Math 156 — Machine Learning — Summer Session A

Time and location: MWR 09:00–10:50, virtual on Zoom: PMI = 377 051 7025 / Passcode = zXvH38
`https://zoom.us/j/3770517025?pwd=VzI2YUFLdTNHdjdFRHo5bWlrRUkvQT09`

Recitation sections: T 09:00–10:50, virtual on Zoom (see TA zoom info, below)

Instructor: Dr. Dominique Zosso

E-mail: zosso@math.ucla.edu
Howto: `www.insidehighered.com/views/2015/04/16/advice-students-so-they-dont-sound-silly-emails-essay`

Virtual office hours: MWR 12:30–1:30pm
Zoom room for class and office hours: PMI = 377 051 7025 / Passcode = zXvH38
`https://zoom.us/j/3770517025?pwd=VzI2YUFLdTNHdjdFRHo5bWlrRUkvQT09`

Teaching Assistant (section 1A): Zeyu Wang

E-mail: TBA

Virtual office hours: Zoom-room for discussion section and virtual office hours: TBA

Teaching Assistant (section 1B): Jiawei Zhang

E-mail: jwzcharlie@gmail.com

Virtual office hours: Zoom-room for discussion section and virtual office hours: TBA

Course text: *Pattern Recognition and Machine Learning*, by Christopher M. Bishop, Springer, 2006 (ISBN-13: 978-0387-31073-2), *plus complementary sources provided where necessary*.

Description: "Machine Learning" is an *introductory course* on mathematical models for pattern recognition and machine learning. The students will become familiar with fundamental concepts such as learning of parametric and non-parametric probability distributions, the curse of dimensionality, correlation analysis and dimensionality reduction, and concepts of decision theory. Advanced machine learning and pattern recognition problems will be covered, including data classification and clustering, regression, kernel methods, artificial neural networks, and Markov-based models such as hidden Markov models and Markov random fields. While these methods are fairly generic and widely applicable, they will be accompanied and illustrated by practical examples drawn from imaging, computer vision, document and social network analysis, etc.

Learning outcomes: Upon completion of the course, students will be able to:

1. Describe and understand the mathematics of basic models used in machine learning, and their training
2. Explain various mathematical approaches to dimensionality reduction with PCA (minimum error, maximum variance, probabilistic)
3. Understand the mathematical underpinnings of linear models for regression and classification, and kernel-based extensions
4. Understand and apply basic artificial neural network structure and training, from perceptron to multilayer networks
5. Build, train, and use basic graphical models such as Hidden Markov models (fields and chains)

Prerequisites: courses 115A, 164, 170A or 170E or Statistics 100A, and Computer Science 31 or Program in Computing 10A. Strongly recommended requisite: Program in Computing 16A or Statistics 21.

Computing device: It is important that students be able to use a personal computing device for this class, for completion of some practical classwork. This can technically be any device with a web-browser to run MATLAB online (see below; note that Safari on iOS devices is not optimal).

Homework: Homework problems will be assigned regularly. Homework problems are integrative part of the curriculum. It is strongly encouraged to routinely check any paper-and-pencil calculations with MATLAB (Emphasis on: as a check, not to get the solution in the first place). Homework assignments will not be collected, corrected or graded. But, to learn this material (and to do well on exams and quizzes), you should master all of the homework problems. Indeed:

Quizzes: About 2-3 times a week, there will be a quiz roughly covering current lectures and homework problems, available as PDF on CCLE and due on gradescope. The quizzes will take you 5–10 minutes to complete, but are not timed. The two lowest (or two missed) quizzes will be dropped, but make-up quizzes will not be given.

MATLAB assignments: Students will be given 8 MATLAB-based lab assignments with practical problems. Lab code and reports are to be submitted as pdf-files through gradescope, and will be graded. The lowest (or a missed) lab will be dropped.

Exams: There will be midterm, tentatively on **XXX**, as 24-hour takehome exam (it should take you about 75 minutes to complete). There will be a final exam on **XXX**, as 24-hour takehome exam. The final exam will cover the entire semester, but emphasize later parts.Failure to take the final exam will result in an automatic fail grade being assigned. **All exams are open book: your books and notes are permitted, however, NO other resources (calculators, online tools, friends, etc.) will be allowed during exams.** All exams will become available as PDF 24 hours before the due date/time.

Grading policy: 7 (out of 9) Quizzes: 20%, 7 (out of 8) Labs: 20%, 1 Midterm: 30%, Final: 30%. All scores will be available on gradescope.

Grading Scales: The lab assignments in this course will be graded on the GPA scale:

4 — excellent work; no real complaints on content, code commenting or on writing.

3 — work basically correct but missing some details/less clearly argued or commented than I would like.

2 — argument mostly correct, but there is a misstep in the mathematics, choice of algorithm. An especially poorly written answer, paper or commented code might merit a 2, as well.

1 — serious gaps in the mathematics, some ideas in the right direction, but didn't really get anywhere.

0 — didn't do the problem or it was completely wrong.

Seminar attendance: Graduate students are generally expected to attend research seminars. The research seminar most relevant for this course is the "Applied Mathematics Seminar", most weeks on Thursdays 3:10–4:00pm in Wilson Hall, 1-144. I strongly recommend regular attendance—it will serve you well. Undergraduates are encouraged to attend as well; they can receive champ change.

