Practical information

- Lectures: Tues/Thurs, 2:00–3:30 Location: Leconte Hall 2
- Course web page: http://www.stat.berkeley.edu/~mjwain/stat241a
  All announcements and homeworks will be posted at this site; please check it regularly.
- Instructors:
  
  Name: Martin Wainwright
  Email: wainwrig AT SYMBOL {stat, eecs} DOT berkeley DOT edu
  Offices: 263 Cory Hall or 421 Evans Hall
  Office hours: Tues/Thurs, 3:30–4:30, 263 Cory Hall

- Graduate student instructors:
  
  Name: Andre Wibisono
  Email: wibisono AT SYMBOL eecs DOT berkeley DOT edu
  Office hours: Monday 4–5 pm, 411 Soda Hall

  Name: Hongwei Li
  Email: hwli AT SYMBOL stat DOT berkeley DOT edu
  Office hours: Friday 2–3 pm, 307 Evans Hall

- Course reader: An Introduction to Probabilistic Graphical Models, by M. Jordan. Available at Copy Central, 48 Shattuck Squares. (Pick-up starting August 28).

Course outline

This course is a 3-unit course that provides an introduction to the area of probabilistic models based on graphs. This class of models provides a flexible and powerful framework for capturing statistical dependencies in complex, multivariate data. Key issues to be addressed include representation, efficient algorithms, and various aspects of statistical inference with graphical models. The primary focus of the course is on theoretical and methodological aspects of graphical models and their associated algorithms. The concepts are relevant to a broad range of application areas, including statistical machine learning, signal processing, computer vision, natural language processing, neuroscience, communication theory, computational biology, econometrics etc. However, this is not a course in applied machine learning—it is devoted to fundamental aspects of models and algorithms.

A selection of topics to be covered:

- prediction and classification problems
  - linear regression
  - batch and on-line algorithms
  - logistic regression
- fundamentals of directed and undirected graphical models
- methods for exact inference
  - elimination; sum-product algorithm; max-product algorithm
  - multivariate Gaussians; Kalman filtering; Rauch-Tung Striebel smoothing
– hidden Markov models; forward-backward algorithm
– junction tree framework

• exponential families, generalized linear models and graphical models
• methods for approximate inference
  – sampling-based methods
  – variational methods
• estimation, inference and model selection
  – basics: maximum likelihood, MAP, Bayesian
  – estimation based on discriminative criteria
  – mixture models; k-means; EM algorithm
  – model selection

Prerequisites
The prerequisites are previous coursework in linear algebra, multivariate calculus, basic probability and statistics (at the level of EECS 126, STAT 134/135). Some degree of mathematical maturity is also required. Coursework or background in graph theory, information theory, optimization theory and statistical physics is relevant, and could be helpful but is not required. Familiarity with a matrix-oriented programming language (e.g., MATLAB, Octave, R etc.) will be helpful.

Evaluation
Students will be evaluated based on a combination of regular homework assignments (60%), and depending on final class size:

• an exam (20%) and final project (20 %), or
• final project (40 %)

Homework: Although it is acceptable for students to discuss the homework assignments with one another, each student must write up his/her homework on an individual basis. Each student must indicate with whom (if anyone) they discussed the homework problems. Homeworks must be turned in at the beginning of class on the due date. Late homeworks will not be accepted.

Course project: The course project will involve independent work on a topic of the student’s own choosing. Course projects will be presented in an informal poster session at the end of semester, and the work will be summarized in a write-up.

Academic policy: Please see the EECS department policy on academic dishonesty at: http://www.eecs.berkeley.edu/Policies/acad.dis.shtml.