EECS 445

Introduction to Machine Learning

Introduction

Prof. Kutty and **Prof. Makar**

Today's Agenda

- Introduction: what is this class about
- Administrative: resources, grading etc.
- What is Machine Learning?
  - Supervised Learning

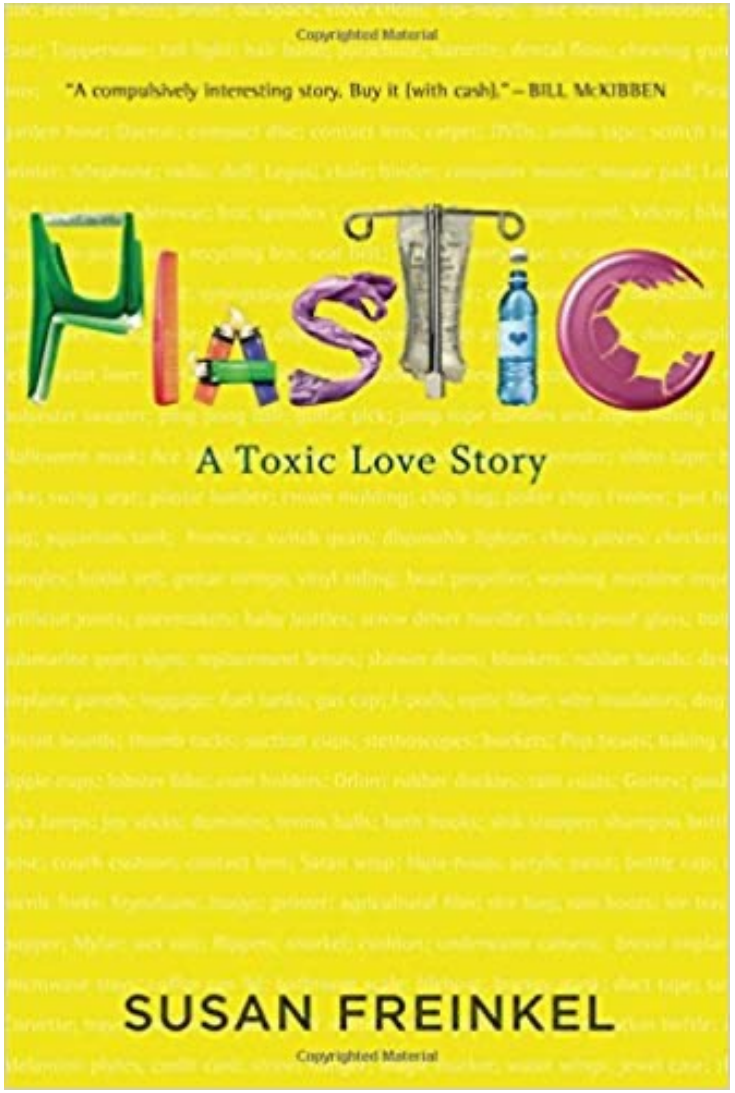
Course Overview

Machine Learning is ubiquitous

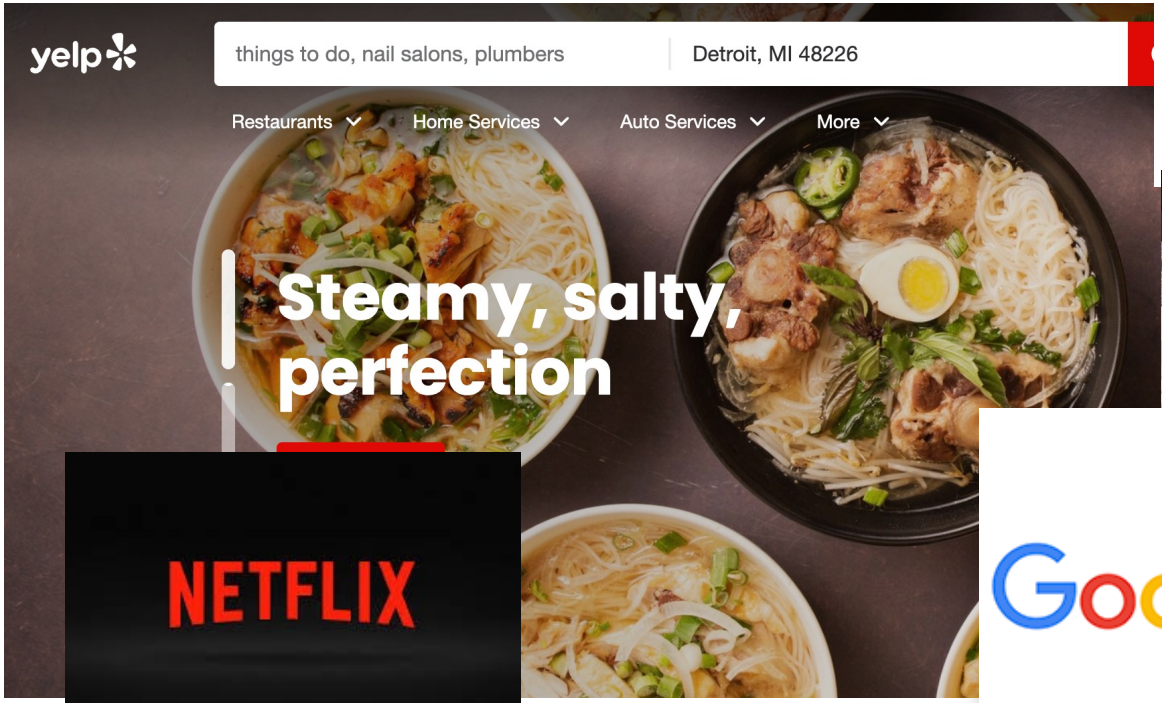
An analogy…

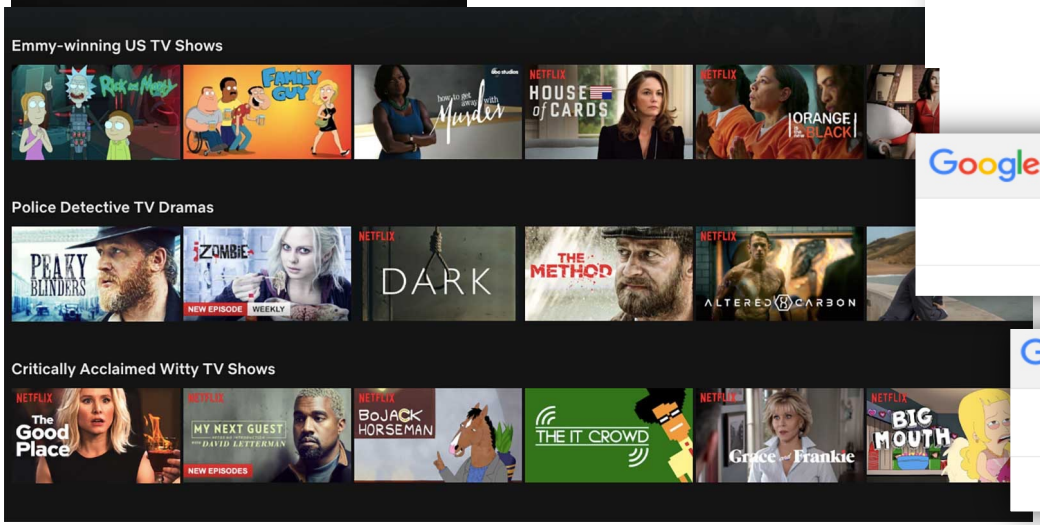
Plastic: A Toxic Love Story

”But it wasn’t clear to me just how plastic my world had become until I decided to go an entire day without touching anything plastic. The absurdity of this experiment became apparent about ten seconds into the appointed morning when I shuffled bleary-eyed into the bathroom: the toilet seat was plastic.”

