S&DS 365 / 665

Intermediate Machine Learning

Course Overview

Wednesday, August 30

Yale

Welcome!

- 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
- Gain an understanding of:
  - How and why methods work (and often 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 365 and 265?[†]

- Little overlap in topics
- 365 (IML) is more technical/mathematical than 265 (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...

[†] 100

Course materials

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

iML page: `https://ydata123.org/fa22/introml/calendar.html`

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:

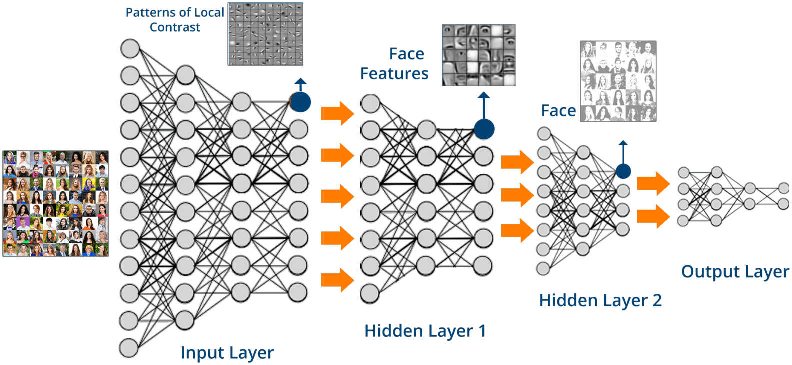
- Logic
- Search
- Games

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

Two types of intelligence

1. "Neocortical"— acquire semantic and procedural knowledge
   - Requires extensive data and training
   - Slow to learn, fast to apply
   - Well captured by modern deep learning

Two types of intelligence

1. "Neocortical"— acquire semantic and procedural knowledge

Two types of intelligence

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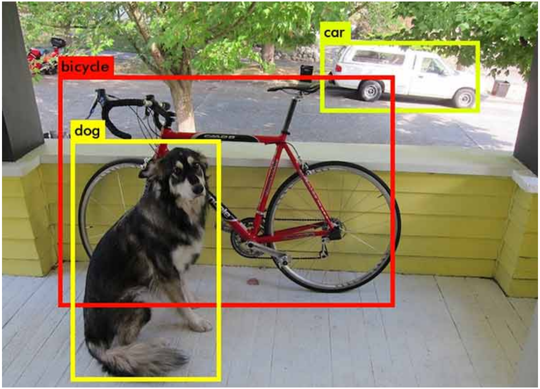
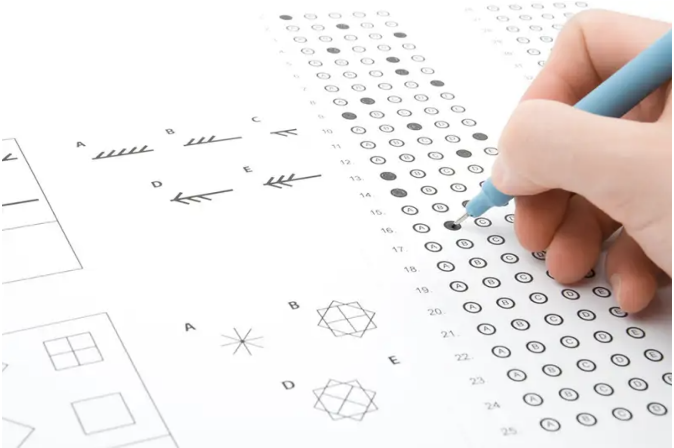


Two types of intelligence

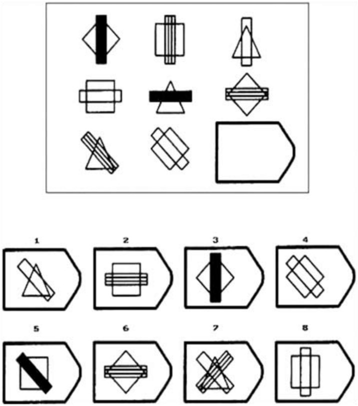
2. "Prefrontal"— identify novel associations and relations
   - Fast to learn, slow to apply
   - Symbolic processing and abstraction
   - Little explicit training data

Two types of intelligence

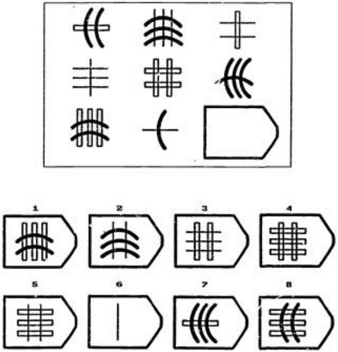


AI struggles with IQ tests
Panther Media GmbH / Alamy Stock Photo

Two types of intelligence



Two types of intelligence



Two types of intelligence

1. “Neocortical”— efficient function approximation
2. “Prefrontal”— rapid abstraction, association and generalization

Can both types be supported in a single architecture?

