Statistics and Data Science 265 / 565

Introductory Machine Learning

Janary 12

Version of 2026/01/11 at 19:39

Yale

Outline

- Overview of course
- Perspectives on ML (and AI)
- Syllabus and logistics
- Questions

Course objectives

Gain understanding of and experience with basic machine learning methodology

Course objectives

- Gain some new perspective
- Appreciate some of the power and limitations of ML
- Reflect on societal implications of AI/ML
- Have fun
- Want to learn more

Related course

- This course introduced for Certificate in Data Science
- Intended to be accessible intro to ML for wide range of students
- S&DS 365/665 “Intermediate Machine Learning” can be taken as a follow up course; more technical and in-depth
- Happy to chat if unclear this course is right for you

Common questions

“What’s the difference between AI and Machine Learning?”

“Is Deep Learning the same as Machine Learning?”

“What’s the difference between Statistics and Machine Learning?”

August 31, 1955

John McCarthy, Marvin L. Minsky, Nathaniel Rochester,
and Claude E. Shannon

A Proposal for the

DARTMOUTH SUMMER RESEARCH PROJECT ON ARTIFICIAL INTELLIGENCE

June 17 - Aug. 16

We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.

The New York Times

SUNDAY, OCTOBER 19, 1958

MACHINE TO COPY BRAIN'S METHODS

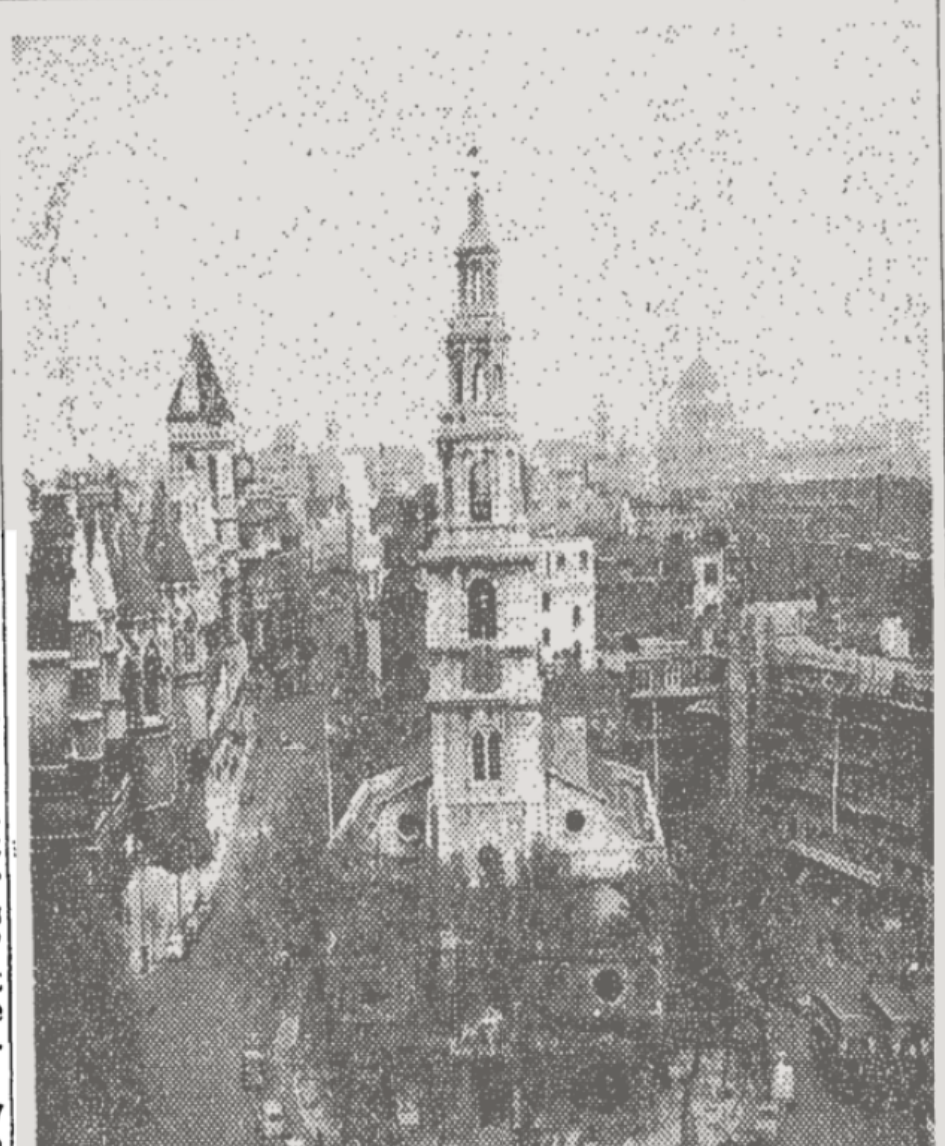
Huge Computer in London to 'Think' Like a Person for Study of Learning

Special to The New York Times.

LONDON, Oct. 15—Investigators in neurology at University College here are building a massive automatic computer for the principal purpose of testing theories about the learning capacity of the brain.

The machine will "think"; that is, it will scan shapes such as the letters of the alphabet and simple words and after analyzing and absorbing this visual information it will "say" (through a loudspeaker) what it has seen at precisely the same rate as that of a fairly intelligent human subject.

This is being achieved by

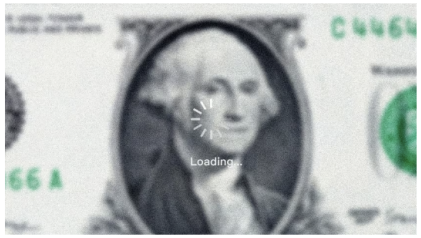


Today: A major force

Science & technology

Robots can learn new actions faster thanks to AI techniques

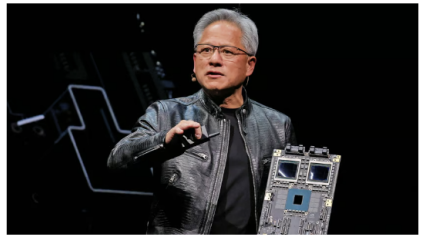
They could soon show their moves in settings from car factories to care homes



Finance & economics

Computers unleashed economic growth. Will artificial intelligence?

Two years after ChatGPT-3.5 arrived, progress has been slower than expected



Business

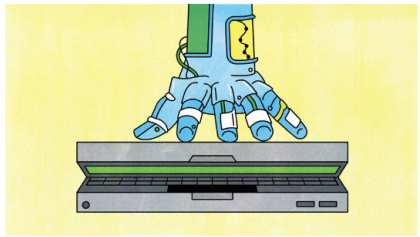
Nvidia's boss dismisses fears that AI has hit a wall

But it's "urgent" to get to the next level, Jensen Huang tells The Economist

Babbage

How AI will lead to a new scientific renaissance

Our podcast on science and technology. Nobel laureates Demis Hassabis and Jennifer Doudna, plus Google's James Manyika, present their vision for how AI is transforming science



Business

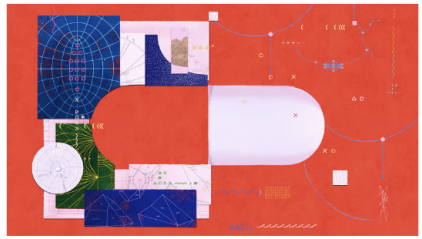
What ChatGPT's corporate victims have in common

