

Applied Machine Learning

Introduction

Reihaneh Rabbany

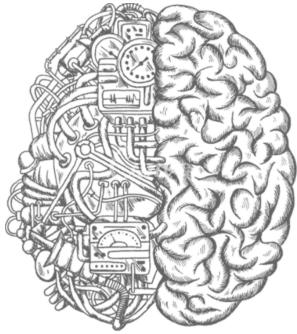
Logistics

- Course website: <http://www.reirab.com/comp551.html>
- **Reply to the polls on Mycourses** by the end of this week
- Be on lookout for the first quiz coming up after the class
- Ed vs Slack?
- Any questions on the logistics?

Outline

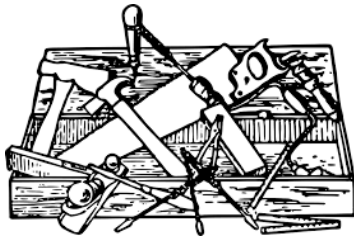
- a short history of machine learning
- understanding the scope of machine learning
 - relation to other areas
- understanding types of machine learning

What is Machine Learning?



ML is the set of "algorithms and statistical models that computer systems use to perform a specific task without using explicit instructions"

ML is the "study of computer algorithms that improve automatically through experience"



while there are some unifying principles,
machine learning may still look like a toolbox
with different tools suitable for different tasks

Placing Machine Learning

- **Artificial Intelligence:** it's a broader domain (includes search, planning, multiagent systems, robotics, etc.)
- **Statistics:** historically precedes ML. ML is more focused on algorithmic, practical and powerful models (e.g., neural networks) and is built around AI
- **Vision & Natural Language Processing:** use many ML algorithms and ideas
- **Optimization:** extensively used in ML
- **Data mining:** scalability, and performance comes before having theoretical foundations, more space for using heuristics, exploratory analysis, and unsupervised algorithms
- **Data science:** an umbrella term for the above mostly used in industry when the output is knowledge/information to be used for decision making

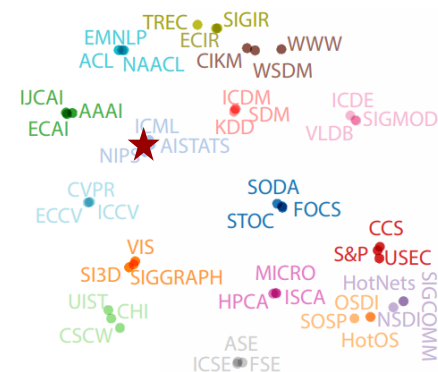
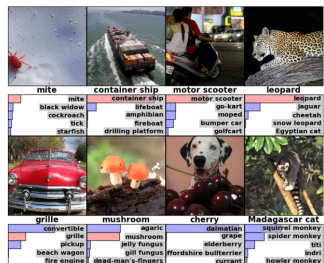


Figure from Dong et al.

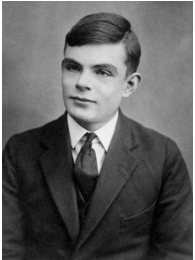
A short history of Machine Learning



- 1950: Turing test
- 1956: checker player that learned as it played (Arthur Samuel)
- 1958: first artificial neural networks called Perceptron (Frank Rosenblatt),
- 1963: support vector machines (Vapnick & Chervonenkis)
- 1969: Minsky and Pappert show the limitations of single-layer neural networks
- 1970-80s: rule-based and symbolic AI dominates (two AI winters)
- 1980's: Bayesian networks (Judea Pearl)
- 1986: Backpropagation rediscovered (Rumelhart, Hinton & Williams)
- 1980-1990s: expert systems are being replaced with general-purpose computers
- ...
- 2012: AlexNet wins Imagenet by a large margin
- 2012 - now: a new AI spring around deep learning ...
- what is next?

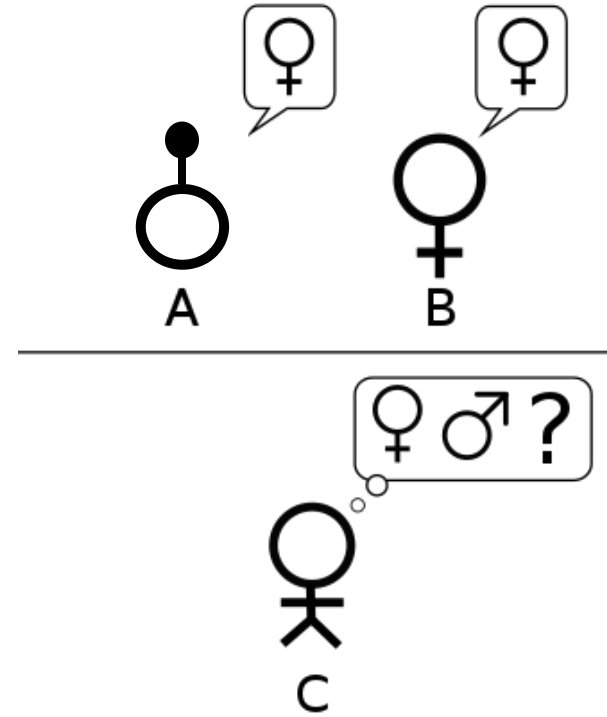
Turing test

In his paper on "Computing Machinery and Intelligence" by Alan Turing (**1950**), Turing tried to replace the abstract question of "can machine think?" with something more tangible, the Turing test designed based on a party game.



