Hao Wei

Date of Birth: 1997/12 — Gender: Male — Nationality: Chinese
+49-15231614364 howw1225@gmail.com Hao-Wei Hao Wei

Education

Technical University of Munich **Dec. 2023 – Present**
Ph.D. Candidate in Computer Science (Research on encoding physics into ML) *Munich, Germany*
Topic: Hard-coding physical laws to build robust, trustworthy, and stable rollout machine learning algorithms.

Zhejiang University **Sep. 2020 – Mar. 2023**
M.S. in Energy Engineering (Research on ML for industry) *Hangzhou, China*
Awards: China Education Foundation Scholarship, Outstanding Graduate Leader, Excellent Student Scholarship.
Topic: Modeling complex processes (co-pyrolysis) with machine learning for industrial applications (CFD).

Northeastern University **Sep. 2016 – Jun. 2020**
B.S. in Energy Engineering (Research on computational combustion) *Shenyang, China*
Awards: China National Scholarship, Top Ten Student of NEU, Outstanding Graduate.
Topic: Building algorithms for flame-speed calculation with optimized mechanisms and modeling flammability limits.

Technical Skills

Languages: Python, C++, MATLAB, CUDA, FORTRAN
Tools: PyTorch, NumPy, JAX, OpenFOAM, Scikit-Learn, Eigen, Taichi, Cantera
Machine Learning: Equivariant Networks, Transformers, ViT, FNO, PINN, On-policy Distillation

Internships & Lab Experiences

Microsoft Research Asia **Aug. 2022 – Nov. 2022**
Research Intern, AI4Science Lab *Beijing, China*

∗ Developed a hybrid PDE solver by integrating a Fourier Neural Operator (FNO) into a differentiable FDM solver.

Zhejiang University **Mar. 2023 – Jun. 2023**
Research Assistant, Computational Physics Lab *Hangzhou, China*

∗ Developed two general models for tobacco pyrolysis: a chemical-based FORTRAN model and an ML-based model.

Hong Kong University of Science and Technology **Jul. 2023 – Nov. 2023**
Research Assistant, Thrust of Data Science and Analytics Lab *Guangzhou, China*

∗ Developed an efficient neural PDE solver for unstructured inputs based on Message Passing Neural Networks (MPNNs).

Publications & Scientific Awards

× **2 Scientific Contest Awards** (as main contributor)
∗ National Science Contest on Emission Reduction; ∗ National Science Contest on Metallurgical Science and Technology

× **8 Publications** (top-tier engineering and AI venues: NeurIPS, ICML, JCP, Fuel; selected below)
∗ **Wei, H.** List, B. et al., ReViT: Rotational-equivariant Vision Transformers for Neural PDE Solvers. *ICML*, **Oral**.
∗ **Wei, H.**, Franz, A., et al., INC: An Indirect Neural Corrector for Auto-Regressive Hybrid PDE Solvers. *NeurIPS*, 2025.
∗ Franz, A., **Wei, H.**, et al., PICT: A Differentiable, GPU-Accelerated Multi-Block PISO Solver for Simulation-Coupled Learning Tasks in Fluid Dynamics. *Journal of Computational Physics*, 2025.
∗ **Wei, H.**, Xing, J., et al., Predicting tobacco pyrolysis based on chemical constituents and heating conditions using machine learning approaches. *Fuel*, 2023.

Selected Projects

PICT | *A Differentiable, CUDA-Based, PyTorch-Supported CFD Solver*
∗ Developed a differentiable, CUDA-based, PyTorch-supported solver for hybrid learning and gradient-based optimization.
∗ Validated both forward accuracy and solver gradients on standard fluid benchmarks, and enabled supervised and unsupervised learning of stable sub-grid scale models for 2D and 3D turbulent flows.

INC | *A new framework embedding physical laws for long-horizon auto-regressive rollouts with provably bounded error*
∗ Proposed a hybrid neural PDE framework that injects learned corrections into the governing equations, improving stability in long-horizon auto-regressive rollouts.
∗ Established formal error-reduction theoretical analysis and demonstrated up to 158.7% improvement in long-term trajectory performance, stabilization under aggressive coarsening, and orders-of-magnitude speedups on 3D turbulence.

ReViT | *Rotational-Equivariant Vision Transformers for scientific data (scalar, vector, tensor)*
∗ Inspired by the strain-rate tensor in fluid dynamics, designed a hard-coded rotational-equivariant Vision Transformer for grid-based physical fields using local canonical bases.
∗ Evaluated on diverse 2D and 3D PDE benchmarks including turbulent channel flow and magnetohydrodynamics, achieving stronger generalization and reducing MSE by up to 65% versus leading baselines.