The first casualties of generative AI offer lessons for other businesses

Science & technology in 2025

Supercomputers and AI are helping build better climate models

The coming year will be a big one for the advance of climate science



Science & technology in 2025

AI will boost drug development in 2025

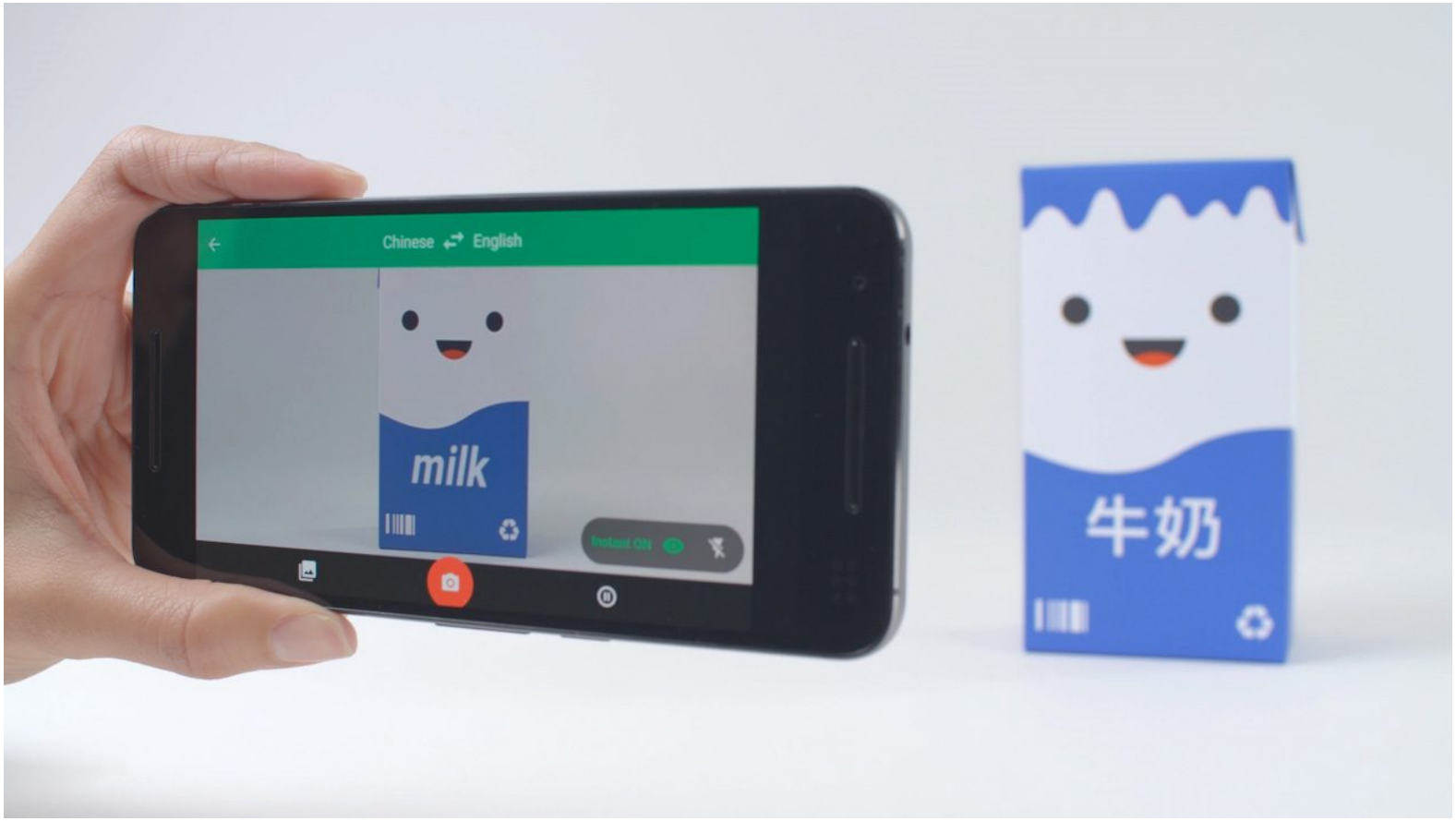
Software-inspired medicines are getting closer to prime time

Finance in 2025

There will be no immediate productivity boost from AI

Everyone calm down a little

Translation



http://www.sciencemag.org/

Translation

HOME > SPORTS

A Belarusian Olympian who complained about her coaches used Google Translate to relay her plea for help to Japanese police

Lauren Frias Aug 5, 2021, 6:46 PM

Belarusian Olympic sprinter Krystsina Tsimanouskaya said she was taken to the airport against her wishes and would not return home. Reuters

More translation

More translation

More translation

The New York Times

OPINION

Will Translation Apps Make Learning Foreign Languages Obsolete?

July 25, 2023

Prompt: “An AI taking over the world. Polygonal style. Retro Futurist.”

https://dimillian.medium.com/chatgpt-and-midjourney-will-change-our-life-forever-d5590836fbd9

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

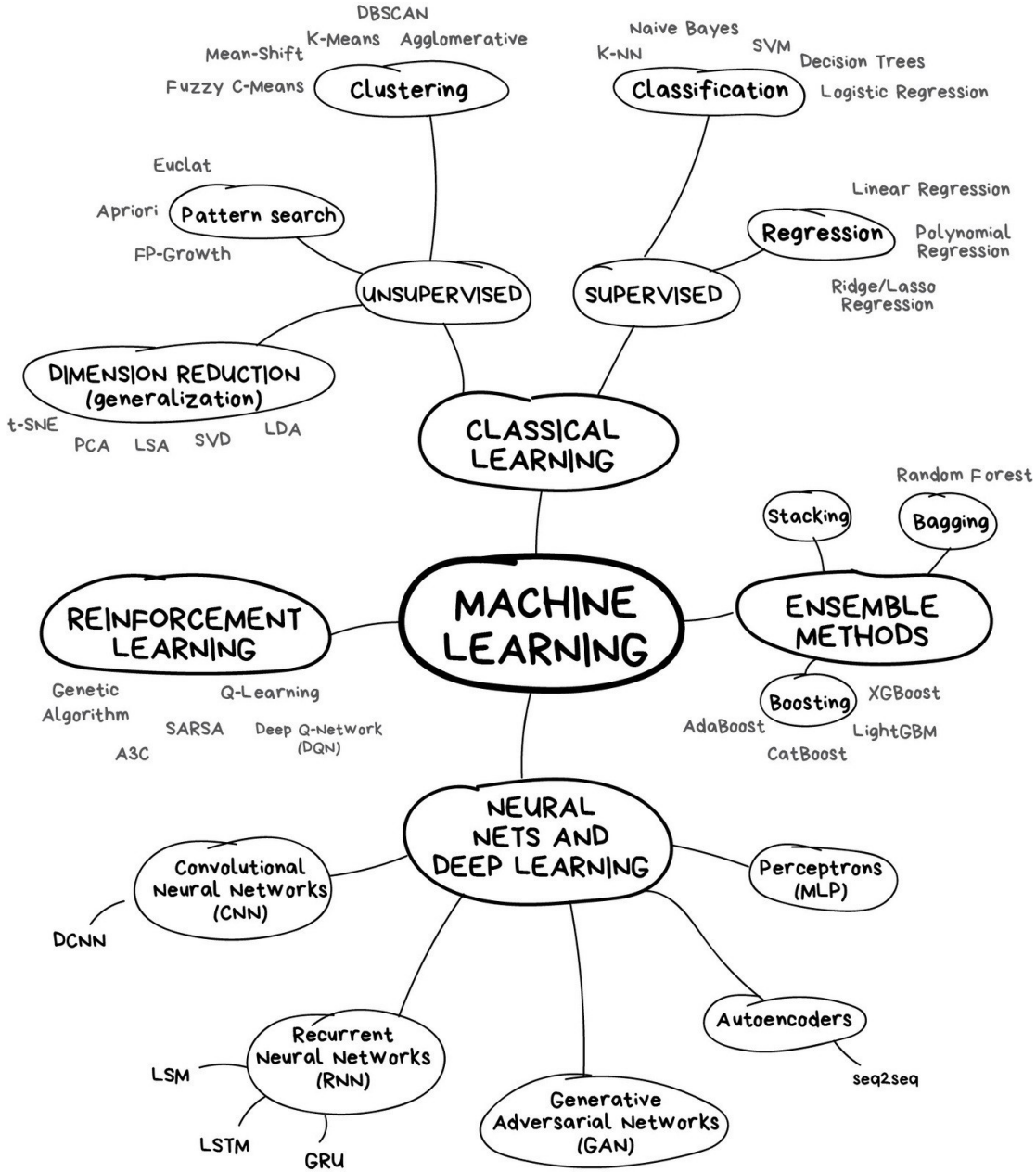
Machine learning focuses on making predictions and inferences from data.

