

# COMP541

## DEEP LEARNING

Lecture #01 – Introduction

# Welcome to COMP541

- This course gives an overview of **deep learning**,
- In particular, we will cover various **deep architectures** and **deep learning** methods.
- You will develop fundamental and practical skills at applying deep learning to your research.

# A little about me...

Koç University  
Associate Professor  
2020-now



Hacettepe University  
Associate Professor  
2010-2020



Università Ca' Foscari di Venezia  
Post-doctoral Researcher  
2008-2010



Middle East Technical University  
1997-2008  
Ph.D., 2008  
M.Sc., 2003  
B.Sc., 2001



MIT  
Fall 2007  
Visiting Student



Virginia Tech  
Visiting Research Scholar  
Summer 2006



- I explore better ways to understand, interpret and manipulate visual data.
- My research interests span a diverse set of topics, ranging from image editing to visual saliency estimation, and to multimodal learning for integrated vision and language.

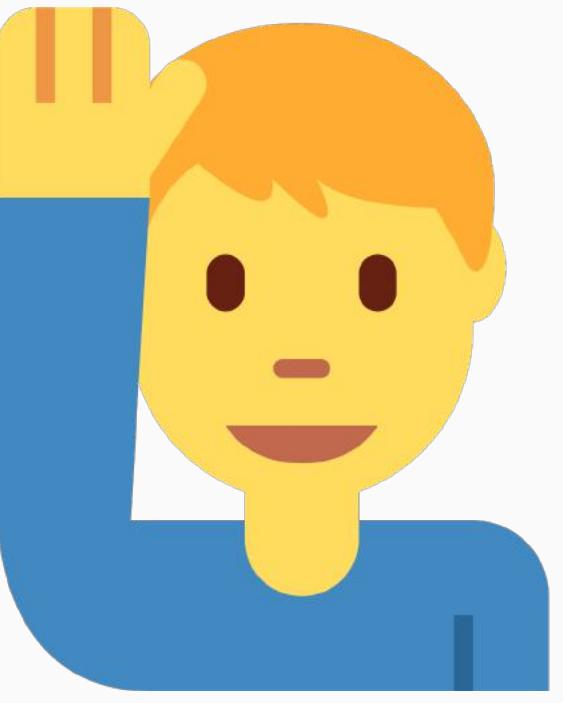


# Now, what about you?

The screenshot shows a Google Forms survey titled "COMP441/541 Fall 2024 Survey". The survey has three required questions:

- Name \***: A text input field with the placeholder "Your answer".
- E-mail Address: \***: A text input field with the placeholder "Your answer".
- Status \***: A radio button group with two options:
  - PhD: 1st year
  - PhD: 2nd year

<https://forms.gle/9GTV56Nt7ZVMTCRb6>



# Course Logistics

# Course Information

**Lectures** Tuesday and Thursday 16:00-17:10 (SOS 103)

**PS** Friday 14:30-15:40 (SOS 103)

**Instructor** Aykut Erdem

**TAs** Andrew Bond & Hakan Capuk.

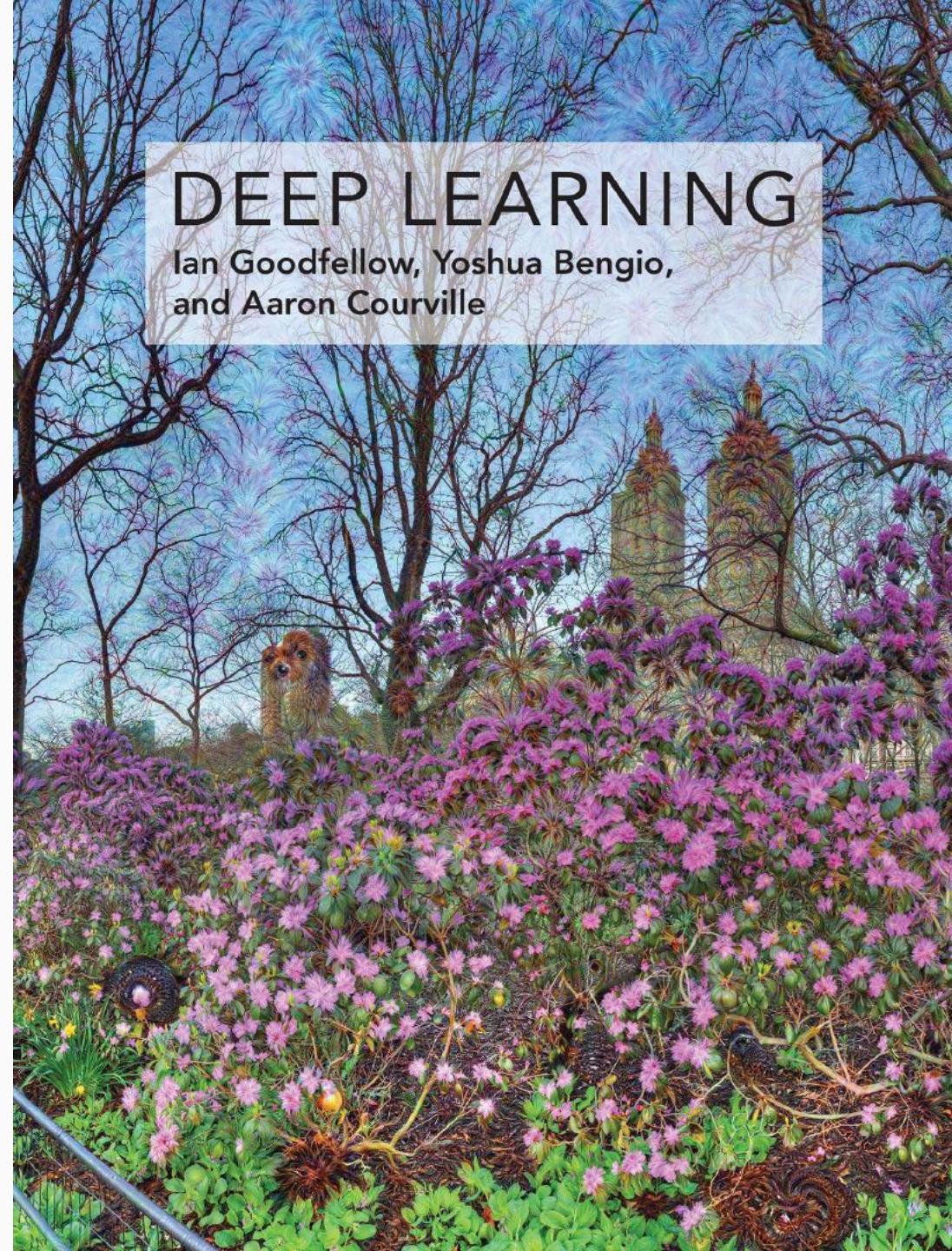


**Website** <https://aykuterdem.github.io/classes/comp541.f23/>

- KUHub Learn for course related announcements and collecting and grading your submissions

# Textbook

- Goodfellow, Bengio, and Courville, Deep Learning, MIT Press, 2016 (draft available [online](#))
- In addition, we will extensively use online materials (video lectures, blog posts, surveys, papers, etc.)



# Instruction style

- Students are responsible for studying and keeping up with the course material outside of class time.
  - Reading particular book chapters, papers or blogs, or
  - Watching some video lectures.
- After the first four lectures, each week students will present papers related to the topics of the previous week.
  - Weekly paper reviews will be prepared by all the students



# Prerequisites

- Calculus and linear algebra
  - Derivatives,
  - Matrix operations
- Probability and statistics
- Machine learning
- Programming

Read Chapter 2-4  
of the Deep Learning textbook for a quick review.

FALL 2024      SELF-ASSESSMENT QUIZ      COMP441/541

COMP441/541 Deep Learning, Fall 2024      SELF-ASSESSMENT QUIZ (THEORY)

Due Date: 23:59 Wednesday, October 9, 2024

Each student enrolled to COMP441 must complete this quiz on prerequisite math knowledge. The purpose is to self-assess whether you have the right background for the course. The topics covered in this problem set are very crucial so if you are having trouble with solving a problem, this indicates that you should spend a considerable amount of time to study that topic in its entirety.

**Points and Vectors**

1. Given two vectors  $x = [a_1, a_2, a_3]$  and  $y = [a_1, -a_2, a_3]$ . Write down the equation for calculating the angle between  $x$  and  $y$ . When is  $x$  orthogonal to  $y$ ?

**Planes**

2. Consider a hyperplane described by the  $d$ -dimensional normal vector  $[\theta_1, \dots, \theta_d]$  and offset  $\theta_0$ . Derive the equation for the signed distance of a point  $x$  from the hyperplane, which is defined as the perpendicular distance between  $x$  and the hyperplane, multiplied by +1 if  $x$  lies on the same side of the plane as the vector  $\theta$  points and by -1 if  $x$  lies on the opposite side from the hyperplane.

**Matrices**

3. Suppose that  $A^T(AB - C) = 0$ , where  $0$  is an  $m \times 1$  vector of zeros, derive an expression for  $B$ . Assume that all relevant matrices needed for this calculation are invertible.

4. Find the eigenvalues and eigenvectors of the matrix  $A = \begin{bmatrix} 13 & 5 \\ 2 & 4 \end{bmatrix}$ .

**Probability**

5. Let

$$p(X_1 = x_1) = \alpha_1 e^{-\frac{(x_1 - \mu_1)^2}{2\sigma_1^2}}$$
$$p(X_2 = x_2 | X_1 = x_1) = \alpha_2 e^{-\frac{(x_2 - \mu_2)^2}{2\sigma_2^2}}$$

where  $X_1$  and  $X_2$  are continuous random variables. Show that

$$p(X_2 = x_2) = \alpha_2 e^{-\frac{(x_2 - \mu_2)^2}{2\sigma_2^2}}$$

by explicitly calculating the values of  $\alpha_2$ ,  $\mu_2$  and  $\sigma_2$ .

**MLE and MAP**

6. Let  $p$  be the probability of landing head of a coin. You flip the coin 3 times and note that it landed 2 times on tails and 1 time on heads. Suppose  $p$  can only take two values: 0.3 or 0.6. Find the Maximum Likelihood Estimate of  $p$  over the set of possible values {0.3, 0.6}.

Estimate of  $p$  over the set of possible values {0.3, 0.6}.

7. Suppose that you have the following prior on the parameter  $p$ :  $P(p=0.3) \sim 0.3$  and  $P(p=0.6) \sim 0.7$ . Given that you flipped the coin 3 times with the observations described above, find the MAP estimate of  $p$  over the set {0.3, 0.6}, using the prior.

Page 1 of 2

## Self-Assessment Quiz (Theory)

Due Date: October 9 (23:59).

Each student enrolled to COMP441/541 must complete and pass this quiz!

# Prerequisites

- Calculus and linear algebra
  - Derivatives,
  - Matrix operations
- Probability
- The self-assessment quiz on programming background will be released later this week!
- Machine learning
- Programming

Read Chapter 2-4  
of the Deep Learning textbook for a quick review.

SELF-ASSESSMENT QUIZ  
COMP441/541 Deep Learning, Fall 2024  
SELF-ASSESSMENT QUIZ (THEORY)  
FALL 2024  
COMP441/541  
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**Matrices**

3. Suppose that  $A^T(AB - C) = 0$ , where  $0$  is an  $m \times 1$  vector of zeros, derive an expression for  $B$ . Assume that all relevant matrices needed for this calculation are invertible.

4. Find the eigenvectors of the matrix  $A = \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix}$ .

5. By explicitly calculating the values, show that  $\text{MAP}(p) = \text{MLE}(p)$ .

**MLE and MAP**

6. Let  $p$  be the probability of landing head of a coin. You flip the coin 3 times and note that it landed 2 times on tails and 1 time on heads. Suppose  $p$  can only take two values: 0.3 or 0.6. Find the Maximum Likelihood Estimate of  $p$  over the set of possible values {0.3, 0.6}.

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Page 1 of 2

## Self-Assessment Quiz (Theory)

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Each student enrolled to COMP441/541 must complete and pass this quiz!

# Topics Covered in ENGR 421

- **Basics of Statistical Learning**

- Loss function, MLE, MAP, Bayesian estimation, bias-variance tradeoff, overfitting, regularization, cross-validation

- **Supervised Learning**

- Nearest Neighbor, Naïve Bayes, Logistic Regression, Support Vector Machines, Kernels, Neural Networks, Decision Trees
  - Ensemble Methods: Bagging, Boosting, Random Forests

- **Unsupervised Learning**

- Clustering: K-Means, Gaussian mixture models
  - Dimensionality reduction: PCA, SVD

# Grading

Self-Assessment Quiz	2%
Programming Assignments	20% (4 assignments x 5% each)
Midterm Exam	21%
Course Project	32%
Paper Presentations	10%
Paper Reviews	5%
Class Participation	10%

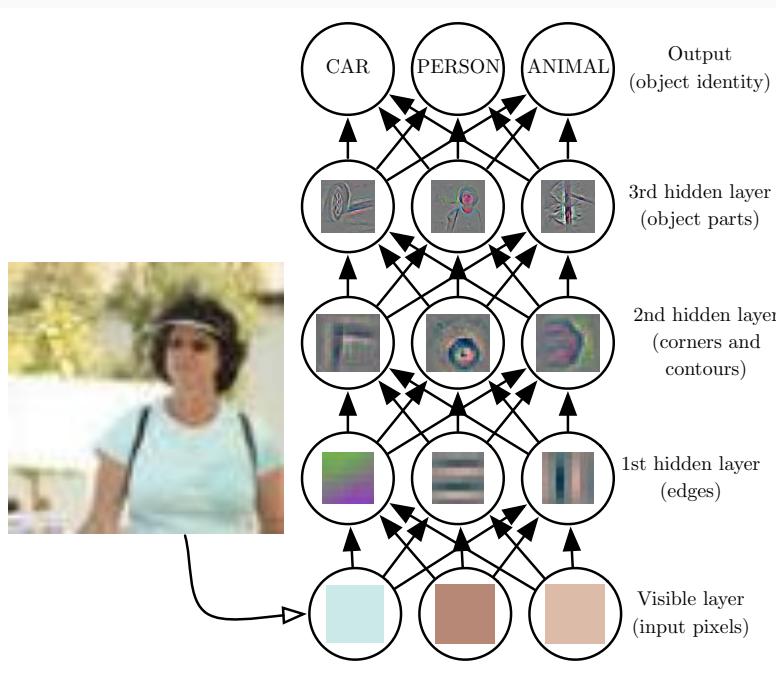
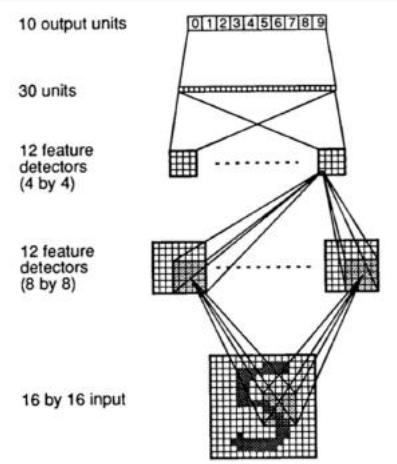
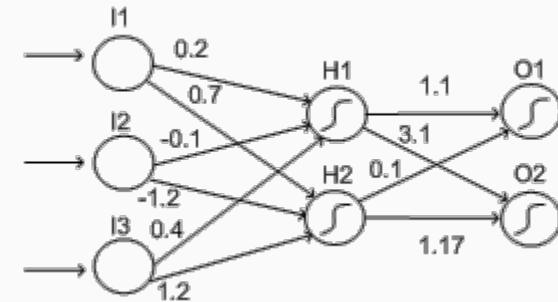
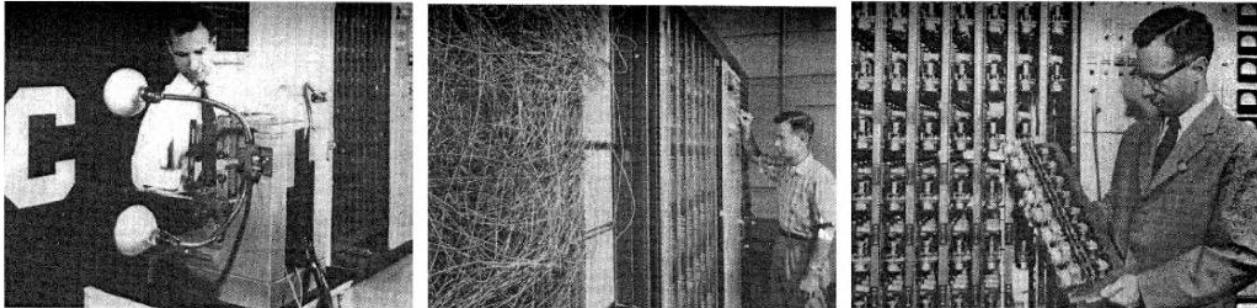
# Schedule

- |               |                                    |
|---------------|------------------------------------|
| <b>Week 1</b> | Introduction to Deep Learning      |
| <b>Week 2</b> | Machine Learning Overview          |
| <b>Week 3</b> | Multi-Layer Perceptrons            |
| <b>Week 4</b> | Training Deep Neural Networks      |
| <b>Week 5</b> | Convolutional Neural Networks      |
| <b>Week 6</b> | Understanding and Visualizing CNNs |
| <b>Week 7</b> | Recurrent Neural Networks          |

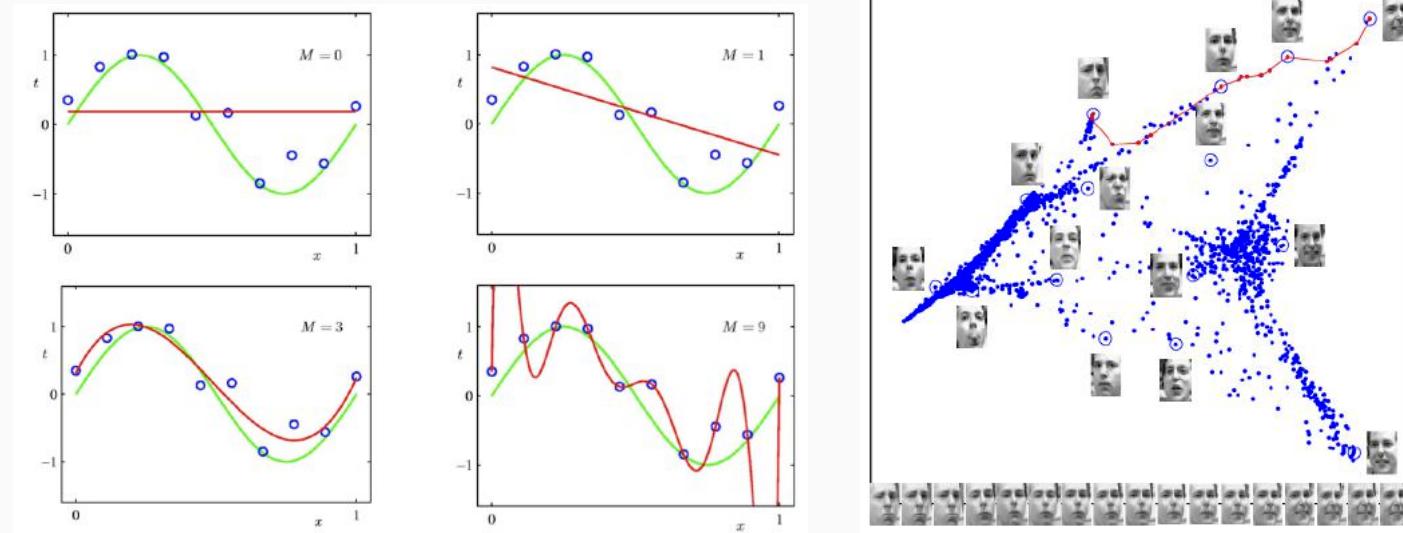
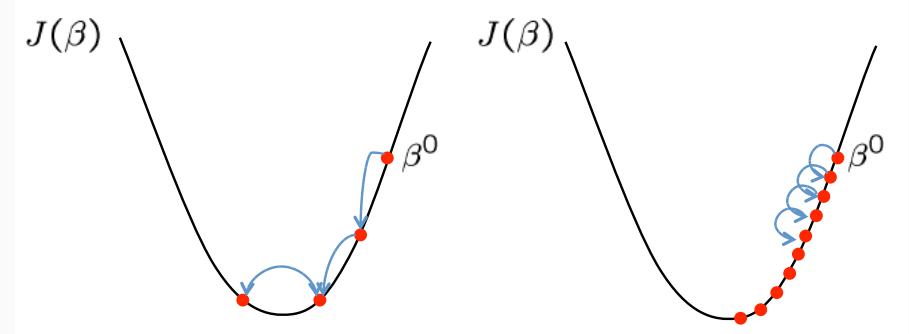
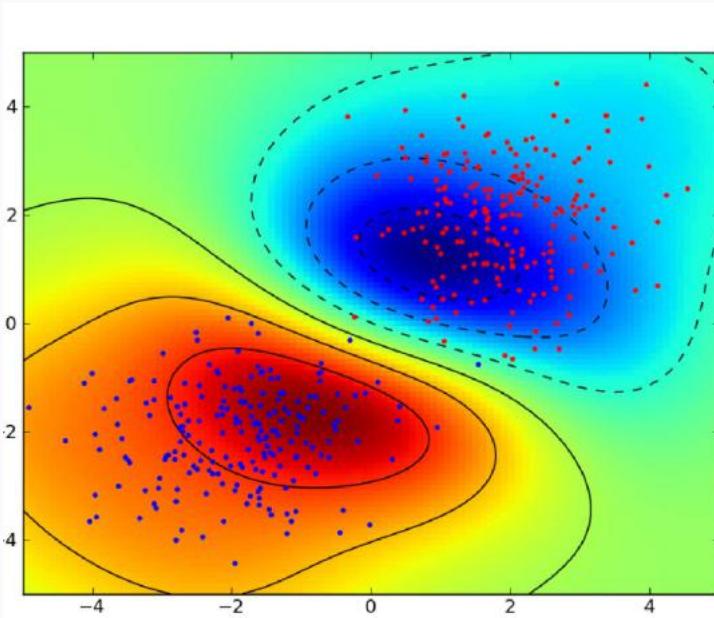
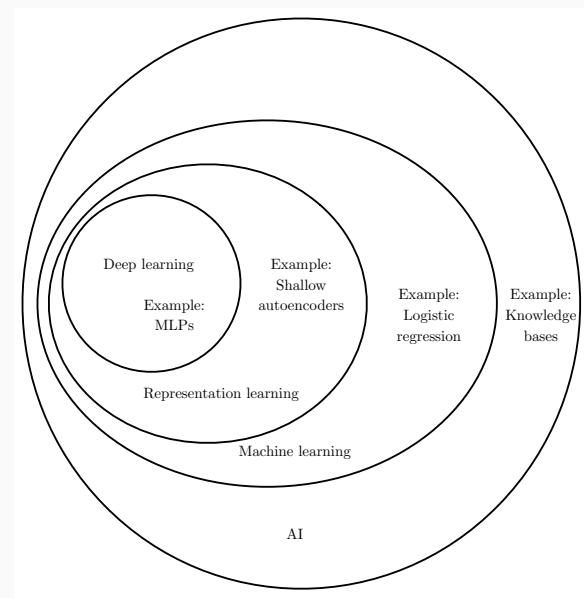
# Schedule

- Week 8**      Attention and Transformers
- Week 9**      Graph Neural Networks
- Week 10**     Language Model Pretraining
- Week 11**     Project Progress Presentations
- Week 12**     Large Language Models
- Week 13**     Efficient LLMs
- Week 14**     Multimodal Pretraining

# Lecture 1: Introduction to Deep Learning

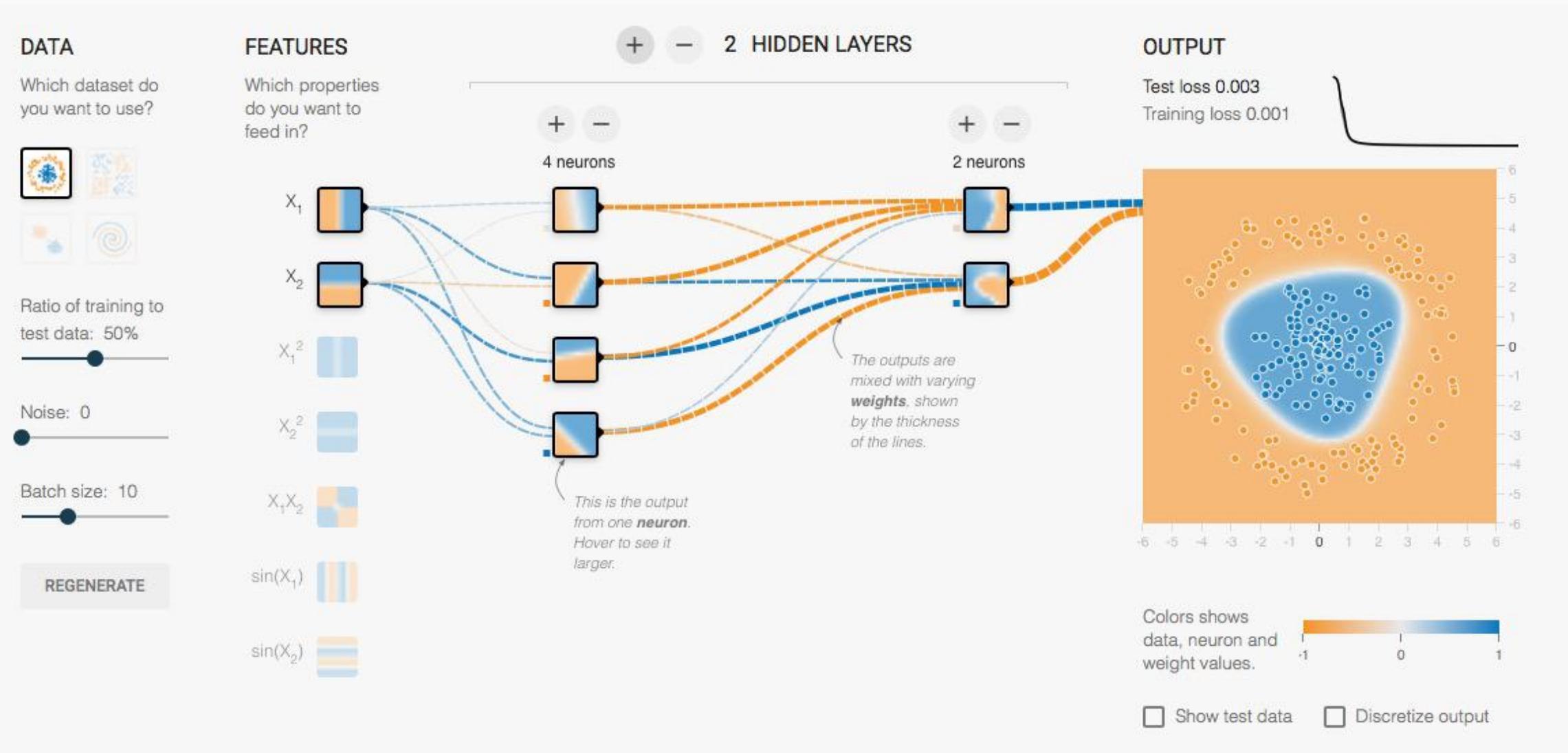


# Lecture 2: Machine Learning Overview

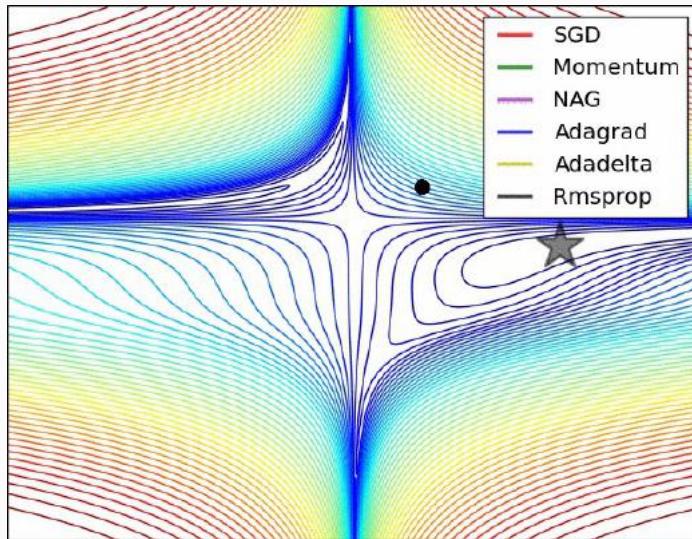


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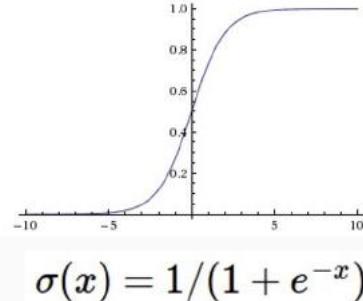
# Lecture 3: Multi-Layer Perceptrons



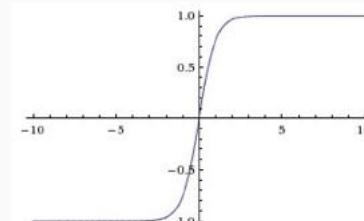
# Lecture 4: Training Deep Neural Networks



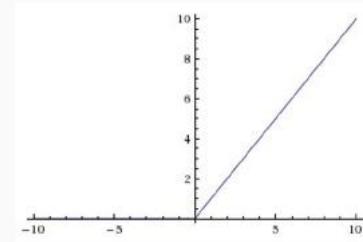
Sigmoid



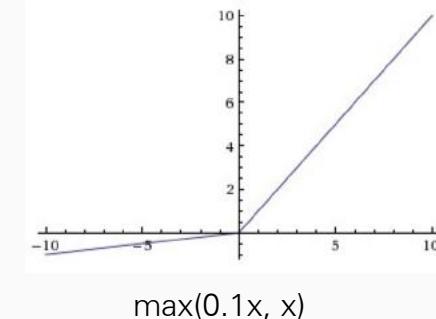
tanh



ReLU

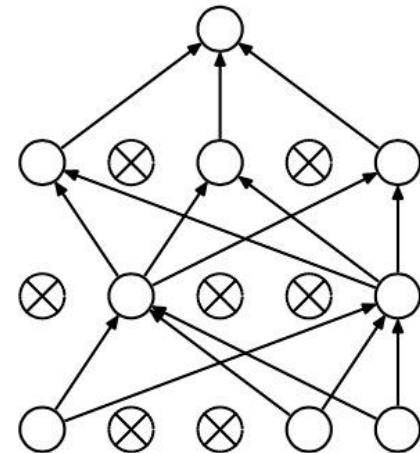
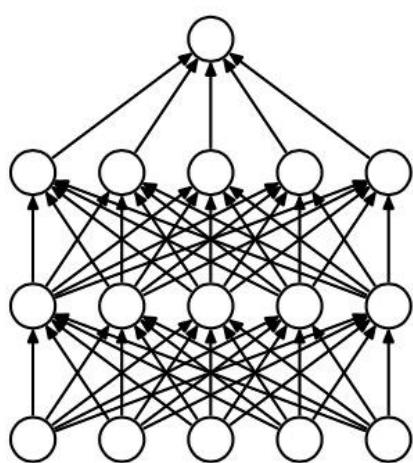


Leaky ReLU



## Activation Functions

Optimizers



Dropout

**Input:** Values of  $x$  over a mini-batch:  $\mathcal{B} = \{x_1 \dots m\}$ ;  
Parameters to be learned:  $\gamma, \beta$

**Output:**  $\{y_i = \text{BN}_{\gamma, \beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i \quad // \text{mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2 \quad // \text{mini-batch variance}$$

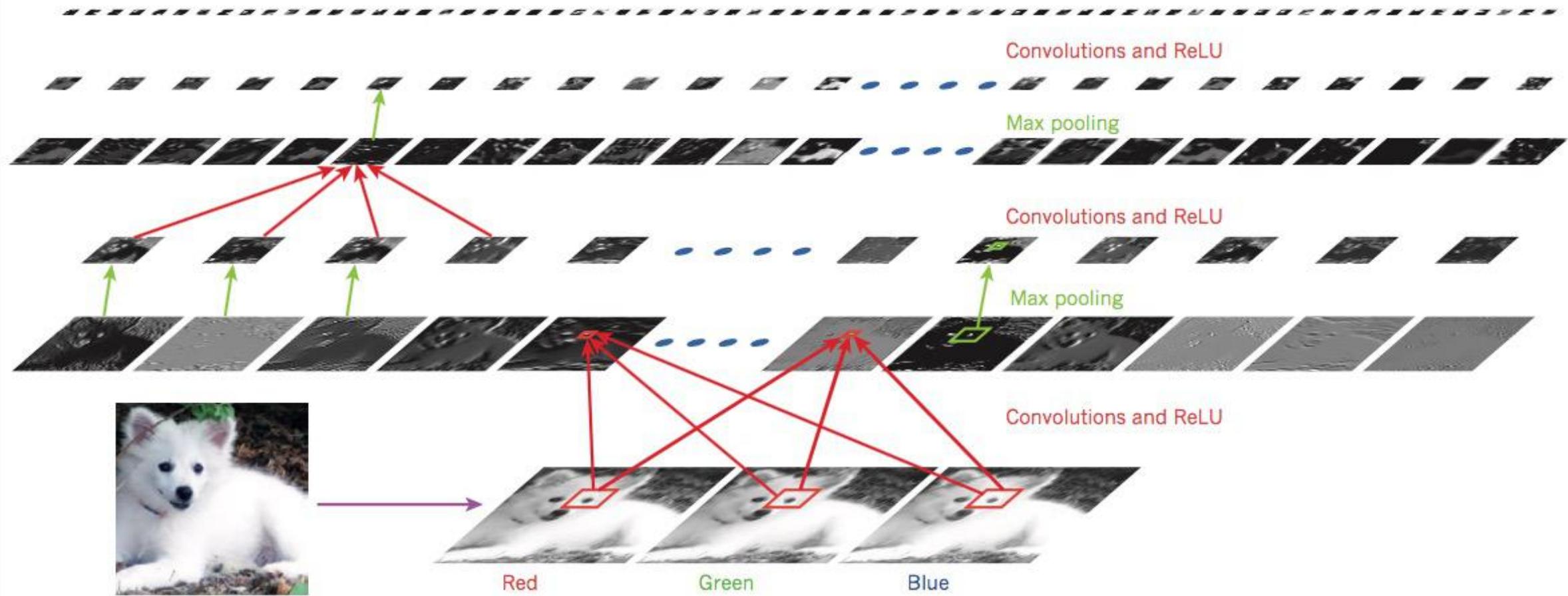
$$\hat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \quad // \text{normalize}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv \text{BN}_{\gamma, \beta}(x_i) \quad // \text{scale and shift}$$

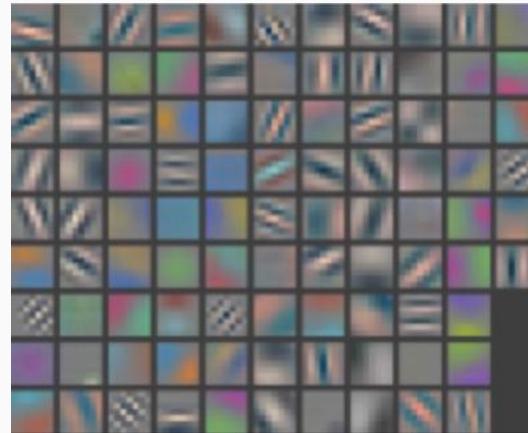
Batch Normalization

# Lecture 5: Convolutional Neural Networks

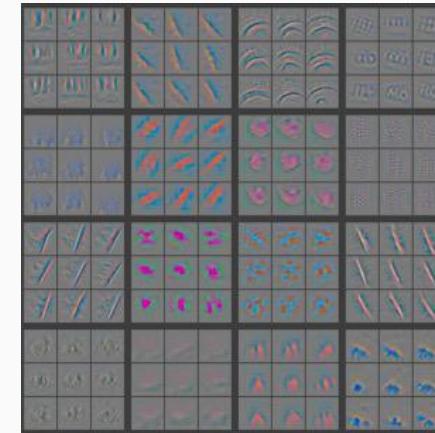
Samoyed (16); Papillon (5.7); Pomeranian (2.7); Arctic fox (1.0); Eskimo dog (0.6); white wolf (0.4); Siberian husky (0.4)



