I have been fortunate to be able to teach and mentor many wonderful students during my undergraduate studies at Yale, my graduate studies at the University of Oxford, and my faculty fellow appointment at New York University. These experiences have been a driving factor in my desire to become a professor and have strengthened my belief that being an empathetic, encouraging, and supportive teacher and mentor is integral to being a professor and research advisor.

Overview

- **Teaching.** I have taught five courses where I was the instructor of record (two at New York University, three at Oxford). I was the head teaching assistant for four courses at Oxford and a teaching assistant and grader for an additional two courses, also at Oxford. As an undergraduate student at Yale, I was a mathematics and economics tutor for two years.
- **Mentoring and Advising.** I have closely mentored 12 undergraduate and (pre-PhD) master's students and nine PhD students and have published 17 papers with them. Additionally, I have mentored students as a First-Year advisor at Yale, as a mentor at Arbeiterkind (a German initiative that matches mentors with first-generation, low-income students), and through regular mentoring sessions that I advertised online.
- **Talks & Invited Lectures.** I was invited to give over 29 talks since 2019, including two guest lectures on Bayesian deep learning, one talk at NATO's Office of the Chief Scientist, one talk at the United States Joint Artificial Intelligence Center's Subcommittee on Responsible AI, one talk at the Rhodes Scholarship's 120 Year Anniversary Celebration, and four contributed talks given to the top submissions at conference workshops.
- **Public & Research Community Engagement.** As AI Fellow at Georgetown University's Center for Security & Emerging Technology, I have authored a series of papers on safety and reliability challenges in modern machine learning [1, 2, 3, 4, 5] that have been cited in reports by the United Nations and AI policy research institutes, and I co-authored a report on classifying AI systems with the OECD [6].

Teaching Philosphy

Teaching has been one of the most rewarding experiences as a graduate student at Oxford and as a faculty fellow at New York University—a role I chose partly because it involved teaching opportunities in computer science and data science. It is a great privilege to be able to expose students to new ideas and concepts for the first time and to help them learn and grow. I have taught advanced graduate courses at NYU and Oxford as well as NYU's flagship introductory data science course, *Data Science for Everyone* with more than 150 students. While distinct in course materials, the key challenge in introductory and advanced courses is fundamentally similar: to first understand how students will be able to best learn the material and then tailor its presentation accordingly. Doing so requires an openness to feedback from students—not just at the end of the term but throughout—and the flexibility to adapt based on feedback. My teaching philosophy is based on the following three principles:

Empathy, Encouragement, and Feedback. Learning mathematical concepts is challenging for many students. I experienced this first-hand as an undergraduate student at Yale. Unlike many of my classmates, I had not taken any advanced mathematics or participated in mathematics competitions. Building solid mathematical foundations can take a long time and require a high frustration tolerance, and I am fortunate to have had many formidable teachers who encouraged me to pursue a mathematics major, but I am also aware that many students give up early in their mathematics education. To help students from all backgrounds succeed, empathy and an appreciation for the challenges students may encounter are crucial. Empathy is important since explaining mathematical concepts effectively requires understanding why some students may find them difficult to understand in the first place. In preparing my lectures, I ask myself which concepts may be most difficult to understand, and why, and design the lecture in a way that addresses potential sources of confusion head-on. As one of my students noted in a teaching evaluation for the Oxford course *Data, Estimation, and Inference*:

> "*I initially struggled with many of the concepts and implementation details, but Tim's methodical and clear explanations meant that by the end of the course I had the satisfaction of understanding an entirely new area.*"

Establishing Foundations and Building Connections. Understanding the foundations is crucial for understanding advanced concepts. In my teaching, I emphasize foundational knowledge and connections between simple concepts and intuitions to more advanced and abstract topics. For example, in *Data, Estimation, and Inference*, I introduce Gaussian processes by first introducing parametric linear functions, then showing how stochasticity in a linear model's parameters induces a distribution over predictions, and finally demonstrating how to use this insight to explicitly define distributions over functions—a concept that is difficult to grasp for many students. Noting that my lectures are built up from foundational concepts, one student wrote in a teaching evaluation that my lecture is effective at "*bridg[ing] concepts and highlight[ing] crucial points*" and establishes "*both intuition and further theoretical background*." Machine learning builds on a wide range of related disciplines, such as computer science, statistics, economics, physics, and many others, and as such, requires a breadth of foundational knowledge. Enabling students to relate advanced concepts to fundamental ideas not only enables them to better understand and appreciate advanced concepts but also to see and understand connections between ideas *across* disciplines.

Interaction. Interaction with students in the classroom, at office hours, and via online discussion portals is a central component of my teaching philosophy. While I have found that there are typically at least a few particularly engaged students who are eager to answer questions in class, I try to use lectures to interact with as many students as possible—even in large courses with more than 150 students—by making lectures a "conversation." To encourage students to ask questions and engage in discussions about the class material, I seek to create a judgment-free environment by making myself easily accessible and emphasizing that there are no "stupid" questions. One of my students noted in a teaching evaluation that this atmosphere "*made [them] more comfortable in joining in the discussions*."

