Instructor: Clayton Scott

This course will cover rigorous performance guarantees for machine learning algorithms. The first half of the course will focus on statistical learning theory for supervised learning algorithms in the offline (batch) setting, and will include topics such as: concentration inequalities, consistency of learning algorithms, Vapnik-Chervonenkis theory and Rademacher complexity, kernel methods, and design of surrogate losses. The second half of the course will address unsupervised and online learning.

Students are expected to have (1) a strong background in probability at the level of EECS 501, (2) prior exposure to machine learning algorithms, such as EECS 545 or Stat 605, and (3) some experience with writing formal mathematical proofs as might be acquired in an upper level undergraduate mathematics course.

Grading will be based on: (1) occasional homework assignments, (2) lecture note typesetting for at most one lecture, and (2) an individual end-of-semester report on a topic of the student’s choosing.

The primary desired outcome for students taking this course is an ability to read research articles in the field of machine learning and appreciate the significance of the theoretical performance guarantees describe in those articles. Students developing new algorithms can also expect to learn techniques that will help them analyze their algorithms.