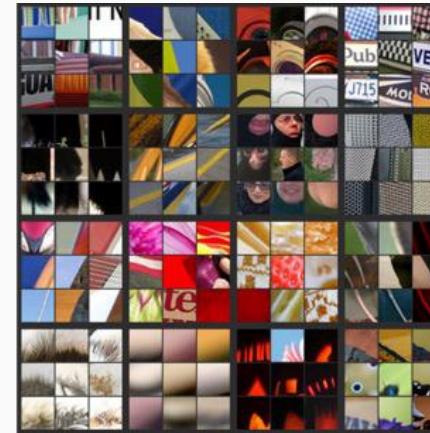
# Lecture 6: Understanding and Visualizing CNNs



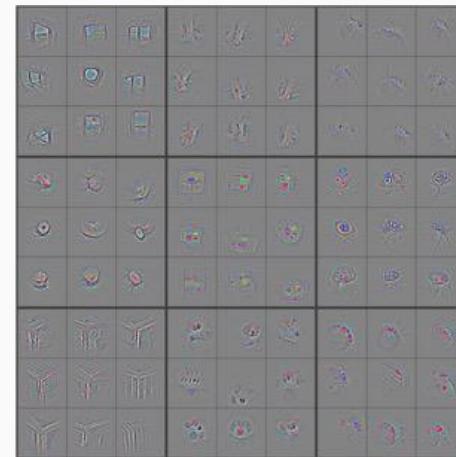
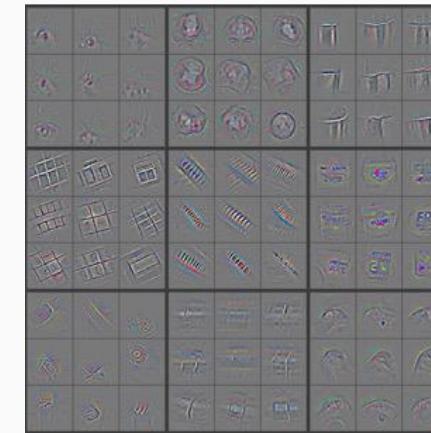
Layer 1



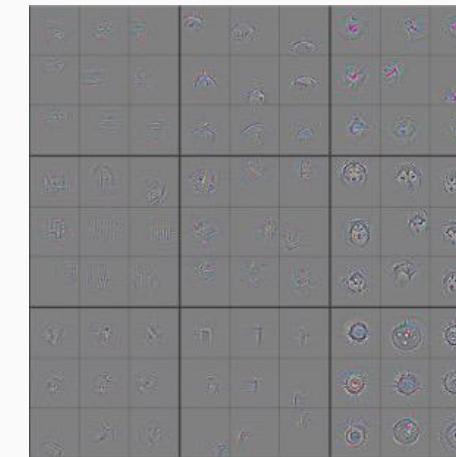
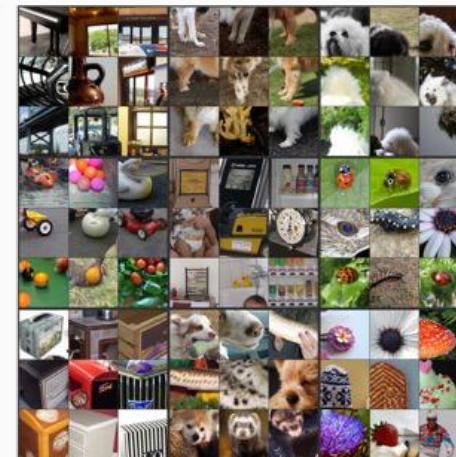
Layer 2



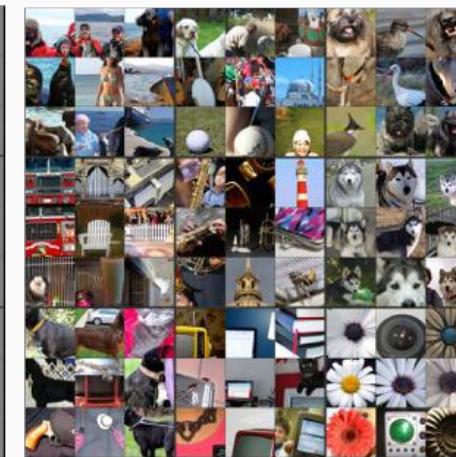
Layer 3



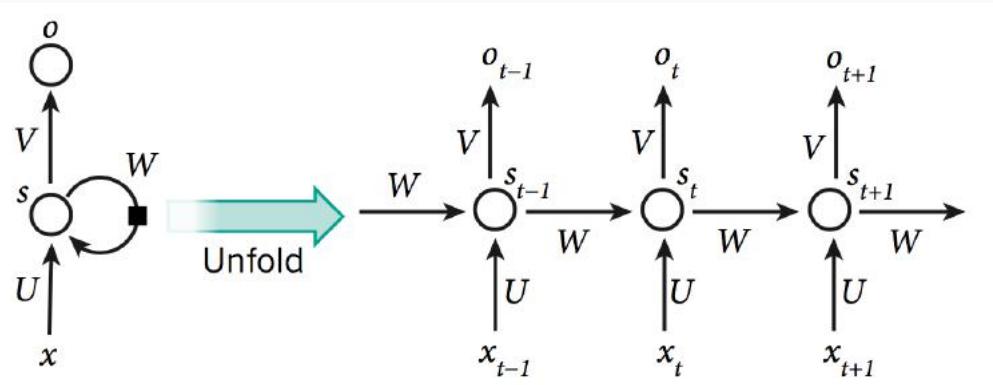
Layer 4



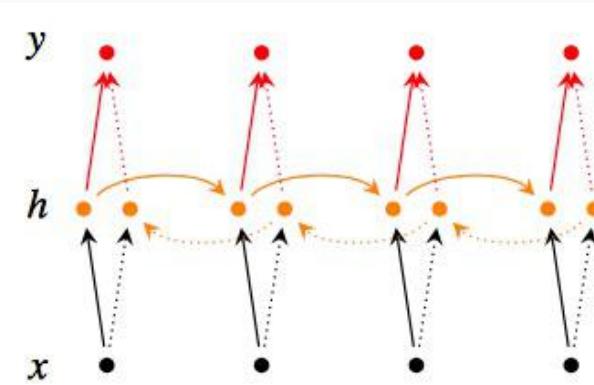
Layer 5



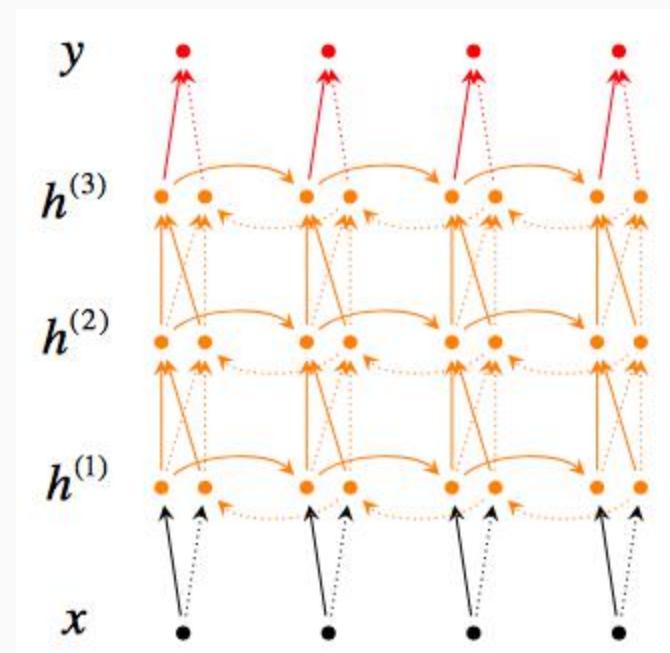
# Lecture 7: Recurrent Neural Networks



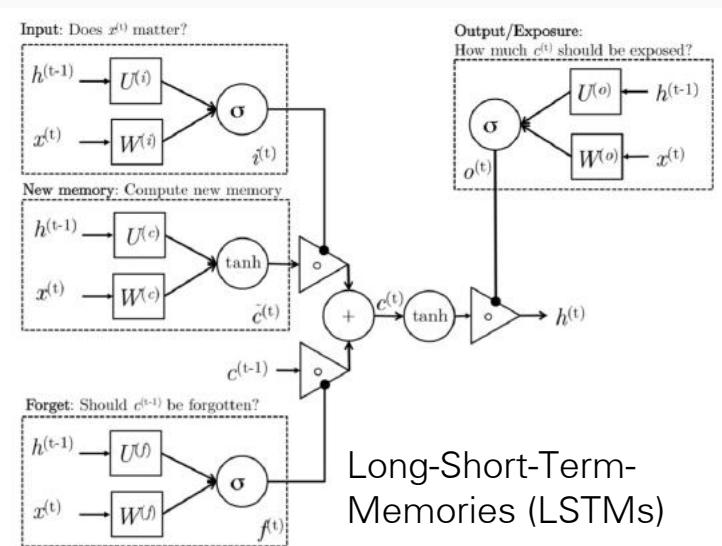
A Recurrent Neural Network (RNN)  
(unfolded across time-steps)



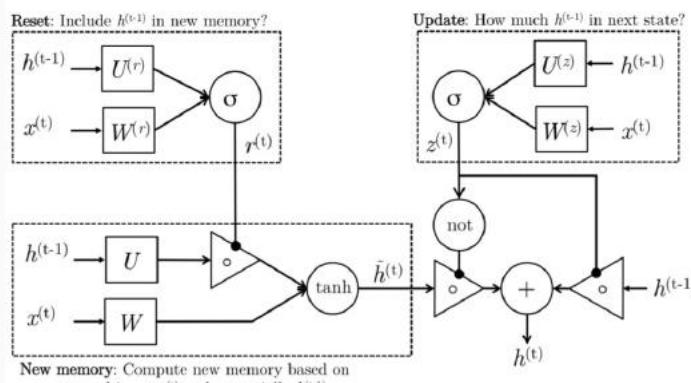
A bi-directional RNN



A deep bi-directional RNN



Long-Short-Term-Memories (LSTMs)



Gated Recurrent Units (GRUs)

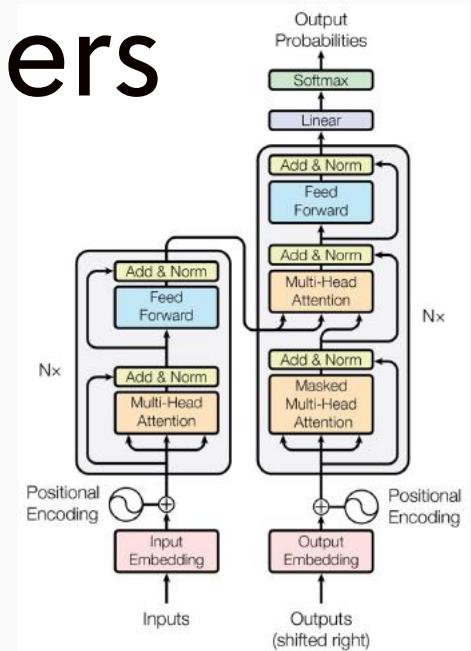
# Lecture 8: Attention and Transformers



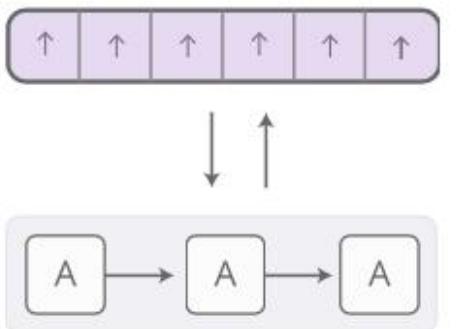
A little girl sitting on a bed with a teddy bear.



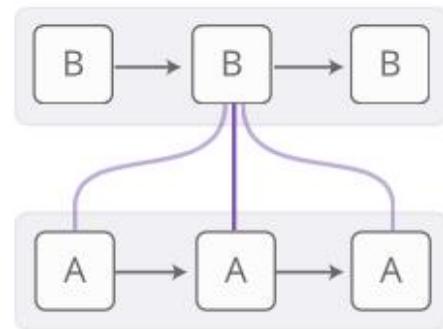
A group of people sitting on a boat in the water.



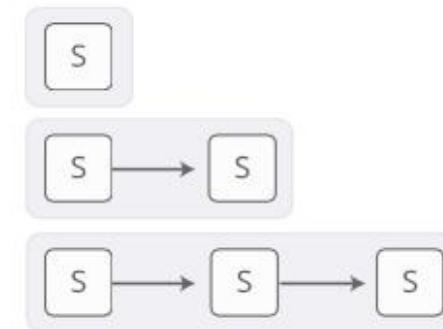
Transformer Architecture



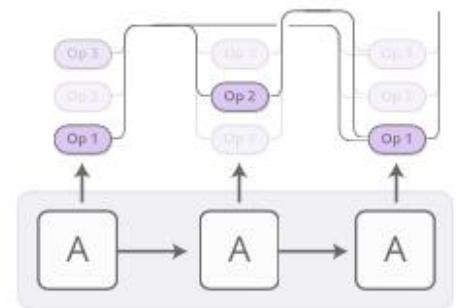
Neural Turing  
Machines



Attentional  
Interfaces



Adaptive  
Computation Time



Neural  
Programmers

K. Xu et al., "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

C. Olah and S. Carter, "Attention and Augmented Recurrent Neural Networks", Distill, 2016

A. Vaswani et al. "Attention is All You Need", NeurIPS 2017.

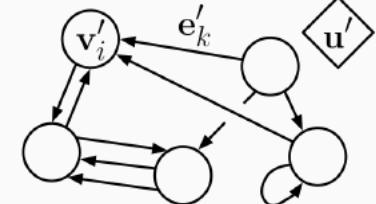
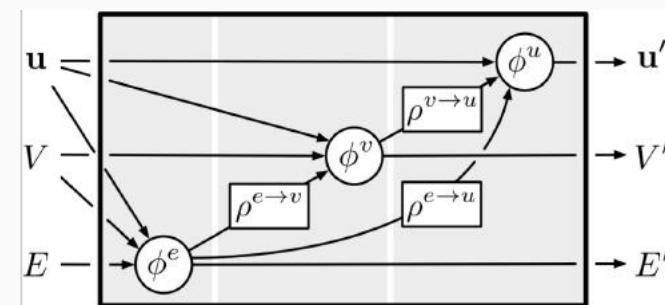
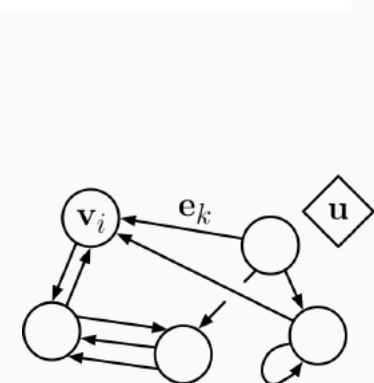
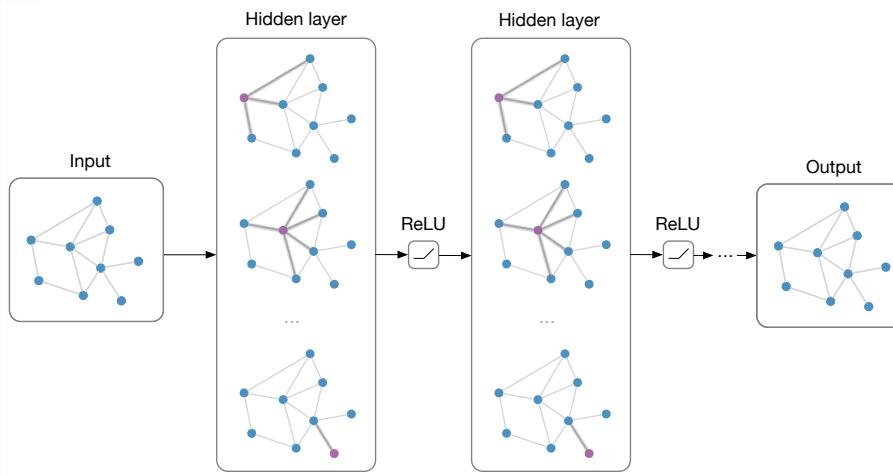
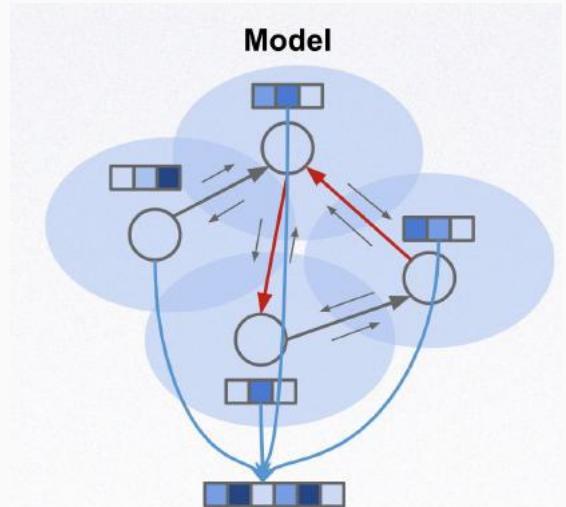
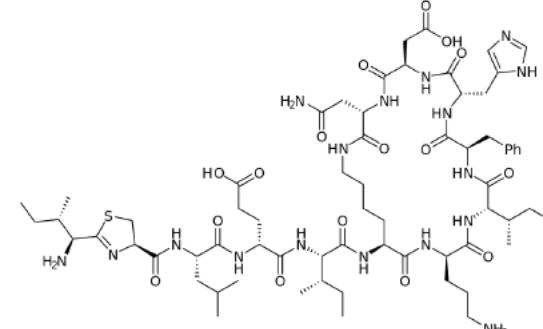
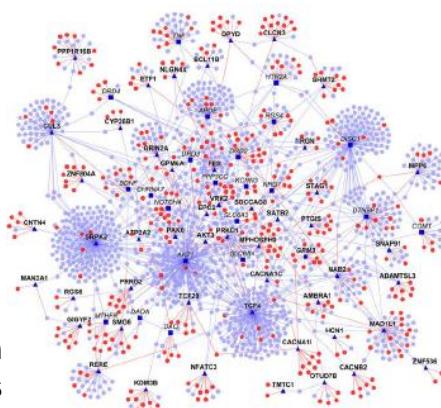
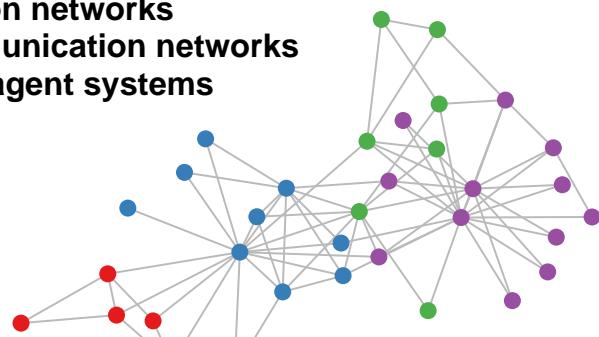
# Lecture 9: Graph Networks

Social networks

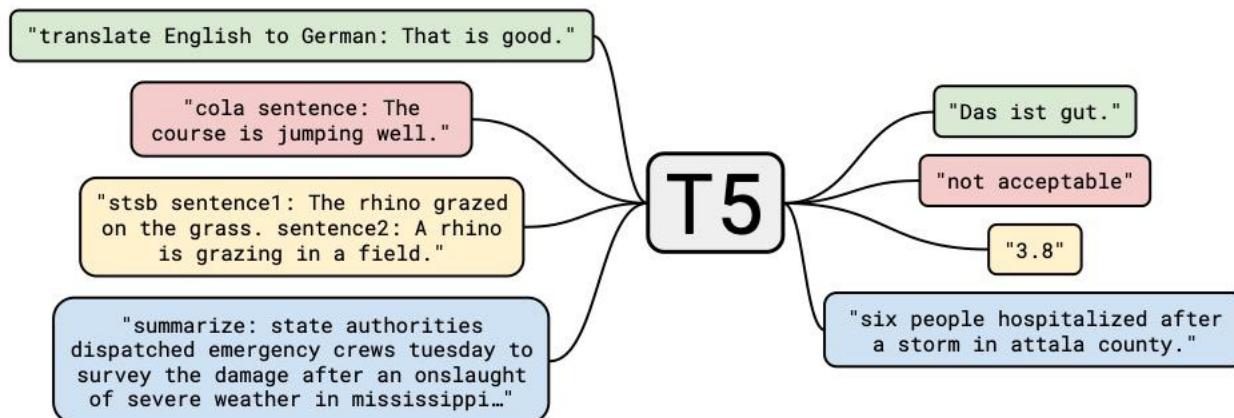
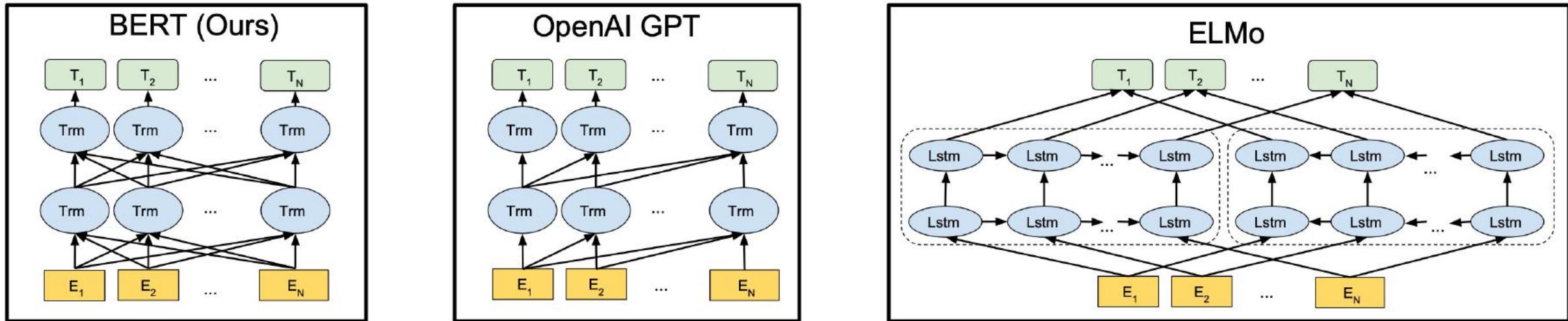
Citation networks

Communication networks

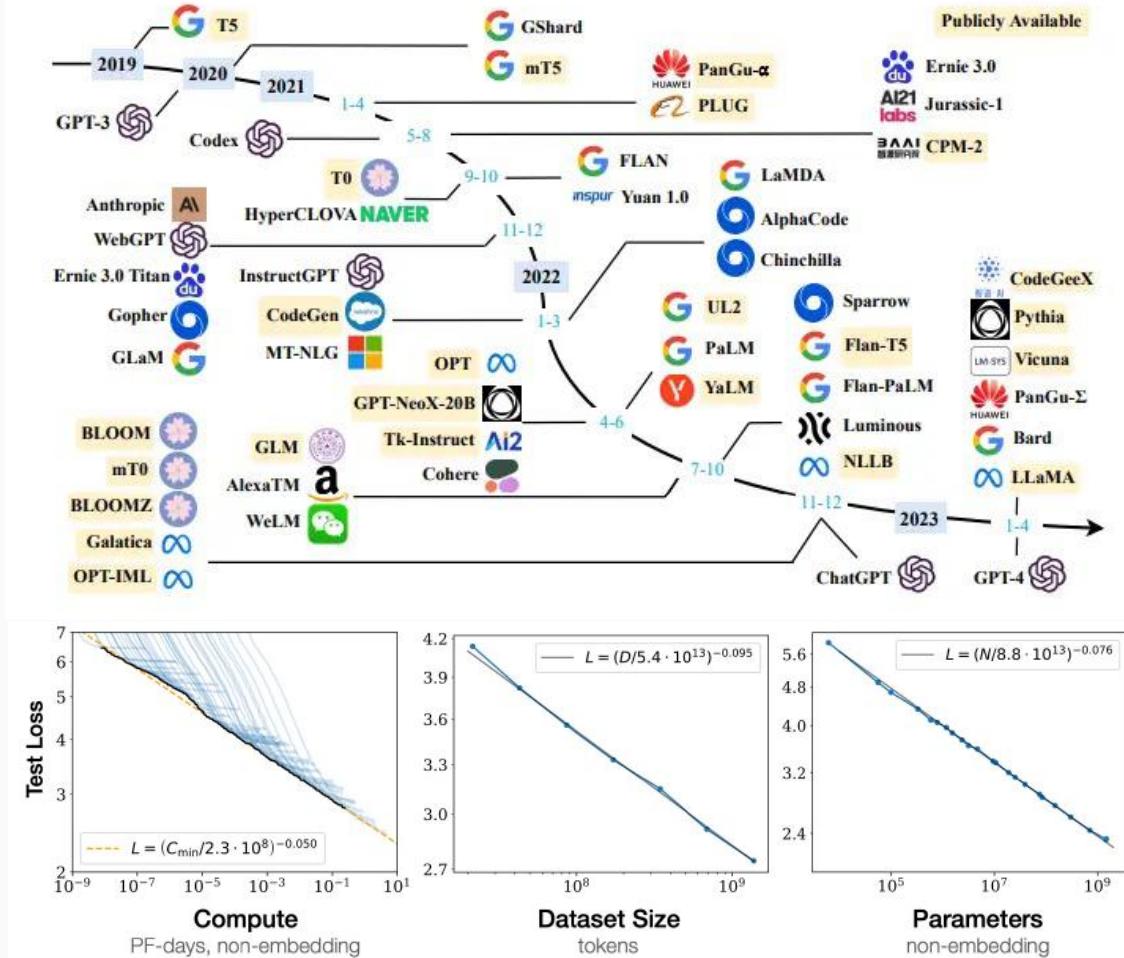
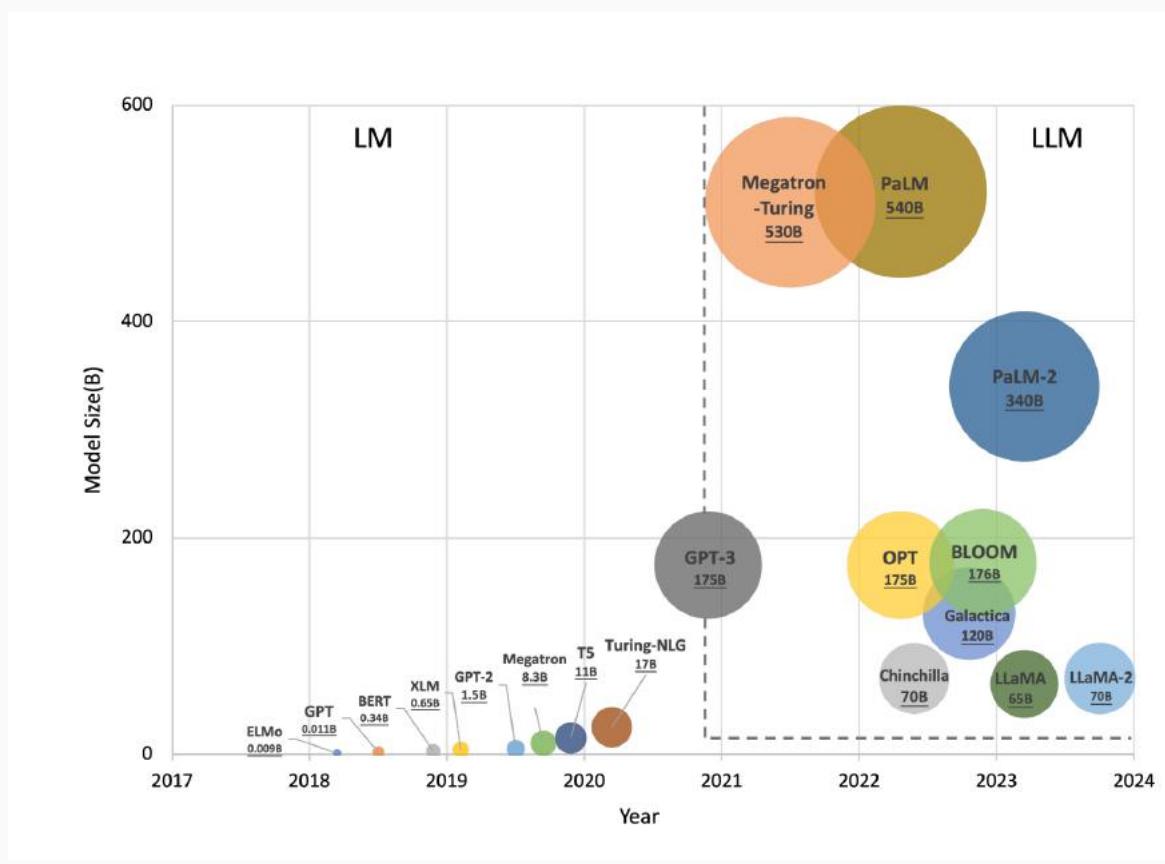
Multi-agent systems



# Week 10: Pretraining Language Models



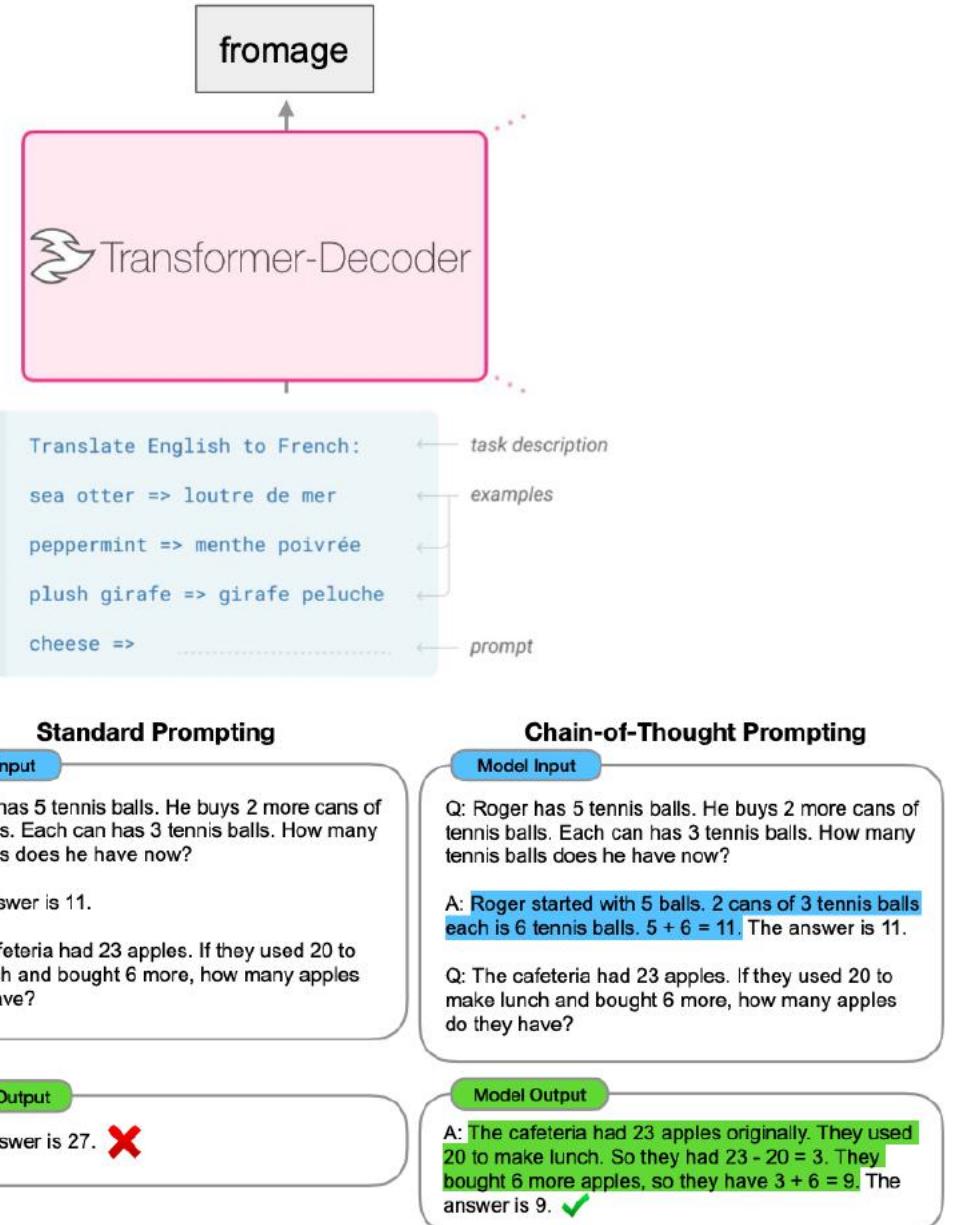
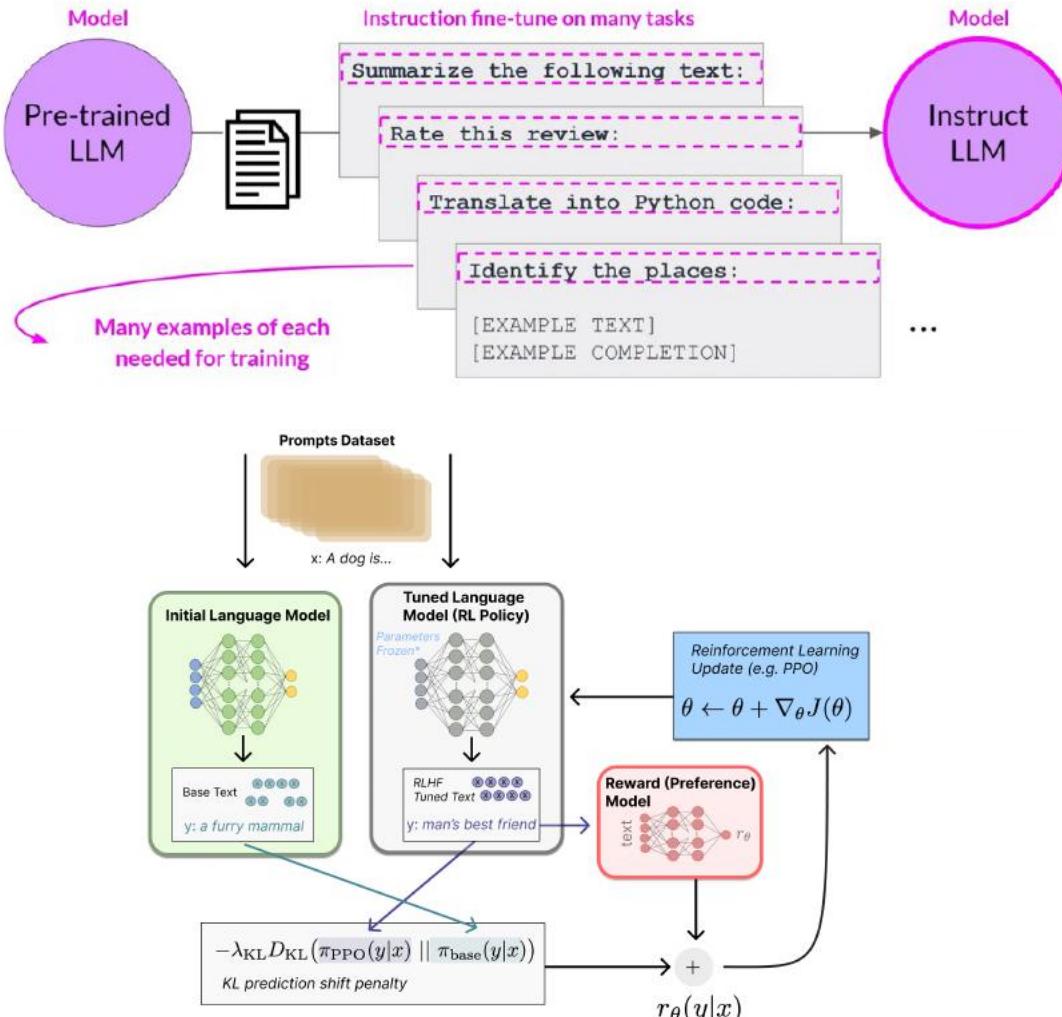
# Lecture 11: Large Language Models



**Figure 1** Language modeling performance improves smoothly as we increase the model size, dataset size, and amount of compute<sup>2</sup> used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.

Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, Dario Amodei, **Scaling Laws for Neural Lanquage Models**”, arXiv preprint, 2020.

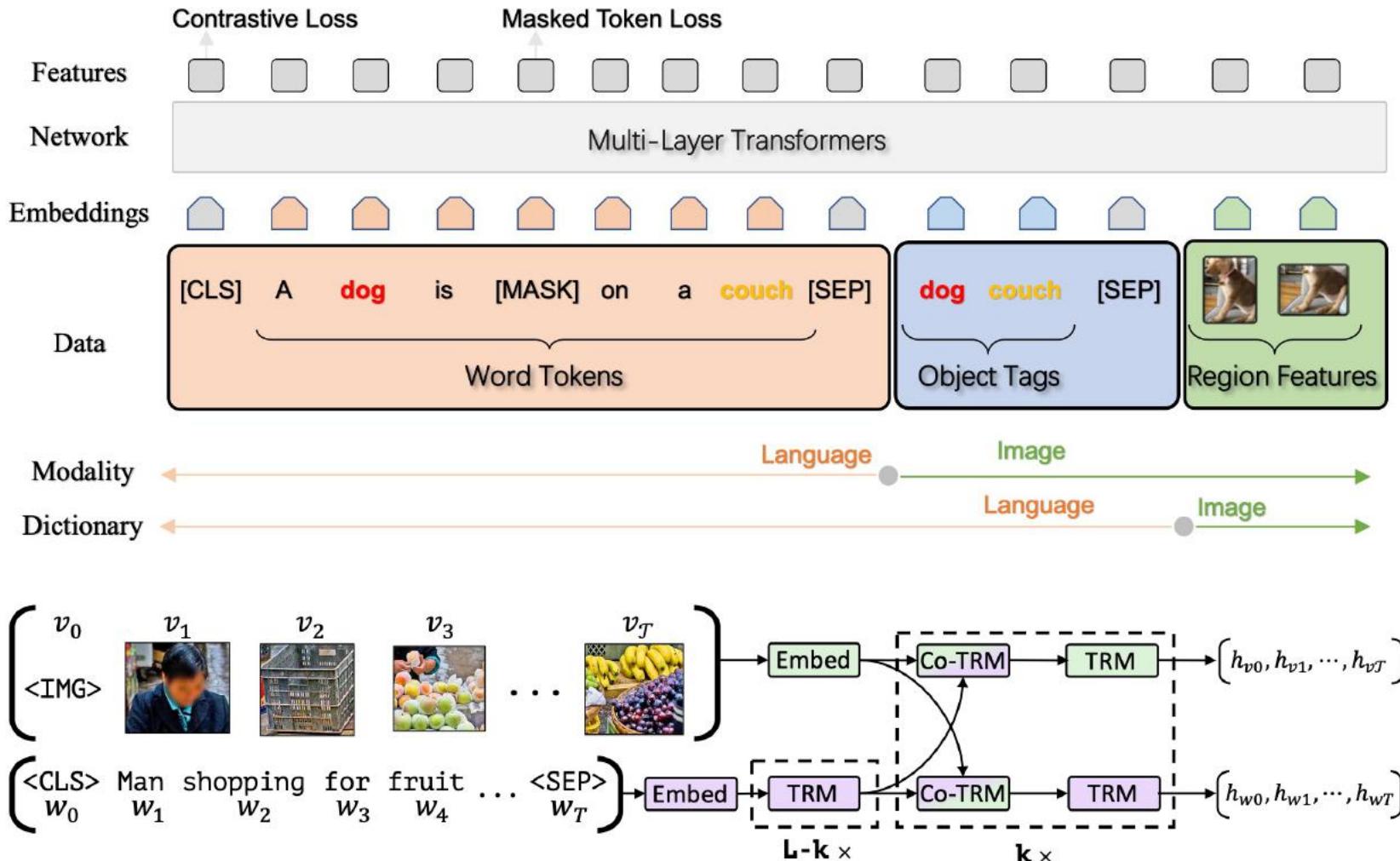
# Lecture 12: Adapting LLMs



Tom B. Brown, Benjamin Mann, Nick Ryder, et al., [Language Models are Few-Shot Learners](#), NeurIPS 2020.

Daniel M. Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B. Brown, Alec Radford, Dario Amodei, Paul Christiano, Geoffrey Irving, [Fine-Tuning Language Models from Human Preferences](#), Open AI Technical Report, 2020

# Week 13: Multimodal Pre-training



# Schedule

**L1** Introduction to Deep Learning

[Self-Assessment Quiz \(Theory\)](#)

**L2** Machine Learning Overview

[Self-Assessment Quiz \(Programming\)](#)

**L3** Multi-Layer Perceptrons

[Assignment 1 out](#)

**L4** Training Deep Neural Networks

**L5** Convolutional Neural Networks

[Start of paper presentations](#)

[Assignment 1 in, Assignment 2 out](#)

**L6** Understanding and Visualizing CNNs

[Project proposals due](#)

**L7** Recurrent Neural Networks

[Assignment 2 in, Assignment 3 out](#)

**L8** Attention and Transformers

[Midterm Exam](#)

**L9** Graph Neural Networks

[Assignment 3 in, Assignment 4 out](#)

**L10** Language Model Pretraining

**L11** Project Progress Presentations

[Project progress reports due](#)

**L12** Large Language Models (LLMs)

[Assignment 4 in](#)

**L13** Adapting LLMs

**L14** Multimodal Pretraining

[Final project reports due](#)

# Paper Presentations

We will discuss 10 recent papers related to the topics covered in the class.

- (14 mins) One group of students will be responsible from providing an overview of the paper.
- (8 mins) Another group will present the strengths of the paper.
- (8 mins) Another one will discuss the weaknesses of the paper.
- (10 mins) QA

See the rubrics on the course web page for the details,

Week	Topic
Week 1	Introduction to Deep Learning
Week 2	Machine Learning Overview
Week 3	Multi-Layer Perceptrons
Week 4	Training Deep Neural Networks
Week 5	Convolutional Neural Networks
Week 6	Understanding and Visualizing CNNs
Week 7	Recurrent Neural Networks
Week 8	Attention and Transformers
Week 9	Graph Neural Networks
Week 10	Language Model Pretraining
Week 11	Project Progress Presentations
Week 12	Large Language Models
Week 13	Efficient LLMs
Week 14	Multimodal Pre-training
Week 15-16	Final Project Presentations

Paper presentations start on Week 5

# Paper Reviews

Think deeply about the papers we read and try to learn from them as much as possible (and then even more). If you do not understand something, we should discuss it and dissect it together. Whatever you think others understand, they understand less (the instructor included), but together we will get it.

- Identify the key questions the paper studies, and the answers it provides to these questions.
- Consider the challenges of the problem or scenario studied, and how the paper's approach addresses them.
- Deconstruct the formal and technical parts to understand their fine details. Note to yourself aspects that are not clear to you

# Paper Reviewing Guidelines

- When reviewing the paper, start with 1–2 sentences summarizing what the paper is about.
- Continue with the strength of the paper. Outline its contribution, and your main takeaways. What did you learn?
- Highlight shortcomings and limitations. Please focus on weaknesses that are fundamental to the method. Unlike conference or journal reviewing, this part is intended for your understanding and discussion.
- Try to suggest ways to address the paper's limitations. Any idea is welcome and will contribute to the discussion.
- Suggest questions for discussion in class. As part of the discussion in class, you are asked to raise these questions during the class.

# Programming Assignments

- 4 programming assignments (5% each)
- Learning to implement basic neural architectures
- Should be done individually
- **Late policy:** You have 7 grace days in the semester.
- **Assignments**
  - Assignment 1: MLPs and Backpropagation
  - Assignment 2: Convolutional Neural Networks
  - Assignment 3: Recurrent Neural Networks
  - Assignment 4: Transformers and GNNs

# Midterm Exam

- **Date:** Week 8
- **Topics:** Everything covered in the first part of the course
- Format to be a classical exam with derivations and short discussion questions.

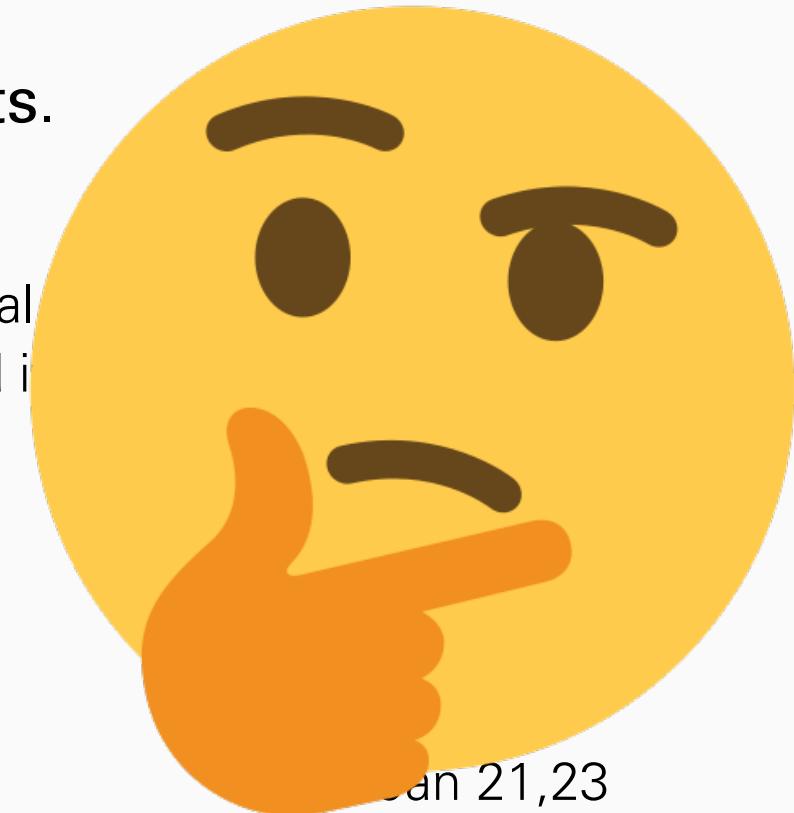
# Course Project

- The course project gives students a chance to apply deep learning models discussed in class to a research-oriented project
- Projects should be done **in groups of 2 to 3 students.**
- The course project may involve
  - Design of a novel approach/architecture and its experimental analysis, or
  - An extension to a recent study of non-trivial complexity and its experimental analysis.
- **Deliverables**

- Proposals (2%)	Nov 17
- Project progress presentations (4%)	Dec 17,19
- Project progress reports (6%)	Dec 22
- Final project presentations (8%)	Jan 21,23
- Final reports (12%)	Jan 25
- The quality of the contributions/The difficulty of implementation (4%)	

# Course Project

- The course project gives students a chance to apply deep learning models discussed in class to a research-oriented project
  - Projects should be done **in groups of 2 to 3 students.**
  - The course project may involve
    - Design of a novel approach/architecture and its experimental evaluation
    - An extension to a recent study of non-trivial complexity and its implications
  - Deliverables
    - Proposals (2%)
    - Project progress reports (6%)
    - Final project presentations (8%)
    - Final reports (12%)
    - The quality of the contributions/The difficulty of implementation (4%)
- Start thinking about project ideas!**



Jan 21, 23

Jan 25

# Lecture Overview

- what is deep learning
- a brief history of deep learning
- compositionality
- end-to-end learning
- distributed representations

**Disclaimer:** Some of the material and slides for this lecture were borrowed from  
—Dhruv Batra's CS7643 class  
—Yann LeCun's talk titled "Deep Learning and the Future of AI"

# What is Deep Learning

10 Breakthrough

# MIT Technology Review

Forbes / Tech

APR 1, 2016 @ 06:47 AM 3,207 VIEWS

## What Is Deep Lea



Kevin Murnane  
CONTRIBUTOR

I write about science, technology and the people that connect them.



Opinions expressed by Forbes Contributors are their own.

TWEET THIS

Deep learning unl  
to use it

FULL BIO >

Credit: Google

Deep learning re  
GOOGL +1.40% Alpha  
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networks to build a program that picks out an attractive still from a  
understand language and then make inferences and decisions on its

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## How AI is transforming science

Researchers are unleashing artificial intelligence (AI) on torrents of big data

KIYOSHI TAKAHASE SEGUNDO/ALAMY STOCK PHOTO

## Contents 07 JULY 2017 VOL 357, ISSUE 6346

### Special Issue The cyberscientist

INTRODUCTION TO SPECIAL ISSUE

#### The scientists' apprentice

BY TIM APPENZELLER  
SCIENCE | 07 JUL 2017 : 16-17 | 6

Artificial intelligence helps scientists cope with torrents of data

Summary Full Text PDF

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- Book and Media Reviews
- About Science
  - Mission and Scope
  - Editors and Advisory Boards
  - Editorial Policies
  - Information for Authors
  - Information for Reviewers
  - Staff

IN 2013 was where Facebook CEO Mark Zuckerberg  
in 2013 to announce the company's plans to form an AI laboratory and where a  
startup named DeepMind showed off an AI that could learn to play computer games  
before it was acquired by Google.

Sign in



Photographer: Tomohiro Ohsumi/Bloomberg

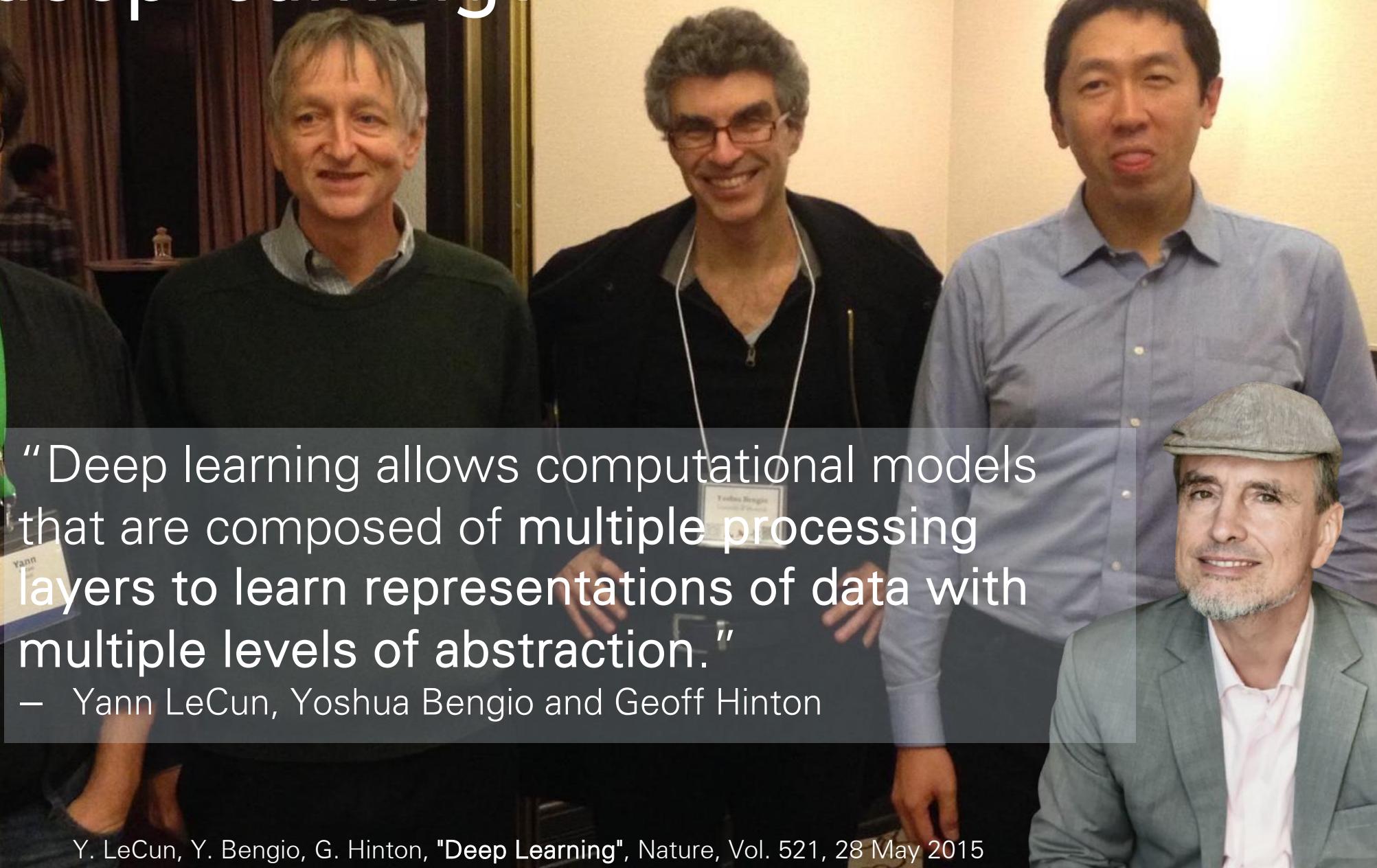
# What is deep learning?



“Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction.”

– Yann LeCun, Yoshua Bengio and Geoff Hinton

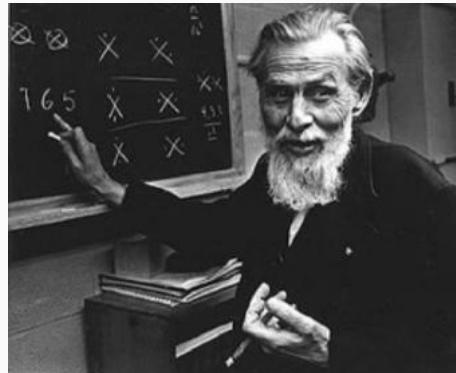
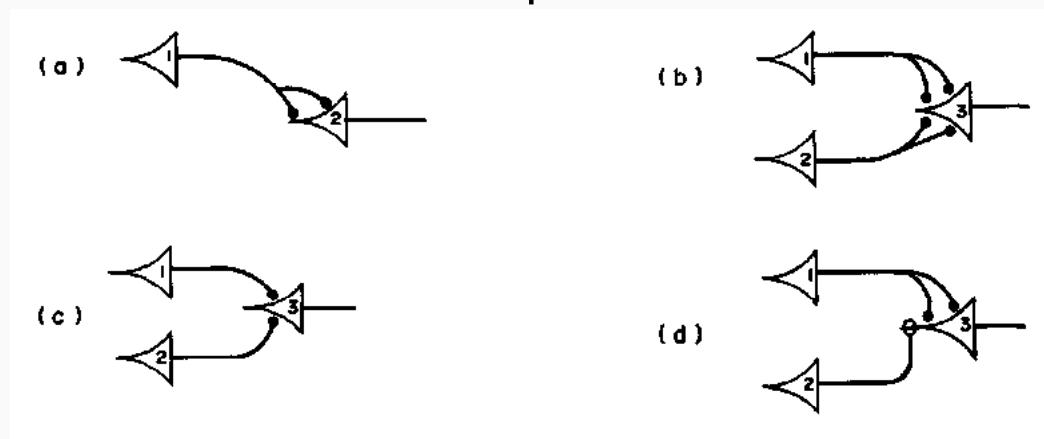
Y. LeCun, Y. Bengio, G. Hinton, "Deep Learning", Nature, Vol. 521, 28 May 2015



# 1943 – 2006: A Prehistory of Deep Learning

# 1943: Warren McCulloch and Walter Pitts

- First computational model
- Neurons as logic gates (AND, OR, NOT)
- A neuron model that sums binary inputs and outputs a 1 if the sum exceeds a certain threshold value, and otherwise outputs a 0



Action of Mathematical Biology, Vol. 32, No. 1/2, pp. 99-113, 1990  
Printed in Great Britain

0875-8260/90\$10.00 + 0.00  
© 1990 Society for Mathematical Biology

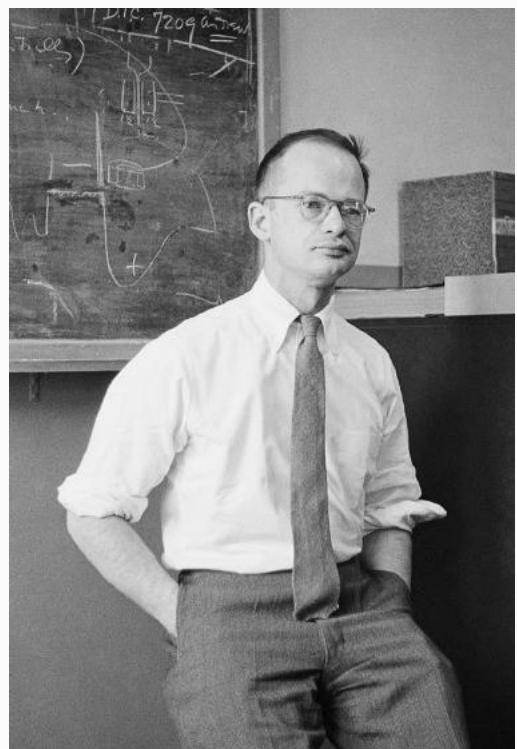
## A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY\*

■ WARREN S. McCULLOCH AND WALTER PITTS  
University of Illinois, College of Medicine,  
Department of Psychiatry at the Illinois Neuropsychiatric Institute,  
University of Chicago, Chicago, U.S.A.

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that two particular choices among possible neurophysiological assumptions are equivalent, in the sense that for any behavior under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

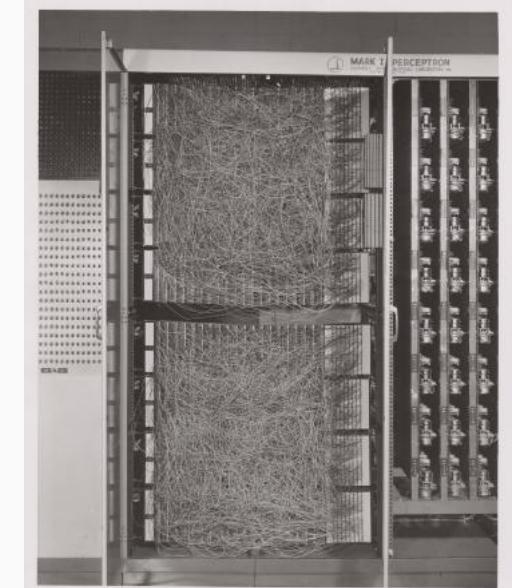
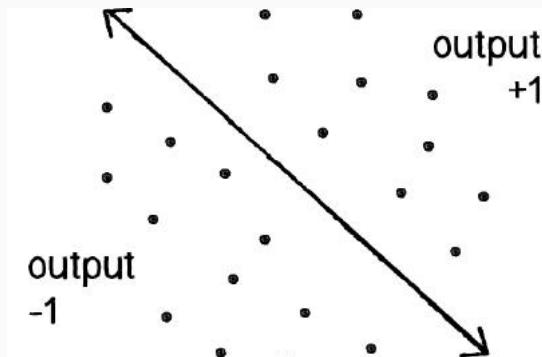
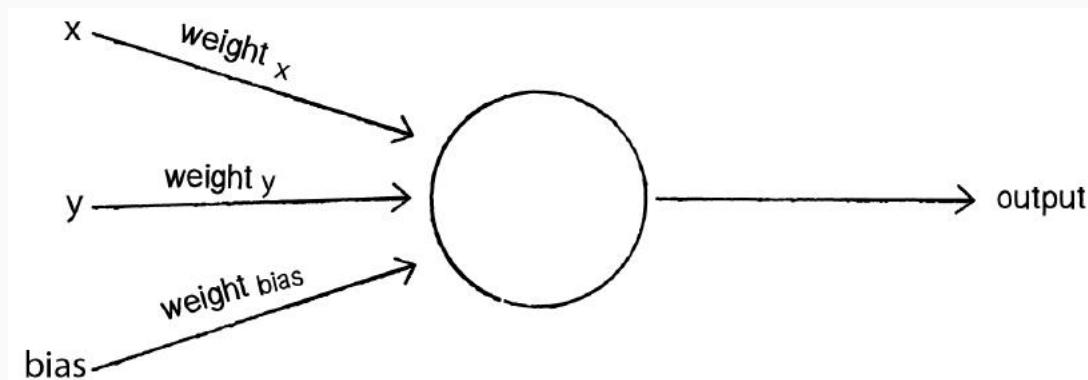
**1. Introduction.** Theoretical neurophysiology rests on certain cardinal assumptions. The nervous system is a net of neurons, each having a soma and an axon. Their adjunctions, or synapses, are always between the axon of one neuron and the soma of another. At any instant a neuron has some threshold, which excitation must exceed to initiate an impulse. This, except for the fact and the time of its occurrence, is determined by the neuron, not by the excitation. From the point of excitation the impulse is propagated to all parts of the neuron. The velocity along the axon varies directly with its diameter, from  $< 1 \text{ ms}^{-1}$  in thin axons, which are usually short, to  $> 150 \text{ ms}^{-1}$  in thick axons, which are usually long. The time for axonal conduction is consequently of little importance in determining the time of arrival of impulses at points unequally remote from the same source. Excitation across synapses occurs predominantly from axonal terminations to somata. It is still a moot point whether this depends upon reciprocity of individual synapses or merely upon prevalent anatomical configurations. To suppose the latter requires no hypothesis *ad hoc* and explains known exceptions, but any assumption as to cause is compatible with the calculus to come. No case is known in which excitation through a single synapse has elicited a nervous impulse in any neuron, whereas any neuron may be excited by impulses arriving at a sufficient number of neighboring synapses within the period of latent addition, which lasts  $< 0.25 \text{ ms}$ . Observed temporal summation of impulses at greater intervals

\* Reprinted from the *Bulletin of Mathematical Biophysics*, Vol. 5, pp. 115-133 (1943).



# 1958: Frank Rosenblatt's Perceptron

- A computational model of a single neuron
- Solves a **binary classification** problem
- Simple training algorithm
- Built using specialized hardware

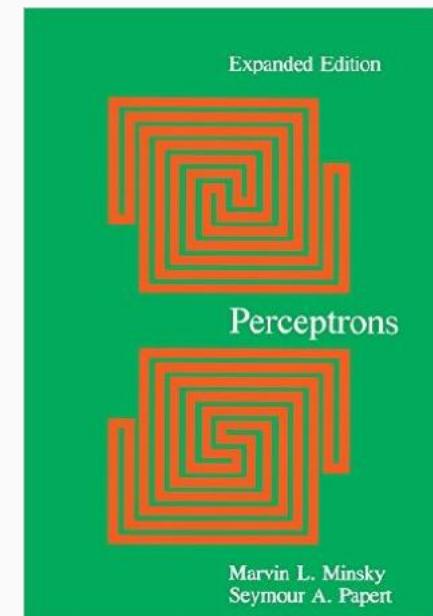
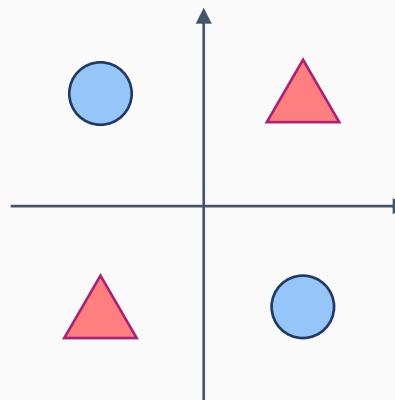


# 1969: Marvin Minsky and Seymour Papert

“No machine can learn to recognize X unless it possesses, at least potentially, some scheme for representing X.” (p. xiii)

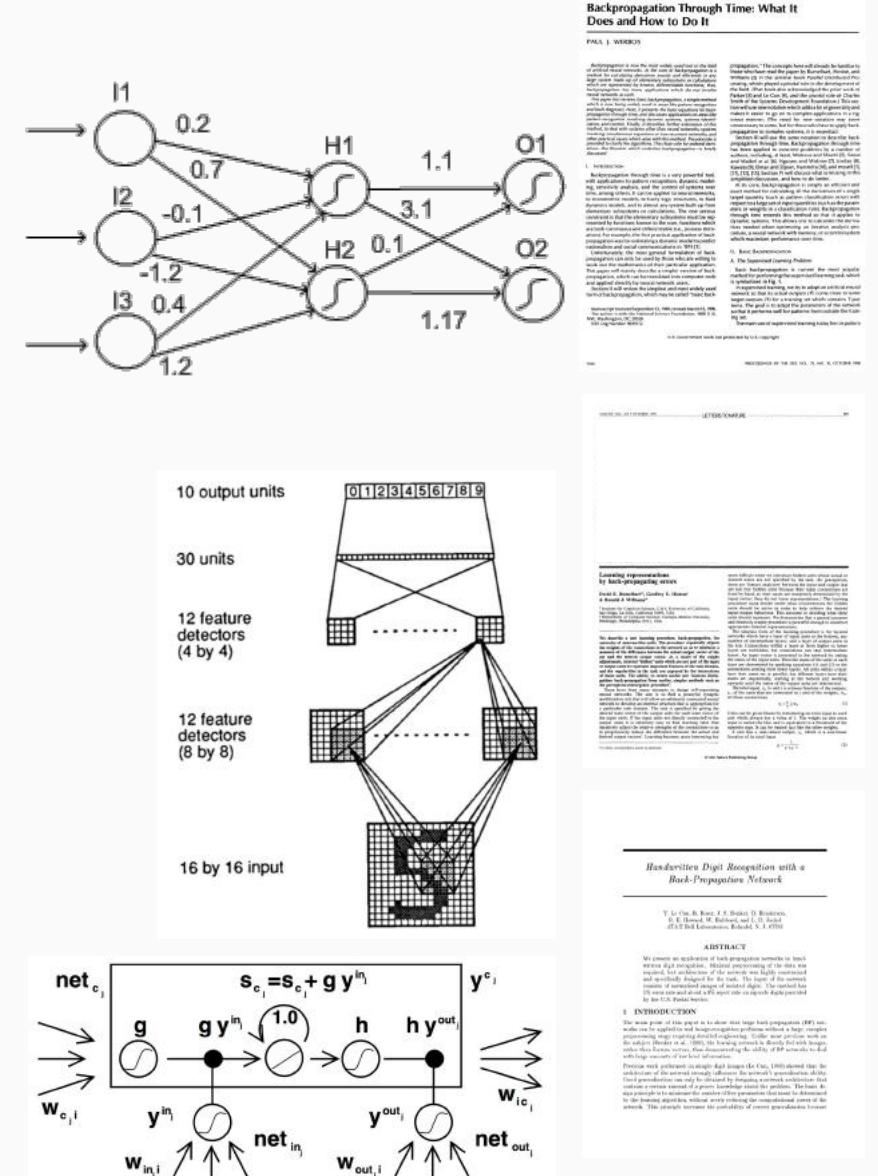


- Perceptrons can only represent linearly separable functions.
  - such as **XOR** Problem
- Wrongly attributed as the reason behind the **AI winter**, a period of reduced funding and interest in AI research



# 1990s

- Multi-layer perceptrons can theoretically learn any function (Cybenko, 1989; Hornik, 1991)
  - Training multi-layer perceptrons
    - Back propagation (Rumelhart, Hinton, Williams, 1986)
    - Backpropagation through time (BPTT) (Werbos, 1988)
  - New neural architectures
    - Convolutional neural nets (LeCun et al., 1989)
    - Long-short term memory networks (LSTM)  
(Schmidhuber, 1997)



# Why it failed then

- Too many parameters to learn from few labeled examples.
- “I know my features are better for this task”.
- Non-convex optimization? No, thanks.
- Black-box model, no interpretability.
  
- Very slow and inefficient
- Overshadowed by the success of SVMs (Cortes and Vapnik, 1995)

A major breakthrough in 2006



# The 2012 revolution

# ImageNet Challenge

- **IMAGENET** Large Scale Visual Recognition Challenge (ILSVRC)
  - **1.2M** training images with **1K** categories
  - Measure top-5 classification error



Output  
Scale  
T-shirt  
**Steel drum**  
Drumstick  
Mud turtle



Output  
Scale  
T-shirt  
Giant panda  
Drumstick  
Mud turtle

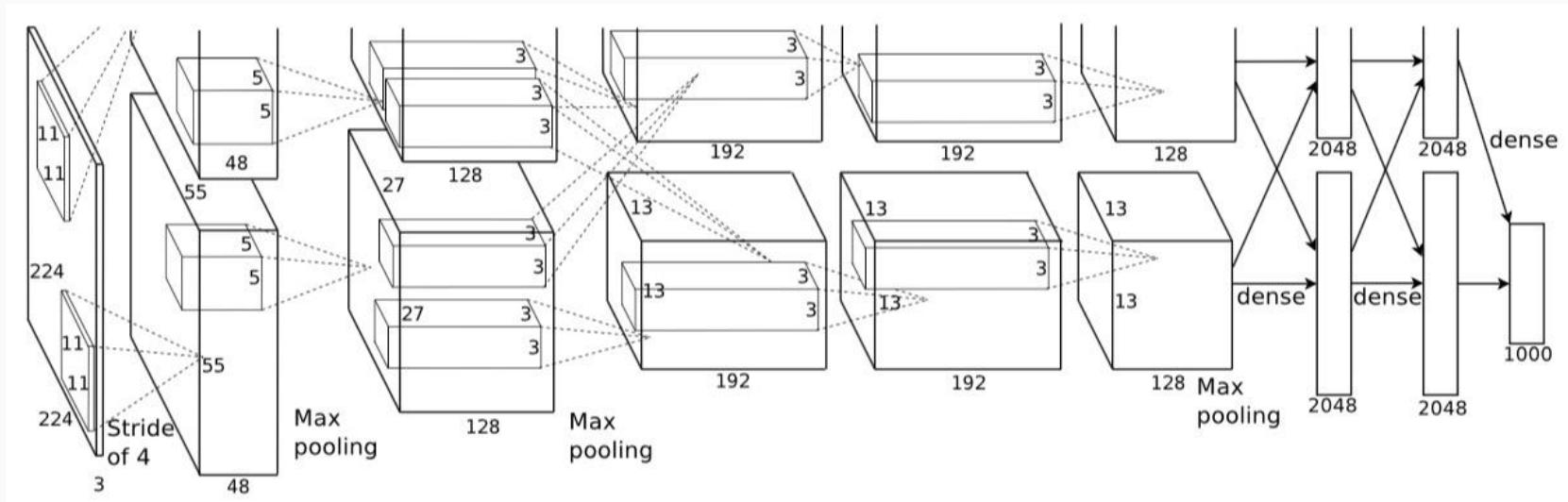


J. Deng, Wei Dong, R. Socher, L.-J. Li, K. Li and L. Fei-Fei , "ImageNet: A Large-Scale Hierarchical Image Database", CVPR 2009.  
O. Russakovsky et al., "ImageNet Large Scale Visual Recognition Challenge", Int. J. Comput. Vis., Vol. 115, Issue 3, pp 211-252, 2015.

