S&DS 365 / 665

Intermediate Machine Learning

Course Overview

Monday, January 12

Yale

Welcome!

- Overview of course
- Topics
- Syllabus and logistics
- Start on sparse regression (if time)

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
`https://ydata123.org/sp26/interml/calendar.html`;
sometimes to Canvas

iML page: `https://ydata123.org/sp26/introml/calendar.html`

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

Please use email `sds365@yale.edu` for all course/administrative questions

What is Machine Learning?

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

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The study of algorithms and statistical models to develop *computer programs that create 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

- Object recognition and scene classification
- Translation from one language to another
- 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.

AI vs. ML: An analogy

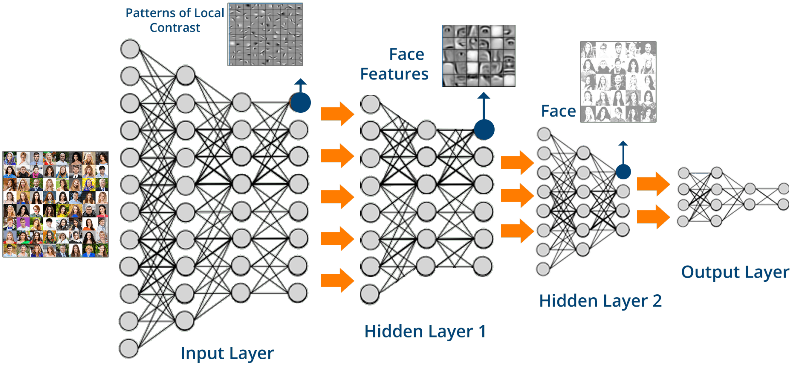
AI $\approx$ nuclear power. Tied up with issues of engineering at scale, economics, jobs, politics and legal infrastructure.

ML $\approx$ nuclear physics. You can't build a nuclear power plant without a handle on the physics of nuclear fission, isotope separation and uranium enrichment.

Machine learning frameworks

- Supervised learning
- Unsupervised (and self-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. Sensory ("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

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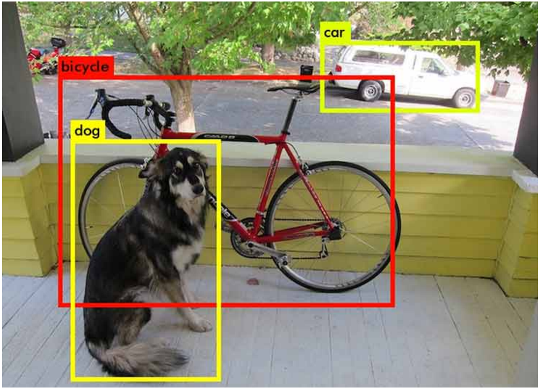
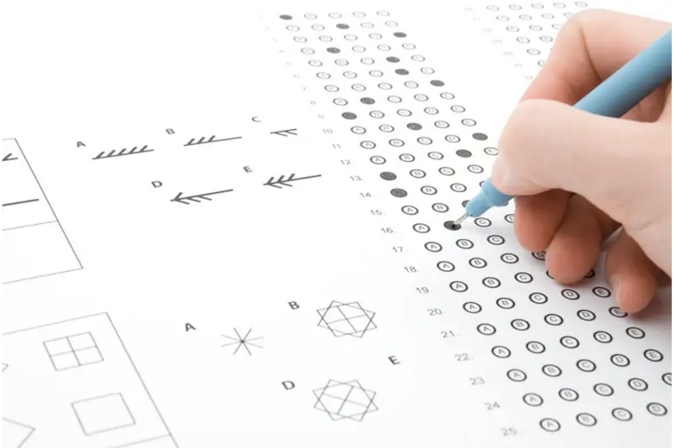


Two types of intelligence

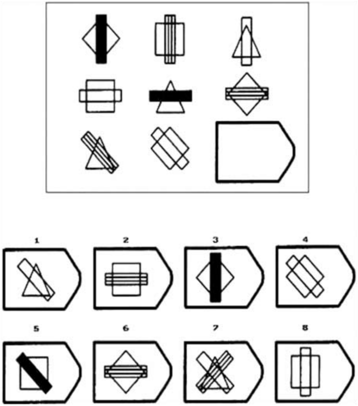
2. Relational ("Prefrontal")— identify novel associations and relations
   - Fast to learn, slow to apply
   - Symbolic processing and abstraction
   - Little explicit training data

