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Teaching Statement

1. Introduction

My passion for research in Machine Learning (ML) 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 the following 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, several prestigious recognitions, my research at the intersection of computer science and applied mathematics, 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 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 ML 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

I am deeply enthusiastic about 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. These project ideas all stem from the "use-inspired" research culture I look forward to fostering within my research group [5].

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. Example Graduate Course: Applied Scientific Machine Learning

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 Partial Differential Equation (PDE) solvers using modern automatic differentiation frameworks (JAX, PyTorch, Julia) on High-Performance Computing (HPC) clusters.
- Design, train, and evaluate a range of Scientific Machine Learning (SciML) models for direct and inverse problems commonly encountered in industrial settings.

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

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), without assuming prior student exposure. The focus will be on their implementation on HPC systems, thus establishing performance baselines.

Part 1: The Modern SciML Toolkit. This part focuses on the core implementation techniques required for cutting-edge research. 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:

- *Advanced Architectures for SciML:* Neural ODEs, Physics-Informed Neural Networks (PINNs), 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 [4].
- *Opportunities for AI:* We will discuss how to frame industrial challenges as solvable SciML problems, from surrogate modelling to inverse problems [1].

References

[1] **R. D. Nzoyem**, E. Franck, L. Navoret, V. Vigon, and C. PRUD'HOMME. Simulation 2d de l'équation du transfert radiatif et reconstruction de la densité par un réseau de neurones. *University of Strasbourg*, 2020.

[2] **R. D. Nzoyem**, D. A. Barton, and T. Deakin. A comparison of mesh-free differentiable programming and data-driven strategies for optimal control under pde constraints. In *SC'23 Workshops*, pages 21–28, 2023.

[3] **R. D. Nzoyem**, D. A. Barton, and T. Deakin. Neural context flows for meta-learning of dynamical systems. In *ICLR*, 2025. URL https://openreview.net/forum?id=8vzMLo8LDN.

[4] **R. D. Nzoyem**, N. Keshtmand, I. Tsayem, D. A. Barton, and T. Deakin. Weight-space linear recurrent neural networks. *arXiv*, 2025.

[5] D. E. Stokes. *Pasteur's quadrant: Basic science and technological innovation.* Brookings Institution Press, 2011.