TEACHING STATEMENT

Hanbaek Lyu

My mission as a course instructor and research supervisor is to convey to the students an understanding and appreciation of mathematical sciences as *knowledge discovering processes* rather than just sets of statements to be studied. The key to achieve this goal is to maximize the collaborative interaction among the instructor and the students at various levels.

One of the best form to achieve this is to involve the students in research projects and guide them through various stages of the process. My extensive experience in supervising undergraduate research projects and detailed plans to involving students in summer REU (Research Experiences for Undergraduates) projects on an interdisciplinary project that bridges dynamical systems, probability, and machine learning played a critical role in awarding a NSF research grant DMS-2010035 in 2020, in which I serve as the Principal Investigator.

On the other hand, regular courses are learning opportunities for much broader range of students, so it is important that individual courses are thoughtfully designed and instructed. At the department level, it is desirable to develop multi-quarter or year-long curricula that makes the best synergy out of individual courses, and also to involve cross-disciplinary opportunities where students of different strengths and perspectives can collaborate and help each other's knowledge discovering process. In doing so, it is also equality important to create environments where students at varying levels, postdocs, and faculties are encouraged to communicate in various forms of topic seminars and colloquia.

In the remainder of this teaching statement, I summarize my student research supervision, teaching philosophy, teaching experience, and and course development.

1. Research supervision

As a Hedrick assistant professor at UCLA, I have advised sixteen undergraduate and two graduate students in various research projects, including natural language processing, dynamical systems and machine learning, optimization and network data analysis, and COVID-19 and financial time-series prediction. Some of these projects also involved graduate students and faculty members.

Below are brief descriptions of the projects and my work with undergraduates:

1. REU 2020: "*Machine learning approaches to oscillator and clock synchronization.*" This REU project is supported by my own NSF grant DMS-2010035.

I conducted this project in summer 2020, which was only after two months of the award of the grant. The goal is to develop machine learning based prediction algorithms for complex dynamics of coupled oscillators on randomly generated underlying graphs. I have advised Hardeep Bassi (Berkeley), Rohith Kodukula (UCLA), Josh Vendrow (UCLA), Richard Yim (UCLA), and Cherlin Zhu (ZHU), and we are currently writing a paper on our discovery and planning to submit to a top journal in dynamical systems.

2. REU 2019: "*Sequence learning and building topic-aware chatbot using Recurrent Neural Network and Nnonnegative Matrix Factorization*" (Preprint, GitHub) (2019).

In this interdisciplinary project between machine learning and optimization, I mentored the following nine students: Henry Sojico (Harvey Mudd), Nicholas Liskij (UCLA), Nicholas Hanoian (Vermont, now a full-time data scientist at Milliman), Zhexiao Lin (Zhejiang U.), Jiajao Qu (UCLA, now doctoral student at EPFL), Yuchen Guo (Hunan U.), Yuliang Wang (Shanghai Jiao Tong U., now doctoral student at Northwestern), Xiong Zhe (Shanghai Jiao Tong U.), Zhenhong Zou (Beihang U.). We combined neural network based chatbot algorithm with a topic modeling algorithm so that the chatbot can be aware of the topics of the context and generate the responses accordingly. The paper is in submission to a machine learning conference.

3. Network Dictionary Learning: "*Learning low-rank latent mesoscale structures of networks*" (Joint with Yacoub Kureh, Joshua Vendrow, and Mason A. Porter) (Preprint, GitHub, Python package "*ndlearn*") (2020).

I initiated this as my personal project in Winter 2019 aiming to develop a comprehensive theory, algorithms and software for learning "dictionary of latent motifs" from network data. Later I invited a doctoral student Yacoub Kureh into and then a undergraduate student Joshua Vendrow (double majoring in math and CS) for collaboration, rather than supervising their research (and later also invited an applied mathematician Mason A. Porter). Each member has contributed significantly to the project with their own expertise, and the collaboration with undergraduate and graduate students as well as a faculty stimulated a number of new and exciting ideas, and ended up with a much strongest paper than I initially envisioned.