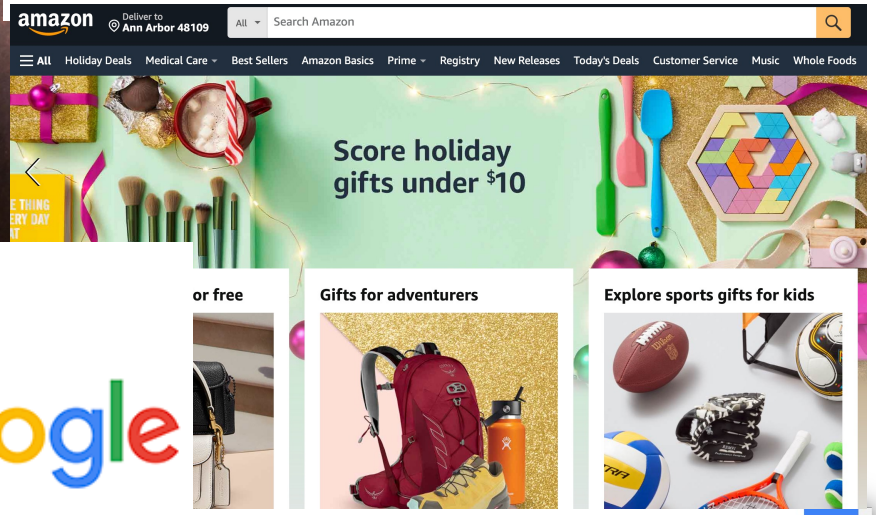


Applications of ML

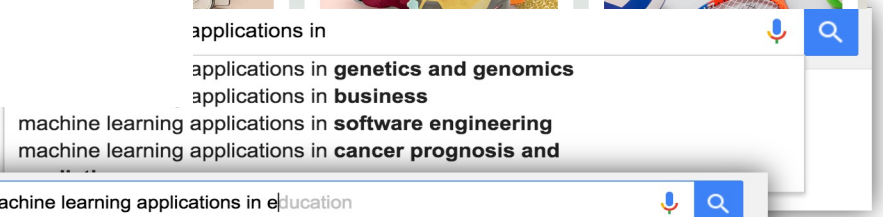


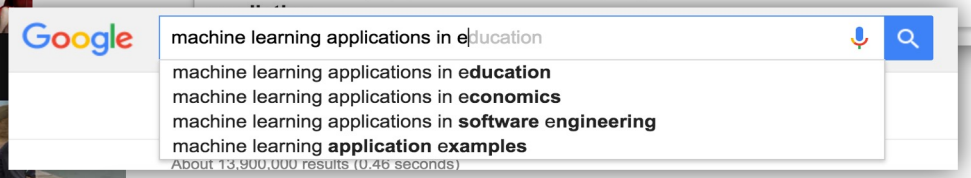


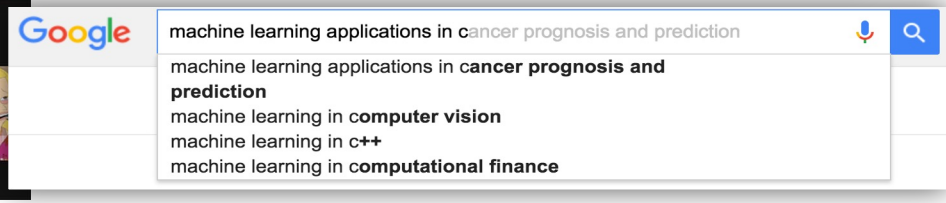
amazon



Google



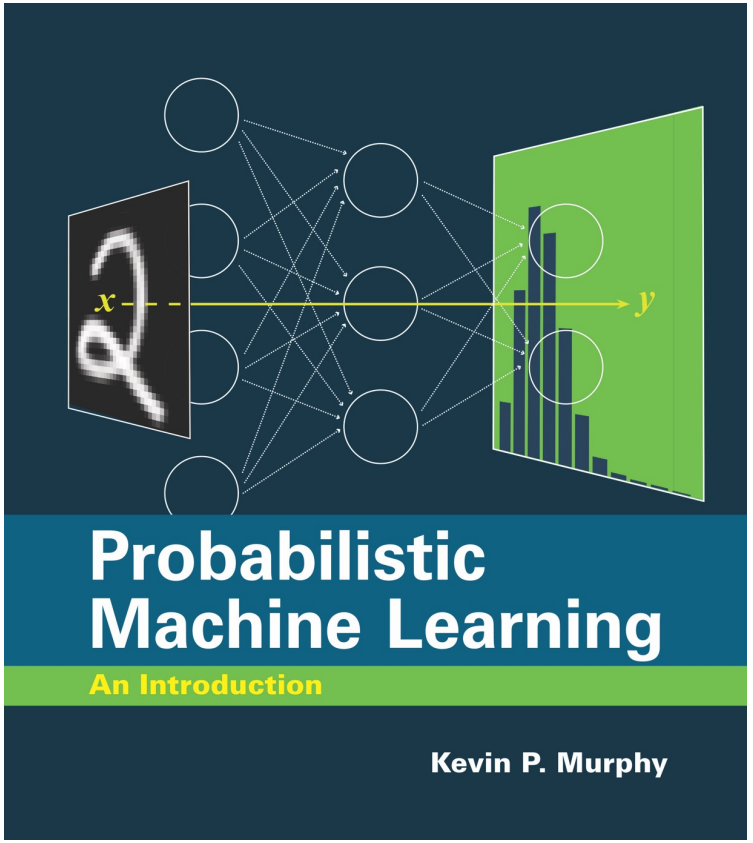




Machine Learning

"A computer program is said to learn from experience E with respect to some class of tasks T, and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."

– Mitchell 1997



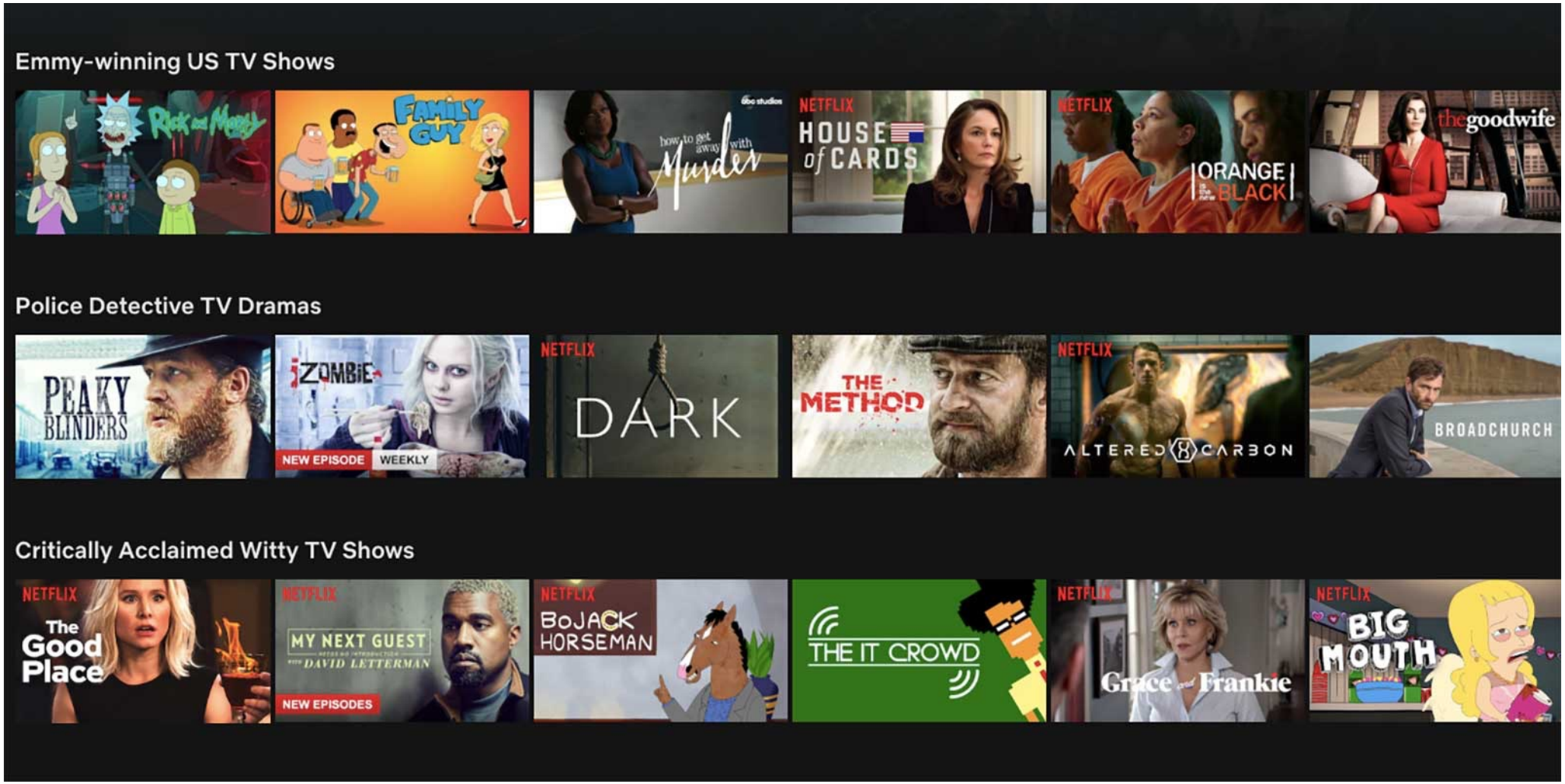
Use Face ID on your iPhone or iPad Pro

Face ID lets you securely unlock your iPhone or iPad, authenticate purchases, sign in to apps, and more — all with just a glance.

