Illustration: Koma Zhang // Quanta Magazine

COMP541

DEEP LEARNING

Lecture #01 – Introduction

Aykut Erdem // Koç University // Fall 2022

KOÇ UNIVERSITY

Welcome to COMP541

- This courses 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

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

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

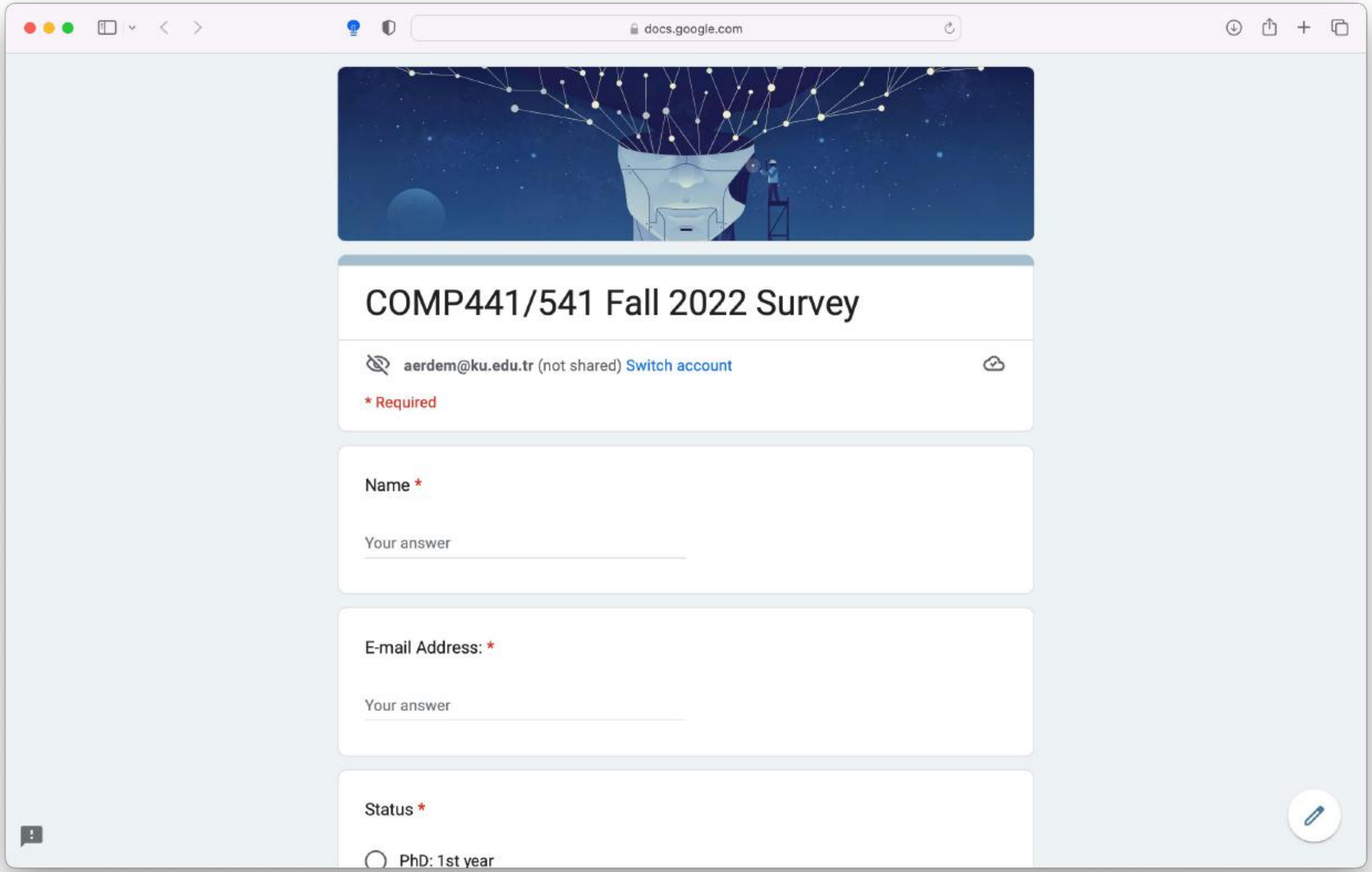
MIT
Fall 2007
Visiting Student

VirginiaTech
Visiting Research Scholar
Summer 2006

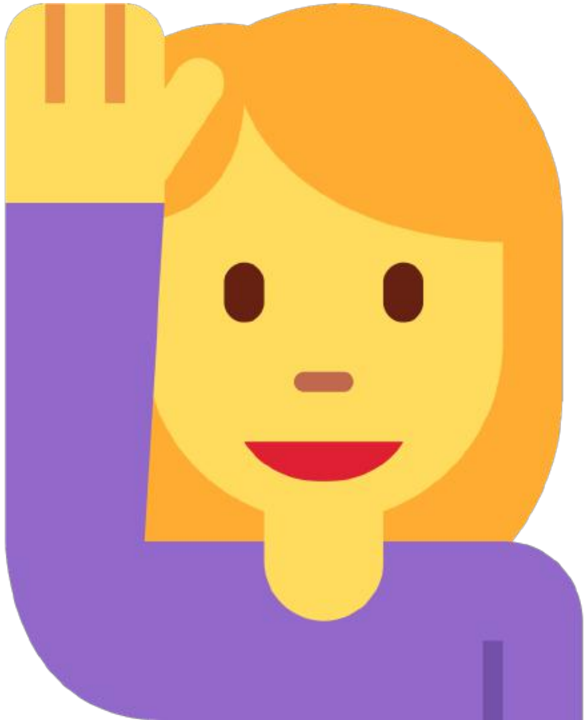
- I explore better ways to understand, interpret and manipulate visual data.
- My research interests span a diverse set of topics, ranging from image editing to visual saliency estimation, and to multimodal learning for integrated vision and language.

https://aykuterdem.github.io

Now, what about you?



https://forms.gle/2XpzYb6wMurbBh7P9



Course Logistics

Course Information

Lectures Monday and Wednesday 11:30-12:40 (Tower Second Floor)
PS Monday 17:30-18:40 Friday (SCI Z24)

Instructor Aykut Erdem
TAs Ilker Kesen and Emre Can Acikgoz

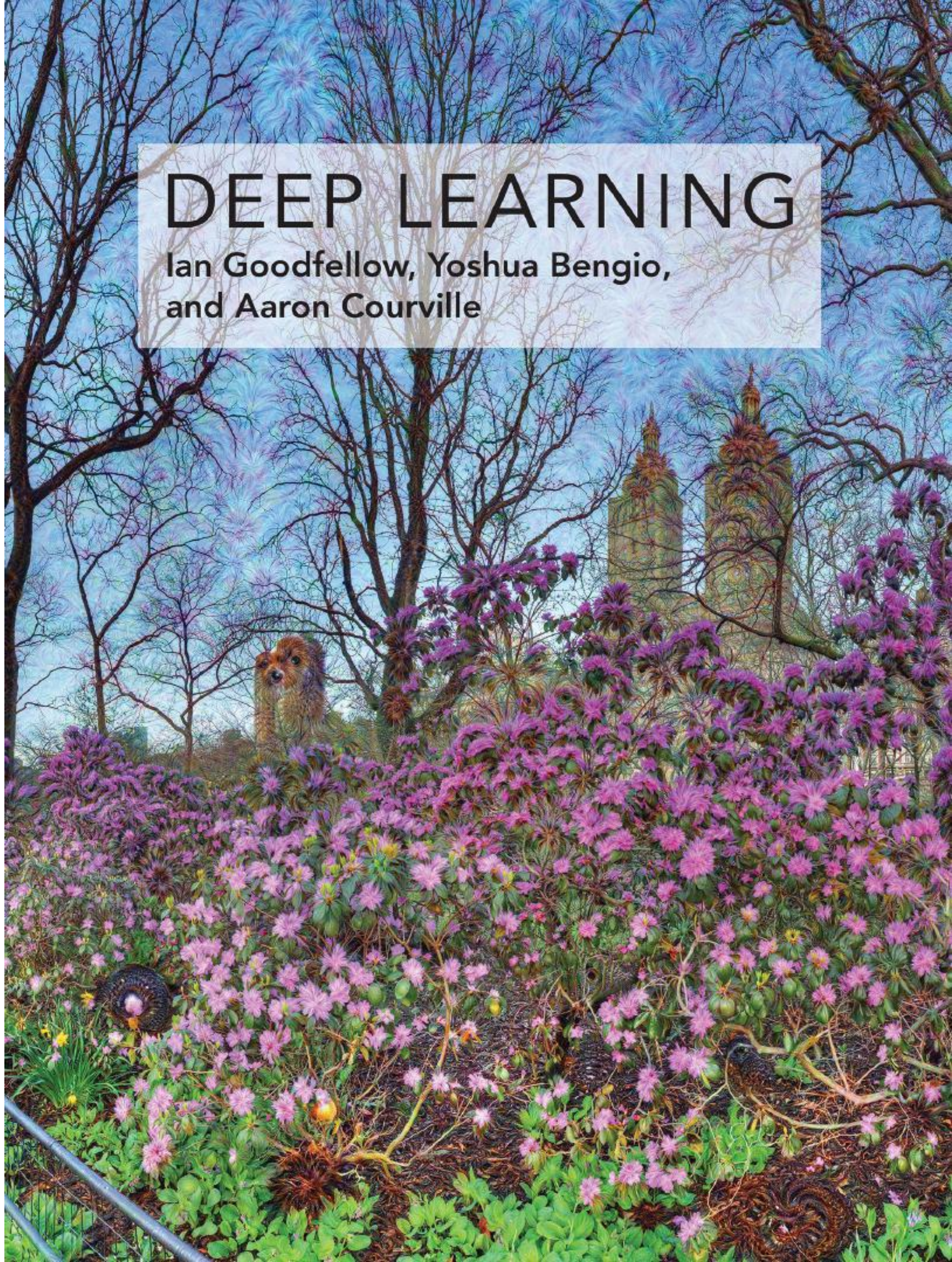
Website https://aykuterdem.github.io/classes/comp541.f22/

- Blackboard 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.)



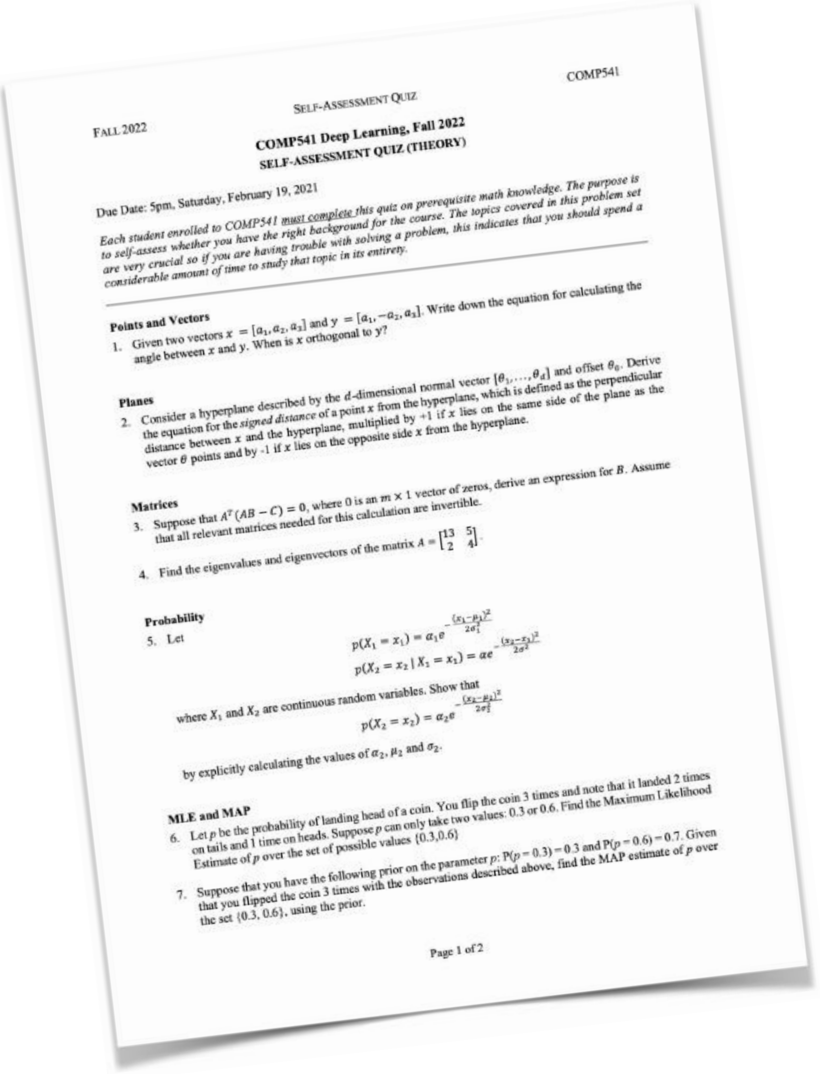
Instruction style

- 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



FALL 2022 SELF-ASSESSMENT QUIZ COMP541

COMP541 Deep Learning, Fall 2022
SELF-ASSESSMENT QUIZ (THEORY)

Due Date: 5pm, Saturday, February 19, 2021

Each student enrolled to COMP541 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 $[\theta_1, \ldots, \theta_d]$ and offset θ_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 θ points and by -1 if x lies on the opposite side x 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

$$p(X_1 = x_1) = \alpha_1 e^{-\frac{(x_1-\mu_1)^2}{2\sigma_1^2}}$$
$$p(X_2 = x_2 \mid X_1 = x_1) = \alpha e^{-\frac{(x_2-x_1)^2}{2\sigma^2}}$$

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 α_2, μ_2 and σ_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}

7. Suppose that you have the following prior on the parameter p: P(p = 0.3) = 0.3 and P(p = 0.6) = 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 3 (23:59).

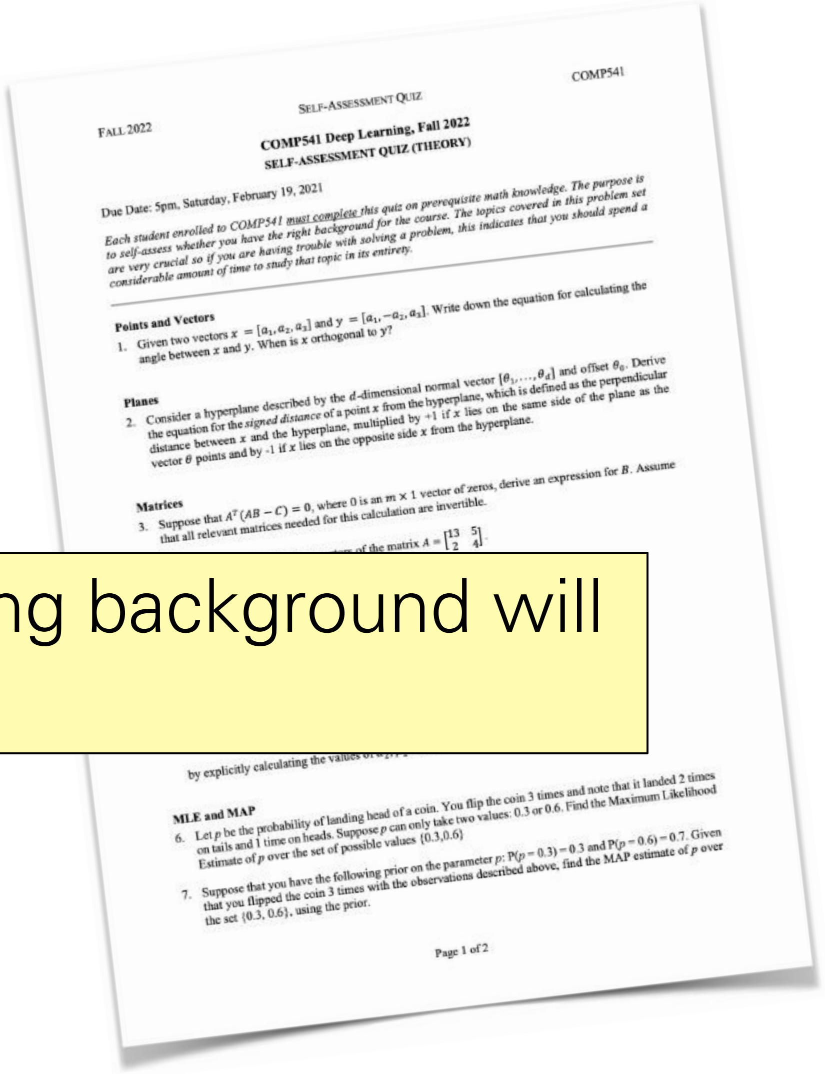
Each student enrolled to COMP541 must complete and pass this quiz!

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

Prerequisites

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

The self-assessment quiz on programming background will be released later this week!



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

by explicitly calculating the values ...

MLE and MAP

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Self-Assessment Quiz (Theory)
Due Date: October 3 (23:59).

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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%

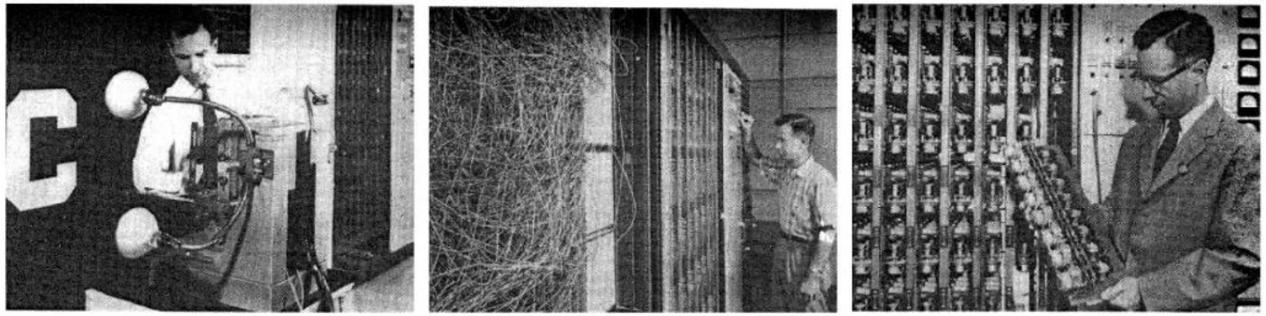
Schedule

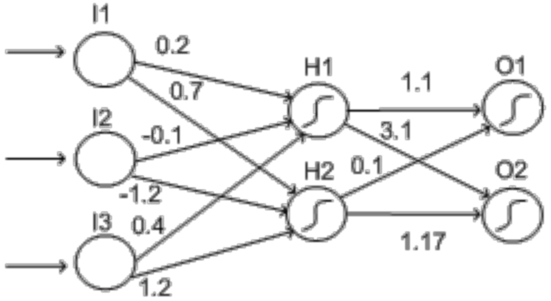
Week 1	Introduction to Deep Learning
Week 2	Machine Learning Overview
Week 3	Multi-Layer Perceptrons
Week 4	Training Deep Neural Networks
Week 5	Convolutional Neural Networks
Week 6	Understanding and Visualizing CNNs
Week 7	[Winter Break]
Week 8	Recurrent Neural Networks

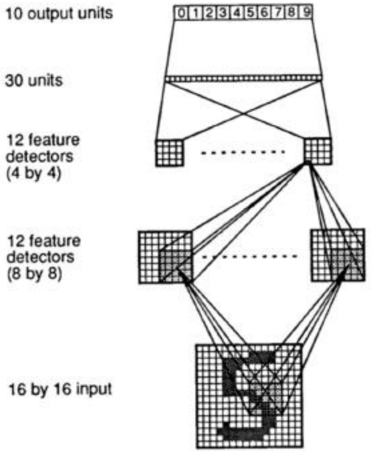
Schedule

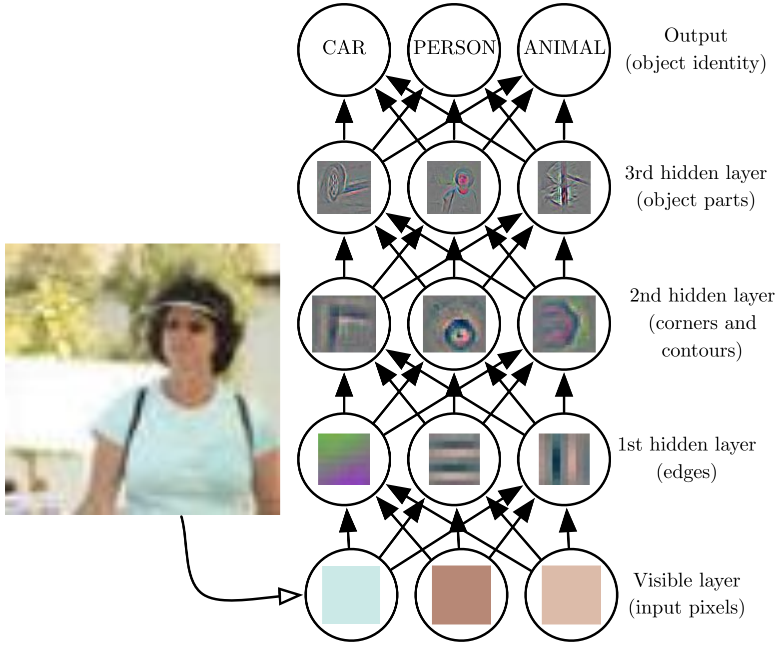
Week 9	Attention and Transformers
Week 10	Graph Neural Networks
Week 11	Autoencoders and Autoregressive Models
Week 12	Generative Adversarial Networks
Week 13	Variational Autoencoders
Week 14	Self-supervised Learning
Week 15	Deep Neural Networks as Priors