*"What will happen when a machine takes the part of A in this [Imitation] game? Will the interrogator decide wrongly as often when the game is played like this as he does when the game is played between a man and a woman? These questions replace our original, "**Can machines think?**"*

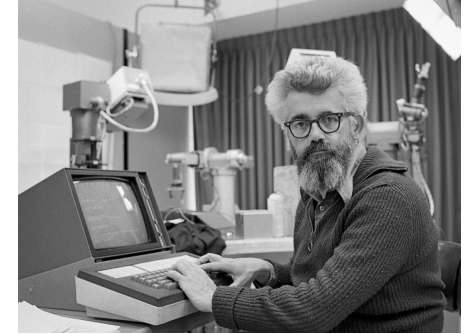
See more on: https://en.wikipedia.org/wiki/Turing_test



Player C, through a series of written questions, attempts to determine which of the other two players is a man, and which of the two is the woman. Player A, the man, tries to trick player C into making the wrong decision, while player B tries to help player C.

Artificial Intelligence

John McCarthy coined the term Artificial Intelligence (AI) and organized the first AI conference in 1956 to bring together researchers to design thinking machines, read more about it [here](#)



The [Logic Theorist program](#), "the first artificial intelligence program", designed by Allen Newell, Herbert A. Simon and Cliff Shaw was presented in this conference. It was able to do automated **reasoning**, i.e. proving mathematical theorems from scratch by exploring a **search** tree, with the hypothesis as the root and branches as logical deductions, plus ad hoc rules, **heuristics**, to trim some branches and avoid exponential grow

[brute force or exhaustive search looks at all the possible options, to find the solution: a simple but expensive approach]

Machine Learning

In 1959 Arthur Samuel popularized the term Machine Learning through his seminal paper on "Some Studies in Machine Learning Using the Game of Checkers"

[you can read the paper [here](#)]

*“ Can a computer can learn to play a better game of checkers than its programmer given only rule of the game, a sense of direction, and a redundant and incomplete list of **parameters** that have something to do with the game but whose values are unknown and unspecified. Programming computers to **learn from experience** should eventually eliminate the need for much of this detailed programming efforts.*



“ Game as a vehicle for studying ML

many important concepts: self-play, temporal difference learning, function approximation



How it learned/was trained?

min-max search with alpha-beta pruning,
learning to estimate the value of a state

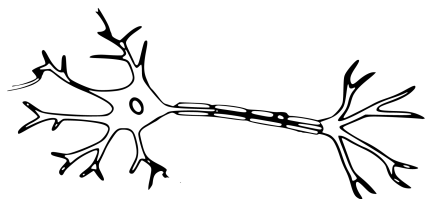
“ In 1954, four different IBM 704 machines working from midnight to 7 AM playing checkers with themselves and assimilating statistics that they used for the running scheme

[read about Samuel [here](#)]

Neural Networks

The Perceptron - A Perceiving and Recognizing Automaton
by Frank Rosenblatt (1957), [you can read the paper, [here](#)]

The first device to think as the human brain, **learns by doing**
based on McCulloch-Pitts mathematical model of neurons (1943)



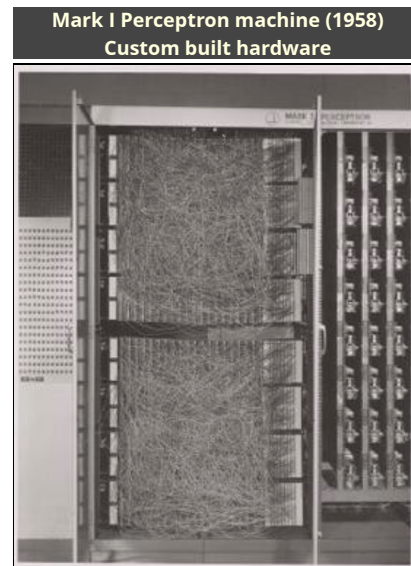
$$f(x) = \sigma \left(\sum_i w_i x_i \right)$$

activation function

which was in turn based on **Hebbian learning**

We will discuss Perceptron later in the course

[read more about Perceptron [here](#), and on Rosenblatt's [here](#)]



**NEW NAVY DEVICE
LEARNS BY DOING**

Psychologist Shows Embryo
of Computer Designed to
Read and Grow Wiser

WASHINGTON, July 7 (UPI)—The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

The embryo—the Weather Bureau's \$2,050,000 "TOD" computer—learned to differentiate between right and left after fifty attempts in the Navy's demonstration for newsmen.