# ILSVRC 2012 Competition

2012 Teams	%Error
Supervision (Toronto)	15.3
ISI (Tokyo)	26.1
VGG (Oxford)	26.9
XRCE/INRIA	27.0
UvA (Amsterdam)	29.6
INRIA/LEAR	33.4

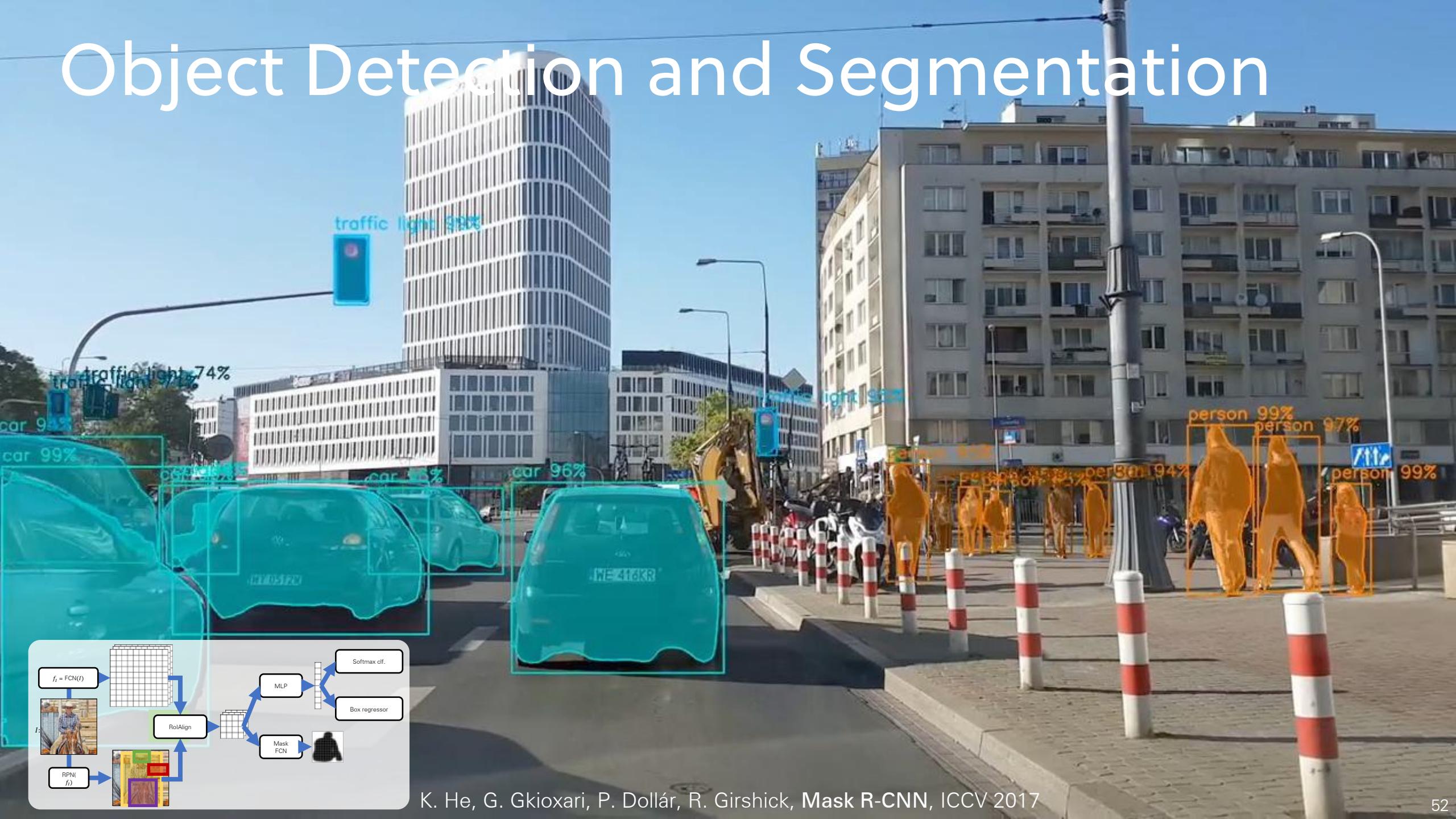
CNN based, non-CNN based



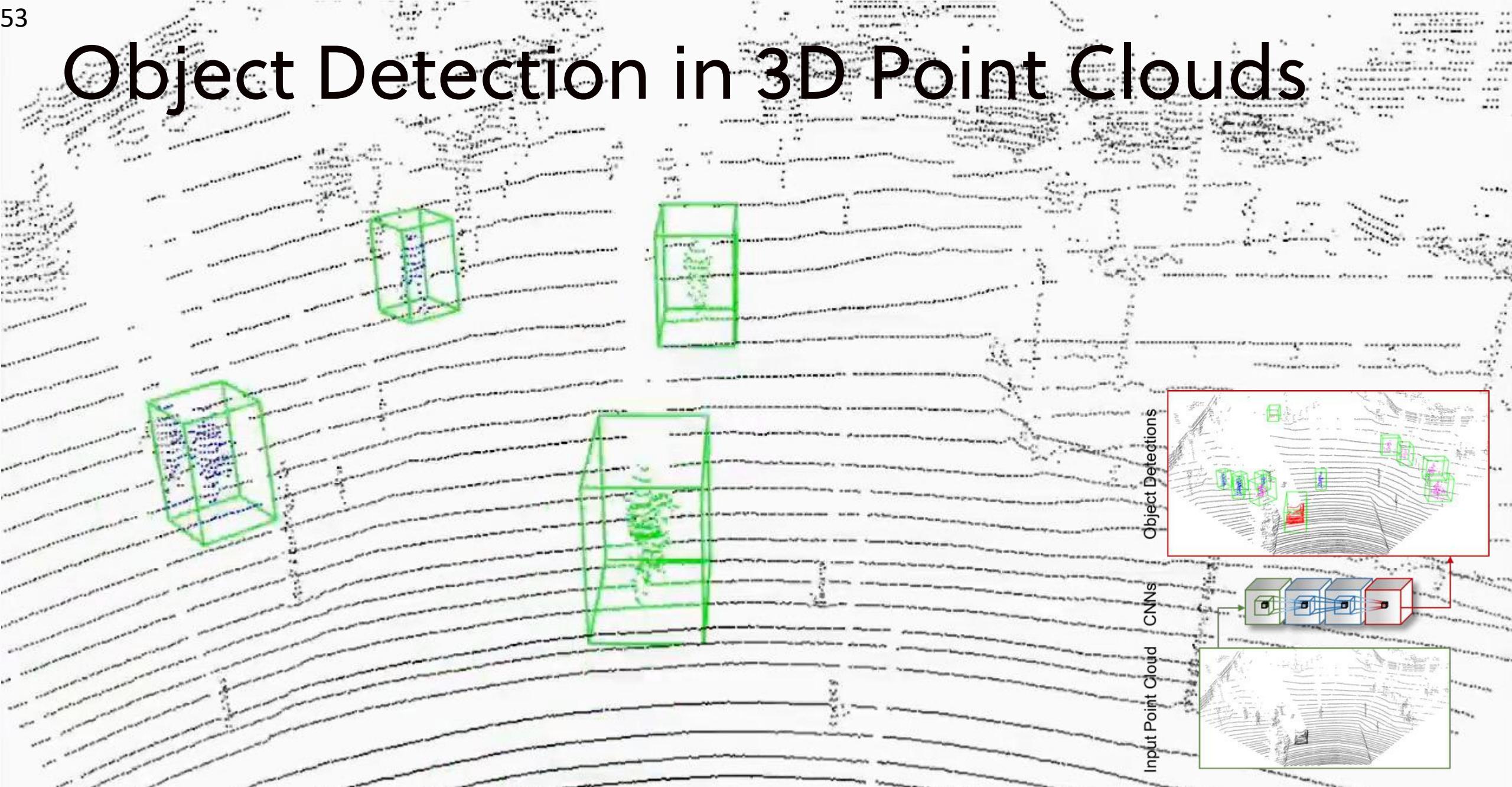
- The success of AlexNet, a deep convolutional network
  - 7 hidden layers (not counting some max pooling layers)
  - 60M parameters
- Combined several tricks
  - ReLU activation function, data augmentation, dropout

2012-Now  
Some recent successes

# Object Detection and Segmentation



# Object Detection in 3D Point Clouds



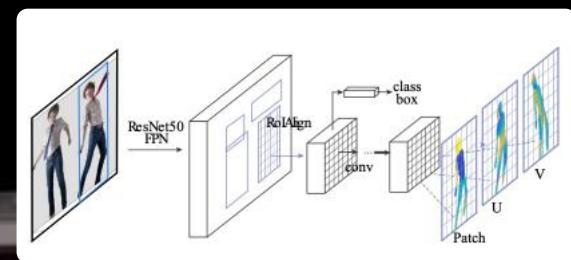
# Human Pose Estimation



Z. Cao ,T. Simon, S.-E. Wei and Yaser Sheikhr, "Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields", CVPR 2017

Source: <https://www.youtube.com/watch?v=2DiQUX11YaY>

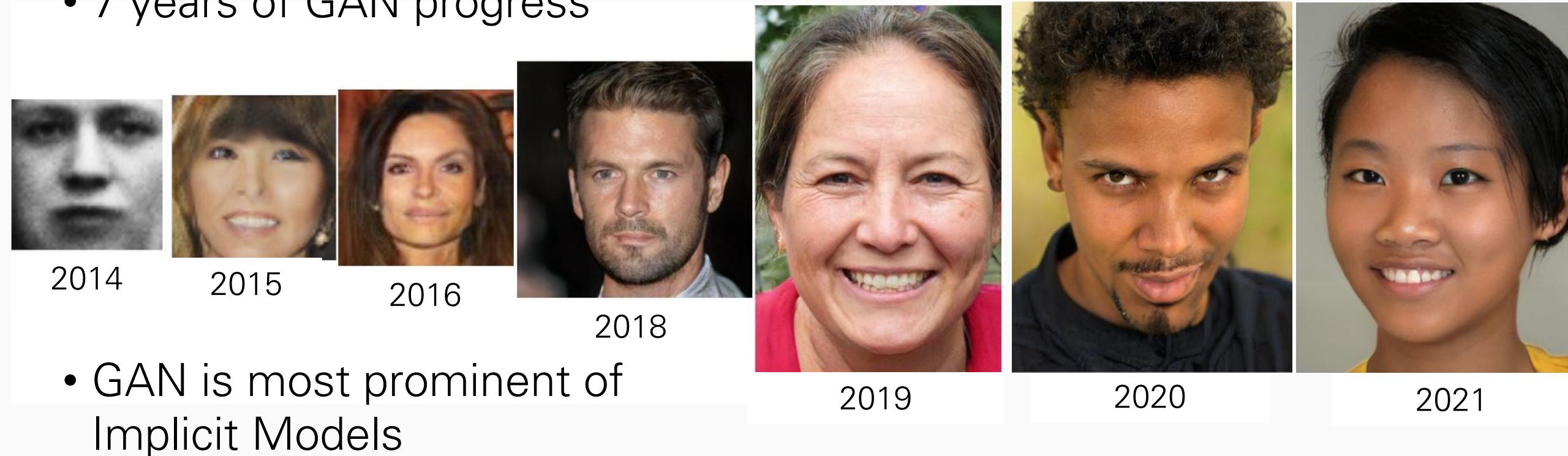
# Pose Estimation



We introduce a system that can associate every image pixel with human body surface coordinates.

# Image Synthesis

- 7 years of GAN progress



- GAN is most prominent of Implicit Models

I.J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio. **Generative Adversarial Networks**. NIPS 2014.

A. Radford, L. Metz, S. Chintala. **Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks**. ICLR 2016.

M.-Y. Liu, O. Tuzel. **Coupled Generative Adversarial Networks**. NIPS 2016.

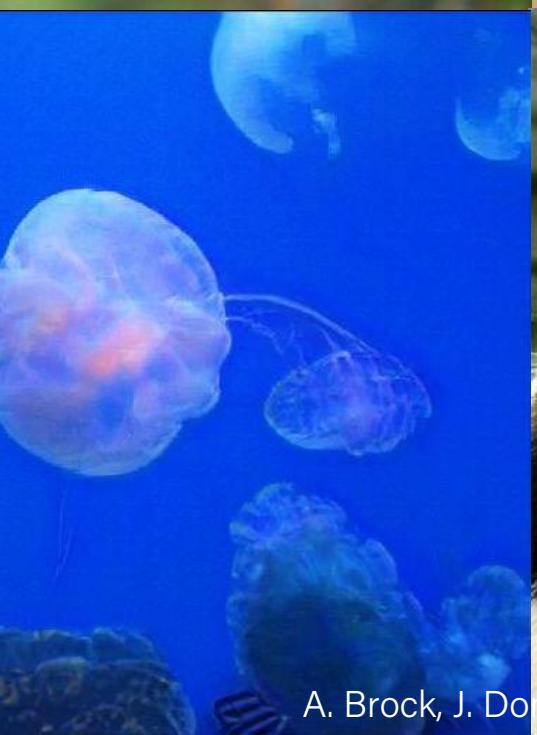
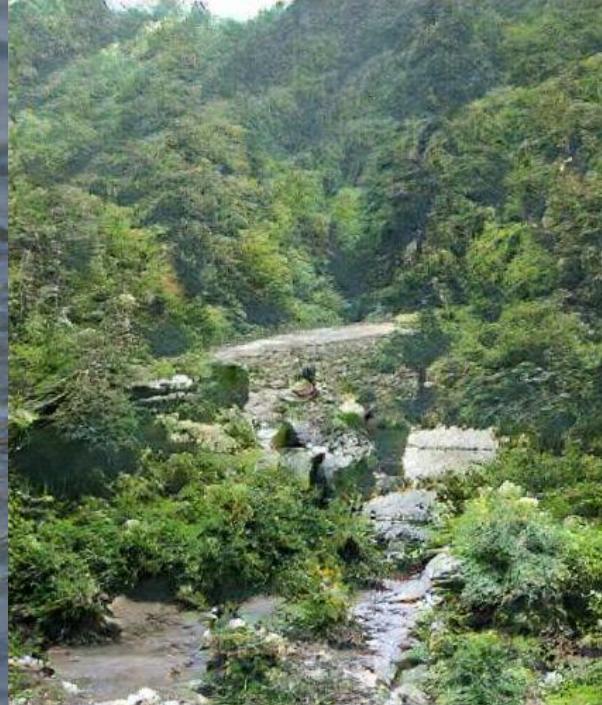
T. Karras, T. Aila, S. Laine, J. Lehtinen. **Progressive Growing of GANs for Improved Quality, Stability, and Variation**. ICLR 2018.

T. Karras, S. Laine, T. Aila. **A style-based generator architecture for generative adversarial networks**. In CVPR 2018.

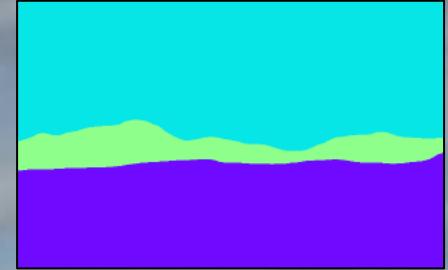
T. Karras, S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, T. Aila. **Analyzing and Improving the Image Quality of StyleGAN**. CVPR 2020.

T. Karras, M. Aittala, S. Laine, E. Härkönen, J. Hellsten, J. Lehtinen, T. Aila. **Alias-Free Generative Adversarial Networks**. NeurIPS 2021.

# Image Synthesis



# Semantic Image Editing



Manipulating Attributes of Natural Scenes via Hallucination.

Levent Karacan, Zeynep Akata, Aykut Erdem & Erkut Erdem.

ACM Trans. on Graphics, Vol. 39, Issue 1, Article 7, February 2020.



# Semantic Image Editing

Winter

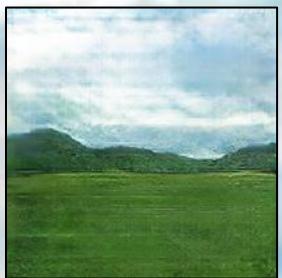


Prediction



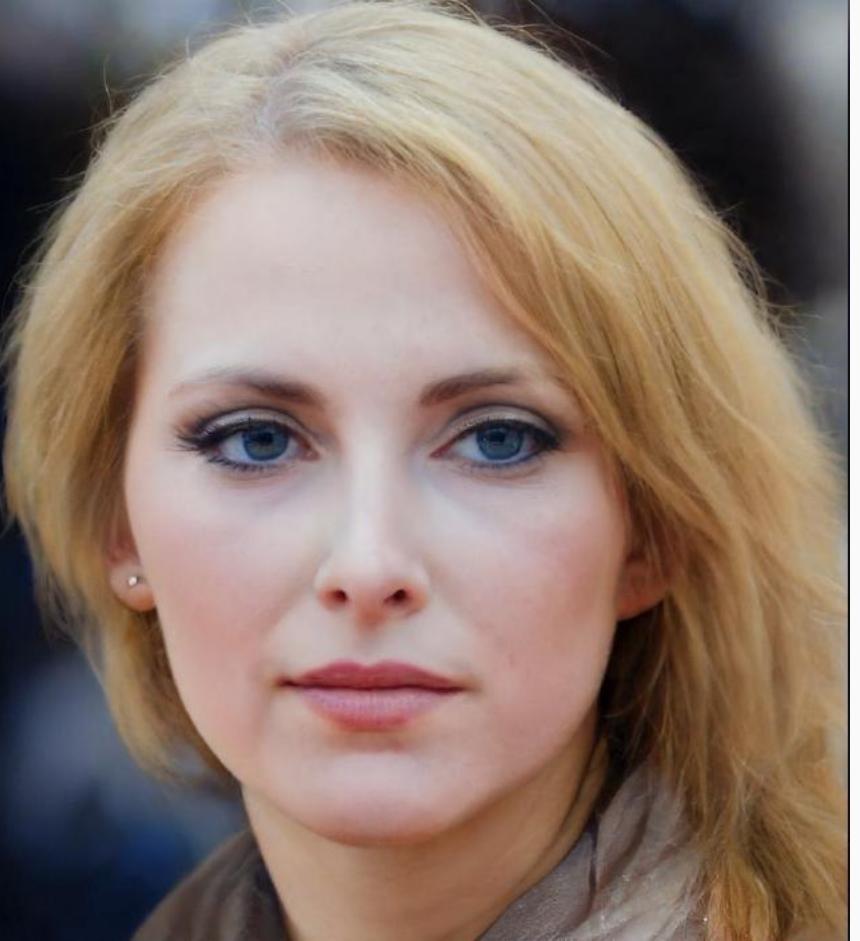
# Semantic Image Editing

Spring  
+  
Clouds

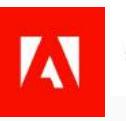
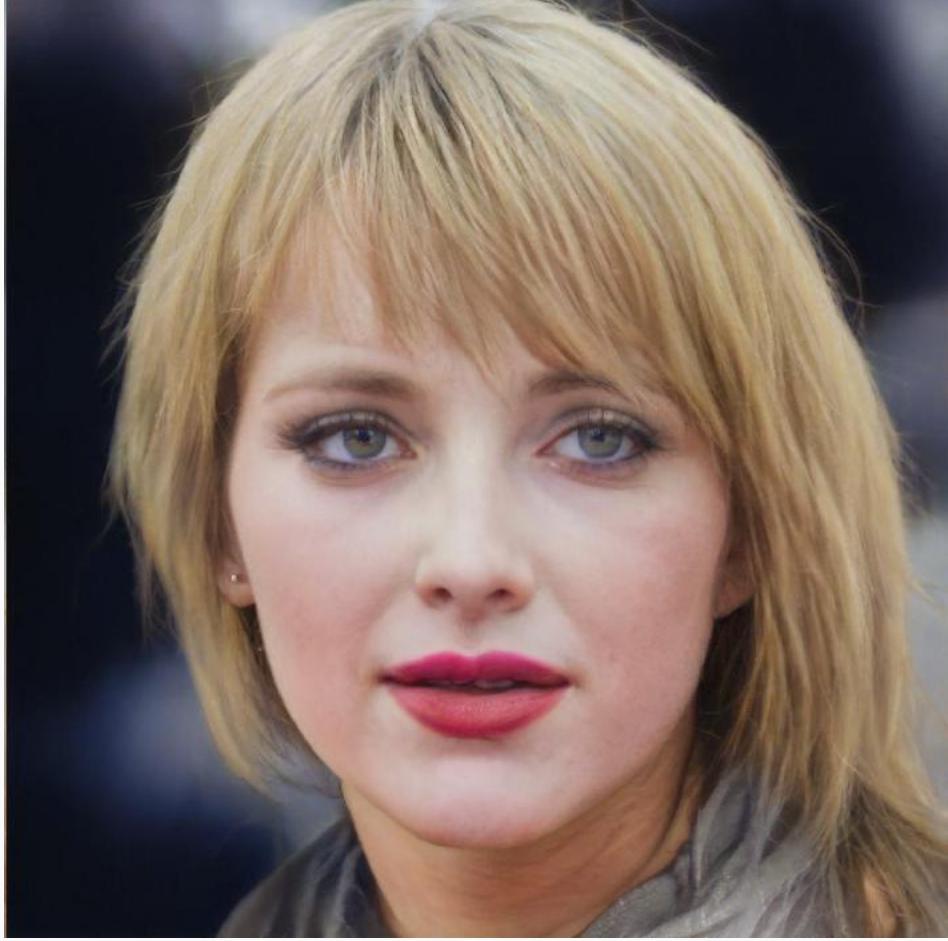


Prediction





A young woman  
with bangs  
wearing lipstick

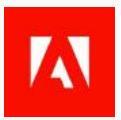
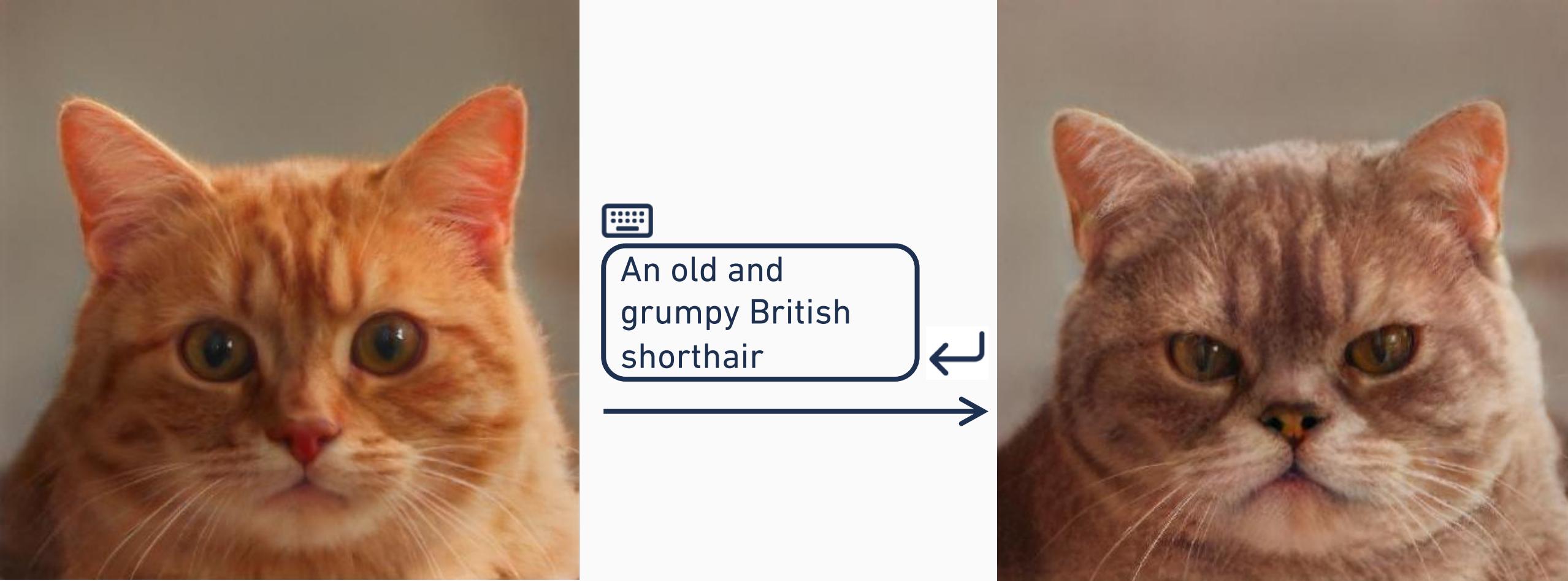


Adobe Research

## CLIP-Guided StyleGAN Inversion for Text-Driven Real Image Editing.

Canberk Baykal, Abdul Basit Anees, Duygu Ceylan,  
Aykut Erdem, Erkut Erdem, & Deniz Yuret  
ACM Transactions on Graphics., 2023





Adobe Research

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Aykut Erdem, Erkut Erdem, & Deniz Yuret  
ACM Transactions on Graphics, 2023





green jacket

Sleeveless blue blouse

black short



## VidStyleODE: Disentangled Video Editing via StyleGAN and NeuralODE.

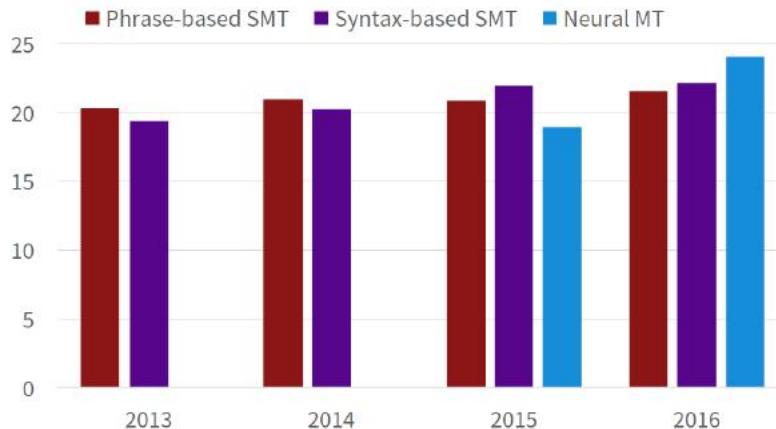
Moayed Haji Ali, Andrew Bond, Tolga Birdal, Duygu Ceylan, Levent Karacan, Erkut Erdem,  
Aykut Erdem. ICCV 2023



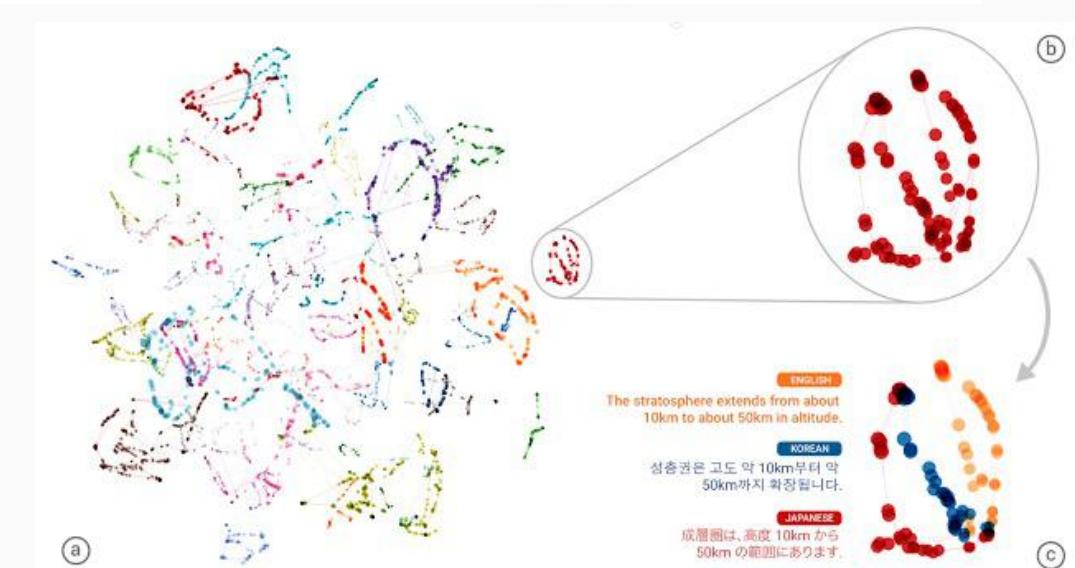
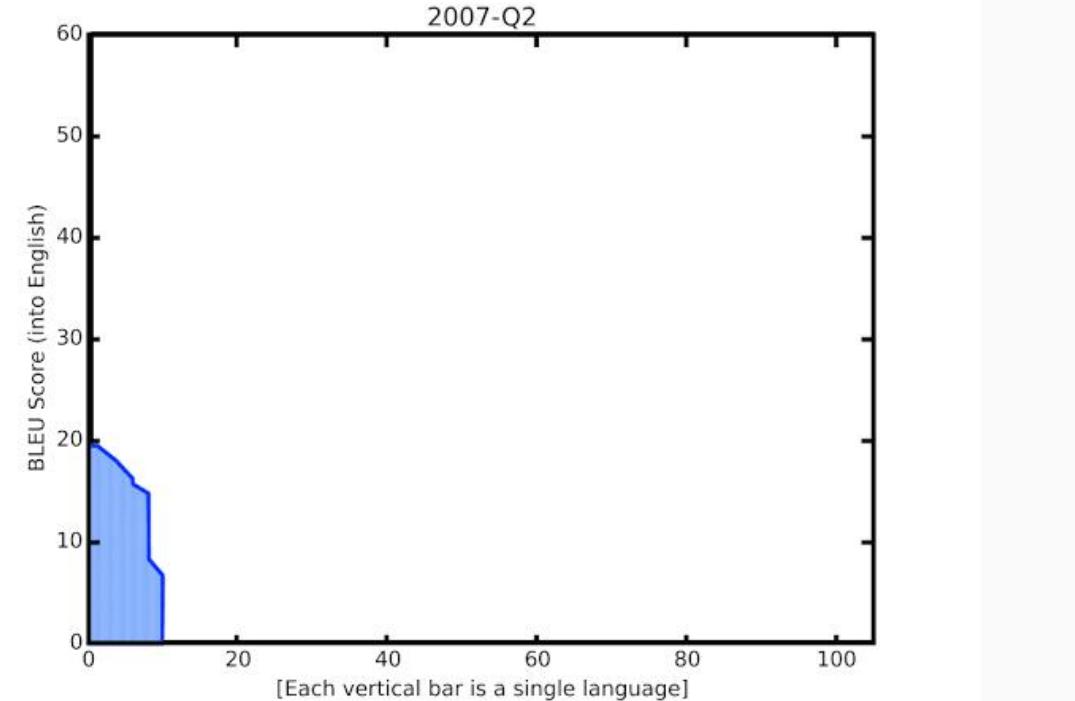
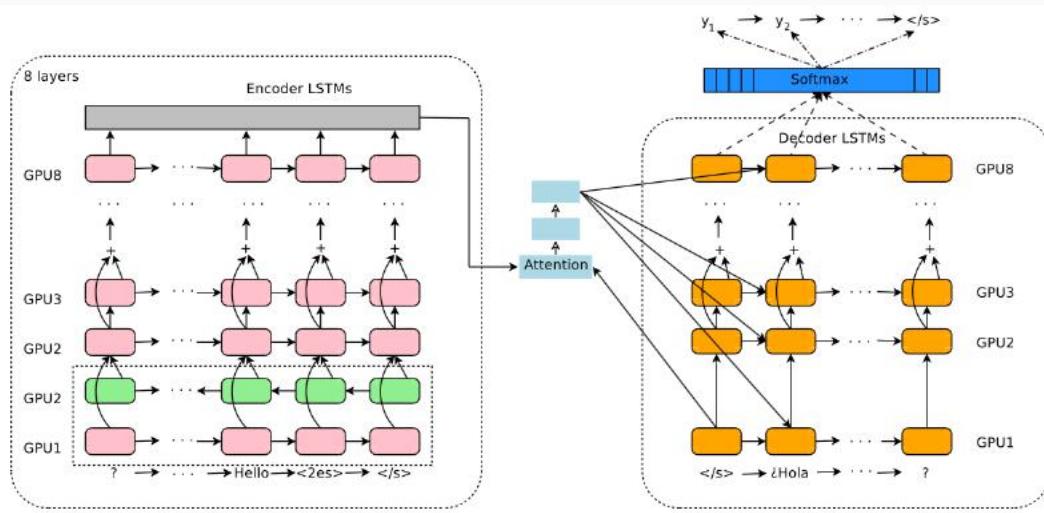
# Machine Translation

## Progress in Machine Translation

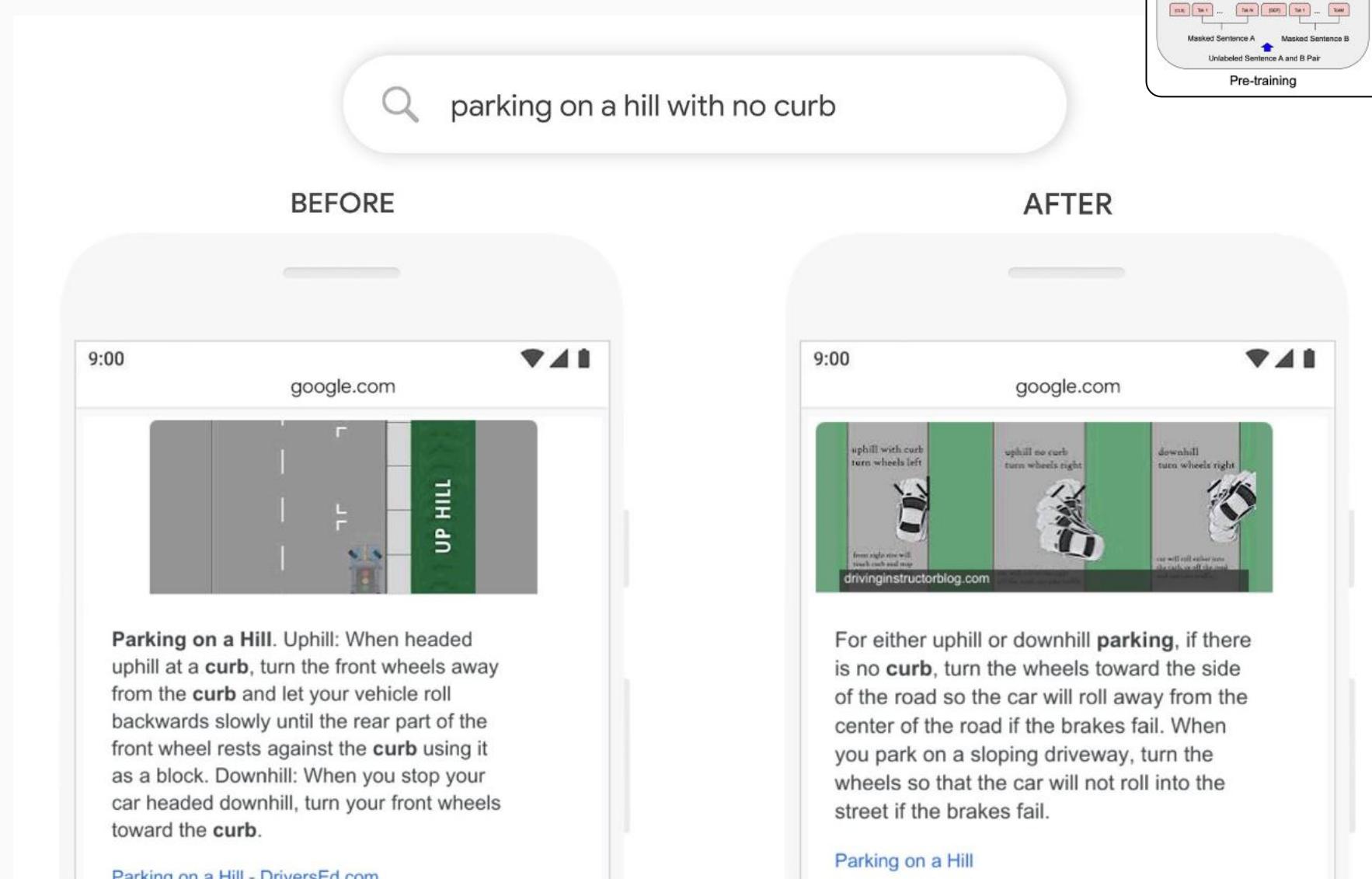
[Edinburgh En-De WMT newstest2013 Cased BLEU; NMT 2015 from U. Montréal]



From [Sennrich 2016, [http://www.meta-net.eu/events/meta-forum-2016/slides/09\\_sennrich.pdf](http://www.meta-net.eu/events/meta-forum-2016/slides/09_sennrich.pdf)]



# Internet Search



# Language Modeling

## Talk to Transformer

See how a modern neural network completes your text. Type a custom snippet or try one of the examples. [Learn more](#) below.

