

S&DS 365 / 665
Intermediate Machine Learning

Course Overview

Wednesday, August 31

Outline

- Overview of course
- Topics
- Syllabus and logistics

Course objectives

Gain a solid understanding of concepts and methods of modern machine learning

- Become comfortable with the core ideas (and notation!)
- Gain an understanding of:
 - ▶ How and why methods work (and sometimes don't!)
 - ▶ Which models are appropriate for a given problem
 - ▶ How to adapt and extend methods when needed
- Get close to the research frontier

What does “Intermediate” imply?

- A second course in machine learning
- Assume familiar with things like PCA, bias/variance, maximum likelihood, basics of neural nets
- Have experimented with basic ML methods on some data sets
- Previous exposure to Python
- More on this later...

What's the difference between 265 and 365?

- Little overlap in topics
- IML is more technical/mathematical than iML
- We'll do some theory (but not for theory's sake!)
- The courses have similar organization (lectures, demos, assignments...)
- IML is required for S&DS majors (BS); iML aims to be accessible to broad cross-section of Yale students
- More on differences later...

IML Team

- Instructor: John Lafferty
- Teaching Fellows
 - Louis Deschuttere (Masters student, S&DS)
 - Chris Xu (PhD student, S&DS)
 - Sophia Zhu (Masters student, S&DS)
- ULAs
 - Benjamin Christensen
 - Jacques Morris
 - Eric Sun
- Course Manager
 - Siddhartha Chatterjee

Course materials

Materials posted to <http://interml.ydata123.org>; sometimes to Canvas

Please use Ed Discussion for any questions about lectures, homework, etc.

Please use email for questions about grading and grades.

What is Machine Learning?

The study of algorithms and statistical models to develop computer programs that improve with experience.

What is Machine Learning?

Machine Learning is closely aligned with Statistics, but with a focus on computation, scalability, prediction, representation, and complex problems

- Speech recognition
- Machine translation
- Object recognition and scene classification
- Autonomous driving...

Subproblems of these and other complex problems are concrete, statistical estimation and inference problems that can be studied in isolation.

AI vs. ML

Machine learning focuses on making predictions and inferences from data.

AI combines machine learning components into a larger system that includes a decision making component.

An AI system exhibits a behavior, resulting from the collective decisions that are made.

Machine Learning and AI

The focus in AI courses in the computer science curriculum used to be very different:

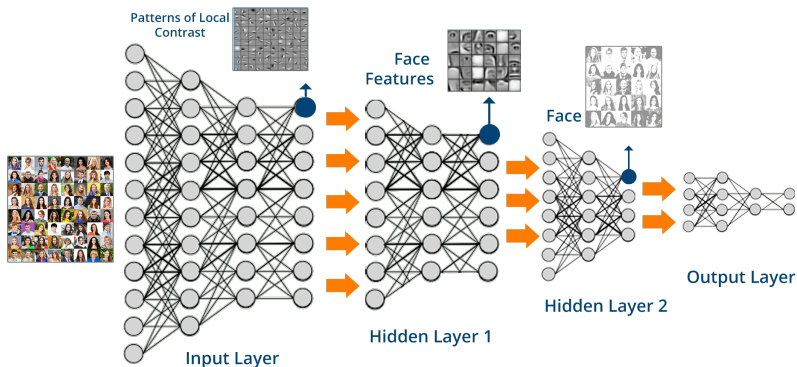
- Logic
- Search
- Games

Now much more “core” ML material than can be fit in a one semester course.

Machine learning frameworks

- Supervised learning
- Unsupervised (and semi-supervised) learning
- Reinforcement learning
- {Representation learning}

Deep learning is a type of machine learning

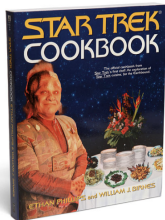


- Heuristics motivated from simplified view of the brain
- A particular form of nonlinear classification/regression/density estimation

This course

- Part 1: Supervised learning
- Part 2: Unsupervised learning
- Part 3: Reinforcement learning
- Part 4: Sequence learning

Machine learning *modus operandi* (1/2)

