Statistics and Data Science 265 / 565

Introductory Machine Learning

Thursday, August 29

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

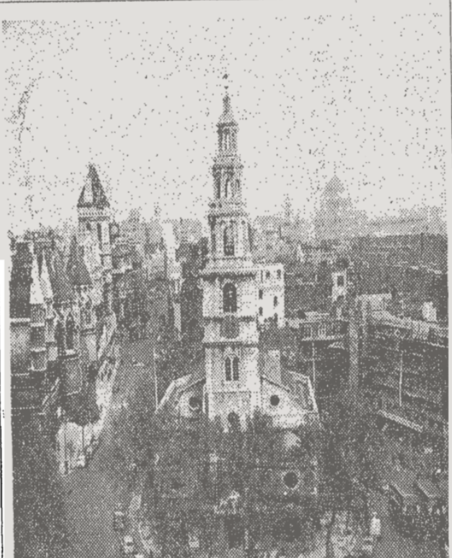
Huge Computer in London to 'Think' Like a Person for Study of Learning

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.

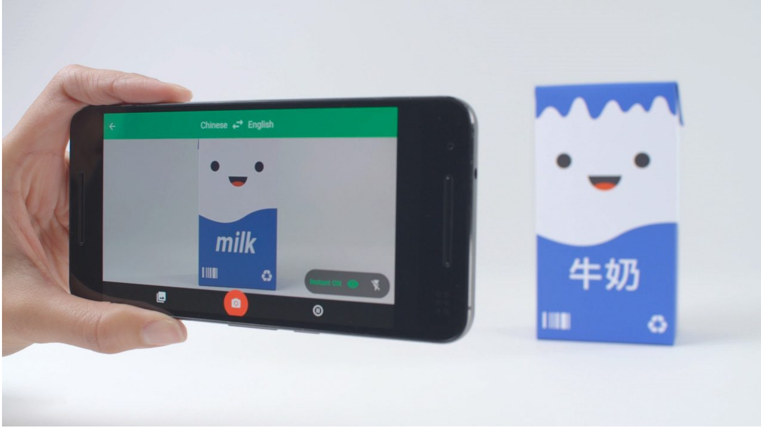
The machine will "think"; that is, it will scan shapes such as the letters of the alphabet and simple words and after analyzing and absorbing this visual information it will "say" (through a loudspeaker) what it has seen at precisely the same rate as that of a fairly intelligent human subject.

This is being achieved by



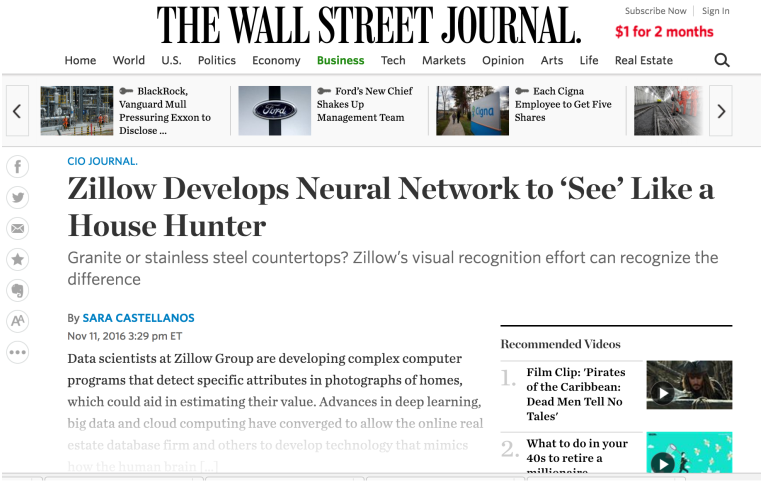
Today: Home assistants

Translation



http://www.sciencemag.org/

Pricing and recommending homes



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Each Cigna Employee to Get Five Shares

CIO JOURNAL.

Zillow Develops Neural Network to 'See' Like a House Hunter

Granite or stainless steel countertops? Zillow's visual recognition effort can recognize the difference

By SARA CASTELLANOS

Nov 11, 2016 3:29 pm ET

Data scientists at Zillow Group are developing complex computer programs that detect specific attributes in photographs of homes, which could aid in estimating their value. Advances in deep learning, big data and cloud computing have converged to allow the online real estate database firm and others to develop technology that mimics how the human brain [...]