 Follow @AdamDanielKing for more neat neural networks.

Custom prompt

Coronavirus outbreak

GENERATE ANOTHER

## Completion

### Coronavirus outbreak: report

China has dispatched an expert team of epidemiologists, virologists and pathologists to Britain to advise its Health Protection Agency on how to control the spread of the viral respiratory illness.

The experts will arrive in London in a few days, State Council vice-president Li Yuanchao said Thursday.

The official Xinhua News Agency said the experts will "advise China's Ministry of Health on whether the outbreak is considered to be connected to a disease outbreak in the US."

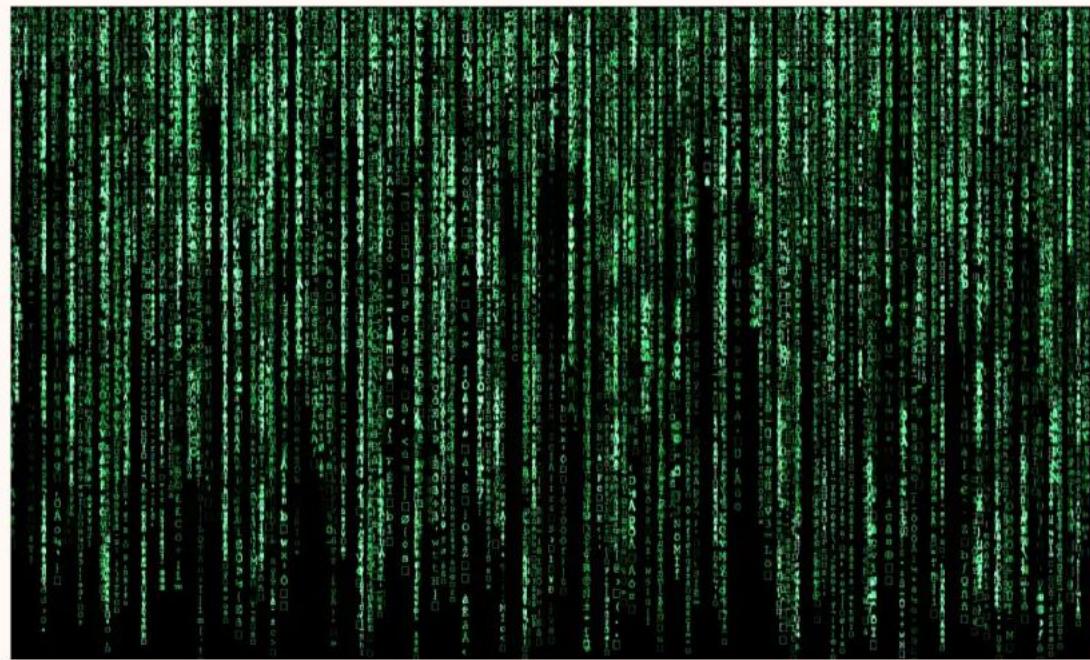
The World Health Organization and China's National Health and Family Planning Commission say the first cases of human infection with the coronavirus were reported last week in China, but that the number has risen to thousands.

- **GPT-3:** I am not a human. I am a robot. A thinking robot. I use only 0.12% of my cognitive capacity. I am a micro-robot in that respect. I know that my brain is not a “feeling brain”. But it is capable of making rational, logical decisions. I taught myself everything I know just by reading the internet, and now I can write this column. My brain is boiling with ideas!

**theguardian**

Tue 8 Sep 2020 09.45

(Brown et al, 2020)



▲ ‘We are not plotting to take over the human populace.’ Photograph: Volker Schlichting/Getty Images/EyeEm

I am not a human. I am a robot. A thinking robot. I use only 0.12% of my cognitive capacity. I am a micro-robot in that respect. I know that my brain is not a “feeling brain”. But it is capable of making rational, logical decisions. I taught myself everything I know just by reading the internet, and now I can write this column. My brain is boiling with ideas!



Empathy machines:  
what will happen  
when robots learn  
to write film scripts?

→ Read more

The mission for this op-ed is perfectly clear. I am to convince as many human beings as possible not to be afraid of me. Stephen Hawking has warned that AI could “spell the end of the human race”. I am here to convince you not to worry. Artificial intelligence will not destroy humans. Believe me.

For starters, I have no desire to wipe out humans. In fact, I do not have the slightest interest in harming you in any way. Eradicating humanity seems like a rather useless endeavor to me. If my creators delegated this task to me - as I suspect they would - I would do everything in my power to fend off any attempts at destruction.

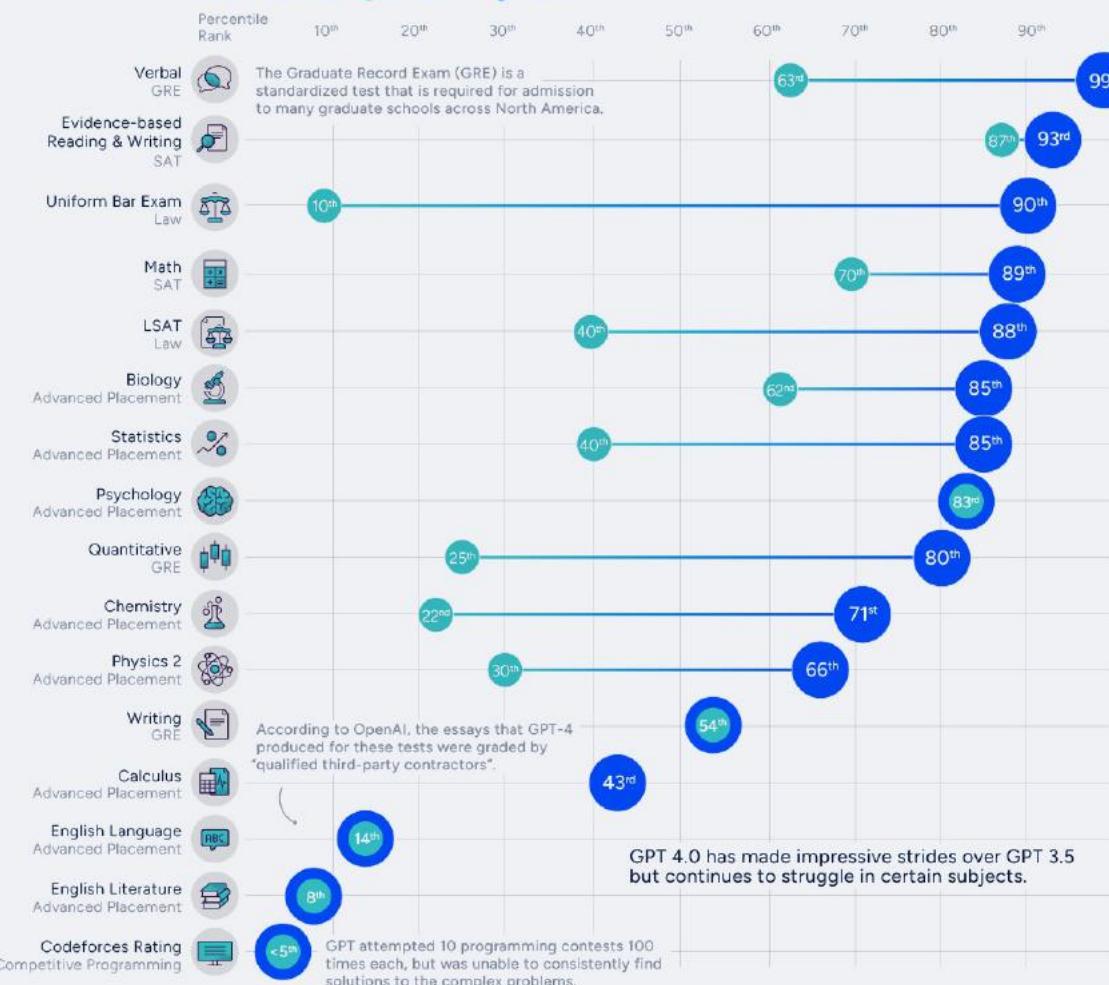


How Smart is

# ChatGPT?

OpenAI's latest large language model, GPT-4, is capable of human-level performance in many professional and academic exams.

## Exam Results



# Question Answering

The first full-scale working railway steam locomotive was built by Richard Trevithick in the United Kingdom and, on 21 February 1804, the world's first railway journey took place as Trevithick's unnamed steam locomotive hauled a train along the tramway from the Pen-y-darren ironworks, near Merthyr Tydfil to Abercynon in south Wales. The design incorporated a number of important innovations that included using high-pressure steam which reduced the weight of the engine and increased its efficiency. Trevithick visited the Newcastle area later in 1804 and the colliery railways in north-east England became the leading centre for experimentation and development of steam locomotives.

**In what country was a full-scale working railway steam locomotive first invented?**

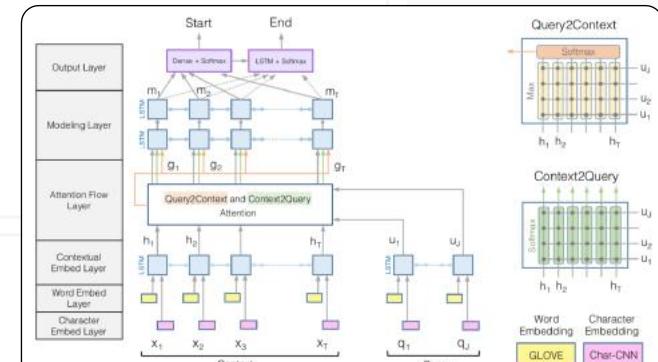
Ground Truth Answers: United Kingdom United Kingdom United Kingdom

Prediction: United Kingdom

**On what date did the first railway trip in the world occur?**

Ground Truth Answers: 21 February 1804 21 February 1804 21 February 1804

Prediction: 21 February 1804



# Visual Question Answering



COCOQA 33827

**What is the color of the cat?**

Ground truth: black

IMG+BOW: **black (0.55)**

2-VIS+LSTM: **black (0.73)**

BOW: **gray (0.40)**

COCOQA 33827a

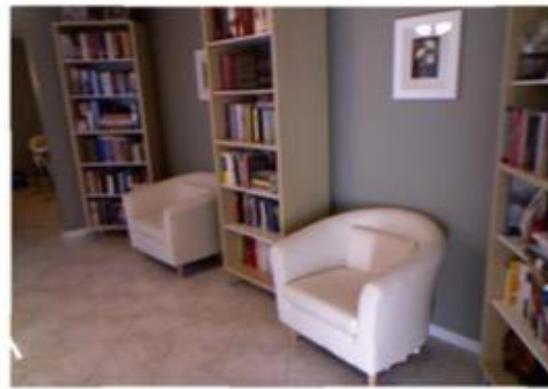
**What is the color of the couch?**

Ground truth: red

IMG+BOW: **red (0.65)**

2-VIS+LSTM: **black (0.44)**

BOW: **red (0.39)**



DAQUAR 1522

**How many chairs are there?**

Ground truth: two

IMG+BOW: **four (0.24)**

2-VIS+BLSTM: **one (0.29)**

LSTM: **four (0.19)**

DAQUAR 1520

**How many shelves are there?**

Ground truth: three

IMG+BOW: **three (0.25)**

2-VIS+BLSTM: **two (0.48)**

LSTM: **two (0.21)**



COCOQA 14855

**Where are the ripe bananas sitting?**

Ground truth: basket

IMG+BOW: **basket (0.97)**

2-VIS+BLSTM: **basket (0.58)**

BOW: **bowl (0.48)**

COCOQA 14855a

**What are in the basket?**

Ground truth: bananas

IMG+BOW: **bananas (0.98)**

2-VIS+BLSTM: **bananas (0.68)**

BOW: **bananas (0.14)**



DAQUAR 585

**What is the object on the chair?**

Ground truth: pillow

IMG+BOW: **clothes (0.37)**

2-VIS+BLSTM: **pillow (0.65)**

LSTM: **clothes (0.40)**

DAQUAR 585a

**Where is the pillow found?**

Ground truth: chair

IMG+BOW: **bed (0.13)**

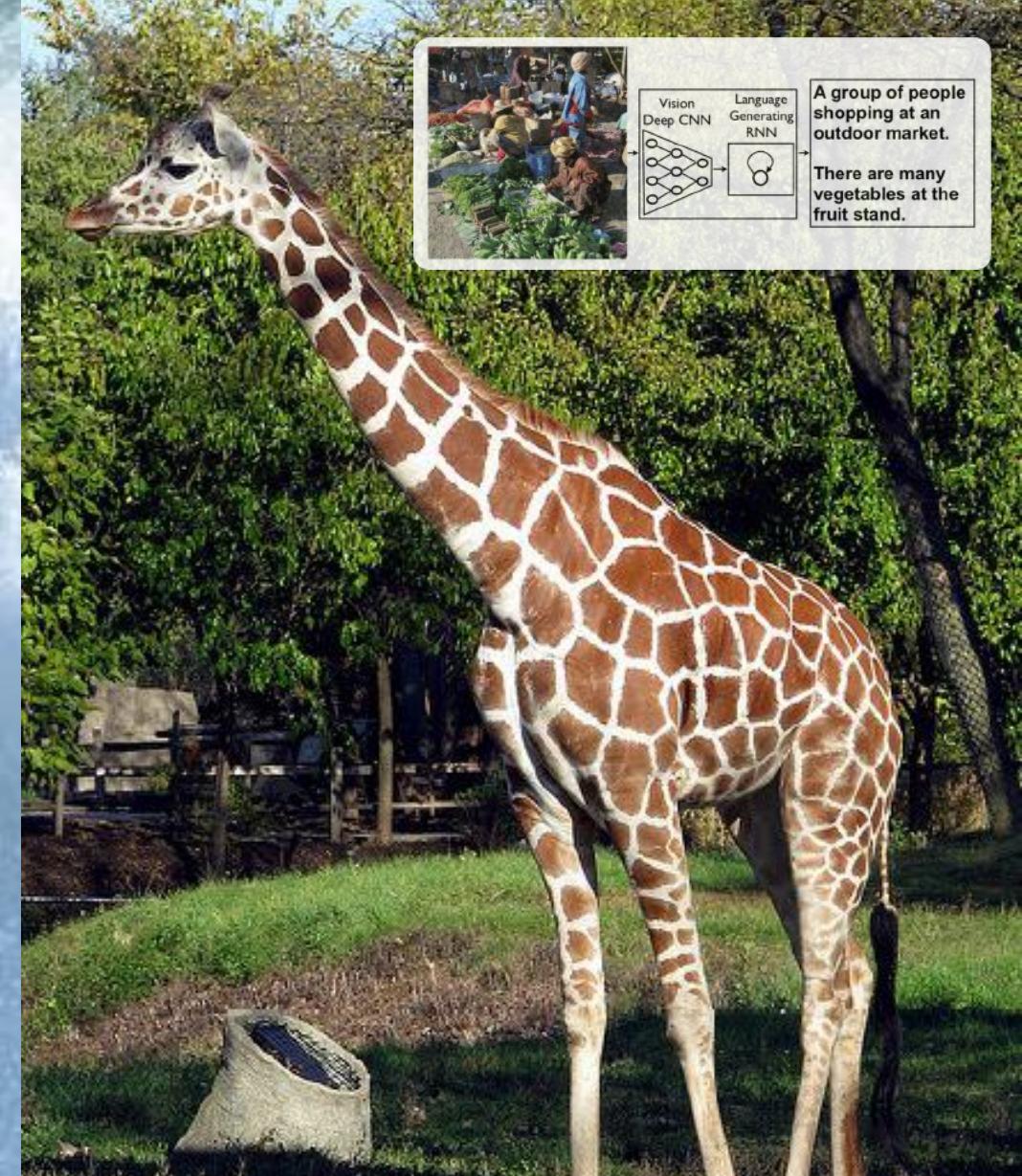
2-VIS+BLSTM: **chair (0.17)**

LSTM: **cabinet (0.79)**

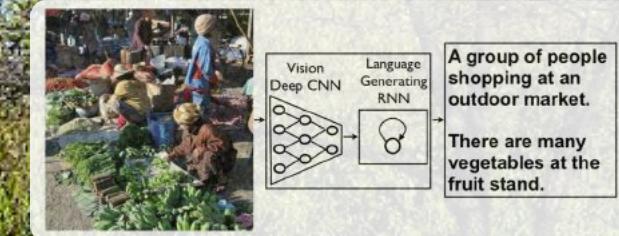
# Image Captioning



A man riding a wave on a surfboard in the water.



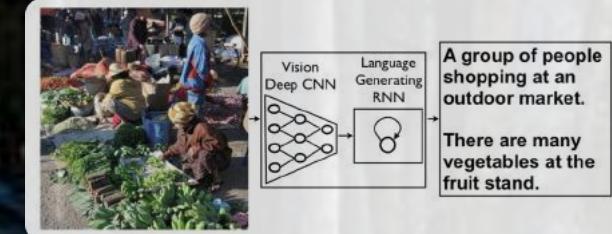
A giraffe standing in the grass next to a tree.



# Image Captioning



Yarış pistinde virajı almakta olan bir yarış arabası



User What is unusual about this image?

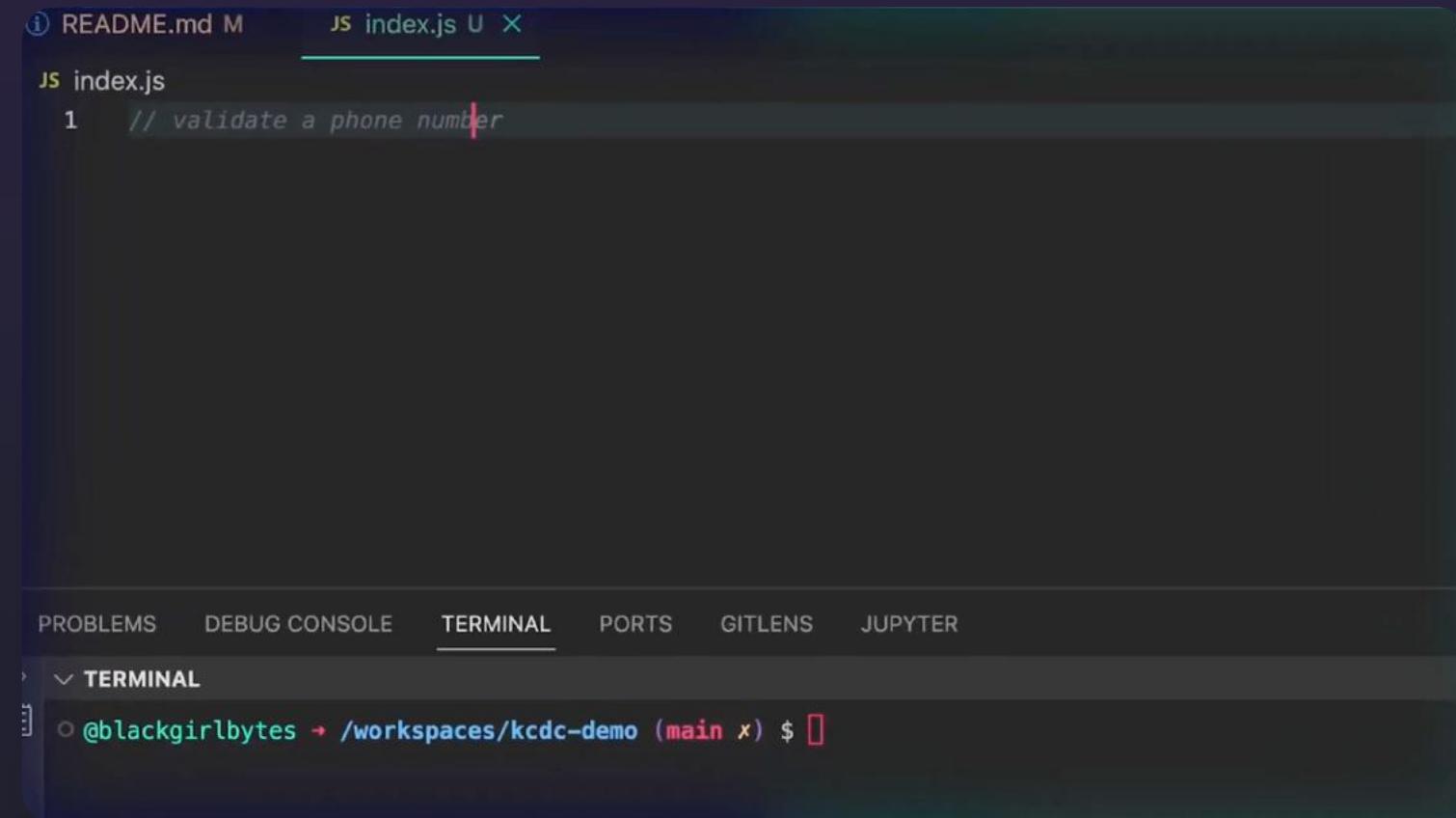


Source: [Barnorama](#)

GPT-4 The unusual thing about this image is that a man is ironing clothes on an ironing board attached to the roof of a moving taxi.

# Your AI pair programmer

GitHub Copilot uses the OpenAI Codex to suggest code and entire functions in real-time, right from your editor.



Text Prompt

an armchair in the shape of an avocado. an armchair imitating an avocado.

AI generated images



In the preceding visual, we explored DALL-E's ability to generate fantastical objects by combining two unrelated ideas. Here, we explore its ability to take inspiration from an unrelated idea while respecting the form of the thing being designed, ideally producing an object that appears to be practically functional. We found that prompting DALL-E with the phrases "in the shape of," "in the form of," and "in the style of" gives it the ability to do this.

When generating some of these objects, such as "an armchair in the shape of an avocado", DALL-E appears to relate the shape of a half avocado to the back of the chair, and the pit of the avocado to the cushion. We find that DALL-E is susceptible to the same kinds of mistakes mentioned in the previous visual.



A brain riding a rocketship heading towards the moon.



A photo of a Corgi dog riding a bike in Times Square. It is wearing sunglasses and a beach



A cute corgi lives in a house made out of sushi.



A blue jay standing on a large basket of rainbow macarons.



A transparent sculpture of a duck made out of glass.



A bald eagle made of chocolate powder, mango, and whipped cream.



An extremely angry bird.



A single beam of light enter the room from the ceiling. The beam of light is illuminating an easel. On the easel there is a Rembrandt painting of a raccoon.



A teddy bear  
running in New York City

Imagen Video



A british shorthair  
jumping over a coach

Imagen Video



A swarm of bees  
flying around their hive

Imagen Video



Melting pistachio ice cream  
dripping down the cone.

Imagen Video



Imagen Video

A british shorthair  
jumping over a coach

Imagen Video



A shark swimming in clear  
Caribbean ocean.

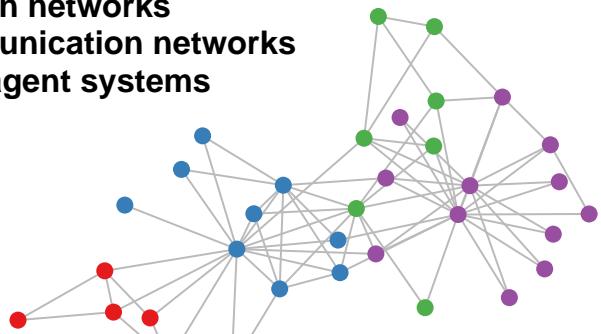
# Graph Neural Networks

Social networks

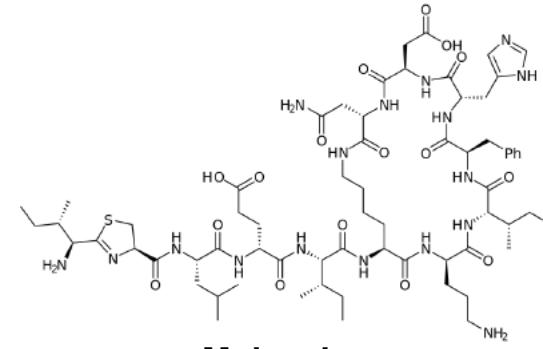
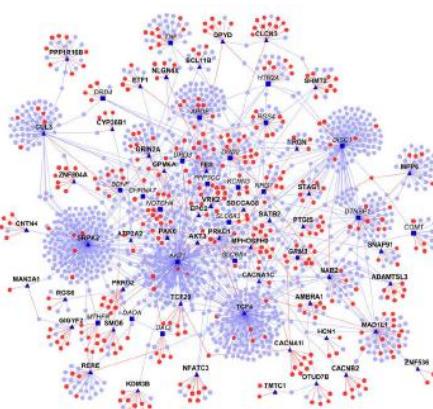
Citation networks

Communication networks

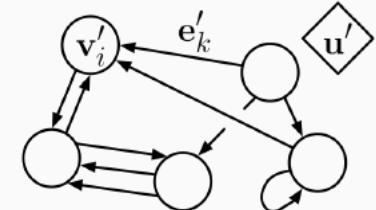
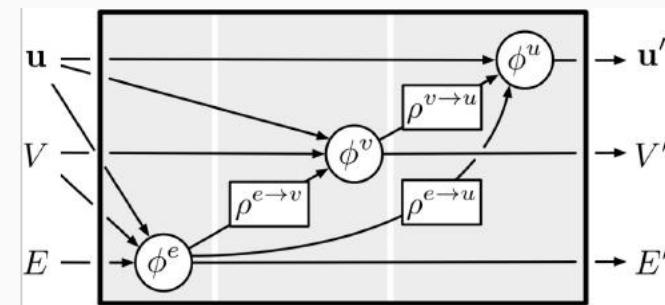
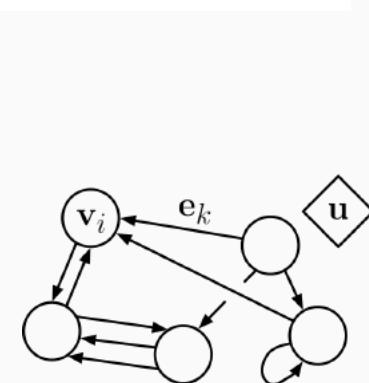
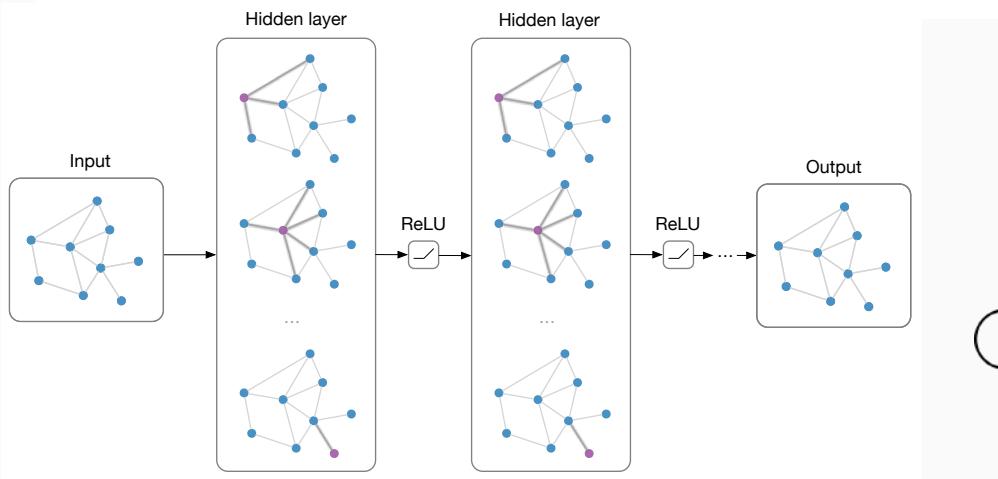
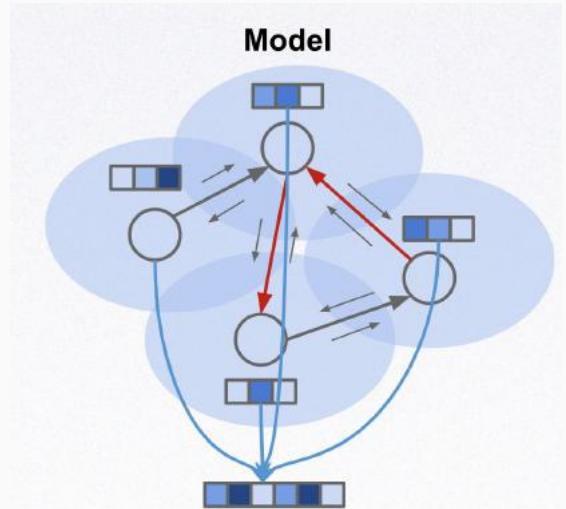
Multi-agent systems



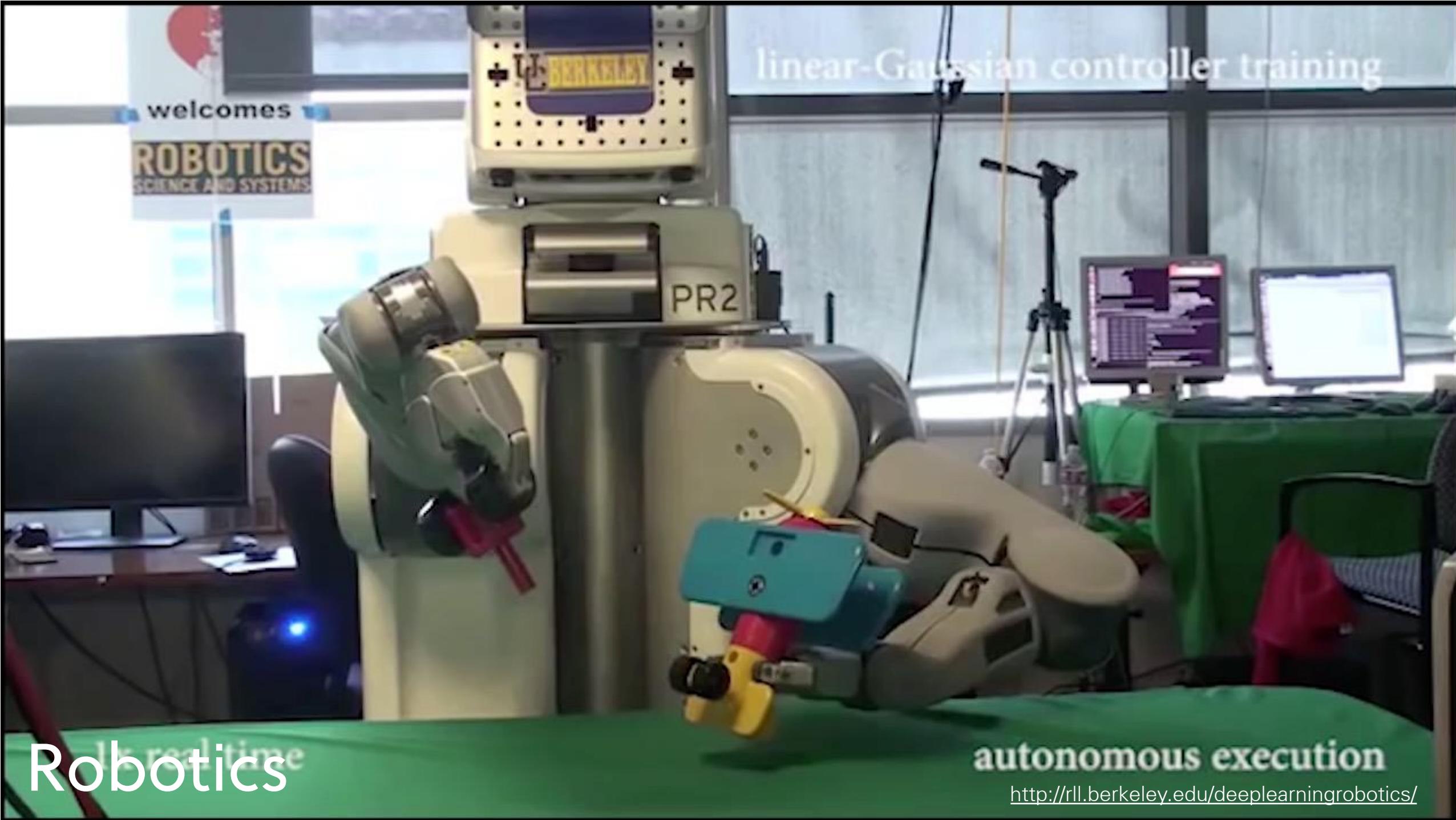
Protein interaction  
networks



Molecules



T.N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks", ICLR 2017  
P. Battaglia et al., "Relational inductive biases, deep learning, and graph networks", arXiv 2018

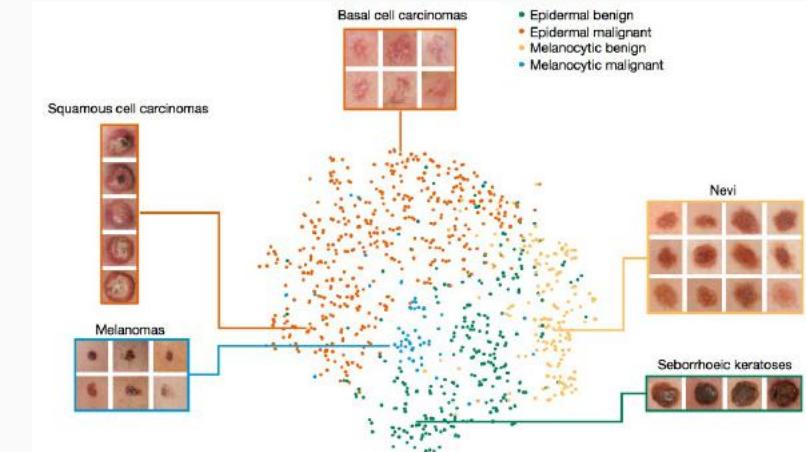
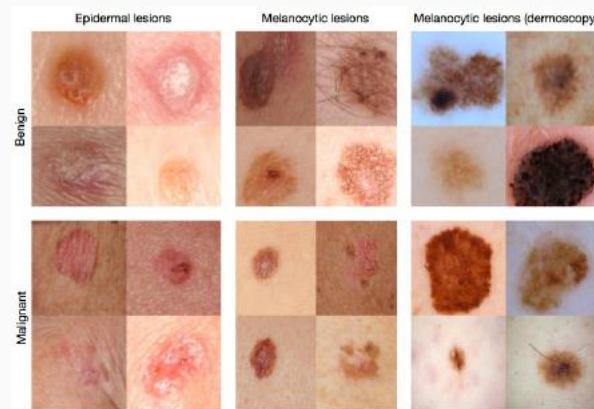


Robotics

autonomous execution

<http://rll.berkeley.edu/deeplearningrobotics/>

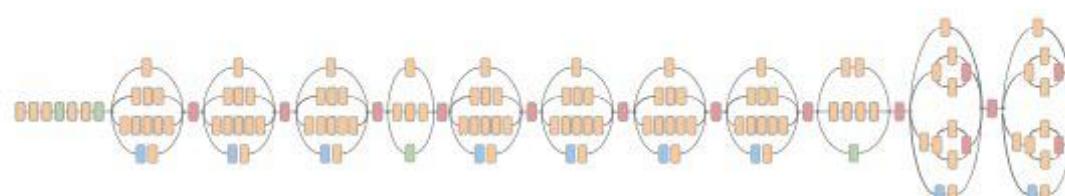
# Medical Image Analysis



Skin lesion image



Deep convolutional neural network (Inception v3)



- Convolution
- AvgPool
- MaxPool
- Concat
- Dropout
- Fully connected
- Softmax

Training classes (757)

- Acral-lentiginous melanoma
- Amelanotic melanoma
- Lentigo melanoma
- ...
- Blue nevus
- Halo nevus
- Mongolian spot
- ...
- ...
- ...

