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Teaching Statement

We go to university to learn the craft of thinking. And just as an apprentice does not become a cabinetmaker by simply practicing with the tools or grasping the typical forms of cabinets, we do not learn to think by repeating exercises or accumulating knowledge. We must instead constantly make ourselves respond to the essentials that address us. Hence, while classrooms and laboratories have been forced to change, I believe my role as a teacher and advisor remains two-fold. First, to *point out the essentials addressing the students* by connecting their past experiences to the material. Second, to *let learn*, i.e., to provide the conditions for students to think, not necessarily correctly, but purposefully about the material and the needs it addresses.

I have developed and applied this philosophy while *TA'ing for undergraduate probability and circuits classes* at the University of São Paulo, Brazil; *teaching non-destructive testing to senior engineers* at INSACAST, France; *co-lecturing stochastic processes and signal processing courses* at the University of Pennsylvania (Penn); and over *7 years of mentoring undergraduate and graduate research.* I next illustrate how these ideas manifests in practice using instructional videos I developed to teach probability and a guest lecture recording. The links will take you directly to the relevant events.

Teaching. Be it physically or virtually, I find that *students engage more with the material if they connect to it emotionally.* During lectures, I build this connection through practical, day-to-day illustrations [YouTube] and historical context, e.g., by telling the history behind concepts and personalities [YouTube, Portuguese with English subtitles] or exploring philosophical aspects such as "What is a probability?" [YouTube, Portuguese]. To avoid burdening lectures with this extra content, I cover part of it in instructional videos that have received over 130.000 views [YouTube channel].

This historical context also provides an opportunity to explore the narratives that lead to the *marginalization of certain groups in the sciences* and the political reasons why certain results are associated with Babage and not Lovelace, Watson–Crick and not Franklin, Kalman and not Stratonovich. Additionally, it allows me to highlight contributions of individuals from those groups. I believe pointing out the work of Ingrid Daubechies on wavelets, David Blackwell on Bayesian statistics, or Artur Avila on dynamical systems, helps provide underrepresented students with more relatable references.

Diversity of backgrounds and experiences means that while students walk together in the (virtual) classroom, *they are heterogeneously prepared* for it. Besides making myself available to help them, I also make sure they are given enough time and space to think. Though interacting in class is fundamental in this process, I find that students are often reluctant to do so out of shyness, an anxiety of being right, or because they are used to a silent-note-taking type of attendance. This problem is only exacerbated by online learning. I overcome these barriers using the scientific process. For instance, I insist that as in research, every classroom question must be answered, correctly or not, and wait as long as necessary for students to respond [YouTube]. As in science, however, I make it clear that I expect only a "guess" [YouTube]. These guesses (hypotheses) are then analyzed on the path to a correct answer [YouTube]. Outside of the classroom, I allow homework to be corrected and resubmitted for grading as many times as necessary. I believe the exercise of *going over ones own mistakes* is often more pedagogical than getting the right answer in the first place. What is more, these multiple attempts *provide additional time and feedback for those students that need it without their having to ask for it* or feel less capable than their peers.

Mentoring. I take a similar holistic approach when mentoring research by teaching not only the science, but also ancillary skills such as methodology, communication, and peer-reviewing. For instance, when serving as the research mentor of SUNFEST, an NSF-sponsored undergraduate research experience program at Penn, I would take time after weekly research seminars to discuss not the content of the presentation, but the research and communication techniques deployed by the speaker. I have used the same approach when directly advising undergraduate students, such as Alexandre Amice who published two papers in major control venues before moving to MIT for his Ph.D., and junior graduate students, such as Maria Peifer, Luana Ruiz, and Vinícius Lima. In these setting, I often use my own diverse experience with research, from having to apply for my own IEEE grants to fund undergraduate projects in Brazil, to studying in top acoustic laboratories in France, to completing my Ph.D. at Penn in the USA, to help guide students through their struggles with failures, heterogeneous backgrounds, and, when necessary, culture shock.

Teaching interests and plans. I look forward to deploying these techniques in physical and virtual classrooms, where I intend to leverage my experience producing instructional videos [YouTube channel] and using platforms such as Piazza and Moodle. I am willing to teach any class from the engineering curriculum, from general-knowledge introductory classes such as probability and signals and systems to more domain-specific courses such as signal processing, machine learning, and control.

At a more advanced level, I am keen to introduce courses on statistical learning and (non-)convex optimization. The goal of the first course is to provide a mathematical overview of learning theory, covering both classical results (PAC learning, VC dimension), recent advances, and open problems. In particular, I would cover cutting-edge material from my research on constrained (reinforcement) learning, showcasing the new challenges compared to classical learning and how they can be tackled. The second course would cover advanced topics scarcely discussed in optimization courses, such as discrete (submodular) optimization, semi-infinite programming, functional optimization, and non-convex aspects duality theory. I intend to illustrate how these different approaches can be leveraged to solve practical problems in the contexts of signal processing, control, and machine learning. I believe these research-focused courses would serve to complement more practical machine learning and convex optimization courses targeted at interdisciplinary audiences.