Teaching Statement

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1 Teaching Philosophy

The interdisciplinary nature of my research is the single most important influence on my teaching philosophy: my primary teaching goal is to create a supportive educational environment, in which students with diverse backgrounds, interests, and learning styles can learn as productively and enjoyably as possible. I am committed to encouraging students to take an active role in their education, working with students to identify the ways in which they learn best, fostering excitement, exposing students to cutting-edge research as early as possible, supporting students in discovering and pursuing their own interests, and reaching out to students beyond the classroom.

My teaching philosophy is anchored by two fundamental principles:

- **Adopt a “growth mindset”:** I grew up in the UK during the '80s and '90s. At that time, the prevailing attitude within the British education system was one of “either you’re inherently good at something—in which case you should pursue it—or you’re not—in which case there’s no point in trying.” Over the past decade there’s been a considerable amount of research, mostly by Prof. Carol Dweck at Stanford University, indicating that adopting a “growth mindset” (i.e., believing that ability is something that can be cultivated via effort) rather than a “fixed mindset” (i.e., believing that ability is something that one is born with and cannot control) leads to increased perseverance and therefore eventually success. I first learned about these findings from Hill et al.’s 2010 report on the under-representation of women in science, technology, engineering, and math: Hill et al. state that in addition to contributing to success, consciously promoting a growth mindset, especially with regard to science and math abilities, can alleviate the negative effects of “stereotype threat” on women’s and girls’ math performance [1]. By encouraging my students to adopt a growth mindset, I hope to positively influence recruitment and retention of women in computer science.

- **Fail in order to succeed:** Few people are immediately successful at everything they try. The only way to become an expert at anything is to persevere—i.e., to try as hard as possible, to test one’s boundaries, and to learn from failures encountered along the way. This viewpoint is consistent with research by Prof. Angela Duckworth at the University of Pennsylvania, who asserts that the single personality trait that best predicts success is “grit.” Duckworth defines grit as “a passion for a single mission with an unswerving dedication to achieve that mission, whatever the obstacles and however long it might take” [2]. Furthermore, she asserts that grit is built through failure. Therefore, in order to succeed, one first needs to learn how to fail. As a result, I encourage my students to develop grit and to recognize the immense value in trying and failing.

Although these principles are important in any discipline, they are absolutely crucial in a cutting-edge, interdisciplinary area such as computational social science. There is no established path to becoming a successful computational social scientist and there are very few undergraduate or graduate computational social science degree programs. As a result, students wishing to learn more about computational social science at any level must educate themselves in computer science, statistics, and the social sciences. In other words, they must learn about

[1] https://www.stanford.edu/dept/psychology/cgi-bin/drupalm/cdweck
material that lies outside their major or department, often in their own time. Developing ability and maintaining balance in multiple fields—especially traditionally disparate fields—necessarily requires one to adopt a growth mindset along with exceptional levels of passion, dedication, and perseverance—i.e., grit. Promoting these principles in my classroom, as well as in my research group and in the wider academic community, is therefore crucial to the success of my students and to the success of computational social science as a whole.

2 In the Classroom

Modern computer science is universally relevant and interdisciplinary. Reaching out to students with broad skills and interests is therefore vitally important. One of the best ways to recruit and retain a diverse set of students—at undergraduate and graduate levels—is to offer innovative introductory courses focused on interdisciplinary applications of computer science. Such courses make a clear statement to students that modern computer science is more than programming or designing computers and can offer a wide range of highly fulfilling careers.

As a visiting graduate student at the University of Pennsylvania, I audited a course—taught by Prof. Michael Kearns and aimed at undergraduates in computer science, business, and the social sciences—called “Networked Life.” This course provided a broad overview of the field of network science, which examines how the world is connected from technological, economic, and social perspectives. Although many of the topics were highly technical, the material was presented so as to ensure that students with less technical backgrounds gained a firm understanding of the motivations, concepts, and ideas, while students with more technical backgrounds also grasped the underlying mathematics. Courses like this are the future of computer science education. Not only do they provide an entry point into computer science for students with less technical backgrounds, they also provide students with a “big picture” understanding of the utility of complex mathematical and computational concepts.

Being part of UMass Amherst’s interdisciplinary Computational Social Science Initiative provides me with a fantastic opportunity to design computer science courses inspired by “Networked Life”, as well as to work with other faculty to design similarly innovative and interdisciplinary courses in the social sciences. As a first step toward this goal, I designed and taught an interdisciplinary graduate course on computational social science. The course focused on providing an introduction to computational social science centered around seminal and cutting-edge papers from disciplines including machine learning, statistics, political science, and sociology. These papers introduced students to core motivations and ideas in computational social science, as well as providing them with a more technical introduction to concepts from machine learning, Bayesian inference, network science, and text analysis. From my perspective, this course was enormously successful: one student, then an MA student in linguistics with joint BA in linguistics and political science, is now undertaking a PhD in my research group.

In many areas of computer science and statistics, researchers and practitioners routinely work with three different representations: intuition, mathematics, and code. Students must therefore be fluent in all three of these representations. Presenting the intuition behind mathematical concepts using slides, computer simulations, and video clips can significantly enhance students’ interest and understanding. Following a recent guest lecture, I received the following email from a student: “I appreciated your use of simple intuitive examples to explain the ideas. This helped me understand the key concepts rather than getting bogged down in the math. Thank you.” When presenting mathematics, however, digital technologies can encourage educators to present material too fast, thereby impeding students’ ability to think critically about the material as it is presented. “Multimodal learning”—i.e., actively thinking and writing as well as listening—can help students understand and retain new material. One of the best ways to facilitate multimodal learning is to present mathematical material on a whiteboard, while using digital educational technologies to provide intuition. This combination ensures that the teaching pace is such that students can understand the material and take notes without feeling pressured.