Recommended Videos

1. Film Clip: 'Pirates of the Caribbean: Dead Men Tell No Tales'
2. What to do in your 40s to retire a millionaire

https://blogs.wsj.com/cio/2016/11/11/zillow-develops-neural-network-to-see-like-a-home-buyer/

YouTube

Amazing ways YouTube uses ML and AI: https://www.forbes.com/sites/bernardmarr/2019/08/23/the-amazing-ways-youtube-uses-artificial-intelligence-and-machine-learning

YouTube

- Each month: 1.9 billion users
- Each day: 1 billion hours of video watched
- Each minute: 300 hours of video uploaded
- ML: Automatically remove objectionable content
- ML: “Up Next” feature

Amazing ways YouTube uses ML and AI: https://www.forbes.com/sites/bernardmarr/2019/08/23/the-amazing-ways-youtube-uses-artificial-intelligence-and-machine-learning

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

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

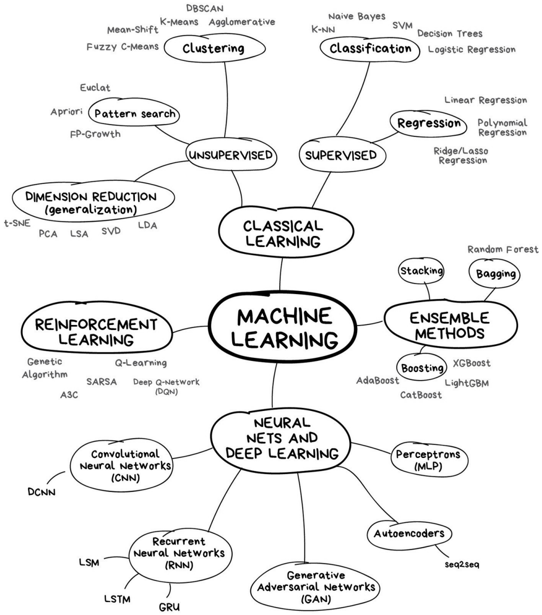
Machine learning focuses on making predictions and inferences from data.

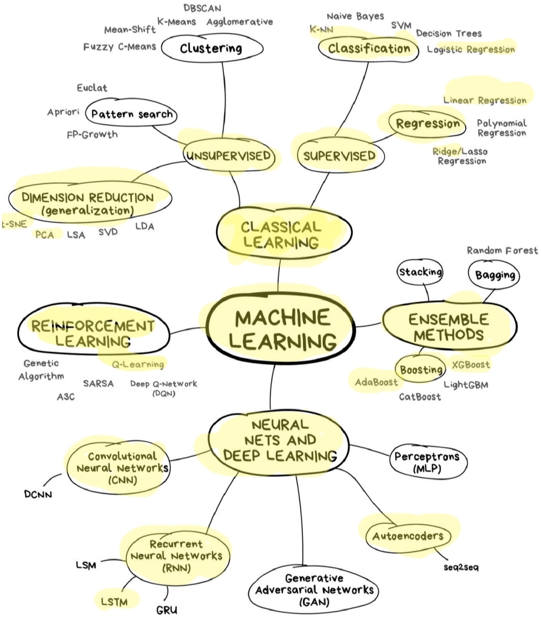
AI combines machine learning components into a larger system that includes a decision making component.