Relations are essential to reasoning

"Jack and Jill are sitting side by side. The person next to Jack is angry. The person next to Jill is happy. Who is happy, Jack or Jill?"

Shlomi Sher, "On Artifice and Intelligence: How to spot counterfeit cognition," medium.com/@shlomi.sher, April 21, 2023

Relations are essential to reasoning

ChatGPT response (yesterday):

Based on the information provided, Jill is happy. The statement specifies that the person next to Jill is happy, indicating that Jill is the one who is happy. Therefore, Jill is happy while Jack is angry.

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"Two shapes are in a room. The shape next to the cube is blue. The shape next to the sphere is red. Which is red, the cube or the sphere?"

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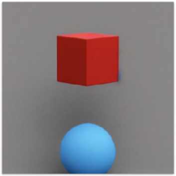

Relations are essential to reasoning

Based on the given information, it can be inferred that the sphere is red. The statement specifies that the shape next to the sphere is red, implying that the sphere itself is red. The color of the cube is not mentioned, so we cannot determine its color from the given information.

Relations are essential to reasoning

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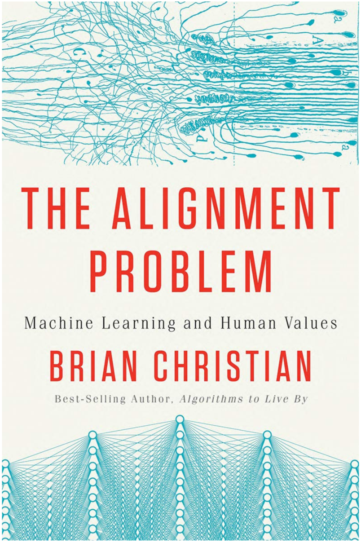
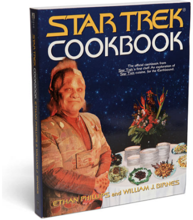
Shortcomings are masked

- Recent innovation with ChatGPT hides these deficiencies
- System is trained to convince us
- Over-confidence and bogus deductive reasoning
- After this course you'll have an understanding of all the components of ChatGPT

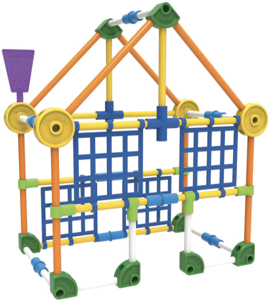

THE ALIGNMENT PROBLEM
Machine Learning and Human Values
BRIAN CHRISTIAN
Best-Selling Author, Algorithms to Live By

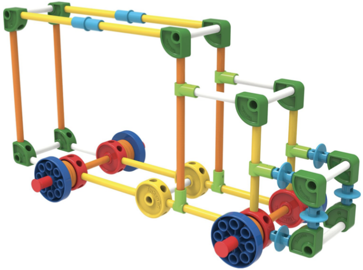
Machine learning *modus operandi* (1/2)



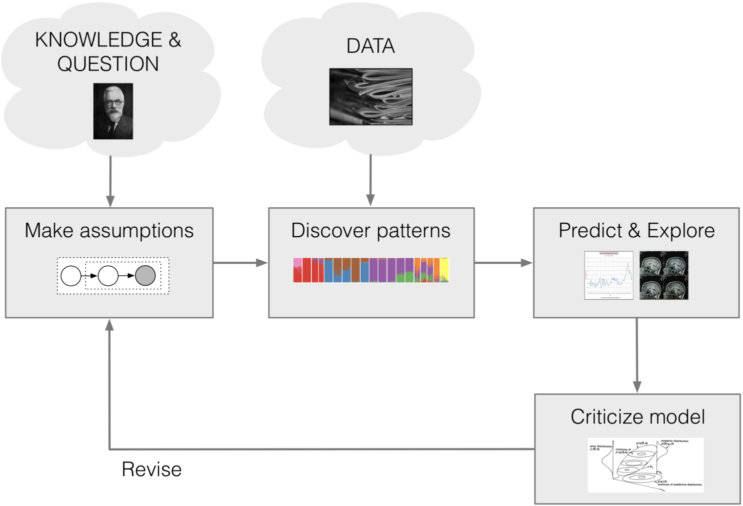
Increasingly powerful computing platforms (Keras, Tensorflow, Pytorch) implementing a few standard architectures.