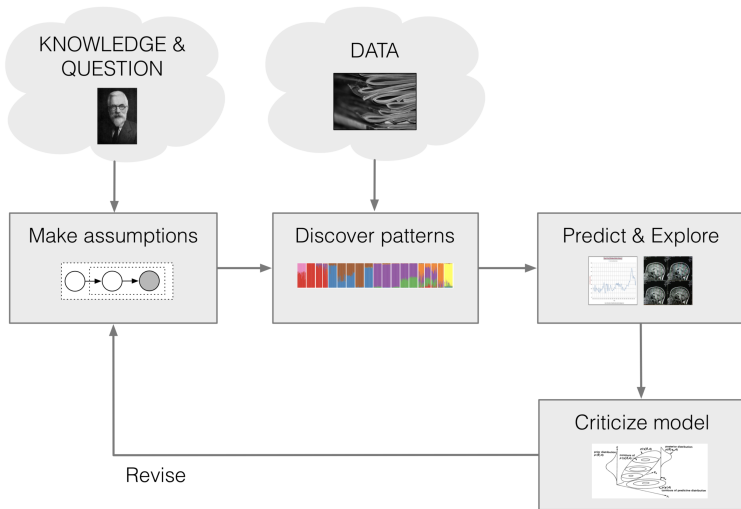


Increasingly powerful computing platforms (Keras, Tensorflow, Pytorch) implementing a few standard architectures.

Machine learning *modus operandi* (2/2)



More challenging to design and implement. Computation typically not “off the shelf”



Logistics

IML Team

- Instructor: John Lafferty
- Teaching Fellows
 - Louis Deschuttere (Masters student, S&DS)
 - Chris Xu (PhD student, Biomedical Engineering)
 - Sophia Zhu (Masters student, S&DS)
- ULAs
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Syllabus

Intermediate Machine Learning is a second course in machine learning at the advanced undergraduate or beginning graduate level. The course assumes familiarity with the basic ideas and techniques in machine learning, for example as covered in S&DS 265. The course treats methods together with mathematical frameworks that provide intuition and justifications for how and when the methods work. Assignments give students hands-on experience with machine learning techniques, to build the skills needed to adapt approaches to new problems.

Syllabus

Topics include nonparametric regression and classification, kernel methods, risk bounds, nonparametric Bayesian approaches, graphical models, attention and language models, generative models, sparsity and manifolds, and reinforcement learning. Programming is central to the course, and is based on the Python programming language and Jupyter notebooks.

Prerequisites

- Background in probability and statistics, at the level of S&DS 242 (Theory of Statistics)
- Familiarity with the core ideas from linear algebra, for example through Math 222 (Linear Algebra with Applications)
- Computational skills at the level of S&DS 265 (Introductory Machine Learning) or CPSC 200 (Introduction to Information Systems)
- Previous familiarity with Python is recommended

Installing Jupyter

- See installation guide on course Canvas site: Files > Getting started
- Use Python 3.x version

Assessment

- Assignments (50%)
- Mid-semester exam (20%)
- Final exam: 20%
- Quizzes (10%)

Assignments due on a Wednesday at midnight. Late assignments not accepted.

Assignments

- Five assignments total
- Roughly every 2 weeks
- Due at 11:59pm on a Wednesday
- Late assignments not accepted
- Submitted using Gradescope
- Mix of concepts, problem solving and data analysis
- Prepared using Python notebooks


Collaboration

Collaboration on homework assignments with fellow students is encouraged. However, such collaboration should be clearly acknowledged, by listing the names of the students with whom you have had any discussions concerning the problem. *You may not share written work or code—after discussing a problem with others, the solution must be written by yourself.*

Quizzes

- Five quizzes total
- Taken online (Canvas)
- Short, 10-20 minutes
- Assess understanding of essentials

http://interml.ydata123.org

Week	Dates	Topics	Demos & Tutorials	Lecture Slides	Readings & Notes	Assignments & Exams
1	Aug 31, Sep 2	Course overview	Python elements Pandas and regression Lasso example	Aug 31: Course overview Sep 2: Sparse regression	PML Section 11.4	
2	Sep 7	Smoothing and kernels	Smoothing example Using different kernels	Sep 7: Smoothing	PML Sections 16.3, 17.1	Sep 7: Quiz 1
3	Sep 12, 14	Density estimation and risk bounds	Mercer kernels Density estimation demo	Sep 12: Mercer Kernels Sep 14: Density estimation	 Notes on Mercer kernels Bias-variance tradeoff for density estimation	Sep 14: Assn 1 out
4	Sep 19, 21	Neural networks for classification	TensorFlow playground Convolution demo	Sep 19: Neural networks Sep 21: Convolutional neural networks	PML Sections 13.1, 13.2 Notes on backpropagation	Sep 21: Quiz 2
5	Sep 26, 28	Nonparametric Bayes	Parametric Bayes Gaussian processes	Sep 26: Gaussian processes Sep 28: Gaussian processes continued	PML Section 17.2 Notes on Bayesian inference Notes on nonparametric Bayes	Sep 28: Assn 1 in; Assn 2 out
6	Oct 3, 5	Gibbs sampling and approximate inference	Gibbs sampling	Oct 3: Gibbs sampling Oct 5: Introduction to approximate inference	Notes on Gibbs sampling	Oct 5: Quiz 3
7	Oct 10, 12	Variational Inference	Variational autoencoders	Oct 10: Variational inference and VAEs Oct 12: VAEs and review	PML Section 20.3 Notes on variational inference	Oct 12: Assn 2 in; Assn 3 out