Lecture 1: Introduction to Deep Learning

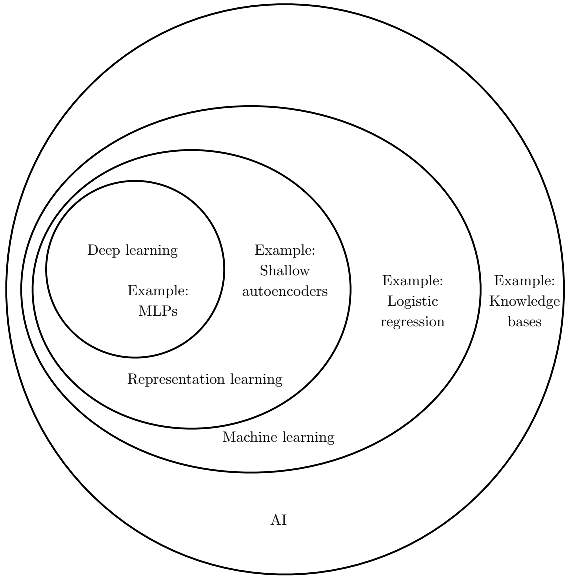


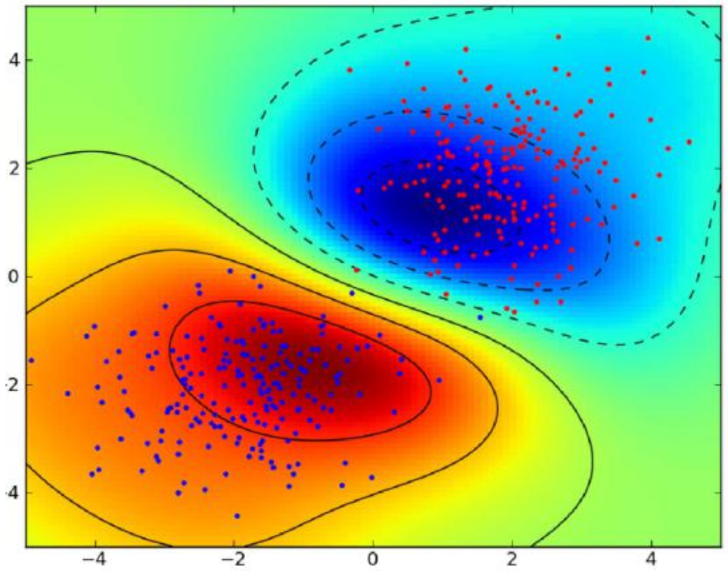


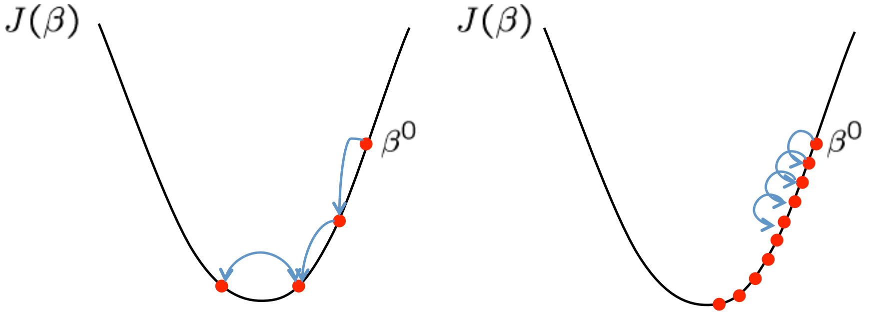


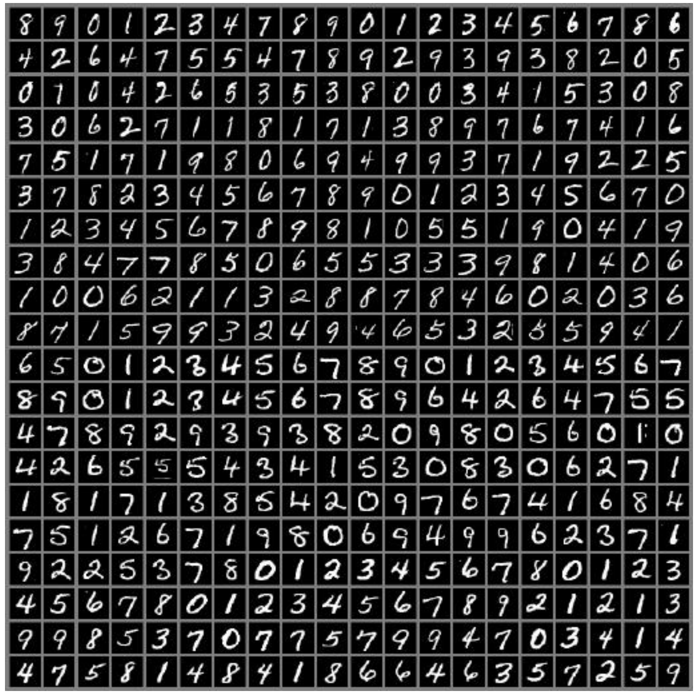


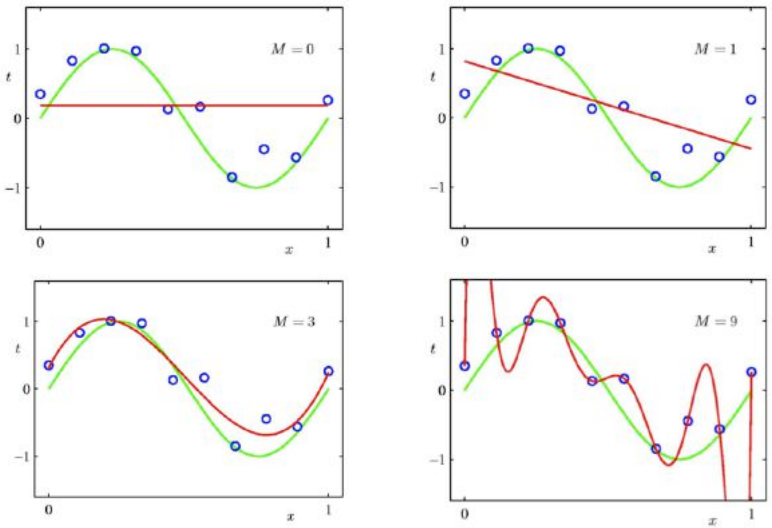
Lecture 2: Machine Learning Overview

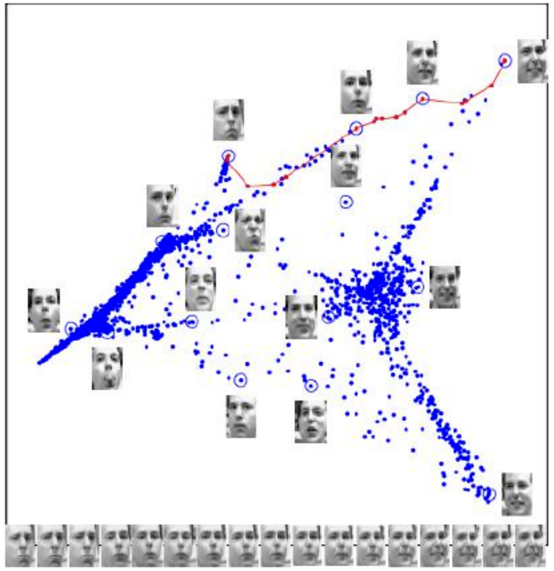




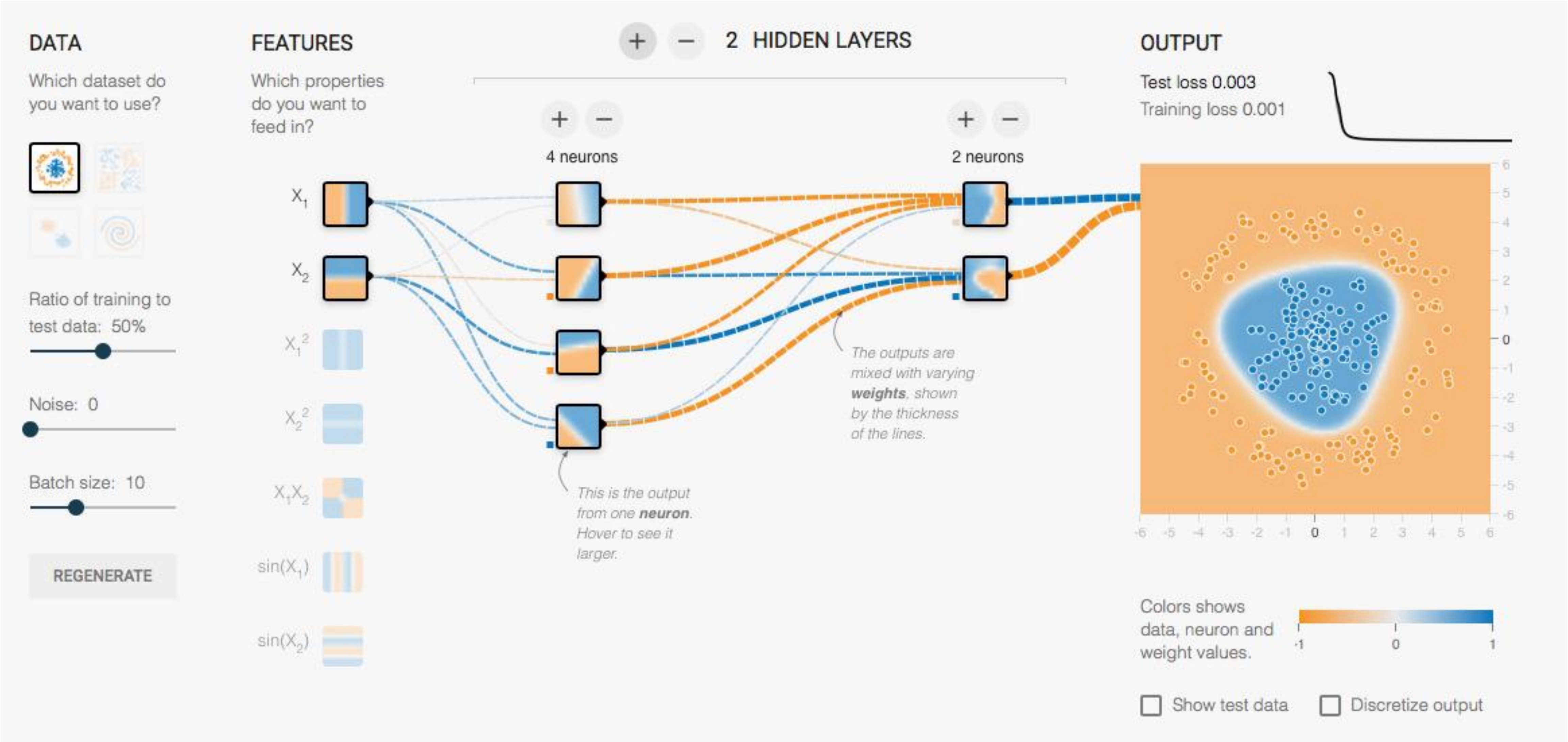






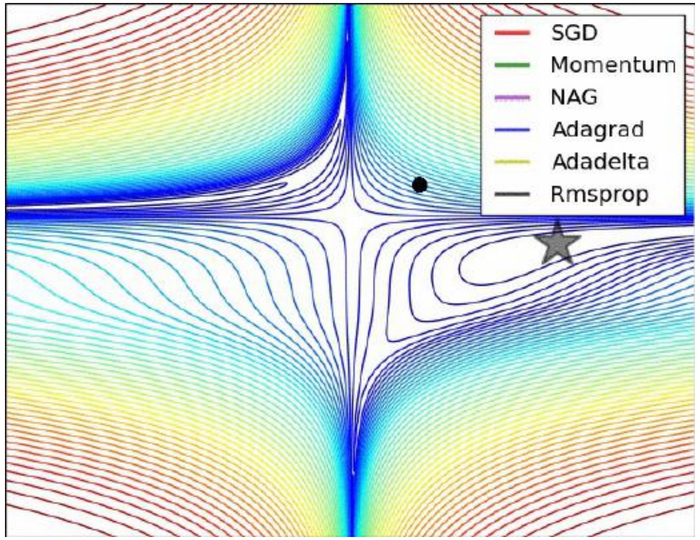


Lecture 3: Multi-Layer Perceptrons



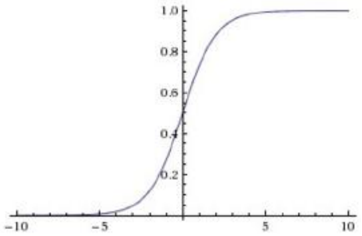
http://playground.tensorflow.org

Lecture 4: Training Deep Neural Networks



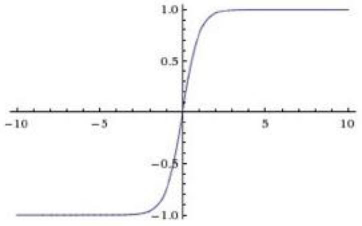
Optimizers

Sigmoid



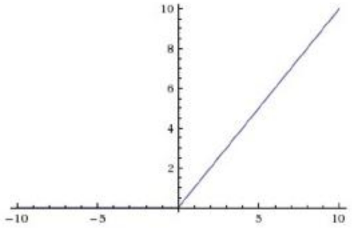
$\sigma(x) = 1/(1+e^{-x})$

tanh



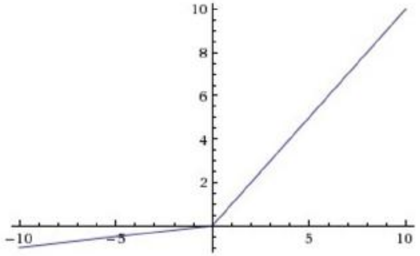
tanh(x)

ReLU



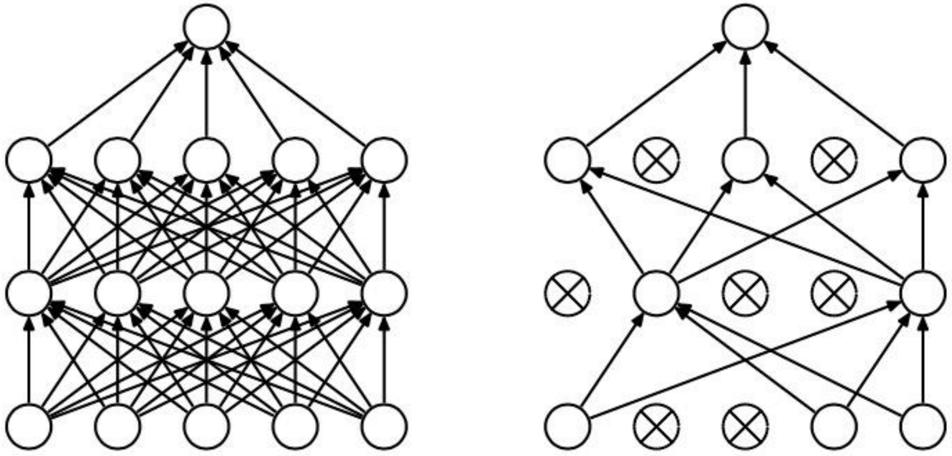
max(0,x)

Leaky ReLU



max(0.1x, x)

Activation Functions



(a) Standard Neural Net (b) After applying dropout.

Dropout

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

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

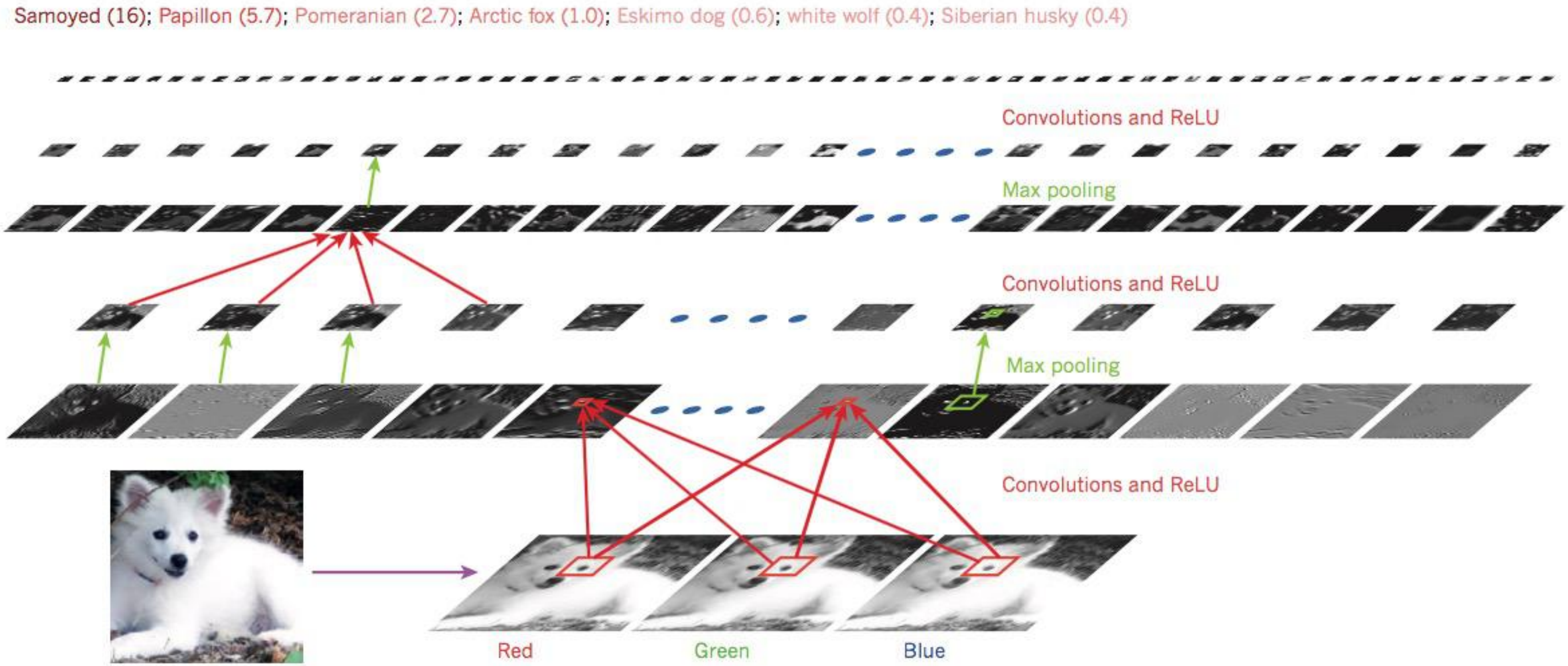
$$\sigma_\mathcal{B}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_\mathcal{B})^2 \qquad \text{// mini-batch variance}$$

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

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

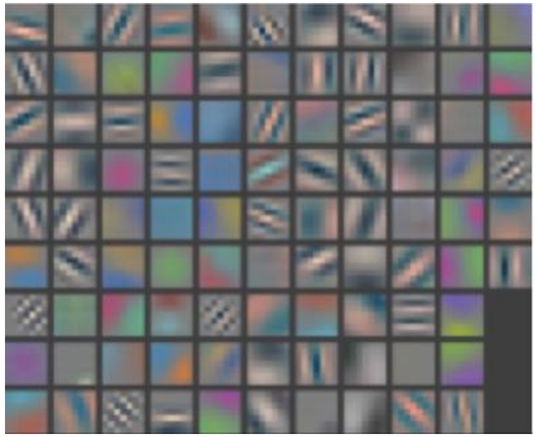
Batch Normalization

Lecture 5: Convolutional Neural Networks

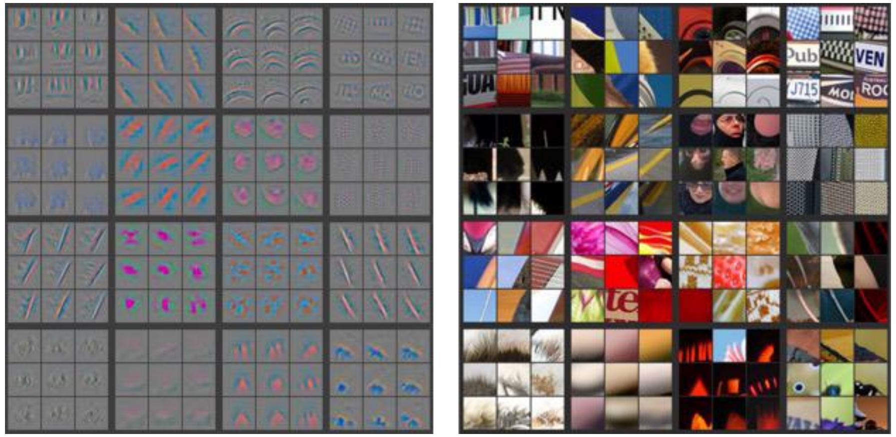


Y. LeCun, Y. Bengio, G. Hinton, **"Deep Learning"**, Nature, Vol. 521, 28 May 2015

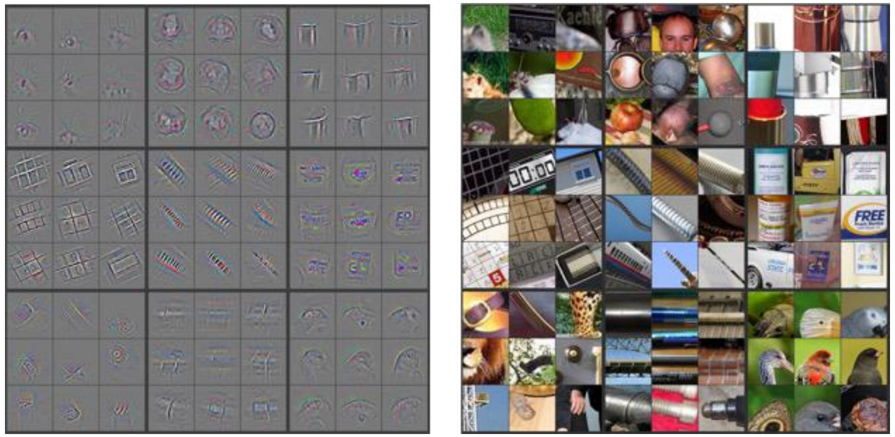
Lecture 6: Understanding and Visualizing CNNs



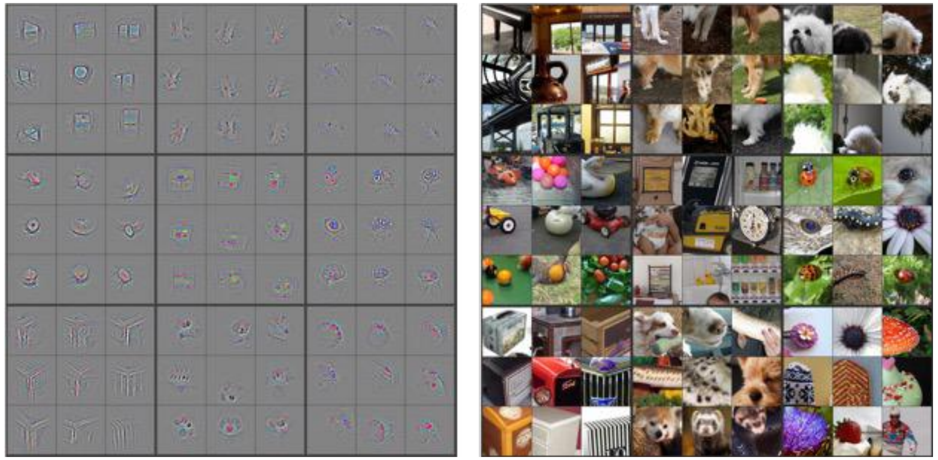
Layer 1



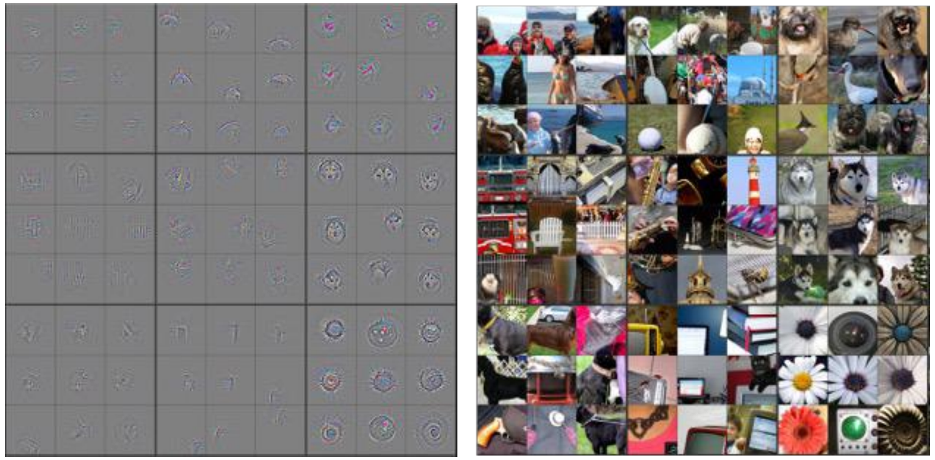
Layer 2



Layer 3



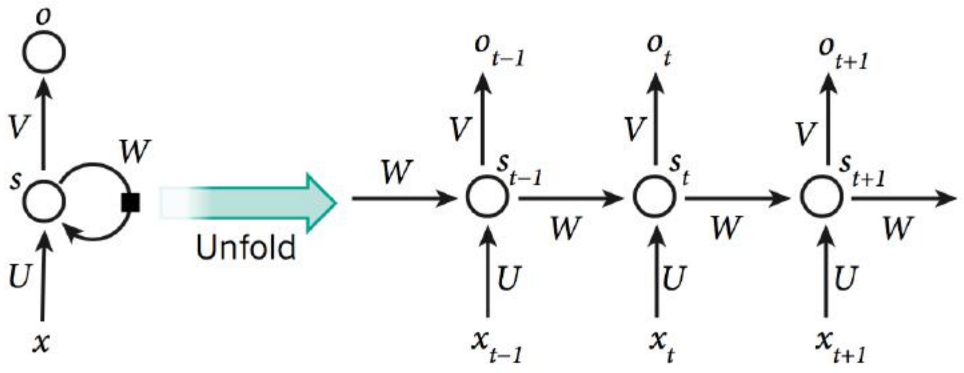
Layer 4



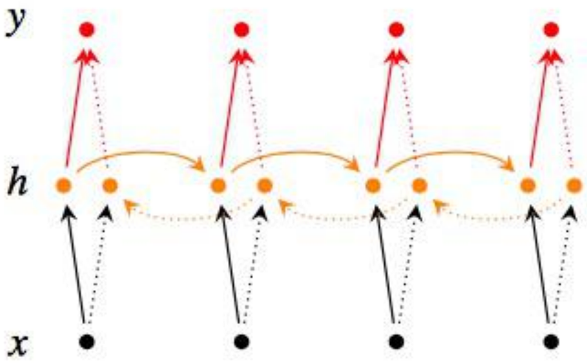
Layer 5

M. D. Zeiler and R. Fergus, **"Visualizing and Understanding Convolutional Networks"**, ECCV 2014

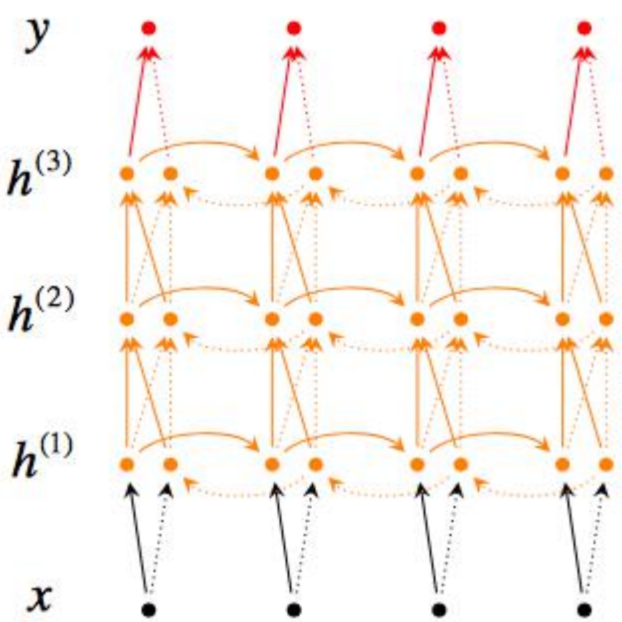
Lecture 7: Recurrent Neural Networks



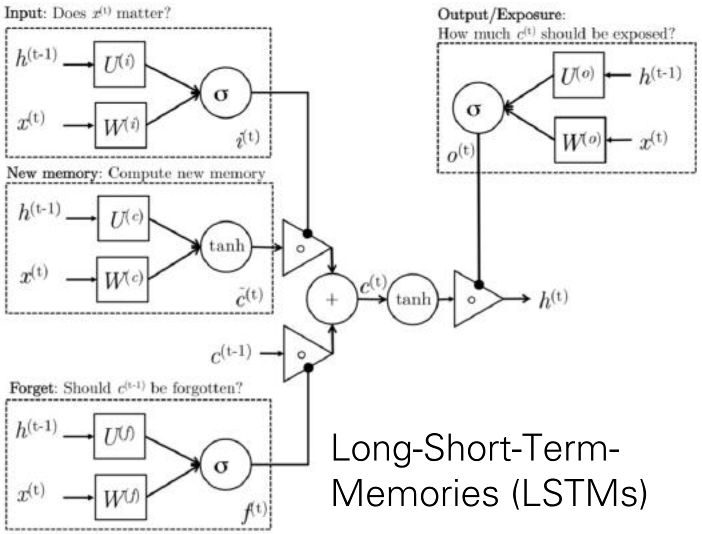
A Recurrent Neural Network (RNN)
(unfolded across time-steps)



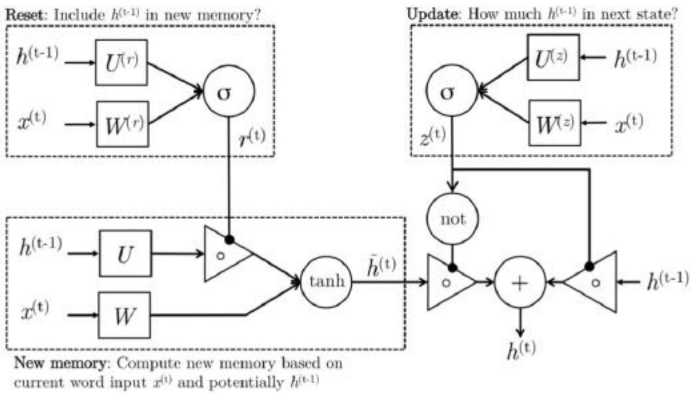
A bi-directional RNN



A deep bi-directional RNN



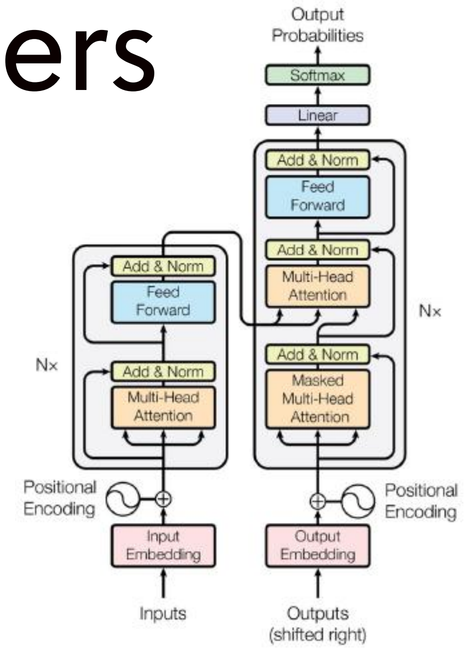
Long-Short-Term-
Memories (LSTMs)



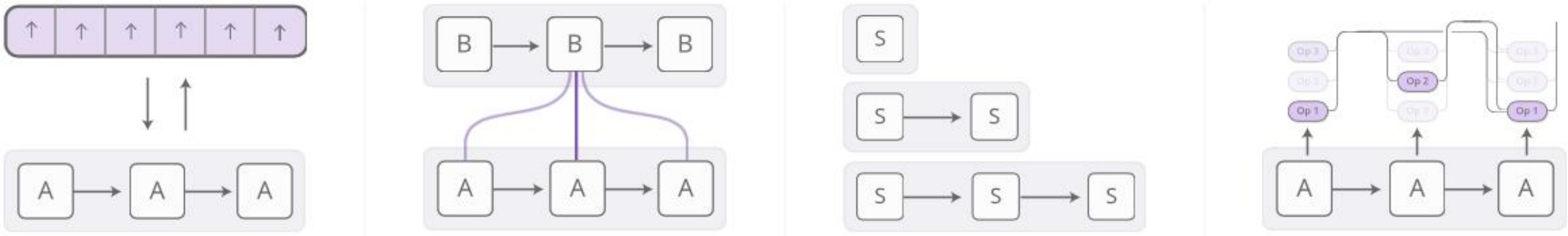
Gated Recurrent Units (GRUs)

C. Manning and R Socher, **Stanford CS224n** Lecture 8 Notes
Y. LeCun, Y. Bengio, G. Hinton, "**Deep Learning**", Nature, Vol. 521, 28 May 2015

Lecture 8: Attention and Transformers



Transformer Architecture

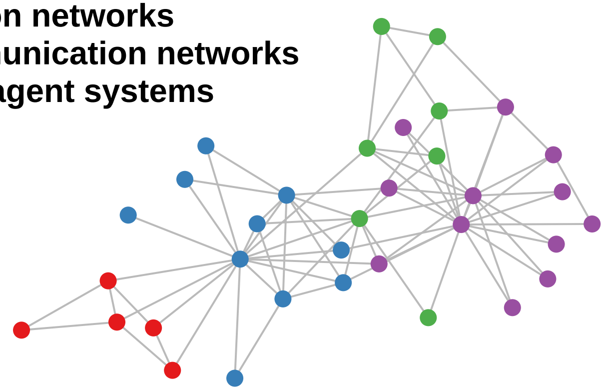


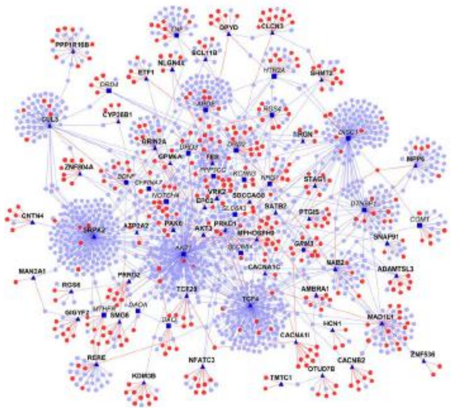
Neural Turing Machines | **Attentional Interfaces** | **Adaptive Computation Time** | **Neural Programmers**

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.