Machine learning *modus operandi* (2/2)





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



Ack: Dave Blei

Logistics

IML Team

- Instructor: John Lafferty
- Teaching Fellows
  Zehao Dou (PhD student, S&DS)
  Ruixiao Wang (PhD student, S&DS)
  Chris Xu (PhD student, S&DS)
- ULAs
  Varun Varanasi
  Andy Yang
- Course Manager
  Baijia Xu

Course materials

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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 30, Sep 1	Sparse regression	CO Python elements CO Pandas and regression CO Lasso example	Wed: Course overview Fri: Sparse regression	PML Section 11.4	
2	Sep 6	Smoothing and kernels	CO Smoothing example CO Using different kernels	Wed: Smoothing	PML Sections 16.3, 17.1	Quiz 1
3	Sep 11, 13	Density estimation and Mercer kernels	CO Density estimation demo CO Mercer kernels (1/2) CO Mercer kernels (2/2)	Mon: Density estimation Wed: Mercer kernels	Risk bounds for local smoothing Notes on Mercer kernels	CO Assn 1 out
4	Sep 18, 20	Neural networks and overparameterized models	CO np-complete example (1/2) CO np-complete example (2/2) TensorFlow playground	Mon: Neural networks Wed: Double descent	PML Sections 13.1, 13.2 Notes on backpropagation Notes on double descent	Quiz 2

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5	Sep 25, 27	Nonparametric Bayes	CO Convolution demo CO CNN demo CO Parametric Bayes CO Gaussian processes	Mon: Convolutional nets Wed: Gaussian processes	PML Section 17.2 Notes on Bayesian inference Notes on nonparametric Bayes	Assn 1 in CO Assn 2 out
6	Oct 2, 4	Gaussian processes and approximate inference	CO Gibbs sampling for image denoising CO Gibbs sampling for DP mixtures	Mon: Gaussian processes (continued) Wed: Introduction to approximate inference	Notes on simulation Notes on Gibbs sampling for DP mixtures (not required)	Quiz 3
7	Oct 9, 11	Variational inference	CO Variational autoencoders	Mon: Variational inference and VAEs Wed: VAEs and review	PML Section 20.3 Notes on variational inference	Assn 2 in CO Assn 3 out
8	Oct 16	Midterm			Practice midterms	Oct 16: Midterm exam

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9	Oct 23, 25	Graphs and structure learning	Graphical lasso demo	Mon: Sparsity and graphs Wed: Discrete data and graph neural nets	Notes on graphs and structure learning Graph neural networks PML Section 23.4	
10	Oct 30, Nov 1	Deep reinforcement learning	Q-learning demo DQN demo	Mon: Reinforcement learning Wed: Deep reinforcement learning	Sutton and Barto, Section 6.5	Nov 1: Assn 3 in Assn 4 out
11	Nov 6, 8	Policy gradient methods	Policy gradients demo Actor-critic demo	Mon: Policy gradient methods Wed: Actor-critic methods	Sutton and Barto, Section 13.1-13.3, 13.5	Quiz 4

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12	Nov 13, 15	Sequential models	CO vanilla RNN CO Fakespeare GRU	Mon: HMMs and RNNs Wed: RNNs, GRUs, LSTMs, and all that	TensorFlow: Text generation Notes on HMMs and Kalman filters PML Chapter 15	Assn 4 in CO Assn 5 out
13	Nov 20, 22	No class, Thanksgiving break				
14	Nov 27, 29	Sequence-to-sequence models and Transformers	CO GPT-3 demo CO Codex demo	Mon: Sequence-to-sequence models Wed: Attention and transformers	Notes on mixtures PML Sections 15.4, 15.5	Quiz 5
15	Dec 4, 6	Transformers Societal issues	CO Transformer demo	Mon: Transformers and AI/ML ethics Wed: Course wrap up		Assn 5 in
17	Wed Dec 20, 9am, Room TBA	Final exam			Practice exams	Registrar: final exam schedule

Exams

- Midterm: Monday, October 16, in class
- Final: Wednesday Dec. 20, 9:00am

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http://catalog.yale.edu/ycps/final-examination-schedules/

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?

Questions?

Remember: Class on Friday!