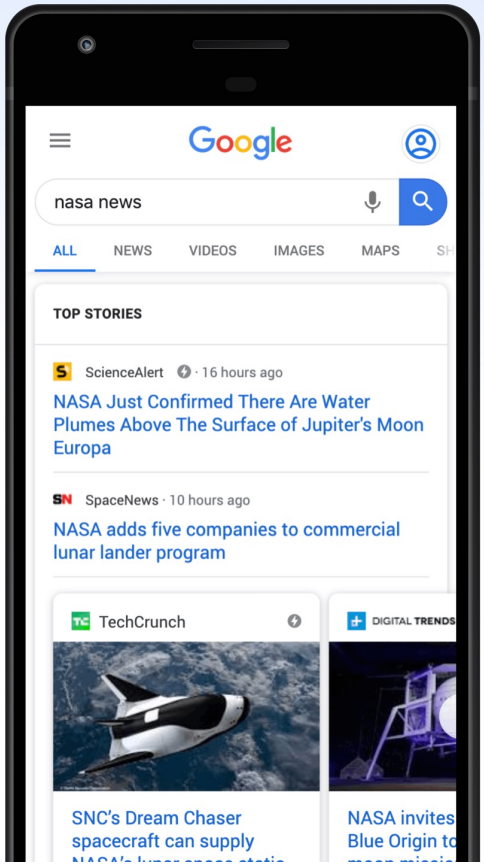
adaptable to changing needs

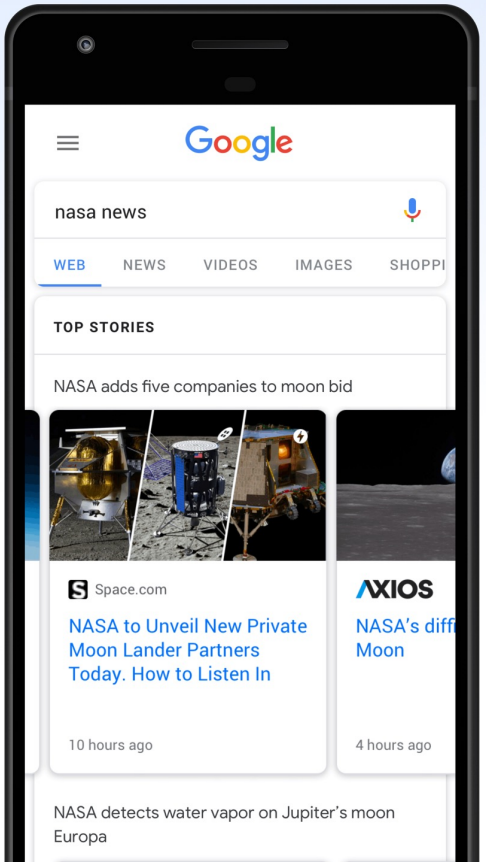
now with a mask

Related topic: Convolutional Neural Networks



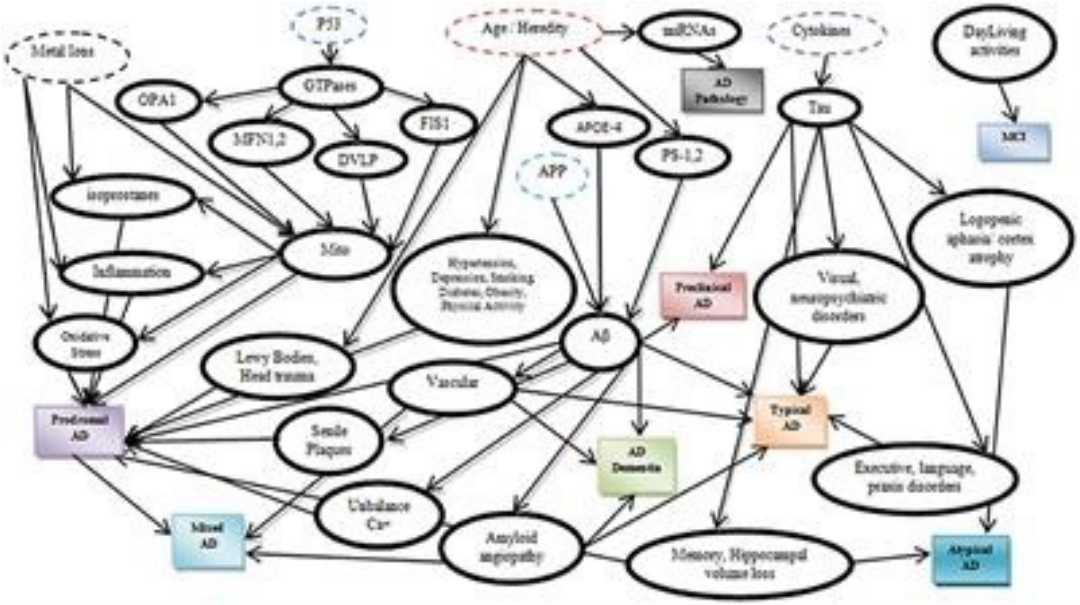
Related topic: Collaborative filtering

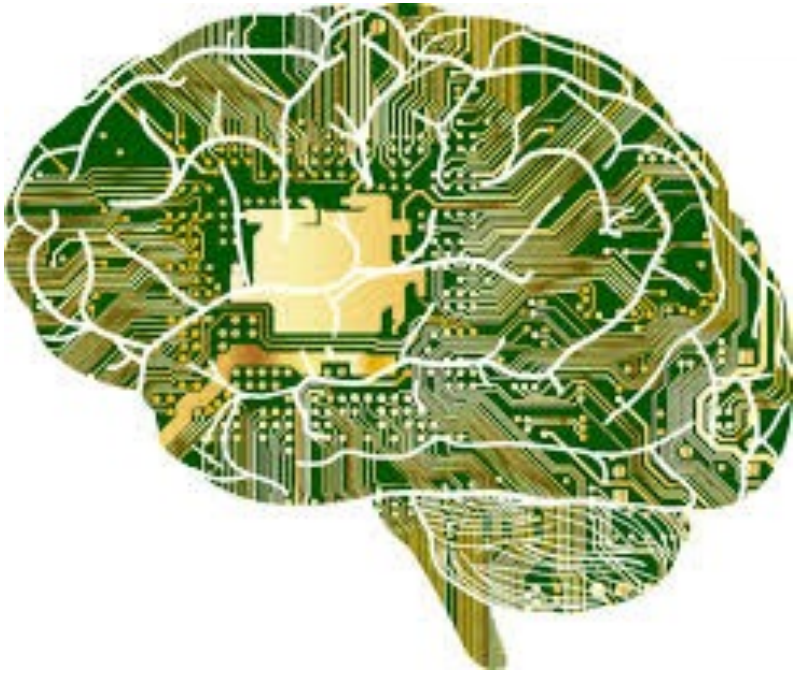




”Now, when there are multiple stories related to your search, we'll also organize the results by story so it's easier to understand what's most relevant and you can make a more informed decision on which specific articles to explore. ”

Related topic: Clustering



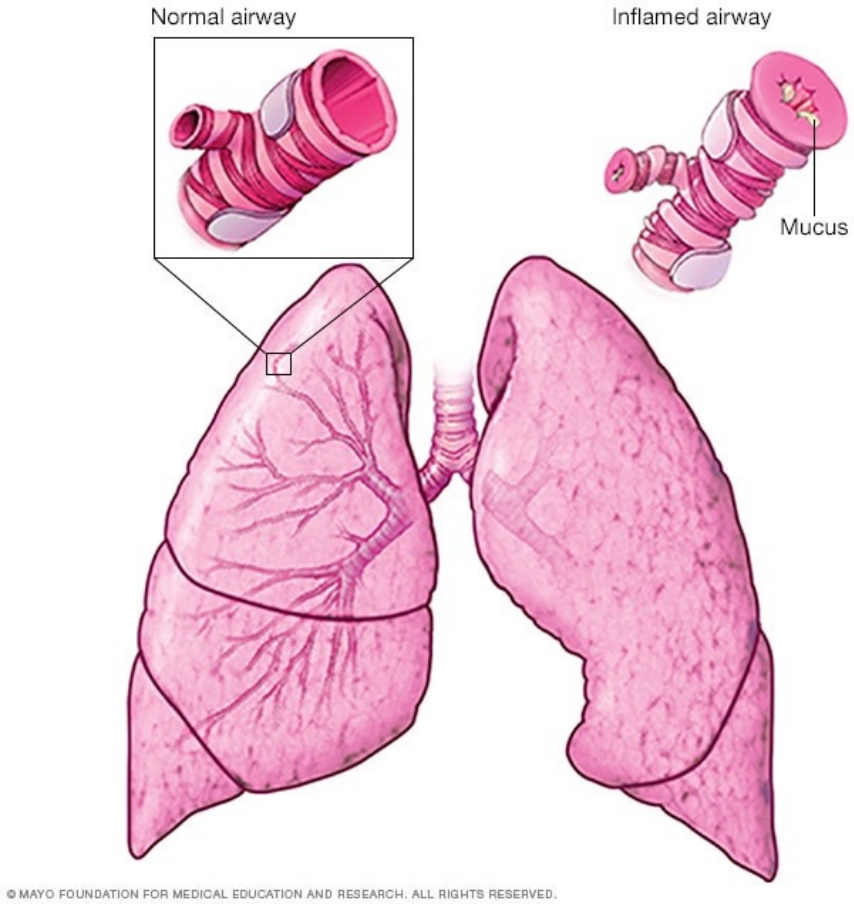


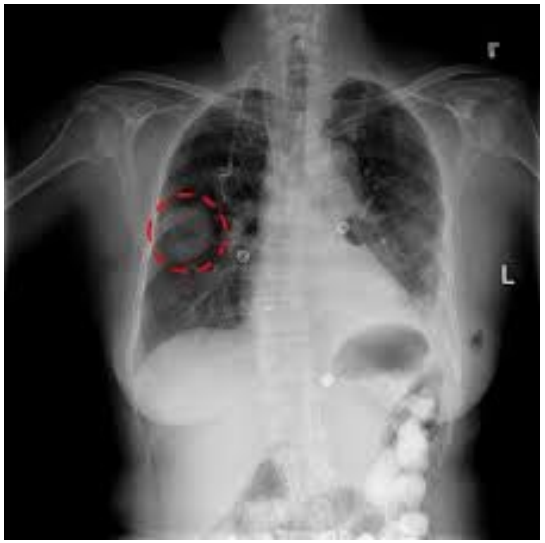
Related topic: Bayesian Networks

Toxicity in Machine Learning

Use with caution!

"But what the O.C. Bible should've said is: 'Thou shalt not make a machine to counterfeit a *human* mind.'



