2$  nodes.

#### Numerical results - Improve numerical costs

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

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

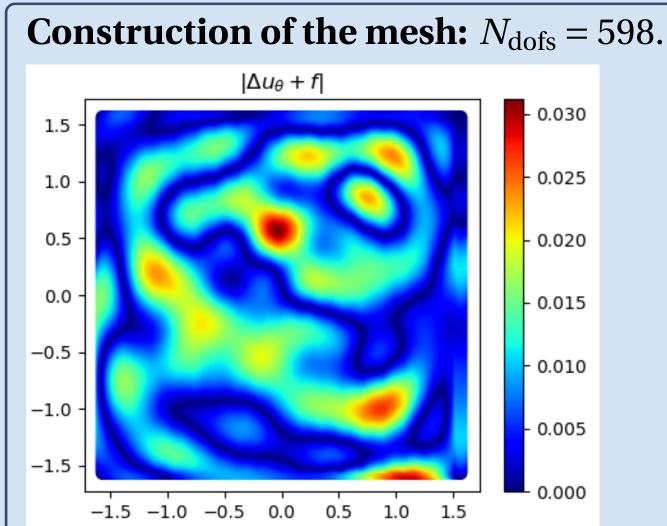
Less degrees of freedom ⇒

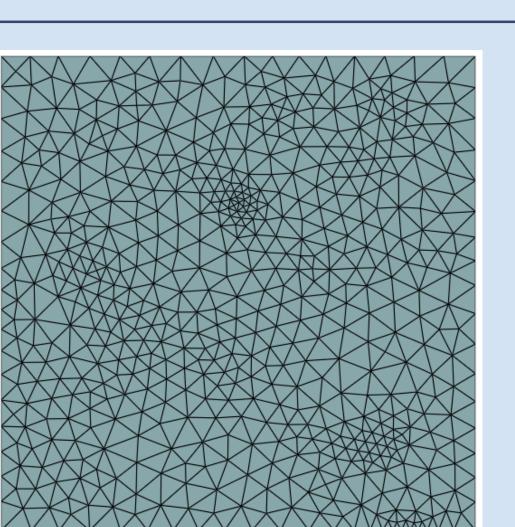


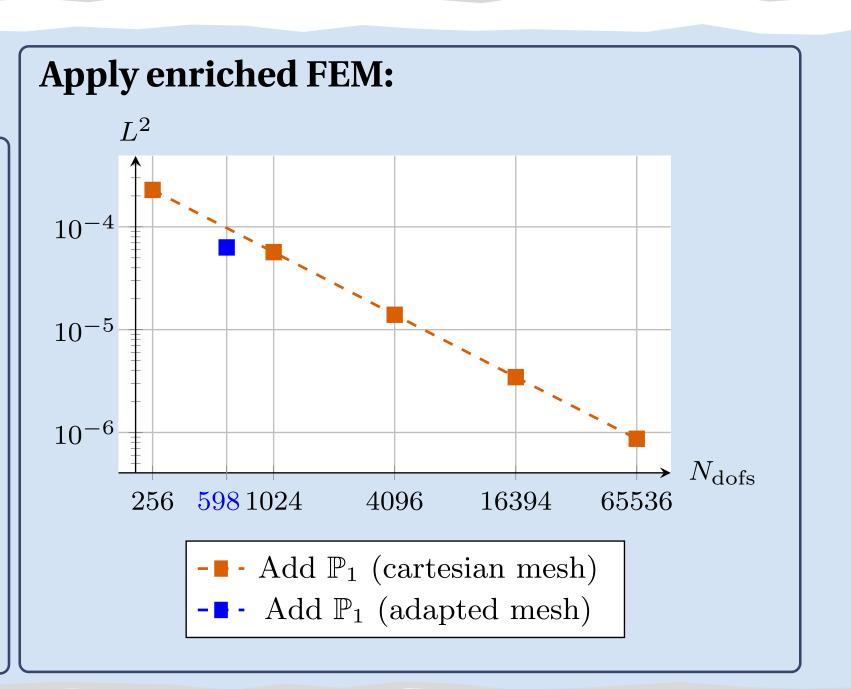
Lower numerical cost Faster simulation

# **Perspectives**

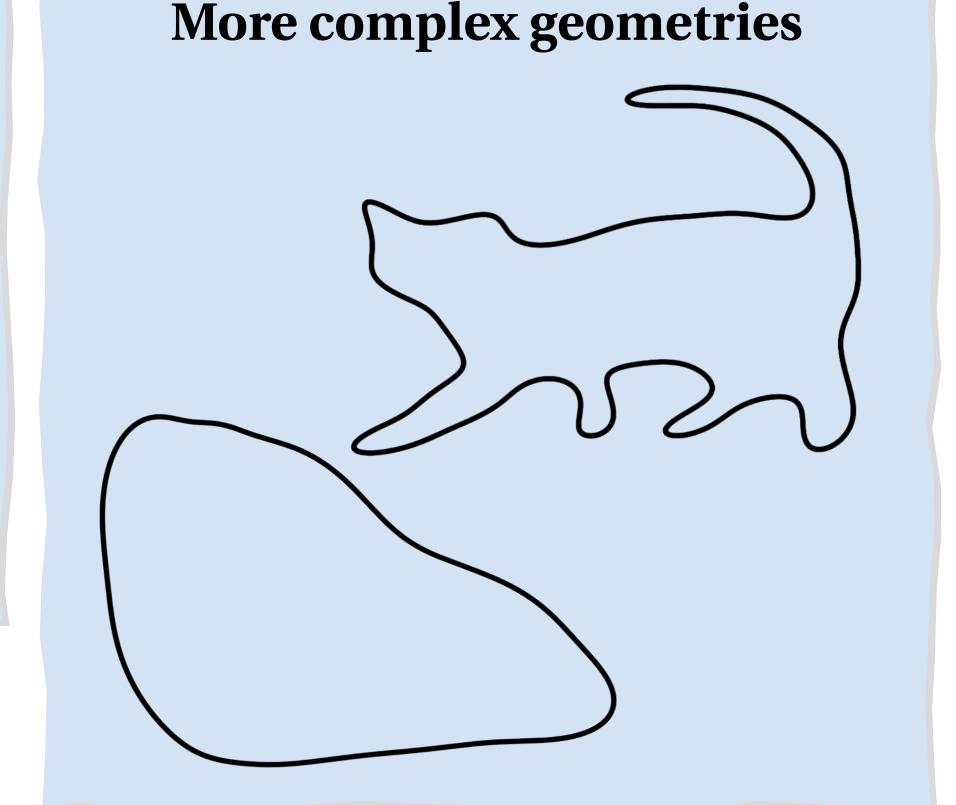
# Mesh adaptation







#### Mara complan goomatrias



[EG] A. Ern and J.-L. Guermond. Theory and Practice of Finite Elements. Springer New York (2004).

[F L+25] **F. Lecourtier** et al. Enriching continuous Lagrange finite element approximation spaces using neural networks. 2025.

[RPK19] M. Raissi, P. Perdikaris, and G. E. Karniadakis. "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations". In: *J. Comput. Phys.* 378 (2019), pp. 686–707.