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

Machine learning frameworks

- Supervised, unsupervised, semi-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
ENSEMBLE METHODS
Stacking
Bagging
Random Forest
Boosting
XGBoost
AdaBoost
LightGBM
CatBoost
REINFORCEMENT LEARNING
Genetic Algorithm
Q-Learning
SARSA
Deep Q-Network (DQN)
A3C
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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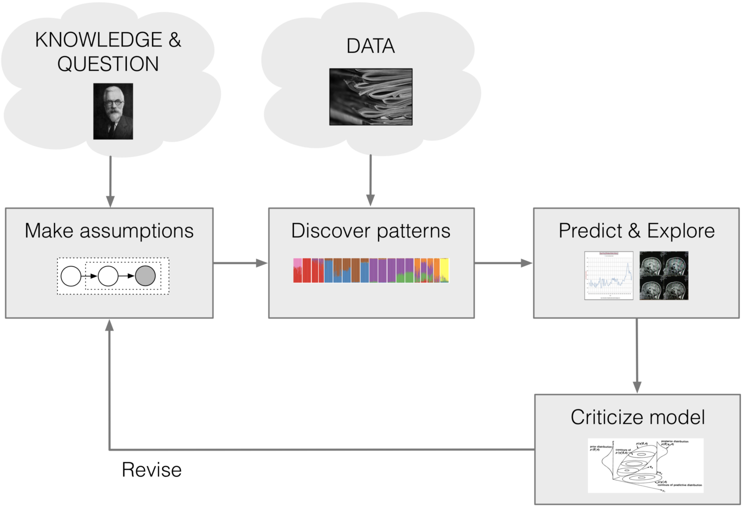
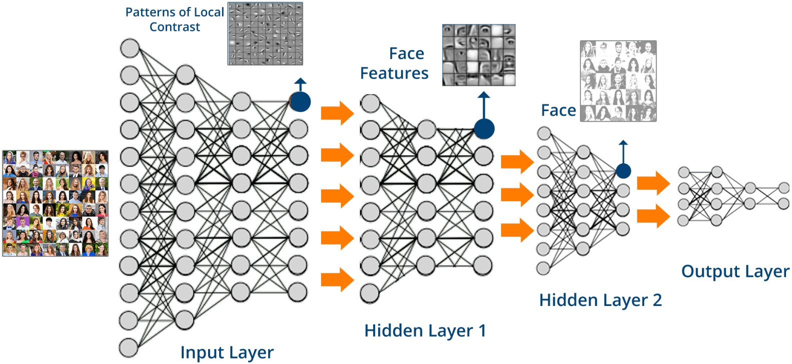

KNOWLEDGE &
QUESTION
DATA
Make assumptions
Discover patterns
Predict & Explore
Criticize model
Revise

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


DALL·E 2
DALL·E 2 is a new AI system that can create realistic images and art from a description in natural language.
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DALL·E Now Available in Beta

We'll invite 1 million people from our waitlist over the coming weeks. Users can create with DALL·E using free credits that refill every month, and buy additional credits in 115-generation increments for $15.

JOIN DALL·E 2 WAITLIST ↗

July 20, 2022
3 minute read

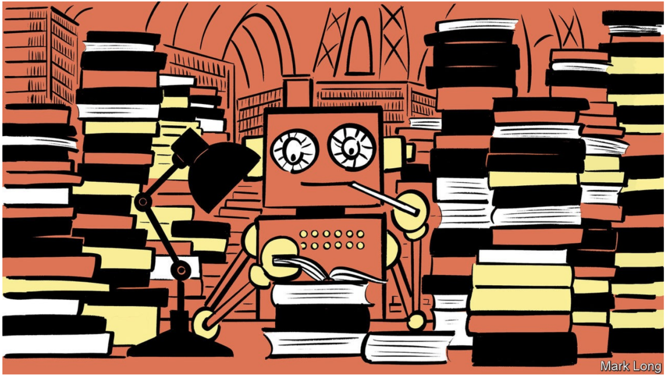
Science & technology

Aug 6th 2020 edition ›

Artificial intelligence

A new AI language model generates poetry and prose

GPT-3 can be eerily human-like—for better and for worse



Mark Long

≡ The New York Times Account

Meet GPT-3. It Has Learned to Code (and Blog and Argue).

The latest natural-language system generates tweets, pens poetry, summarizes emails, answers trivia questions, translates languages and even writes its own computer programs.