Teaching Experience

I was the instructor of record for two at New York University and three courses at Oxford. Additionally, although my PhD program had no teaching requirements, I opted to serve as the head teaching assistant for four courses at Oxford and as a teaching assistant and grader for another two courses.

Data Science for Everyone. In the fall of 2023, I co-taught *Data Science for Everyone*, New York University's flagship undergraduate introduction to data science. I sought out this course since, for many students, it is their first exposure to data science. The course is mandatory for all students who want to major in data science, and it is popular with students who would like to understand basic concepts in statistics and machine learning. Many students major in humanities subjects, and the majority of students in the class have not taken any college-level mathematics courses. The goal is to go from being a passive consumer of conclusions about data that other people have made into becoming an informed, empowered, and critical reader, evaluator, and producer of discoveries about the world using data. To achieve this goal, the course covers foundational concepts in statistics, machine learning, and other related topics, including causal inference and selected topics in machine learning safety.

Bayesian Machine Learning. In the fall of 2023, I taught a graduate course on *Bayesian Machine Learning* at New York University. To answer scientific questions, and reason about data, we must build models and perform inference within those models. But how should we approach model construction and inference to make the most successful predictions? How do we represent uncertainty and prior knowledge? How flexible should our models be? The course approaches these fundamental questions from a Bayesian perspective. From this perspective, the goal is to faithfully incorporate all of our beliefs into a probabilistic model and represent uncertainty over these beliefs using probability distributions. Due to its small size, the course allowed me to build lasting relationships with many of my students and support them in achieving their professional and academic goals, which has been particularly rewarding. At the end of the course, 5 out of 25 students who took the course asked me to write recommendation letters for their PhD applications. Below, I'm sharing feedback from my students in the course:

"This is the best class I have taken."

—

"The instructor was absolutely fantastic!"

—

"He is an outstanding professor with the respect of every student I've talked to."

—

"I have encountered many great professors at NYU in my studies and Tim stands out among them as one of the best I have seen."

"Tim is brilliant and he really cares about his students."

—

"Professor Rudner is without a doubt the most engaged professor in my time here (this is my 11th class in the program). [...] He should absolutely be incentivized to stay at the university. I was not paid to write this, and I normally do not give feedback this unequivocally positive."

—

"This is the BEST class I have taken at NYU."

—

"I appreciate his caring disposition and expertise in teaching!"

Data, Estimation, and Inference. In the Fall of 2020, 2021, and 2023, I was a co-instructor in a PhD course on data, estimation, and inference at the University of Oxford. I co-developed the syllabus for the course, which focuses on probability theory, foundations of probabilistic machine learning, and methods at the forefront of Bayesian deep learning research. It introduces students to advanced probabilistic modeling concepts, including Gaussian processes and Bayesian neural networks, and features several applied problems to help the students practice using the techniques learned in the course. Below, I'm sharing feedback from my students in the course:

"Tim was an amazing lecturer."

—

"Tim was an incredibly patient, helpful and capable lecturer."

"Tim is fantastic. The depth of his knowledge comes through in his clear explanations of concepts. On top of that, he is approachable and always happy to help."

Teaching Plans

I am interested in teaching a wide variety of courses, with a particular interest in machine learning and data science courses that help students develop critical machine learning skills. I plan to do this at the undergraduate and graduate levels. On the undergraduate level, I would be particularly excited to develop and teach: (i) a course that is geared toward students with a strong quantitative background but little to no training in statistics and computer science to introduce them to probabilistic machine learning methods, or (ii) an updated version of NYU's "Data Science for Everyone" course, focused on making fundamental machine learning concepts accessible to students of a wide range of academic backgrounds. On the graduate level, I would be particularly interested in developing and teaching: (i) a course on **responsible machine learning** that covers ethical and legal dimensions of machine learning research and data collection, responsible data science, as well as algorithmic fairness, transparency, and privacy, (ii) a course on **trustworthy machine learning** that covers both methods and theory as well as interdisciplinary topics in law/policy, journalism, and healthcare/medicine, with guest speakers from each of these disciplines, and (iii) a course on **modern probabilistic machine learning** with applications to problems in scientific discovery that prepares students to use probabilistic methods in their own research across the sciences or conduct research on probabilistic machine learning.

Mentoring and Advising

I believe that high-quality mentoring and advising are the cornerstones of building an inclusive and productive research group. My approach to mentoring and advising emphasizes positive reinforcement, constructive feedback, and support of my students' goals. I am passionate about mentoring and advising undergraduate and master's students. I have closely mentored 12 undergraduate and (pre-PhD) master's students and nine PhD students and have published 17 papers with them. Many of my undergraduate and master's student mentees have progressed to highly competitive PhD programs in machine learning in the United States and the United Kingdom.

References

[1] **T. G. J. Rudner** and H. Toner. Key Concepts in AI Safety: An Overview. In *CSET Issue Briefs*, 2021.

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