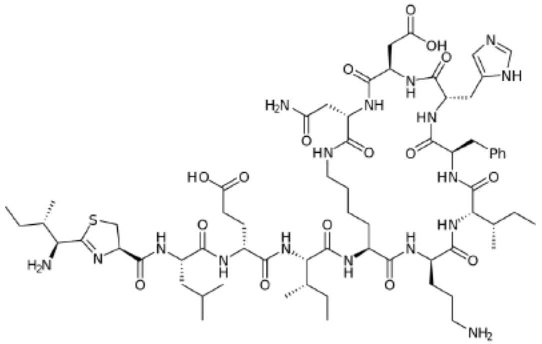
Lecture 9: Graph Networks

Social networks
Citation networks
Communication networks
Multi-agent systems

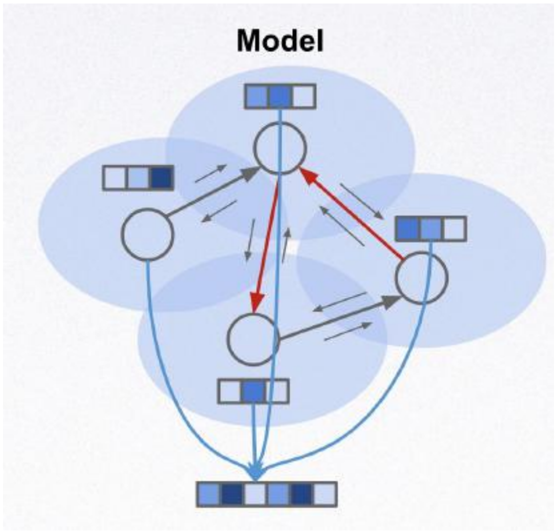


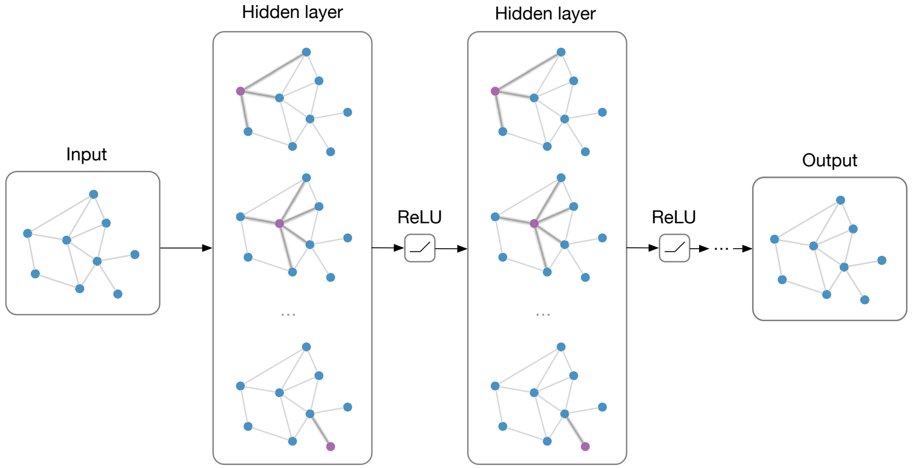


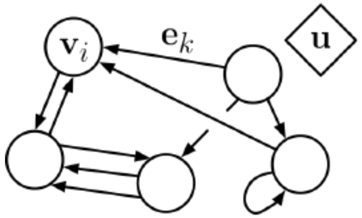
Protein interaction networks

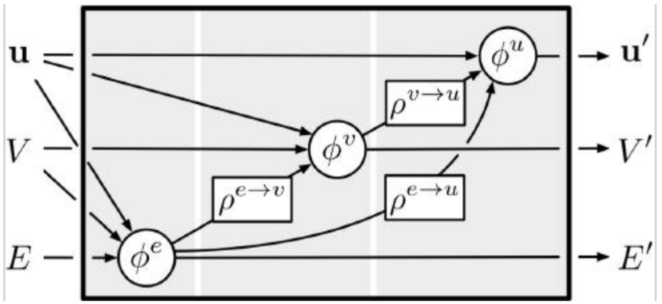


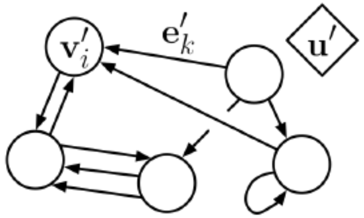
Molecules





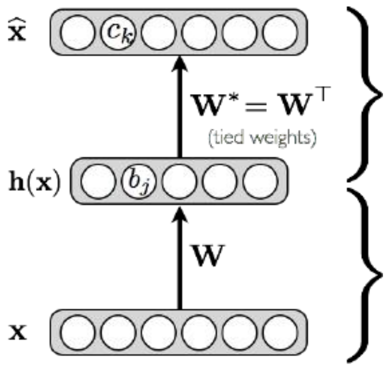






T.N. Kipf and M. Welling, "**Semi-supervised classification with graph convolutional networks**", ICLR 2017
P. Battaglia et al., "**Relational inductive biases, deep learning, and graph networks**", arXiv 2018

Lecture 10: Autoencoders and Autoregressive Models



Decoder

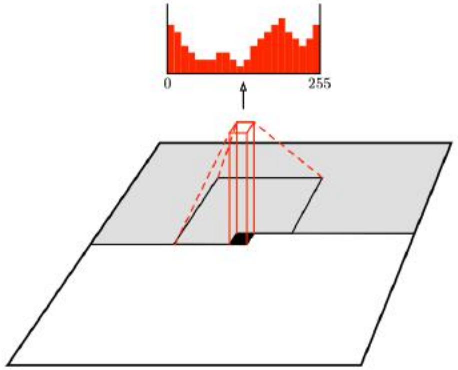
$$\begin{aligned}\hat{\mathbf{x}} &= o(\hat{\mathbf{a}}(\mathbf{x})) \\ &= \underbrace{\mathrm{sigm}}_{\text{For binary units}}(\mathbf{c} + \mathbf{W}^*\mathbf{h}(\mathbf{x}))\end{aligned}$$

Encoder

$$\begin{aligned}\mathbf{h}(\mathbf{x}) &= g(\mathbf{a}(\mathbf{x})) \\ &= \mathrm{sigm}(\mathbf{b} + \mathbf{W}\mathbf{x})\end{aligned}$$

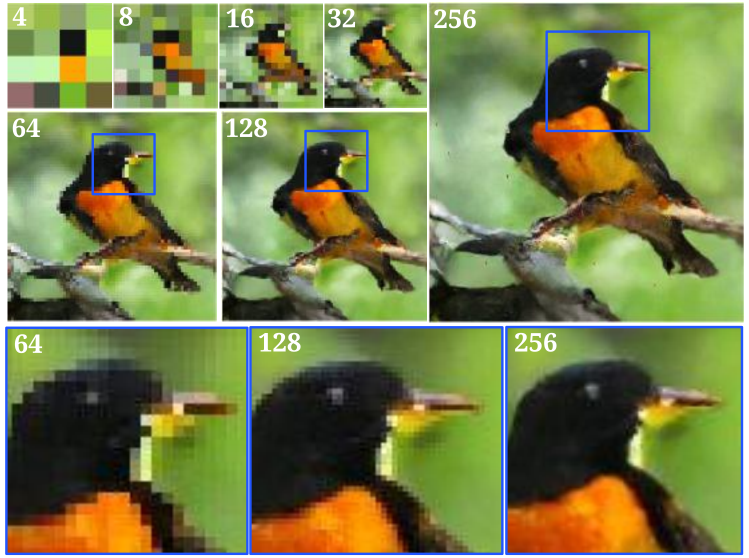
retrieved using 256 bit codes

retrieved using Euclidean distance in pixel intensity space



PixelCNN

Class conditioned samples generated by PixelCNN

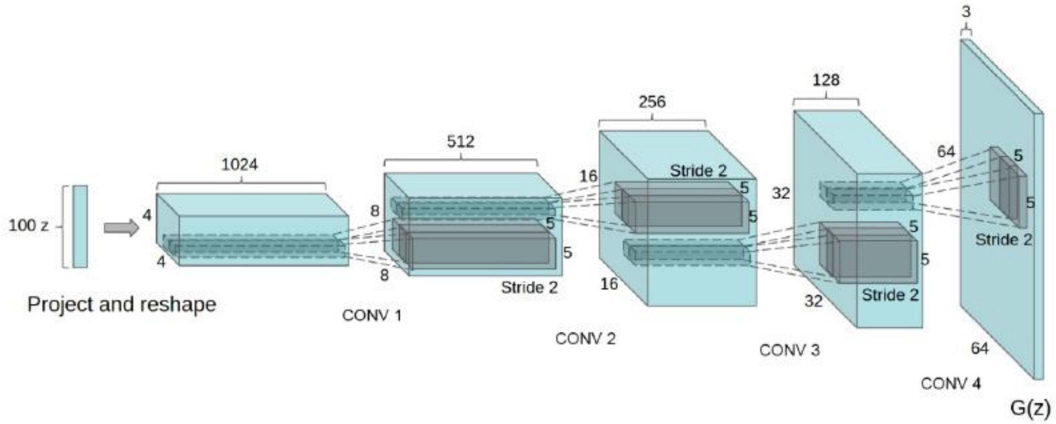


Text-to-image synthesis with Parallel Multiscale PixelCNNs

"A yellow bird with a black head, orange eyes and an orange bill."

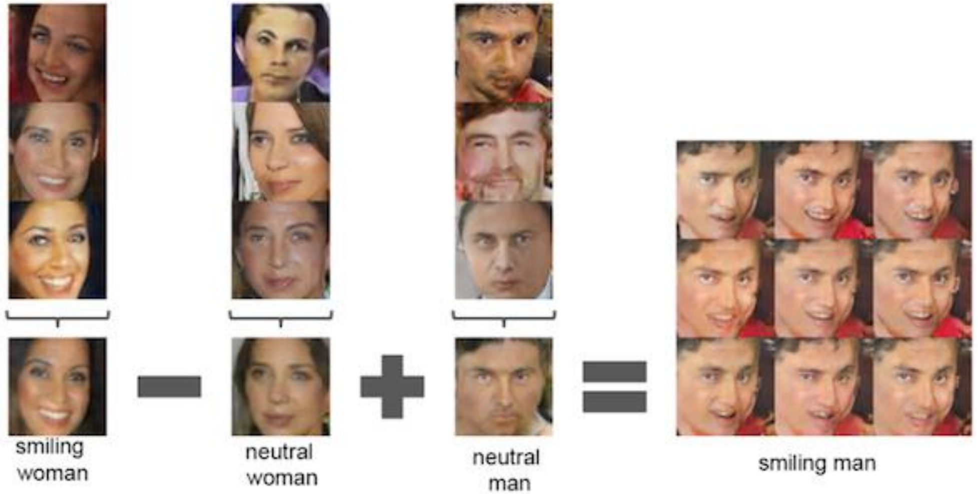
A. Krizhevsky and G. E. Hinton, "**Using Very Deep Autoencoders for Content-Based Image Retrieval**", ESANN 2011
A. van den Oord et al., "**Conditional Image Generation with PixelCNN Decoders**", NeurIPS 2016
S. Reed et al., "**Parallel Multiscale Autoregressive Density Estimation**", ICML 2017

Lecture 11: Generative Adversarial Networks



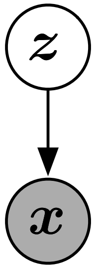
$$\min_{\theta} \max_{\omega} \mathbb{E}_{x\sim Q}[\log D_{\omega}(x)] + \mathbb{E}_{x\sim P_{\theta}}[\log(1 - D_{\omega}(x))]$$

Class-conditioned samples generated by BigGAN

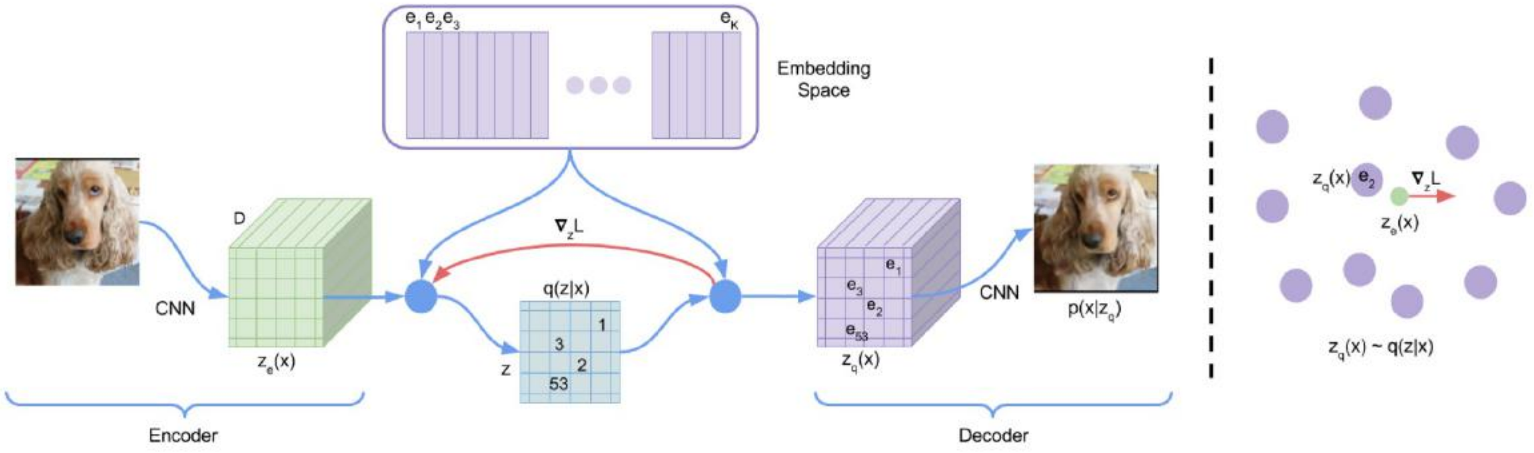


I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "**Generative adversarial nets**", NIPS 2014.
A. Radford, L. Metz, and S. Chintala, "**Unsupervised representation learning with deep convolutional generative adversarial networks**", ICLR 2016
L. Karacan, Z. Akata, A. Erdem and E. Erdem, "**Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts**", arXiv preprint 2016
A. Brock, J. Donahue, K. Simonyan, "**Large Scale GAN Training for High Fidelity Natural Image Synthesis**", ICLR2019

Lecture 12: Variational Autoencoders



$$\log p(\boldsymbol{x}) \geq \log p(\boldsymbol{x}) - D_{\mathrm{KL}}\left(q(\boldsymbol{z}) \| p(\boldsymbol{z} \mid \boldsymbol{x})\right)$$
$$= \mathbb{E}_{\boldsymbol{z} \sim q} \log p(\boldsymbol{x}, \boldsymbol{z}) + H(q)$$

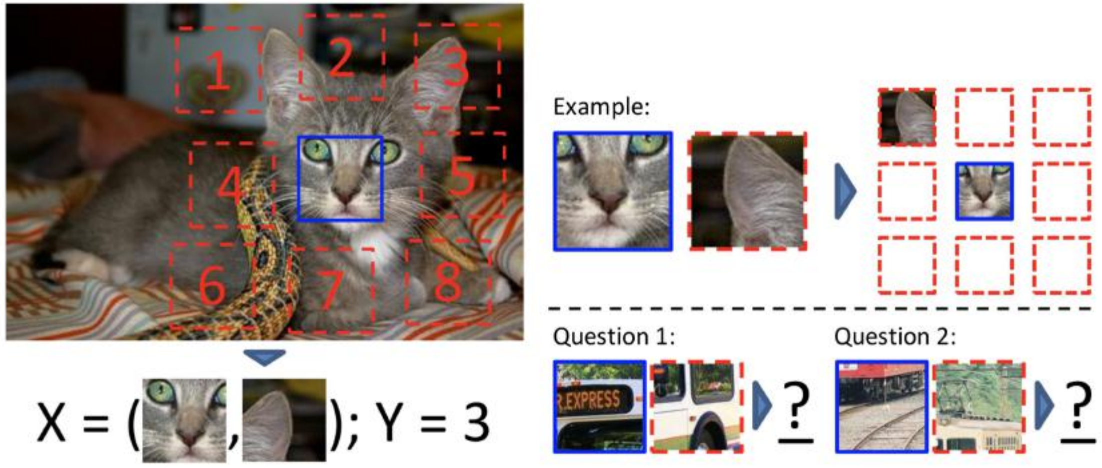


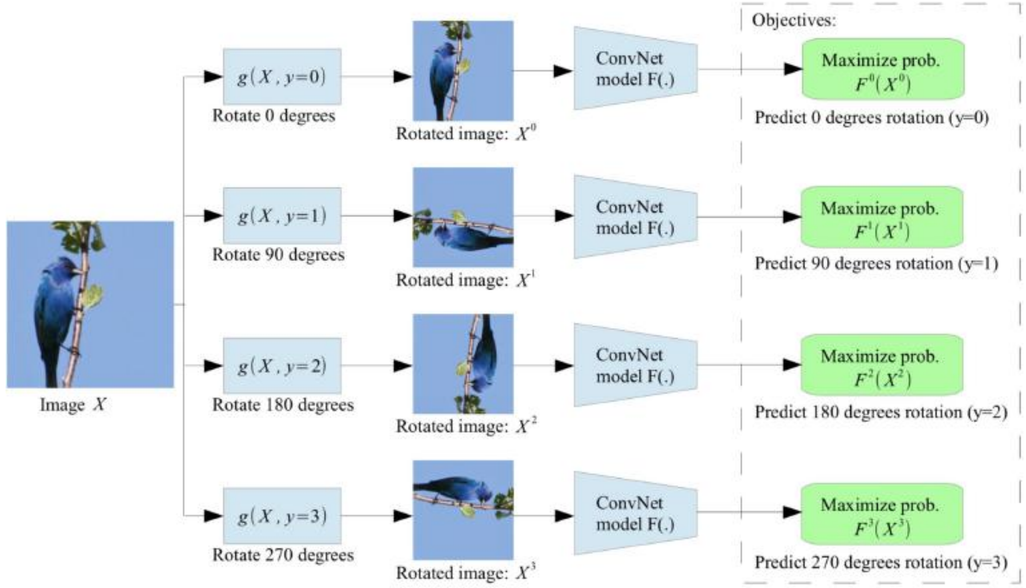
Vector Quantized- Variational AutoEncoder (VQ-VAE)

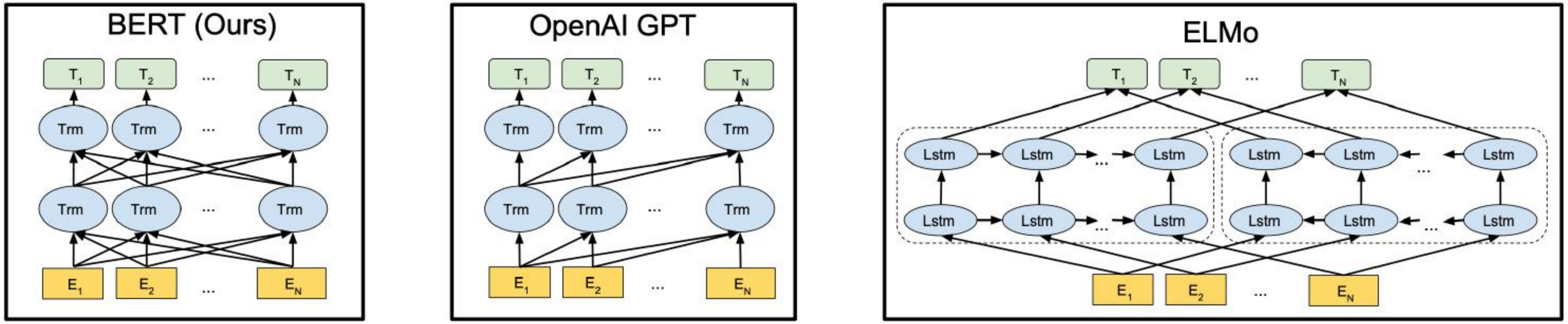
Synthetic images generated by VQ-VAE2

D. P. Kingma and M. Welling, "**Auto-encoding variational Bayes**", ICLR 2014
A. van den Oord, O. Vinyals, K. Kavukcuoglu, "**Neural Discrete Representation Learning**", NeurIPS 2017
A. Razavi, A. van den Oord, O. Vinyals, "**Generating Diverse High-Fidelity Images with VQ-VAE-2**",

Lecture 13: Self-supervised Learning

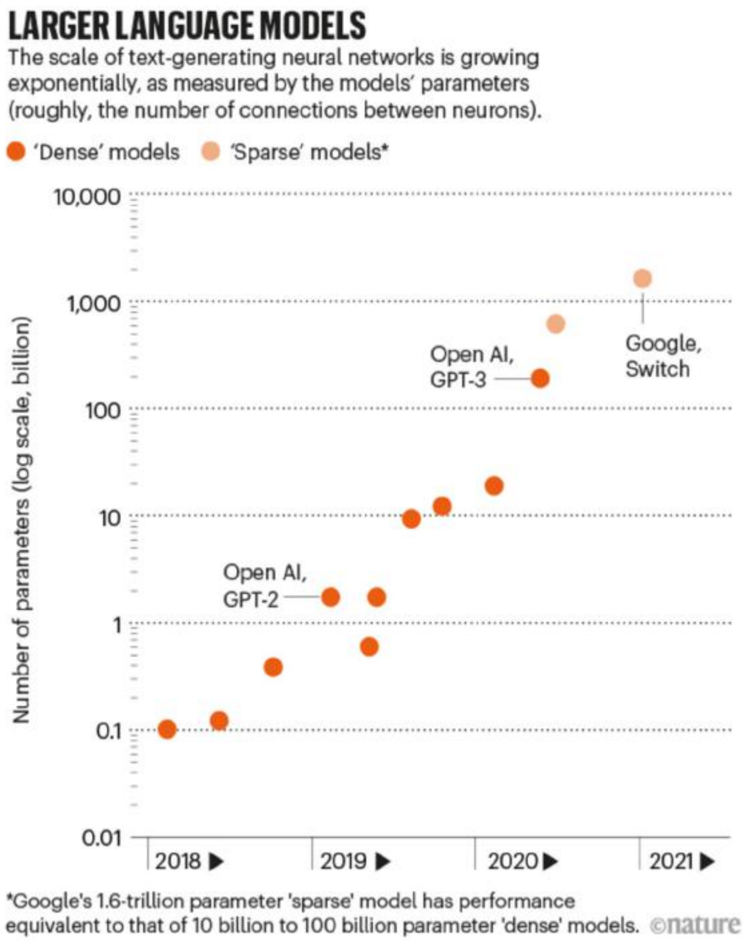






C. Doersch, A. Gupta, A. A. Efros, "**Unsupervised Visual Representation Learning by Context Prediction**", ICCV 2015.
S. Gidaris, P. Singh, N. Komodakis, "**Unsupervised Representation Learning by Predicting Image Rotations**", ICLR2018.
J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, "**BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**", NAACL-HLT 2019.

Lecture 14: Deep Neural Networks as Priors



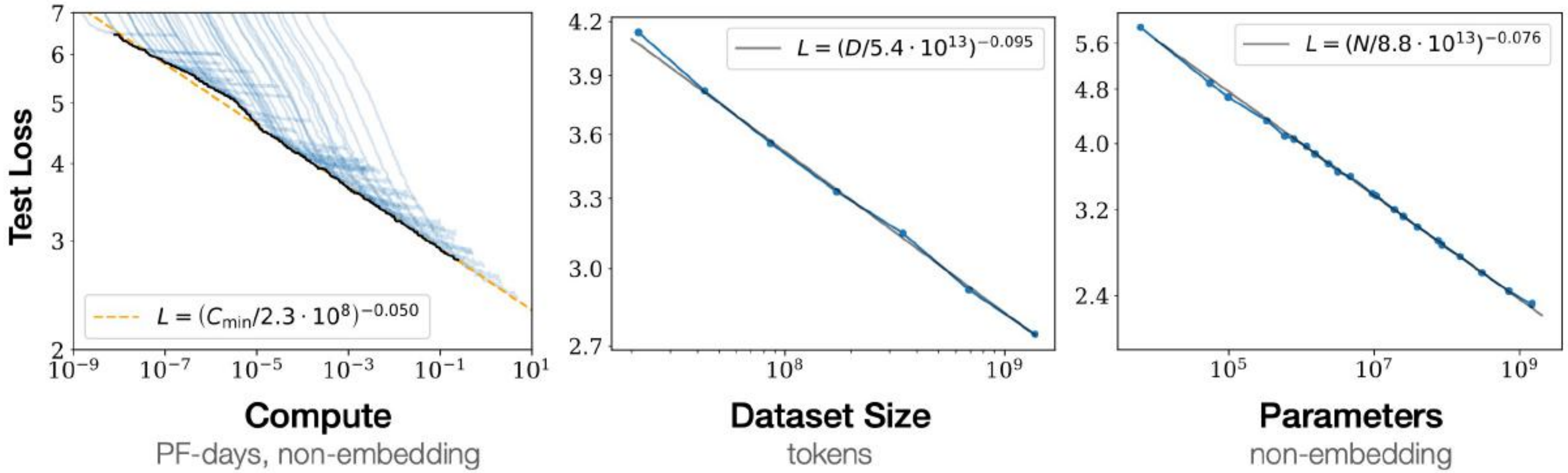


Figure 1 Language modeling performance improves smoothly as we increase the model size, datasetset size, and amount of compute[2] used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when 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 Language Models**", arXiv preprint, 2020.

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
Start of paper presentations

L5 Convolutional Neural Networks
Assignment 1 due, Assignment 2 out

L6 Understanding and Visualizing CNNs
Project proposals due

L7 Recurrent Neural Networks
Assignment 2 due, Assignment 3 out

L8 Attention and Transformerns
Midterm Exam

L9 Graph Neural Networks
Assignment 3 due, Assignment 4 out

L10 Autoencoders and Autoregressive Models
Project progress reports due

L11 Generative Adversarial Networks
Assignment 4 due

L12 Variational Autoencoders

L13 Self-supervised Learning

L14 Deep Neural Networks as Priors
Final project reports due

Paper Presentations

We will discuss 8 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,

Date	Topic
Oct 3	Introduction to Deep Learning
Oct 10	Machine Learning Overview
Oct 17	Multi-Layer Perceptrons
Oct 24	Training Deep Neural Networks
Oct 31	Convolutional Neural Networks
Nov 7	Understanding and Visualizing CNNs
Nov 14	*Winter Break*
Nov 21	Recurrent Neural Networks
Nov 28	Attention and Transformers
TBA	Midterm Exam
Dec 5	Graph Neural Networks
Dec 12	Autoencoders and Autoregressive Models
Dec 19	Generative Adversarial Networks
Dec 26	Variational Autoencoders
Jan 2	Self-supervised Learning
Jan 9	Deep Neural Networks as Priors
Jan 16	Final Project Presentations
Jan 23	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

Borrowed from Yoav Artzi

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 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.

Borrowed from Yoav Artzi

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:** December 3 or 4
- **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 3
  - Project progress reports (6%) Dec 18
  - Final project presentations (8%) Jan 16,18,23,25
  - Final reports (12%) Jan 29
  - The quality of the contributions/The difficulty of implementation (4%)

Course Project

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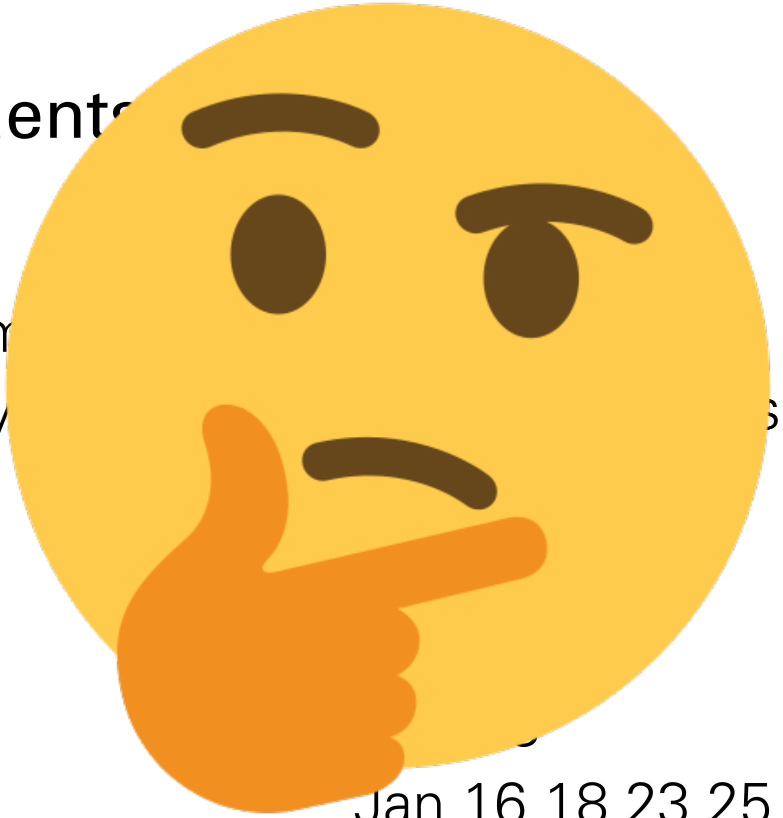
  - An extension to a recent study of non-trivial complexity s.

Start thinking about project ideas!



