Syllabus

Descrizione corso

Titolo insegnamento	Physics Informed Neural Networks
Codice insegnamento	71082
Titolo aggiuntivo	
Settore Scientifico-Disciplinare	IINF-05/A
Lingua	Inglese
Corso di Studio	Corso di Dottorato di ricerca in Scienze e Tecnologie informatiche
Altri Corsi di Studio (mutuati)	
Docenti	dottore di ricerca Alessandro Bombini, Alessandro.Bombini@unibz.it https://www.unibz.it/en/faculties/engineering/academic-staff/person/53352
Assistente	
Semestre	Tutti i semestri
Anno/i di corso	2025-2026
CFU	2
Ore didattica frontale	20
Ore di laboratorio	0
Ore di studio individuale	50
Ore di ricevimento previste	0
Sintesi contenuti	The course introduces the concept of Physics Informed Deep Neural Networks (PINN), discuss its implementation from scratch in PyTorch and using advanced ad-hoc developed open-source libraries such as Nvidia PhysicsNemo for addressing real-world problems in various fields (engineering, physics, petroleum reservoir). We discuss recent topics such as Mixture-of-Models, Neural Operators, Physics-Informed Kolmogorov-Arnold Networks and Physics-Informed Computer Vision.
Argomenti	• General Introduction to the Course: PDEs, Functional Analysis,

dell'insegnamento	Monte Carlo Integration • An Introduction to numerical resolution of PDEs • Finite Difference Methods to solve PDEs with Python • Introduction to PINNs: forward problems, inverse problems and parametric PINNs • Solving Heat equation with PINN in PyTorch (lightning) • Advanced PINNs methods - Learning strategies, Architectures, Losses, and other approaches • Introduction to PhysicsNemo-SYM to solve PDEs with PINNs • Advanced methods for PINNs in PhysicsNemo • PIKANs and Neural Operators • Solving Darcy Flow with DeepONets and FNOs in PhysicsNemo
Parole chiave	Deep Learning; Physics-Informed Neural Networks
Prerequisiti	Basics of Python; Real Analysis; Numerical Methods; Machine Learning
Insegnamenti propedeutici	Basics of Python; Real Analysis; Numerical Methods; Machine Learning
Modalità di insegnamento	Each lecture will consist of a frontal lecture (using presentation materials) and an hands-on section (using Google Colab, Jupyter Lab)
Obbligo di frequenza	Attendance is not compulsory, but non-attending students have to contact the lecturers at the start of the course to agree on the modalities of the independent study.
Obiettivi formativi specifici e risultati di apprendimento attesi	The goal of the course is to introduce the concept of Physics Informed Deep Neural Networks (PINN), discuss its implementation from scratch in PyTorch and using advanced ad-hoc developed open-source libraries such as nvidia-modulus for addressing real-world problems in various fields (engineering, physics, petroleum reservoir). We discuss recent topics such as Mixture-of-Models, Neural Operators, Physics-Informed Kolmogorov-Arnold Networks and Physics-Informed Computer Vision. Knowledge and understanding • D1.1 – Ability to analyse and solve complex problems in computational science by integrating physics-informed neural networks with advanced numerical methods. • D1.2 – Ability to read, understand, and critically evaluate state-

	of-the-art scientific literature on PINNs, Neural Operators, and Physics-Informed Computer Vision. Applying knowledge and understanding • D2.1 – Ability to design and implement PINNs from scratch, demonstrating mastery of both theoretical and practical aspects. • D2.2 – Ability to apply innovative architectures (e.g. Mixture-of-Models, Kolmogorov-Arnold Networks) to extract knowledge from complex, high-dimensional physical systems. Making judgements • D3.1 – Ability to autonomously select and integrate specialist documentation, libraries, and datasets to advance research in physics-informed AI. • D3.2 – Ability to work with broad autonomy in multidisciplinary projects, taking responsibility for the design and validation of computational experiments. Communication skills • D4.1 – Ability to present PINN-based research results clearly and effectively to both specialist and non-specialist audiences, including through scientific publications. Learning skills • D5.1 – Ability to independently extend knowledge in emerging areas of physics-informed machine learning, keeping pace with rapid developments in AI and computational science.
Obiettivi formativi specifici e risultati di apprendimento attesi (ulteriori info.)	
Modalità di esame	Option a: Discussion of a research work on the topic, selected by the student and accepted by the instructor; it must be presented orally with a presentation and with a Git repo offering the students implementation of the code Option b: Resolution of a small research problem discussed jointly with the instructor; presented either orally with a brief presentation or a written essay, and a git repo.
Criteri di valutazione	The exam is pass/fail and no marks are awarded. Relevant for the assessment are the following: clarity of exposition, ability to summarize, evaluate, and establish relationships between topics,

	ability to present scientific notions, ability to evaluate research results by others.
Bibliografia obbligatoria	All the required reading material including slides and lecture notes will be provided during the course and will be available in electronic format. Materials for hands-on sessions will be made available on the course github repository.
Bibliografia facoltativa	Maziar Raissi, Paris Perdikaris, George Em Karniadakis. Physics Informed Deep Learning (Part I): Data-driven Solutions of Nonlinear Partial Differential Equations. arXiv 1711.10561 Maziar Raissi, Paris Perdikaris, George Em Karniadakis. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. J. Comp. Phys. 378 pp. 686-707 DOI: 10.1016/j.jcp.2018.10.045 Toscano, Juan Diego et al. “From PINNs to PIKANs: Recent Advances in Physics-Informed Machine Learning.” (2024). arXiv:2410.13228 Chayan B., Kien N., Clinton F., and Karniadakis G.. 2024. Physics-Informed Computer Vision: A Review and Perspectives. ACM Comput. Surv. (August 2024). https://doi.org/10.1145/3689037 Cuomo, S., Cola, V.S., Giampaolo, F., Rozza, G., Raissi, M., & Piccialli, F. (2022). Scientific Machine Learning Through Physics–Informed Neural Networks: Where we are and What’s Next. Journal of Scientific Computing, 92. ArXiV 2201.05624
Altre informazioni	Python, PyTorch, Nvidia PhysicsNemo 2504, JupyterLab/Hub
Obiettivi di Sviluppo Sostenibile (SDGs)	Istruzione di qualità