Getting MATLAB

Site license: UCLA has a campus-wide license for MATLAB; see https://softwarecentral.ucla.edu/matlab-getmatlab for more information.
If you do not want to install MATLAB, locally (it is quite big), you may use “Apporto”-virtual machines (be in touch with support@pic.ucla.edu for help on that). Most conveniently, though, we suggest using MATLAB on the web:

MATLAB on the web: To avoid the need of installation, we suggest using MATLAB on the web, instead. This service is available to students, staff, and faculty of UCLA at no cost. The only requirement is to sign up for a MATLAB account with a `ucla.edu`-email-address.

Follow the instructions on https://www.mathworks.com/academia/tah-portal/ucla-31454052.html to create your UCLA-MATLAB account. Once complete, you have access to MATLAB online at `matlab.mathworks.com` (iOS safari browser is discouraged). Note that your MATLAB workspace is persistent across sessions, devices, and there is an online filesystem!

`.m`-files or Livescripts You are encouraged to organize your online filesystem appropriately. It is recommended that for each MATLAB assignment, you create one or more `.m`-files or livescripts as required. Make sure to include an appropriate amount of comments to make your code understandable. Use `disp(...)` to print values of variables on the screen, and use plots and figures as suitable. You can create sections to your script (for reporting purposes) by using `%%`-signs. Use comments at the end of the file to discuss results and observations as required.

publish and submit For MATLAB assignments, you will need to submit .pdf-files to gradescope with your code, experiments, results, and observations. A simple way is to use MATLAB’s **publish**-function to create .pdf-reports. The publish button will run the current file, and render the code along with output (command line and figures) into a single .pdf-file. **This method is simple enough—it is your responsibility though to make sure the report is complete!**
Note: The publish function *does in general not play well with functions that require parameters, and scripts that include user interaction* (e.g. `input`). Use a wrapper script that calls such a function with parameters, and include the code of the inner function using <include>.
A few helpful items[1]:

- Use `%% ...` to create a new section; this embeds all results of a section before moving on to the next.
- Use `% comments...` to include your observations.
- To include the code of *separate* function files, use <include> *exactly* as follows (spacing between `%` and ¡ matters!):

```
%% Beginning of the wrapper script which we will publish
%
% <include>SeparateFunctionFileToBeIncludedInTheReport.m</include>
%
```

LaTeX reports Preferably, use LaTeX to properly typeset your report, including background, comments, code, experimental setup, results, discussion, and conclusion.
Submit your report as a single pdf-file per assignment, through gradescope.

[1] Check https://www.mathworks.com/help/matlab/matlab_prog/marking-up-matlab-comments-for-publishing.html

Tentative class schedule:		Section numbers (§) refer to the book.	
M 1/13	§1.2, §1.5, §1.6	1. Course introduction. Recap on linear algebra, probabilities	
W 1/15	§2.3, §2.4	2. Gaussian, exponential pdf; Learning parametric pdf	
F 1/17		Hands-on (Lab 1: MATLAB)	
W 1/22	§2.5	3. Learning non-parametric pdf	**Lab 1 due**
F 1/24		Hands-on (Lab 2: Model fitting, Kernel density estimation)	
M 1/27	§12.1	4. PCA: maximum variance, minimum error, high-dimensional PCA	
W 1/29	§12.2	5. Probabilistic PCA (ML-PCA, EM, Bayesian PCA)	**Lab 2 due**
F 1/31		Hands-on (Lab 3: PCA)	
M 2/03	§12.3	6. Non-linear latent variable models: kPCA	
W 2/05	§3.1	7. Linear basis function models, least squares and maximum likelihood	**Lab 3 due**
F 2/07		Hands-on (Lab 4: Linear regression)	
M 2/10	§3.3	8. Bayesian linear regression	
W 2/12	§3.4, §3.5	9. Model evidence / comparison / marginal likelihood	**Lab 4 due**
F 2/14		Hands-on	
W 2/19	§4.1	10. Discriminant functions; least squares	
F 2/21		Hands-on / Review	
M 2/24		**MIDTERM** (in class)	
W 2/26	§4.2, §4.3	11. Logistic regression: prob. generative & discriminative models	
F 2/28		Hands-on	
M 3/02	§14.2, §14.3	12. Mixture of linear classifiers: Boosting and Bagging	
W 3/04	§9.1	13. k-Means	
F 3/06		Hands-on (Lab 5: Ensemble methods)	
M 3/09	§9.2, §9.3	14. Gaussian mixture model, Expectation-Maximization	
W 3/11	§6.1, §6.2	16. Dual representation, kernel trick; Constructing kernels	**Lab 5 due**
F 3/13		Hands-on (Lab 6: k-Means)	
M 3/23	§6.4	17. Gaussian processes, GP regression, GP classification	
W 3/25	§7.1	18. Support vector machines, k-SVM	**Lab 6 due**
M 3/30		Hands-on (Lab 7: SVM)	
W 4/01	§4.1.7, §5.1	19. Biological motivation; The perceptron; Feed-forward Network	**Lab 7 due**
F 4/03	§5.2, §5.3	20. Network training	
M 4/06		Hands-on (Lab 8: Deep Learning)	
W 4/08	§8.1	21. Bayesian Networks	**Lab 8 due**
M 4/13	§8.3	22. Markov Random Fields; Iterated conditional modes	
W 4/15	§13.1, §13.2	23. Hidden Markov Models	
F 4/17	§13.1, §13.2	23. HMM: forward-backward, Viterbi algorithm	
W 4/20	n/a	15. Spectral clustering	
W 4/22		Leeway and Review	
F 4/24		Hands-on	
M 4/27		Project presentations 1/3	
W 4/29		Project presentations 2/3	
F 5/01		Project presentations 3/3	

FINAL EXAM — May 05, 4:00–5:50pm — WIL 1-143