The service said it would use this principle to build the first of its Perceptron thinking machines that will be able to read and write. It is expected to be finished in about a year at a cost of \$100,000.

Dr. Frank Rosenblatt, designer of the Perceptron, conducted the demonstration. He said the machine would be the first device to think as the human brain. As do human beings, Perceptron will make mistakes at first, but will grow wiser as it gains experience, he said.

Dr. Rosenblatt, a research psychologist at the Cornell Aeronautical Laboratory, Buffalo, said Perceptrons might be first to the planets as mechanical space explorers.

Without Human Controls

The Navy said the perceptron would be the first non-living mechanism "capable of receiving, recognizing and identifying its surroundings without any human training or control."

The "brain" is designed to remember images and information it has perceived itself. Ordinary computers remember only what is fed into them on punch cards or magnetic tape.

Later Perceptrons will be able to recognize people and call out their names and instantly translate speech in one language to speech or writing in another language, it was predicted.

Mr. Rosenblatt said in principle it would be possible to build brains that could reproduce themselves on an assembly line and which would be conscious of their existence.

In today's demonstration, the "TOD" was fed two cards, one with squares marked on the left side and the other with squares on the right side.

Learns by Doing

In the first fifty trials, the machine made no distinction between them. It then started registering a "Q" for the left squares and "O" for the right squares.

Dr. Rosenblatt said he could explain why the machine learned only in highly technical terms. But he said the computer had undergone a "self-induced change in the wiring diagram."

The first Perceptron will have about 1,000 electronic "association cells" receiving electrical impulses from an eye-like scanning device with 400 photo-cells. The human brain has 10,000,000,000 responsive cells, including 100,000,000 connections with the eyes.

42

Books Today

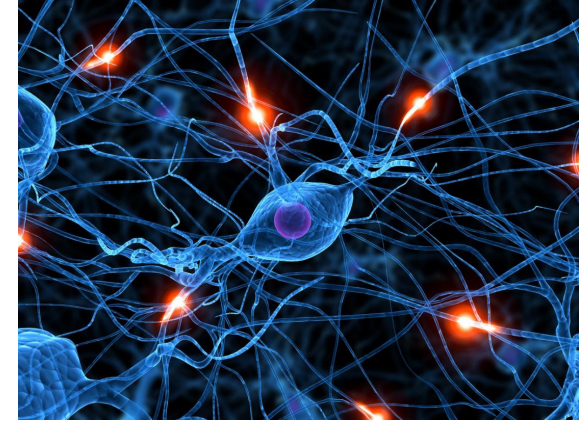
[read the [article](#) from nytimes on July 8, 1958]

How do humans think?



Earliest works in the 1930s and 1940s by **Donald Hebb**, a psychologist at **McGill**, Studying behaviour in terms of brain function and connections between neuron assemblies

*“ I am referring to the general type of studies based on Donald Hebb's work at McGill. The argument goes something like this. **The brain of man, like that of the animals, is made up of many cells of a certain type called neurons. These cells... react on an all-or-none basis ('fire'; ...) and transmit a pulse to other neurons through synaptic connections. Each neuron is connected to many others, and a number of input signals are, in general, required before a neuron will 'fire'. ...Learning seems to consist of alterations in the strength and even perhaps in the number of these synaptic interconnections.** Now it is possible to devise a variety of mechanical, chemical, and electrical devices which simulate the behavior of individual neurons in a crude sort of way, and we can interconnect these devices in some random fashion to simulate the synaptic interconnections that exist within the brain, and, finally, we can arrange for the **automatic strengthening or weakening of these interconnections using a training routine.***



Early Real World Applications

ADALINE (Adaptive Linear Neuron) and MADALINE (Many ADALINEs) are similar to Perceptron and were proposed by Bernard Widrow et al., 1958 and 1960 [you can read the paper [here](#)]

Had many real-world applications including adaptive echo canceler for telephones, automatic equalizations for modems, speech and pattern recognition, weather forecasting etc. [read more about it, [here](#)]