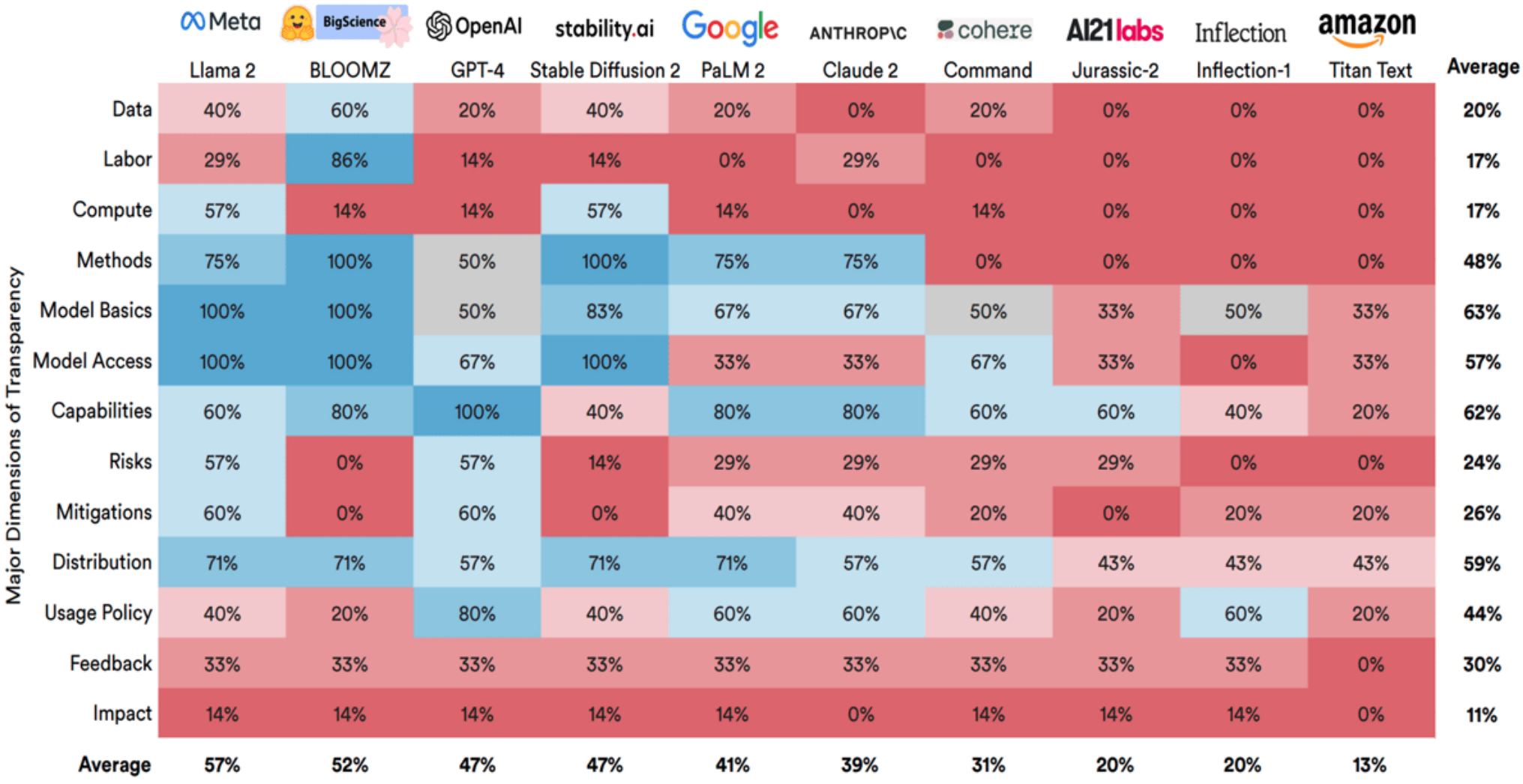


"HasAsthma(x) ⇒ LowerRisk(x)"

Intelligible Models for HealthCare: Predicting Pneumonia Risk and Hospital 30-day Readmission
Caruana et. al. 2015

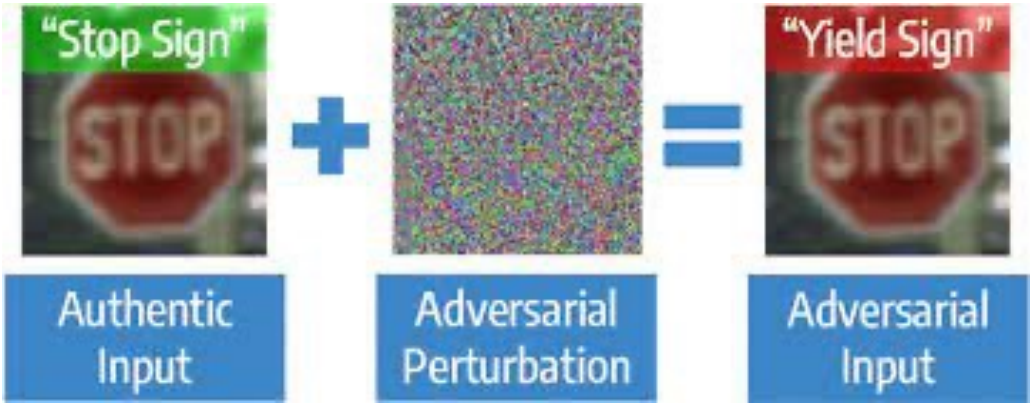
trade-off between interpretability and accuracy

Foundation Model Transparency Index



Major Dimensions of Transparency	Meta Llama 2	BigScience BLOOMZ	OpenAI GPT-4	stability.ai Stable Diffusion 2	Google PaLM 2	ANTHROPIC Claude 2	cohere Command	AI21labs Jurassic-2	Inflection Inflection-1	amazon Titan Text	Average
Data	40%	60%	20%	40%	20%	0%	20%	0%	0%	0%	20%
Labor	29%	86%	14%	14%	0%	29%	0%	0%	0%	0%	17%
Compute	57%	14%	14%	57%	14%	0%	14%	0%	0%	0%	17%
Methods	75%	100%	50%	100%	75%	75%	0%	0%	0%	0%	48%
Model Basics	100%	100%	50%	83%	67%	67%	50%	33%	50%	33%	63%
Model Access	100%	100%	67%	100%	33%	33%	67%	33%	0%	33%	57%
Capabilities	60%	80%	100%	40%	80%	80%	60%	60%	40%	20%	62%
Risks	57%	0%	57%	14%	29%	29%	29%	29%	0%	0%	24%
Mitigations	60%	0%	60%	0%	40%	40%	20%	0%	20%	20%	26%
Distribution	71%	71%	57%	71%	71%	57%	57%	43%	43%	43%	59%
Usage Policy	40%	20%	80%	40%	60%	60%	40%	20%	60%	20%	44%
Feedback	33%	33%	33%	33%	33%	33%	33%	33%	33%	0%	30%
Impact	14%	14%	14%	14%	14%	0%	14%	14%	14%	0%	11%
Average	**57%**	**52%**	**47%**	**47%**	**41%**	**39%**	**31%**	**20%**	**20%**	**13%**	

source: Stanford Center for Research on Foundation Models



Szegedy, C., Zaremba, W., Sutskever, I., Bruna, J., Erhan, D., Goodfellow, I. and Fergus, R., 2013. Intriguing properties of neural networks.

Buolamwini, J., Gebru, T. [2018]
"Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification."

https://www.nytimes.com/2018/02/09/technology/facial-recognition-race-artificial-intelligence.html

Color Matters in Computer Vision

Facial recognition algorithms made by Microsoft, IBM and Face++ were more likely to misidentify the gender of black women than white men.

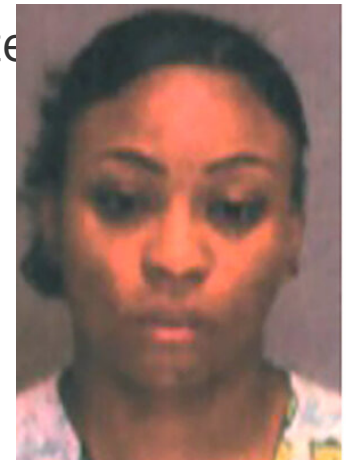
Gender was misidentified in **up to 1 percent of lighter-skinned males** in a set of 385 photos.

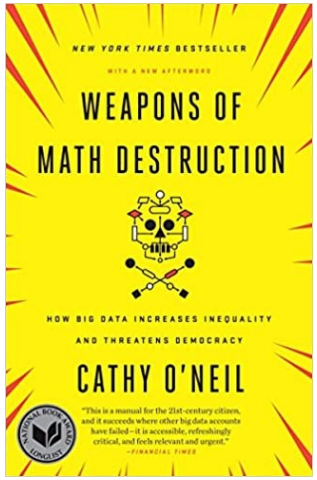
Gender was misidentified in **up to 7 percent of lighter-skinned females** in a set of 296 photos.

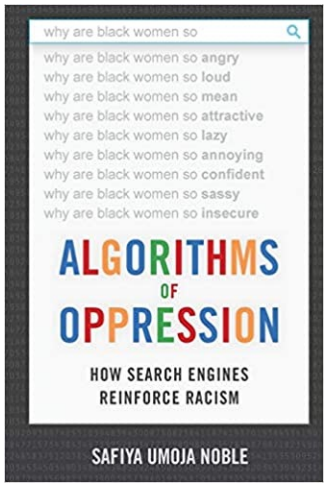
Gender was misidentified in **up to 12 percent of darker-skinned males** in a set of 318 photos.

Gender was misidentified in **35 percent of darker-skinned females** in a set of 271 photos.

