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Teaching Statement

1. Introduction

My passion for research in Scientific Machine Learning (SciML) is matched by my dedication to teaching. My research explores how models can rapidly acquire new skills and adapt to unseen scenarios; I believe my role as an educator is fundamentally the same: to equip students with the skills and mental models they need to adapt and thrive in a world being reshaped by Artificial Intelligence (AI). Like my research, my teaching philosophy is guided by the principle: "First you Understand, second you Apply, and only then you Improve". It is built on three pillars, which I prioritize in this order:

1) **To train the next generation** of scientists and engineers with the cutting-edge computational tools essential for modern industry and research.
2) **To consolidate my own knowledge** following the Feynman learning technique. I strongly believe the act of teaching is the ultimate test of understanding, forcing me to clarify and deepen my own expertise.
3) **To give back to the community** by serving as an accessible role model and mentor, fostering a culture of inclusive excellence.

This philosophy has been shaped by direct experience as a Teaching Assistant at the University of Bristol, my research at the intersection of applied mathematics and high-performance computing, and my extensive community outreach work.

2. Teaching Philosophy and Experience

2.1 Empowering the Next Generation of Scientists

The central challenge for modern applied mathematics education is building a bridge between classical, theory-driven disciplines and modern, data-driven methods. My teaching is designed to construct this bridge by grounding abstract concepts in tangible, "use-inspired" problems. I structure my pedagogy around three key questions:

- **What can AI do for you?** I introduce concepts as tools to solve problems students understand. A Graph Neural Network is not just a mathematical construct, but a method to accelerate state-of-the-art solvers for large sparse linear systems [1] or to model carbon capture in reservoir simulation, thus informing climate-related decisions.
- **How do you make it work?** True understanding comes from building. I emphasize a hands-on implementation of the full machine learning pipeline, using industry-standard tools and cutting-edge differentiable programming techniques that I have benchmarked in my own work [2].
- **What can you do for AI?** Most critically, I challenge students to see that their domain expertise is essential. The future of SciML lies in encoding physical laws and constraints directly into models to create generalizable AI, a principle demonstrated in my research on Neural Context Flows [3].

2.2 Deeper Understanding via Broad Teaching Experience

My hands-on experience as a Teaching Assistant at the University of Bristol has been foundational to my growth as an educator. I have had the privilege of designing and delivering lectures, tutorials, and support sessions across a wide range of units in the BSc and MSc curricula. This dual role as researcher and educator creates a virtuous cycle: my research provides practical, modern examples for the classroom, while teaching core mathematics ensures my research remains grounded in fundamentals. My teaching responsibilities have spanned core subjects in mathematics, computer science, and engineering:

Courses Supported at the University of Bristol

- **MSc Level Units:**
  - Introduction to Artificial Intelligence
  - High-Performance Computing
  - Overview of Computer Architecture
  - Cloud Computing
- **BSc Level Units:**
  - Scientific Computing
  - Engineering Mathematics 1 & 2

2.3 Giving Back Through Inclusive Mentorship and Outreach

My commitment to teaching extends far beyond the university classroom. As an Outreach Ambassador for the University of Bristol, I lead the *CodeMakers* initiative, designing and running after-school programming activities to foster scientific curiosity in young students. I have also served as a Widening Participation Tutor, delivering STEM sessions to aspiring university students. My volunteer work has included serving as a private mathematics instructor for primary and secondary school pupils with ExamStar, and as a language tutor at the University of Bristol Global Lounge. This work is integral to my academic identity and informs my classroom practice, reinforcing my dedication to creating a learning environment where students from all backgrounds feel seen, respected, and empowered.

