Over seven years of academic training at ETH Zurich and Caltech, I grasped the opportunity to participate in a variety of teaching activities: As a Ph.D. student at ETH Zurich, I was a teaching assistant for an advanced undergraduate course on *Information Theory and Coding* (30 students) and two graduate-level courses, namely *Data Mining* and *Probabilistic Artificial Intelligence* (100-150 students), and a co-examiner for a graduate-level course on *Advanced Topics in Machine Learning*. My duties as a teaching assistant included giving tutorials to the class, leading ad-hoc recitation and exercise sessions, as well as designing homework and exam questions. At ETH Zurich, I worked with six master students as their thesis co-supervisor, and mentored four undergraduate and graduate students on their semester projects. As a postdoc at Caltech, I have been actively working with students from all levels (including graduate, undergraduate, and high school students) on various research projects. Recently, I co-organize the AI4Science program[1] at Caltech, where I advise scientists and engineers with diverse backgrounds on machine learning related topics on a regular basis.

Teaching Philosophy

My teaching and mentoring experience has not only been a source of inspiration for my own research, but also laid the foundation of my teaching philosophy: be *motivational*, *systematic*, *engaging* and *adaptive*. In the following, I will elaborate on each of these pedagogical principles with concrete examples from my own experience, and conclude with potential courses I look forward to teaching.

Preparation: Motivational and Systematic

When developing new materials for a tutorial or a technical talk, I am, to some extent, relearning the topic from a fresh perspective: rather than drowning in the technical details, my role as a teacher/mentor drives me towards the more fundamental questions — *what* is the problem we are facing, and *why* does it matter. Properly addressing these two questions opens the door to many others, and has proven to be the key for an efficient and productive interaction with the audience. Therefore, when preparing a tutorial, a talk or a lecture, I am committed to the following principles:

1. seeking motivational cases to keep the subject practically grounded;
2. maintaining a systematic view of the big picture while keeping away overwhelming details.

Motivational Most students take a course because they have a prior interest in the subject. Therefore, one of my priorities as a teacher is to keep up this momentum throughout the course. Instead of overloading the class with new principles and foreign concepts, I prefer to build modular, illuminating examples that are easy to be related to, so as to instill confidence in the students to explore the subject independently. One approach I find particularly effective is to complement traditional classroom presentations with *hands-on* mini-tutorials. For example, when introducing "binary classification" in a machine learning course, I often start with a minimal demo of a binary classifier (e.g., a spam classifier implemented in JupyterLab[2]), and provide detailed instructions on how to implement a full-fledged mini-application from scratch; when introducing the abstract mathematical concept "Gaussian process", I begin by illustrating the concept with random samples (of smooth functions) drawn from various Gaussian process kernels, and provide step-by-step instructions on how to generate such distributions in Python/Matlab. Through these practices, students not merely accumulate hands-on experiences of applying new algorithmic/mathematical tools to practical problems, but also have a chance to discover new problems and challenges as they broaden their horizons, which further motivates them to study more advanced topics in the curriculum.

Systematic When composing a storyline, it is important that each part is indispensable to the ending. Analogously, when teaching a course, each point, principle, and example should relate to the theme of the subject. To minimize unnecessary confusion and tangential distractions, my primary task is to properly structure course materials, and develop a smooth and consistent narrative to deliver the content. As an example, for the course *Probabilistic Artificial Intelligence*, I iterate over the "big picture" (as shown in the figure below) in every session to set the tone for each class. Such strategy proves to be convenient for transitioning from one topic to another, as it helps students develop a systematic view of the course structure, and gain a deeper understanding of different components by connecting the dots.