Fully understanding the concepts and models found in machine learning and statistics involves not only grasping the intuition and mathematics, but also the development of software implementations. Carefully designed homework assignments, in combination with longer projects, provide an excellent context for students to improve

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3 http://www.cis.upenn.edu/~mkearns/teaching/NetworkedLife/
4 http://www.cssi.umass.edu/
their skills at moving between intuition, mathematics, and code in an integrated fashion. In fall 2010 and spring 2012, I taught an undergraduate course on “Reasoning Under Uncertainty,” intended to introduce sophomores and juniors in computer science to key ideas from probability, machine learning, and information theory. In order to provide students with practical, hands-on experience using probability in real world computer science problems, I designed several programming assignments on topics including spam filtering and predictive language modeling. One student commented: “The programming assignments were really cool. Building a naïve Bayes classifier and Markov text generator was the most interesting, most rewarding programming I’ve done.”

In fall 2012, I designed and taught a course on “Bayesian Methods for Text Analysis.” This course, which involved discussing, deriving, and implementing a number of Bayesian models of text and their associated inference algorithms, was designed to help students develop the knowledge and skills needed to design, implement, and apply such models to real world data. Rather than providing a high-level overview of many different Bayesian models of text, the course focused on developing a deep understanding of the fundamental building blocks that form the foundation of such models. Unlike many mathematically sophisticated courses, code played an integral role in the course: In addition to questions that tested students’ intuitive and mathematical grasp of the material, each homework assignment involved implementation of these ideas in Python. By the end of the course, students not only understood the intuition and mathematics underlying Bayesian models of text, but also how to implement them. They also had their own code base for use in future research projects. A graduate student who took this course recently emailed me to say, “The course is giving me a profoundly valuable understanding not only of models for text analysis but Bayesian inference in general. I’m beginning to develop intuitions about complex models that are critical to my research questions through its meticulous, granular approach.”

3 In the Research Group

My research group is organized around practical principles that positively impact my students’ successes and experiences. For example, I encourage my students to visit other research groups, not only to establish collaborations, but to learn how different research groups function and what works best for them. Where possible, I pair junior and senior students on short- and medium-term research projects, thereby encouraging collaboration and fostering informal mentoring relationships. In order to facilitate productive student–advisor relationships, I treat my students as collaborators and provide guidance intended to help them to develop as independent researchers, while conveying to them that research involves unknowns. I aim to act as role model for my students and to demonstrate the value in adopting a growth mindset, learning from one’s failures, and cultivating grit.

One of my goals as a professor is to foster an interdisciplinary research community for my graduate students. As a result, my entire research group meets on a regular basis in order to exchange ideas and learn from one another. So as to expose my students to diverse perspectives, students from other research groups or departments are welcome to attend my group meetings. Seven graduate students in labor studies, economics, and computer science have regularly attended these meetings, along with one undergraduate student in computer science.

I recently joined forces with Profs. Benjamin Marlin and Daniel Sheldon at UMass Amherst to form an umbrella research community encompassing our individual research groups. This community—which spans a wide range of research interests in machine learning and data science—meets weekly in order to provide students with regular opportunities to obtain feedback on their own work or to discuss important machine learning concepts and papers. Due to the diverse nature of this group, students must learn how to construct clear, unified presentations of complex concepts—a necessary skill for any interdisciplinary researcher. One of Benjamin Marlin’s PhD students recently said, “The thing I love about [these meetings] is that you have to explain something that feels second nature to a diverse group; you have to explain things in a deep way that tests your understanding.”

http://openscholar.cs.umass.edu/mlds/
4 In the Wider Community

Teaching and learning do not stop outside the classroom or research group. Successful researchers and practitioners—especially those undertaking interdisciplinary work—continue to learn throughout their careers. One of my aims as an interdisciplinary researcher is to educate my peers and colleagues as well as my students. I am therefore committed to the clear exposition of complex mathematical and computational concepts in a manner that is accessible to researchers and practitioners in computer science, statistics, and the social sciences.

My tutorial on conditional random fields [4] and my MSc thesis on which it was based [3] have 450 citations in Google Scholar. They have also been used in courses, seminars, and reading groups at universities around the world, including Carnegie Mellon University, Cornell University, Iowa State University, National University of Singapore, University of British Columbia, University of California San Diego, University of Edinburgh, University of Maryland, University of Siena, University of Southern California, and University of Toronto.

I am currently writing tutorial on Bayesian models of text in (short) book form. In fall 2011, I taught an informal semester-long course using a first draft of this material as a trial run for my current graduate class on Bayesian methods for text analysis. After hearing about my tutorial, a colleague at Carnegie Mellon University asked if he could distribute sections of the current draft to his graduate students, saying “I’m super excited that this book is happening—this is exactly the kind of subject that could really benefit from a clean, unified presentation.”

In addition to writing tutorials, workshops can be a highly effective way to facilitate learning in the wider academic community. Since 2009, I have co-organized three workshops at the NIPS conference—one on “Applications for Topic Modeling and Beyond” and two on “Computational Social Science and the Wisdom of Crowds.” These educational contributions are described in more detail in my service statement.

References