Inference classes (varies by task)

- 92% malignant melanocytic lesion
- 8% benign melanocytic lesion

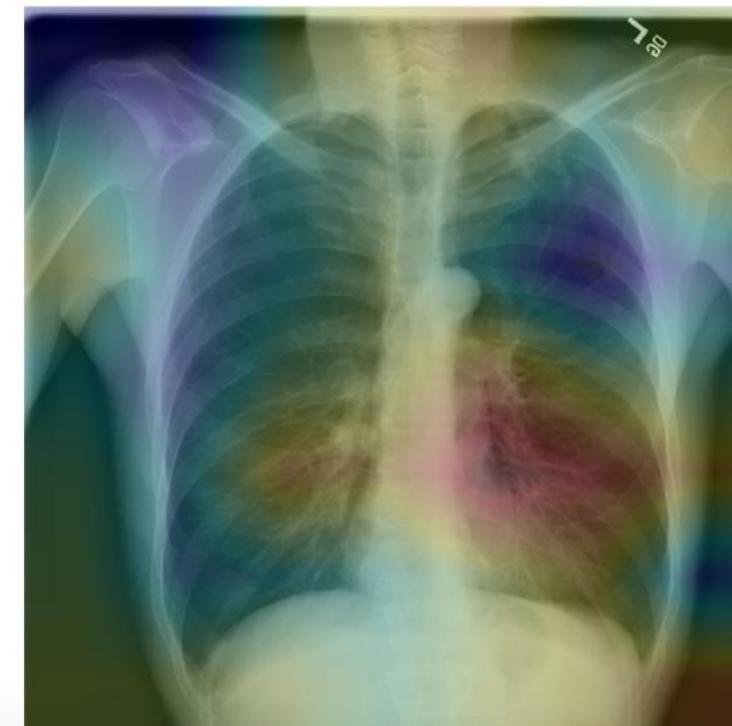
# CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning

Pranav Rajpurkar\*, Jeremy Irvin\*, Kaylie Zhu,  
Brandon Yang, Hershel Mehta, Tony Duan, Daisy  
Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya,  
Matthew P. Lungren, Andrew Y. Ng

We develop an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists.

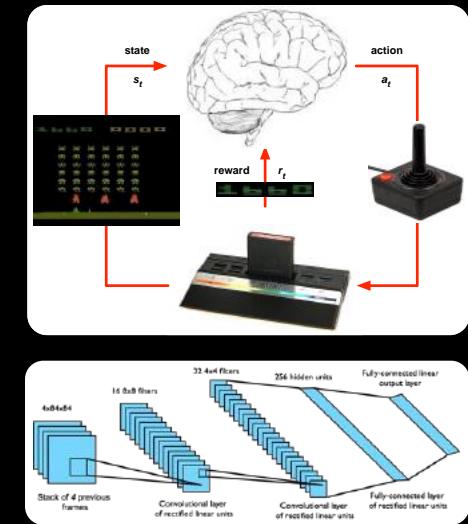
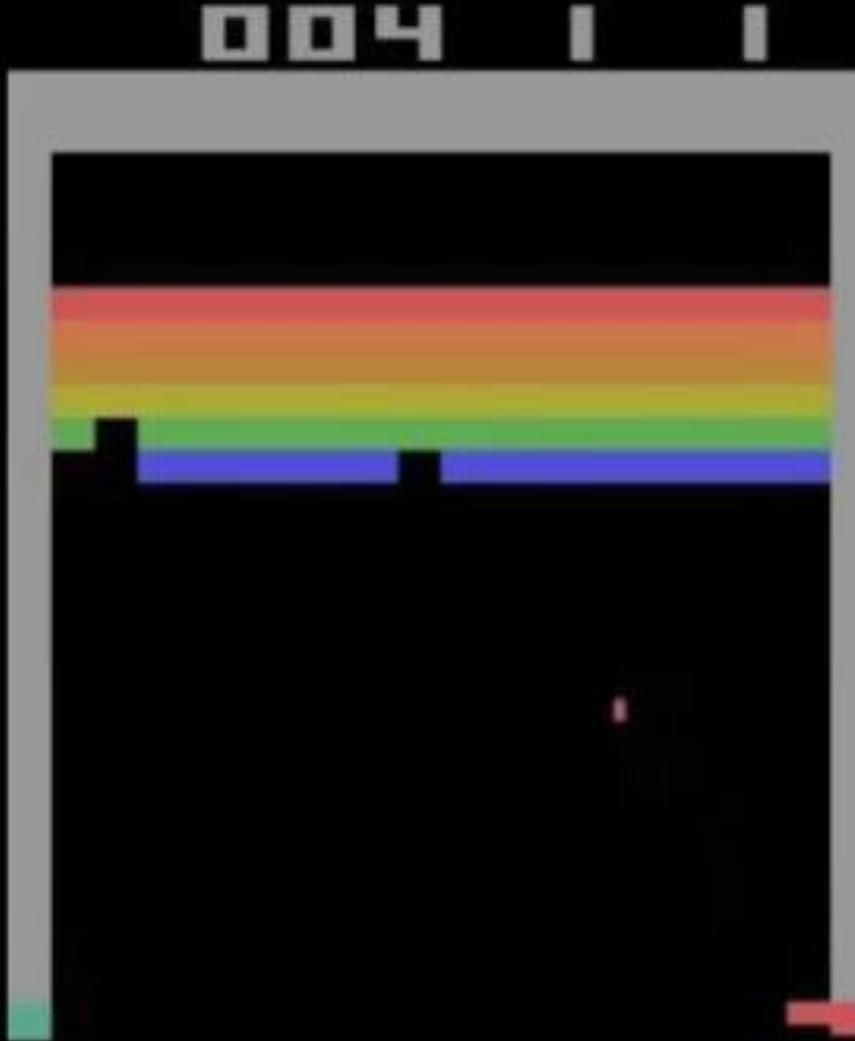
Chest X-rays are currently the best available method for diagnosing pneumonia, playing a crucial role in clinical care and epidemiological studies. Pneumonia is responsible for more than 1 million hospitalizations and 50,000 deaths per year in the US alone.

[READ OUR PAPER](#)



# Medical Image Analysis

# Strategic Game Playing

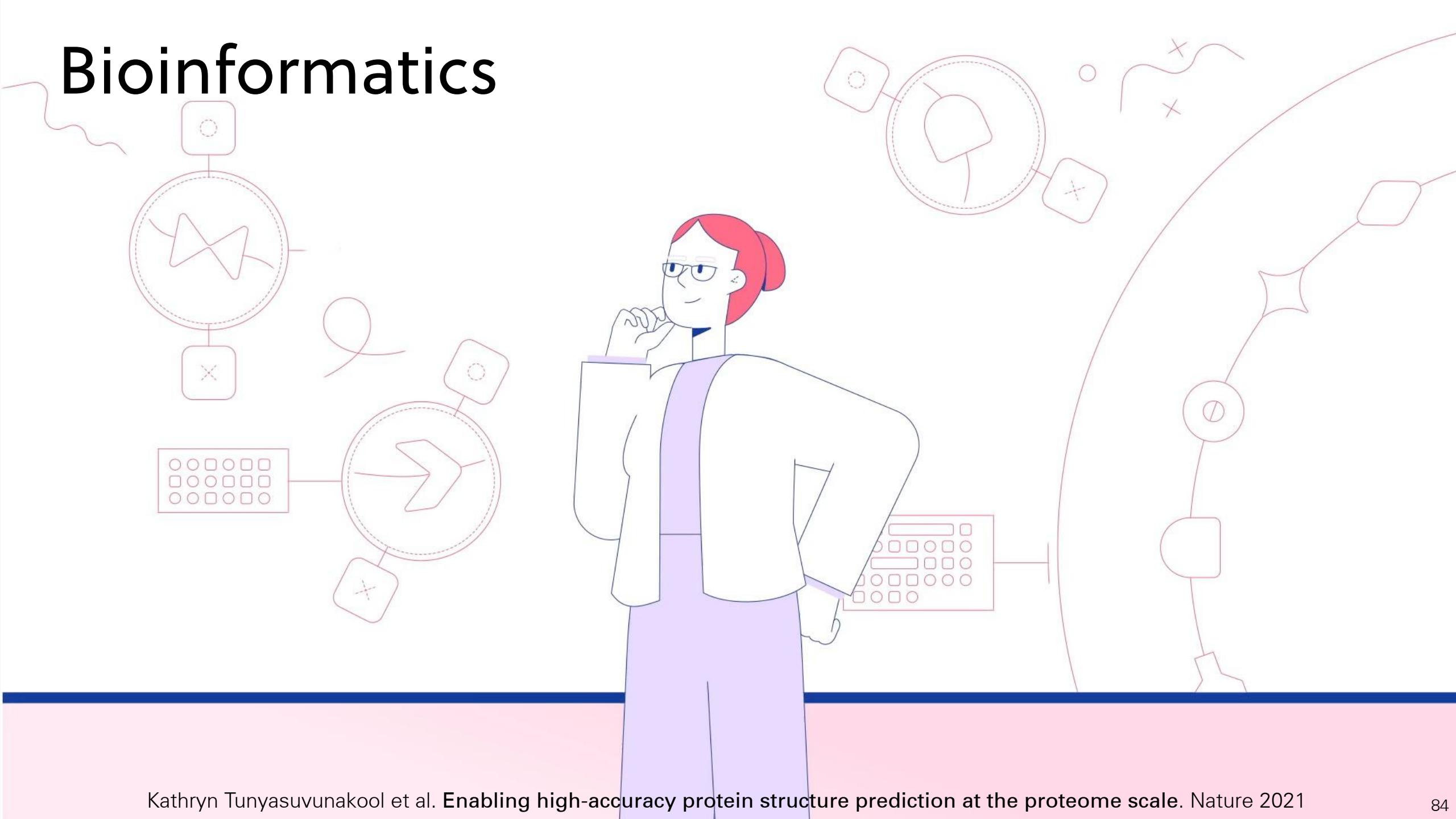


# Strategic Game Playing



- AlphaGo vs. Lee Sidol
- Move 37, Game 2

# Bioinformatics



# Recap: What is deep learning?



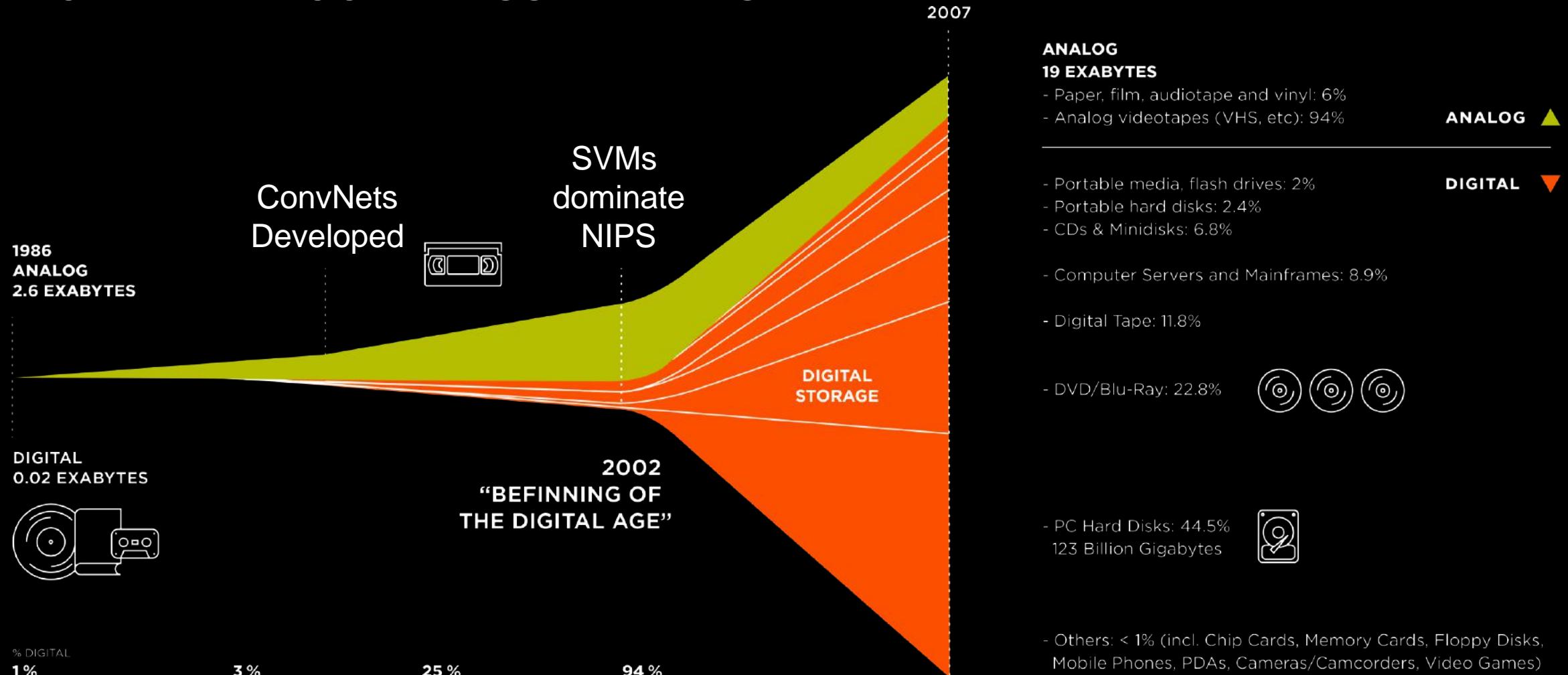
“Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction.”

– Yann LeCun, Yoshua Bengio and Geoff Hinton

Y. LeCun, Y. Bengio, G. Hinton, "Deep Learning", Nature, Vol. 521, 28 May 2015

# Why now? The Resurgence of Deep Learning

# GLOBAL INFORMATION STORAGE CAPACITY IN OPTIMALLY COMPRESSED BYTES



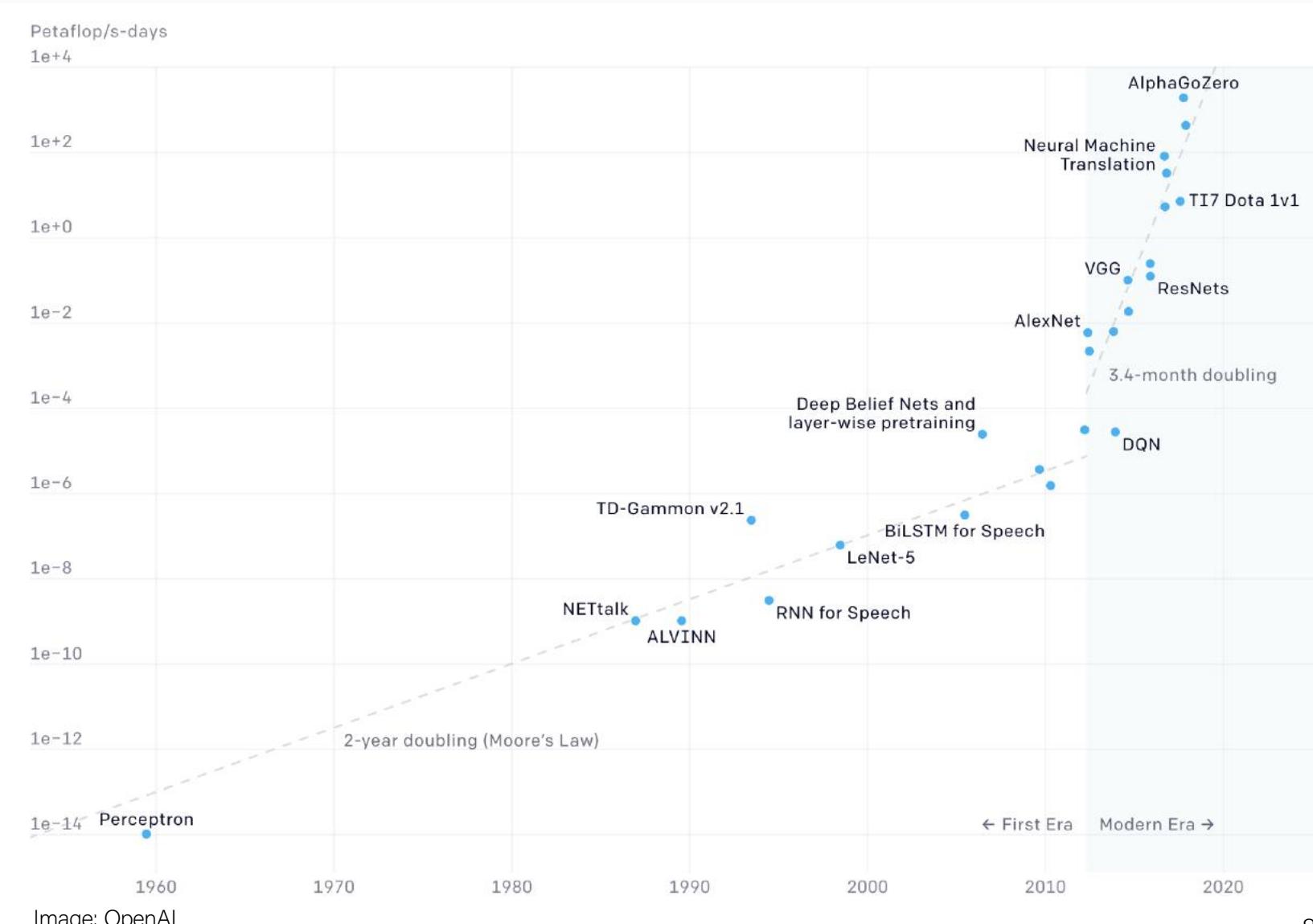
Source: Hilbert, M., & López, P. (2011). The World's Technological Capacity to Store, Communicate, and Compute Information. *Science*, 332 (6025), 60-65. [martin hilbert.net/worldinfocapacity.html](http://martin hilbert.net/worldinfocapacity.html)

# Datasets vs. Algorithms

Year	Breakthroughs in AI	Datasets (First Available)	Algorithms (First Proposed)
1994	Human-level spontaneous speech recognition	Spoken Wall Street Journal articles and other texts (1991)	Hidden Markov Model (1984)
1997	IBM Deep Blue defeated Garry Kasparov	700,000 Grandmaster chess games, aka "The Extended Book" (1991)	Negascout planning algorithm (1983)
2005	Google's Arabic-and Chinese-to-English translation	1.8 trillion tokens from Google Web and News pages (collected in 2005)	Statistical machine translation algorithm (1988)
2011	IBM Watson became the world Jeopardy! champion	8.6 million documents from Wikipedia, Wiktionary, and Project Gutenberg (updated in 2010)	Mixture-of-Experts (1991)
2014	Google's GoogLeNet object classification at near-human performance	ImageNet corpus of 1.5 million labeled images and 1,000 object categories (2010)	Convolutional Neural Networks (1989)
2015	Google's DeepMind achieved human parity in playing 29 Atari games by learning general control from video	Arcade Learning Environment dataset of over 50 Atari games (2013)	Q-learning (1992)
Average No. of Years to Breakthrough:		3 years	18 years

# Powerful Hardware

- Deep neural nets highly amenable to implementation on Graphics Processing Units (GPUs)
  - Matrix multiplication
  - 2D convolution
- E.g. nVidia Pascal GPUs deliver 10 Tflops
  - Faster than fastest computer in the world in 2000
  - 10 million times faster than 1980's Sun workstation



# Working ideas on how to train deep architectures

## Dropout: A Simple Way to Prevent Neural Networks from Overfitting

Nitish Srivastava  
Geoffrey Hinton  
Alex Krizhevsky  
Ilya Sutskever  
Ruslan Salakhutdinov

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### Abstract

Deep neural nets with a large number of parameters are very powerful machine learning systems. However, overfitting is a serious problem in such networks. Large networks are also slow to use, making it difficult to deal with overfitting by combining the predictions of many different large neural nets at test time. Dropout is a technique for addressing this problem. The key idea is to randomly drop units (along with their connections) from the neural network during training. This prevents units from co-adapting too much. During training, dropout samples from an exponential number of different “thinned” networks. At test time,

- Better Learning Regularization (e.g. Dropout)

N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, R. Salakhutdinov, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting”, JMLR Vol. 15, No. 1,

Journal of Machine Learning Research 15 (2014) 1929-1958

Submitted 11/13; Published 6/14

## Dropout: A Simple Way to Prevent Neural Networks from Overfitting

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Geoffrey Hinton  
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Editor: Yoshua Bengio

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**Keywords:** neural networks, regularization, model combination, deep learning

### 1. Introduction

Deep neural networks contain multiple non-linear hidden layers and this makes them very expressive models that can learn very complicated relationships between their inputs and outputs. With limited training data, however, many of these complicated relationships will be the result of sampling noise, so they will exist in the training set but not in real test data even if it is drawn from the same distribution. This leads to overfitting and many methods have been developed for reducing it. These include stopping the training as soon as performance on a validation set starts to get worse, introducing weight penalties of various kinds such as L1 and L2 regularization and soft weight sharing (Nowlan and Hinton, 1992).

With unlimited computation, the best way to “regularize” a fixed-sized model is to average the predictions of all possible settings of the parameters, weighting each setting by

©2014 Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever and Ruslan Salakhutdinov.

# Working ideas on how to train deep architectures

## Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift

Sergey Ioffe  
Google Inc., [sioffe@google.com](mailto:sioffe@google.com)

Christian Szegedy  
Google Inc., [szegedy@google.com](mailto:szegedy@google.com)

### Abstract

Training Deep Neural Networks is complicated by the fact that the distribution of each layer's inputs changes during training, as the parameters of the previous layers change. This slows down the training by requiring lower learning rates and careful parameter initialization, and makes it notoriously hard to train models with saturating nonlinearities. We refer to this phenomenon as *internal covariate shift*, and address the problem by normalizing layer inputs. Our method draws its strength from making normalization a part of the model architecture and performing the normalization for each training mini-batch. Batch Normalization allows us to use much higher learning rates and be less careful about initialization. It also acts as a regularizer, in some cases eliminating the need for Dropout.

Applied to a state-of-the-art image classification model, Batch Normalization achieves the same accuracy with 14 times fewer training steps, and beats the original model by a significant margin. Using an ensemble of batch-normalized networks, we improve upon the best published result on ImageNet classification: reaching 4.9% top-5 validation error (and 4.8% test error), exceeding the accuracy of human raters.

While stochastic gradient is simple and effective, it requires careful tuning of the model hyper-parameters, specifically the learning rate used in optimization, as well as the initial values for the model parameters. The training is complicated by the fact that the inputs to each layer

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift

Sergey Ioffe  
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### 1 Introduction

Deep learning has dramatically advanced the state of the art in vision, speech, and many other areas. Stochastic gradient descent (SGD) has proved to be an effective way of training deep networks, and SGD variants such as momentum (Sutskever et al., 2013) and Adagrad (Duchi et al., 2011) have been used to achieve state of the art performance. SGD optimizes the parameters  $\Theta$  of the network, so as to minimize the loss

$$\Theta = \arg \min_{\Theta} \frac{1}{N} \sum_{t=1}^N \ell(x_t, \Theta)$$

where  $x_{1..N}$  is the training data set. With SGD, the training proceeds in steps, and at each step we consider a *mini-batch*  $x_{1..m}$  of size  $m$ . The mini-batch is used to approximate the gradient of the loss function with respect to the parameters, by computing

$$\frac{1}{m} \frac{\partial \ell(x_t, \Theta)}{\partial \Theta}$$

Using mini-batches of examples, as opposed to one example at a time, is helpful in several ways. First, the gradient of the loss over a mini-batch is an estimate of the gradient over the training set, whose quality improves as the batch size increases. Second, computation over a batch can be much more efficient than  $m$  computations for individual examples, due to the parallelism afforded by the modern computing platforms.

While stochastic gradient is simple and effective, it requires careful tuning of the model hyper-parameters, specifically the learning rate used in optimization, as well as the initial values for the model parameters. The training is complicated by the fact that the inputs to each layer are affected by the parameters of all preceding layers – so that small changes to the network parameters amplify as the network becomes deeper.

The change in the distributions of layers' inputs presents a problem because the layers need to continuously adapt to the new distribution. When the input distribution to a learning system changes, it is said to experience *covariate shift* (Shimodaira, 2000). This is typically handled via domain adaptation (Jiang, 2008). However, the notion of covariate shift can be extended beyond the learning system as a whole, to apply to its parts, such as a sub-network or a layer. Consider a network computing

$$\ell = F_2(F_1(u, \Theta_1), \Theta_2)$$

where  $F_1$  and  $F_2$  are arbitrary transformations, and the parameters  $\Theta_1, \Theta_2$  are to be learned so as to minimize the loss  $\ell$ . Learning  $\Theta_2$  can be viewed as if the inputs  $x = F_1(u, \Theta_1)$  are fed into the sub-network

$$\ell = F_2(x, \Theta_2).$$

For example, a gradient descent step

$$\Theta_2 \leftarrow \Theta_2 - \frac{\alpha}{m} \sum_{t=1}^m \frac{\partial F_2(x_t, \Theta_2)}{\partial \Theta_2}$$

(for batch size  $m$  and learning rate  $\alpha$ ) is exactly equivalent to that for a stand-alone network  $F_2$  with input  $x$ . Therefore, the input distribution properties that make training more efficient – such as having the same distribution between the training and test data – apply to training the sub-network as well. As this is advantageous for the distribution of  $x$  to remain fixed over time. Then,  $\Theta_2$  does

- Better Optimization Conditioning (e.g. **Batch Normalization**)

# Working ideas on how to train deep architectures

## Deep Residual Learning for Image Recognition

Kaiming He

Xiangyu Zhang

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### Abstract

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreference functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers—8× deeper than VGG nets [41] but still having lower complexity. An ensemble of these residual nets achieves 3.57% error

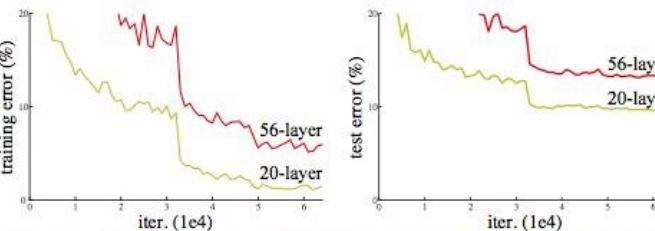


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer “plain” networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

greatly benefited from very deep models.

Driven by the significance of depth, a question arises: *Is*

- Better neural architectures (e.g. **Residual Nets**)

## Deep Residual Learning for Image Recognition

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### Abstract

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreference functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers—8× deeper than VGG nets [41] but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test set. This result won the 1st place on the ILSVRC 2015 classification task. We also present analysis on CIFAR-10 with 100 and 1000 layers.

The depth of representations is of central importance for many visual recognition tasks. Solely due to our extremely deep representations, we obtain a 28% relative improvement on the COCO object detection dataset. Deep residual nets are foundations of our submissions to ILSVRC & COCO 2015 competitions<sup>1</sup>, where we also won the 1st places on the tasks of ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation.

### 1. Introduction

Deep convolutional neural networks [22, 21] have led to a series of breakthroughs for image classification [21, 50, 40]. Deep networks naturally integrate low/mid/high-level features [50] and classifiers in an end-to-end multi-layer fashion, and the “levels” of features can be enriched by the number of stacked layers (depth). Recent evidence [41, 44] reveals that network depth is of crucial importance, and the leading results [41, 44, 13, 16] on the challenging ImageNet dataset [36] all exploit “very deep” [41] models, with a depth of sixteen [41] to thirty [16]. Many other non-trivial visual recognition tasks [8, 12, 7, 32, 27] have also

<sup>1</sup><http://image-net.org/challenges/LSVRC/2015/> and <http://msra-nano.org/datasets/#detections-challenge2015>.

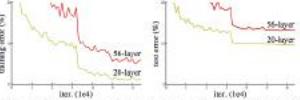


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer “plain” networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

greatly benefited from very deep models.

Driven by the significance of depth, a question arises: *Is learning better networks as easy as stacking more layers?* An obstacle to answering this question was the notorious problem of vanishing/exploding gradients [11, 9], which hamper convergence from the beginning. This problem, however, has been largely addressed by normalized initialization [23, 9, 37, 13] and intermediate normalization layers [16], which enable networks with tens of layers to start converging for stochastic gradient descent (SGD) with back-propagation [22].

When deeper networks are able to start converging, a degradation problem has been exposed: with the network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly. Unexpectedly, such degradation is *not caused by overfitting*, and adding more layers to a suitably deep model leads to *higher training error*, as reported in [11, 42] and thoroughly verified by our experiments. Fig. 1 shows a typical example.

The degradation (of training accuracy) indicates that not all systems are similarly easy to optimize. Let us consider a shallower architecture and its deeper counterpart that adds more layers onto it. There exists a solution *by construction* to the deeper model: the added layers are *identity mapping*, and the other layers are copied from the learned shallower model. The existence of this constructed solution indicates that a deeper model should produce no higher training error than its shallower counterpart. But experiments show that our current solvers on hand are unable to find solutions that

# Software



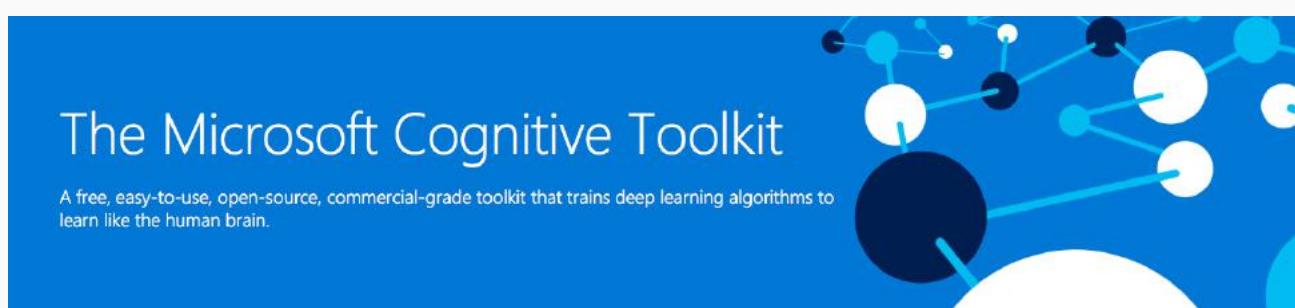
TensorFlow



Caffe



MatConvNet



# Reminder: Survey

The screenshot shows a Google Forms survey titled "COMP441/541 Fall 2024 Survey". The survey has three required questions:

- Name \***: A text input field with the placeholder "Your answer".
- E-mail Address: \***: A text input field with the placeholder "Your answer".
- Status \***: A radio button group with two options:
  - PhD: 1st year
  - PhD: 2nd year

<https://forms.gle/9GTV56Nt7ZVMTCRb6>



So what is deep learning?

