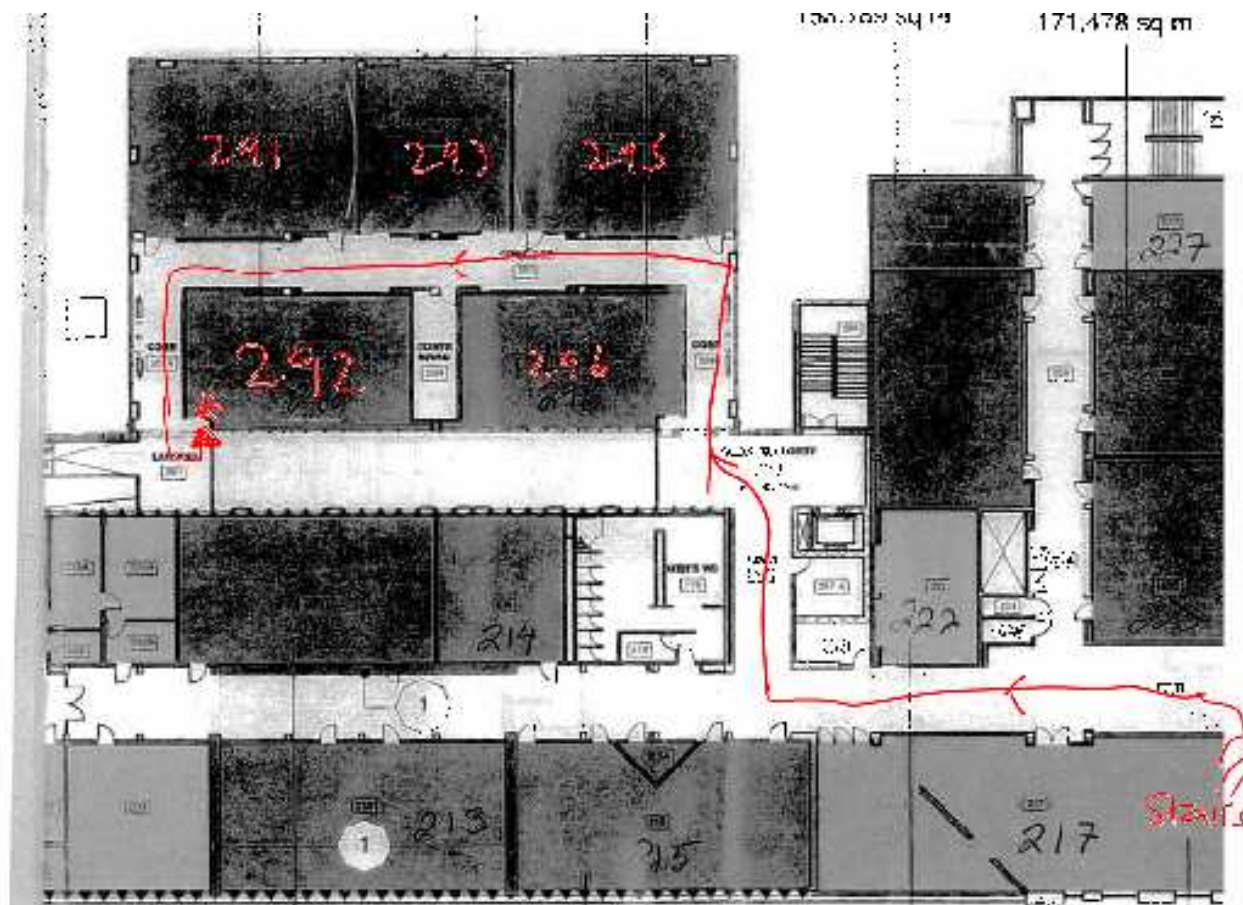


CS540 Machine learning  
Lecture 1  
Introduction

# Administrivia

- Class web page  
[www.cs.ubc.ca/~murphyk/Teaching/CS540-Spring10](http://www.cs.ubc.ca/~murphyk/Teaching/CS540-Spring10)
- Join <http://groups.google.ca/group/cs540-spring10>
- Office hours: Fri 3.30-4.30 CS 187, or by appointment
- New rooms: Tuesdays [Forestry 1613](#) (next to Tim Hortons).  
Thursdays [Angus 292](#), a brand new room in the Sauder business school.
- Midterm: Thu Mar 4th
- Last class: Thur Apr 15th
- Final project due Tue Apr 27th

# Map to Angus 292



# Grading

## Grading

Midterm (open-book): 35%

Final project: 40%

Weekly Assignments: 25%

# Homeworks

Weekly homeworks, out on Tue, due back on Tue

- Collaboration policy:
  - You can collaborate on homeworks if you write the name of your collaborators on what you hand in; however, you must understand everything you write, and be able to do it on your own (eg. in the exam!)
- Sickness policy:
  - If you cannot do an assignment or an exam, you must come see me in person; a doctor's note (or equivalent) will be required.

