# Machine Learning: Course Overview

CS 760@UW-Madison





# **Class enrollment**



- typically the class was limited to 30
- we've allowed ~70 to register
- the waiting list full
- unfortunately, many on the waiting list will not be able to enroll
- but CS760 will be offered in the Spring semester!





 Yingyu Liang email: yliang@cs.wisc.edu office hours: 3-4pm, Monday office: 6393 Computer Sciences





#### Jiewei Hong email: jhong58@wisc.edu office hours: 1-2pm Thursday, 1-2pm Friday office: CS 5364



- we'll have ~30 lectures in all, just like a standard TR class
- will push the lectures forward (finish early, leave time for projects and review)
- see the schedule on the course website: http://pages.cs.wisc.edu/~yliang/cs760\_fall18



- a variety of learning settings: supervised learning, unsupervised learning, reinforcement learning, active learning, etc.
- a broad toolbox of machine-learning methods: decision trees, nearest neighbor, neural nets, Bayesian networks, SVMs, etc
- some underlying theory: bias-variance tradeoff, PAC learning, mistake-bound theory, etc.
- experimental methodology for evaluating learning systems: cross validation, ROC and PR curves, hypothesis testing, etc.

# Two major goals



- 1. Understand what a learning system should do
- 2. Understand how (and how well) existing systems work

# Course requirements



- 5 homework assignments: 65%
  - programming
  - computational experiments (e.g. measure the effect of varying parameter x in algorithm y)
  - some written exercises
- final project: 35%
  - project group: 3-5 people

# Expected background



- CS 540 (Intro to Artificial Intelligence) or equivalent
- good programming skills
- probability
- linear algebra
- calculus, including partial derivatives

# **Programming languages**



for the programming assignments, you can use

C C++ Java Perl Python R

Matlab

• programs must be callable from the command line and *must run on the CS lab machines (this is where they will be tested during grading!)* 

# Course readings



#### Recommend to get <u>one</u> of the following books

- Machine Learning. T. Mitchell. McGraw Hill, 1997.
- Pattern Recognition and Machine Learning. C. Bishop. Springer, 2011.
- Machine Learning: A Probabilistic Perspective. K. Murphy. MIT Press, 2012.
- Understanding Machine Learning: From Theory to Algorithms. S. Shalev-Shwartz, S. Ben-David. Cambridge University press, 2014.



# Course readings



- the books can be found online or at Wendt Commons Library
- additional readings will come from online articles, surveys, and chapters
- will be posted on course website

# What is machine learning?



- the study of algorithms that improve their performance *P* at some task *T* with experience *E*
- to have a well defined learning task, we must specify: < *P*, *T*, *E* >

# ML example: spam filtering



O Delete

9/4/12 8:42 AM

04 September 2012

 Read Nature's news online Subscribe to Nature

Forward

Seply

Other Actions

Archive

🔸 Reply 🗟 Reply List 🔹 ➡ Forward 📓 Archive 🛕 Junk 🛇 Dele

🕰 Junk

O Delet

8/29/12 6:52 A

Other Action

6/25/12 4:48

Other Actic



## ML example: spam filtering



- T: given new mail message, classify as spam vs. other
- P: minimize misclassification costs
- *E* : previously classified (filed) messages

### ML example: predictive text input





# ML example: predictive text input



- *T* : given (partially) typed word, predict the word the user intended to type
- *P* : minimize misclassifications
- E: words previously typed by the user
  (+ lexicon of common words + knowledge of keyboard layout)

domain knowledge

# ML example: Netflix Prize

















Our best guess for Mark: ★★★★☆☆

# ML example: Netflix



- *T* : given a user/movie pair, predict the user's rating (1-5 stars) of the movie
- *P* : minimize difference between predicted and actual rating
- *E* : histories of previously rated movies (user/movie/rating triples)

# ML example: autonomous helicopter





video of Stanford University autonomous helicopter from http://heli.stanford.edu/

# ML example: autonomous helicopter



- *T* : given a measurement of the helicopter's current state (orientation sensor, GPS, cameras), select an adjustment of the controls
- *P* : maximize reward (intended trajectory + penalty function)
- *E* : state, action and reward triples from previous demonstration flights