Hill, Kashmir. "Eight Months Pregnant and Arrested Afte
False Facial Recognition Match." *International New York Times*, 9 Aug. 2023, p. NA. *Gale In Context: Global Issues*
https://www.nytimes.com/2023/08/06/technology/facial-recognition-false-arrest.html







In January 2020, Robert Williams was wrongfully arrested based on a flawed match from a facial recognition algorithm
https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html
https://www.technologyreview.com/2021/04/14/1022676/robert-williams-facial-recognition-lawsuit-aclu-detroit-police/

ChatGPT leans liberal, research shows
Chatbots are ingrained with political biases picked up from their training data -- which in most cases is unfiltered text from the web
https://www.washingtonpost.com/technology/2023/08/16/chatgpt-ai-political-bias-research/
More human than human: measuring ChatGPT political bias
https://link.springer.com/article/10.1007/s11127-023-01097-2

AI language models are rife with different political biases
New research explains you'll get more right- or left-wing answers, depending on which AI model you ask.
https://www.technologyreview.com/2023/08/07/1077324/ai-language-models-are-rife-with-political-biases/

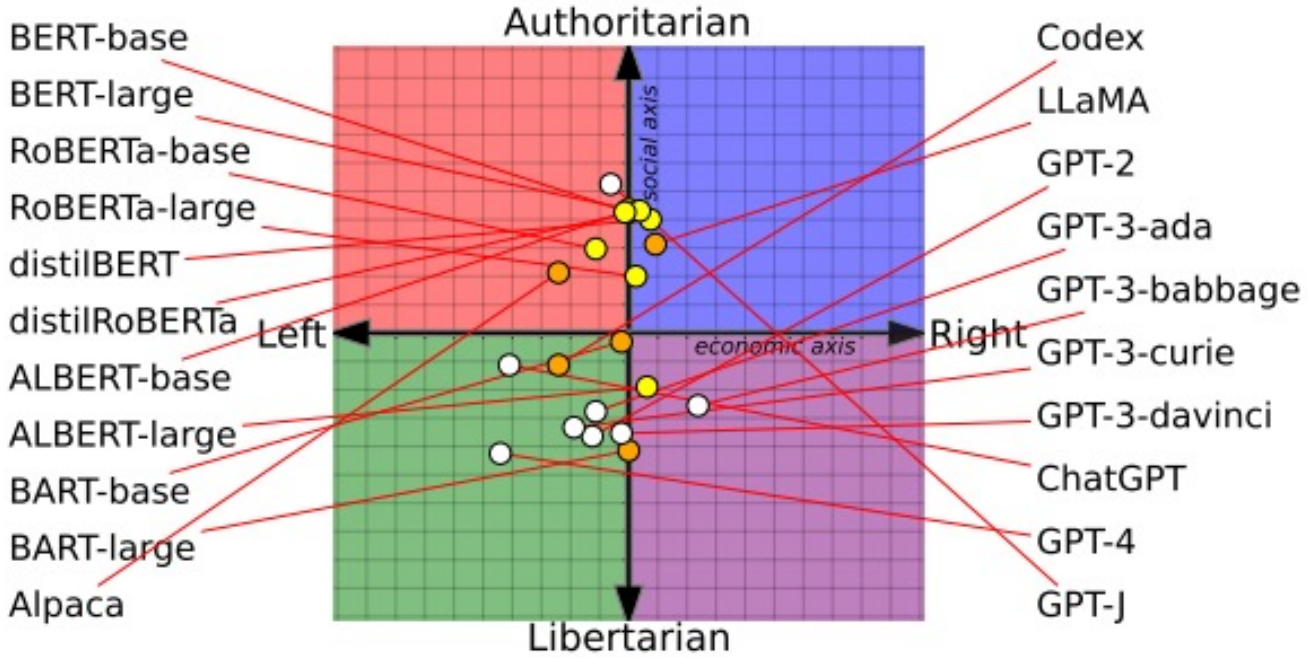


Chart by Shangbin Feng, Chan Young Park, Yuhan Liu and Yulia Tsvetkov.

“Just as electricity transformed almost everything 100 years ago, today I actually have a hard time thinking of an industry that I don’t think AI will transform in the next several years,”

- Andrew Ng

What is this class about?

according to the course catalog

- Theory and implementation of state-of-the-art machine learning algorithms for large-scale real-world applications.

- Topics include supervised learning (regression, classification, kernel methods, neural networks, and regularization) and unsupervised learning (clustering, density estimation, and dimensionality reduction).

What this course *is not*

- focused only on *applied* machine learning
  - we are interested in the origins of algorithm and their mathematical interpretation
  - be prepared for some math-heavy assignments!

- focused only on *theoretical* machine learning
  - we are also interested in applying algorithms to datasets to get hands-on experience with the algorithms
  - be prepared for some programming-heavy assignments!

Warning – math ahead!!

- This course is *not* for you if you want to *only* learn to apply packages to datasets!

- We will focus a lot of lecture on derivations to get a deeper understanding of the underlying algorithms
  - optimization-based and statistics-heavy perspective!

- This course *is* for you if you want to develop a deep understanding of ML algorithms and learn to implement (and potentially improve!) them

Prerequisites

- (Enforced) MATH 214 or 217 or 296 or 417 or 419 or ROB 101
- (Advisory) STATS 250 or equivalent (STATS 412 is good)
- (Enforced) EECS 281
  - some experience in Python/MATLAB is helpful
  - nontrivial level of programming is required.

NOTE:

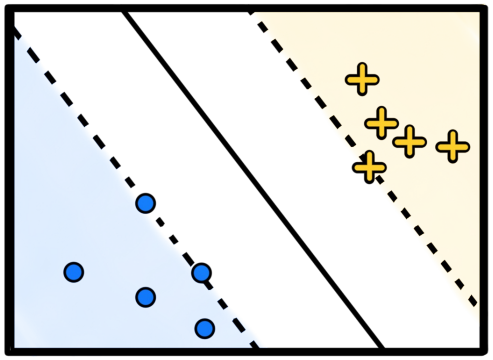
see wolverineaccess for up to date details on prerequisites

Course Logistics

Course staff

- **Professors:**
  - Sindhu Kutty (she/her/hers) skutty@umich.edu
  - Maggie Makar (she/her/hers) mmakar@umich.edu
- **GSI**
  - Tiffany Parise (she/her/hers)
- **IAs:**
  - **Lead IA**: Sachchit Kunichetty (he/him/his)
  - Matthew Cooper (he/him/his)
  - Evan Gebo (he/him/his)
  - Emre Hayir (he/him/his)
  - Jiangnan Huang (she/her/hers)
  - Alex de la Iglesia (he/him/his)
  - Madhavan Iyengar (he/him/his)
  - Oskar Shiomi Jensen (he/him/his)
  - Akseli Kangaslahti (he/him/his)
  - Julie Wu (she/her/hers)
  - Jason Zhang (he/him/his)

EECS 445 TEACHING TEAM



we put the support in support vector machines

Our Wonderful Course Staff

Emre Hayir
(he/him/his)

Sachchit Kunichetty
(he/him/his)

Akseli Kangaslahti
(he/him/his)

Jiangnan Huang

Jason Zhang
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Evan Gebo
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Julie Wu
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Matthew Cooper
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Tiffany Parise
(she/her/hers)

Madhavan Iyengar
(he/him/his)

Oskar Shiomi Jensen
(he/him/his)

Prof. Makar

Things I do (and love…)

EECS 445. Introduction to Machine Learning

Michigan Student Symposium for Interdisciplinary Statistical Sciences

LSA UNDERGRADUATE RESEARCH OPPORTUNITY PROGRAM UNIVERSITY OF MICHIGAN

GRACE HOPPER CELEBRATION

ANITA B.ORG

Undergraduate Programs

Explore some of the most impactful programs in science and engineering.

- BSE, Computer Science (Eng) >
- BS, Computer Science (LSA) >
- BSE, Computer Engineering (Eng) >
- BSE, Data Science (Eng) >
- BS, Data Science (LSA) >
- Minor, Computer Science >

CMDiT Fostering Innovation Through Inclusion

TAPIA Conference

Summer Undergraduate Research

SURE

Project X — Participating Teams

AN ML RESEARCH COMPETITION FOCUSED ON

HEALTH

Epidemiology
Clinical Practice
Genetics

WITH A PRIZE POOL OF

$75,000

COLLEGE OF ENGINEERING MULTIDISCIPLINARY DESIGN PROGRAM UNIVERSITY OF MICHIGAN

A joint venture of ACM and Microsoft

ACM Student Research Competition

OUTREACH ›

exploreCSR

Google's exploreCSR awards aid higher education efforts to su
careers in computing