# Workload

- This class will be quite time consuming.
  - Attending lectures: 3h.
  - Weekly homeworks: about 6h.
  - Weekly reading: about 6h.
  - Total: 15h/week.
- 
- If the pace is too fast, why not take Stat406 with me this spring instead?

# Pre-requisites

- You should know
  - Basic multivariate calculus e.g.,

$$\nabla_{\mathbf{x}} \mathbf{x}^T \mathbf{a} = \mathbf{a}$$

- Basic linear algebra e.g.,

$$A\vec{u}_i = \lambda_i \vec{u}_i$$

- Basic probability/ statistics e.g.

$$\text{Cov}(X, Y) = E[(X - EX)(Y - EY)] = E[XY] - E[X]E[Y]$$

- Basic data structures and algorithms (e.g., trees, lists, sorting, dynamic programming, etc)

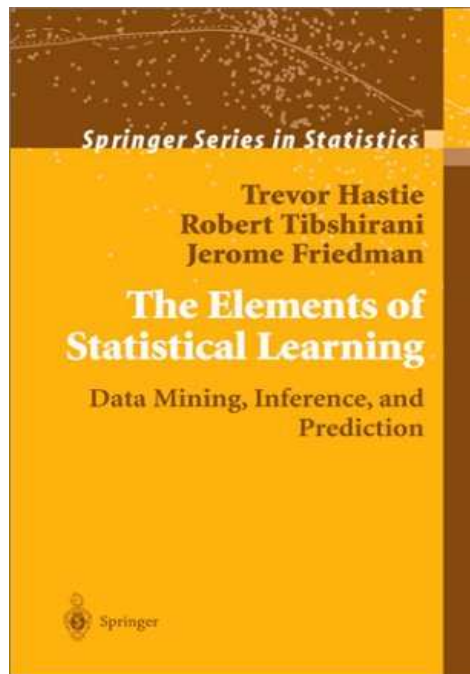
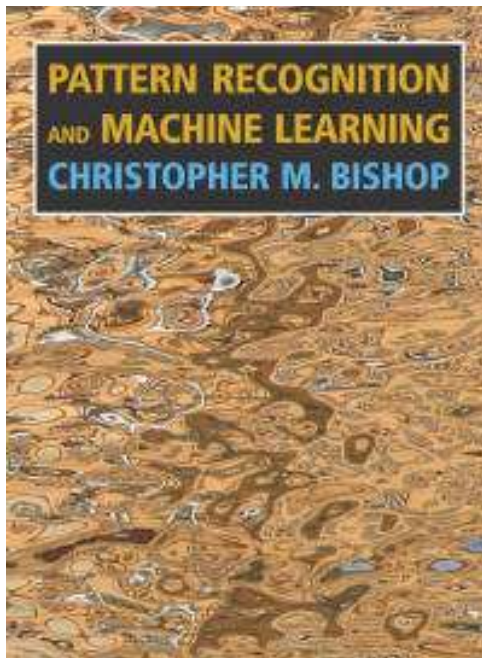
# Textbook

- “Machine learning: a probabilistic approach”
- Draft copies available from Copiesmart in the UBC Village (next to Macdonald’s) for \$56.50
- Extra credit (up to 5% of your grade) for finding errors (5 points) or typos (1 point) – more details later
- Please bring your book to every class (and the exam).
- Ch1 is online for free, so you can see if you want to take or drop the course