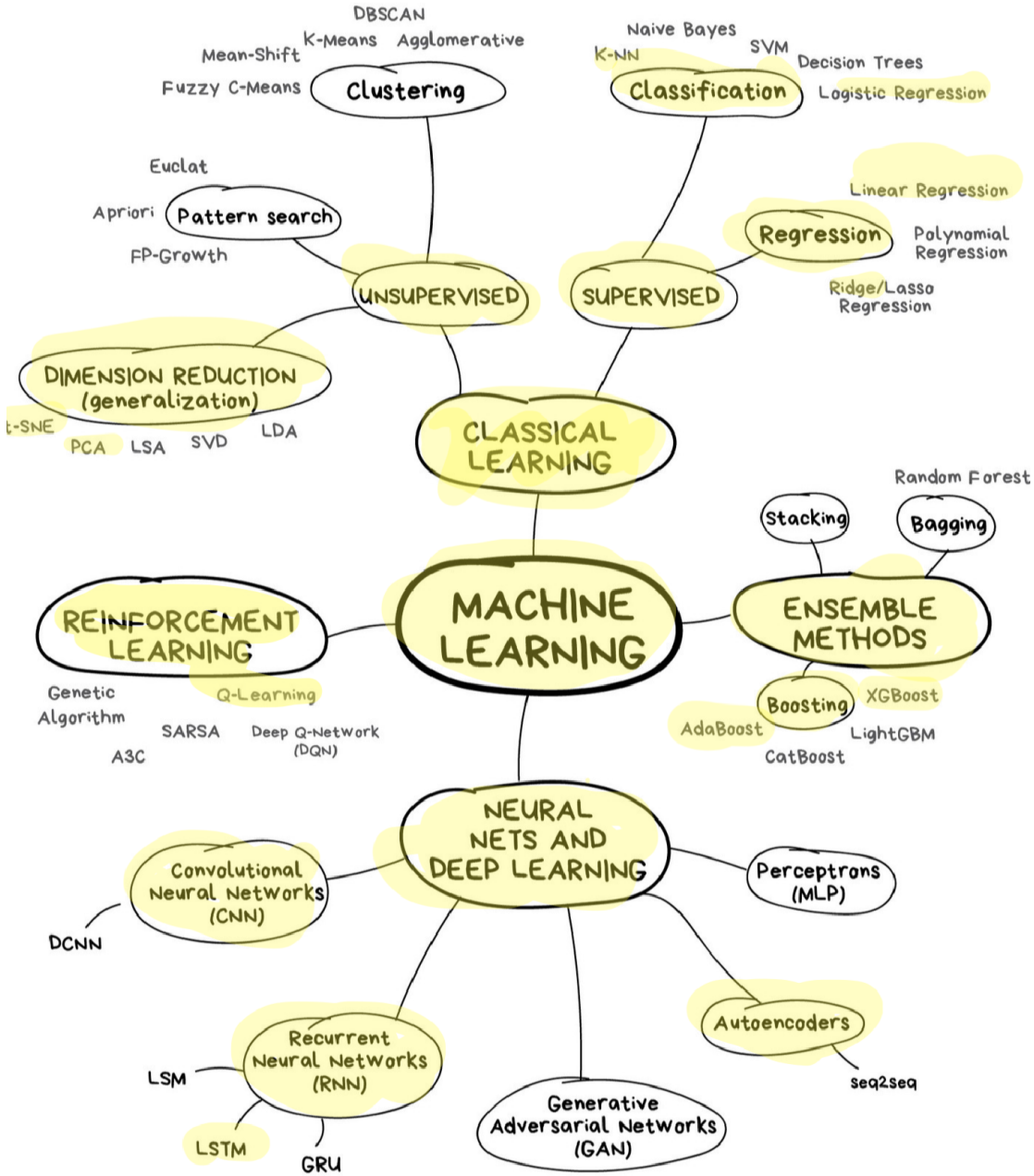
AI combines machine learning components into a larger system that includes a decision making component.

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

Machine learning frameworks

- Supervised
- Unsupervised, self-supervised
- Reinforcement learning
- Generative vs. discriminative models
- Representation learning