3. Recognition of Teaching Excellence

My commitment to education, both within the university and in the broader community, has been recognized through the following honours:

- **Bristol Teaching Award:** In recognition of my contributions to student learning, I was honoured to be nominated for a Bristol Teaching Award. My nomination was a direct result of my dedicated work designing and delivering engaging lectures for the foundational courses in *Engineering Mathematics (EMAT 1&2)*, and for providing exceptional, student-focused support that earned consistently positive feedback.
- **"Engineering Includes Me":** In the *CodeMakers* program, I taught GCSE students ($\sim$ 16 year-olds) how to use Python libraries to design their own amazing tools, instilling creativity and a passion for technology. We helped address gender imbalance in STEM by focusing on girls and students on free school meals. As a result of this impactful work, my photograph and story were featured on a faculty wall and in a university blog post, celebrating my commitment to inclusive science education. The feature can be viewed here: engineering.blogs.bristol.ac.uk.

These honours serve as a meaningful affirmation of my commitment to providing high-quality, engaging, and supportive instruction to students at all levels.

4. Teaching and Mentoring Vision

4.1 Example Graduate Course: Applied Scientific Machine Learning for PDEs

Building on my educational background in Applied Mathematics (BSc and MSc) and Machine Learning (PhD), and my extensive experience with high-performance scientific computing, I propose to develop a new hands-on, graduate-level course designed to equip students with the practical skills to implement modern SciML solutions for PDE-based problems.

Course Objectives. This is an implementation-heavy course. By the end of this unit, students will be able to:

- Implement and parallelize PDE solvers using modern automatic differentiation frameworks (JAX, PyTorch, Julia).
- Develop and train a range of SciML models, including Physics-Informed Neural Networks (PINNs), for direct and inverse problems.
- Critically evaluate and benchmark SciML approaches against traditional numerical methods (FD, FEM, FV) using rigorous metrics, including convergence analysis.
- Frame complex industrial and scientific challenges as solvable SciML problems.

Prerequisites. Students should have a strong programming background (preferably Python) and a solid foundation in undergraduate-level numerical analysis and partial differential equations.

Course Structure. The course is divided into two main parts, supplemented by a recap of classical methods which will serve as baselines.

Recap of Classical Baselines. We will briefly review traditional numerical methods (FD, FEM, FV), assuming prior student exposure. The focus will be on their implementation and establishing performance baselines, analyzing their convergence rates and evaluation strategies. These classical solvers will be used to benchmark our SciML models.

Part 1: The Modern SciML Toolkit. This part focuses on the core implementation techniques required for cutting-edge research. We will move beyond theoretical methods to practical, high-performance coding. Topics include:

- *Automatic Differentiation:* Understanding and applying forward- and reverse-mode automatic differentiation, using libraries like JAX, PyTorch, or Julia.
- *High-Performance Differentiable Programming:* Hands-on labs on deriving robust adjoint equations to complement efficient and parallelizable code for optimal control under PDE constraints.

Part 2: SciML Methods for PDEs. The capstone of the course, connecting the implementation toolkit to the frontiers of research. We will explore:

- *Physics-Informed Neural Networks (PINNs):* A deep dive into the theory and implementation of PINNs for solving PDEs, enforcing physical laws as soft constraints in the loss function.
- *Advanced Architectures for SciML:* Neural ODEs, Graph Neural Networks (GNNs), Fourier Neural Operators (FNOs), and Transformers.
- *Adaptation and Generalization:* We will explore meta-learning approaches like Neural Context Flows [3] and the gradient-free adaptation enabled by models like WARP [5].
- *Opportunities for AI:* We will discuss how to frame industrial challenges as solvable SciML problems, from surrogate modelling to inverse problems [6].

4.2 Undergraduate Teaching and Mentoring

I am equally enthusiastic about teaching core undergraduate courses and mentoring students. My research program is rich with projects suitable for BSc, MSc and PhD students, and I am currently co-supervising two MSc Data Science students at Bristol. I look forward to fostering a collaborative and "use-inspired" research culture within my own group.

References

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[3] R. D. Nzoyem, D. A. W. Barton, and T. Deakin. "Neural Context Flows for Meta-Learning of Dynamical Systems." In *The Thirteenth International Conference on Learning Representations (ICLR)*, 2025.

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