4. Online nonnegative matrix/tensor factorization and Joint time-series prediction: I have been working closely with a doctoral student Christopher Strohmeier at UCLA on various projects related to developing theory and application of online nonnegative matrix/tensor factorization algorithms. Our first work on joint time-series prediction using online nonnegative matrix factorization has been published in Information Theory and Applications Workshop (2020). Based on this work, we have developed a theory and a software that learns correlation patterns from a collection of time-series related to COVID-19 and gives prediction on the future evolution, which is now available as a Preprint and also its software on GitHub. Our recent work on nonnegative tensor factorization (NTF) proposes the first online algorithm for NTF with convergence guarantee, and outperforms classical algorithms for the same task (Preprint).

5. COVID-19 times series prediction project (GitHub): In this project, I am advising two UCLA undergraduate math majors Jacob Li and Charlotte Huang to further develop my previous work on predicting joint COVID-19 time-series using online nonnegative matrix factorization. We are developing algorithms to learn correlation patterns between time series in one state (e.g., daily new cases, current hospitalization, ICU beds occupation) and transfers that knowledge to predict the data for other states. Results of such transfer-prediction between states will give a new way to quantitatively study similarity and differences between latent parameters governing COVID-19 dynamics in each states, which will help some of the decision making process in the society level.

2. Teaching experience/interests and course development

2.1. **Teaching philosophy.** It is my belief that we learn scientific principles most effectively by actually discovering them, observing many examples and then making analogies about repeated patterns. However, for the sake of clarity and elegance, most math textbooks are written in the opposite order – abstract principles and formulas are followed by examples. I think a great instructor should reconstruct the process of discovering subject principles from the bottom up, and guide the students to discover them by themselves. Through this way of teaching, or rather, guiding and discovering together, I seek to achieve my ultimate goal as an instructor: *to teach students mathematical sciences as knowledge-discovering processes.*

My philosophy in teaching mathematics stems from my personal experience as a student. I spent my middle and high school years in the highly competitive environment in South Korea. High school mathematics in Korea covers up to a typical curriculum of Calculus 2 in the US, and the focus is on solving non-trivial problems quickly without making errors. I was overwhelmed by all kinds of clever tricks and formulas to memorize. As most other students do, I thought math was only for the smartest and those who would easily come up with such tricks by themselves. It was during a summer in high school that I spent in a Buddhist temple, that I realized that everything is written backward. The unpredictable (but most exciting) part of the process of discovering mathematical principles was hidden behind the refined results.

2.2. **Experience and Method of conducting courses.**

2.2.1. *Teaching experience.* During the two years as a Hedrick Assistant Professor at UCLA, including Summer sessions in 2019 and 2020, I have taught 12 quarter courses on probability theory, stochastic processes, statistics, and mathematical finance. As of Fall 2020, I am serving as the course coordinator for MATH 170S: Statistics II. In Spring 2021, I will be teaching a course in machine learning, emphasizing mathematical principles behind some of the popular algorithms.

2.2.2. *Lecture notes.* Developing my own extensive lecture notes plays a crucial rule in achieving my teaching goal. I have written very extensive lecture notes for each of the courses with carefully designed exposition and exercise problems, which spans 325 pages altogether (which I share publicly on my website). Below are clickable links to my lecture notes:

Lecture notes: Probability Theory A, Probability Theory B, Probability Theory A/B combined
Stochastic Processes, Mathematical Finance, Introduction to Statistics II

My lecture notes are very well-received by the students at UCLA and also by international students during summer sessions.

One of the characteristics of my notes is that the exercise problems have multiple parts, which are designed and written so that each problem leads the students to reconstruct a non-trivial statement by following a number of easier steps. By following these steps, the students experience deriving interesting conclusions by themselves, and such knowledge-discovering process is more emphasized than the final conclusion.

I also try to give real-world examples and data sets in my lecture notes, and help students to use their knowledge to analyze the data sets. This helps to make the connection between the course materials and real-world applications in data science and machine learning more vivid to the students, which (according to a number of students) motivated them a lot. For example, in one of my Statistics 170S class, I had my students work on my 5-step exercise on solving the least squares problem for linear regression in matrix form, and then asked them to apply the result to a Google stock data using Excel. According to a number of students, it was their "first ever experience" in using linear algebra in a concrete context and the "whole process from deriving the regression formula to data analysis was very satisfying".