MACHINE LEARNING
CLASSICAL LEARNING
UNSUPERVISED
Clustering
DBSCAN
K-Means
Agglomerative
Mean-Shift
Fuzzy C-Means
Pattern search
Euclat
Apriori
FP-Growth
DIMENSION REDUCTION (generalization)
t-SNE
PCA
LSA
SVD
LDA
SUPERVISED
Classification
Naive Bayes
K-NN
SVM
Decision Trees
Logistic Regression
Regression
Linear Regression
Polynomial Regression
Ridge/Lasso Regression
REINFORCEMENT LEARNING
Genetic Algorithm
Q-Learning
SARSA
Deep Q-Network (DQN)
A3C
ENSEMBLE METHODS
Stacking
Bagging
Random Forest
Boosting
XGBoost
AdaBoost
LightGBM
CatBoost
NEURAL NETS AND DEEP LEARNING
Convolutional Neural Networks (CNN)
DCNN
Perceptrons (MLP)
Recurrent Neural Networks (RNN)
LSM
LSTM
GRU
Generative Adversarial Networks (GAN)
Autoencoders
seq2seq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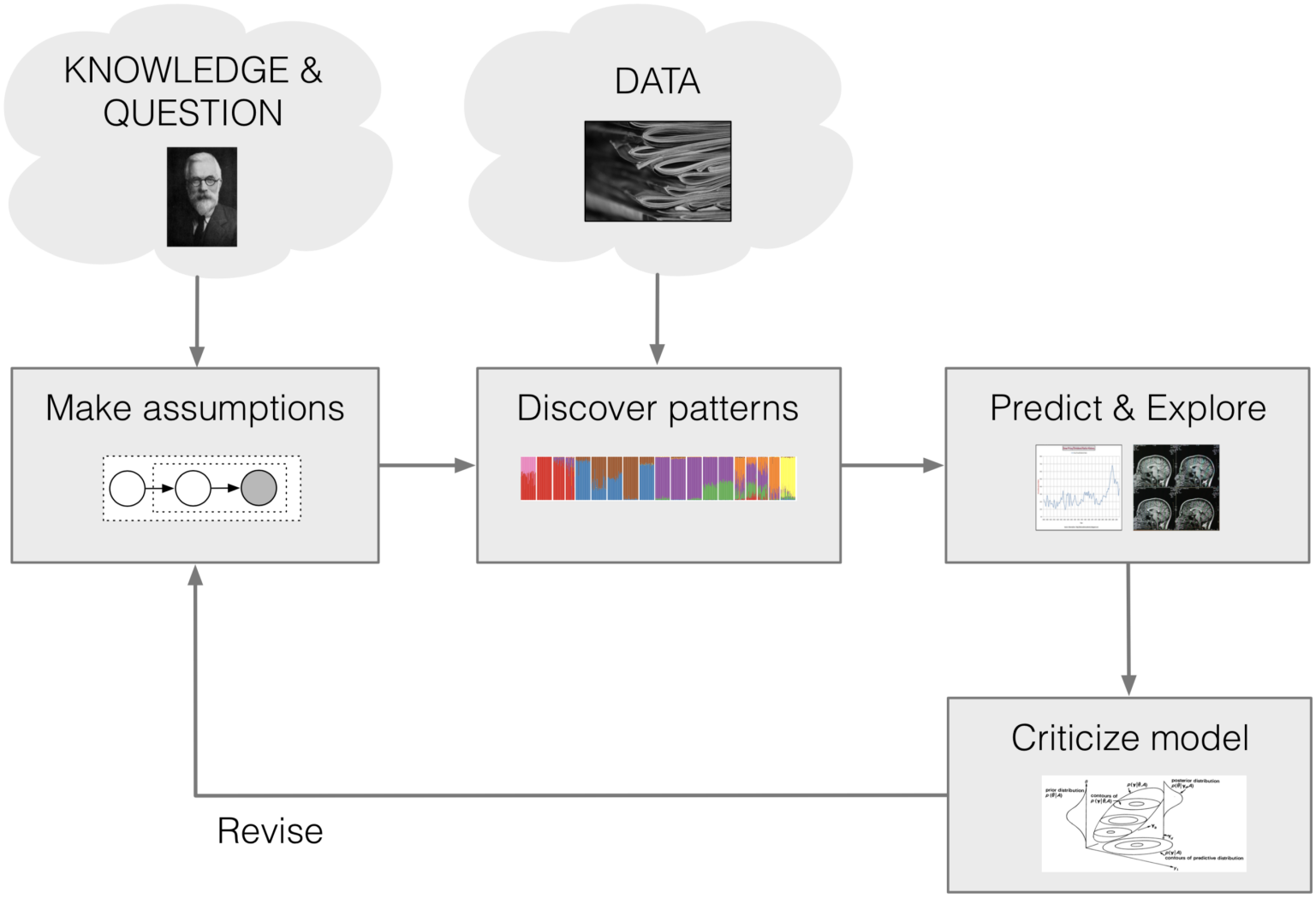
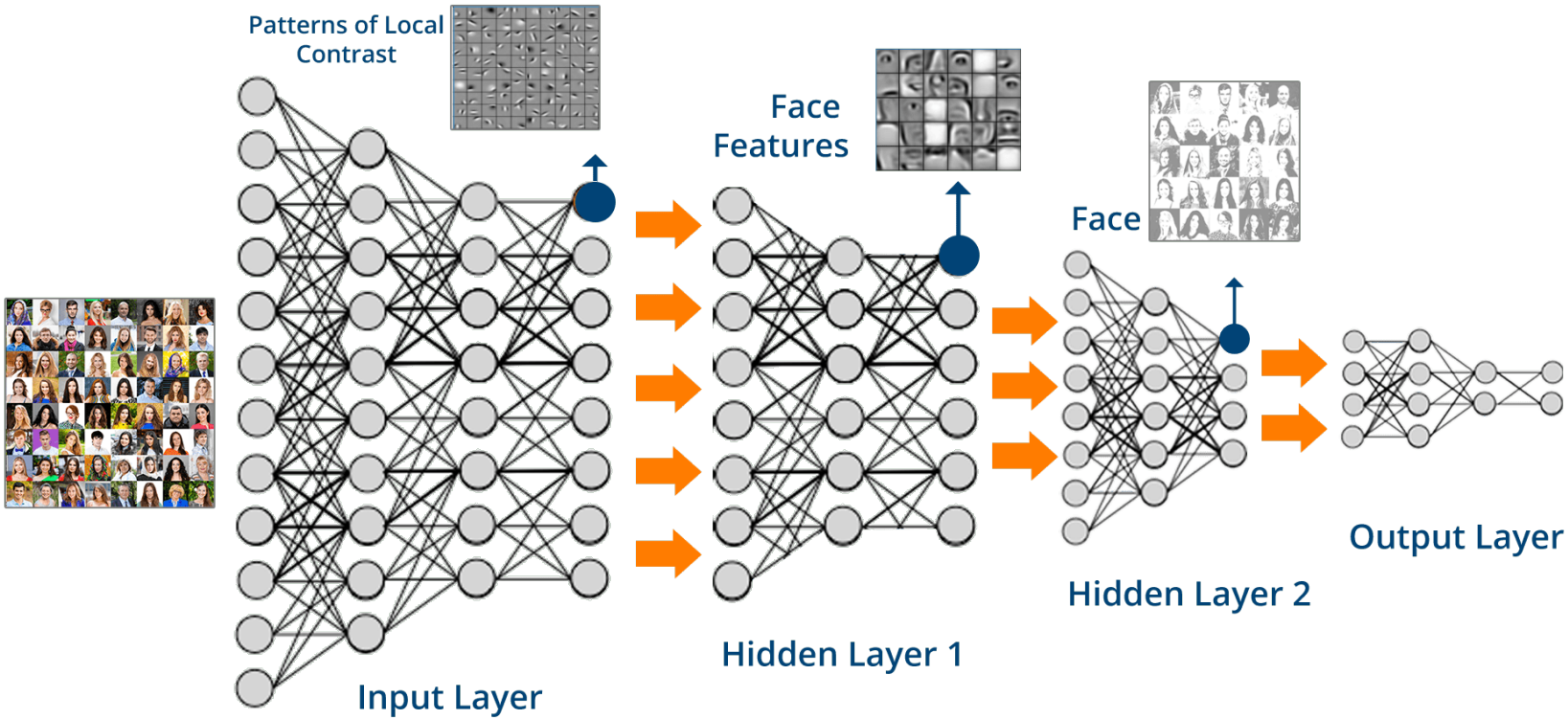

KNOWLEDGE &
QUESTION
DATA
Make assumptions
Discover patterns
Predict & Explore
Criticize model
Revise

Deep learning is a type of machine learning



- Heuristics motivated from simplified view of the brain
- A particular form of nonlinear classification/regression
- Not well-suited to latent variables

Culture of Code

- Great deal of current AI/ML work is purely engineering based
- Informal input/output reasoning

  “that program gave this output...
  maybe this program will give that output”

- Deep learning software engineers develop sophisticated intuitions
- The code is the product