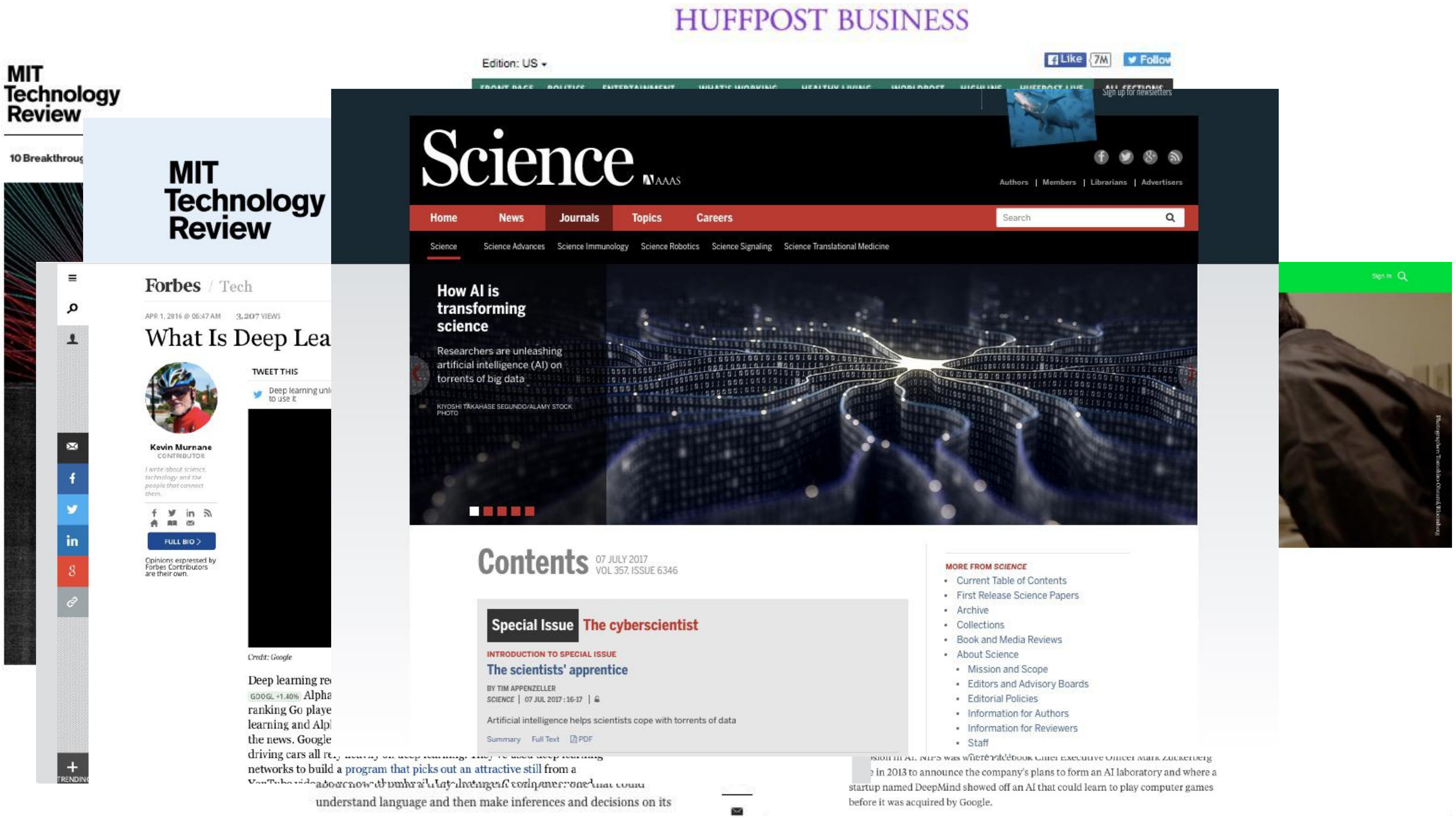
- **Deliverables**
  - Proposals (2%)
  - Project progress reports (6%)
  - Final project presentations (8%) Jan 16,18,23,25
  - Final reports (12%) Jan 29
  - The quality of the contributions/The difficulty of implementation (4%)

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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Science Advances
Science Immunology
Science Robotics
Science Signaling
Science Translational Medicine
How AI is transforming science
Researchers are unleashing artificial intelligence (AI) on torrents of big data
KIYOSHI TAKAHASE SEGUNDO/ALAMY STOCK PHOTO
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BY TIM APPENZELLER
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Artificial intelligence helps scientists cope with torrents of data
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Full Text
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Staff
Forbes / Tech
APR 1, 2016 @ 06:47 AM
3,207 VIEWS
What Is Deep Lea
TWEET THIS
Deep learning unl
to use it
Kevin Murnane
CONTRIBUTOR
I write about science, technology and the people that connect them.
FULL BIO
Opinions expressed by Forbes Contributors are their own.
Credit: Google
Deep learning re
GOOGL +1.40%
Alpha
ranking Go playe
learning and Alp
the news. Google
driving cars all re
networks to build a program that picks out an attractive still from a
understand language and then make inferences and decisions on its
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
TRENDING

What is deep learning?


REVIEW

Deep learning

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

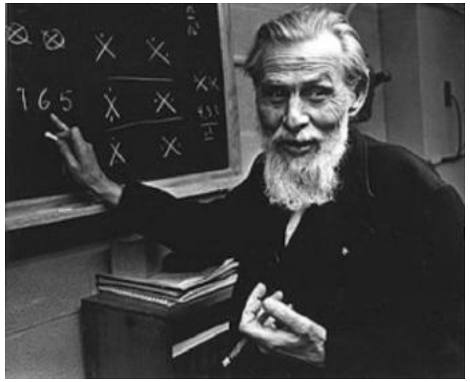
— Yann LeCun, Yoshua Bengio and Geoff Hinton

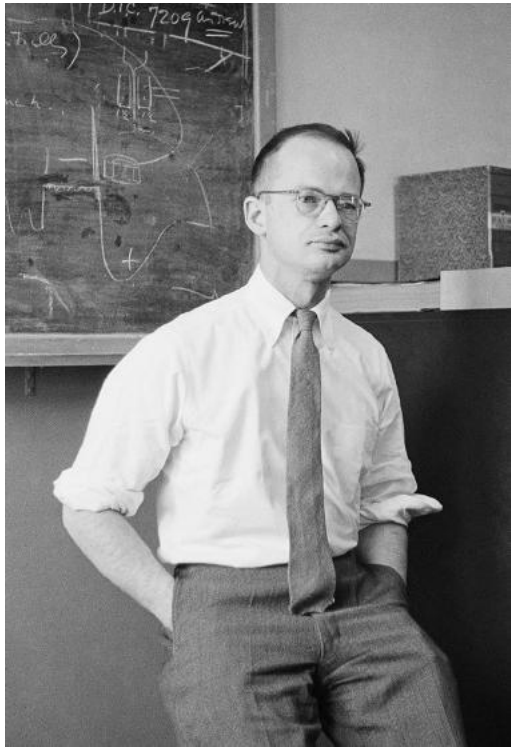
Y. LeCun, Y. Bengio, G. Hinton, **"Deep Learning"**, Nature, Vol. 521, 28 May 2015

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





Bulletin of Mathematical Biology Vol. 52, No. 1/2, pp. 99–115, 1990.
Printed in Great Britain.

0092-8240/90$3.00+0.00
Pergamon Press plc
Society for Mathematical Biology

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY*

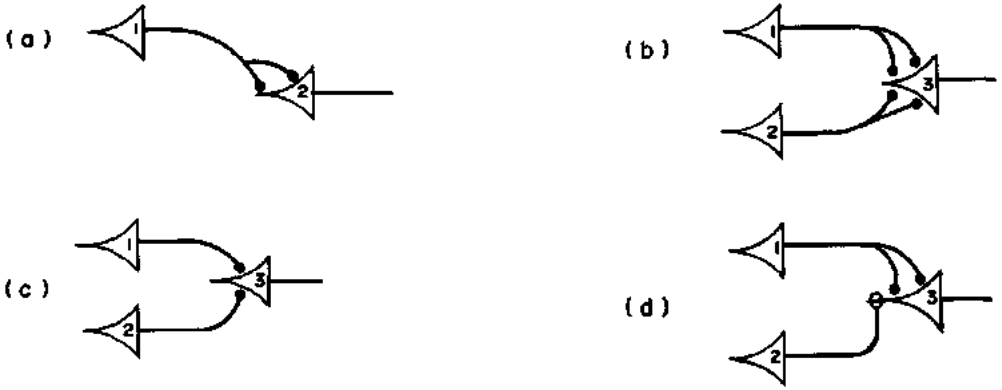
■ WARREN S. MCCULLOCH AND WALTER PITTS
University of Illinois, College of Medicine,
Department of Psychiatry at the Illinois Neuropsychiatric Institute,
University of Chicago, Chicago, U.S.A.

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 many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving 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 occurence, 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 $<1\ \mathrm{ms}^{-1}$ in thin axons, which are usually short, to $>150\ \mathrm{ms}^{-1}$ 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 irreciprocity 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 ms. Observed temporal summation of impulses at greater intervals

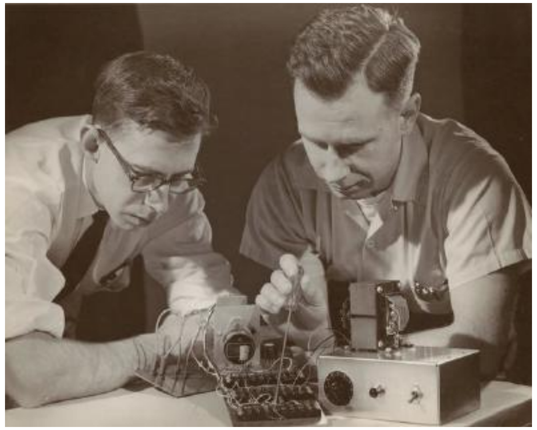
* Reprinted from the *Bulletin of Mathematical Biophysics*, Vol. 5, pp. 115–133 (1943).

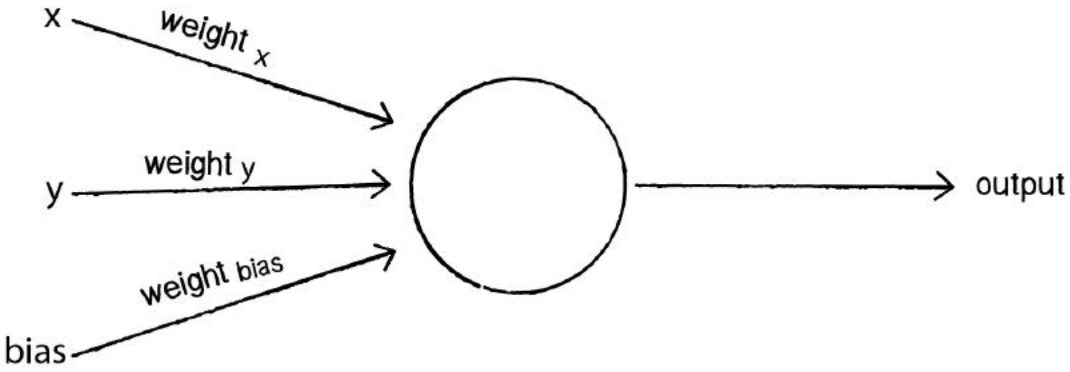
99

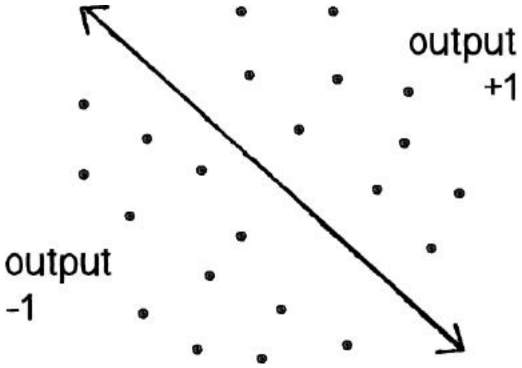


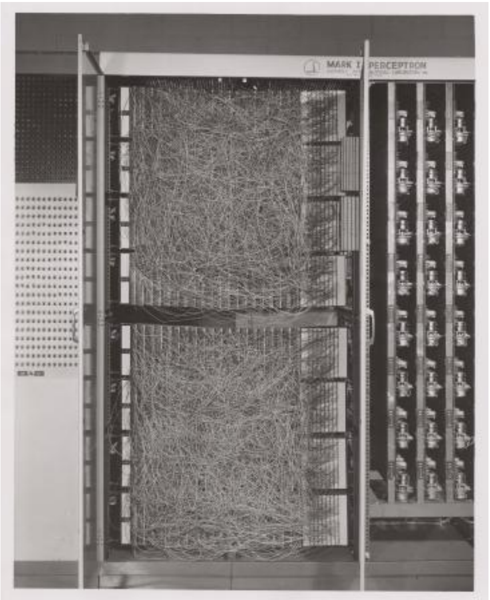
1958: Frank Rosenblatt's Perceptron

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







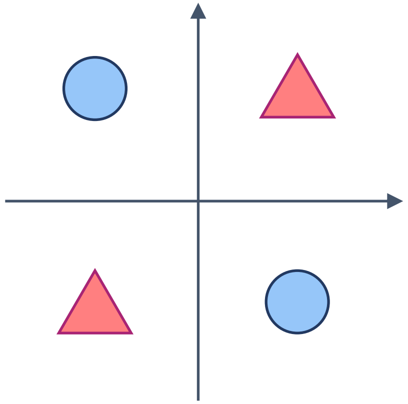


F. Rosenblatt, "**The perceptron: A probabilistic model for information storage and organization in the brain**", Psych. Review, Vol. 65, 1958

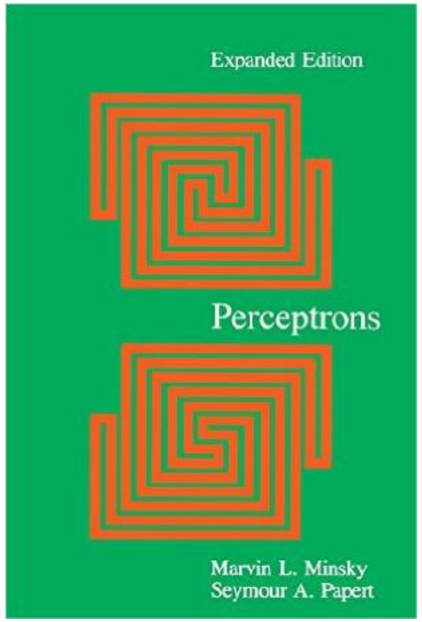
1969: Marvin Minsky and Seymour Papert

"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

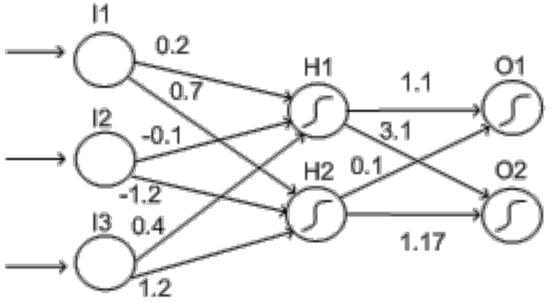


1990s

- **Multi-layer perceptrons** can theoretically learn any function (Cybenko, 1989; Hornik, 1991)

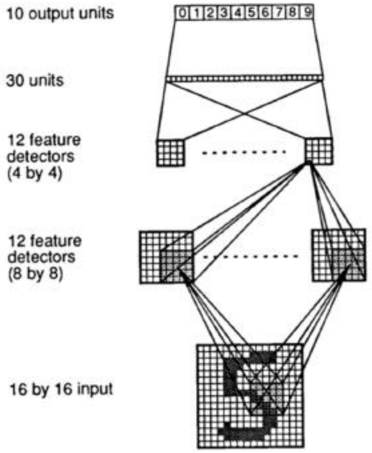
- Training multi-layer perceptrons
  - **Back propagation** (Rumelhart, Hinton, Williams, 1986)
  - **Backpropagation through time** (BPTT) (Werbos, 1988)

- New neural architectures
  - **Convolutional neural nets** (LeCun et al., 1989)
  - **Long-short term memory networks** (LSTM) (Schmidhuber, 1997)



Backpropagation Through Time: What It Does and How to Do It

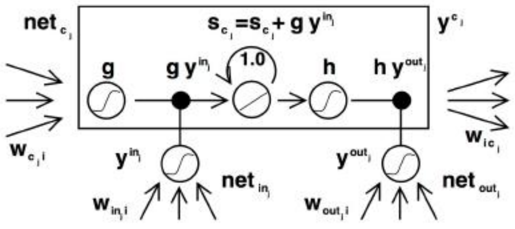
PAUL J. WERBOS



Handwritten Digit Recognition with a Back-Propagation Network

ABSTRACT

1 INTRODUCTION



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)

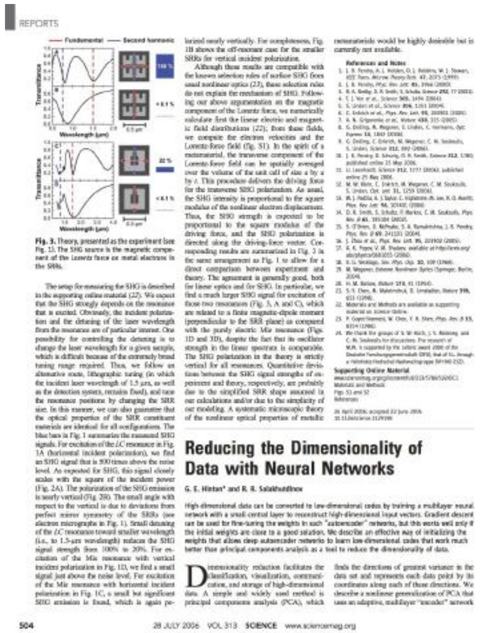
A major breakthrough in 2006

2006 Breakthrough: Hinton and Salakhutdinov

Reducing the Dimensionality of Data with Neural Networks

G. E. Hinton* and R. R. Salakhutdinov

High-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors. Gradient descent can be used for fine-tuning the weights in such "autoencoder" networks, but this works well only if the initial weights are close to a good solution. We describe an effective way of initializing the weights that allows deep autoencoder networks to learn low-dimensional codes that work much better than principal components analysis as a tool to reduce the dimensionality of data.



- The first solution to the **vanishing gradient problem**.
- Build the model in a layer-by-layer fashion using unsupervised learning
  - The features in early layers are already initialized or "pretrained" with some suitable features (weights).
  - Pretrained features in early layers only need to be adjusted slightly during supervised learning to achieve good results.

G. E. Hinton and R. R. Salakhutdinov, "**Reducing the dimensionality of data with neural networks**", Science, Vol. 313, 28 July 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

✗

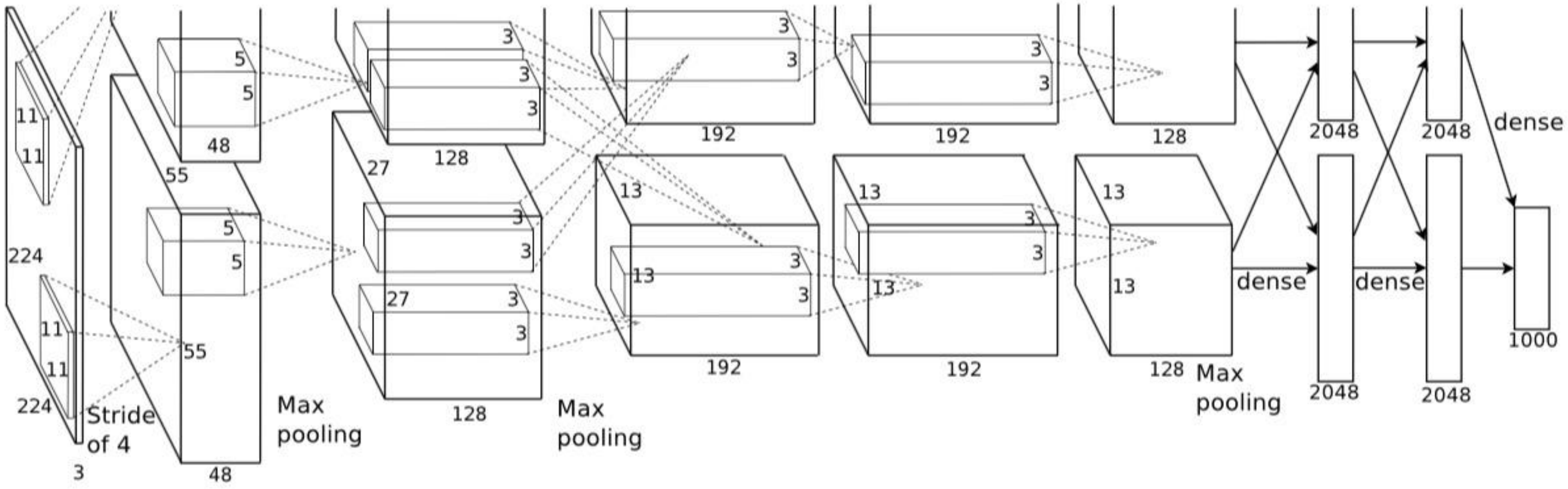
Image classification

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

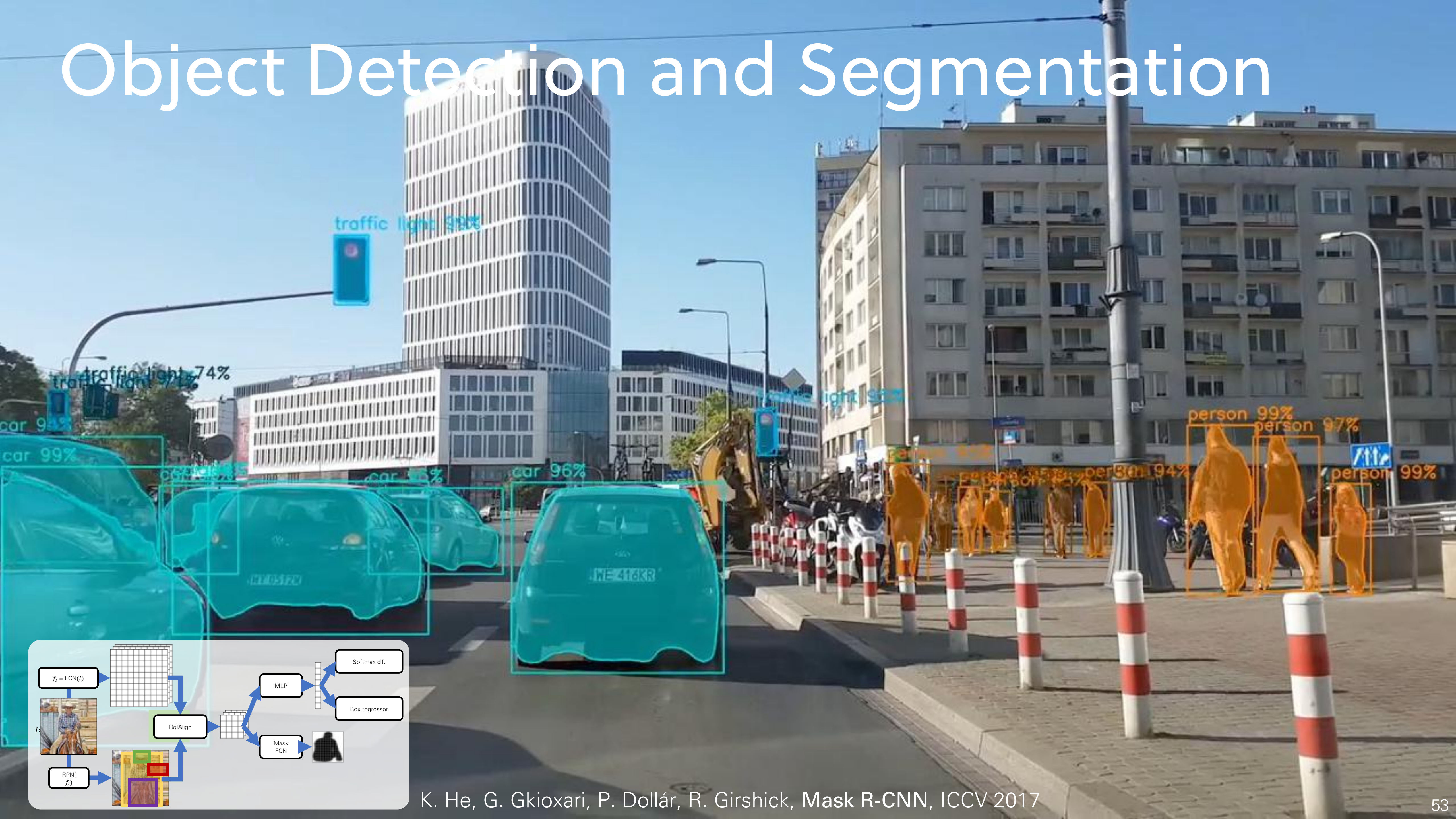


- The success of AlexNet, a deep convolutional network
  - 7 hidden layers (not counting some max pooling layers)
  - 60M parameters
- Combined several tricks
  - ReLU activation function, data augmentation, dropout

A. Krizhevsky, I. Sutskever, G.E. Hinton "**ImageNet Classification with Deep Convolutional Neural Networks**", NIPS 2012

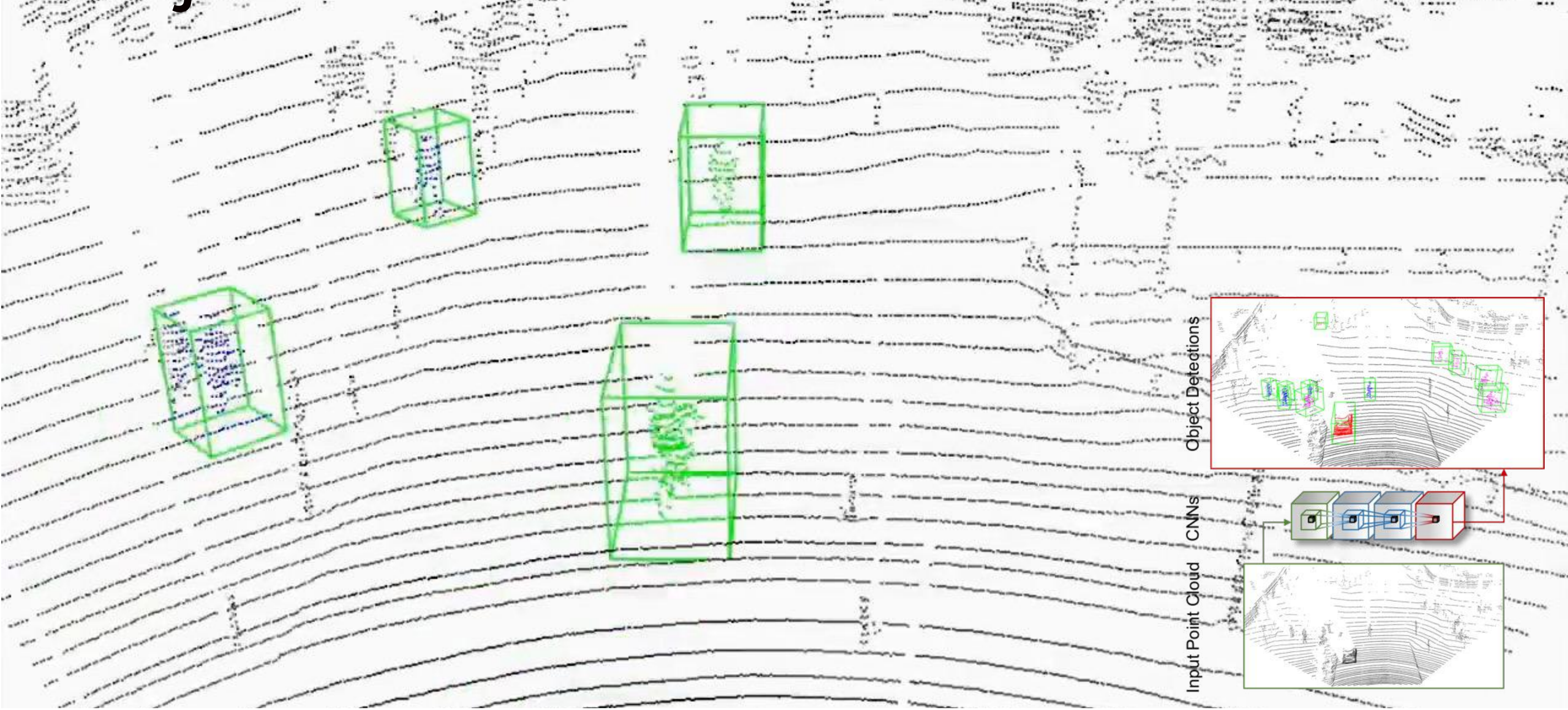
2012-Now
Some recent successes

Object Detection and Segmentation



K. He, G. Gkioxari, P. Dollár, R. Girshick, **Mask R-CNN**, ICCV 2017

Object Detection in 3D Point Clouds



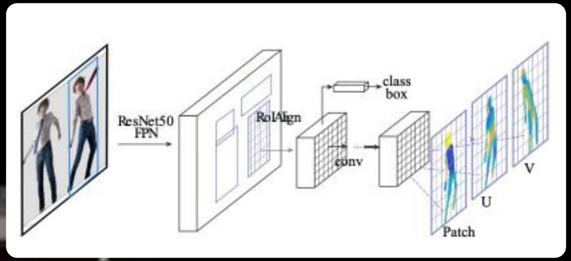
M. Engelcke, D. Rao, D. Z. Wang, C. H. Tong, and I. Posner. **Vote3Deep: Fast Object Detection in 3D Point Clouds Using Efficient Convolutional Neural Networks.** ICRA 2017

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.