8	Oct 17	Midterm			Practice midterm	Oct 17: Midterm exam
9	Oct 24, 26	Graphs and structure learning	Graphical lasso demo Graph neural networks	Oct 24: Sparsity and graphs Oct 26: Discrete data and graph neural nets	Notes on graphs and structure learning PML Section 23.4	
10	Oct 31, Nov 2	Deep reinforcement learning	Q-learning demo	Oct 31: Reinforcement learning Nov 2: Deep reinforcement learning	Sutton and Barto, Section 6.5	Nov 2: Assn 3 in Assn 4 out
11	Nov 7, 9	Policy gradient methods	DQN demo Policy gradients demo Actor-critic demo	Nov 7: Policy gradient methods Nov 9: Actor-critic methods	Sutton and Barto, Section 13.1-13.3, 13.5	Nov 9: Quiz 4
12	Nov 14, 16	Sequential and sequence-to-sequence models	RNN demo: Fakespeare TensorFlow: Text generation	Nov 14: HMMs and RNNs Nov 16: RNNs, GRUs, LSTMs, and all that	PML Chapter 15	Nov 16: Assn 4 in Assn 5 out
13	Nov 21, 23	No class, Thanksgiving break				
14	Nov 28, 30	Attention and language models	GPT-3 demo Codex demo	Nov 28: Sequence-to-sequence models Nov 30: Attention	PML Sections 15.4, 15.5	Nov 30: Quiz 5
15	Dec 5, 7	Transformers	Transformer demo	Dec 5: Attention and transformers Dec 7: Course wrap up		Dec 7: Assn 5 in

Exams

- Midterm: Monday, October 17, in class
- Final: Tuesday Dec. 20, 7:00pm

Auditing

- Auditors are welcome!
- Full access to Canvas
- Just expected to regularly attend class

Questions on logistics?

Topics covered

- Part 1: Supervised learning
- Part 2: Unsupervised learning
- Part 3: Reinforcement learning
- Part 4: Sequence learning

Topics covered

- *Part 1: Supervised learning*
 - ▶ Sparse regression
 - ▶ Smoothing and kernels
 - ▶ Convolutional neural networks
 - ▶ Risk bounds and generalization error
- Part 2: Unsupervised learning
- Part 3: Reinforcement learning
- Part 4: Sequence learning

Topics covered

- Part 1: Supervised learning
- *Part 2: Unsupervised learning*
 - ▶ Nonparametric Bayes
 - ▶ Approximate inference
 - ▶ Approaches to generative models
 - ▶ Structure learning
- Part 3: Reinforcement learning
- Part 4: Sequence learning

Topics covered

- Part 1: Supervised learning
- Part 2: Unsupervised learning
- *Part 3: Reinforcement learning*
 - ▶ Deep Q-Learning
 - ▶ Policy gradient methods
 - ▶ Actor-Critic approaches
- Part 4: Sequence learning

Topics covered

- Part 1: Supervised learning
- Part 2: Unsupervised learning
- Part 3: Reinforcement learning
- *Part 4: Sequence learning*
 - ▶ Classical techniques (Kalman filters, HMMs)
 - ▶ LSTMs and GRUs
 - ▶ Attention and language models
 - ▶ Transformers

References

- “The Elements of Statistical Learning: Data Mining, Inference, and Prediction,” by T. Hastie, R. Tibshirani, and J. Friedman,
<http://www-stat.stanford.edu/~tibs/ElemStatLearn/>
- “Probabilistic Machine Learning: An Introduction,” by K. Murphy, MIT Press, <https://probml.github.io/pml-book/book1.html>

Questions?