# **Reading assignment**



- for Friday, read
  - Chapter 1 of Mitchell or Chapter 1 of Murphy
  - article by Dietterich on course website
  - article by Jordan and Mitchell on course website
- course website:

http://pages.cs.wisc.edu/~yliang/cs760\_fall18/

# HW1: Background test



- posted on course website; due in two weeks (Sep 19)
- will set up how to submit the solutions on Canvas
- contains: minimum and medium tests
- if pass both: in good shape
- if pass minimum but not medium: can still take but expect to fill in background
- if fail both: suggest to fill in background before taking the course

# Minimum background test

- 80 pts in total; pass: 48pts
- linear algebra: 20 pts
- probability: 20 pts
- calculus: 20 pts
- big-O notations: 20 pts



## Minimum test example



$$X = \begin{pmatrix} 9 & 8 \\ 7 & 6 \end{pmatrix} \qquad \mathbf{y} = \begin{pmatrix} 9 \\ 8 \end{pmatrix} \qquad \mathbf{z} = \begin{pmatrix} 7 \\ 6 \end{pmatrix}$$

- 1. What is the inner product of the vectors  $\mathbf{y}$  and  $\mathbf{z}$ ? (this is also sometimes called the *dot product*, and is sometimes written as  $\mathbf{y}^T \mathbf{z}$ )
- 2. What is the product Xy?
- 3. Is X invertible? If so, give the inverse, and if no, explain why not.
- 4. What is the rank of X?



- 1. If  $y = 4x^3 x^2 + 7$  then what is the derivative of y with respect to x?
- 2. If  $y = \tan(z)x^{6z} \ln(\frac{7x+z}{x^4})$ , what is the partial derivative of y with respect to x?

# Medium background test

- 20 pts in total; pass: 12 pts
- algorithm: 5 pts
- probability: 5 pts
- linear algebra: 5 pts
- programming: 5 pts



Match the distribution name to its probability density / mass function. Below,  $|\mathbf{x}| = k$ . (f)  $f(\boldsymbol{x};\boldsymbol{\Sigma},\boldsymbol{\mu}) = \frac{1}{\sqrt{(2\pi)^k \boldsymbol{\Sigma}}} \exp\left(-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})\right)$ (g)  $f(x; n, \alpha) = {n \choose x} \alpha^x (1 - \alpha)^{n-x}$  for  $x \in \{0, \dots, n\}; 0$ otherwise (h)  $f(x; b, \mu) = \frac{1}{2b} \exp\left(-\frac{|x-\mu|}{b}\right)$ (a) Laplace (i)  $f(\boldsymbol{x}; n, \boldsymbol{\alpha}) = \frac{n!}{\prod_{i=1}^{k} \alpha_{i}^{x_{i}}} \prod_{i=1}^{k} \alpha_{i}^{x_{i}}$  for  $x_{i} \in \{0, ..., n\}$  and (b) Multinomial (c) Poisson  $\sum_{i=1}^{k} x_i = n; 0$  otherwise (d) Dirichlet (j)  $f(x; \alpha, \beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$  for  $x \in (0, +\infty)$ ; 0 oth-(e) Gamma erwise (k)  $f(\boldsymbol{x}; \boldsymbol{\alpha}) = \frac{\Gamma(\sum_{i=1}^{k} \alpha_i)}{\prod_{i=1}^{k} \Gamma(\alpha_i)} \prod_{i=1}^{k} x_i^{\alpha_i - 1}$  for  $x_i \in (0, 1)$  and  $\sum_{i=1}^{k} x_i = 1; 0$  otherwise (1)  $f(x; \lambda) = \lambda^x \frac{e^{-\lambda}}{x!}$  for all  $x \in Z^+$ ; 0 otherwise



Draw the regions corresponding to vectors  $\mathbf{x} \in \mathbb{R}^2$  with the following norms:

- 1.  $||\mathbf{x}||_1 \le 1$  (Recall that  $||\mathbf{x}||_1 = \sum_i |x_i|$ )
- 2.  $||\mathbf{x}||_2 \le 1$  (Recall that  $||\mathbf{x}||_2 = \sqrt{\sum_i x_i^2}$ )
- 3.  $||\mathbf{x}||_{\infty} \leq 1$  (Recall that  $||\mathbf{x}||_{\infty} = \max_{i} |x_{i}|$ )

# THANK YOU



Some of the slides in these lectures have been adapted/borrowed from materials developed by Mark Craven, David Page, Jude Shavlik, Tom Mitchell, Nina Balcan, Elad Hazan, Tom Dietterich, and Pedro Domingos.