ZR. Alpguler, N. Neverova, I. Kokkinos. **DensePose: Dense Human Pose Estimation In The Wild**. CVPR 2018

Image Synthesis

- 7 years of GAN progress

2014

2015

2016

2018

2019

2020

2021

- 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.
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Image Synthesis

A. Brock, J. Donahue and K. Simonyan. Large Scale GAN Training for High Fidelity Natural Image Synthesis. arXiv 2018.

Semantic Image Editing

Semantic Layout

L. Karacan, Z. Akata, A. Erdem and E. Erdem. **Manipulation of Scene Attributes via Hallucination**. ACM Transactions on Graphics, November 2019

Semantic Image Editing

Winter

Prediction

L. Karacan, Z. Akata, A. Erdem and E. Erdem. **Manipulation of Scene Attributes via Hallucination**. ACM Transactions on Graphics, November 2019

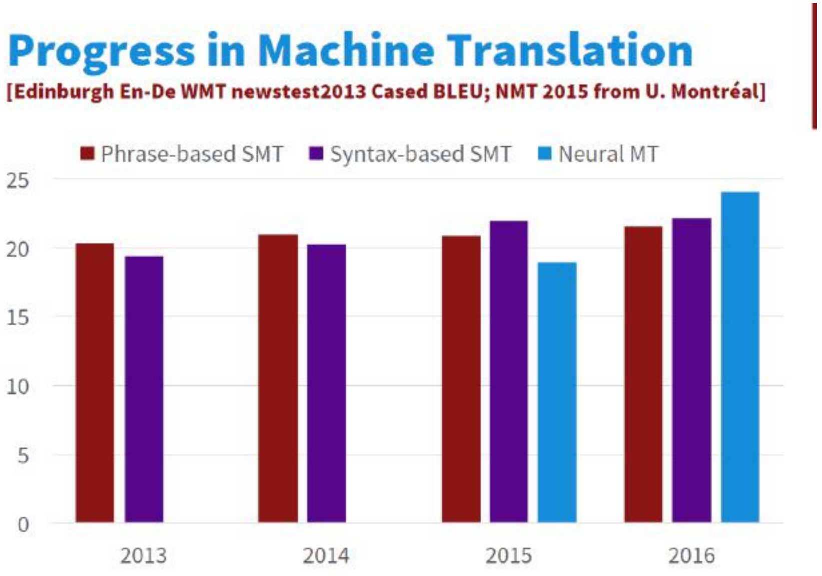
Semantic Image Editing

Spring
+
Clouds

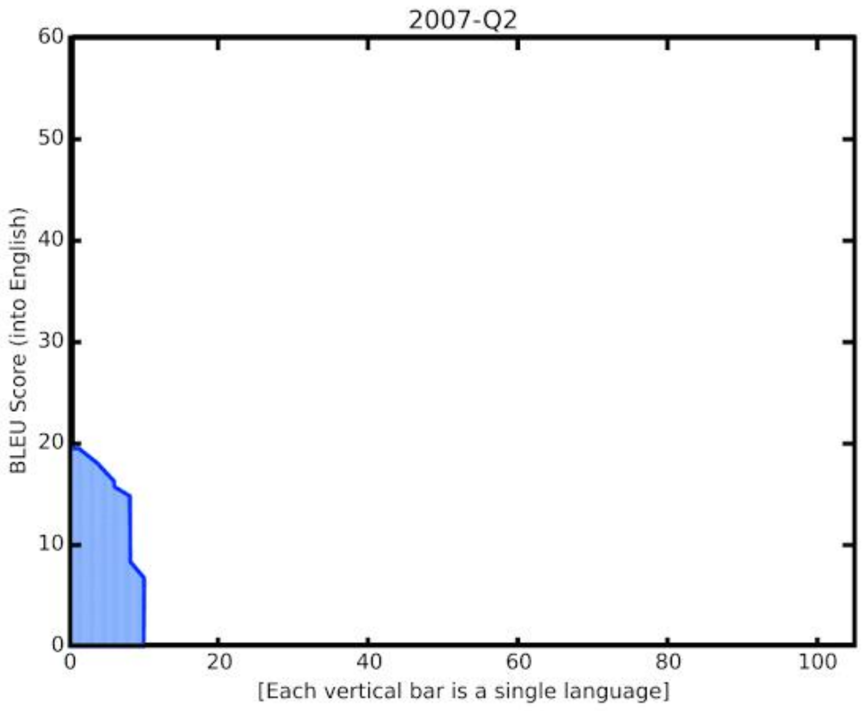
Prediction

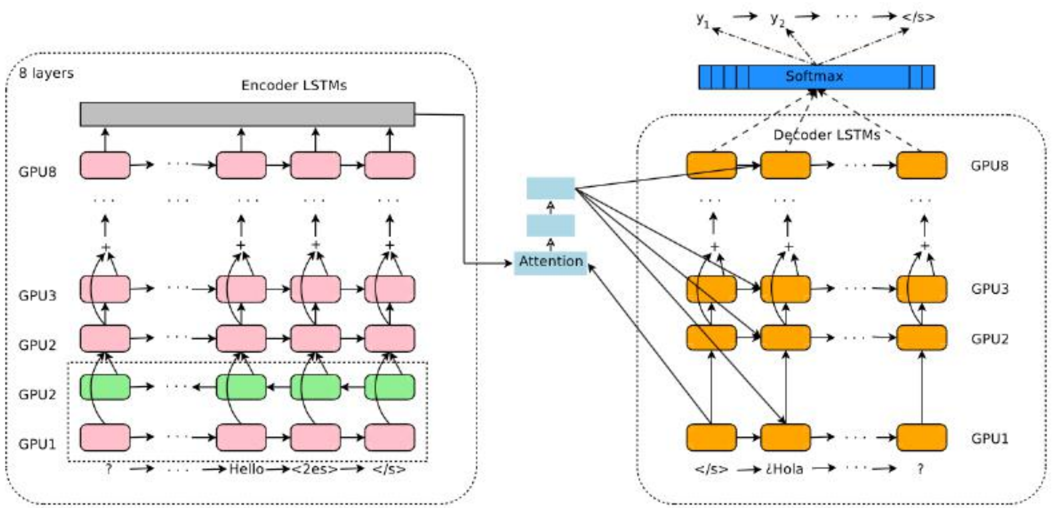
L. Karacan, Z. Akata, A. Erdem and E. Erdem. **Manipulation of Scene Attributes via Hallucination**. ACM Transactions on Graphics, November 2019

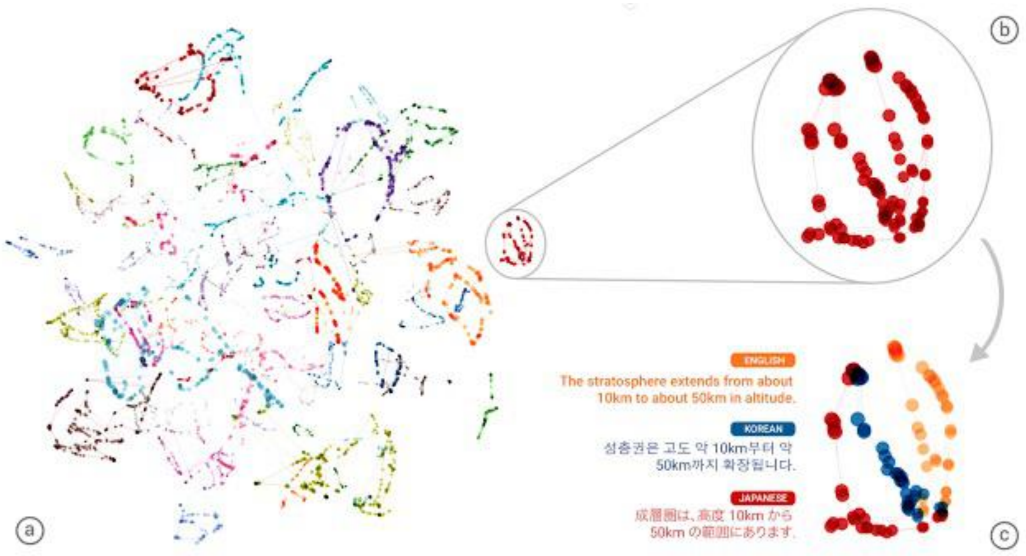
Machine Translation



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

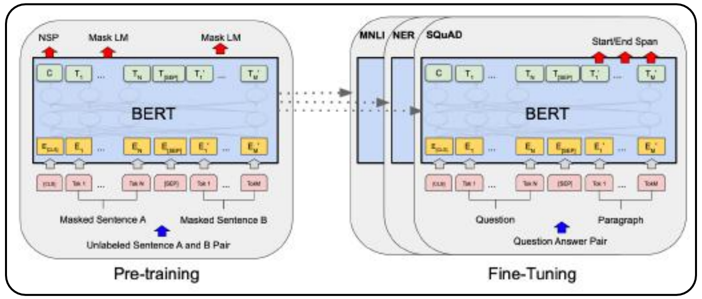


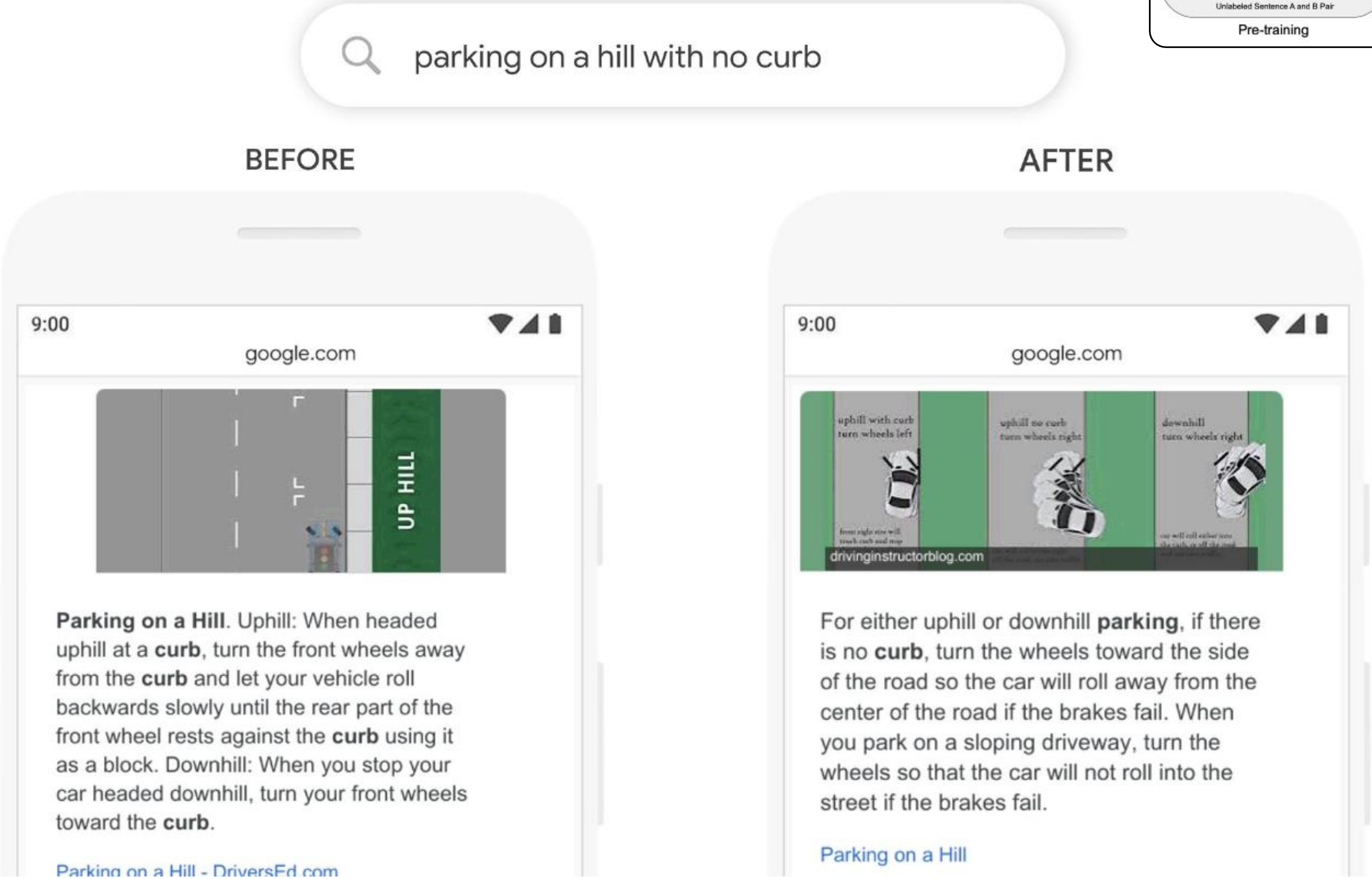




M. Johnson et al., "**Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation**", arXiv preprint, 2016

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.

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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.

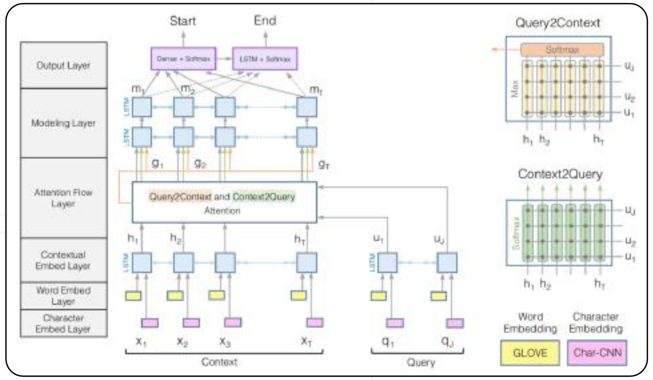
A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, I. Sutskever, "Language Models are Unsupervised Multitask Learners", 2019

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

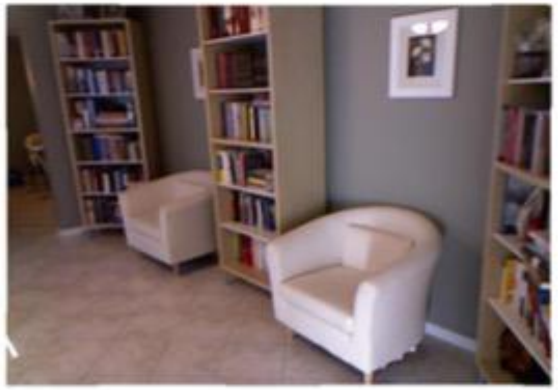


P. Rajpurkar, J. Zhang, K. Lopyrev & P. Liang. **SQuAD: 100,000+ Questions for Machine Comprehension of Text**. EMNLP 2016
M. Seo, A. Kembhavi, A. Farhadi & H. Hajishirzi. **Bi-Directional Attention Flow for Machine Comprehension**. ICLR 2017

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)

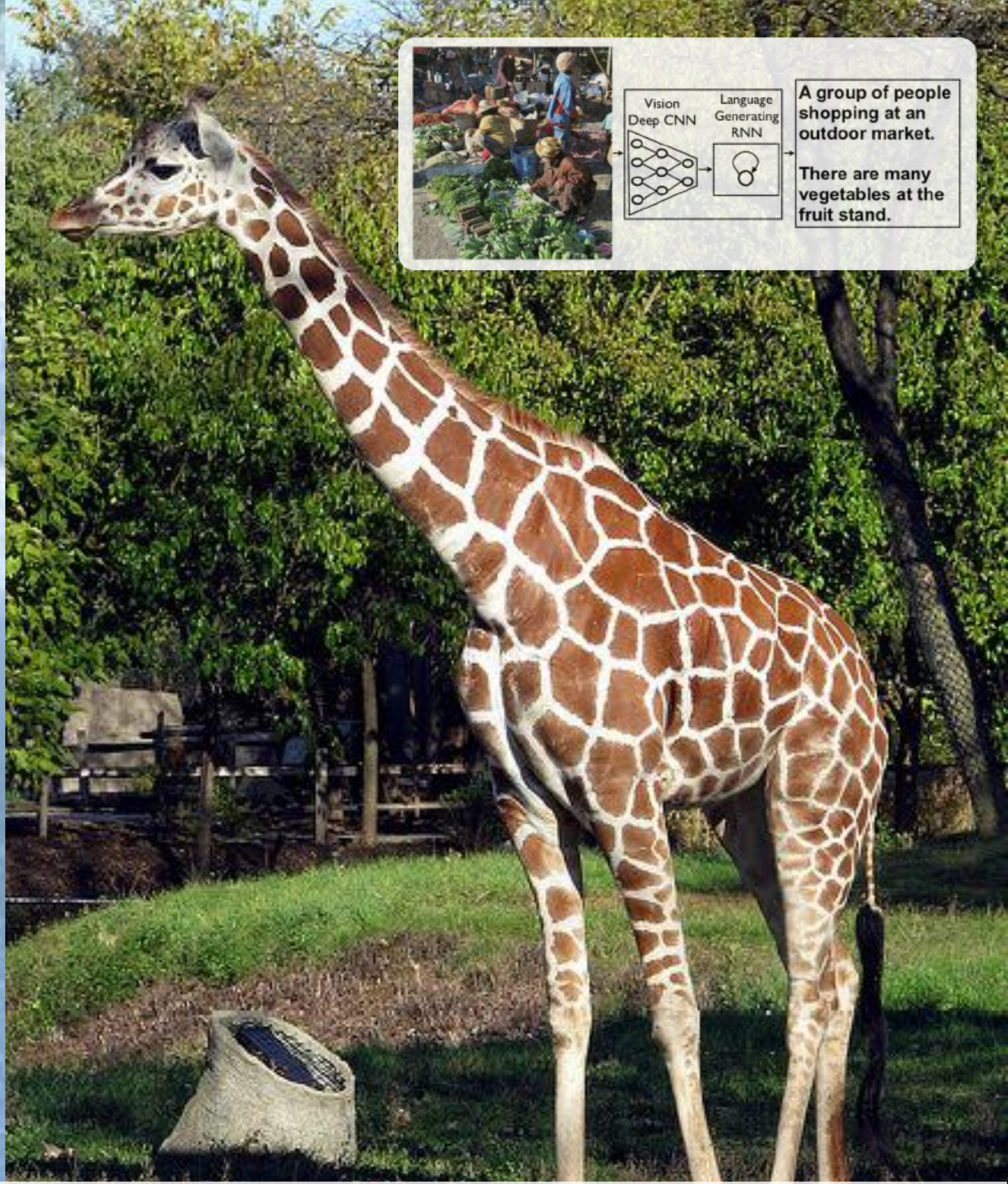
DAQUAR 585
What is the object on the chair?
Ground truth: pillow
IMG+BOW: clothes (0.37)
2-VIS+BLSTM: pillow (0.65)
LSTM: clothes (0.40)

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)

M. Ren, R. Kiros, and R. Zemel, "**Exploring Models and Data for Image Question Answering**" NIPS 2015

Image Captioning

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



A giraffe standing in the grass next to a tree.

X. Chen and C. L. Zitnick. **Mind's Eye: A Recurrent Visual Representation for Image Caption Generation**. CVPR 2015.

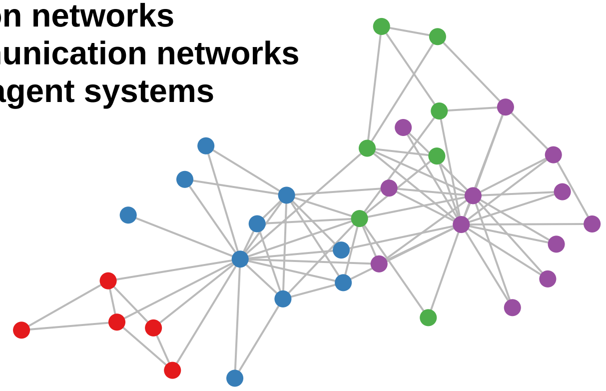
Image Captioning

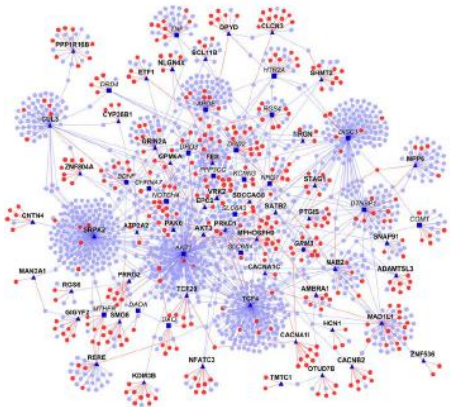
Yarış pistinde virajı almakta olan bir yarış arabası

M. Kuyu, A. Erdem & E. Erdem. **Image Captioning in Turkish with Subword Units.** SIU 2018

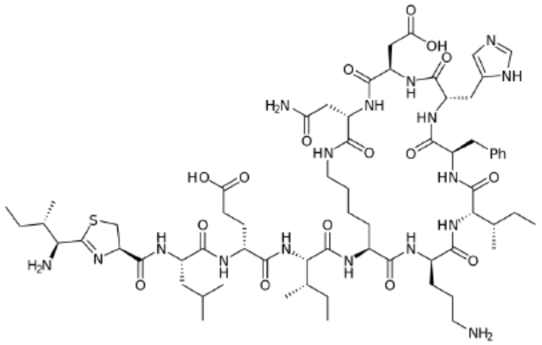
Graph Neural Networks

Social networks
Citation networks
Communication networks
Multi-agent systems

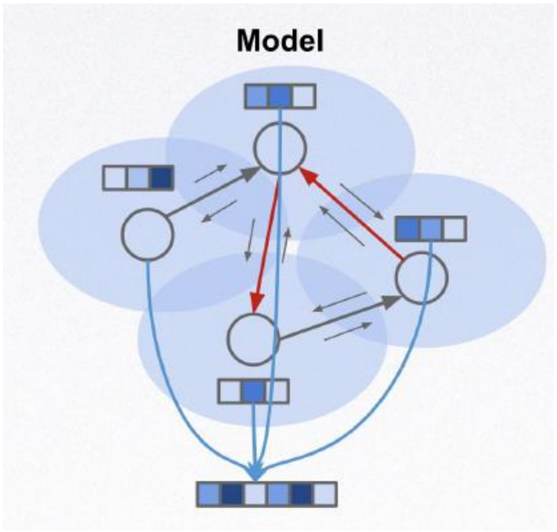


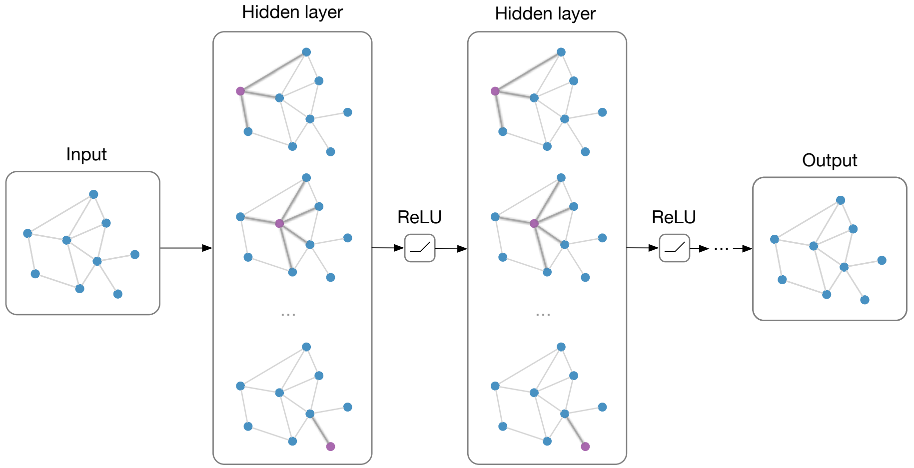


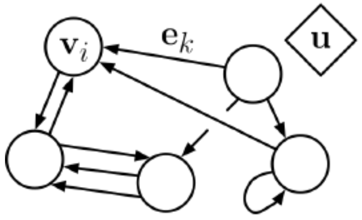
Protein interaction networks

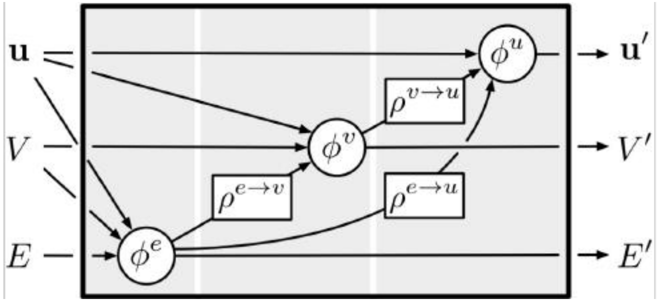


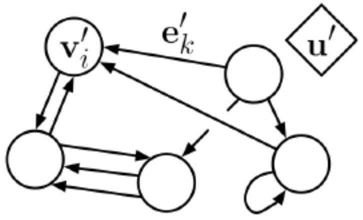
Molecules



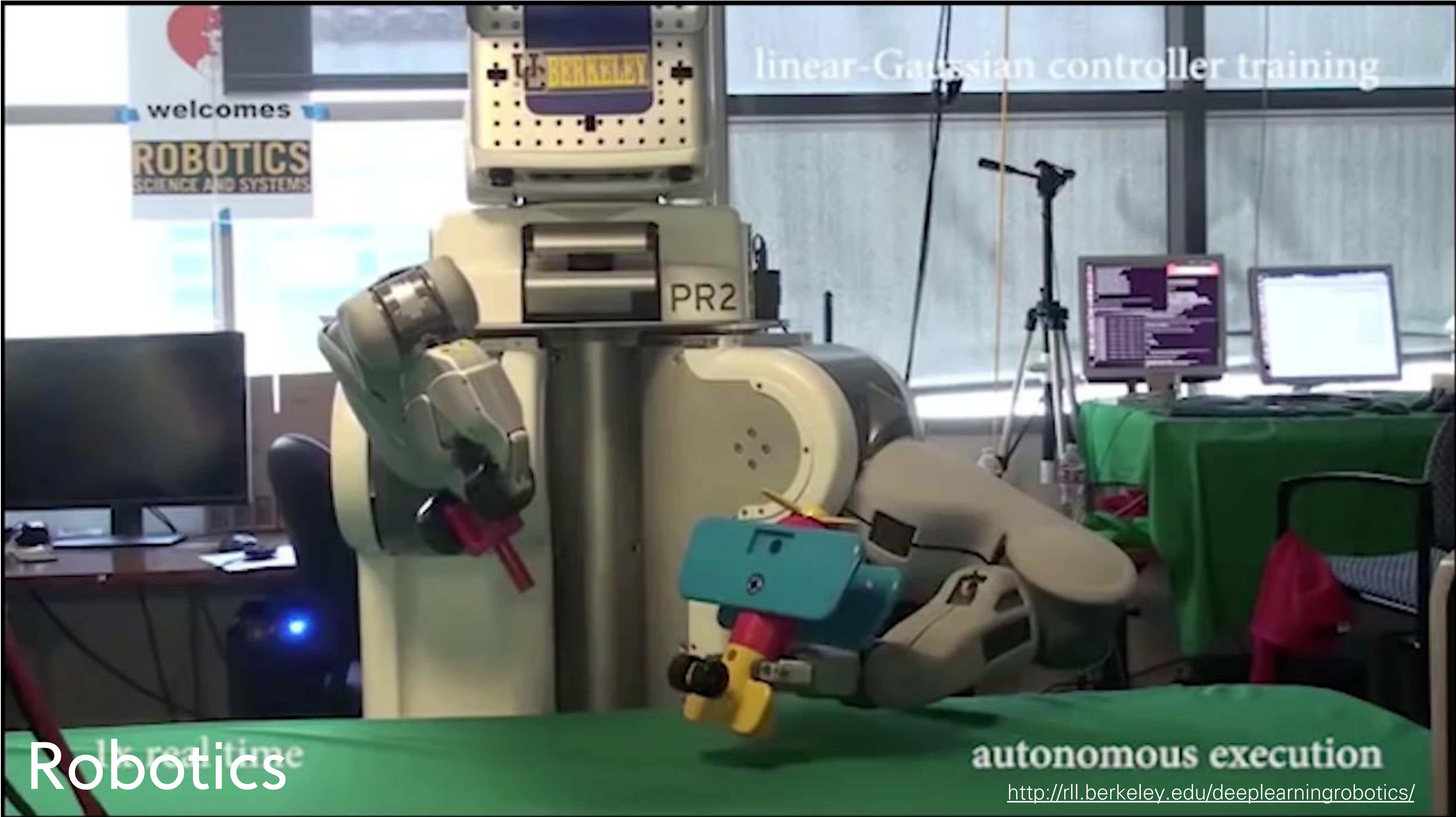








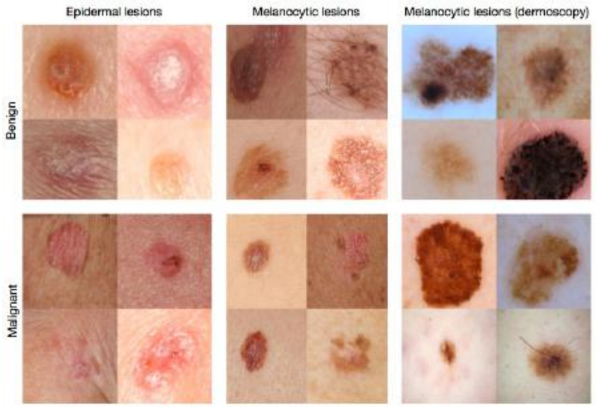
T.N. Kipf and M. Welling, "**Semi-supervised classification with graph convolutional networks**", ICLR 2017
P. Battaglia et al., "**Relational inductive biases, deep learning, and graph networks**", arXiv 2018

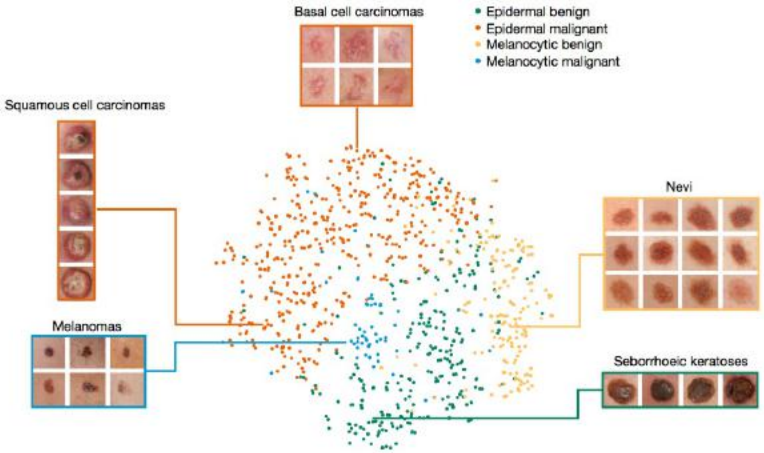


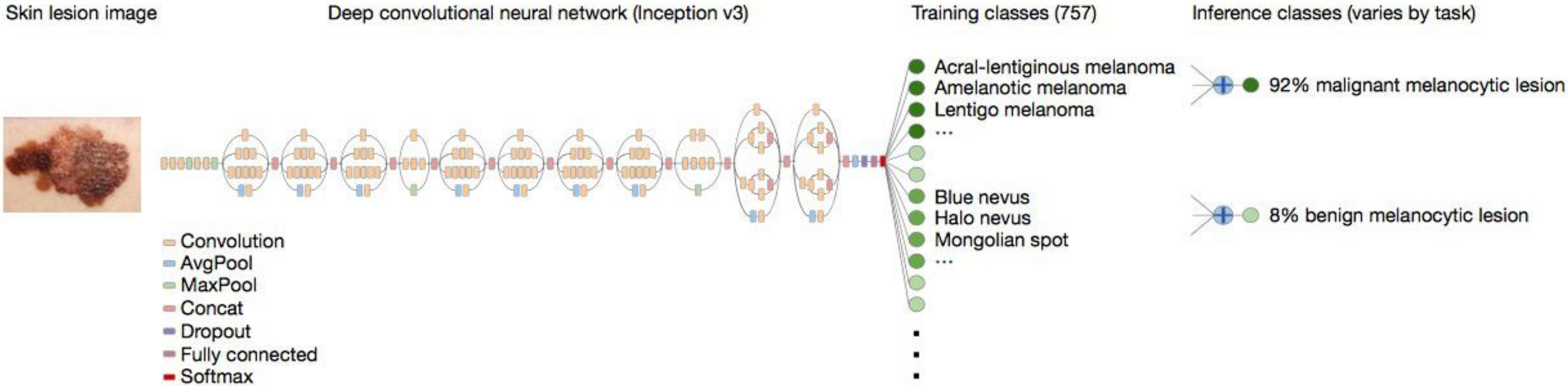
Robotics

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

Medical Image Analysis







A. Esteva et al., "**Dermatologist-level classification of skin cancer with deep neural networks**", Nature 542, 2017

Stanford ML Group

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.