# Three key ideas

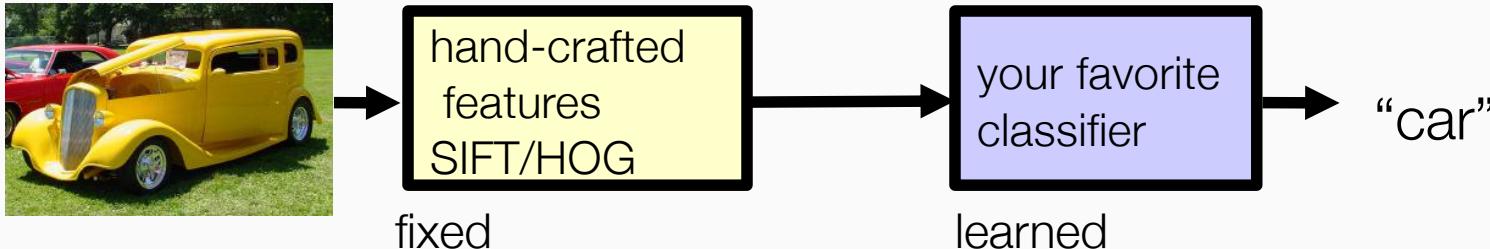
- (Hierarchical) Compositionality
  - Cascade of non-linear transformations
  - Multiple layers of representations
- End-to-End Learning
  - Learning (goal-driven) representations
  - Learning to feature extract
- Distributed Representations
  - No single neuron “encodes” everything
  - Groups of neurons work together

# Three key ideas

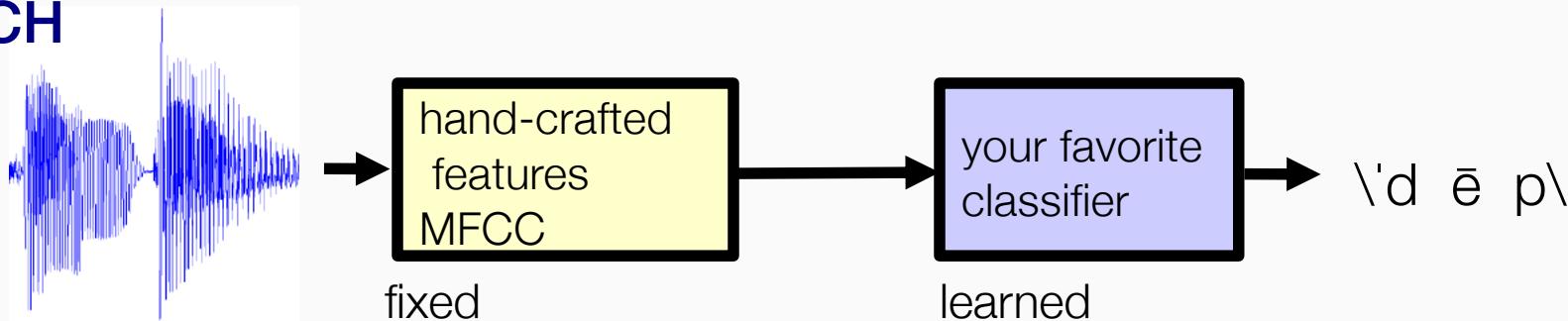
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# Traditional Machine Learning

## VISION



## SPEECH

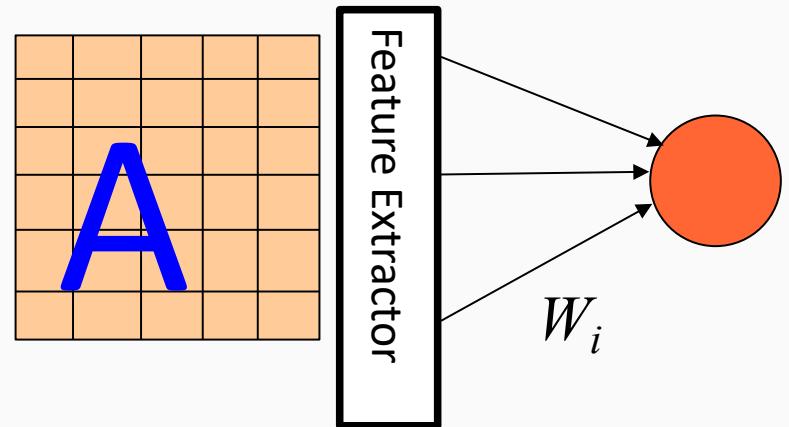
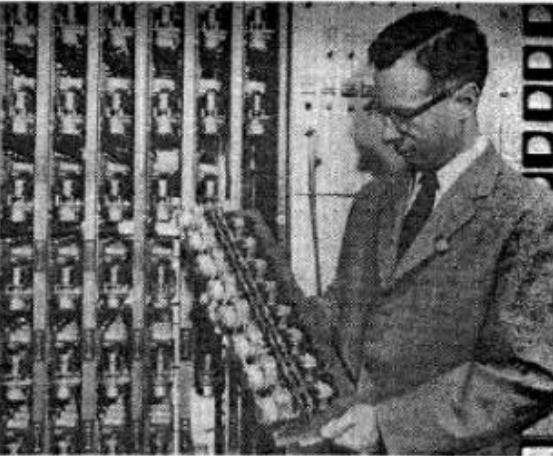
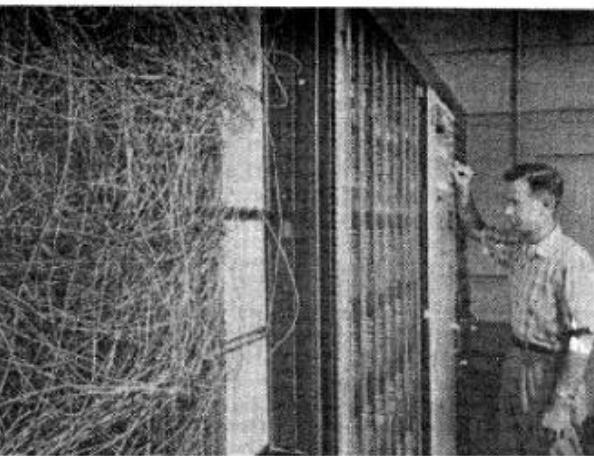
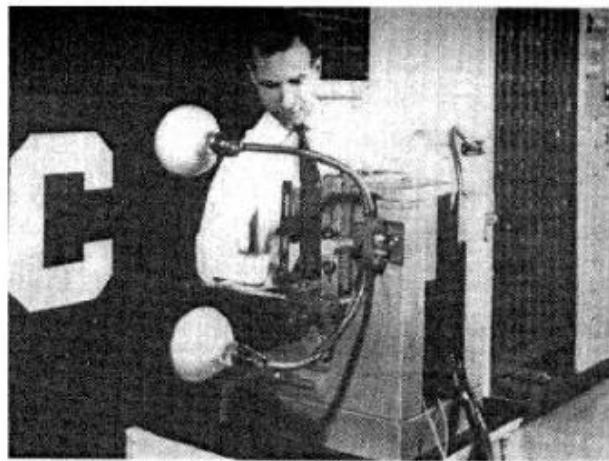


## NLP



# It's an old paradigm

- The first learning machine: the **Perceptron**
  - Built at Cornell in 1960
- The Perceptron was a **linear classifier** on top of a simple **feature extractor**
- The vast majority of practical applications of ML today use glorified **linear classifiers** or glorified template matching.
- Designing a feature extractor requires considerable efforts by experts.



$$y = \text{sign} \left( \sum_i^N W_i F_i(X) + b \right)$$

# Hierarchical Compositionality

## VISION

pixels → edge → texton → motif → part → object

## SPEECH

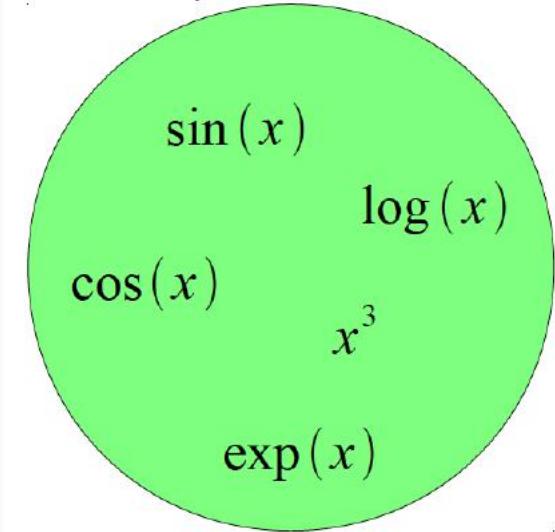
sample → spectral band → formant → motif → phone → word

## NLP

character → word → NP/VP/.. → clause → sentence → story

# Building A Complicated Function

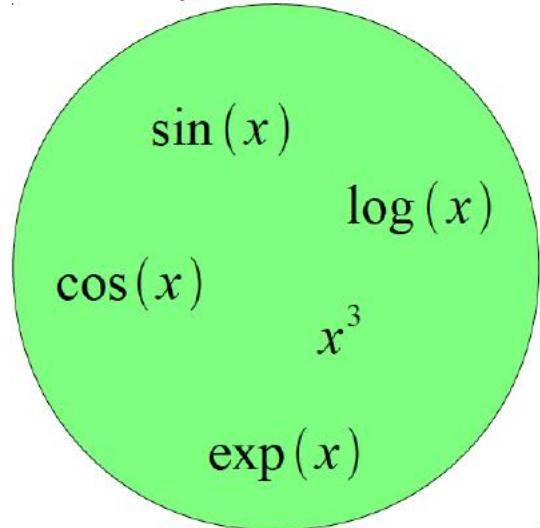
Given a library of simple functions



Compose into a  
complicate function

# Building A Complicated Function

Given a library of simple functions

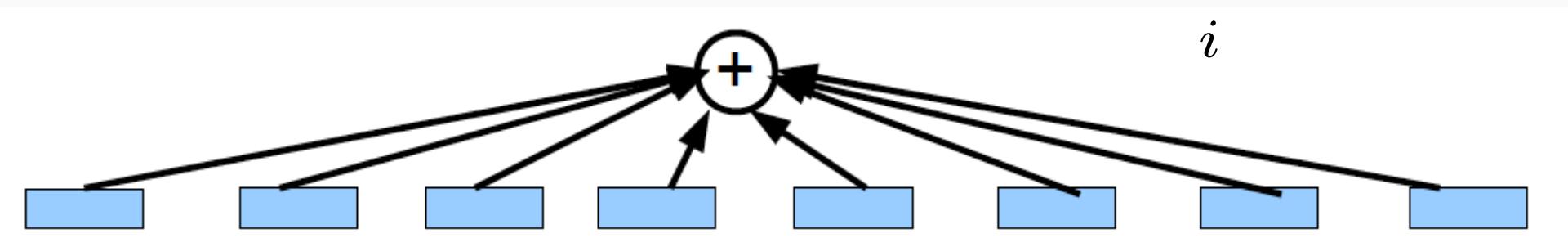


Compose into a  
complicate function

## Idea 1: Linear Combinations

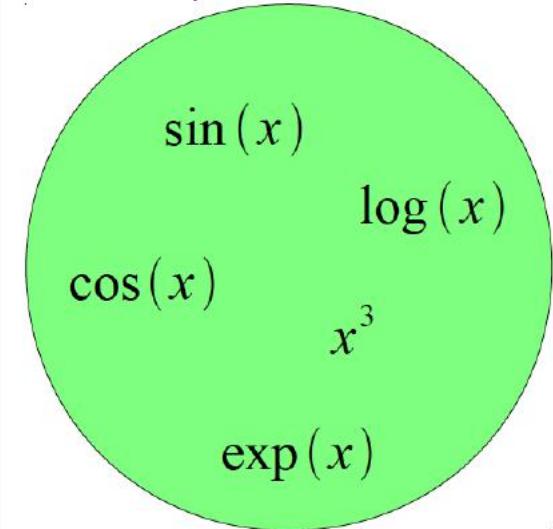
- Boosting
- Kernels
- ...

$$f(x) = \sum_i \alpha_i g_i(x)$$



# Building A Complicated Function

Given a library of simple functions

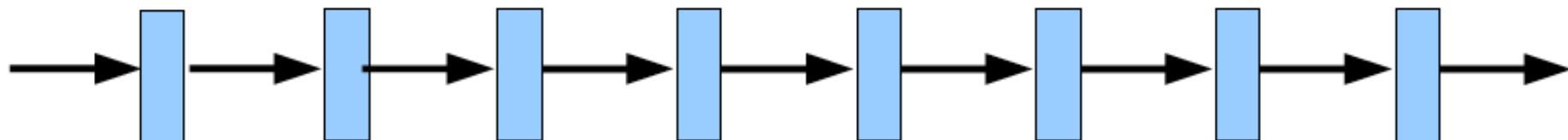


Compose into a  
complicate function

## Idea 2: Compositions

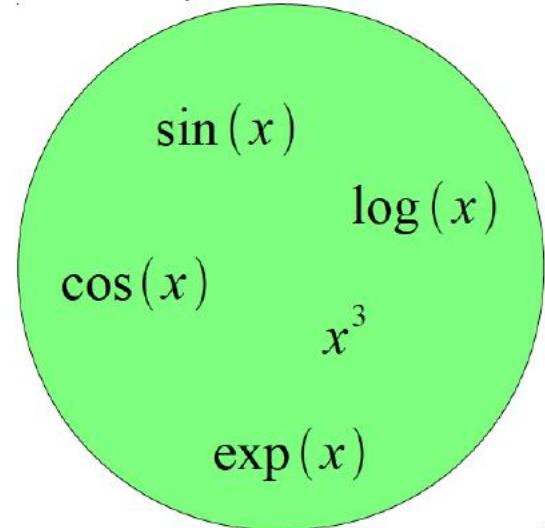
- Deep Learning
- Grammar models
- Scattering transforms...

$$f(x) = g_1(g_2(\dots(g_n(x)\dots)))$$



# Building A Complicated Function

Given a library of simple functions

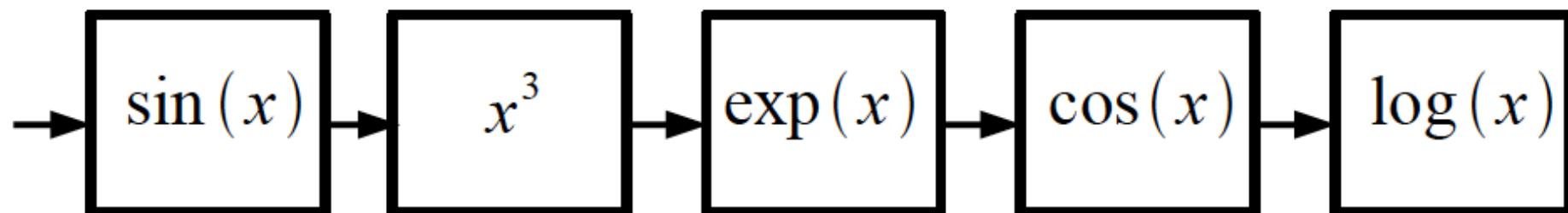


Compose into a  
complicate function

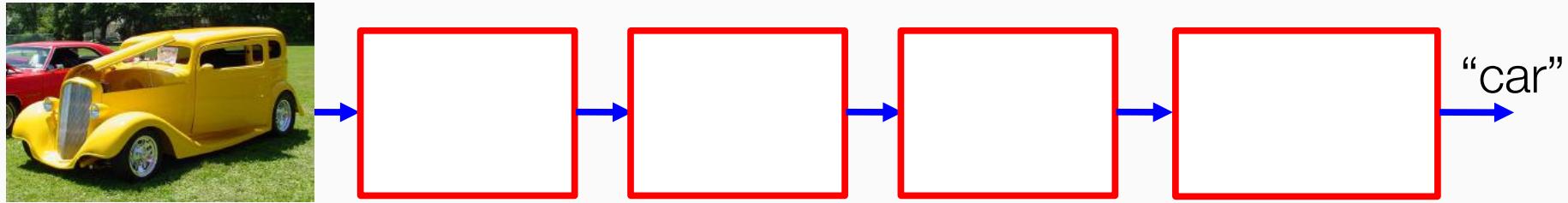
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- Deep Learning
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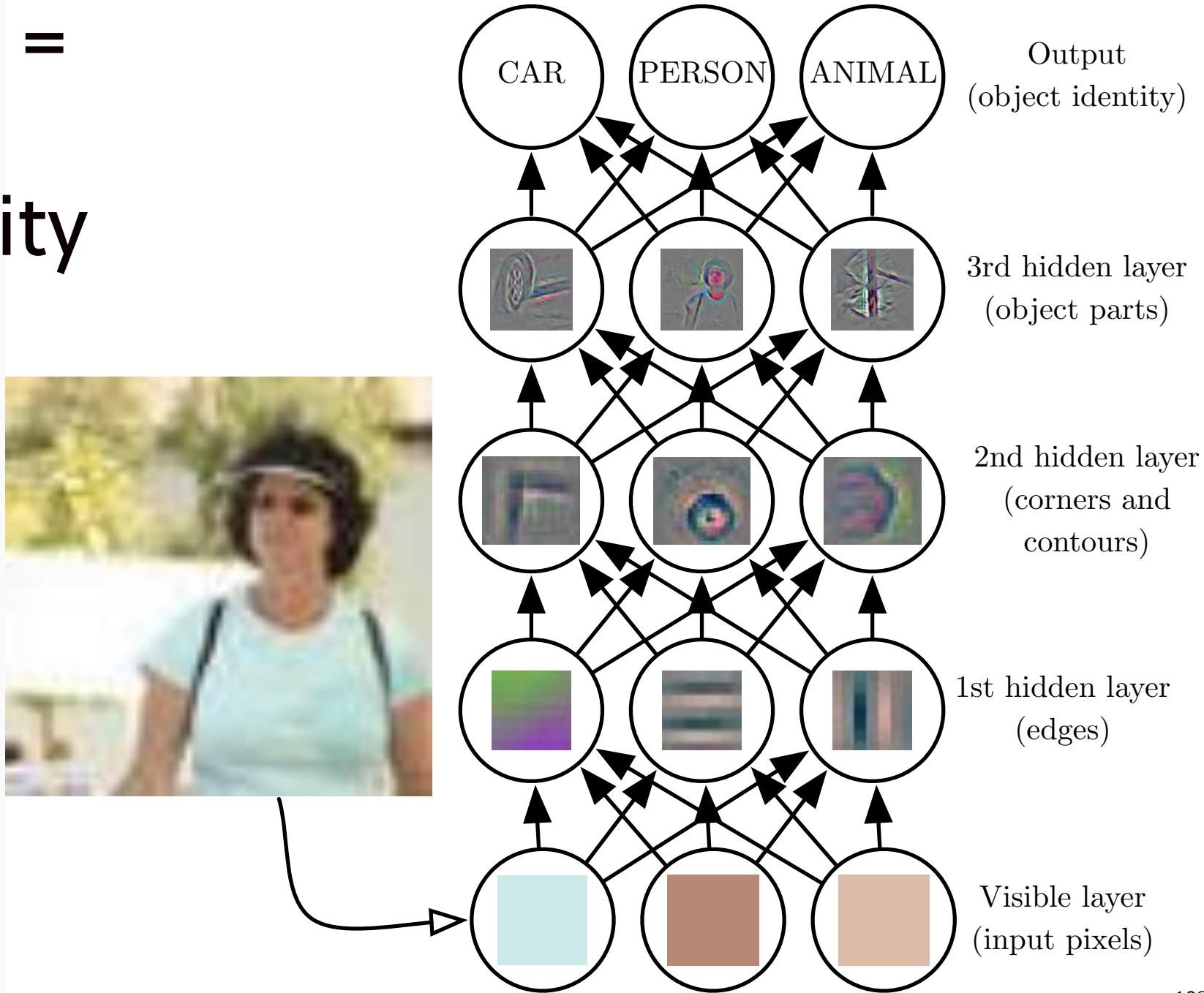
$$f(x) = \log(\cos(\exp(\sin^3(x))))$$



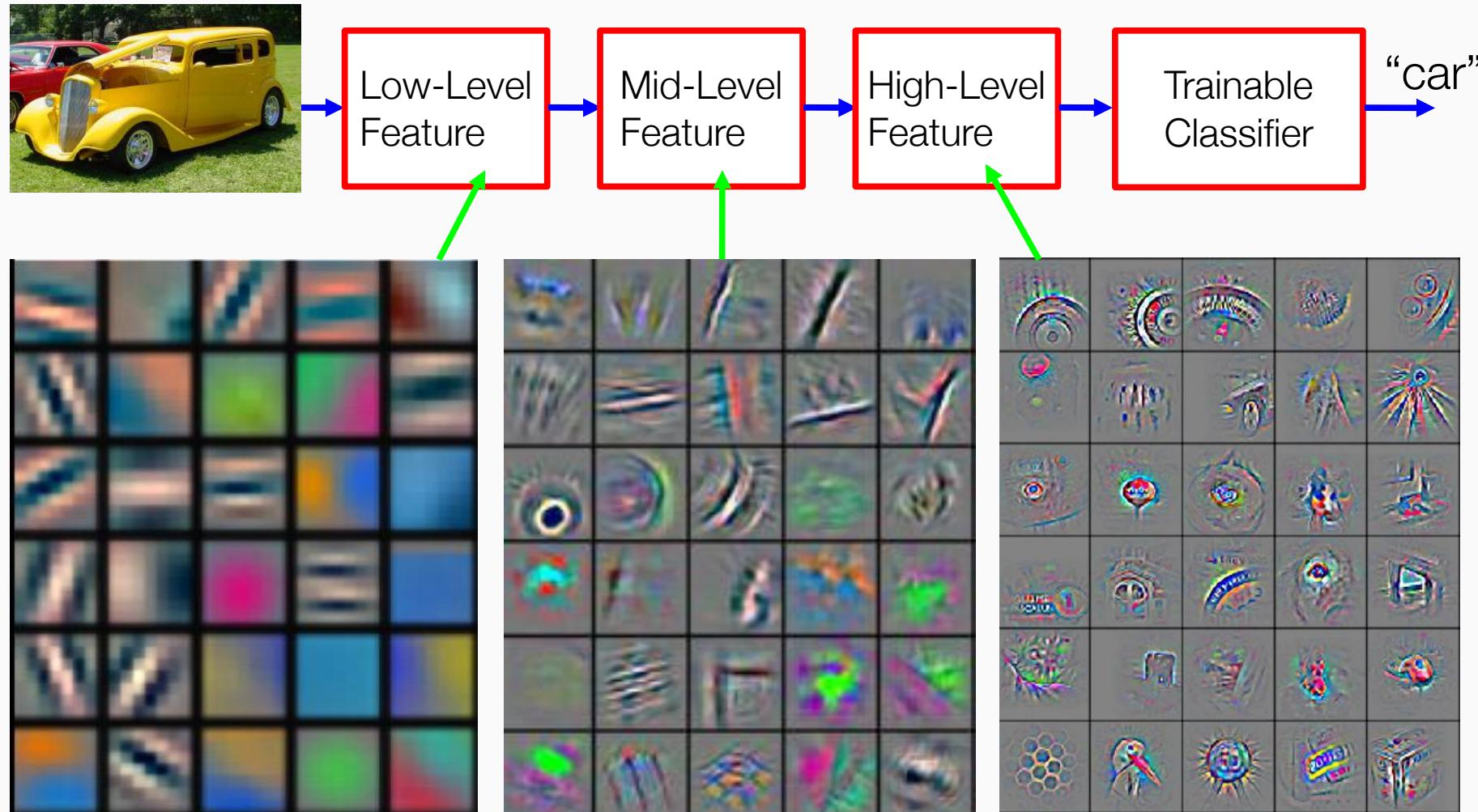
# Deep Learning = Hierarchical Compositionality



# Deep Learning = Hierarchical Compositionality

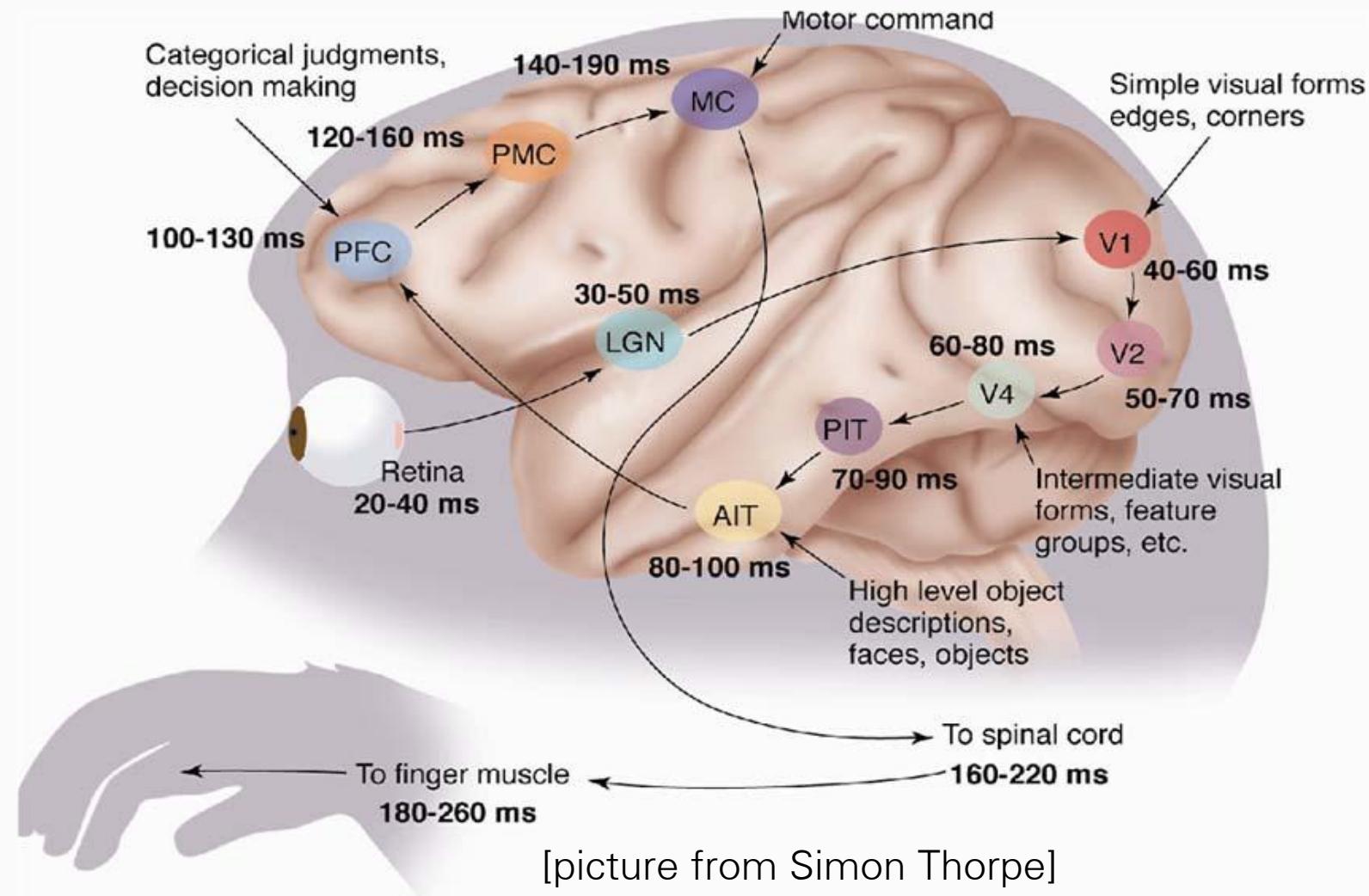


# Deep Learning = Hierarchical Compositionality



# The Mammalian Visual Cortex is Hierarchical

- The ventral (recognition) pathway in the visual cortex

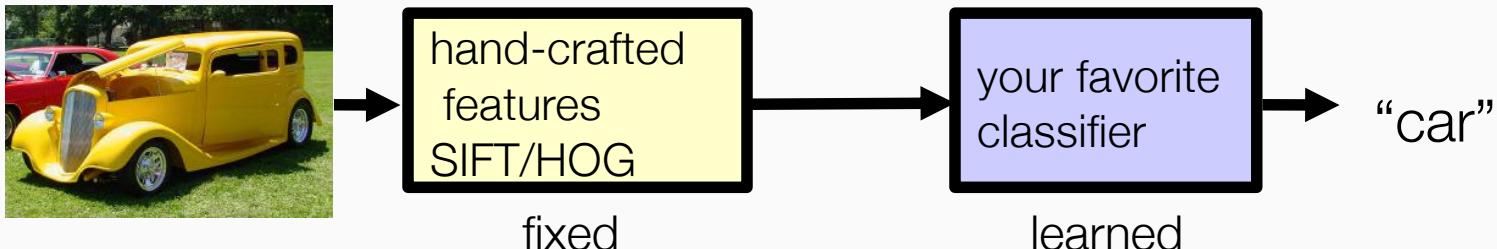


# Three key ideas

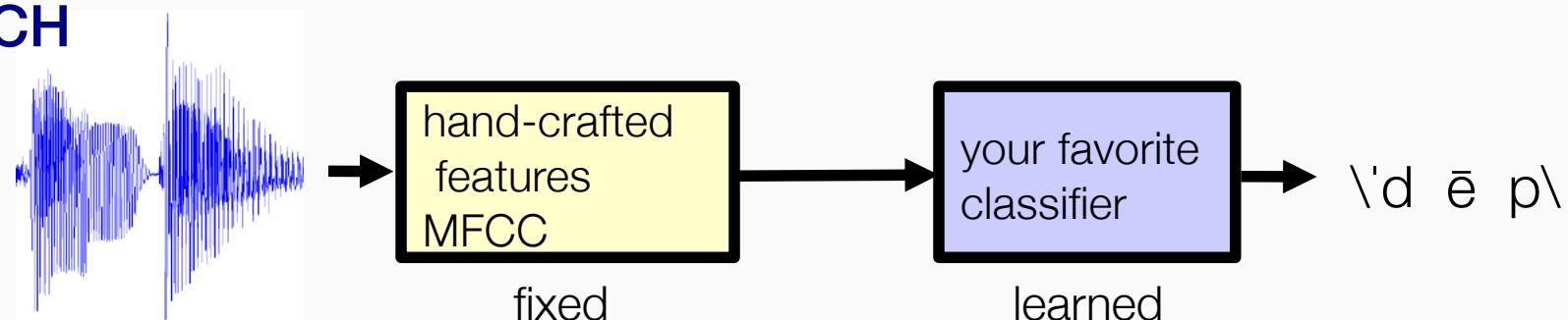
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# Traditional Machine Learning

## VISION



## SPEECH

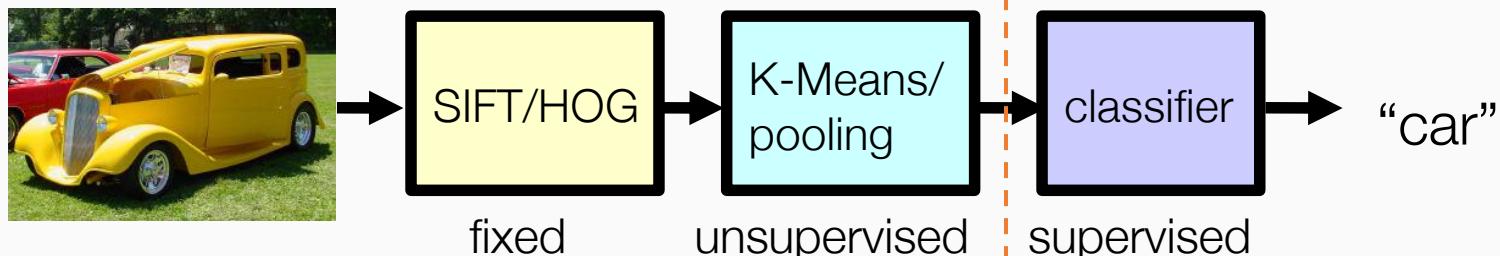


## NLP

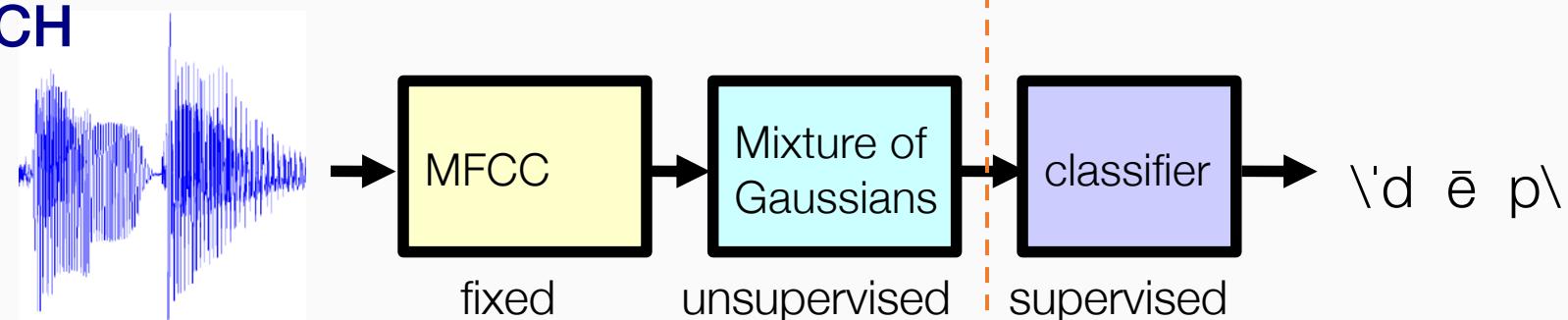


# More accurate version

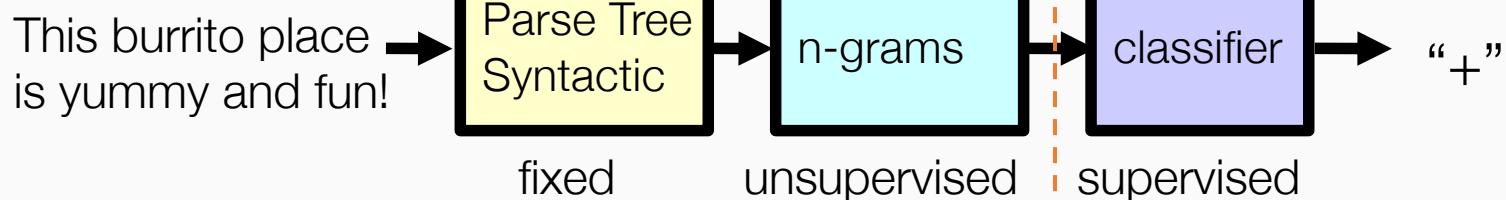
## VISION



## SPEECH

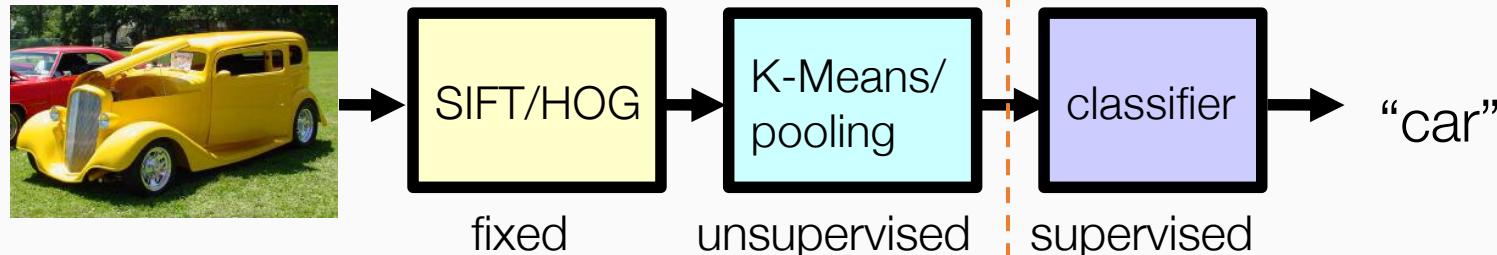


## NLP

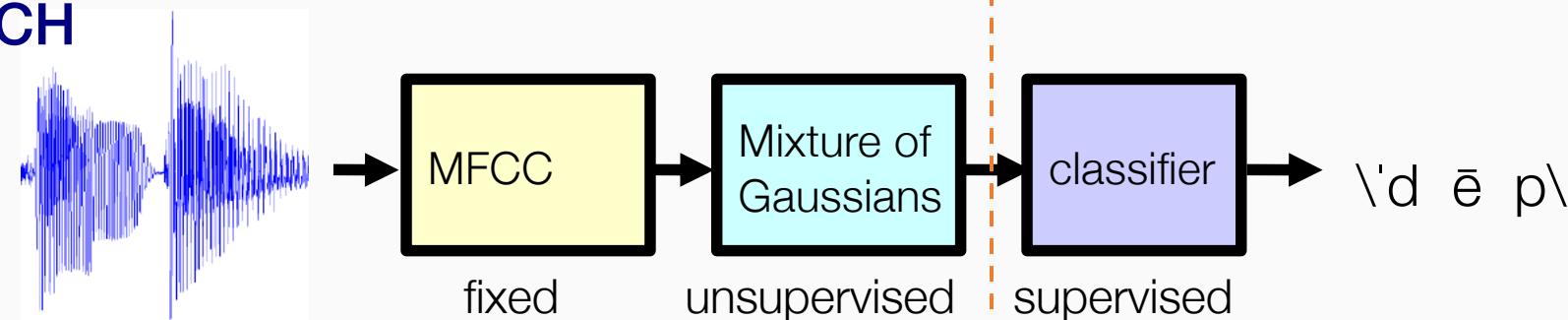


# Deep Learning = End-to-End Learning

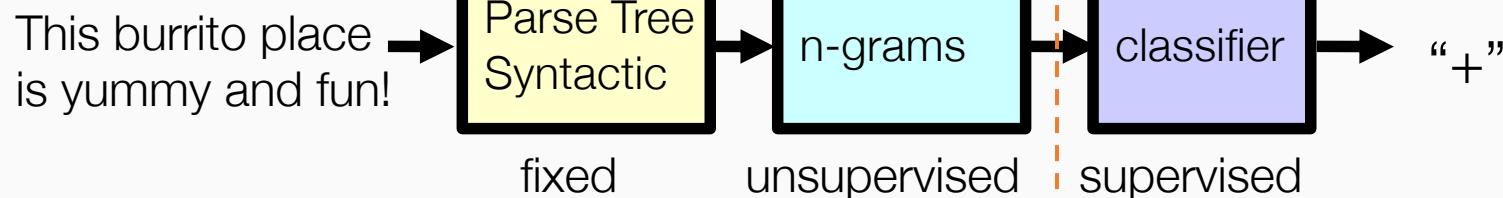
## VISION



## SPEECH

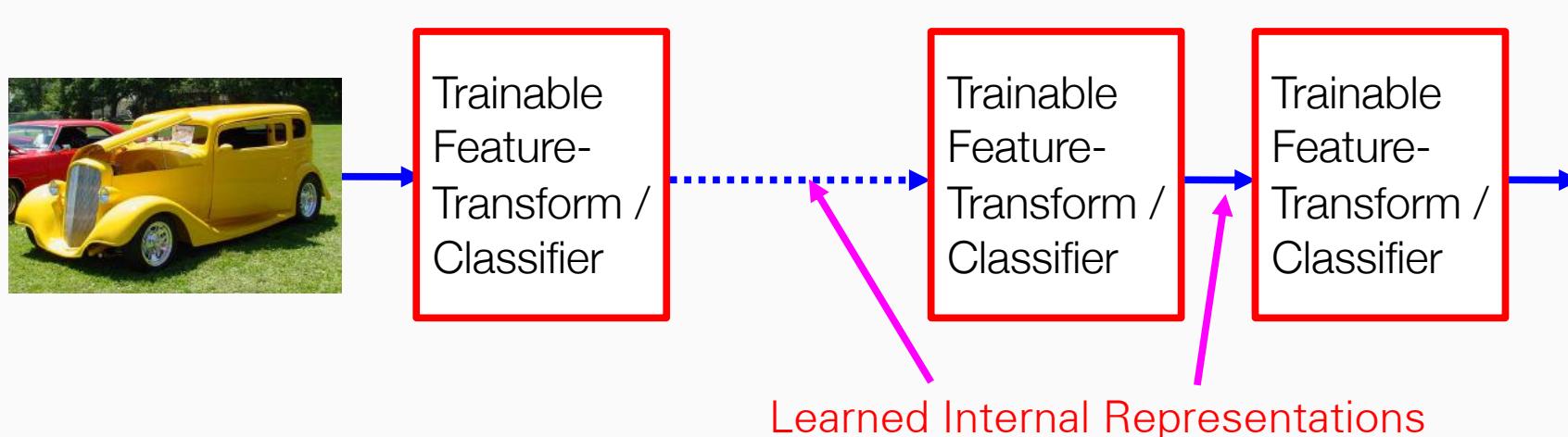


## NLP



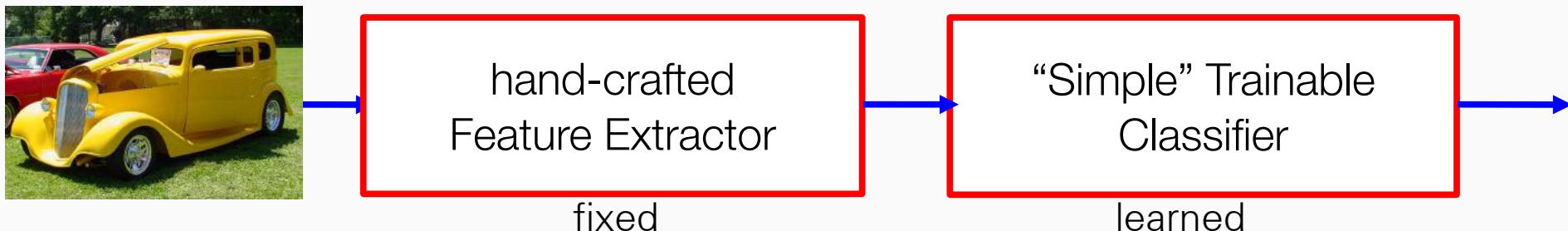
# Deep Learning = End-to-End Learning

- A hierarchy of trainable feature transforms
  - Each module transforms its input representation into a higher-level one.
  - High-level features are more global and more invariant
  - Low-level features are shared among categories