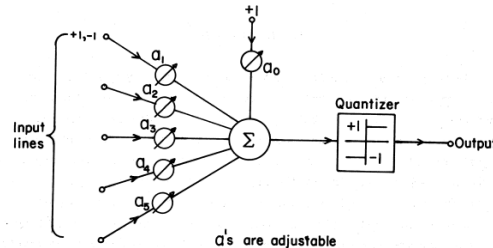


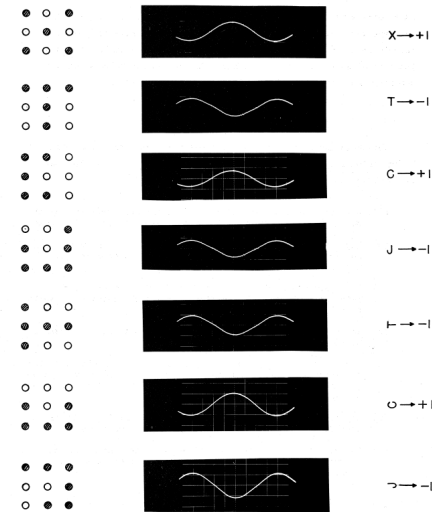
FIG. 1. -- AN ADJUSTABLE NEURON.

Trained using LMS algorithm: adjusting the weights based on the approximate gradient predecessor to backpropagation

Letter Recognition



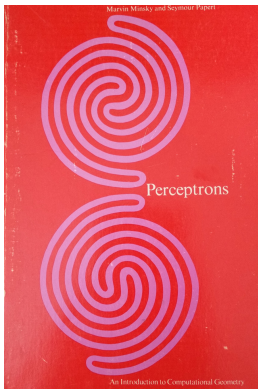
FIG. 2. -- ADALINE.



60 ~ sine waves; vertical scale is 0.1 volts/cm

FIG. 12. WAVE-FORMS OF A MEMISTOR NEURON AFTER A TRAINING EXPERIMENT.

A short history of Machine Learning

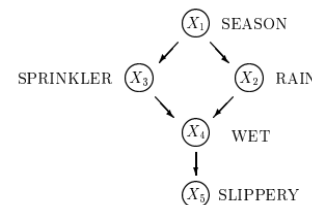


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- 1958: first artificial neural networks called Perceptron (Frank Rosenblatt),
- **1963**: support vector machines (Vapnick & Chervonenkis)
 - we will discuss SVM's idea later in the course
- **1969**: Minsky and Pappert show the limitations of single-layer neural networks
 - for example, it cannot learn a simple XOR function
 - the limitation does not extend to a multilayer perceptron (which was known back then)
 - one of the factors in so-called AI winter
- **1970-80s**: rule-based and symbolic AI dominates
 - in contrast to connectionist AI as in neural networks
 - expert systems find applications in industry
 - these are rule-based systems with their specialized hardware

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- 1970-80s: rule-based and symbolic AI dominates
- **1980s:** Bayesian networks (Judea Pearl)
 - combine graph structure with probabilistic (and causal) reasoning
 - related to both symbolic and connectionist approach
- **1986:** Backpropagation rediscovered (Rumelhart, Hinton & Williams)
 - an efficient method for learning the weights in neural networks using gradient descent
 - it was rediscovered many times since the 1960s
 - we discuss it later in the course
- **1980-1990s:** expert systems are being replaced with general-purpose computers



A short history of Machine Learning

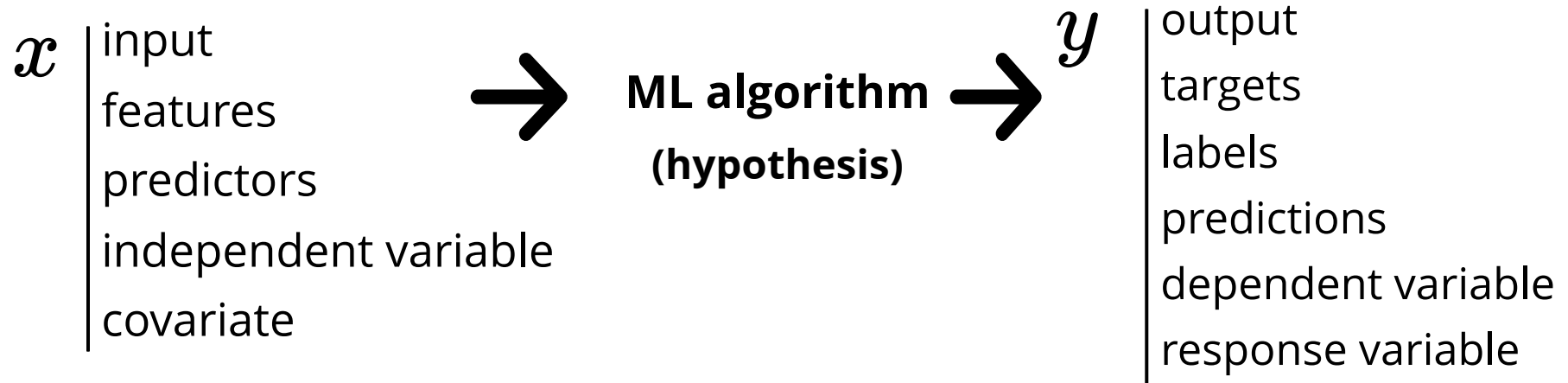
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...