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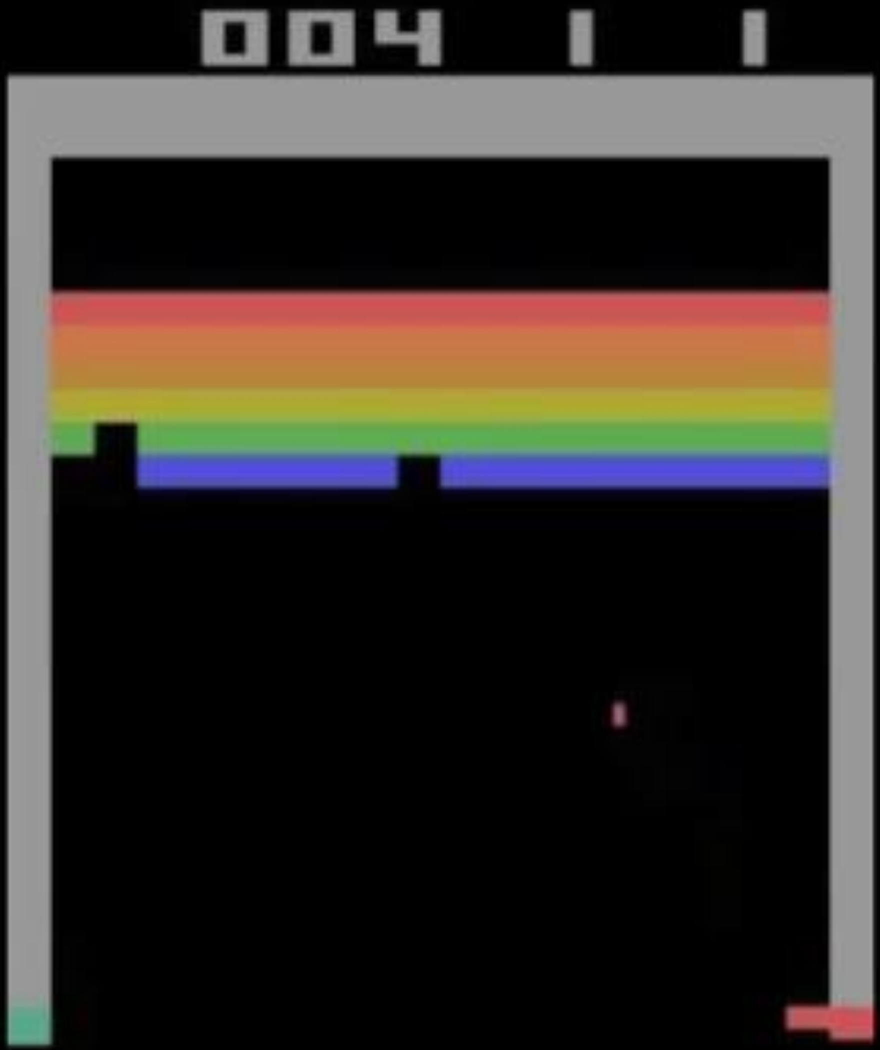
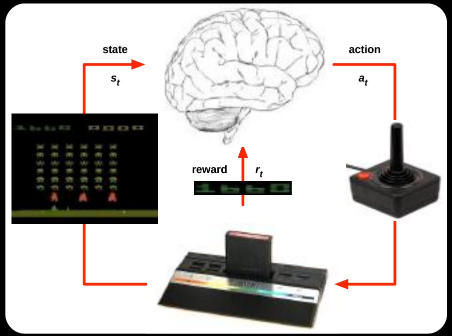
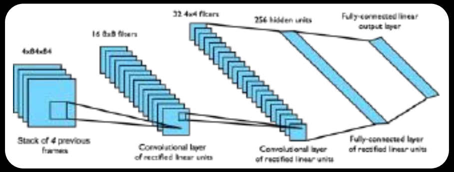
Medical Image Analysis

Strategic Game Playing







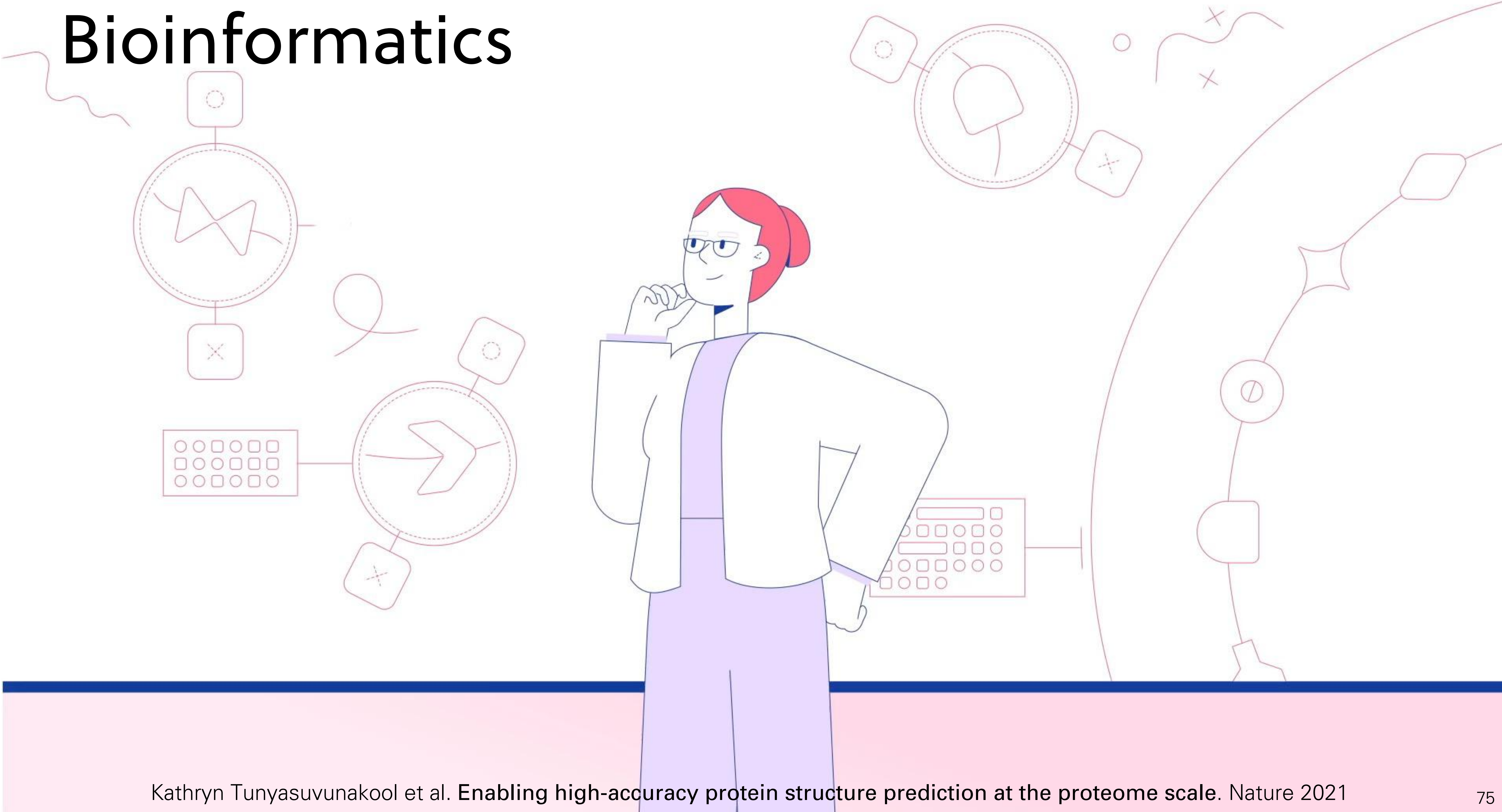
V. Mnih et al., **Human level control through deep reinforcement learning**, Nature 518:529-533, 2015

Strategic Game Playing

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

Silver et al. **Mastering the game of Go with deep neural networks and tree search.** Nature 529, 2016

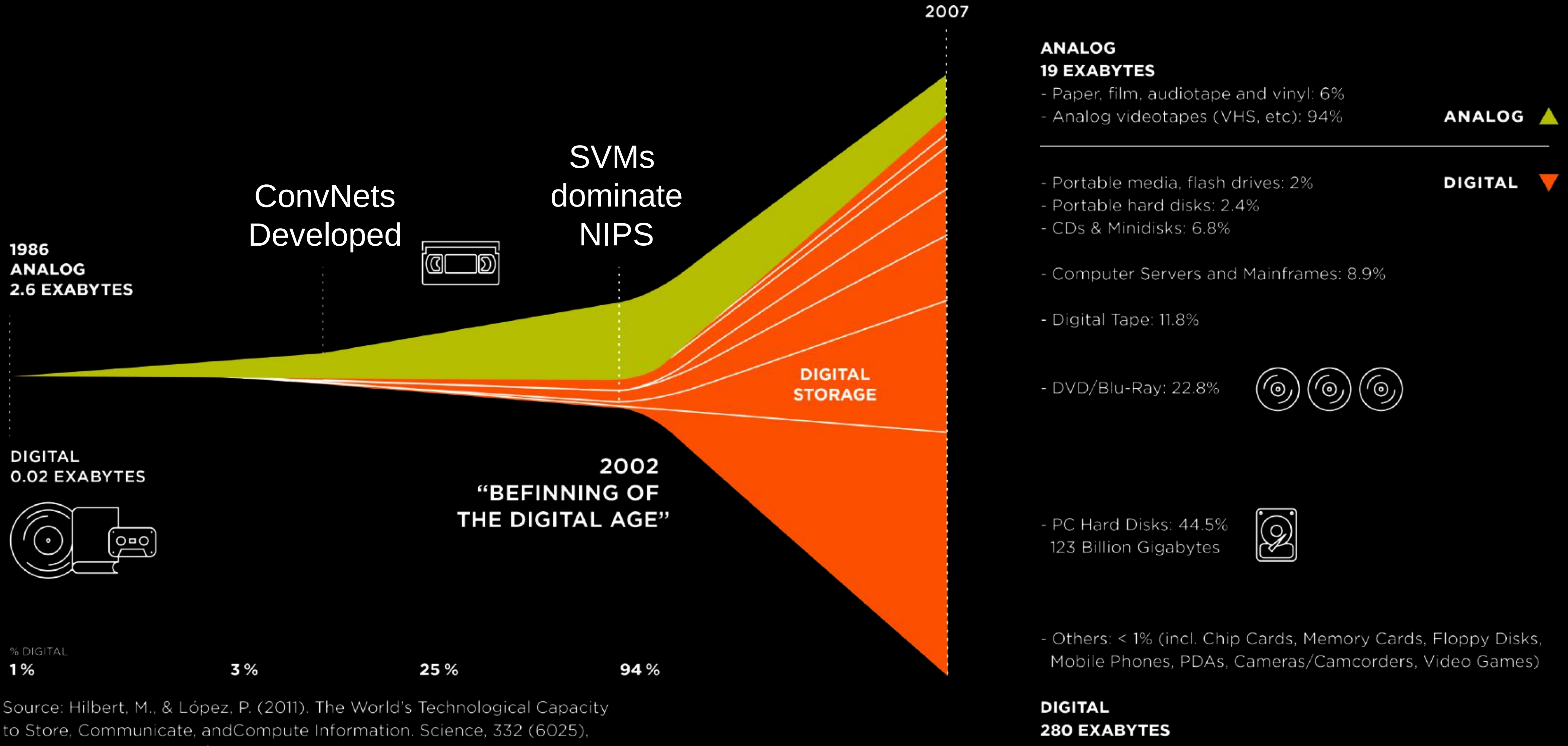
Bioinformatics



Kathryn Tunyasuvunakool et al. **Enabling high-accuracy protein structure prediction at the proteome scale**. Nature 2021

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, andCompute Information. Science, 332 (6025), 60-65. martinhilbert.net/worldinfocapacity.html

Slide credit: Neil Lawrence

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**

Table credit: Quant Quanto

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

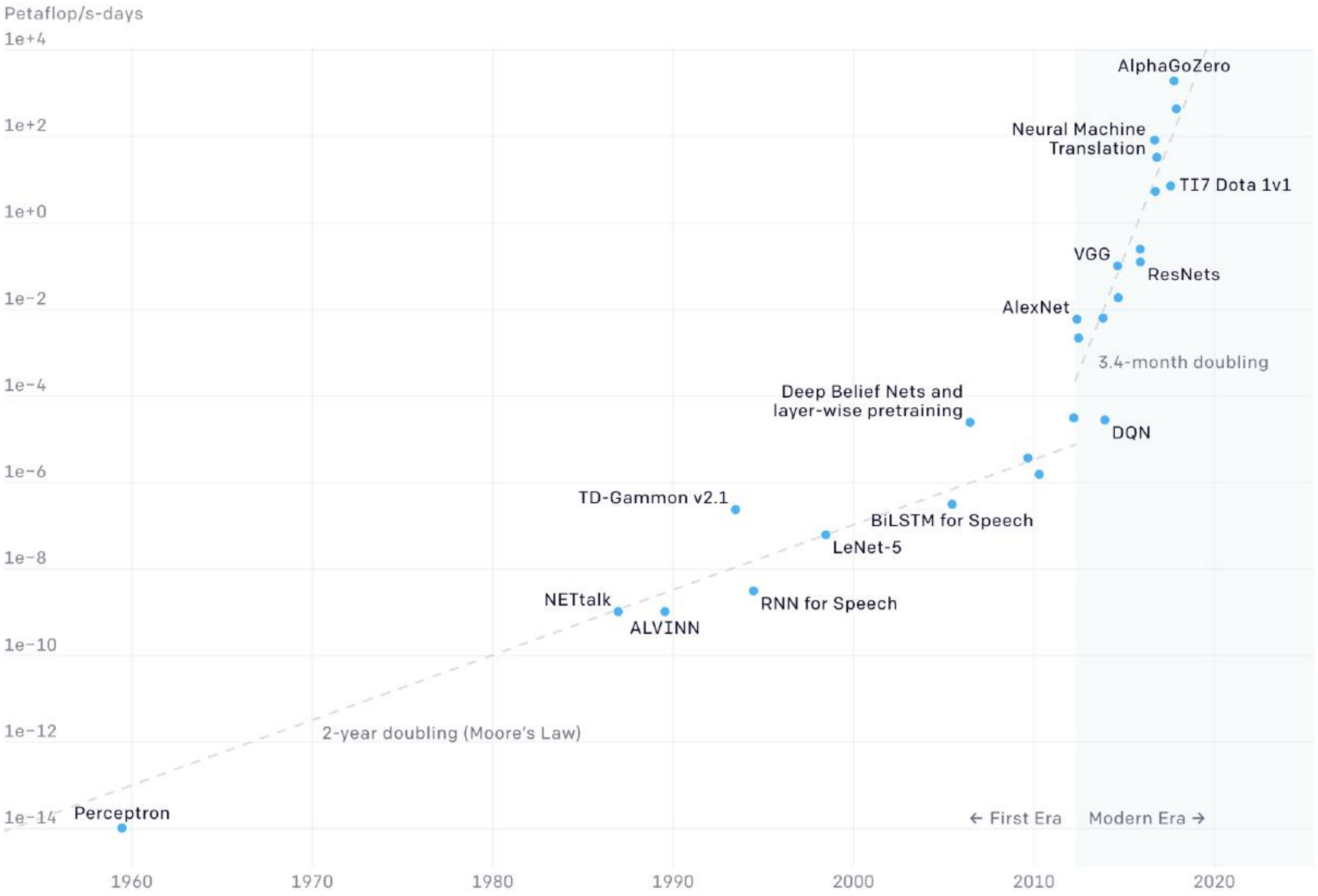
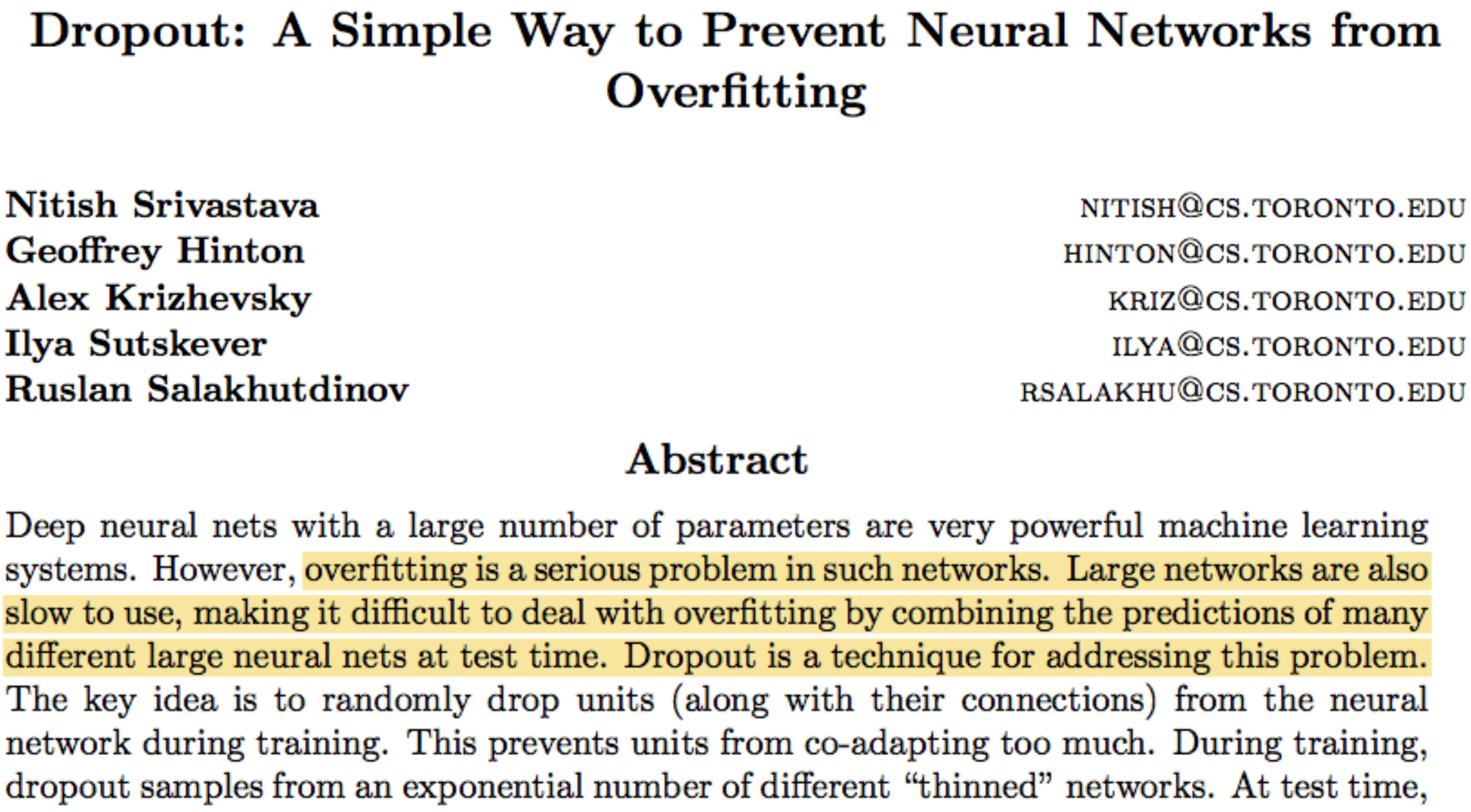


Image: OpenAI

Slide adapted from Rob Fergus

Working ideas on how to train deep architectures



Dropout: A Simple Way to Prevent Neural Networks from Overfitting

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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,

Journal of Machine Learning Research 15 (2014) 1929-1958 Submitted 11/13; Published 6/14

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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

- 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,

Working ideas on how to train deep architectures

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

Sergey Ioffe
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Christian Szegedy
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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 Nor-

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

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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 Θ of the network, so as to minimize the loss

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

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

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

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 Θ_1, Θ_2 are to be learned so as to minimize the loss ℓ. Learning Θ_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

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

(for batch size m and learning rate α) 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 such it is advantageous for the distribution of x to remain fixed over time. Then, Θ_2 does

1

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

S. Ioffe, C. Szegedy, "**Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift**", In ICML 2015

Working ideas on how to train deep architectures

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 unreferenced 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

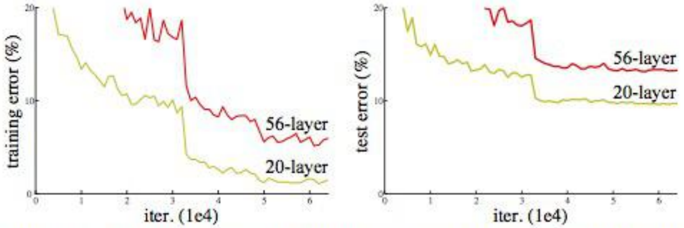

Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

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

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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[1], 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

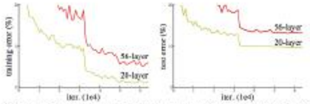


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

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 [1, 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

[1] http://image-net.org/challenges/LSVRC/2015/ and http://mscoco.org/dataset/#detections-challenge2015.

1

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

K. He, X. Zhang, S. Ren, J. Sun, "**Deep Residual Learning for Image Recognition**", In CVPR 2016

Software

TensorFlow

torch

mxnet

theano

Caffe

Caffe2

MatConvNet

The Microsoft Cognitive Toolkit

A free, easy-to-use, open-source, commercial-grade toolkit that trains deep learning algorithms to learn like the human brain.

PYTORCH

So what is deep learning?

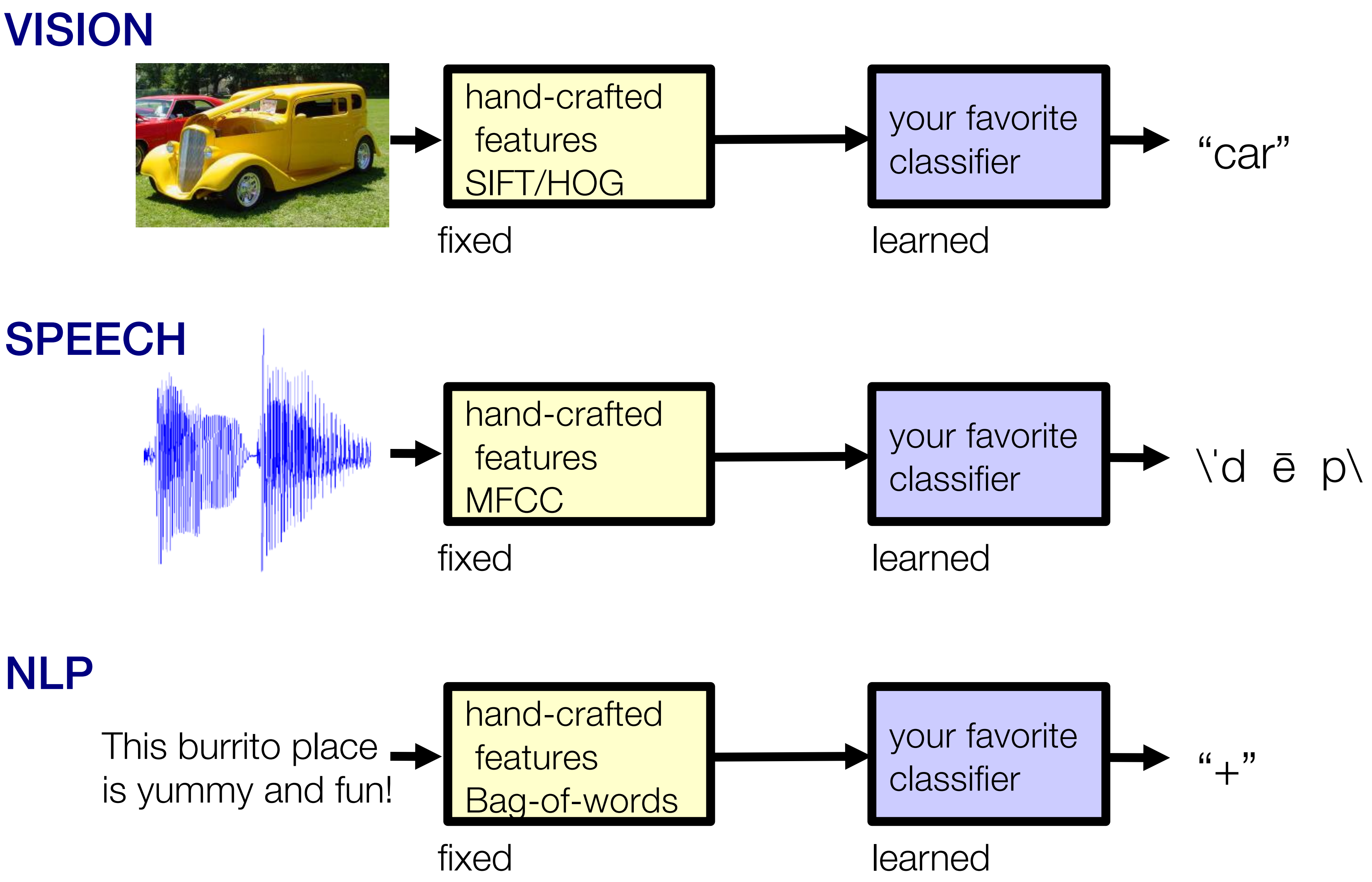
Three key ideas

- (Hierarchical) Compositionality
- End-to-End Learning
- Distributed Representations

Three key ideas

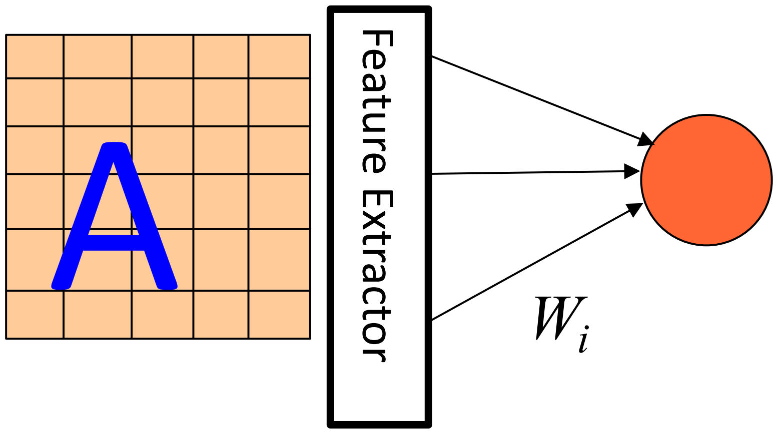
- **(Hierarchical) Compositionality**
  - Cascade of non-linear transformations
  - Multiple layers of representations
- End-to-End Learning
  - Learning (goal-driven) representations
  - Learning to feature extract
- Distributed Representations
  - No single neuron “encodes” everything
  - Groups of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

Traditional Machine Learning

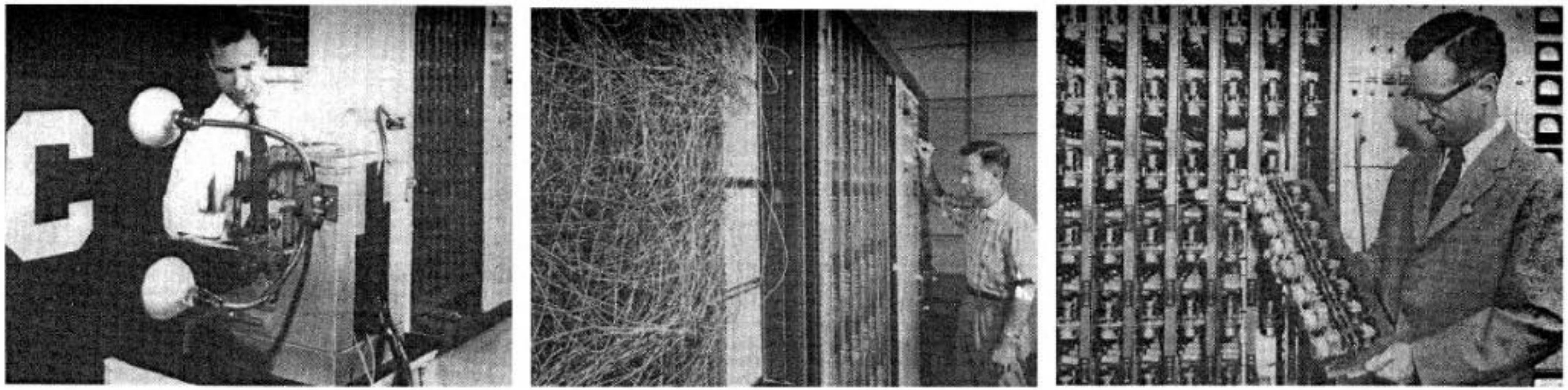


It’s an old paradigm

- 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.