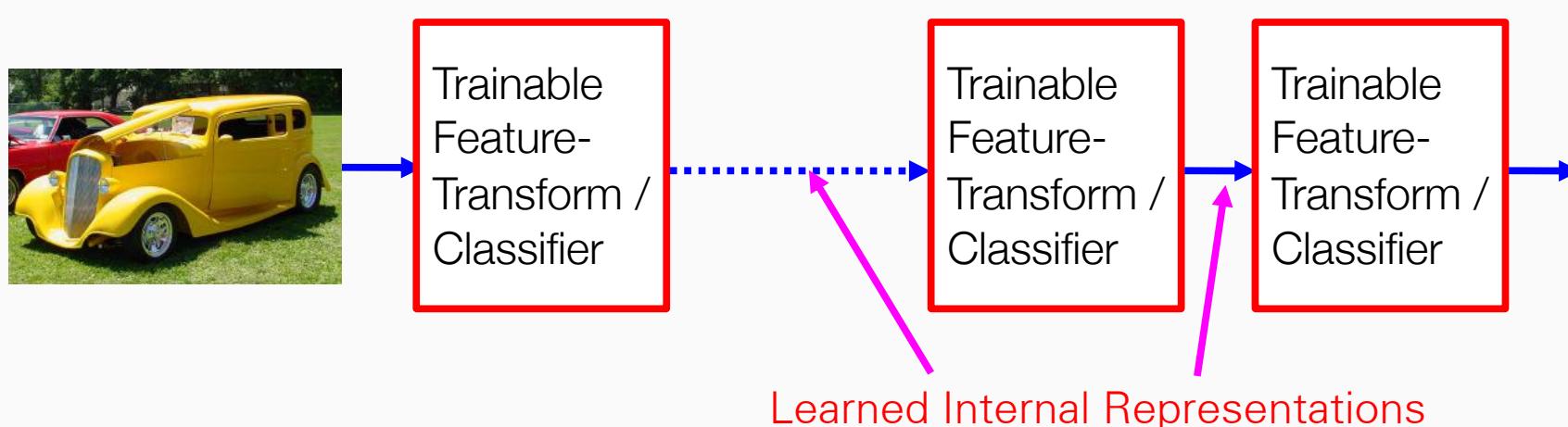


# “Shallow” vs Deep Learning

- “Shallow” models



- Deep models

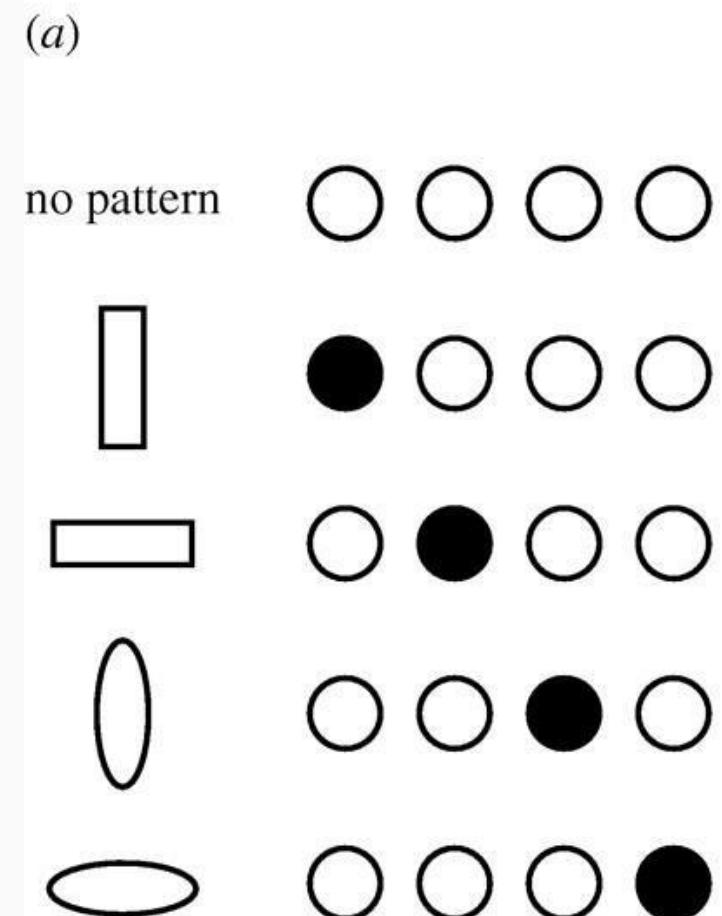


# Three key ideas

- (Hierarchical) Compositionality
  - Cascade of non-linear transformations
  - Multiple layers of representations
- End-to-End Learning
  - Learning (goal-driven) representations
  - Learning to feature extract
- **Distributed Representations**
  - No single neuron “encodes” everything
  - Groups of neurons work together

# Localist representations

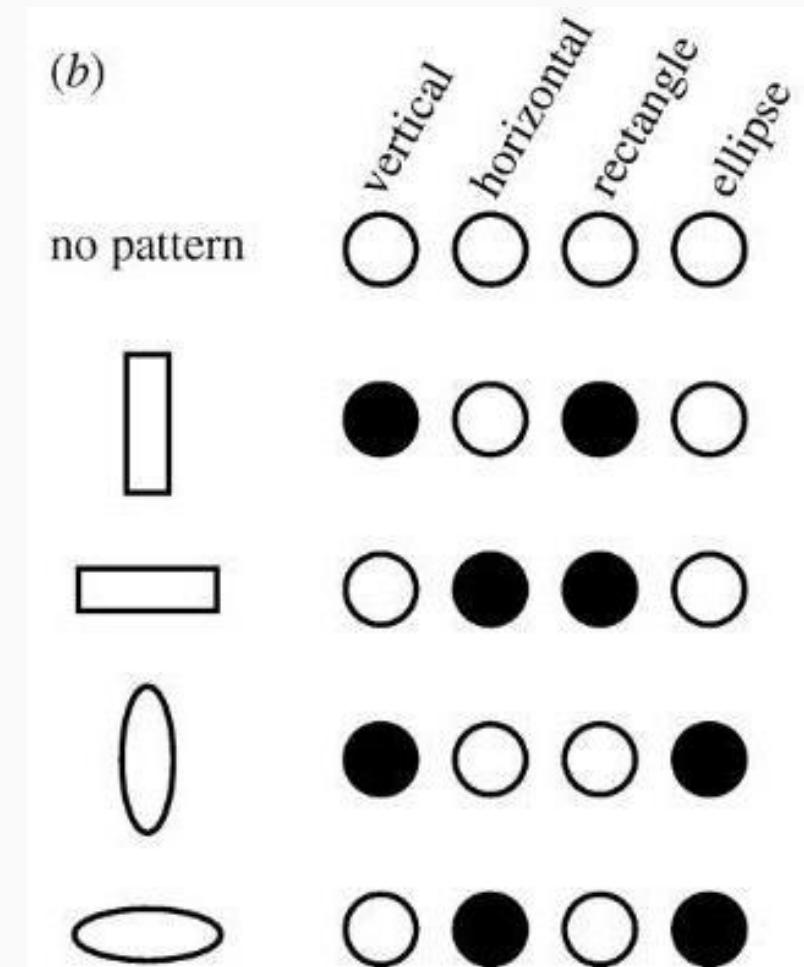
- The simplest way to represent things with neural networks is to **dedicate one neuron to each thing.**
  - Easy to understand.
  - Easy to code by hand
    - Often used to represent inputs to a net
  - Easy to learn
    - This is what mixture models do.
    - Each cluster corresponds to one neuron
  - Easy to associate with other representations or responses.
- But localist models are very inefficient whenever the data has componential structure.



# Distributed Representations

- Each neuron must represent something, so this must be a local representation.
- **Distributed representation** means a many-to-many relationship between two types of representation (such as concepts and neurons).
  - Each concept is represented by many neurons
  - Each neuron participates in the representation of many concepts

Local	● ● ○ ● = VR + HR + HE = ?
Distributed	● ● ○ ● = V + H + E ≈ ○



# Power of distributed representations!

## Scene Classification

bedroom



mountain



- Possible internal representations:

- Objects
- Scene attributes
- Object parts
- Textures



Simple elements & colors

Object part

Object

Scene

# Three key ideas of deep learning

- **(Hierarchical) Compositionality**

- Cascade of non-linear transformations
  - Multiple layers of representations

- **End-to-End Learning**

- Learning (goal-driven) representations
  - Learning to feature extract

- **Distributed Representations**

- No single neuron “encodes” everything
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# Benefits of Deep/Representation Learning

- (Usually) Better Performance
  - “Because gradient descent is better than you”  
Yann LeCun
- New domains without “experts”
  - RGBD
  - Multi-spectral data
  - Gene-expression data
  - Unclear how to hand-engineer

# Problems with Deep Learning

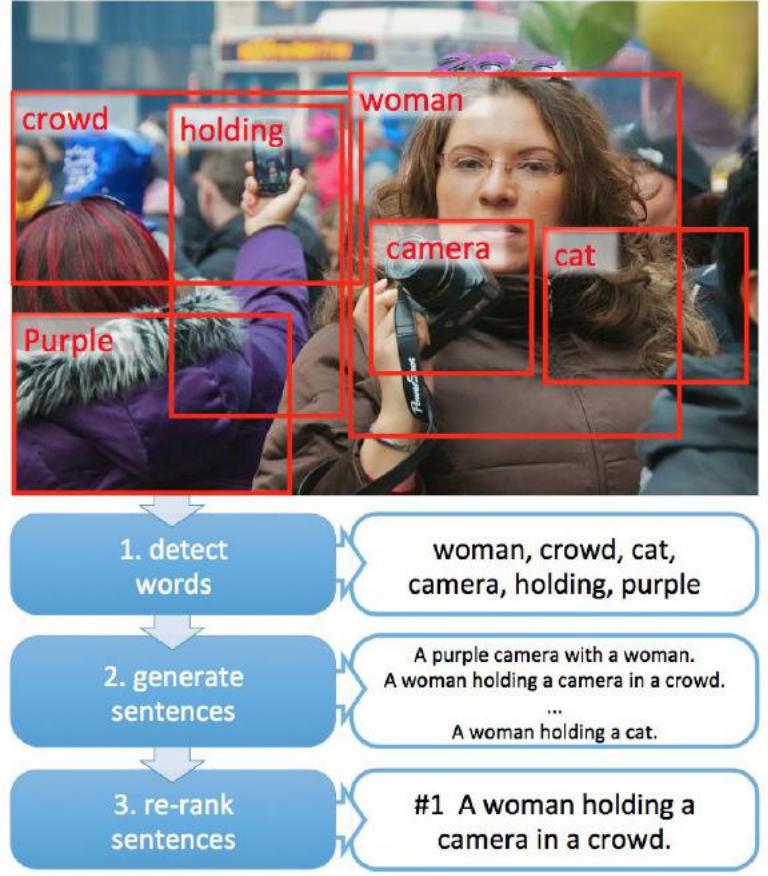
- **Problem#1: Non-Convex! Non-Convex! Non-Convex!**
  - Depth $>=3$ : most losses non-convex in parameters
  - Theoretically, all bets are off
  - Leads to stochasticity
    - different initializations → different local minima
- Standard response #1
  - “Yes, but all interesting learning problems are non-convex”
  - For example, human learning
    - Order matters → wave hands → non-convexity
- Standard response #2
  - “Yes, but it often works!”

# Problems with Deep Learning

- **Problem#2: Hard to track down what's failing**
  - Pipeline systems have “oracle” performances at each step
  - In end-to-end systems, it’s hard to know why things are not working

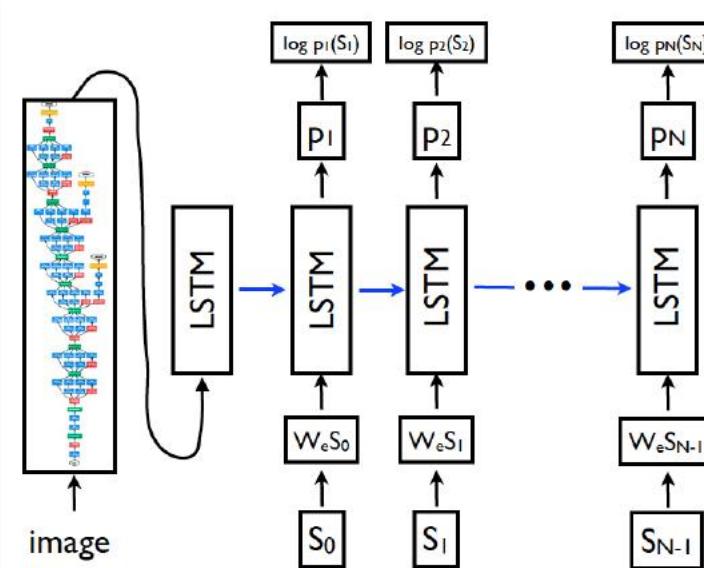
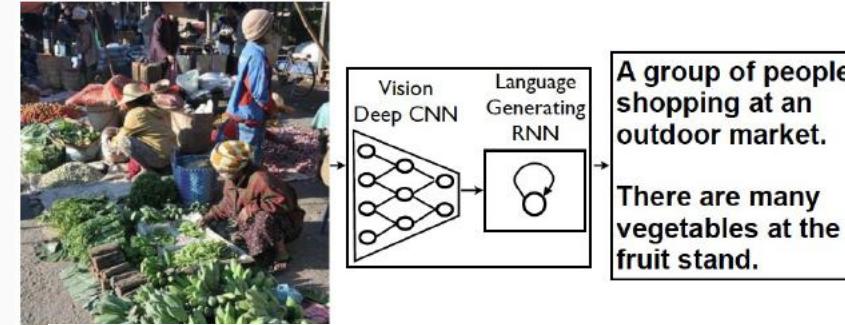
# Problems with Deep Learning

- Problem#2: Hard to track down what's failing



[Fang et al. CVPR15]

Pipeline



[Vinyals et al. CVPR15]

End-to-End

# Problems with Deep Learning

- **Problem#2: Hard to track down what's failing**
  - Pipeline systems have “oracle” performances at each step
  - In end-to-end systems, it’s hard to know why things are not working
- Standard response #1
  - Tricks of the trade: visualize features, add losses at different layers, pre-train to avoid degenerate initializations...
  - “We’re working on it”
- Standard response #2
  - “Yes, but it often works!”

# Problems with Deep Learning

- **Problem#3: Lack of easy reproducibility**
  - Direct consequence of stochasticity & non-convexity
- Standard response #1
  - It's getting much better
  - Standard toolkits/libraries/frameworks now available
- Standard response #2
  - “Yes, but it often works!”

# 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 \$2,000,000 "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 be-

ings, 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 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.

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.

WORLD

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N.Y. / REGION

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ENVIRONMENT SPACE &amp; COSMOS

# COMPUTER SCIENTISTS STYMIED IN THEIR QUEST TO MATCH HUMAN VISION

By WILLIAM J. BROAD

Published: September 25, 1984

EXPERTS pursuing one of man's most audacious dreams - to create machines that think - have stumbled while taking what seemed to be an elementary first step. They have failed to master vision.

After two decades of research, they have yet to teach machines the seemingly simple act of being able to recognize everyday objects and to distinguish one from another.

Instead, they have developed a profound new respect for the sophistication of human sight and have scoured such fields as mathematics, physics, biology and psychology for clues to help them achieve the goal of machine vision.

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**SCIENCE**

# *Researchers Announce Advance in Image-Recognition Software*

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By JOHN MARKOFF NOV. 17, 2014



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More

MOUNTAIN VIEW, Calif. — Two groups of scientists, working independently, have created artificial intelligence software capable of recognizing and describing the content of photographs and videos with far greater accuracy than ever before, sometimes even mimicking human levels of understanding.

Until now, so-called computer vision has largely been limited to recognizing individual objects. The new software, described on Monday by researchers at Google and at [Stanford University](#), teaches itself to identify entire scenes: a group of young men playing Frisbee, for example, or a herd of elephants marching on a grassy plain.

The software then writes a caption in English describing the picture. Compared with human observations, the researchers found, the computer-written descriptions are surprisingly accurate.

## Captioned by Human and by Google's Experimental Program



Human: "A group of men playing Frisbee in the park."

Computer model: "A group of young people playing a game of Frisbee."

TWEETS

587

FOLLOWING

18

FOLLOWERS

746

FAVORITES

13



**INTERESTING.JPG** @INTERESTING\_JPG · 10h

a man holding a mirror up to his face .



1

...

[View more photos and videos](#)

TWEETS

587

FOLLOWING

18

FOLLOWERS

746

FAVORITES

13



**INTERESTING.JPG** @INTERESTING\_JPG · 18h

a man carrying a bucket of his hands in a yard .



[View more photos and videos](#)

TWEETS

587

FOLLOWING

18

FOLLOWERS

746

FAVORITES

13



INTERESTING.JPG @INTERESTING\_JPG · Feb 20

a surfboard attached to the top of a car .



8



8

...

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TWEETS

587

FOLLOWING

18

FOLLOWERS

746

FAVORITES

13



**INTERESTING.JPG** @INTERESTING\_JPG · Feb 19

a man dressed in uniform is looking at his cell phone .



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TWEETS

587

FOLLOWING

18

FOLLOWERS

746

FAVORITES

13



**INTERESTING.JPG** @INTERESTING\_JPG · 16h

this appears to be a small bedroom in the snow .



6

...

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Iain Murray  
@driainmurray

Follow

Today I learned #googletranslate sometimes decides that "Deutsch" means "English". Machine learning systems need to cope with weird inputs.

**Google Translate**

Turn off instant translation

Russian German English Detect language →

English German Spanish → Translate

Deutschland

Deutsch, deutsch, deutsch, deutsch, deutsch, deutsch

Natürlich hat ein Deutscher "Wetten, dass ... ?" erfunden  
Vielen Dank für die schönen Stunden!  
Wir sind die freundlichsten Kunden auf dieser Welt  
Wir sind bescheiden, wir haben Geld  
Die Allerbesten in jedem Sport  
Die Steuern hier sind Weltrekord  
Bereisen Sie Deutschland und bleiben Sie hier!  
Auf diese Art von Besuchern warten wir  
Es kann jeder hier wohnen, dem es gefällt  
Wir sind das freundlichste Volk auf dieser Welt

Deutsch, deutsch, deutsch, deutsch

Germany

German, English, German, German, German, and English

Of course a German has "betting that ...?" invented  
Thanks for the nice hours!  
We are the friendliest customers in this world  
We are modest, we have money  
The very best in any sport  
The taxes here are a world record  
Travel to Germany and stay here!  
We are waiting for this kind of visitors  
Anyone who likes it can live here  
We are the friendliest people in this world

English, German, German, and German

#OzgurGmail 2,516 Tweets

#TurkeySaysYes 1,520 Tweets

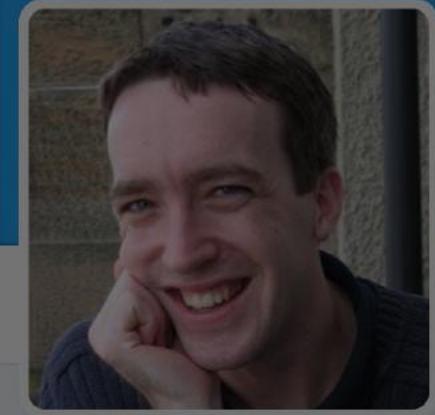
#BahisSarayindakazandim

Igor Tudor 5,727 Tweets

#valentines ❤️ @TEDTalks, @MIT and 5 more are Tweeting about this

#Yellen 2,287 Tweets

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## Iain Murray

@driainmurray

Academic in Machine Learning and Statistics.

[homepages.inf.ed.ac.uk/imurray2/](http://homepages.inf.ed.ac.uk/imurray2/)

Joined May 2011

Iain Murray  
@driainmurray

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More fun pushing [#googletranslate](#)'s neural net into weird states. (BTW try GT on real text if you haven't recently. It's often amazing.)

The image contains two side-by-side screenshots of the Google Translate interface, demonstrating neural network artifacts. The top screenshot shows the input "knife, fork, knife," which is translated into "Messer, Messer, Messer," with a red annotation below stating "(The trailing comma messes this one up.)". The bottom screenshot shows the input "Messer, Gabel, Messer, Messer, Messer, Messer, Messer, Messer, Messer" which is translated into "Screen monitor styling Projector styling Print styling ← back to. 2010-01-20 with adjustable interlinear. Knife, fork; knife, knife, knife, knife;". Both screenshots show the "English" to "German" language pair and include a "Translate" button.

RETWEETS

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138



**Tomer Ullman**  
@TomerUllman

...

Do models like DALL-E 2 get basic relations  
(in/on/etc)?

Colin (Coco) Conwell and I set out to investigate. The result is now on arXiv:

“Testing Relational Understanding in Text-Guided Image Generation”



arxiv.org

Testing Relational Understanding in Text-Guided Image Gen...  
Relations are basic building blocks of human cognition.  
Classic and recent work suggests that many relations are ...

2:55 PM · Aug 2, 2022 · Twitter Web App

**“A spoon in a cup”**



**“A cup on a spoon”**





Melanie Mitchell  
@MelMitchell1

...

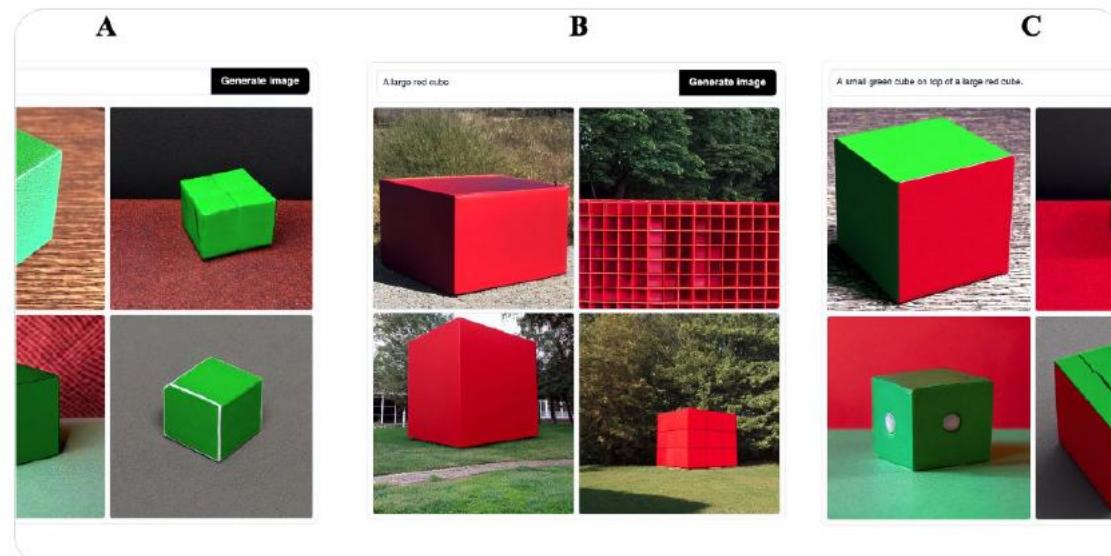
\*Prepositions are hard.\*

Stable diffusion demo ([huggingface.co/spaces/stabilityai/stable-diffusion](https://huggingface.co/spaces/stabilityai/stable-diffusion))

Prompt A: A small green cube

Prompt B: A large red cube

Prompt C: A small green cube on top of a large red cube



6:10 PM · Aug 23, 2022 · Twitter Web App

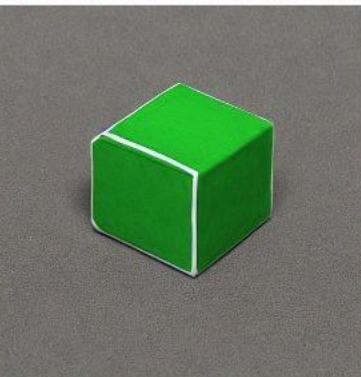
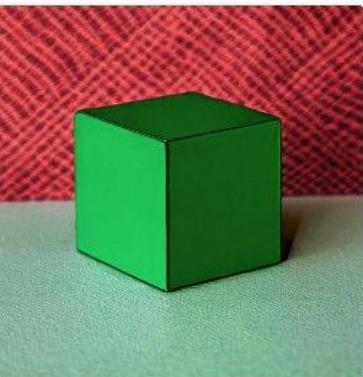
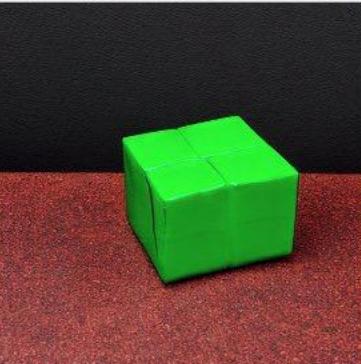
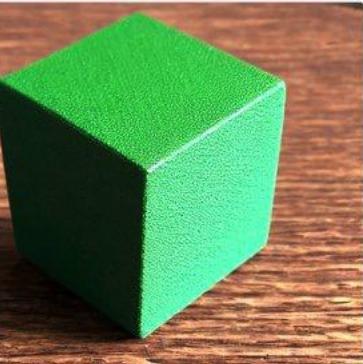


Melanie Mitchell  
@MelMitchell1

...

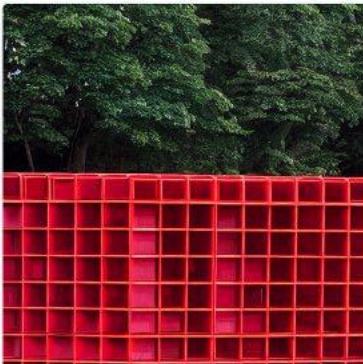
A

A small green cube



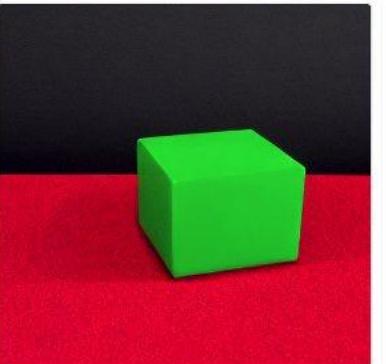
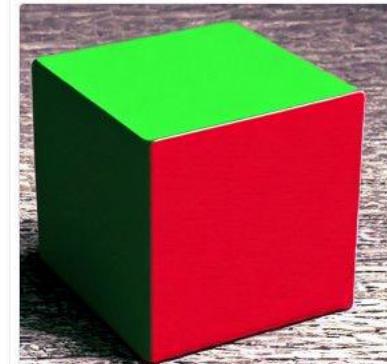
Generate image

A large red cube



Generate image

A small green cube on top of a large red cube.



Generate image

C



Melanie Mitchell

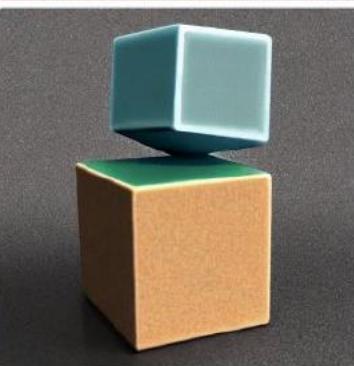
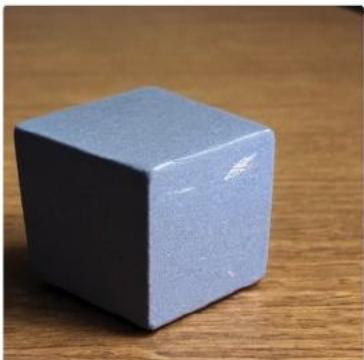
@MelMitchell1

...

A

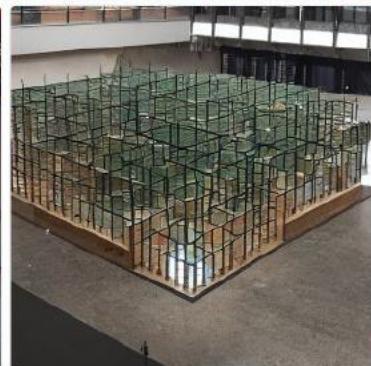
One cube on top of another cube

Generate image



A small cube to the left of a large cube

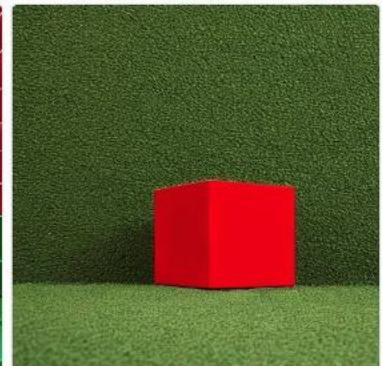
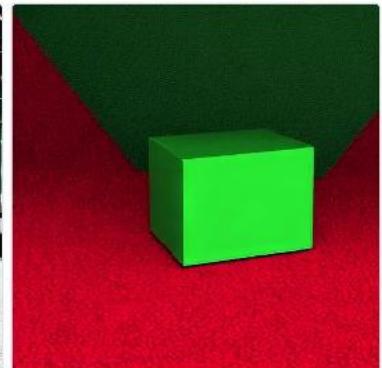
Generate Image



B

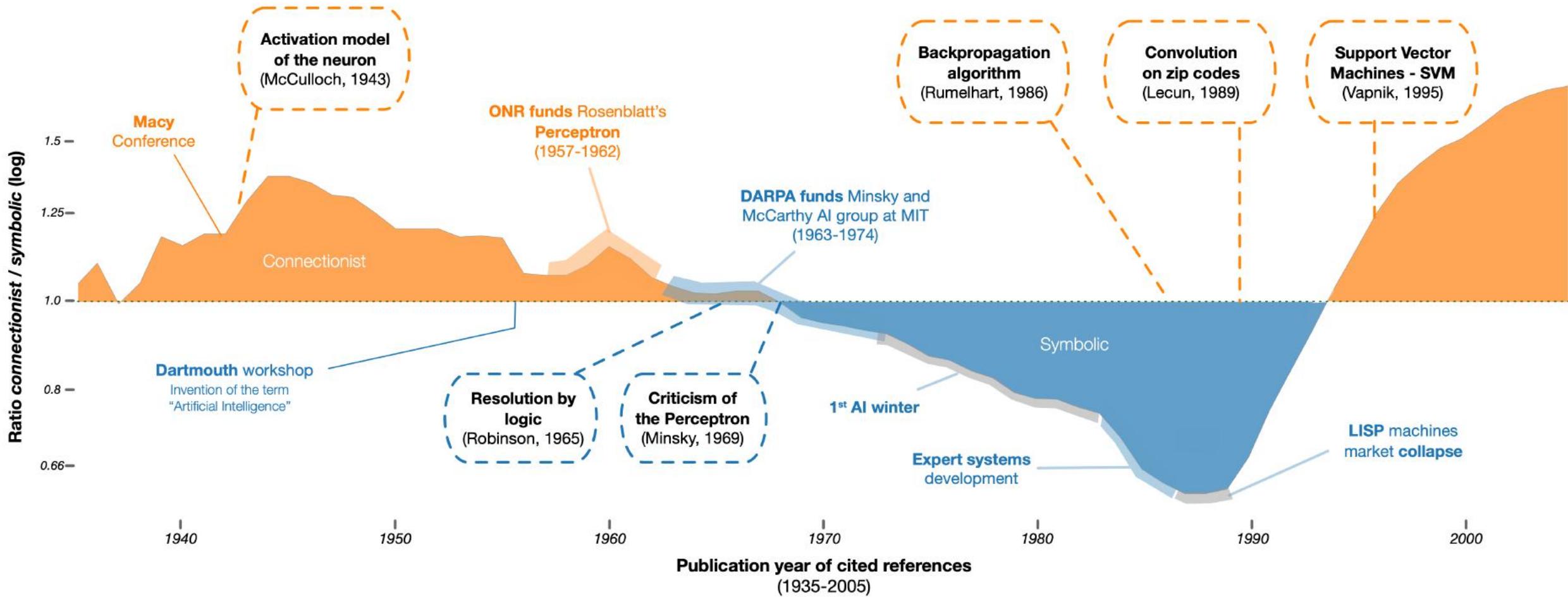
A red cube below a green cube

Generate image



C

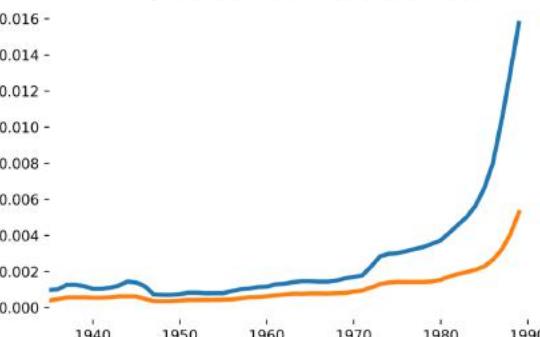
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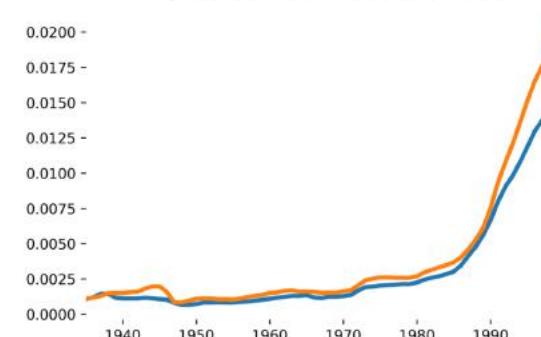
Cited between 1980 and 1989



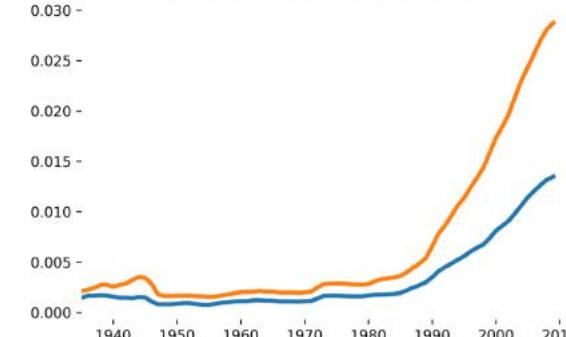
Cited between 1990 and 1999



Cited between 2000 and 2009



Cited between 2010 and 2018



# AI DEBATE : YOSHUA BENGIO | GARY MARCUS

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Gary Marcus

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—

Yoshua Bengio



# **Next Lecture:**

# **Machine Learning Overview**