- **1997**: Deep Blue beats the world chess champion
- **2012**: AlexNet wins Imagenet by a large margin
- **2012 - now** a new AI spring around deep learning ...
 - super-human performance in many tasks
 - **e.g.** AlphaGo defeats Go Master (2017)
- **Future**: what is next?
 - in the short term, AI will impact domain sciences



Basic Terminology



example

<tumorsize, texture, perimeter> = <18.2, 27.6, 117.5> → cancer = No

Basic Terminology

(labelled) **datasets**: consist of many training examples or **instances**

<tumorsize, texture, perimeter> , <cancer, size change>

<18.2, 27.6, 117.5> , < No , +2 >

$x^{(1)}$

<17.9, 10.3, 122.8> , < No , -4 >

$x^{(2)}$

one instance

<20.2, 14.3, 111.2> , < Yes , +3 >

$x^{(3)}$

⋮

⋮

<15.5, 15.2, 135.5> , < No , 0 >

$x^{(N)}$

Basic Terminology

we split the dataset into **train** and **test** sets

Train dataset:

used to build the model

<tumorsize, texture, perimeter>	<cancer, size change>
<18.2, 27.6, 117.5>	< No , +2 >
<17.9, 10.3, 122.8>	< No , -4 >
<20.2, 14.3, 111.2>	< Yes , +3 >
<15.5, 15.2, 135.5>	< No , 0 >
.	.
.	.
.	.



algorithm shouldn't have access to test set when being trained

Test dataset:

used to evaluate the model

<tumorsize, texture, perimeter>	<cancer, size change>
<12.4, 15.7, 120.1>	< No , +5 >
<15.2, 17.2, 113.3>	< Yes , +1 >
<19.3, 15.9, 125.4>	< No , +2 >
<17.5, 11.9, 122.7>	< No , -3 >

Ground-Truth, **True** labels

<cancer, size change>

< Yes , +4 >
< Yes , +1 >
< No , +1 >
< Yes , -2 >

Output labels, algorithm results



algorithm shouldn't see the true labels when being evaluated (making predictions on test set), these true labels are only used to compare against the algorithm's results to measure performance

Families of Machine Learning Methods

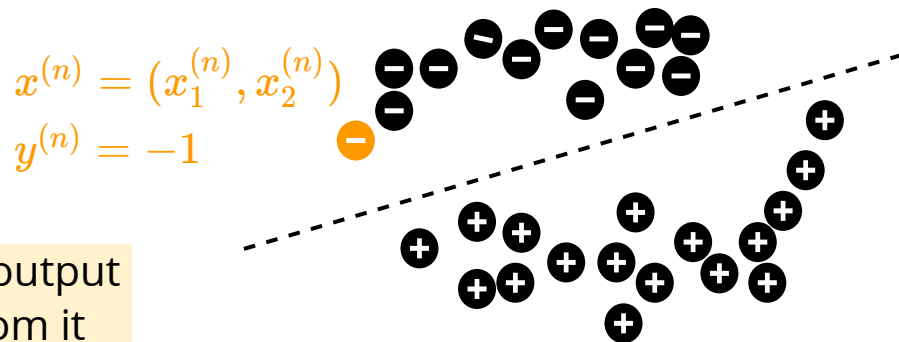
1. Supervised learning
2. Unsupervised learning
3. Semi-supervised learning
4. Reinforcement learning ...

Families of Machine Learning Methods

1. Supervised learning: we have labeled data

most of this course

- classification
- regression
- structured prediction



shows samples with desired output to the algorithm to learn from it

Families of Machine Learning Methods

1. Supervised learning: we have labeled data

Classification: categorical/discrete output

<tumorsize, texture, perimeter>	,	<cancer>
<18.2, 27.6, 117.5>	,	< No >
<17.9, 10.3, 122.8>	,	< No >
<20.2, 14.3, 111.2>	,	< Yes >
<15.5, 15.2, 135.5>	,	< No >

target

Regression: continuous output

<tumorsize, texture, perimeter>	,	<size change>
<18.2, 27.6, 117.5>	,	< +2 >
<17.9, 10.3, 122.8>	,	< -4 >
<20.2, 14.3, 111.2>	,	< +3 >
<15.5, 15.2, 135.5>	,	< 0 >

target

Supervised Learning: Example

MIT
Technology
Review

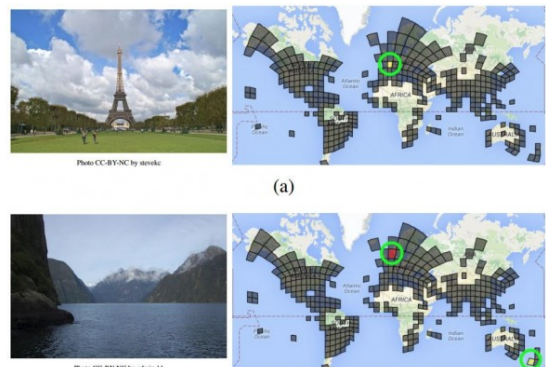
Topics+ The Download

Intelligent Machines

Google Unveils Neural Network with “Superhuman” Ability to Determine the Location of Almost Any Image