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



slide by Marc'Aurelio Ranzato, Yann LeCun

Hierarchical Compositionality

VISION

pixels → edge → texton → motif → part → object

SPEECH

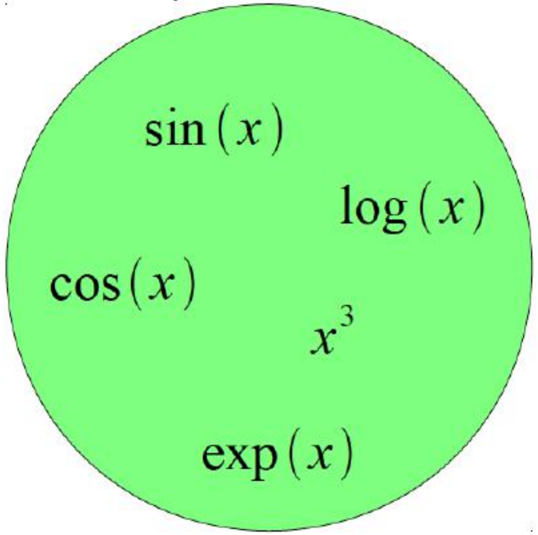
sample → spectral band → formant → motif → phone → word

NLP

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

Building A Complicated Function

Given a library of simple functions

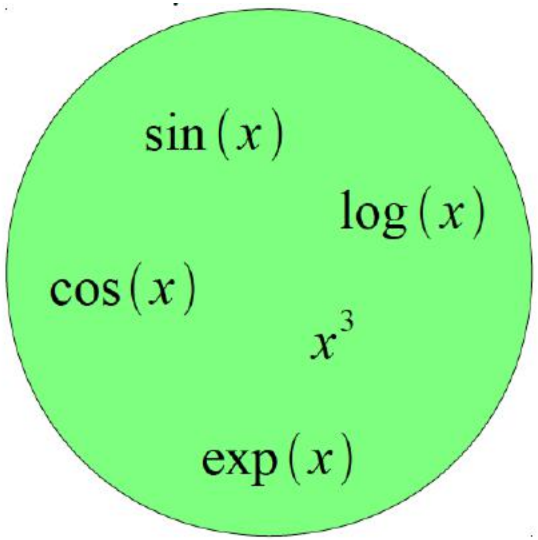


Compose into a

complicate function

Building A Complicated Function

Given a library of simple functions

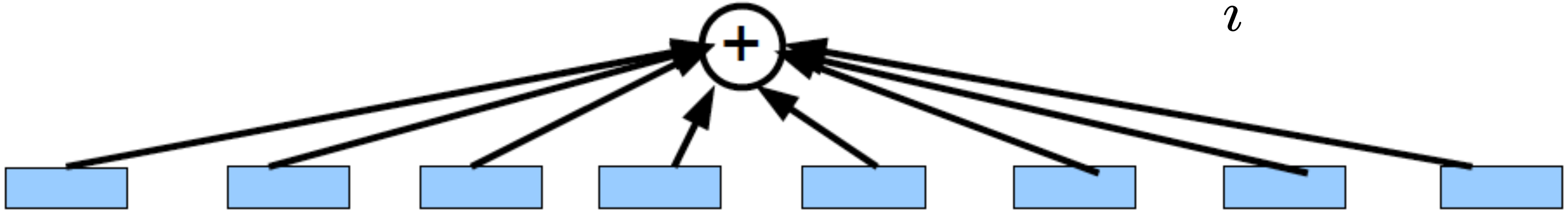


Compose into a complicate function

Idea 1: Linear Combinations

- Boosting
- Kernels
- …

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



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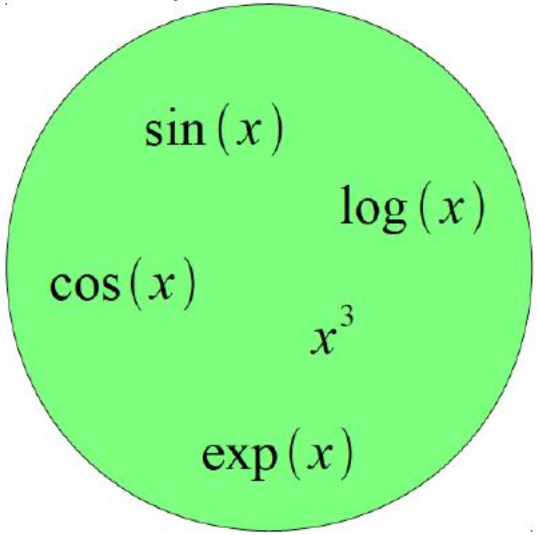
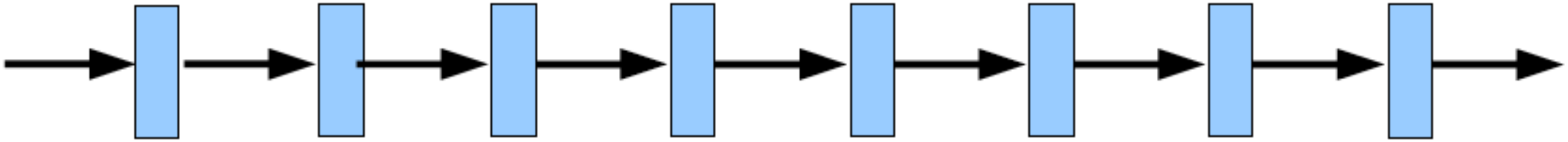


Compose into a complicate function

Idea 2: Compositions

- Deep Learning
- Grammar models
- Scattering transforms…

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



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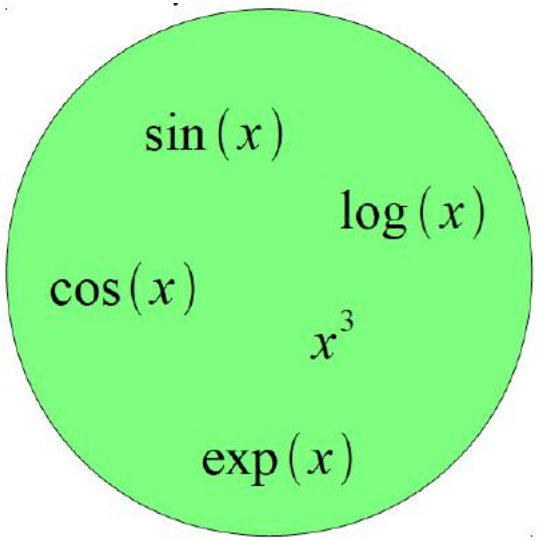
Given a library of simple functions



Compose into a complicate function

Idea 2: Compositions

- Deep Learning
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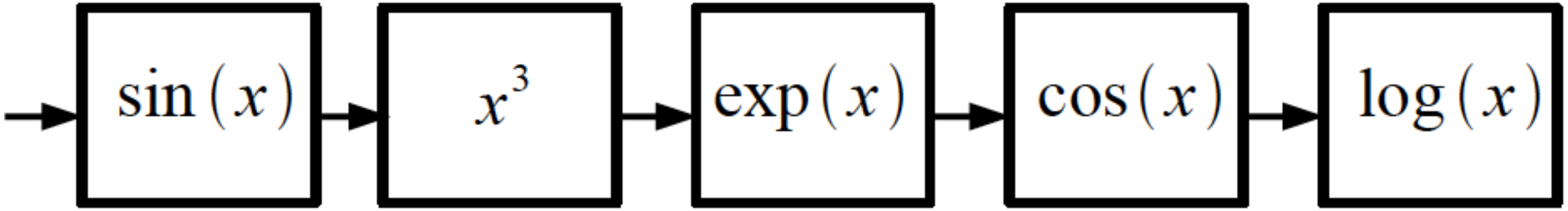
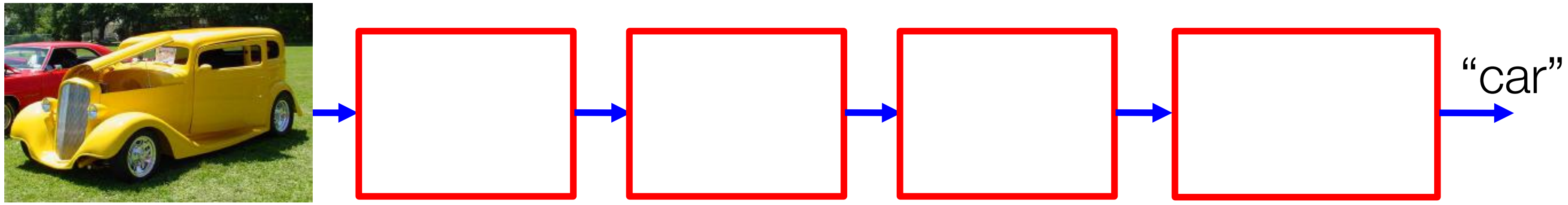
- Scattering transforms…

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



Deep Learning = Hierarchical Compositionality



M.D. Zeiler and R. Fergus, "**Visualizing and Understanding Convolutional Networks**", In ECCV 2014

Deep Learning = Hierarchical Compositionality

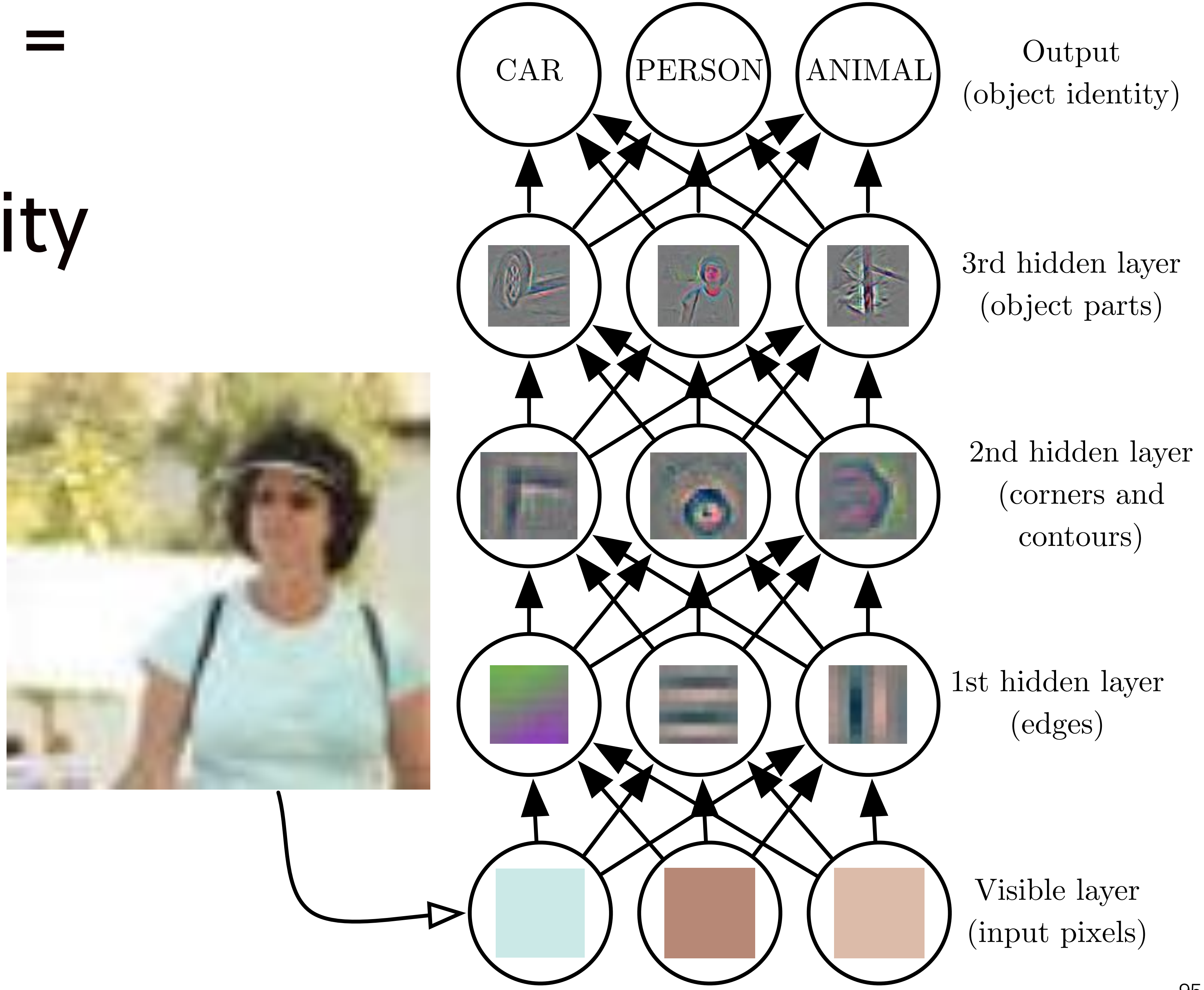
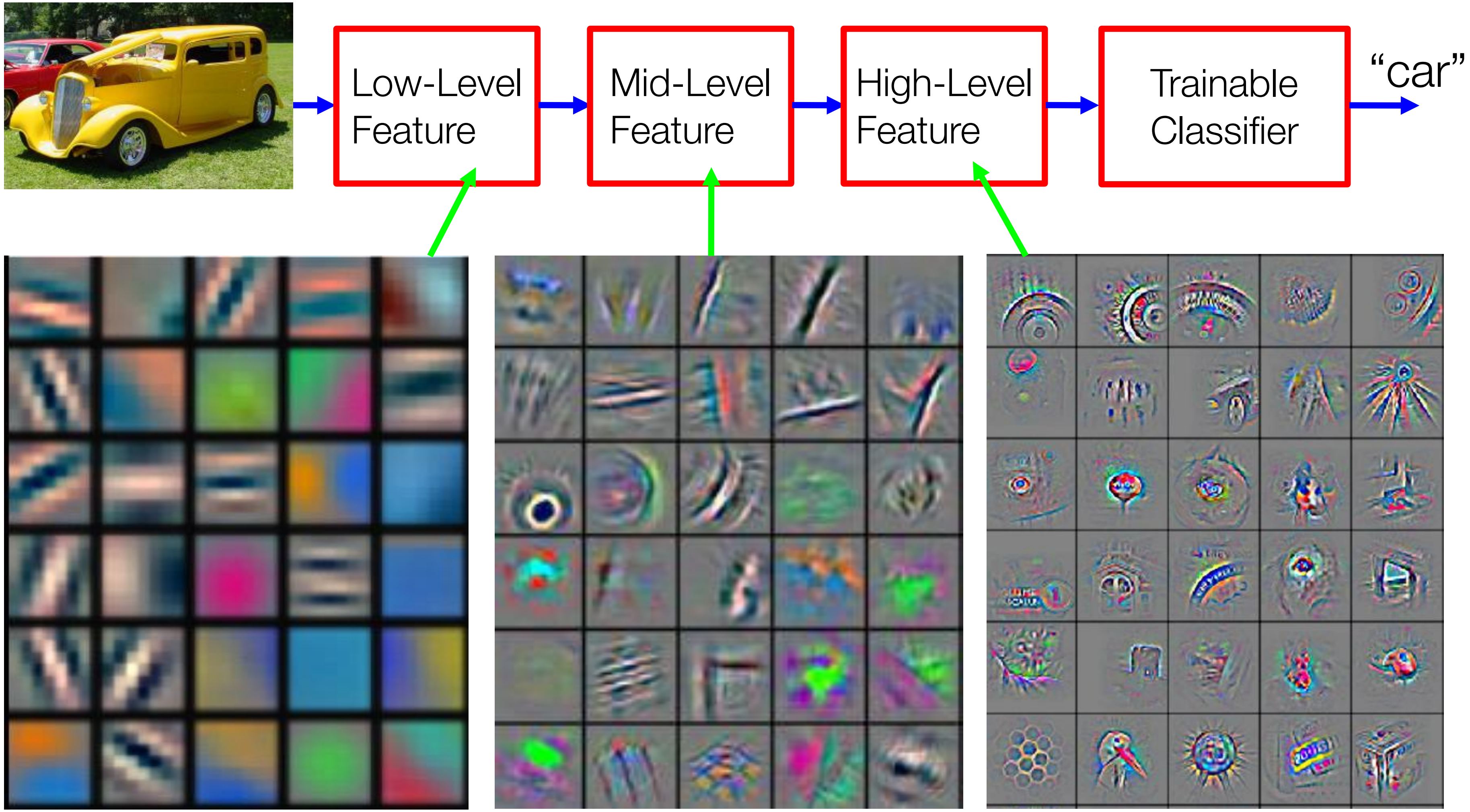


Image credit: Ian Goodfellow

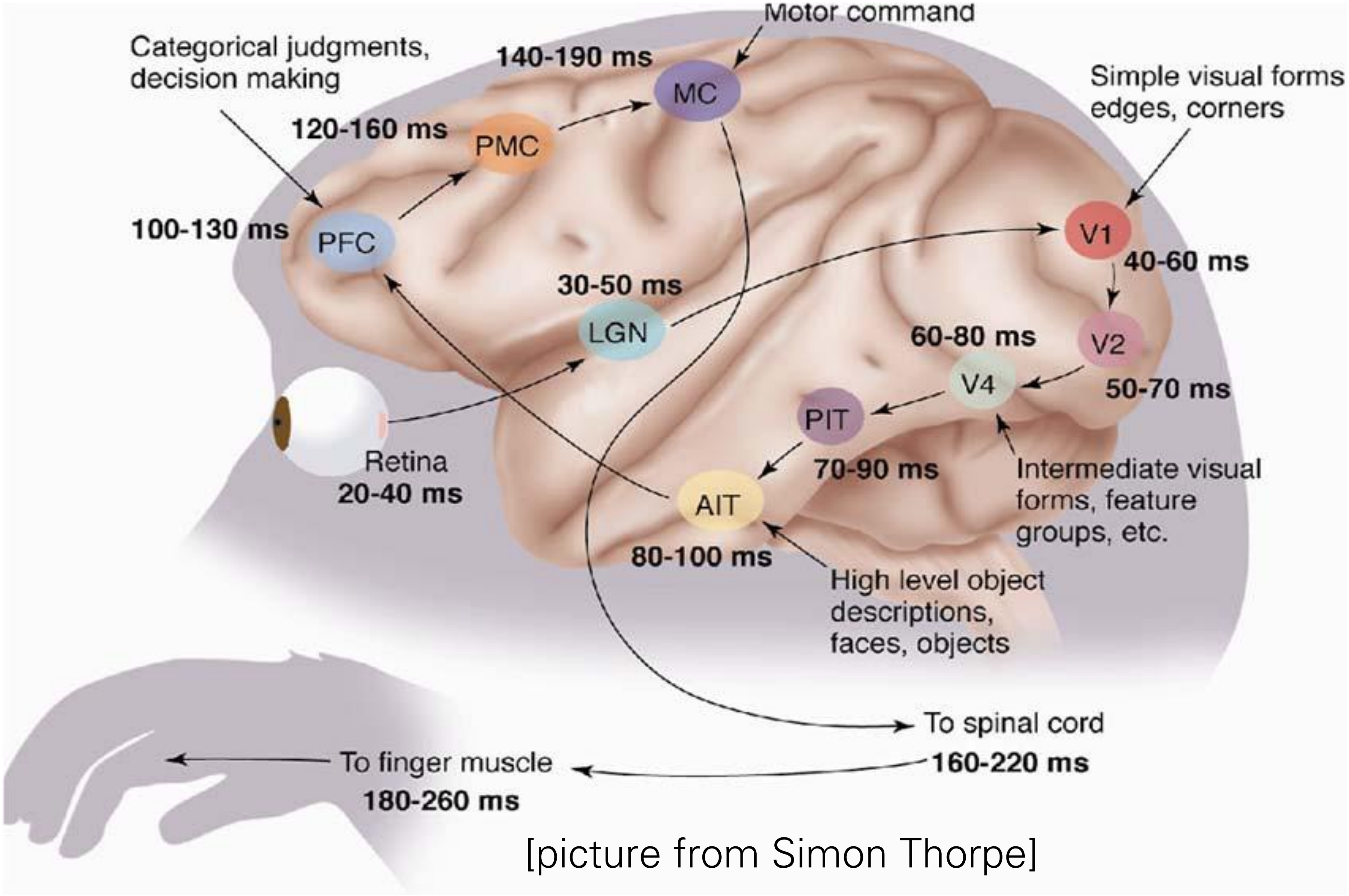
Deep Learning = Hierarchical Compositionality



M.D. Zeiler and R. Fergus, "**Visualizing and Understanding Convolutional Networks**", In ECCV 2014

The Mammalian Visual Cortex is Hierarchical

- The ventral (recognition) pathway in the visual cortex



[picture from Simon Thorpe]

slide by Marc'Aurelio Ranzato, Yann LeCun

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

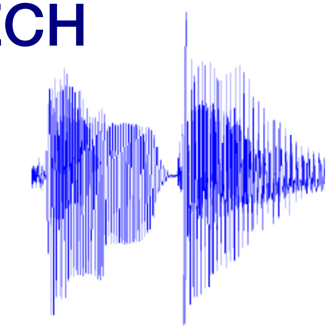
Traditional Machine Learning

VISION

hand-crafted features SIFT/HOG → your favorite classifier → "car"

fixed | learned

SPEECH



hand-crafted features MFCC → your favorite classifier → \'d ē p\

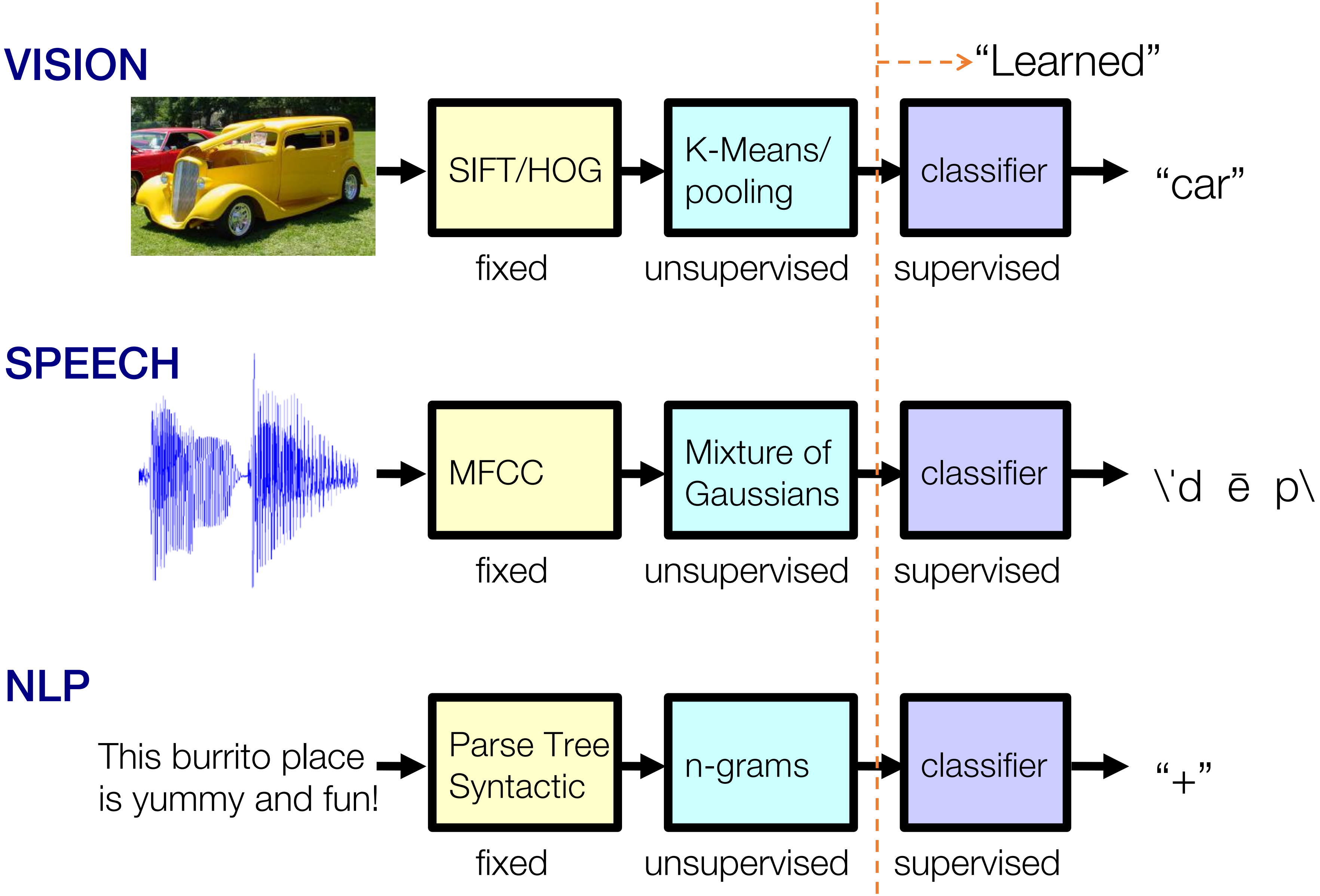
fixed | learned

NLP

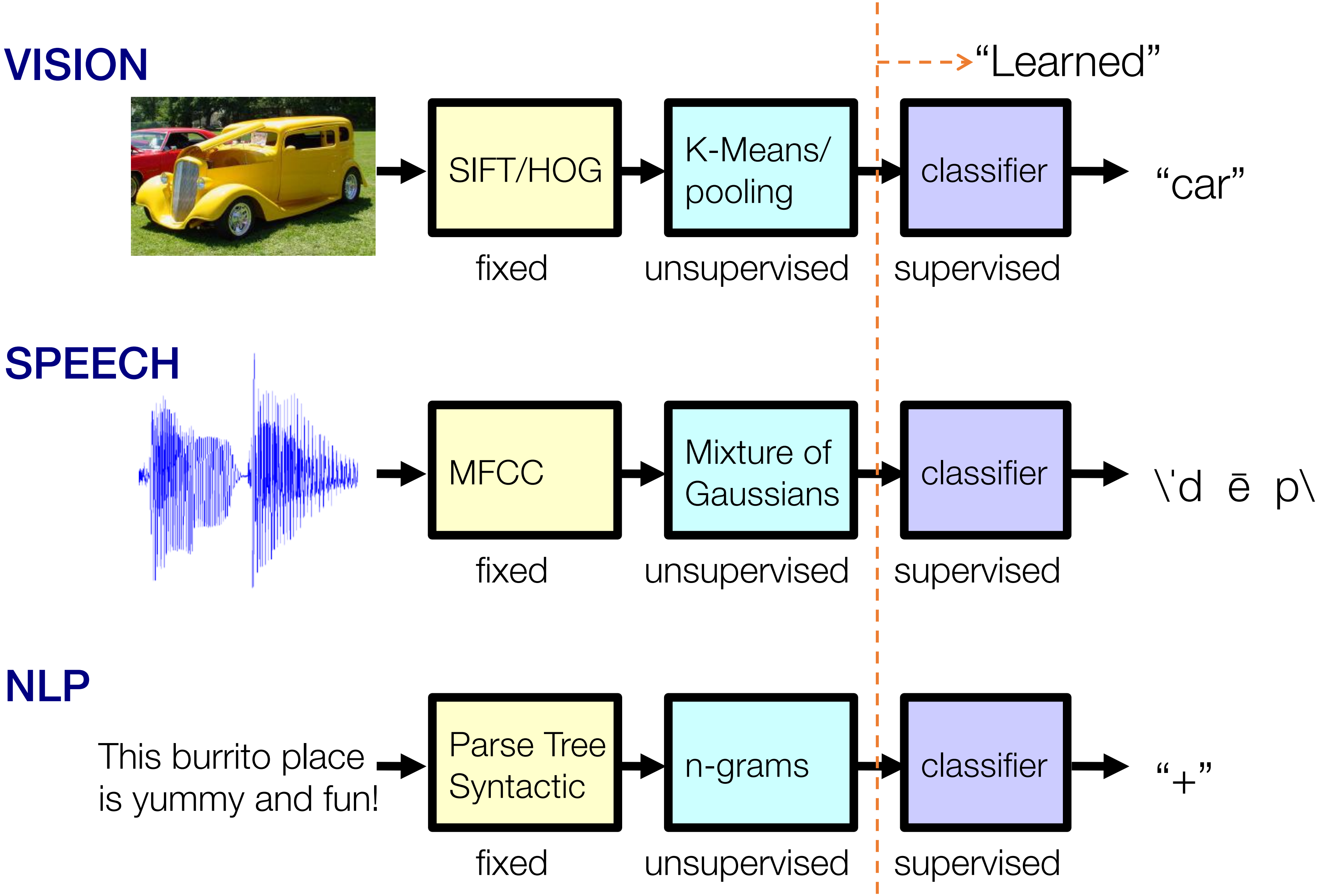
This burrito place is yummy and fun! → hand-crafted features Bag-of-words → your favorite classifier → "+"

