CS 498: Introduction to Deep Learning
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Course website:
http://slazebni.cs.illinois.edu/fall20
What is “deep learning”?
An incomplete timeline of deep learning

• 1943: McCulloch and Pitts neurons
  • Fascinating reading: The Man Who Tried to Redeem the World with Logic, Nautilus, 2/5/2015
An incomplete timeline of deep learning

- 1943: McCulloch and Pitts neurons
- 1958: Rosenblatt’s perceptron

NEW NAVY DEVICE LEARNS BY DOING

Psychologist Shows Embryo of Computer Designed to Read and Grow Wiser

WASHINGTON, July 7 (UP1) — 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 $2,000,000 “704” 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 fired 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 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.

1958 New York Times...

In today’s demonstration, the “704” 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.
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- 1943: McCulloch and Pitts neurons
- 1958: Rosenblatt’s perceptron
- 1969: Minsky and Papert Perceptrons book
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- **1943:** McCulloch and Pitts neurons
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- **1969:** Minsky and Papert Perceptrons book
- **1980:** Fukushima’s Neocognitron
  - Video (short version)
  - Inspired by the findings of Hubel & Wiesel about the hierarchical organization of the visual cortex in cats and monkeys (1959-1977)

Image source

Kunihiko Fukushima
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- 1986: Back-propagation
  - Popularized by Rumelhart, Hinton & Williams (1986)
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  • LeNet to LeNet-5

[Image of Yann LeCun]
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- 2012: AlexNet
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• 2012: AlexNet
• 2018: ACM Turing Award to Hinton, LeCun, and Bengio
Successes of deep learning

• Vision
• Language
• Games
• Robotics
Successes in vision: ImageNet Challenge

ILSVRC

Figure source
Vision: ImageNet Challenge

Figure 1: When presented with a model’s prediction and the original ImageNet label, human annotators now prefer model predictions on average (Section 4). Nevertheless, there remains considerable progress to be made before fully capturing human preferences.

K. Yang, K. Qinami, L. Fei-Fei, J. Deng, O. Russakovsky, Towards Fairer Datasets: Filtering and Balancing the Distribution of the People Subtree in the ImageNet Hierarchy, Conference on Fairness, Accountability, and Transparency (FAT*), 2020
Vision: Detection, segmentation

K. He, G. Gkioxari, P. Dollar, and R. Girshick, Mask R-CNN, ICCV 2017 (Best Paper Award)
Vision: Image generation

• Faces: 1024x1024 resolution, CelebA-HQ dataset

T. Karras, T. Aila, S. Laine, and J. Lehtinen, Progressive Growing of GANs for Improved Quality, Stability, and Variation, ICLR 2018

Follow-up work
Vision: Image generation

- **BigGAN**: Synthesize ImageNet images, conditioned on class label, up to 512 x 512 resolution

A. Brock, J. Donahue, K. Simonyan, *Large scale GAN training for high fidelity natural image synthesis*, ICLR 2019
Vision working too well? Face recognition

The Secretive Company That Might End Privacy As We Know It – New York Times, 1/18/2020
Wrongfully Accused by an Algorithm – New York Times, 6/24/2020
Vision working too well? DeepFakes

Harrison Ford Is Young Han In Solo Deepfake Video

Thanks to deepfake technology, the maligned Solo: A Star Wars Story now stars Harrison Ford instead of Alden Ehrenreich as the young Han.

https://www.youtube.com/watch?v=bC3uH4Xw4Xo

Just a random recent example…

Vision: Origins

Hough, 1959

Roberts, 1963

Rosenfeld, 1969
Successes in natural language

• Neural machine translation
  • The Great AI Awakening – New York Times Magazine, 12/14/2016
• Language models: e.g., GPT-3

OpenAI’s new language generator GPT-3 is shockingly good—and completely mindless

The AI is the largest language model ever created and can generate amazing human-like text on demand but won’t bring us closer to true intelligence.

GPT-3, Bloviator: OpenAI’s language generator has no idea what it’s talking about

Tests show that the popular AI still has a poor grasp of reality.

by Gary Marcus and Ernest Davis


Natural language: Origins

- **Turing test** (1950)
- Machine translation
  - 1954: [Georgetown-IBM experiment](#)
    - Completely automatic translation of more than sixty Russian sentences into English
    - Only six grammar rules, 250 vocabulary words, restricted to organic chemistry
    - Promised that machine translation would be solved in three to five years ([press release](#))
  - 1966: [Automatic Language Processing Advisory Committee (ALPAC) report](#): machine translation is not living up to the hype
- Chatbots: **ELIZA** (1966)
  - Simulated a psychotherapist, could fool naïve users
Successes in games

• 2013: DeepMind uses deep reinforcement learning to beat humans at some Atari games

• 2016: DeepMind’s AlphaGo system beats Go grandmaster Lee Sedol 4-1

• 2017: AlphaZero learns to play Go and chess from scratch

• 2019: DeepMind’s StarCraft 2 AI is better than 99.8 percent of all human players
Games: Origins

- 1952-1959: Arthur Samuel programmed a digital computer to learn to play checkers

- 1960: Donald Michie built a “machine” out of 304 matchboxes that could learn to play tic-tac-toe
Games: Origins

• “In 1959 Arthur Samuel published a paper titled ‘Some Studies in Machine Learning Using the Game of Checkers’, the first time the phrase ‘Machine Learning’ was used”

• “Donald Michie’s description of reinforcement learning comes from 1961, and is the first use of the term reinforcement learning when applied to a machine process … There have been some developments in reinforcement learning since 1961, but only in details”

Rodney Brooks essay, 8/28/2017
Successes in embodied vision and robotics

• Sensorimotor learning

S. Levine, C. Finn, T. Darrell, P. Abbeel, End-to-end training of deep visuomotor policies, JMLR 2016
Embodied vision and robotics

A cross-section of topics from one representative researcher:

- See also: Abhinav Gupta, Pieter Abbeel, Sergey Levine, Chelsea Finn

Lerrel Pinto
Embodied platforms

- Simulation: [AI2Thor](#), [Habitat](#)
- Real robots: [PyRobot](#)
- Robot on your smartphone: [OpenBot](#)
Self-driving cars

- Deep learning crucial for the global success of automotive autonomy – Automotive World, 6/26/2018
Robotics: Origins

Blocks World
MIT, 1960s – 1970s
Copy demo (1970)

Shakey the Robot
SRI, 1966 – 1972
Video
In this class

**ML basics, linear classifiers**

- Inputs
- Weights
- Weighted sum
- Unit step function

**Multilayer neural networks, backpropagation**

- Input layer
- Hidden layers
- Output layer

**Convolutional networks for classification**

- Feature maps
- Pooled feature maps
- Outputs

**Networks for detection**

- Deep ConvNet
- Conv feature map
- Roi pooling layer
- Roi feature vector

**Networks for dense prediction**

- Convolutional encoder-decoder
- Encoder (Forward/Inference)
- Decoder (Backward/Learning)

**Recurrent models**

- Recurrent model schematic

**Generative models (GANs, VAEs)**

- Generator
- Discriminator
- Real Images (x)
- Generated Image (z)

**Deep reinforcement learning**

- Deep reinforcement model schematic