Two types of intelligence

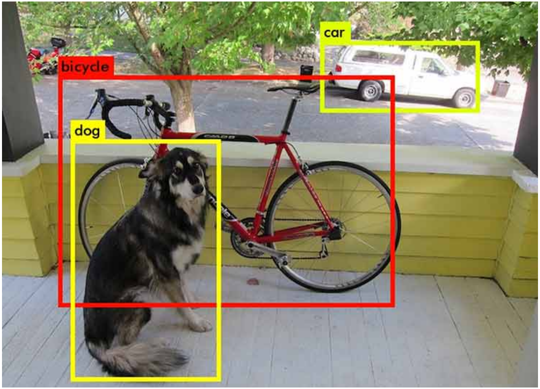
1. “Neocortical”— acquire semantic and procedural knowledge
   - Requires extensive data and training
   - Slow to learn, fast to apply
   - Well captured by modern deep learning

Two types of intelligence

1. "Neocortical"— acquire semantic and procedural knowledge

Two types of intelligence

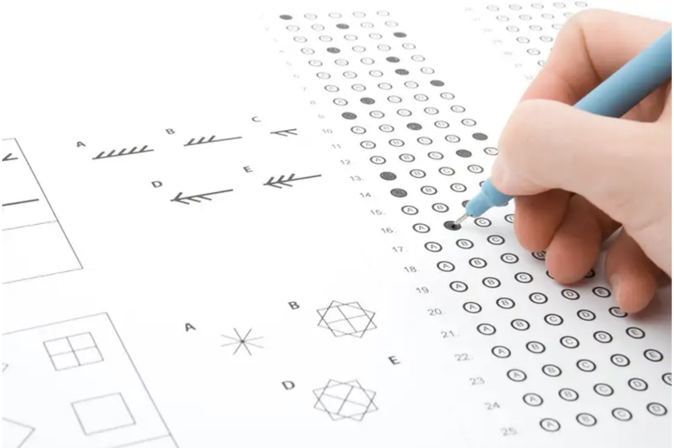
1. "Neocortical"— acquire semantic and procedural knowledge



Two types of intelligence

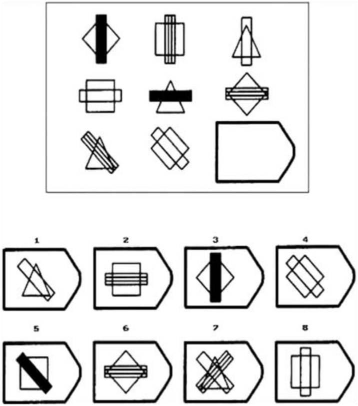
2. "Prefrontal"— identify novel associations and relations
   - Fast to learn, slow to apply
   - Symbolic processing and abstraction
   - Little explicit training data

Two types of intelligence

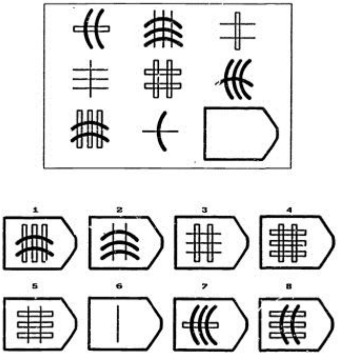


AI struggles with IQ tests
Panther Media GmbH / Alamy Stock Photo

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:

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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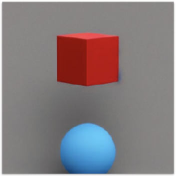
Relations are essential to reasoning

“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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Relations are essential to reasoning

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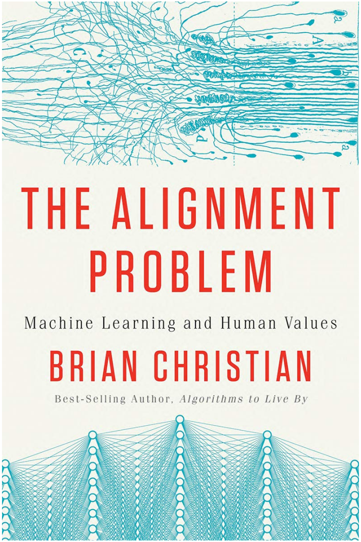
ARC-AGI Prize