2.2.3. *Lecture organization.* Here is how I usually organized my lectures. At the beginning of class, I first give the students a general motivation and bigger picture of what we are going to study. For instance, I would ask them what are differentiation and integration good for. Then I say they are both studies of unknown objects via familiar ones; curves by lines and area under curves by rectangles. Then, I present a couple of examples, which are easy and concrete enough but also contain the essence of the theorem or principle. It is important to go through them with students step by step, asking questions to lead them to take the "most natural next step". After they discover and agree on a common pattern that I intended, we together state the main theorem and principle in a more abstract version. At this point, students have worked out concrete examples from which they can draw analogy when looking at abstract statements. Then we work on less obvious examples, guiding students to see the abstract pattern they have discovered in different contexts. This solidifies their understanding.

2.2.4. *Enhancing student engagements.* An aspect I often incorporate in my classes is to engage the students by assuming a fun situation and have a back and fourth discussion leading to the conclusion. For example, in my Financial mathematics 170E class this summer, I was going over an example on a 'perfect hedging strategy' for short selling a European call option. I started asking the students by "Is there anyone interested in working in an investment bank in the future?" Some students answered yes, and then I continued, "Say you just started your job in a big investment bank, say JP Morgan. Your first task was to short sell 10000 units of a European call on Tesla stock." I could see the students are getting engaged in the situation. I said, "obviously, having taken my fantastic course in financial math, you were able to find that the risk-neutral price of the option is \$6.3158." Students laughed, and I continued, "Now suppose you were able to convince a customer to sell each option at a slightly higher price of \$6.5. Can you tell me your payoff when the stock goes up and down?" After going through a calculation to show that we either get a huge gain or huge loss, I asked them to hedge the profit using delta hedging. The students found that we can get $\$1,944$ of sure profit. Then I asked if this contradicts the no-arbitrage principle. A student responded "But you sold the options at a higher prices than the risk-neutral price". Then I finish the discussion by saying, "Excellent. That's exactly why we can lock in at a sure profit. Now, I do not like to draw this conclusion, but we can see why your business major friends make such a good fortune, usually much better than us math majors". A good laughter follows.

Asking questions and giving examples on point are very effective in involving students in class and also in resolving their misconceptions. For instance, in a Calculus 1 class at OSU, I asked my students a limit problem of the form $\infty-\infty$. Some student said "the answer is ∞ since the first term diverges". I asked him the value of $\lim_{x\to\infty} x-x$, and he realized what goes wrong immediately. Then another student asked, "Then is $\infty-\infty$ always zero?" So I gave her $\lim_{x\to\infty} x^2-x = \lim_{x\to\infty} x(x-1)$. She knew the answer was ∞ obviously. Some other asked what does $\infty-\infty$ even mean. I said, "It means you need to work harder." Everyone laughed, and the point was made. The point here is to give students the right example so that they can figure out and correct their misconception by themselves.

2.2.5. *Comments on online teaching.* Due to the COVID-19 pandemic, various institutions are facing unprecedented challenges in maintaining the quality and inclusiveness in courses conducted in online setting. I have been trying to address these challenges in my own lectures. Part of my effort is to make the lecture materials as easily accessible as possible. My extensive lecture notes are tremendous help for me to navigate through online lectures. Students are finding them particularly helpful, as they can access the lecture materials in detail any time, regardless of possibly different time zone. Moreover, in addition to giving a live online lecture, I record each lecture and share it with students. I am aware that some students are hard to find a block of time that they can concentrate on lectures. Having a recorded lectures available makes it easy for students to go through them at the time of their convenience at faster or slower speed to help their understanding. Another detail that I have in my online lectures is that I use a blackboard app to mimic the unique vibe of offline lectures on classroom boards.

2.3. **Plans for course development.** As a ladder faculty, I am very much interested in developing a new undergraduate course in probabilistic machine learning. The demand on courses on machine learning, especially in undergraduate programs, is arguably high these days and it is continuing to increase. Probability theory plays a central role in modern algorithms and techniques in machine learning, but such connection and concrete use cases can only be described briefly in classical courses in probability or statistics. Therefore, it will be of interest to a number of students (especially in math department) to develop a course that connects essential undergraduate knowledge in probability and statistics to fundamental concepts and algorithms in machine learning with concrete examples. In such a course, I envision incorporating a group project on analyzing a real data set using the class material as a crucial element.