xkcd.com/1838

Latent variables: The elephants in the room

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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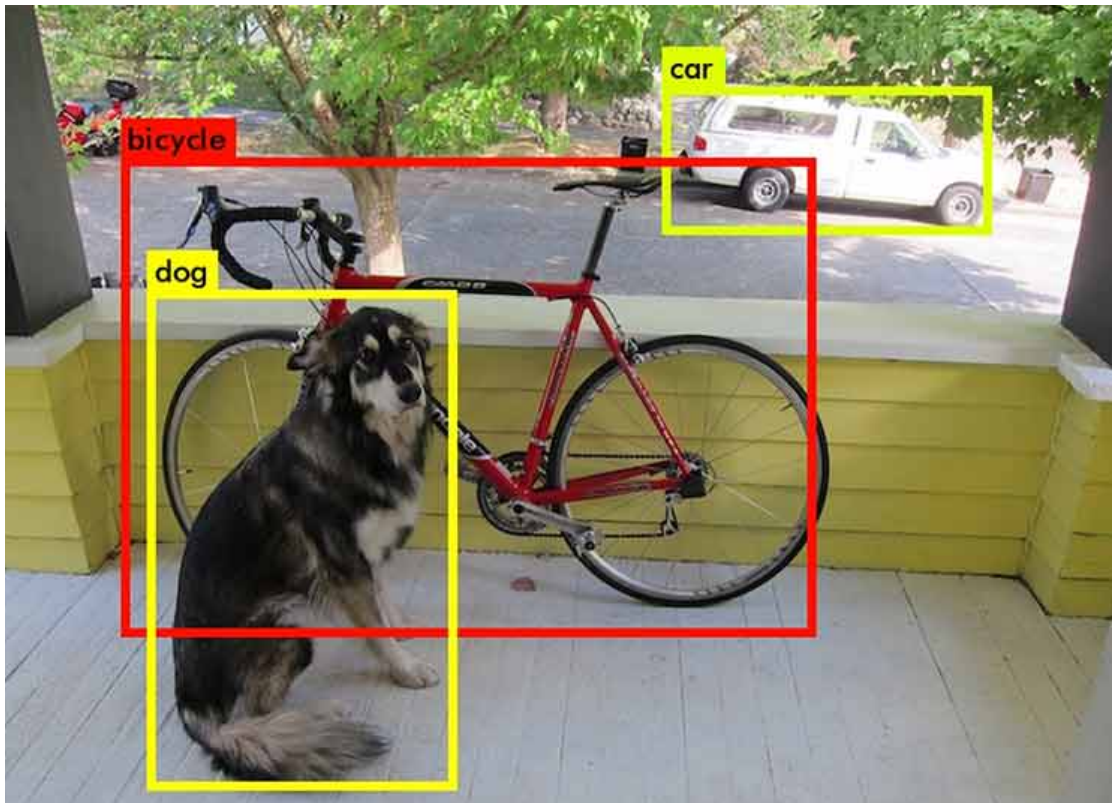
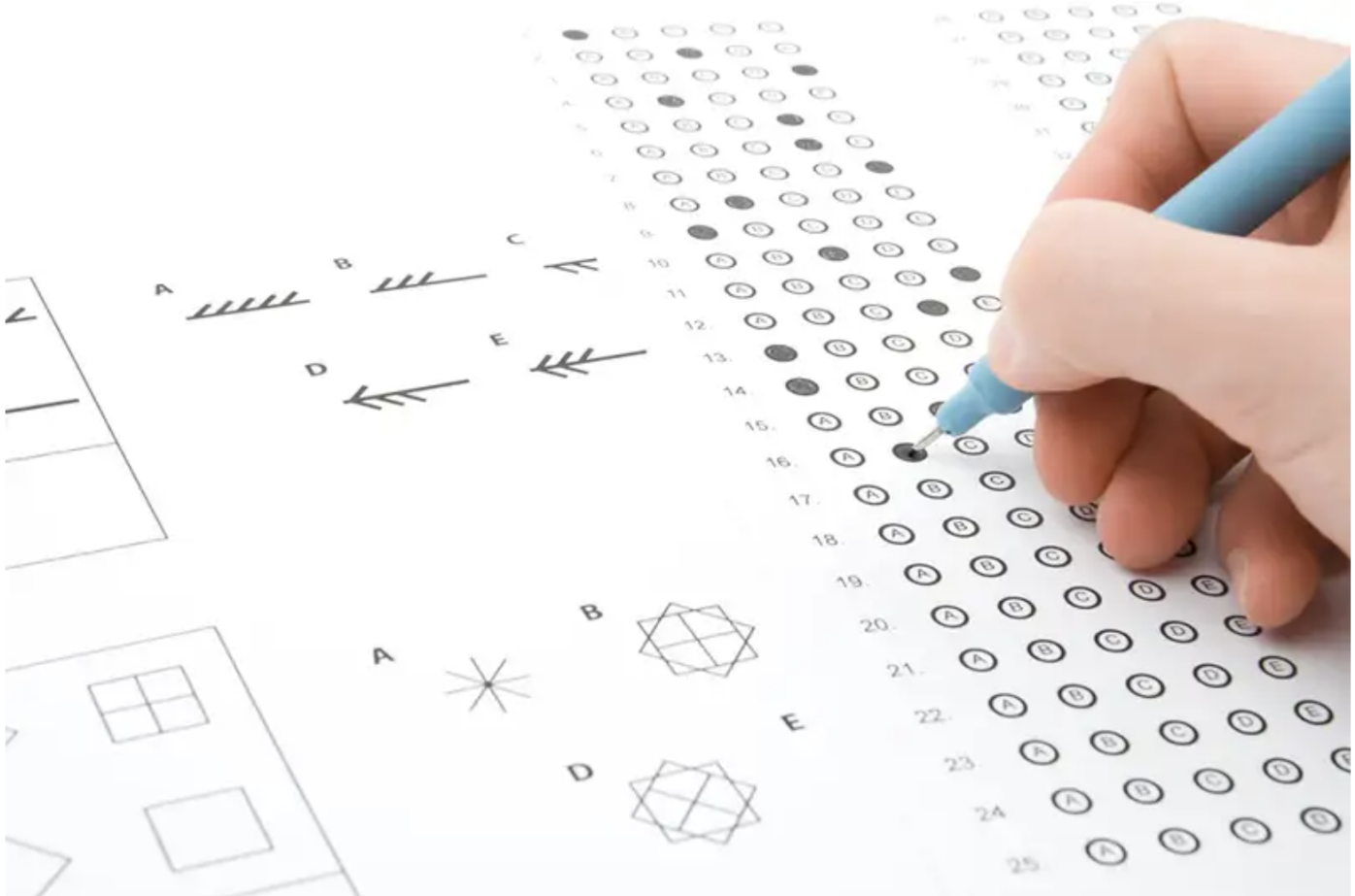


Two types of intelligence

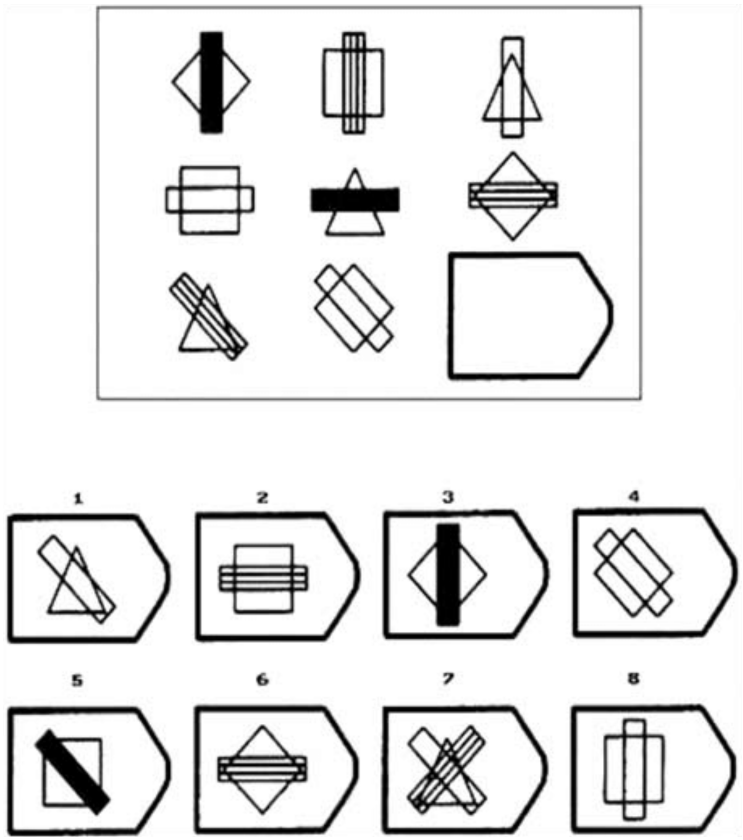
2. “Prefrontal”— identify novel associations and relations
   - Fast to learn, slow to apply
   - Symbolic processing and abstraction
   - Little explicit training data

Two types of intelligence



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

Two types of intelligence



Two types of intelligence

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:

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.

Relations are essential to reasoning

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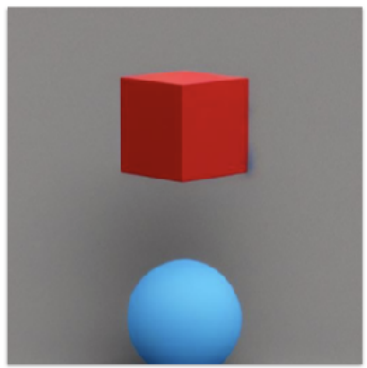
Relations are essential to reasoning

“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?”

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?"