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

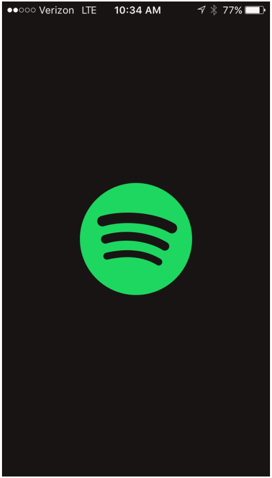
- Each word in vocab is mapped to 100 or 500 dimensional vector
- Based solely on co-occurrence statistics in corpus of text

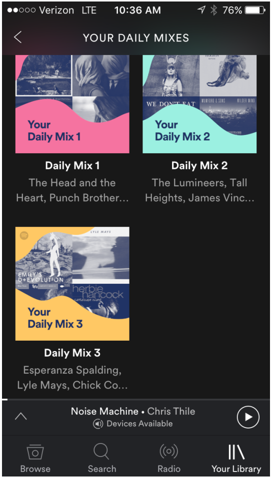
Example of representation learning: Word embeddings

Yale:

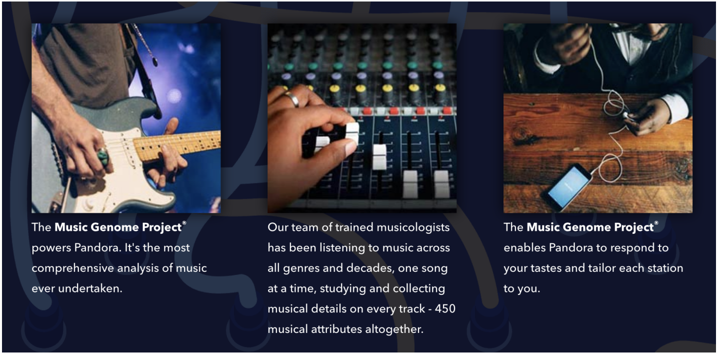
[0.78310001, 0.51717001, -0.38207 , -0.23722 , -0.31615999, 0.30805001, 0.76389998, 0.064106 , -0.74913001, 0.60585999, -0.23871 , -0.16876 , -0.25634 , 1.07270002, -0.29967999, 0.020095 , 0.54500997, -0.17847 , -0.26675999, -0.11798 , -0.48692 , 0.22712 , 0.017473 , -0.4747 , 0.44861001, -0.084281 , -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



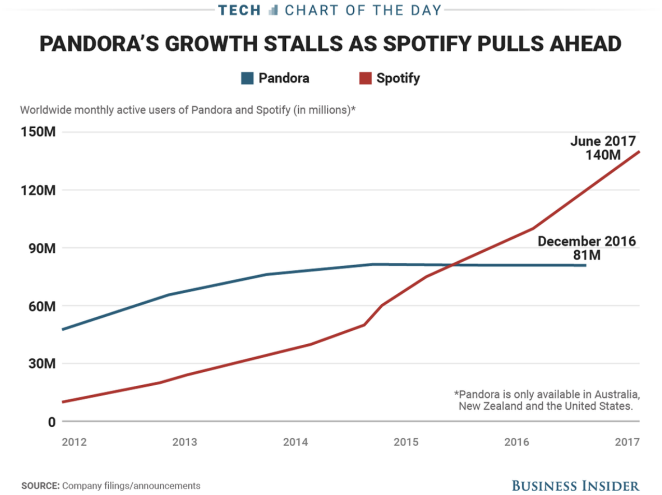
- Pandora's "Music genome": Over 450 musical attributes
- Melody, harmony, rhythm, form, composition, lyrics...

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

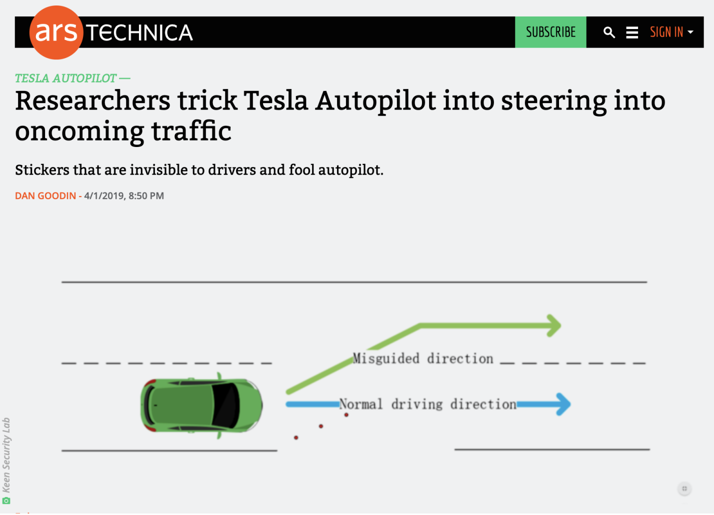
Experts vs. Data: The case of Pandora vs. Spotify