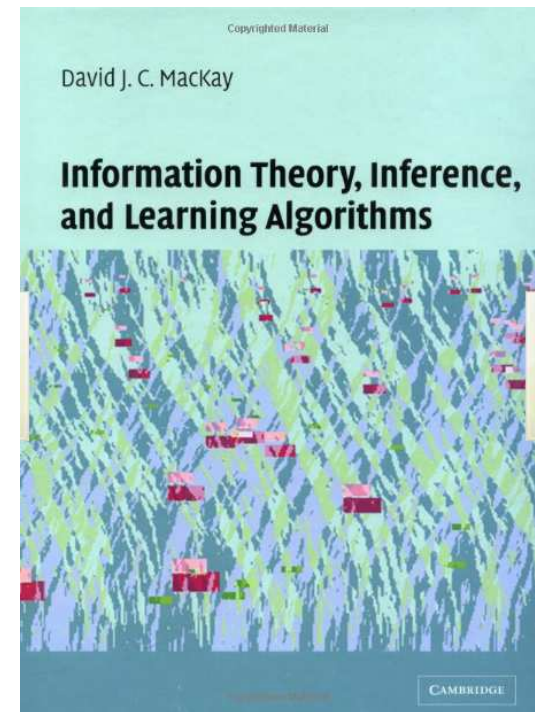


# Other good books

If you want a book that is already “debugged”, see one of these



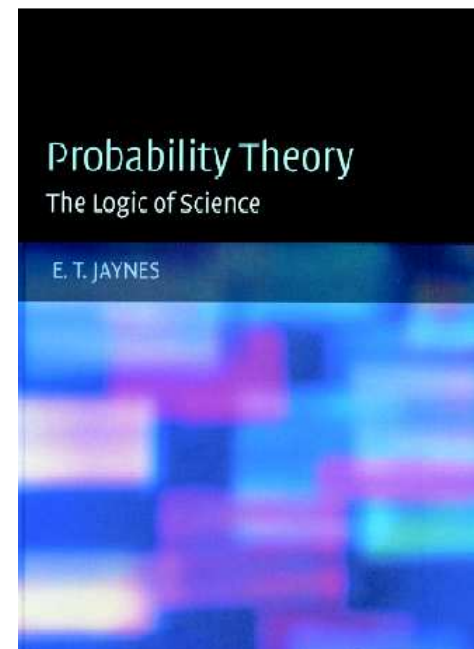
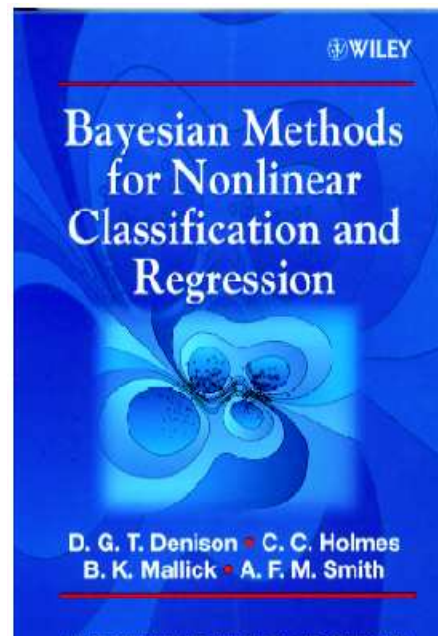
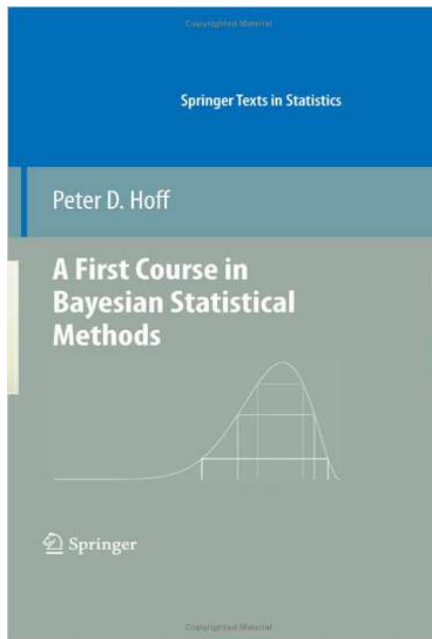
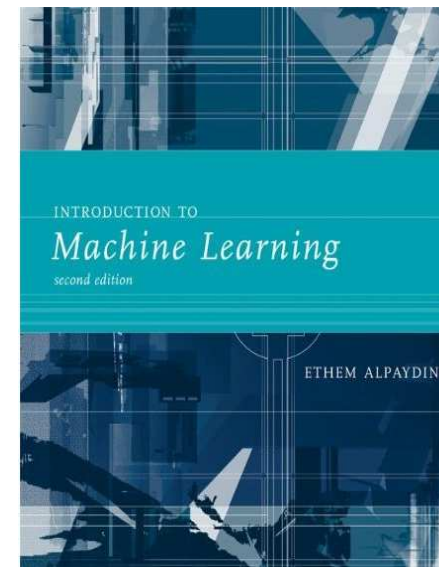
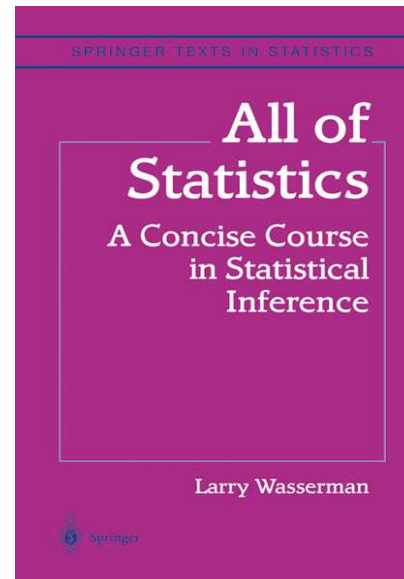
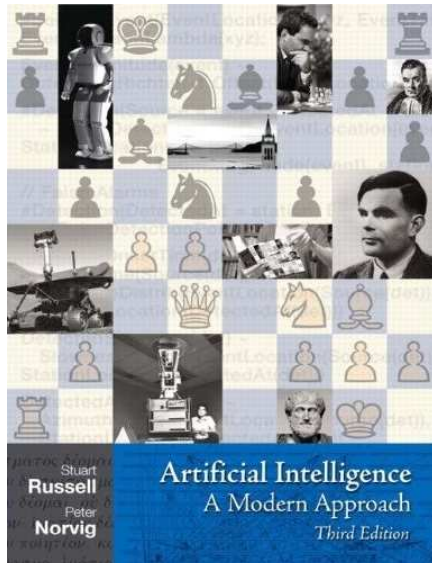
Free online