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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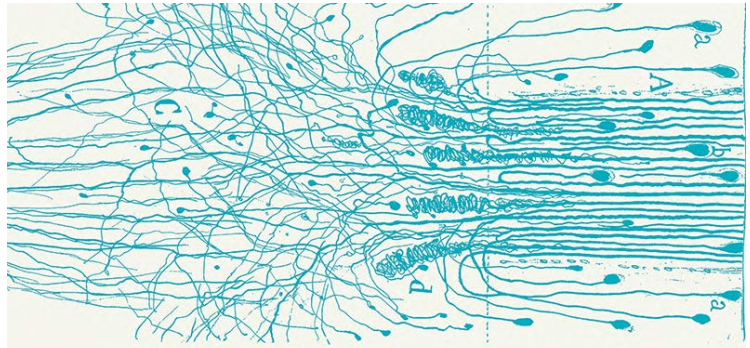
ARC-AGI Prize

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 main components of ChatGPT

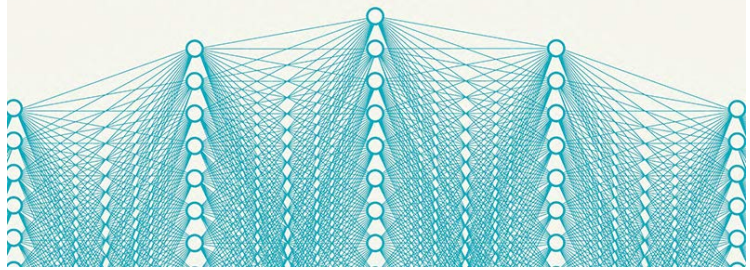


THE ALIGNMENT PROBLEM

Machine Learning and Human Values

BRIAN CHRISTIAN

Best-Selling Author, *Algorithms to Live By*



Example of representation learning: Word embeddings

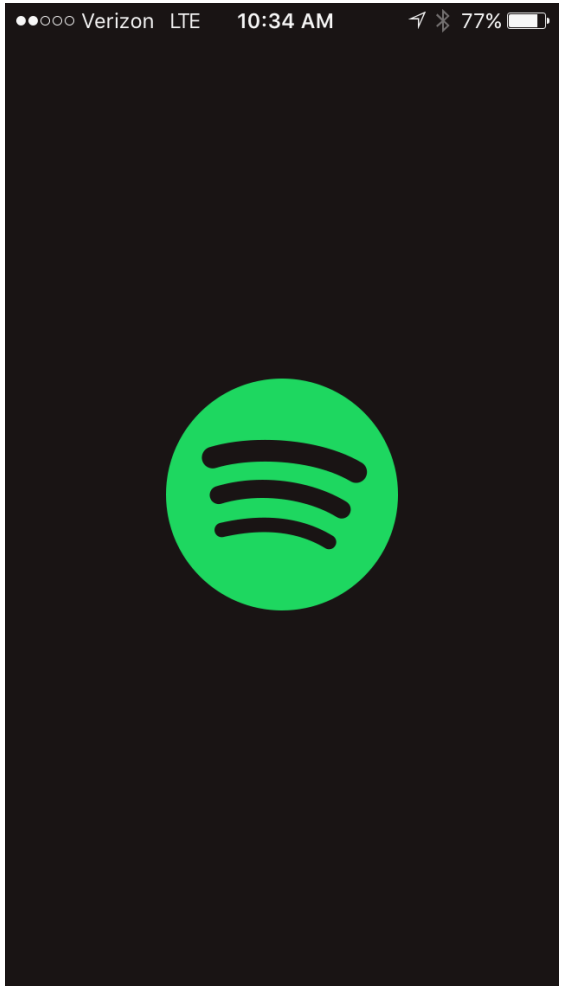
- Each word in vocab is mapped to 100 or 500 dimensional vector
- Based solely on co-occurrence statistics in corpus of text

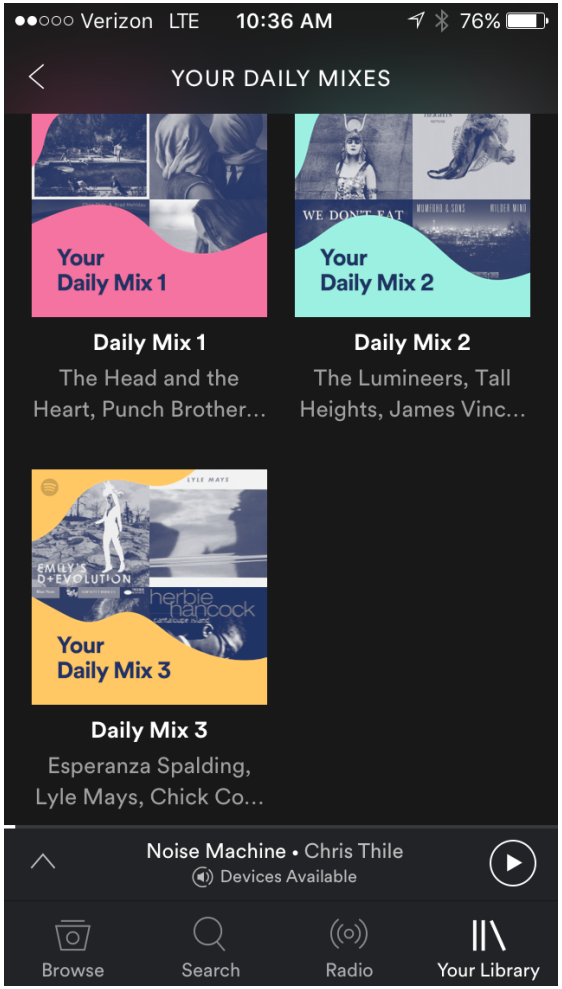
Example of representation learning: Word embeddings

Yale:

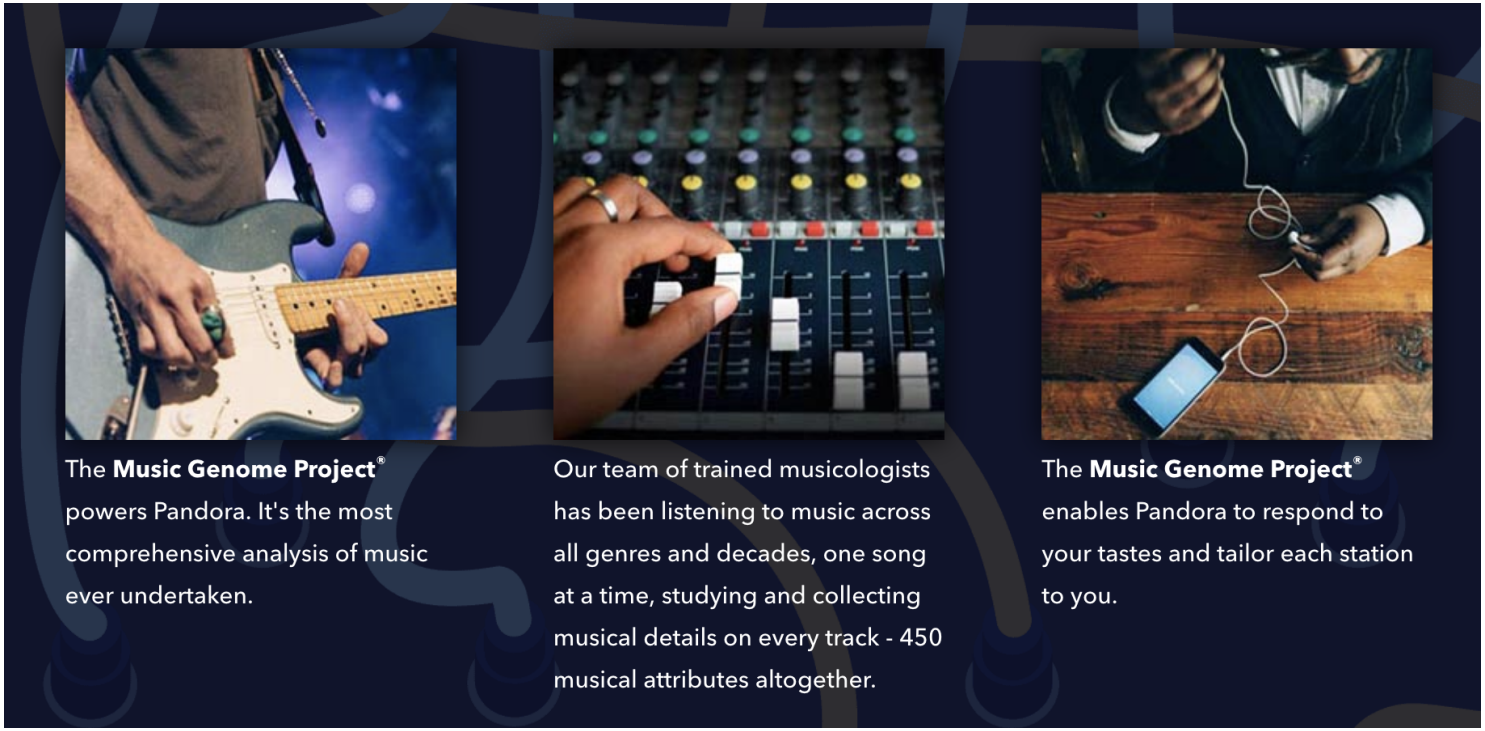
[0.78310001, 0.51717001, -0.38207 , -0.23722 , -0.31615999, 0.30805001, 0.76389998, 0.064106 , -0.74913001, 0.60585999, -0.23871 , -0.16876 , -0.25634 , 1.07270002, -0.29967999, 0.020095 , 0.54500997, -0.17847 , -0.26675999, -0.11798 , -0.48692 , 0.22712 , 0.017473 , -0.4747 , 0.44861001, -0.084281 , -0.30412999, -1.13510001, -0.14869 , -0.11182 , -0.32530001, 1.0029 , -0.35742 , 0.35148999, -1.10679996, -0.064142 , -0.72284001, 0.14114 , -0.41247001, -0.16184001, -0.54576999, -0.12958001, -0.88356 , -0.089722 , 0.10555 , -0.12288 , 0.92851001, 0.50032002, 0.1349 , 0.21457 , 0.35073999, -0.73132998, 0.39633 , -0.43239999, -0.38815999, -1.34669995, 0.37463999, -0.79386002, 0.11185 , 0.18007 , -0.75142998, 0.24975 , -0.094948 , -0.36341 , 0.24869999, -0.22667 , 0.32289001, 1.29489994, 0.42658001, 1.29120004, -0.13954 , 0.68976003, 0.21586999, 0.13715 , -1.00919998, 0.028827 , 0.11011 , -0.1912 , -0.073198 , -0.52449 , 0.49199 , 0.14463 , -0.18844 , -0.75536001, -0.28704 , 0.019113 , 0.30349001, -0.74425 , -0.072221 , -0.40647 , 0.26899001, -0.28318 , 0.72409999, 0.50796002, -0.37845999, -0.13008 , -0.13808 , 0.098928 , 0.16215999, 0.16293]