Here is an example of a possible course description: Probabilistic foundation and application in machine learning. Probability in machine learning, Maximum Likelihood, generative models, Bayesian networks, naive Bayes classifier, Stochastic Gradient Descent, MCMC, Restricted Boltzmann Machine, Recurrent Neural Networks. This course has group projects and presentations. Students will form groups, choose data set of interest, and objective of data analysis using machine learning (e.g., classification, clustering). Groups share their problem formulation and ideas in an early presentation, and continuously work during the quarter under guidance of the instructor. The group project will be evaluated by final presentation and report.

In a ladder faculty position, I envision that I will be interacting with students of broader spectrum – domestic or international undergraduate students with diverse backgrounds, advanced undergraduates or motivated masters/doctoral students, or even high school students. I will adjust the balance between examples and theories accordingly as I interact with them. Nevertheless, my principle of "guiding and discovering together" will be central to my teaching style. I believe the best way to teach how to catch a fish is to help the students catch fish on their own.

HANBAEK LYU, DEPARTMENT OF MATHEMATICS, UNIVERSITY OF CALIFORNIA, LOS ANGELES, CA 91786.
Email address: colourgraph@gmail.com

Appendix A. Example of students' comments

Here are some examples of student's comments on my teaching from UCLA and OSU:

UCLA:

1. I never write reviews on here but I made an account just for this professor. He's an AMAZING professor! His lectures are clear and engaging. He has his own textbook that he posts for the class which is very detailed and helpful for the course. The course consists of homework, one midterm, and final. Both the exams are very fair if you attend lectures and do all the homework. I personally think he is the best professor in the math department! He is very helpful, understanding, and a GREAT lecturer. I would definitely take more of his courses. TAKE A CLASS WITH HIM.
2. Professor Yu explained the concepts in this course very clearly. He is a very competent and informative lecturer. He also provides very complete lecture notes that effectively stand in for the department assigned textbook, a welcome surprise as the exposition and organization of those notes are considerably better than those of the textbook. They also contain supplementary problems that help bring each topic into perspective.
3. Professor Yu is a very effective teacher. He posts his typed out notes online which are very helpful and clearly outlined. The examples he goes over in class help with elucidating the material and providing depth. He answers all questions to the best of his ability and makes sure everyone is on the same page before moving on. You can tell he cares about students actually understanding the material and digesting it. His relaxed teaching approach and calm personality made me motivated to learn and do well in the class rather than feel pressured like in other math classes. His tests are very fair and reasonable. The homework is also relevant and aid in understanding the material. This class made me interested in the topic.
4. Professor Yu was pretty great at teaching us probability. He explained everything, told us what topics were going to be on the exams, and made sure everyone understood the material. I didn't attend any office hours because they conflicted with my other obligations but I would assume if I did go they would just as helpful as the lectures and notes were. His homework was relatively difficult and it did challenge me but it was doable. I do wish he gave us practice exams or just extra problems to test our knowledge but unfortunately he didn't do that. At the end of the day, his teaching was incredibly helpful and efficient. Even though the material is a little difficult to grasp, it was all manageable thanks to the professor.

OSU:

1. Hanbaek is the best math instructor I have had. He has a knack for discern where students are going wrong conceptually and then addressing their mistake in a clear, non-aggressive way.
2. He is really funny and makes the material easier to learn. The way he teaches really helps "dumb down" the concepts, which is really helpful when the material is really hard. Lyu is really sweet and if you need help or have make something up, he would spend time out of class wanting to help.
3. At first I was a bit surprised because Hanbaek has a very different way of teaching that I am not used to. Once I figured out his teaching style I learned Exponentially.
4. The instructor did a great job at clarifying topics covered in class. Difficult principles were broken down to simple and easily understood concepts. In general, I found him more helpful than the professor.

Hanbaek Lyu, Department of Mathematics, University of California, Los Angeles, CA 91786.
Email address: `colourgraph@gmail.com`