

PROPOSITION DE STAGE EN COURS D'ETUDES

Référence : **DAAA-2022-015**

(à rappeler dans toute **correspondance**)

Lieu : Châtillon

Département/Dir./Serv. : DAAA/NFLU

Tél. : +33 1 46 73 37 44

Responsable(s) du stage : Florent RENAC

Email. : florent.renac@onera.fr

DESCRIPTION DU STAGE

Thématique(s) : Computational fluid dynamics, machine learning, , hyperbolic conservation laws

Type de stage : Fin d'études bac+5 Master 2 Bac+2 à bac+4 Autres

Intitulé : Physics-informed artificial neural network for solving hyperbolic conservation laws

Keywords: deep learning, artificial neural network, hyperbolic conservation laws, data-driven technique

Sujet : We focus here on physics-informed artificial neural networks (PINN) recently introduced in [1,2] for the discretization of non-linear partial differential equations (PDEs) by means of a supervised deep artificial neural network (ANN) whose inputs are the space and time coordinates on a randomly sampled grid and whose output is the solution field at these coordinates. The back-propagation mechanism is applied to evaluate the space and time derivatives of the solution field and thus allows to evaluate a discrete residual of the PDEs. This residual then constitutes the cost function to be minimized and thus allows the network to train itself from the initial and boundary conditions that constitute the data. This approach seems to allow the use of rudimentary feed-forward ANNs and modest data sizes.

We propose here to evaluate this method for hyperbolic conservation laws whose solutions may develop discontinuities so those equations have to be considered in a weak sense as opposed to the PINN method. Moreover weak solutions are not necessarily unique and the equations must be supplemented with further admissibility criteria to select the physical solution which is also unclear with this method.

We are here interested to tackle difficulties linked to the consideration of the strong form of the equations and the approximation of derivatives at points of discontinuity. To do this, we will consider, on the one hand, a parabolic regularization by adding an evanescent viscosity to the equations and, on the other hand, a weak formulation of the equations approximated by the ANN [3]. These approaches will be assessed through numerical experiments on a scalar nonlinear hyperbolic equation by means of a prototype that will be developed during this project.

[1] M. Raissi, G.E. Karniadakis, Hidden physics models: machine learning of nonlinear partial differential equations, *J. Comput. Phys.*, 357 (2018), 125–141.

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

[3] R. Ranade, C. Hill, J. Pathak, DiscretizationNet: A machine-learning based solver for Navier-Stokes equations using finite volume discretization, *Comput. Methods Appl. Mech. Engrg.*, 378 (2021), 113722.

Est-il possible d'envisager un travail en binôme ? Non

Méthodes à mettre en oeuvre :

Recherche théorique

Travail de synthèse

Recherche appliquée

Travail de documentation

Recherche expérimentale

Participation à une réalisation

Possibilité de prolongation en thèse :

A renseigner

Durée du stage :

Minimum : 4 mois

Maximum : 5 mois

Période souhaitée : March to July 2022

PROFIL DU STAGIAIRE

Connaissances et niveau requis :

A solid background in Computational Mechanics (numerical analysis of PDEs), programming skills and motivation to learn are required.

Ecoles ou établissements souhaités :

M.Sc. in Applied Mathematics, Mechanics or a related discipline, with excellent academic records.