Embeddings for music recommendations





Experts vs. Data: The case of Pandora vs. Spotify



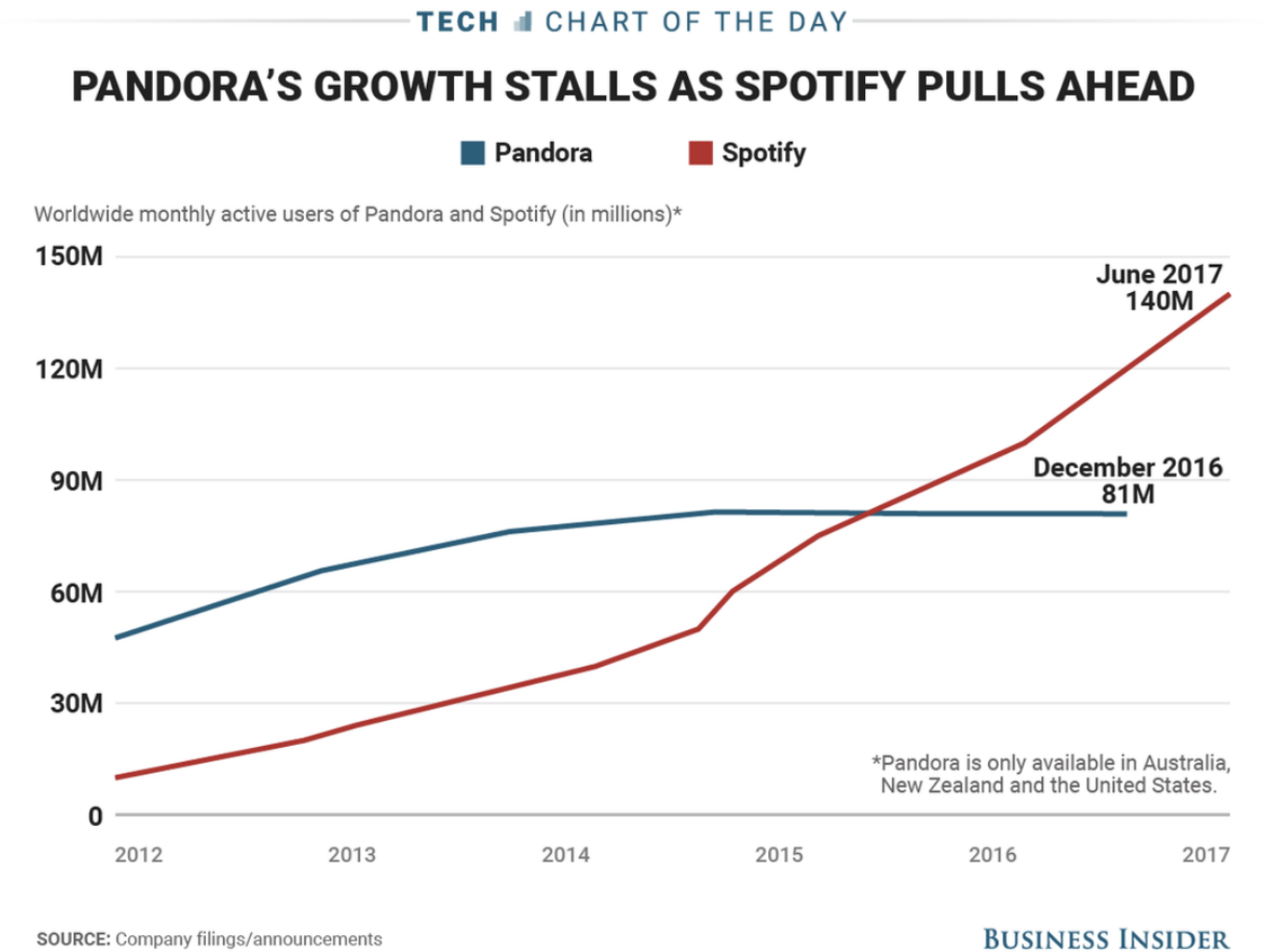
- Pandora's "Music genome": Over 450 musical attributes
- Melody, harmony, rhythm, form, composition, lyrics...

https://arstechnica.com/tech-policy/2011/01/digging-into-pandoras-music-genome-with-musicologist-nolan-gasser/

Experts vs. Data: The case of Pandora vs. Spotify

Spotify: Word embeddings trained from playlists

Experts vs. Data: The case of Pandora vs. Spotify



Hacking ML Systems

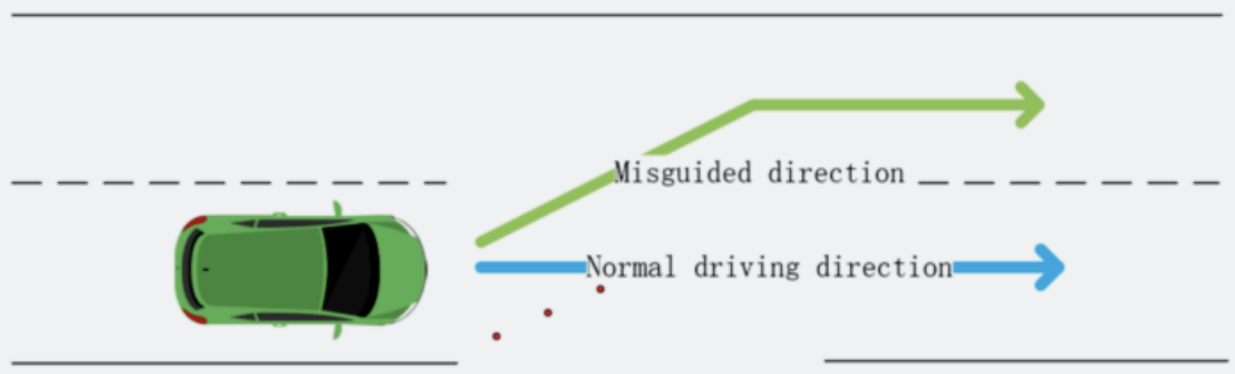
ars TECHNICA SUBSCRIBE SIGN IN

TESLA AUTOPILOT —

Researchers trick Tesla Autopilot into steering into oncoming traffic

Stickers that are invisible to drivers and fool autopilot.