Guessing the location of a randomly chosen Street View image is hard, even for well-traveled humans. But Google's latest artificial-intelligence machine manages it with relative ease.

by Emerging Technology from the arXiv February 24, 2016



trained on a database
of geolocated images
from the Web

[read about it [here](#)]

Supervised Learning: Example

DeepL schools other online translators with clever machine learning

Devin Coldewey, Frederic Lardinois / 1:57 pm EDT • August 29, 2017

[Comment](#)



[Image Credits: H. Armstrong Roberts/Getty Images](#)

trained using billions of high-quality translation segments from reliable sources such as the European Parliament, Unesco patents, and literary works, bilingual sentences collected by Linguee's web crawler on the Internet

Machine Translation: data consists of input-output sentence pairs (x,y) , similarly we may consider **text-to-speech**, with text and voice as input and target (x,y) , or **speech recognition** where input and output above are swapped.

[read about it [here](#), try it out [here](#)]

Supervised Learning: Example

Supervised methods are powered by large datasets often crawled from the web or curated with crowdsourcing

What is COCO?



COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features:

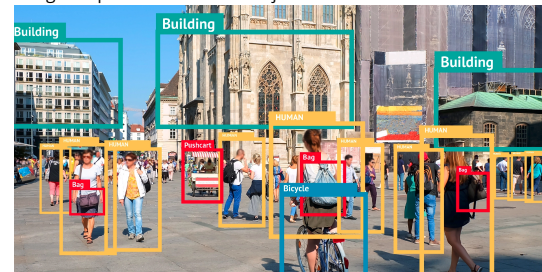
- ✓ Object segmentation
- ✓ Recognition in context
- ✓ Superpixel stuff segmentation
- ✓ 330K images (>200K labeled)
- ✓ 1.5 million object instances
- ✓ 80 object categories
- ✓ 91 stuff categories
- ✓ 5 captions per image
- ✓ 250,000 people with keypoints



Fig. 6: Samples of annotated images in the MS COCO dataset.

Object Recognition

image: <https://bitmovin.com/object-detection/>



input: image

output: a set of bounding box coordinates

Supervised Learning: Example

Image Captioning

input: image

output: text

A person riding a motorcycle on a dirt road.



Two dogs play in the grass.



A skateboarder does a trick on a ramp.



A dog is jumping to catch a frisbee.



A group of young people playing a game of frisbee.



Two hockey players are fighting over the puck.



A little girl in a pink hat is blowing bubbles.



A refrigerator filled with lots of food and drinks.



A herd of elephants walking across a dry grass field.



A close up of a cat laying on a couch.



A red motorcycle parked on the side of the road.



A yellow school bus parked in a parking lot.



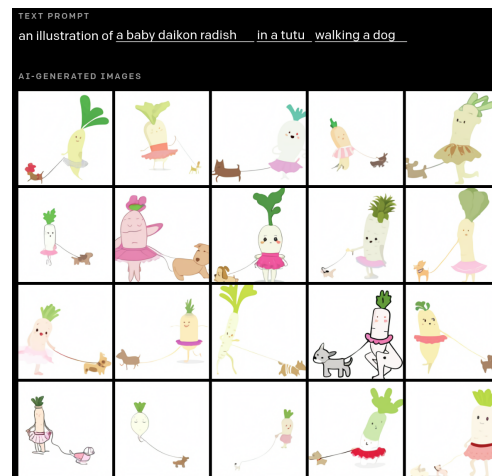
Describes without errors

Describes with minor errors

Somewhat related to the image

Unrelated to the image

read about it [here](#)



DALL·E: Creating Images from Text

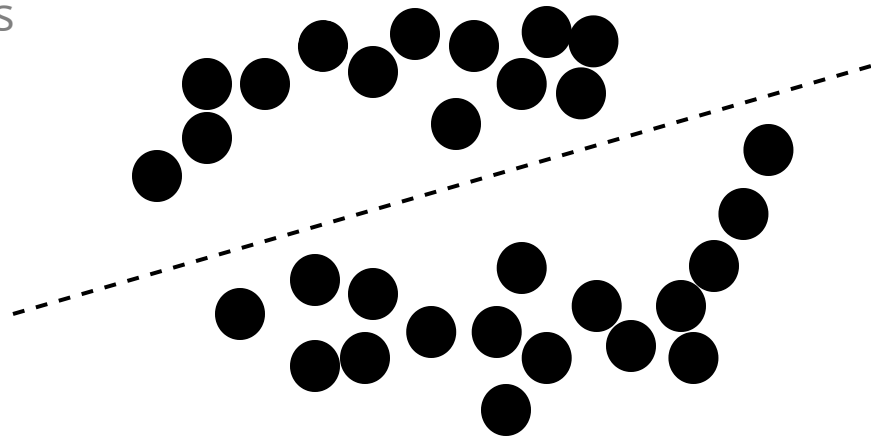
[try it out [here](#)]