Two types of intelligence

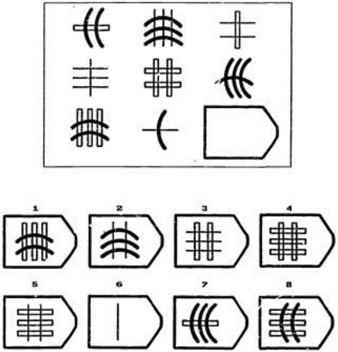


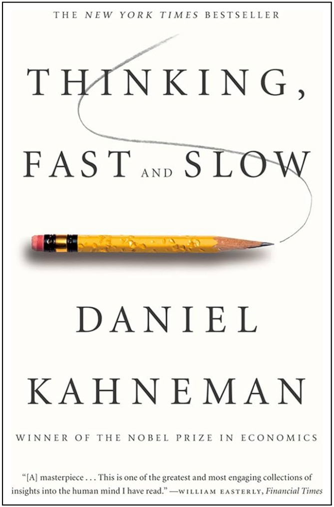
AI struggles with IQ tests
Panther Media GmbH / Alamy Stock Photo

Two types of intelligence



Two types of intelligence





- Sensory (Neocortical):
  slow to learn, fast to apply
- Relational (Prefrontal):
  fast to learn, slow to apply

Two types of intelligence

1. Sensory (“Neocortical”)— efficient function approximation
2. Relational (“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:

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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Relations are essential to reasoning

"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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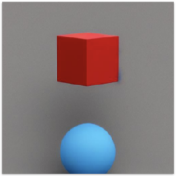

Relations are essential to reasoning

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.

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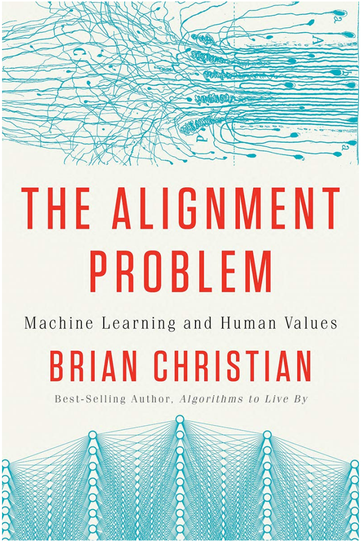
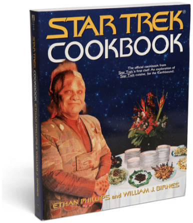
Abstraction and Reasoning Prize

Shortcomings are masked

- Recent innovations in AI bots hide these deficiencies
- Systems are trained to convince us
- Can lead to over-confidence and bogus reasoning
- After this course you’ll have an understanding of core components of AI systems


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

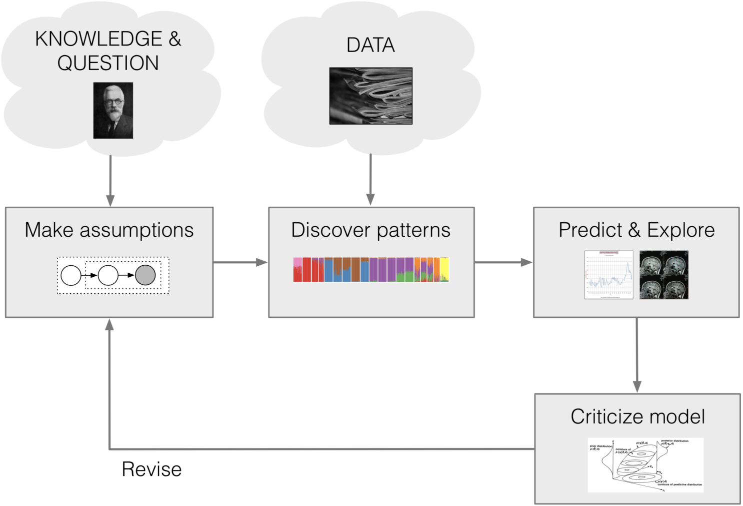
Machine learning *modus operandi* **(1/2)**



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

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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.

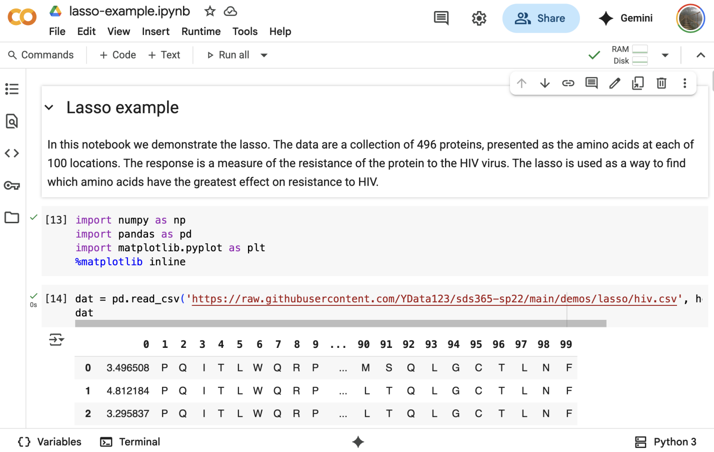
Syllabus

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

Running on Google Colab (preferred)



Running on Google Colab (preferred)

Installing Jupyter locally (discouraged)

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

Assessment

- Assignments (40%)
- Mid-semester exam (25%)
- Final exam (25%)
- Quizzes (10%)

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

Policy on Collaboration

1. Collaboration on homework assignments with fellow students is encouraged.
2. However, such collaboration should be clearly acknowledged, by listing the names of the students with whom you have had any discussions concerning the problem.
3. You may not share written work or code—after discussing a problem with others, the solution must be written by yourself.
4. Treat an AI assistant as a fellow student. That is, use interactively to help develop solutions, but do not copy/paste code and written solutions from the AI assistant. Acknowledge all collaborations with an AI assistant.