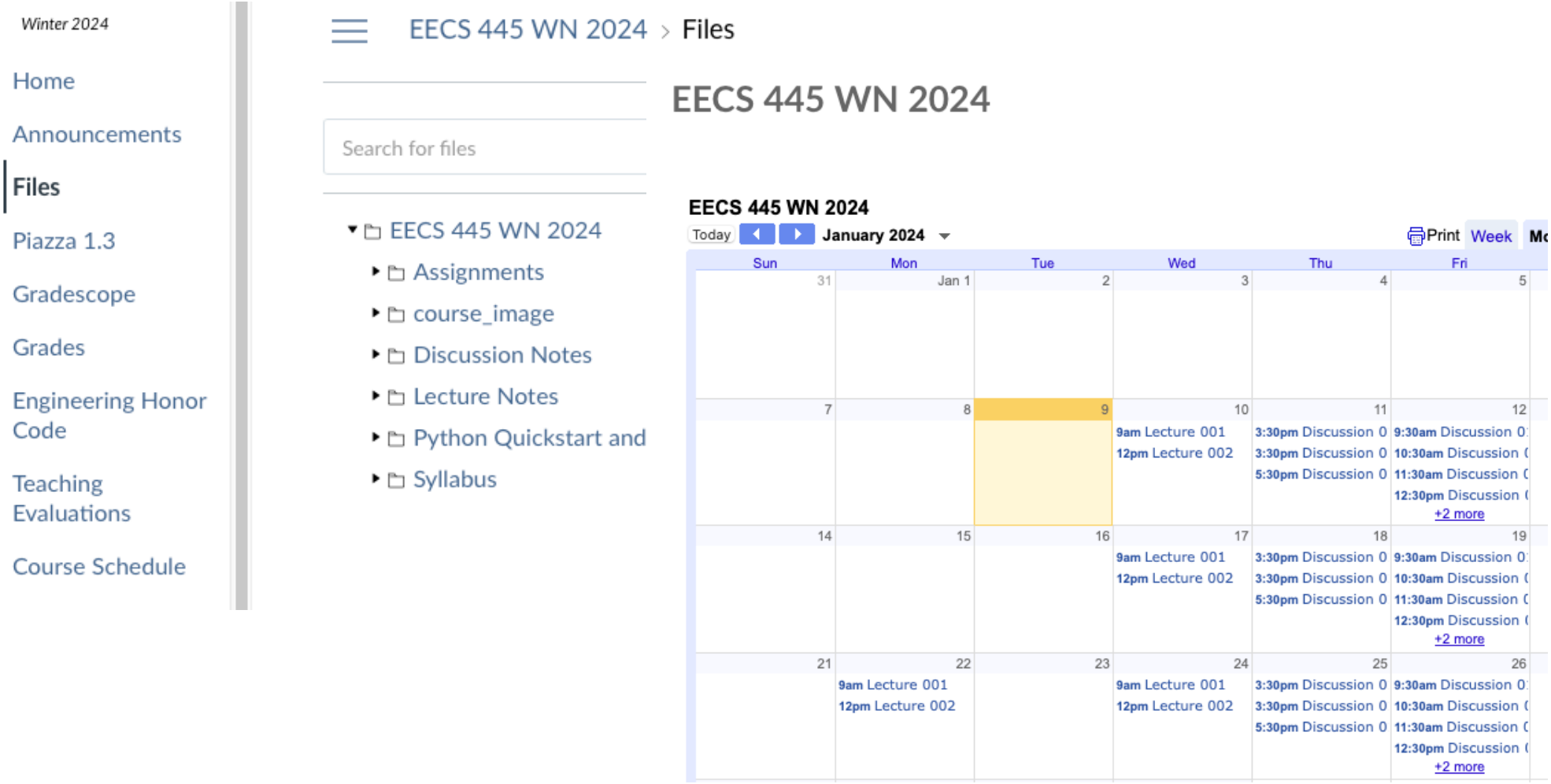
Michigan Student Artificial Intelligence Lab (MSAIL)

MDST

CSE | DEI + CLIMATE

Resources: Canvas

For Logistics. Contains Calendar, Syllabus, Schedule, HWs, Projects, Lecture Recordings and Slides, Discussion, link to Piazza, Gradescope etc..



Course Schedule

embedded content

Course Schedule

EECS445W24Schedule : Schedule

Date	Topic	Instructor	Released	Due @ 10pm
Wed, Jan 10	Lec 1: Introduction	Kutty		
Mon, Jan 15	**MLK Jr Day; No lecture**			
Wed, Jan 17	Lec 2: Learning Linear Classifiers, Perceptron Algorithm	Kutty	HW1	
Mon, Jan 22	Lec 3: Linear Classifiers Non-Separable Case, Gradient Descent	Kutty		
Wed, Jan 24	Lec 4: Generalization Error and Support Vector Machines (Geometric Margin; Primal Form	Kutty		
Mon, Jan 29	Lec 5: Soft Margin SVM	Kutty		
Tue, Jan 30				HW1
Wed, Jan 31	Lec 6: Feature Mapping and Dual Formulation of SVMs	Kutty	Project 1	
Mon, Feb 5	Lec 7: SVMs and the Kernel Trick	Kutty		
Wed, Feb 7	Lec 8: Linear Regression - Empirical Risk & Least Squares, Regularization	Kutty		
Mon, Feb 12	Lec 9: Decision Trees; Entropy	Makar		
Tue, Feb 13				Project 1
Wed, Feb 14	Lec 10: Bagging; Random Forest	Makar	HW2	
Mon, Feb 19	Lec 11: Boosting; Adaboost	Makar		
Tue, Feb 20				
Wed, Feb 21	Lec 12: Introduction to Ne			
Mon, Feb 26				

Optional Reading:
D 1.1, 1.2

KEY

[D] A course in Machine Learning by Hal Daume III (available online

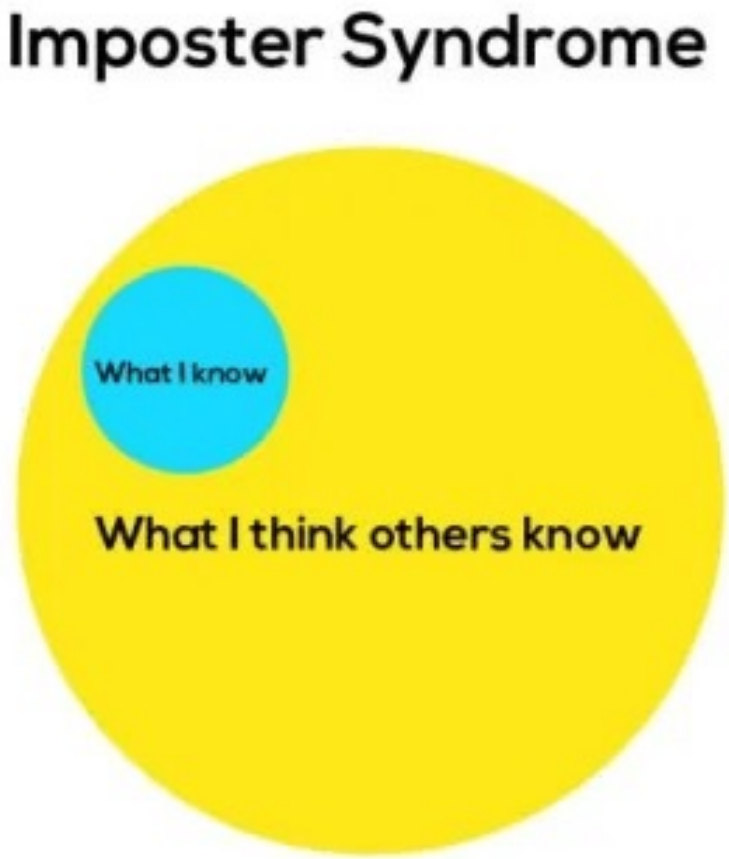
[B] Pattern Recognition and Machine Learning by Christopher Bisho

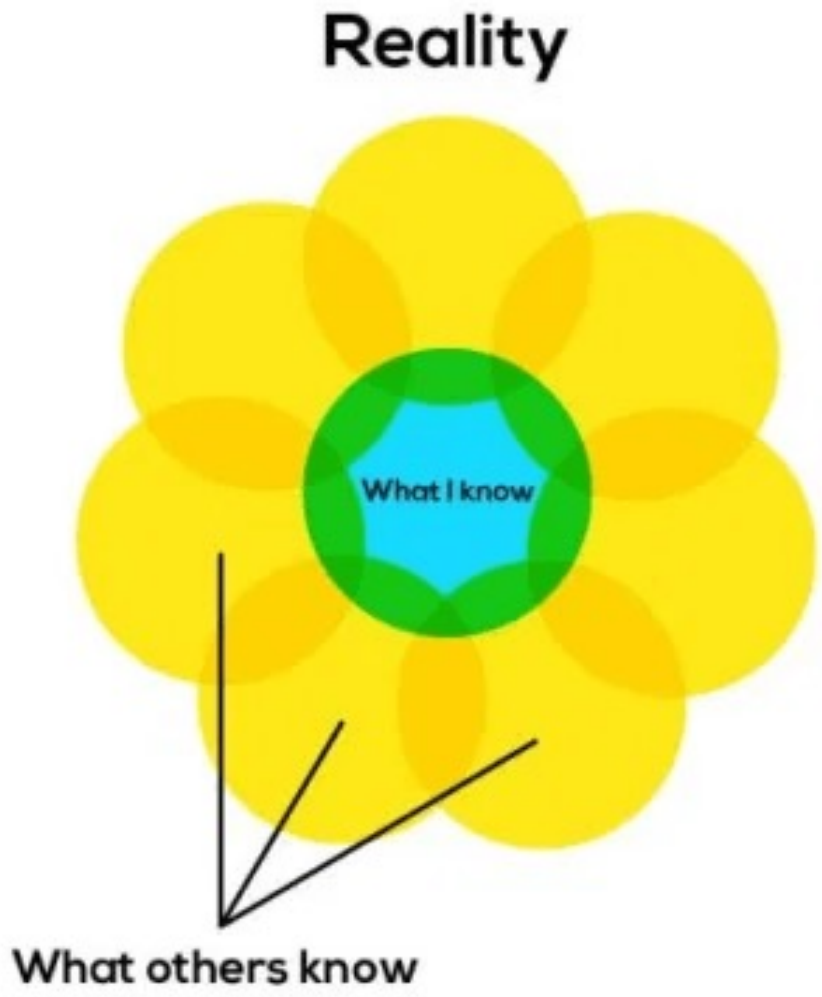
[M] Probabilistic Machine Learning: An Introduction by Kevin Murph

Resources: Lectures

- In person lectures
- Lecture recordings will be posted on canvas
- slides will be provided

A note on (in-class) questions





Resources: Piazza

- **strictly for course content**
  - Piazza can help you connect with other students in the class
  - You can answer each other's questions
  - You can clarify confusion on course material
- **Code of conduct**: Be respectful of each other and course staff

  It is our intention that students from all backgrounds and perspectives will be well served by this course, and that the diversity that students bring to this class will be viewed as an asset. We welcome individuals of all ages, backgrounds, beliefs, ethnicities, genders, gender identities, gender expressions, national origins, religious affiliations, sexual orientations, socioeconomic background, family education level, ability – and other visible and nonvisible differences. All members of this class are expected to contribute to a respectful, welcoming and inclusive environment for every other member of the class. Your suggestions are encouraged and appreciated. Further, we will gladly honor your request to address you by an alternate name or gender pronoun.