Families of Machine Learning Methods

2. **Unsupervised Learning:** only unlabeled data

- clustering
 - dimensionality reduction
 - density estimation / generative modeling
 - anomaly detection
 - discovering latent factors and structures
- helps explore and understand the data
 - closer to data mining
 - we have much more unlabeled data
 - more open challenges

The algorithm doesn't see the desired outputs, mines the patterns in the input data



Unsupervised Learning: Example

Clustering: similar to classification but labels/classes should be inferred and are not given to the algorithm

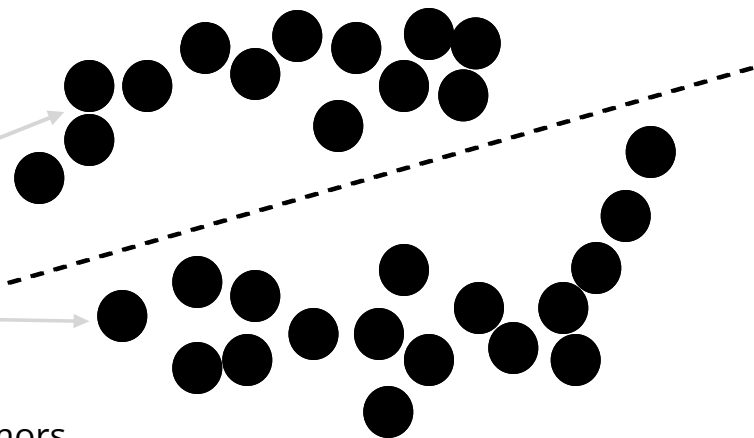
<tumorsize, texture, perimeter>

<18.2, 27.6, 117.5>

<17.9, 10.3, 122.8>

<20.2, 14.3, 111.2>

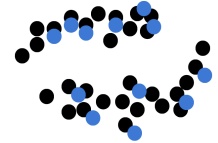
<15.5, 15.2, 135.5>



there seems to be two types of tumors,
larger and rough vs smaller and smooth

Unsupervised Learning: Example

Generative Modelling: model the distribution of the data and learns to generate the data instead of directly categorizing/discriminating the instances into different classes

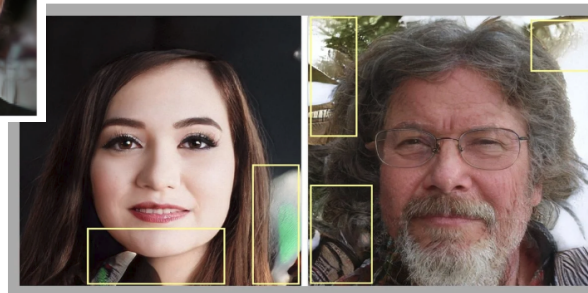


Ethical
Challenges:
Misuse

PAUL MATHIAS BUSINESS 12.28.2018 04:21 PM

Facebook Removes Accounts With AI-Generated Profile Photos

Researchers said it appears to be the first use of artificial intelligence to support an inauthentic social media campaign.



Profile pictures for Facebook accounts "Mary Keen" and "Jacobs Guillermo," admins on groups associated with The BL highlighted by Graphika. COURTESY OF GRAPHIKA

How a fake persona laid the groundwork for a Hunter Biden conspiracy deluge



A viral dossier about Hunter Biden was written by "Martin Aspen," a fake identity whose profile picture was created by artificial intelligence.
TyphoonInvest11 / via Twitter

Experts: Spy used AI-generated face to connect with targets

By RAPHAEL SATER June 13, 2019



Generate faces that look like celebrity images

from the paper [here](#)

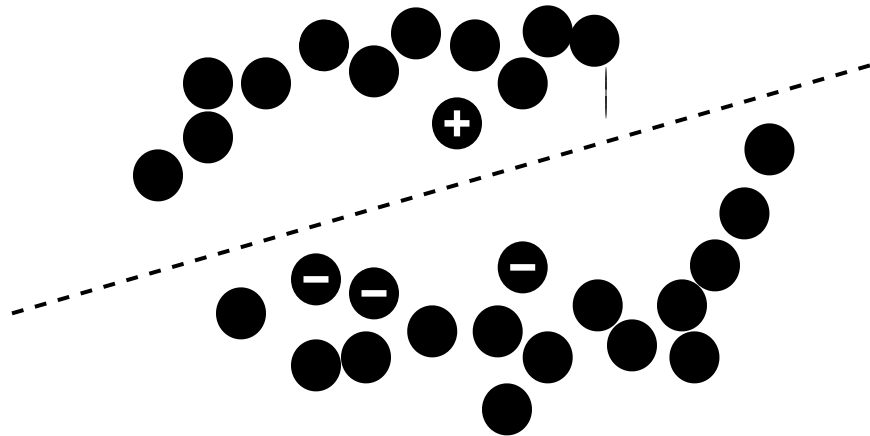
click [here](#) to get a random fake person

