Teaching Statement

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Teaching Philosophy

My teaching philosophy is grounded in the belief that students should learn not only how to build machine learning models, but how to reason about their reliability, limitations, and broader impact. As AI systems increasingly influence real-world decisions, education must emphasize structured thinking, uncertainty awareness, and interpretability alongside technical skill.

In courses ranging from algorithms to machine learning and network science, I focus on helping students develop coherent mental models of how systems behave. Rather than presenting models as black-box tools, I highlight their underlying assumptions, generalization limits, and structural dependencies. I encourage students to ask not only whether a model performs well, but why it works and when it may fail.

I introduce core concepts progressively, connecting mathematical foundations with implementation and empirical evaluation. Through guided exploration of modeling choices, sensitivity analysis, and error interpretation, students build both technical confidence and critical judgment. I aim to cultivate independent thinkers who design systems that are effective, transparent, and responsible.

Teaching Methods and Classroom Practices

I combine structured lectures with active learning and project-based components that emphasize reasoning and evaluation. Lectures establish conceptual foundations and connect algorithms to modeling assumptions and system-level behavior. After introducing key ideas, I incorporate analytical exercises, coding tasks, and discussions that require students to interpret results rather than simply produce them.

Assignments integrate mathematical analysis, implementation, and empirical validation. Students conduct ablation studies, sensitivity analysis, and error diagnosis to understand how performance depends on data, parameters, and structural design choices. Larger projects mirror research workflows: students define modeling goals, justify methodological decisions, evaluate robustness, and communicate findings clearly.

I emphasize reproducibility and transparency through clear experimental protocols and well-documented code. Consistent grading criteria and timely feedback help students track progress. By balancing theory with empirical investigation, I prepare students to assess uncertainty and apply computational tools with sound judgment.

Courses I Can Teach

Given my background in algorithms, machine learning, network science, optimization, and modeling, I am prepared to teach a broad set of undergraduate and graduate courses, including: Data Structures and Algorithms, Introduction to Machine Learning, Graph Machine Learning, Network Science, Modeling and Simulation, Artificial Intelligence, and Data Mining. I also welcome opportunities to teach foundational undergraduate courses, as I believe strong fundamentals are essential for success in advanced work.

Courses I Plan to Develop

I am particularly excited to develop advanced courses that reflect emerging directions in uncertainty-aware and interpretable machine learning.

One potential course is Interpretable and Trustworthy Machine Learning, which would examine attribution methods, sensitivity analysis, uncertainty quantification, and robustness under distribution shift. Students would explore both theoretical foundations and practical evaluation techniques, learning how to assess model reliability beyond accuracy metrics. Topics would include variance-based sensitivity analysis, interaction-aware attribution, robustness diagnostics, and structured experimental design.

A second course, Uncertainty and Decision-Making in AI Systems, would focus on probabilistic modeling, Bayesian reasoning, and decision-making under limited data. The course would connect statistical foundations with real-world deployment challenges, emphasizing calibration, uncertainty propagation, and intervention design in complex systems.

I also plan to develop a course on Structured Learning for Networked and Multilayer Systems, covering graph-based modeling, cross-layer interaction, operator-based dynamics, and structured representation learning. This course would bridge graph theory, machine learning, and system dynamics, preparing students to model interconnected environments in which structure and dynamics jointly influence outcomes.

These courses would equip students with both methodological rigor and critical thinking skills necessary for research and industry roles in modern AI.

Mentorship and Advising

Mentorship is a central component of my academic practice. I view guiding students not only as supporting their technical growth, but also as helping them develop intellectual independence and sound research judgment. My goal is to train students to think carefully about modeling choices, question assumptions, and evaluate results with rigor.

I structure mentorship as a progression from guided learning to independent inquiry. In the early stages of a project, I provide clear direction, concrete milestones, and methodological grounding. As students gain confidence, I encourage them to formulate their own research questions, design experiments, and critically assess the robustness of their conclusions. I emphasize careful evaluation, reproducibility, and transparent communication of uncertainty in research findings.

An important aspect of mentorship in machine learning is cultivating responsibility. Students should understand not only how to improve model performance, but also how to assess limitations, detect failure modes, and communicate uncertainty honestly. I encourage reflection on the broader implications of modeling decisions, particularly when systems may influence real-world outcomes.

I am committed to creating an inclusive and supportive research environment. Students bring diverse backgrounds and strengths, and I strive to provide individualized feedback, structured guidance, and opportunities for collaboration. By combining high expectations with sustained support, I aim to help students develop both technical excellence and confidence in their intellectual contributions.