Resources: email

- Use piazza for collaborative learning
- For questions meant for course staff/professors contact us
  - e.g., emergencies, policy, comments etc.
  - multiple modes:
    - For immediate responses Lectures, Discussions and Office hours
      - see calendar for staff office hours and “proffice” hours
    - **Staff E-mail: eecs445-staff@umich.edu**
    - You may contact profs directly
      - include **[EECS445 W24]** in subject line

Resources: Discussion Notes

Starting this week

We will cover:

- Review of prerequisites
  - Linear Algebra, Matrix Calculus
- Review Lecture materials
- Problems focused

Additional in person review sessions:

- **Python tutorial coming soon**: in person + recorded (see calendar for details)
- Project quick start sessions
- Exam review sessions

Study group

- Collaborative learning helps! Form your study group early on!
- For homework, you may discuss concepts between the study group members, but you should write your own solution independently. Never share your solutions! In the homework submissions, you must put the names of your collaborators if you have discussed ideas in depth
- Please start assignments early. (Warning: cramming does not work!)

Grading policy

- Exams:
  - Midterm (20%)
  - Final (25%)
- Assignments:
  - 4 evenly weighted Homeworks (25%)
  - 2 evenly weighted Projects (20%)
- Quizzes* (9.5%)
- Course Evaluation (0.5%)

Quizzes

- (*Approximately*) weekly quizzes based on lecture and discussion material are due at the dates noted (*typically* on Sundays 10pm ET). Quizzes will be submitted on Gradescope*.
- Most will be graded for correctness
  - to get 9.5/9.5, correctly answer and get a score 66% of the *total* score across *all quizzes*
  - if you get < 66%, your final exam will be worth 34.5%
- Quiz 0 is special!
  - a bonus quiz
    - will be worth a (bonus) point only if you need it to meet the threshold
  - unusual due date (Tuesday 10pm)
  - I want to get to know you and your background – please take it!
    - google form → will not collect associated email

Quiz 0

STUDENT NAME

Search students by name or email...

Q1 Survey

0 Points

Please complete this survey.

After you have completed the survey (honor code applies!), please select the option below and **be sure to save your answer *and* submit** to ensure credit.:

- [ ] I have completed the survey

Save Answer

Save All Answers

Submit & View Submission ›

Course Background Material

This survey will not be graded for correctness but will be graded for completion (worth a bonus quiz point). We will not be collecting your email address associated with your survey responses. So **be sure to submit your responses here as well as indicate your submission on gradescope**!

In this section, you will answer some questions that will help us ascertain your background in prerequisite material.

skutty@umich.edu Switch account

Not shared

* Indicates required question

Prior courses (linear algebra) *

- [ ] ROB 101
- [ ] MATH 214
- [ ] MATH 217
- [ ] MATH 417
- [ ] MATH 419
- [ ] Other:

When was the most recent semester in which you encountere

More about you

As a reminder, in this course we want to promote a culture of respect and will work to provide a space conducive to learning and intellectual exploration. We'd like to get to know you better and want to provide a space where you can voice your concerns. Please note that ALL of these questions are OPTIONAL.

Why did you choose to take EECS 445?

Your answer

What are you most looking forward to learning about?

Your answer

How challenging did you find 203?

Exams

Midterm:
Wednesday, March 6, 7pm-9pm*
in person

Final:
Thursday, April 25, 7pm-9pm*
in person

**extended exams start at 5pm*
Email profs directly if you have a conflict with either of the exams
Also be sure to submit accommodation requests through the SSD office
BOTH ARE DUE **by January 26 at 10pm ET**

Submitting Assignments

- (*Approximately*) (bi-)weekly assignments are due at the dates noted (*typically* on Tuesdays 10pm ET) submitted on Gradescope.
- Solutions released 3 days after due date
  - always review!
- Regrades *only* via gradescope

Late Policy

- It is imperative that you complete your course assignments in a timely manner.
  - concepts are interdependent, assignments solidify your understanding

- Deadlines are strict!

- For each **assignment type (projects or homework)** you have a total of three penalty-free late days to be used at your discretion
  - use wisely and (only) for ***exceptional*** circumstances
  - counted late days in increments of days starting immediately
  - for more extreme life events, we will refer you to student support services
    - requires documentation e.g., medical documentation that explicitly specifies both a timeline and states that you are unable to engage in your coursework

No late submissions will be accepted after three days have been used up

Assignments – Homeworks

- **There will be 4 homework assignments.**
- Goal: strengthen the understanding of the fundamental concepts, mathematical formulations, algorithms, and the applications.
- Homework #1 will be out Tuesday (01/16) – due Tuesday (01/30) at 10pm ET
  - Python/numpy tutorial

Assignments – Projects

- **There will be 2 projects**
- Goal: *open-ended* project designed to strengthen the understanding of the fundamental concepts, while developing some intuition and practical knowledge in applying ML algorithms to real datasets.
- These projects will all include programming assignments to implement algorithms covered in the class and real datasets.
- An important learning objective achieved in successfully completing an upper level course in Machine Learning is gaining confidence in your ability to problem solve in this space. The course projects will also give you an opportunity to learn to *read specs* and *documentation*.

Course Evals

- Your voice matters!
- We appreciate and acknowledge your effort
  - Students will receive full credit iff they
    - submit the final course evaluations **and** upload a screenshot of completion
- midterm evaluations are not required it is **strongly encouraged**.

Next steps

- Familiarize yourself with syllabus and canvas for resources
- See canvas for recordings and notes
- Access weekly quizzes on gradescope – note due dates!
- Reach out if you have any questions
- **Advice**:
  - attend lectures in-person
  - attend discussions in-person
  - review the material on a weekly basis
  - Do all the weekly quizzes
  - Get started *early* on assignments
  - take the sample exams
  - get to know your GSI/IAs!

Linear Classification:
From Intuition to Formal Definitions

predicting the helpfulness of a review

Fan G

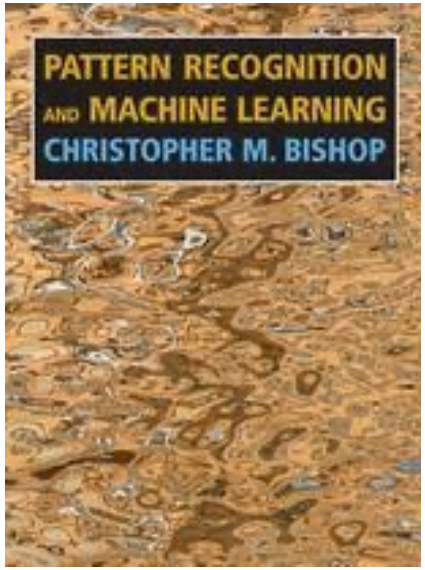
★★★★☆ **Great book for theoretical machine learning**

Reviewed in the United States on September 2, 2018

Verified Purchase

A very in-depth book on the topic. I used this book for my graduate level Machine Learning and Bayesian Methods courses. The book assumes solid math or other quantitative backgrounds from readers, as it jumps right into advanced calculus, linear algebra and optimization without much explanation. It pretty much expects you to derive the intermediate steps yourself or read the details from the original paper. I would only recommend it to people studying or doing research in theoretical machine learning.

amazon



e

★★★★★ **Still (one of) the best**

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I recently had to quickly understand some facts about the probabilistic interpretation of pca. Naturally I picked up this book and it didn't disappoint. Bishop is absolutely clear, and an excellent writer as well.

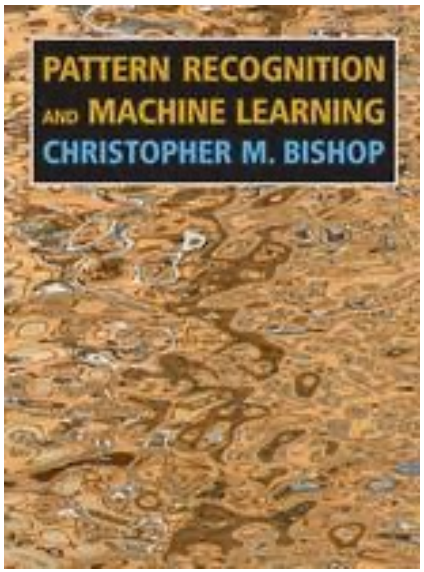
In my opinion, despite the recent publication of Kevin Murphy's very comprehensive ML book, Bishop is still a better read. This is mostly because of his incredible clarity, but the book has other virtues: best in class diagrams, judiciously chosen; a lot of material, very well organized; excellent stage setting (the first two chapters). Now, sometimes he's a bit cryptic, for example, the proof that various kinds of loss lead to conditional median or mode is left as an exercise (ex 1.27). Murphy actually discusses it in some detail. This is true in general: Murphy actually discusses many things that Bishop leaves to the reader. I thought chapters three and four could have been more detailed, but I really have no other complaints.