Families of Machine Learning Methods

3. **Semisupervised learning:** a few labeled examples

- we can include structured problems such as
 - matrix completion (a few entries are observed)
 - link prediction

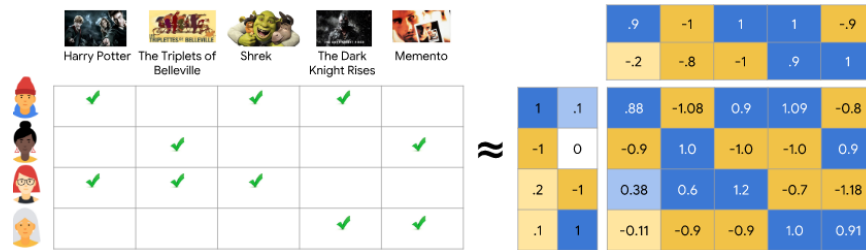
The algorithm sees few examples of the desired outputs



Semisupervised Learning: Example

Matrix Completion in Recommendation Systems

Predict what movies you will like based on what you liked so far and what others users liked who like similar movies to you



[figure from [here](#)]

Ethical
Challenges:
Privacy of Users
Polarizing Users

Netflix Awards \$1 Million Prize and Starts a New Contest

BY STEVE LOHR SEPTEMBER 21, 2009 10:15 AM



Jason Kempin/Getty Images Netflix prize winners, from left: Yehuda Koren, Martin Chabbert, Martin Plotte, Michael Jahner, Andreas Toscher, Chris Volinsky and Robert Bell.

Update | 1:45 p.m. Adding details announced Monday about the extremely close finish to the contest.

RYAN SINGEL SECURITY 03.12.18 02:48 PM

NetFlix Cancels Recommendation Contest After Privacy Lawsuit



Netflix is canceling its second \$1 million Netflix Prize to settle a legal challenge that it breached customer privacy as part of the first contest's race for a better movie-recommendation engine.

[read about it [here](#)]

Families of Machine Learning Methods

4. Reinforcement Learning:

- weak supervision through the reward signal
- sequential decision making
- biologically motivated

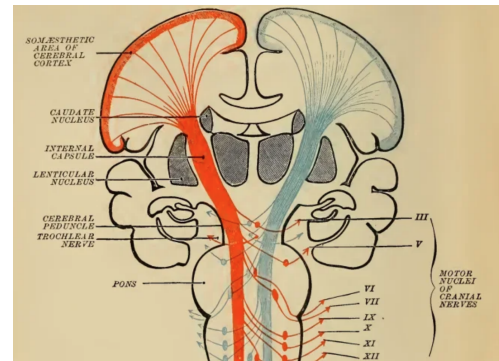
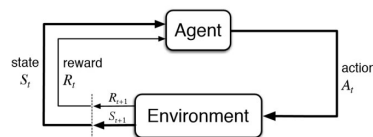


figure from [here](#)

also related:

imitation learning: learning from demonstrations

- behavior cloning (is supervised learning!)
- inverse reinforcement learning (learning the reward function)



figure from [here](#)

Reinforcement Learning: Examples



Human Level Control Through Deep Reinforcement Learning

Abstract

The theory of reinforcement learning provides a normative account deeply rooted in psychological and neuroscientific perspectives on animal behaviour, of how agents may optimize their control of an environment. To use reinforcement learning successfully in situations approaching real-world complexity, however, agents are confronted with a difficult task: they must derive efficient representations of the environment from high-dimensional sensory inputs and use these to generalize

Playing Atari like a pro 2015, see [here](#)

Google's AlphaGo Defeats Chinese Go Master in Win for A.I.





[点击查看本文中文版](#)

By PAUL MOZUR MAY 23, 2017



Ke Jie, the world's top Go player, reacting during his match on Tuesday against AlphaGo, artificial intelligence software developed by a Google affiliate. China Stringer Network, via Reuters

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Playing Go like a pro 2017

Summary

Supervised Learning: we have labeled data

- classification
- regression

Unsupervised Learning: only unlabeled data

- clustering
- density estimation / generative modeling

Semisupervised learning: a few labeled examples

Reinforcement Learning: reward signal