Quizzes

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

Calendar

Week	Dates	Topics	Demos & Tutorials	Lecture Slides	Readings & Notes	Assignments & Exams
1	Jan 12, 14	Sparse regression	CO Python elements CO Pandas and regression CO Lasso example	Mon: Course overview Wed: Sparse regression	Google Colab Basics PML Section 11.4 Notes on linear regression	
2	Jan 21, 23	Smoothing, kernels, and Density estimation	CO Smoothing example CO Using different kernels	Wed: Lasso (continued) and smoothing Fri: Smoothing and density estimation	PML Sections 16.3, 17.1 Notes on computing the lasso	Quiz 1
3	Jan 26, 28	Mercer kernels and Neural networks	CO Density estimation demo CO Mercer kernels (1/3) CO Mercer kernels (2/3) CO Mercer kernels (3/3)	Mon: Mercer kernels Wed: Neural networks	Risk bounds for local smoothing Notes on Mercer kernels	CO Assn 1
4	Feb 2, 4	Overparameterized models and Convolutional neural networks	CO np-complete example (1/2) CO np-complete example (2/2) TensorFlow playground	Mon: Double descent Wed: Convolutional neural networks	PML Sections 13.1, 13.2 Notes on backpropagation Notes on double descent	Quiz 2

Calendar

5	Feb 9, 11	Gaussian processes	CO Convolution demo CO CNN demo (1/2) CO CNN demo (2/2)	Mon: CNNs and Gaussian Processes Wed: Gaussian processes	PML Section 17.2 Notes on Bayesian inference Notes on nonparametric Bayes	Assn 1 in CO Assn 2 out CO ipynb converter
6	Feb 16, 18	Approximate inference and variational inference	CO Parametric Bayes CO Gaussian processes CO Gibbs sampling for image denoising	Mon: Recap of GPs Introduction to approximate inference Wed: Variational inference	Notes on simulation	Quiz 3
7	Feb 23, 25	Variational autoencoders, Graphs and structure learning	CO Variational autoencoders	Mon: VAEs Wed: Sparsity and graphs	PML Section 20.3 Notes on variational inference	Assn 2 in CO Assn 3 out CO ipynb converter
8	Mar 2	Graphs and structure learning	CO Graphical lasso demo	Mon: Discrete data and graph neural nets	Notes on graphs and structure learning Graph neural networks PML Section 23.4	
8	Mar 4	Wed: Midterm				Mar 4: Midterm

Calendar

9	Mar 9, 11	No class, Spring Break				
10	Mar 16, 18	No class, Spring Break				
11	Mar 23, 24	Deep reinforcement learning	CO Q-learning demo CO DQN demo	Mon: Reinforcement learning Wed: Deep reinforcement learning	Sutton and Barto, Section 6.5	Assn 3 in CO Assn 4 out CO ipynb converter
12	Mar 30, Apr 1	Policy methods	CO Policy gradients demo CO Actor-critic demo	Mon: Policy gradient methods Wed: Policy gradients (continued)	Sutton and Barto, Section 13.1-13.3, 13.5	Quiz 4
13	Apr 6, 8	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	CO Assn 5 out

Calendar

14	Apr 13, 15	Sequence-to-sequence models and Transformers	GPT-4 Python API	Mon: Sequence models and attention Wed: Transformers, LLM scaling PML Sections 15.4, 15.5		Quiz 5 Assn 4 in ipynb converter
15	Apr 20, 22	The LLM pipeline; broader issues	Transformer demo Minimal LLM decoder	Mon: LLM finetuning, postprocessing Wed: Course wrap up		Assn 5 in
17	May 5, 2pm	Final exam				Registrar: final exam schedule

Exams

- Midterm: Wednesday, March 4, in class
- Final: Tuesday, May 5, 2026 at 2pm

No rescheduled exams to accommodate early travel plans

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

Auditing

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

Course Staff

Name	Email	Role
Omar Montasser	omar.montasser@yale.edu	Instructor
Zhehao Xu	zhehao.xu@yale.edu	TF20
Jonathan Fan	jonathan.fan@yale.edu	ULA
Arjan Kohli	arjan.kohli@yale.edu	ULA

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)
  - Recurrent neural networks
  - Attention and language models
  - Transformers

References

- "Probabilistic Machine Learning: An Introduction," by K. Murphy, MIT Press, https://probml.github.io/pml-book/book1.html
- "Probabilistic Machine Learning: Advanced Topics," by K. Murphy, MIT Press, https://probml.github.io/pml-book/book2.html
- "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/

Questions?