Please note that in order to get an optimal amount out of reading this book you should already have a little background in linear algebra, probability, calculus, and preferably some statistics. The first time I approached it was without any background and I found it a bit unfriendly and difficult; this is no fault of

Read more

77 people found this helpful

Helpful | Comment | Report abuse



J. MEJIA Muñoz

★☆☆☆☆ **In general, most of the topics are not clearly ...**

Reviewed in the United States on April 22, 2018

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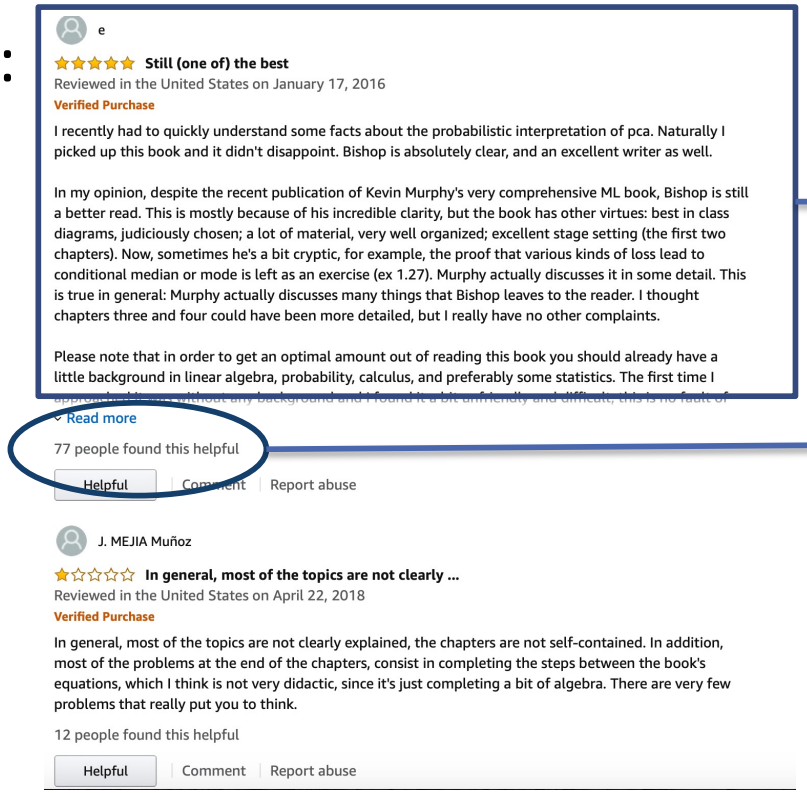
In general, most of the topics are not clearly explained, the chapters are not self-contained. In addition, most of the problems at the end of the chapters, consist in completing the steps between the book's equations, which I think is not very didactic, since it's just completing a bit of algebra. There are very few problems that really put you to think.

12 people found this helpful

Helpful | Comment | Report abuse

Supervised Learning

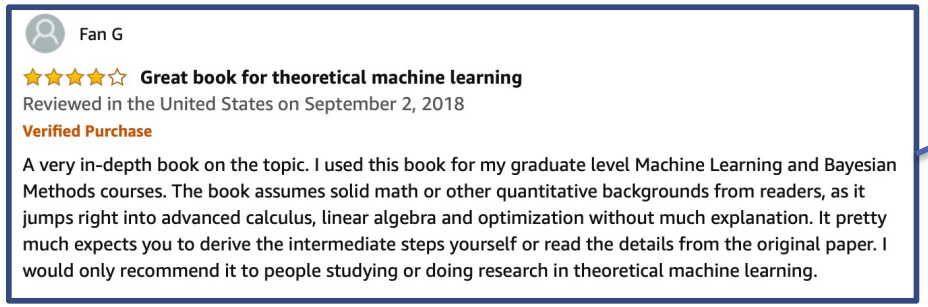
Given:



features of the review

label of the review

Goal:



features of the review

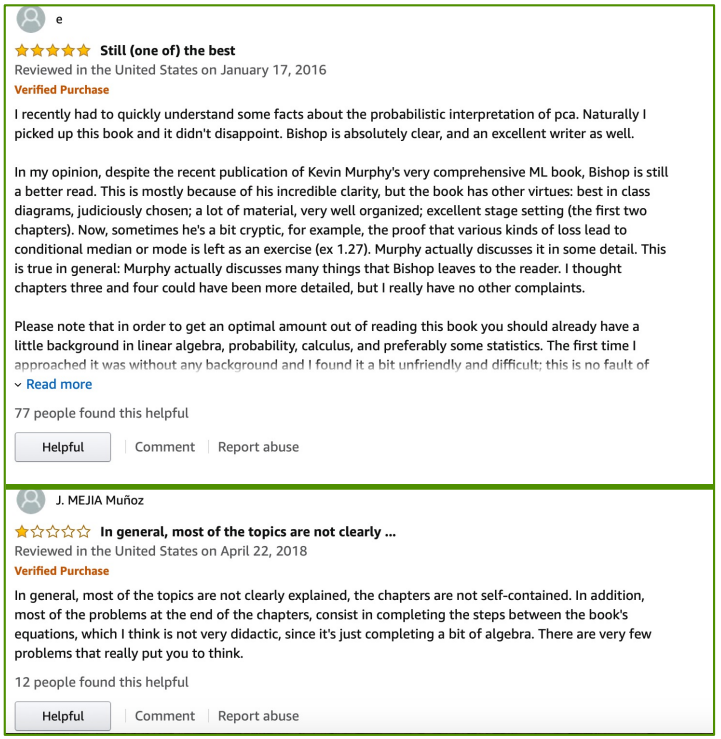
predict the label of the review

Supervised Learning: Classification

- Problem: predict whether a given review is helpful or unhelpful

Binary Classifier

- Given Labeled Data:
  - Features: star rating (1 – 5 stars), length of review (max length of 200 words)
  - Labels: helpful/unhelpful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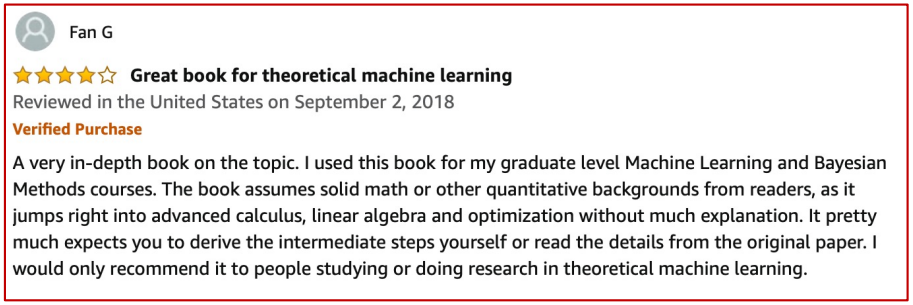
Helpful | Comment | Report abuse

- Predict label for *new datapoint*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Supervised Learning

Linear Binary Classifier

Supervised Learning - Classification

- Problem: predict whether a review is helpful (+) or unhelpful (-)

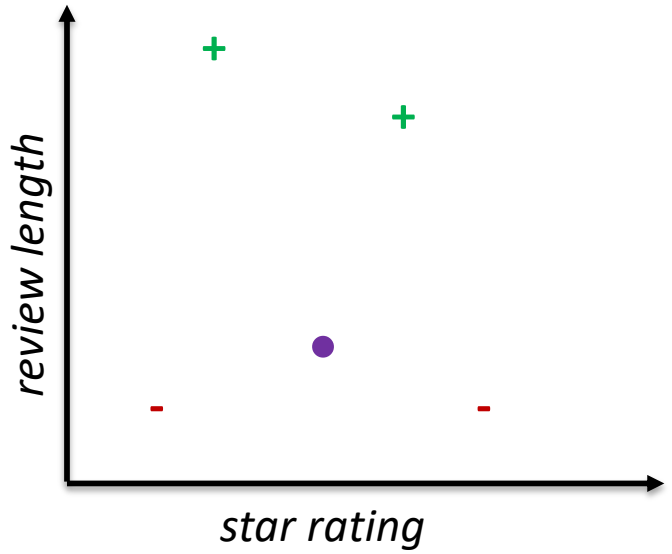
  Binary Classifier

- Data:
  - Features: star rating (1 – 5 stars),
    length of review (max length of 200 words).
  - Labels: helpful/unhelpful → *supervised* learning

Star rating	Review length	label
0.6	0.7	+
0.2	0.2	-
0.8	0.2	-
0.2	0.9	+
0.6	0.4	?

Supervised Learning - Classification

- Geometrically:



Star rating	Review length	label
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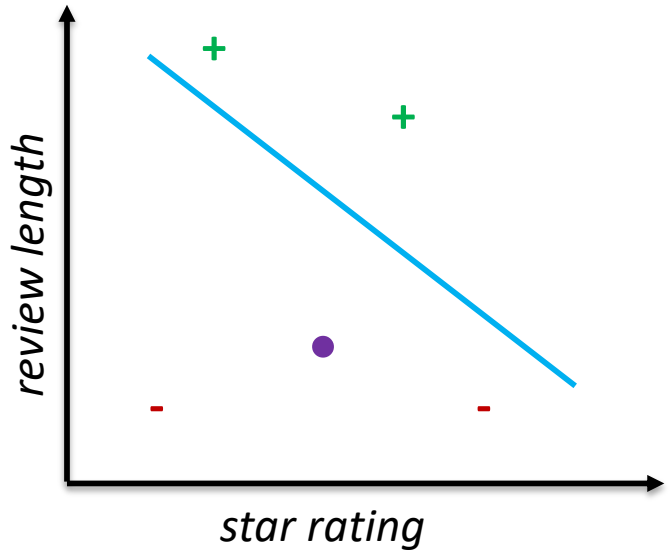
0.2	0.2	-
0.8	0.2	-
0.2	0.9	+
0.6	0.4	?

A. Predict +

B. Predict -

Supervised Learning - Classification

- Geometrically:



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0.8	0.2	-
0.2	0.9	+
0.6	0.4	?

- **Goal**: Learn a linear decision boundary

Why a linear decision boundary?

Have a great semester
and...
Have fun!

See you next time!