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Combining Finite Element Methods and Neural Networks to Solve Elliptic Problems on 2D Geometries

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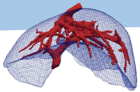
Inria MIMESIS

Scientific context



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

Objective : Develop an hybrid finite element / neural network method.

finite element: accurate

neural network: quick + parameterized

Parametric linear elliptic PDE : For one or several $\boldsymbol{\mu} \in \mathcal{M}$, find $u : \Omega \to \mathbb{R}$ such that

$$\mathcal{L}\big(u; \boldsymbol{x}, \boldsymbol{\mu}\big) = f(\boldsymbol{x}, \boldsymbol{\mu}),$$

where $\mathcal{L}$ is the parametric differential operator defined by

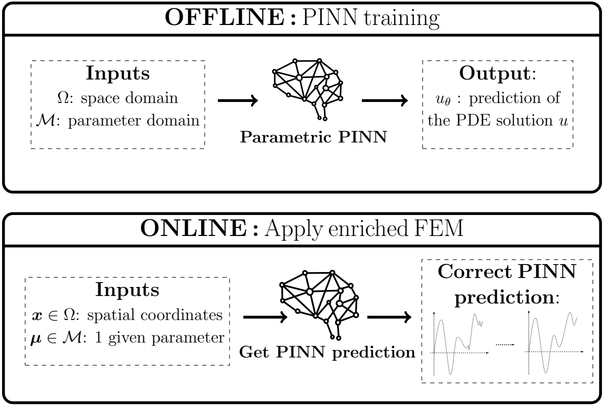
$$\mathcal{L}(\cdot; \boldsymbol{x}, \boldsymbol{\mu}) : u \mapsto R(\boldsymbol{x}, \boldsymbol{\mu})u + C(\boldsymbol{\mu}) \cdot \nabla u - \frac{1}{\mathrm{Pe}} \nabla \cdot (D(\boldsymbol{x}, \boldsymbol{\mu}) \nabla u),$$

and some Dirichlet, Neumann or Robin BC (which can also depend on $\boldsymbol{\mu}$).

Ω	Spatial domain
d	Spatial dimension
$\boldsymbol{x} = (x_1, \dots, x_d)$	Spatial coordinates
$\mathcal{M}$	Parameter space
p	Number of parameters
$\boldsymbol{\mu} = (\mu_1, \dots, \mu_p)$	Parameter vector

f	Right-hand side
R	Reaction coefficient
C	Convection coefficient
D	Diffusion matrix
Pe	Péclet number

Pipeline of the Enriched FEM



Correction : Enriched continuous Lagrange finite element approximation spaces using the PINN prediction.

Physics-Informed Neural Networks

Standard PINNs : Find the optimal weights $\theta^\star$ that satisfy

$$\theta^\star = \underset{\theta}{\operatorname{argmin}} \left(\omega_r J_r(\theta) + \omega_b J_b(\theta)\right), \tag{1}$$

with the residual loss function and the boundary loss function defined by

$$J_r(\theta) = \int_{\mathcal{M}} \int_{\Omega} \left| \mathcal{L}\left(u_\theta(\boldsymbol{x}, \boldsymbol{\mu}); \boldsymbol{x}, \boldsymbol{\mu}\right) - f(\boldsymbol{x}, \boldsymbol{\mu}) \right|^2 d\boldsymbol{x} d\boldsymbol{\mu},$$

$$J_b(\theta) = \int_{\mathcal{M}} \int_{\partial\Omega} \left| u_\theta(\boldsymbol{x}, \boldsymbol{\mu}) - g(\boldsymbol{x}, \boldsymbol{\mu}) \right|^2 d\boldsymbol{x} d\boldsymbol{\mu},$$

where u_θ is a neural network, g is the Dirichlet BC. In (1), the weights ω_r and ω_b (hyperparameters) are used to balance the different terms of the loss function.

Monte-Carlo method : Discretize the cost functions by random process.

Physics-Informed Neural Networks

Improved PINNs[1] **:** Find the optimal weights $\theta^\star$ that satisfy

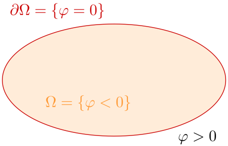
$$\theta^\star = \underset{\theta}{\operatorname{argmin}} \left(\omega_r J_r(\theta) + \cancel{\omega_b J_b(\theta)}\right), \tag{2}$$

with $\omega_r = 1$ and the residual loss function defined by

$$J_r(\theta) = \int_{\mathcal{M}} \int_{\Omega} \left| \mathcal{L}\left(u_\theta(\boldsymbol{x}, \boldsymbol{\mu}); \boldsymbol{x}, \boldsymbol{\mu}\right) - f(\boldsymbol{x}, \boldsymbol{\mu}) \right|^2 d\boldsymbol{x} d\boldsymbol{\mu},$$

where u_θ is a neural network defined by

$$u_\theta(\boldsymbol{x}, \boldsymbol{\mu}) = \varphi(\boldsymbol{x}) w_\theta(\boldsymbol{x}, \boldsymbol{\mu}) + g(\boldsymbol{x}, \boldsymbol{\mu}),$$



with φ a level-set function, w_θ a NN and g the Dirichlet BC.

Monte-Carlo method : Discretize the residual cost function by random process.

[1] Lagaris et al. [1998]; Franck et al. [2024]

Finite Element Method

TODO

How improve PINN prediction with FEM ?

Additive approach

TODO

Theorerical results

TODO

Numerical results - 2D Poisson problem

2D Poisson problem

TODO

Numerical results - 2D anysotropic Elliptic problem

2D anysotropic Elliptic problem

TODO

Conclusion

Conclusion

TODO

References

E. Franck, V. Michel-Dansac, and L. Navoret. Approximately well-balanced Discontinuous Galerkin methods using bases enriched with Physics-Informed Neural Networks. *J. Comput. Phys.*, 512:113144, 2024. ISSN 0021-9991. doi: 10.1016/j.jcp.2024.113144.

I. E. Lagaris, A. Likas, and D. I. Fotiadis. Artificial neural networks for solving ordinary and partial differential equations. *IEEE Trans. Neural Netw.*, 9(5):987–1000, 1998. ISSN 1045-9227. doi: 10.1109/72.712178.

Appendix

Appendix 1 : Standard FEM

Appendix 1 : General Idea

TODO