DAN GOODIN - 4/1/2019, 8:50 PM



Keen Security Lab

Machine learning at a large Internet company

- Typical project lifetime: 6 months to 1 year
- Ads projects involve thousands of software engineers
- Often adding new “feature” to existing black box model
- No single person understands entire model
- Not interpretable
- Potential for large breaches of personal information

Reasons for optimism

- Increasingly part of academic research across disciplines
- Engaging a broad community; wide public awareness
- We’re still in very early stages

Questions or discussion?

Course materials

Materials posted to `https://ydata123.org/sp26/introml/calendar.html`; sometimes to Canvas

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

Email all (non-personal) questions to `sds265@yale.edu`

Syllabus

Introductory Machine Learning covers the key ideas and techniques in machine learning without the use of advanced mathematics. Basic methodology and relevant concepts are presented in lectures, including the intuition behind the methods and a more formal understanding of how and why they work. Assignments give students hands-on experience with the methods on different types of data.

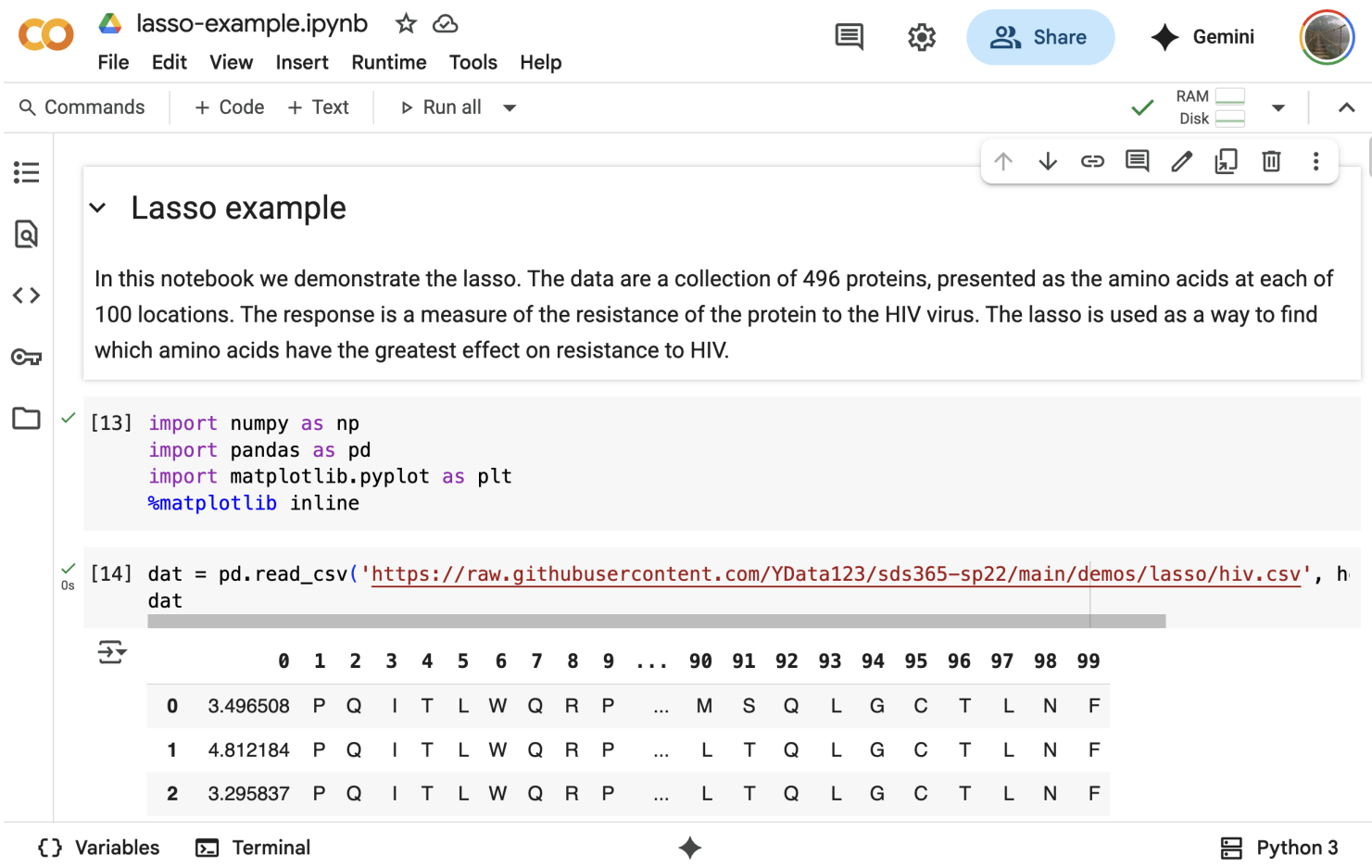
Syllabus

Topics include linear regression and classification, tree-based methods, topic models, word embeddings, recurrent neural networks, deep learning and reinforcement learning. Examples come from a variety of sources including political speeches, archives of scientific articles, real estate listings, natural images, and several others. Programming is central to the course, and is based on the Python programming language.

Prerequisites

- At least two of the following courses: S&DS 230, 238, 240, 241 and 242
- Previous programming experience (e.g., R, Matlab, Python, C++), Python preferred. The course will make extensive use of Python programming, using Jupyter notebooks.

Running on Google Colab (preferred)



Running on Google Colab (preferred)

Course goals

Gain understanding of and experience with basic machine learning methodology

Course goals

- Gain some new perspective
- Appreciate some of the power and limitations of ML
- Reflect on societal implications of AI/ML
- Have fun
- Want to learn more

Evaluation

- Five assignments (40%)
- Mid-semester exam (25%)
- Five quizzes (10%)
- Final exam: (25%)

Lowest assignment and quiz score will be dropped. Late assignments not accepted.

Assignments

- Roughly every two weeks
- Due at midnight (11:59pm), typically Thursdays
- Submitted using Gradescope
- Mix of 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.

Using Chatbots

Use ChatGPT or other AI tools such as Codex, CoPilot on assignments if you find them useful. Acknowledge your use of them—just as for collaboration in general.

However, exams and quizzes will have coding questions, and such tools are expressly forbidden for these evaluations.

Exams

- Midterm exam: Wednesday March 4 in class
- Final exam: Monday May 4 at 2pm
- No rescheduling

Calendar Spring 2026

Lectures: Monday/Wednesday 1:00-2:15pm
Davies Auditorium

Complementary readings marked ISL refer to sections in the book An Introduction to Statistical Learning (Python version, July 2023). Assignments and quizzes are posted and due on Thursday in a given week.

Week	Dates	Topics	Demos & Tutorials	Lecture Slides	Readings and Notes	Assignments & Exams
1	Jan 12, 14	Course overview; Python and background concepts	Python elements Covid trends	Mon: Course overview Wed: Python and Pandas	Data8 Chapters 3, 4, 5	Assn 1 out
2	Jan 21, 23	Linear regression and classification	Covid trends (revisited) Classification examples	Mon: MLK day Wed: Regression concepts Fri: Classification	ISL Sections 3.1, 3.2, 3.5 Notes on regression ISL Sections 4.3, 4.4 Notes on classification	Quiz 1
3	Jan 26,28	Stochastic gradient descent	SGD examples	Mon: Classification (continued) Wed: Stochastic gradient descent	ISL Section 6.2.2 ISL Section 10.7.2	Assn 1 in Assn 2 out

Auditing

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

Questions?