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

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
- We're still in very early stages

Questions or discussion?

Course materials

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

Please use Ed Discussion for any questions about lectures, homework, etc. first, before email!

Email all questions about logistics 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.

Installing Jupyter

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

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

In a strangely self-referential situation, Chatbots are powerful and widely available.

Use ChatGPT or other AI tools such as Codex on assignments if you find them useful.

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

Exams

- Midterm exam: October 15 in class
- Final exam: December 16 at 2pm
- No rescheduling

Week	Dates	Topics	Demos & Tutorials	Lecture Slides	Readings and Notes	Assignments & Exams
1	Aug 31	Course overview		Thu: Course overview		
2	Sept 5, 7	Python and background concepts	CO Python elements CO Covid trends	Tue: Python elements Thu: Pandas and linear regression	Data8 Chapters 3, 4, 5	Quiz 1 CO Assn 1 out
3	Sept 12, 14	Linear regression and classification	CO Covid trends (revisited) CO Classification examples	Tue: Regression concepts Thu: Classification	ISL Sections 3.1, 3.2, 3.5 Notes on regression ISL Sections 4.3, 4.4 Notes on classification	
4	Sept 19, 21	Stochastic gradient descent	CO SGD examples	Tue: Classification (continued) Thu: Stochastic gradient descent	ISL Section 6.2.2 ISL Section 10.7.2	Assn 1 in CO Assn 2 out
5	Sept 26, 28	Bias and variance, cross-validation	CO Bias-variance tradeoff CO Covid trends (revisited) CO California housing	Tue: Bias and variance Thu: Cross-validation	ISL Section 2.2 ISL Section 5.1	Quiz 2

6	Oct 3, 5	Tree-based methods	Trees and forests Visualizing trees Bagging operations	Tue: Trees Thu: Forests	ISL Sections 8.1, 8.2	Assn 2 in Assn 3 out
7	Oct 10, 12	PCA and dimension reduction	PCA examples PCA revisited Used for regression	Tue: PCA Thu: PCA and review	ISL Section 12.2	Quiz 3
8	Oct 17	Midterm exam (in class)			On Canvas: Practice midterms / Sample solns Midterm / Sample soln	
9	Oct 24, 26	Language models, word embeddings	GPT-3 demo Word embeddings	Tue: Language models Thu: Word embeddings	OpenAI: Better language models (GPT-2)	Assn 3 in Assn 4 out
10	Oct 31, Nov 2	Bayesian inference, topic models	Mixtures Bayesian inference Topic models	Tue: Bayesian inference Thu: Topic models	Notes on Bayesian inference	Quiz 4
			Sanity			

X

11	Nov 7, 9	Introduction to neural networks	Sanity check Minimal neural network Regression examples	Tue: Neural networks Thu: Neural networks	ISL Sections 10.1, 10.2	Assn 4 in Assn 5 out
12	Nov 14, 16	Reinforcement learning	Q-learning	Tue: Reinforcement learning Thu: Deep reinforcement learning		Quiz 5
13	Nov 21, 23	No class, Thanksgiving break				
14	Nov 28, 30	Deep neural networks	Tensorflow playground Autoencoder examples	Tue: Deep neural networks Thu: Autoencoders	ISL Section 10.7 Notes on backpropagation	Assn 5 in
15	Dec 5, 7	Societal issues for machine learning		Tue: Societal issues Thu: Course wrap up		Quiz 6
16	Fri, Dec 15, 2pm, Room TBA	Final exam			Registrar: Final exam schedule Practice final	

Auditing

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

Questions?