[1] https://sites.google.com/view/ai-for-science-workshop/

[2] https://jupyterlab.readthedocs.io/

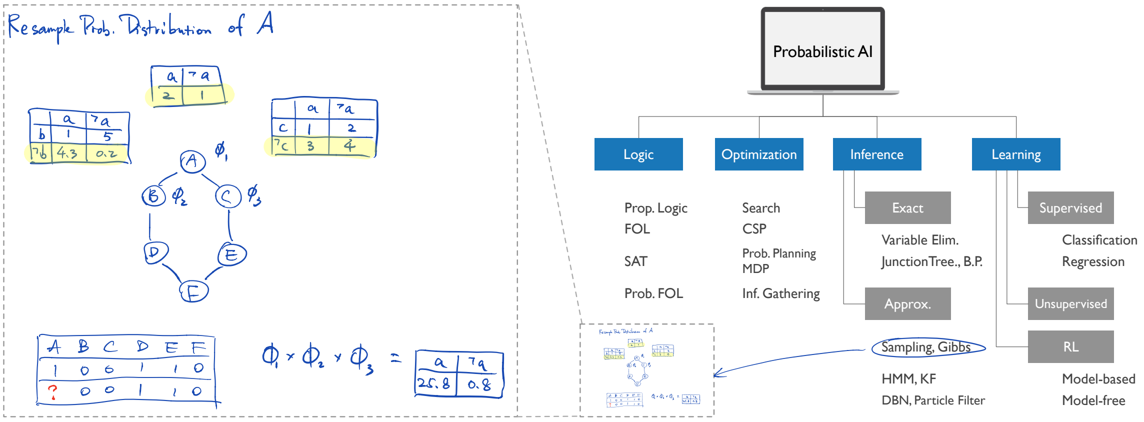

Figure 1: Left: Hand-written lecture notes for *Gibbs sampling*. Right: *Probabilistic AI* course structure.

Delivery: Engaging the Students

Classroom setting Teaching is never simply about going over the course materials. Rather, it is essential to connect with the students through various channels, including both verbal (e.g., presentation) and non-verbal interactions (e.g., movement, eye contact, props, multimedia tools, etc.). For example, instead of keeping a constant pace, I use pauses (or cliffhangers) at crucial moments in the class to give students the chance to digest the content. One of my favorite non-verbal interactions is to maintain eye contacts with the students — apart from drawing a student's attention, it also conveys a sense of confidence when delivering a presentation. Furthermore, to bring technical subjects to life, I use a touch-screen tablet/laptop, in combination with a projector, to annotate slides, sketch ideas and derive proofs, as a substitute of blackboard presentation. The above figure shows an example where I explain "Gibbs sampling" under this setup. I record and upload these annotated slides as well as source code for the mini-tutorials, so that students can easily review the contents offline, for homework assignments, exam preparation, and even more advanced software development.

Mentoring The above tenets, to a certain degree, also apply to advising students in research projects. Although far less structured and much more personalized than teaching a class, advising has a similar goal to guide students towards becoming independent researchers. As such, my goal as a mentor is to help students identify feasible research questions, understand the broader context, and avoid pitfalls. Once the scopes of projects are set, I often encourage students to pursue their own ideas; when necessary, I dedicate longer working hours with students in more detailed discussion sessions to resolve technical problems, or to reshape the project. In my experience, keeping a balance between different levels of interactions has proven to be crucial to a successful mentorship relationship, and students tend to be more engaged and productive if they take the initiative of pushing the boundaries.

Follow-through: Adapting to Feedback

One of the benefits of teaching and mentoring is to *learn* from experiences. This includes learning to adapt the course materials, to improve the quality of the presentation, to adjust the pace of the lecture, and to identify better examples from students' interdisciplinary backgrounds. Importantly, questions from students are valuable sources of new research problems, and more often than not, inspire new ideas for solving one. As such, I treat every teaching and mentoring session as an opportunity of learning and self-improvement. Upon finishing the course materials, I seek advice from colleagues and experts; during the exercise sessions, I sit with students to gather feedback. Such closed-loop interaction allows me to shape my presentation, and in the long run, benefits me as a researcher in general — this is one of the main reasons why I find teaching such a rewarding experience.

Example Courses

I look forward to teaching courses related to machine learning, data mining and artificial intelligence, including (1) introduction to machine learning, (2) probabilistic graphical models, (3) learning from large data sets, and (4) sequential decision making under uncertainty. I would also like to design new introductory and advanced courses related to my research focus, such as introduction/advanced topics for interactive machine learning, interpretable machine learning models, machine teaching, and artificial intelligence for the physical sciences.