Free online

If you plan to “major” in machine learning, you should buy and read all of these!

# Other good books



# Matlab

- Matlab is a mathematical scripting language widely used for machine learning (and engineering and numerical computation in general).
- Everyone should have access to Matlab. If not, ask for a CS guest account.
- You can buy a student version for \$170 from the UBC bookstore. Please make sure it has the Stats toolbox.
- Matt Dunham has written an excellent Matlab tutorial which is on the class web site – please study it carefully!
- On Wed 6<sup>th</sup>, 4-5pm, LSK 302, I will offer a brief Matlab tutorial as part of Stat406; all welcome

# Software

- My textbook is accompanied by Matlab code, called PMTK3 (probabilistic modeling toolkit), which is on the book's webpage. It changes frequently.
- Currently there is not 100% consistency between the book and the code; this will be fixed during the semester.
- I also have 2 older code projects associated with the book (PMTK and PMTK2) which you can ignore, since they are deprecated
- We will also use several other Matlab packages such as Netlab, GPML, etc.

# Learning objectives I

- By the end of this class, you should be able to
- 1. For any given data analysis problem, be able to identify a suitable probabilistic model from those that are currently available, or if none exists, to devise one of your own.
- 2. If the model is novel, be able to derive a suitable algorithm. This includes deriving the update equations for fitting the parameters (eg gradient expressions for the MLE/MAP) and inferring the hidden states (eg variational message passing updates, or full conditionals for Gibbs sampling).
- 3. If the model is novel, be able to implement the above equations in clear and efficient code (preferably Matlab).
- 4. Be able to evaluate the performance of your model/ algorithm in an objective way, and compare to other models/ algorithms.

# Learning objectives II

- 5. Be able to write a clear and concise report summarizing the model, algorithm and results, with a suitable mix of English, Math and (properly labeled) figures. The report should be accompanied by code which enables the reader to easily reproduce all the results and figures.
- 6. Be able to give a clear and concise oral presentation summarizing your work, and answer oral questions on it, including defending your choice of model, algorithm or evaluation method, and discussion of possible alternatives.

# Lecture style

- This year, rather than spend time making lecture slides, I will just project my book onto the screen, and use the blackboard.
- Each “lecture” then becomes just an executive summary of relevant parts of the book.
- I will try to include some in-class demos and/or interactive activities (in the spirit of the Carl Weiman initiative)
- You are expected to carefully read the book either before and/or after each lecture to learn all the details – the relevant sections will be listed on the class web page.
- Homeworks are an essential aid to learning the material; assessing performance is a relatively minor concern