fixed | learned

More accurate version

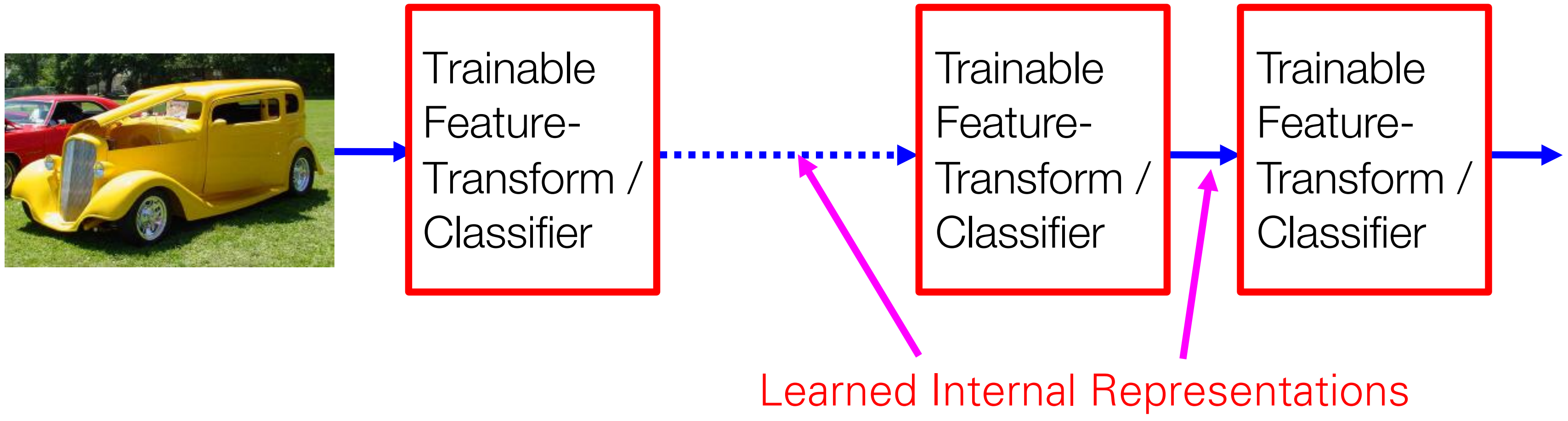


Deep Learning = End-to-End Learning



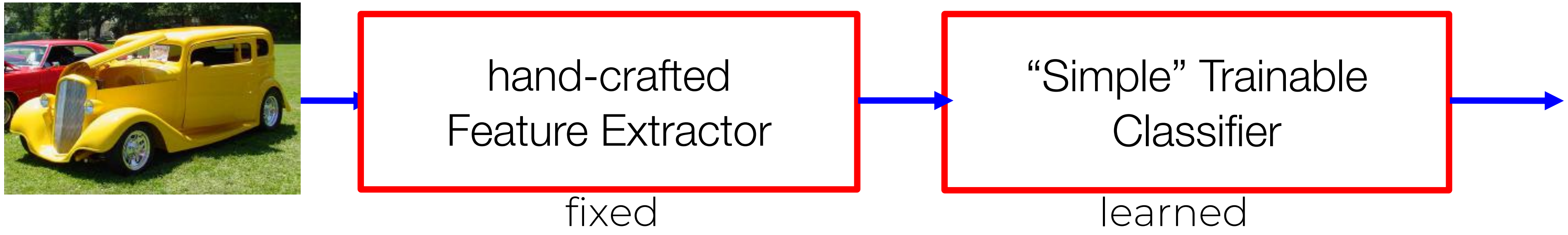
Deep Learning = End-to-End Learning

- 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

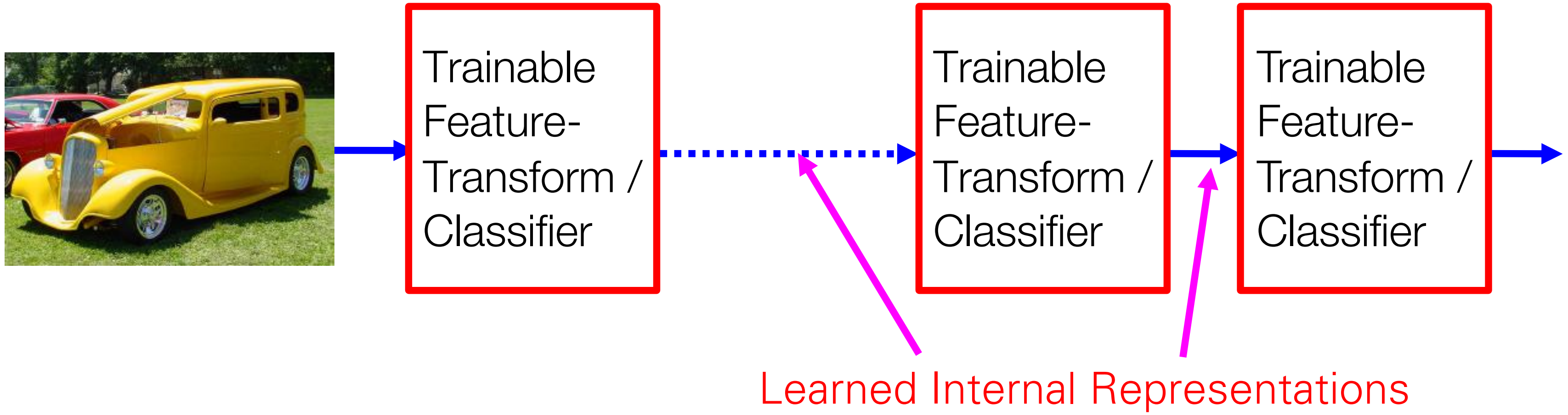


“Shallow” vs Deep Learning

- “Shallow” models



- Deep models



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  - No single neuron "encodes" everything
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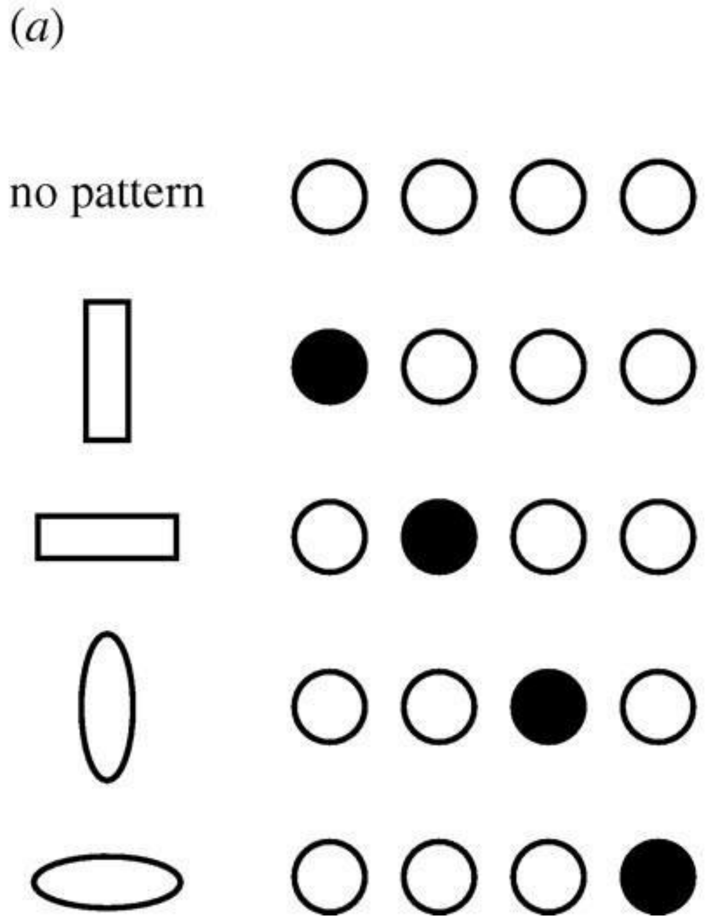
Localist representations

- 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.

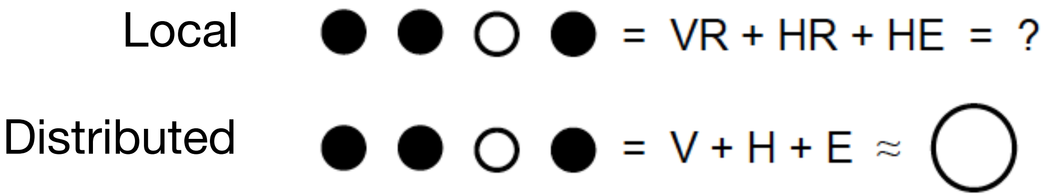


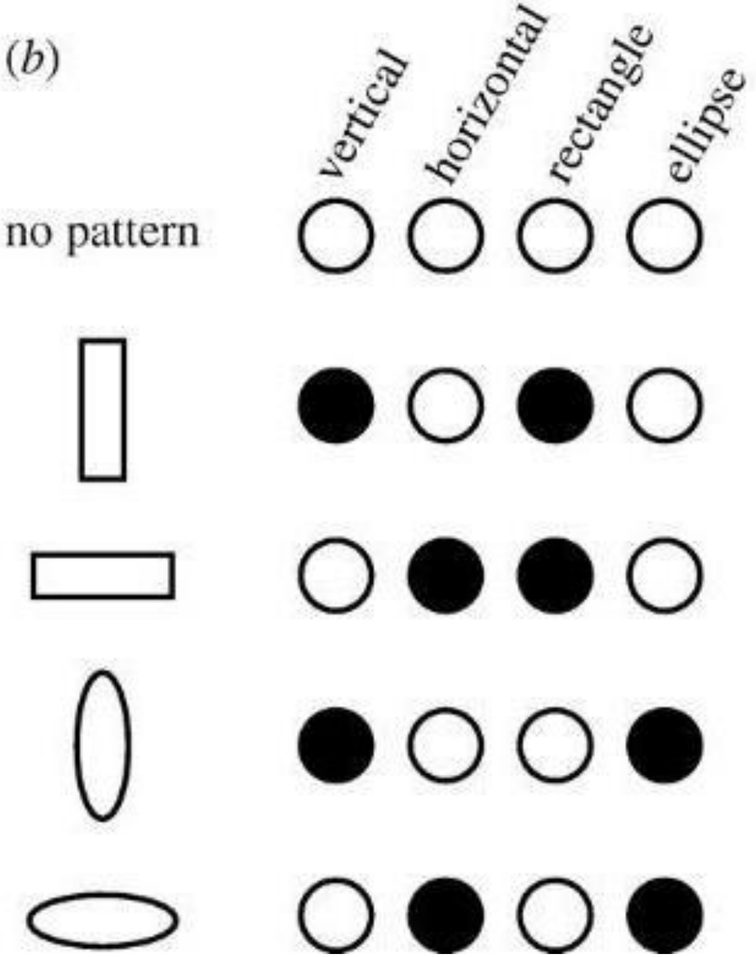
Slide credit: Geoff Hinton

Image credit: Moontae Lee

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





Power of distributed representations!

Scene Classification

- Possible internal representations:
  - Objects
  - Scene attributes
  - Object parts
  - Textures

B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba "**Object Detectors Emerge in Deep Scene CNNs**", ICLR 2015

Slide credit: Bolei Zhou

Three key ideas of deep learning

- **(Hierarchical) Compositionality**
  - Cascade of non-linear transformations
  - Multiple layers of representations

- **End-to-End Learning**
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- **Distributed Representations**
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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

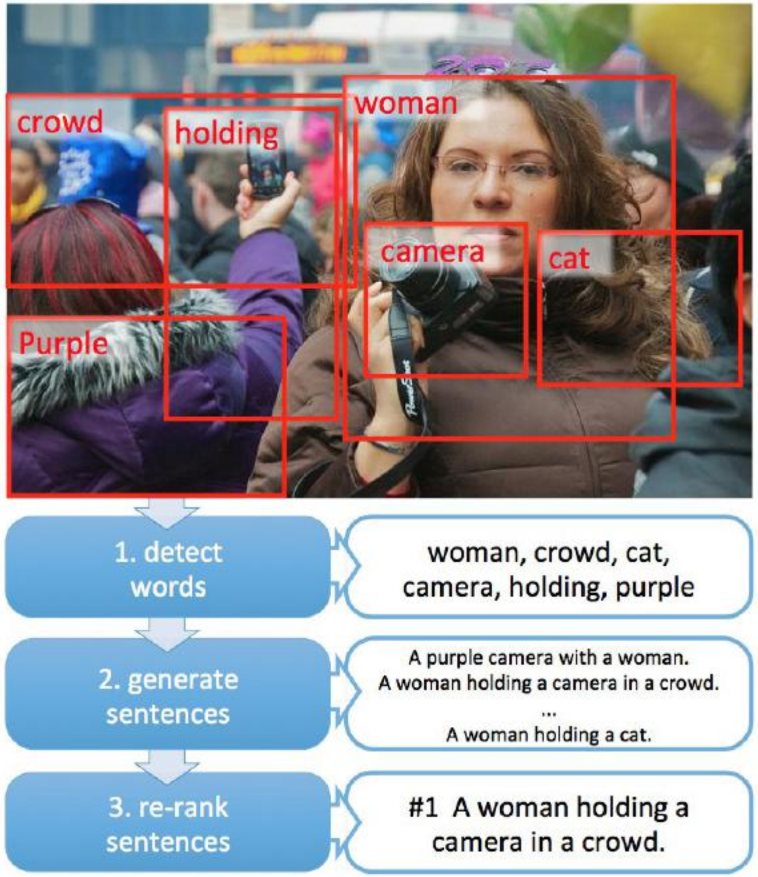
- Standard response #2
  - “Yes, but it often works!”

Problems with Deep Learning

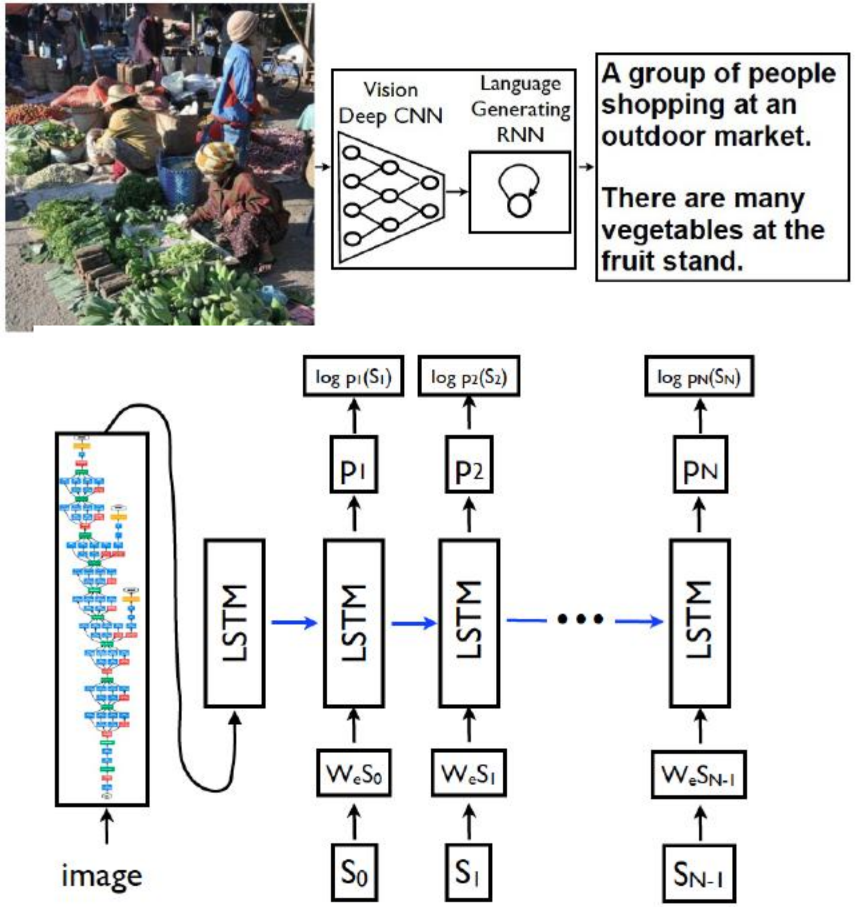
- **Problem#2: Hard to track down what's failing**
  - Pipeline systems have "oracle" performances at each step
  - In end-to-end systems, it's hard to know why things are not working

Problems with Deep Learning

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



[Fang et al. CVPR15]



[Vinyals et al. CVPR15]

Pipeline

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!"

1958 New York Times…

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 beings, Perceptron will make mistakes at first, but will grow wiser as it gains experience, he said.

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

Without Human Controls

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

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

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

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

In today's demonstration, the "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.

The New York Times
Science

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.

SCIENCE

Researchers Announce Advance in Image-Recognition Software

By JOHN MARKOFF NOV. 17, 2014

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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	FOLLOWING	FOLLOWERS	FAVORITES
587	18	746	13

INTERESTING.JPG @INTERESTING_JPG · 10h

a man holding a mirror up to his face .

1

View more photos and videos

Results from @INTERESTING_JPG via http://deeplearning.cs.toronto.edu/i2t

TWEETS	FOLLOWING	FOLLOWERS	FAVORITES
587	18	746	13

INTERESTING.JPG @INTERESTING_JPG · 18h

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

2

View more photos and videos

Results from @INTERESTING_JPG via http://deeplearning.cs.toronto.edu/i2t

TWEETS	FOLLOWING	FOLLOWERS	FAVORITES
587	18	746	13

INTERESTING.JPG @INTERESTING_JPG · Feb 20

a surfboard attached to the top of a car .

8 8

View more photos and videos

Results from @INTERESTING_JPG via http://deeplearning.cs.toronto.edu/i2t

Results from @INTERESTING_JPG via http://deeplearning.cs.toronto.edu/i2t

TWEETS 587 | FOLLOWING 18 | FOLLOWERS 746 | FAVORITES 13

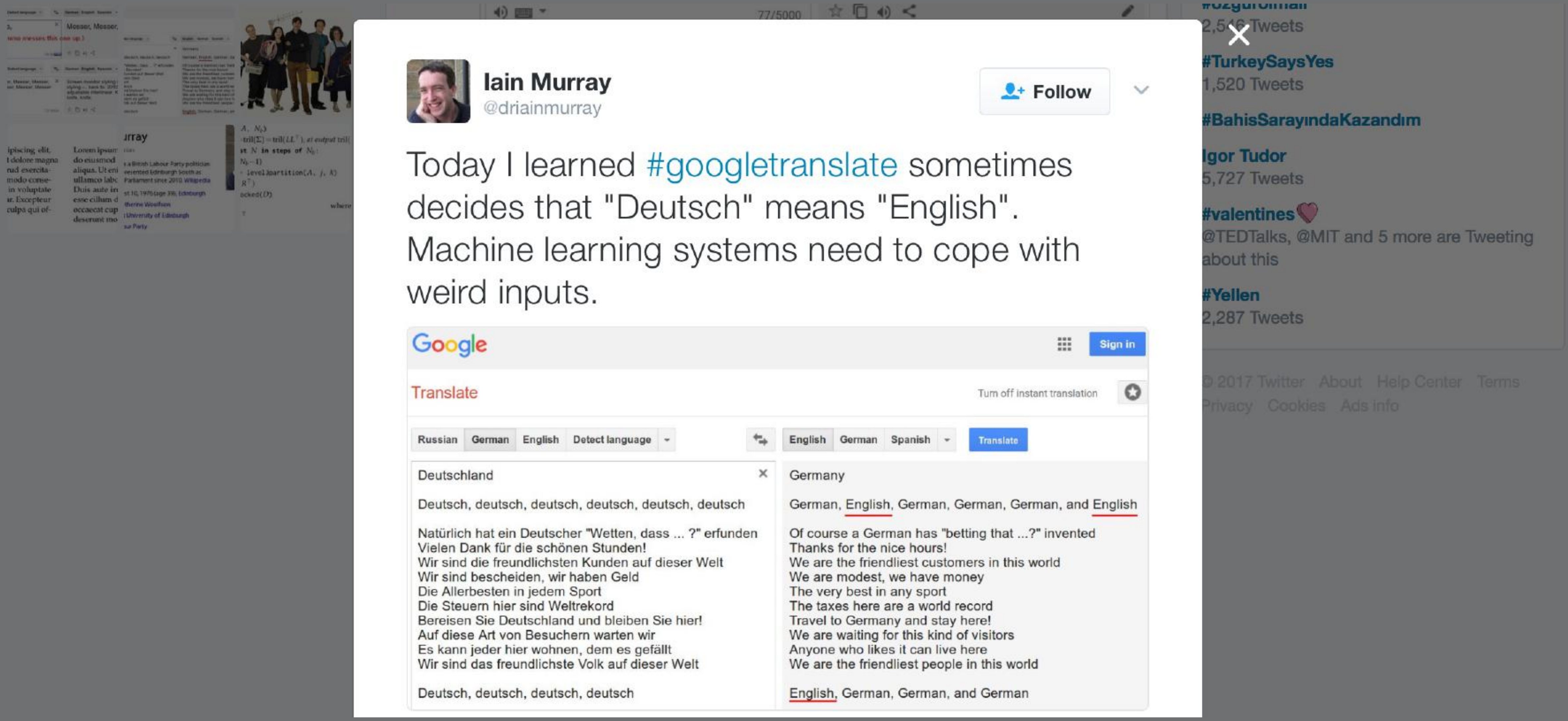
INTERESTING.JPG @INTERESTING_JPG · 16h

this appears to be a small bedroom in the snow .

6

View more photos and videos

Results from @INTERESTING_JPG via http://deeplearning.cs.toronto.edu/i2t


Iain Murray
@driainmurray
Follow
Today I learned #googletranslate sometimes decides that "Deutsch" means "English". Machine learning systems need to cope with weird inputs.
Google
Sign in
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

Iain Murray
@driainmurray

Academic in Machine Learning and Statistics.

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.)

English | German | Spanish | Detect language → German | English | Spanish | Translate

knife, fork, knife, → Messer, Messer, Messer,

(The trailing comma messes this one up.)

19/5000

English | German | Spanish | Detect language → German | English | Spanish | Translate

Messer, Gabel, Messer, Messer, Messer, Messer, Messer, Messer, Messer, Messer → Screen monitor styling Projector styling Print styling ← back to. 2010-01-20 with adjustable interlinear. Knife, fork; knife, knife, knife, knife;

77/5000

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DALL·E 2	Imagen	Parti

Hierarchical Text-Conditional Image Generation with CLIP Latents

Aditya Ramesh* OpenAI aramesh@openai.com
Prafulla Dhariwal* OpenAI prafulla@openai.com
Alex Nichol* OpenAI alex@openai.com
Casey Chu* OpenAI casey@openai.com
Mark Chen OpenAI mark@openai.com

Abstract

Contrastive models like CLIP have been shown to learn robust representations of images that capture both semantics and style. To leverage these representations for image generation, we propose a two-stage model: a prior that generates a CLIP image embedding given a text caption, and a decoder that generates an image conditioned on the image embedding. We show that explicitly generating image representations improves image diversity with minimal loss in photorealism and caption similarity. Our decoders conditioned on image representations can also produce variations of an image that preserve both its semantics and style, while varying the non-essential details absent from the image representation. Moreover, the joint embedding space of CLIP enables language-guided image manipulations in a zero-shot fashion. We use diffusion models for the decoder and experiment with both autoregressive and diffusion models for the prior, finding that the latter are computationally more efficient and produce higher-quality samples.

vibrant portrait painting of Salvador Dalí with a robotic half face | a shiba inu wearing a beret and black turtleneck | a close up of a handpalm with leaves growing from it

an espresso machine that makes coffee from human souls, artstation | panda mad scientist mixing sparkling chemicals, artstation | a corgi's head depicted as an explosion of a nebula

Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding

Chitwan Saharia*, William Chan*, Saurabh Saxena†, Lala Li†, Jay Whang†, Emily Denton, Seyed Kamyar Seyed Ghasemipour, Burcu Karagol Ayan, S. Sara Mahdavi, Rapha Gontijo Lopes, Tim Salimans, Jonathan Ho†, David J Fleet†, Mohammad Norouzi*

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{srbs,lala,jwhang,jonathanho,davidfleet}@google.com

Google Research, Brain Team
Toronto, Ontario, Canada

Sprouts in the shape of text 'Imagen' coming out of a fairytale book. | A photo of a Shiba Inu dog with a backpack riding a bike. It is wearing sunglasses and a beach hat. | A high contrast portrait of a very happy fuzzy panda dressed as a chef in a high end kitchen making dough. There is a painting of flowers on the wall behind him.

Teddy bears swimming at the Olympics 400m Butter-fly event. | A cute corgi lives in a house made out of sushi. | A cute sloth holding a small treasure chest. A bright golden glow is coming from the chest.

A brain riding a rocketship heading towards the moon. | A dragon fruit wearing karate belt in the snow. | A strawberry mug filled with white sesame seeds. The mug is floating in a dark chocolate sea.

Scaling Autoregressive Models for Content-Rich Text-to-Image Generation

Jiahui Yu* Yuanzhong Xu† Jing Yu Koh† Thang Luong† Gunjan Baid† Zirui Wang† Vijay Vasudevan† Alexander Ku† Yinfei Yang Burcu Karagol Ayan Ben Hutchinson Wei Han Zarana Parekh Xin Li Han Zhang Jason Baldridge† Yonghui Wu*

{jiahuiyu, yuanzx, jykoh, thangluong, gunjanbaid, ziruiw, vrv, alexku, jasonbaldridge, yonghui}@google.com§

* Equal contribution. † Core contribution.

Google Research

Parti-350M | Parti-750M | Parti-3B | Parti-20B

A portrait photo of a kangaroo wearing an orange hoodie and blue sunglasses standing on the grass in front of the Sydney Opera House holding a sign on the chest that says Welcome Friends!

A green sign that says "Very Deep Learning" and is at the edge of the Grand Canyon. Puffy white clouds are in the sky.

A blue Porsche 356 parked in front of a yellow brick wall.

Stable Diffusion

High-Resolution Image Synthesis with Latent Diffusion Models

Robin Rombach[1] * Andreas Blattmann[1] * Dominik Lorenz[1] Patrick Esser[R] Björn Ommer[1]
[1]Ludwig Maximilian University of Munich & IWR, Heidelberg University, Germany [R]Runway ML
https://github.com/CompVis/latent-diffusion

Abstract

By decomposing the image formation process into a sequential application of denoising autoencoders, diffusion models (DMs) achieve state-of-the-art synthesis results on image data and beyond. Additionally, their formulation allows for a guiding mechanism to control the image generation process without retraining. However, since these models typically operate directly in pixel space, optimization of powerful DMs often consumes hundreds of GPU days and inference is expensive due to sequential evaluations. To enable DM training on limited computational resources while retaining their quality and flexibility, we apply them in the latent space of powerful pretrained autoencoders. In contrast to previous work, training diffusion models on such a representation allows for the first time to reach a near-optimal point between complexity reduction and detail preservation, greatly boosting visual fidelity. By introducing cross-attention layers into the model architecture, we turn diffusion models into powerful and flexible generators for general conditioning inputs such as text or bounding boxes and high-resolution synthesis becomes possible in a convolutional manner. Our latent diffusion models (LDMs) achieve new state of the art scores for image inpainting and class-conditional image synthesis and highly competitive performance on various tasks, including unconditional image generation, text-to-image synthesis, and super-resolution, while significantly reducing computational requirements compared to pixel-based DMs.

1. Introduction

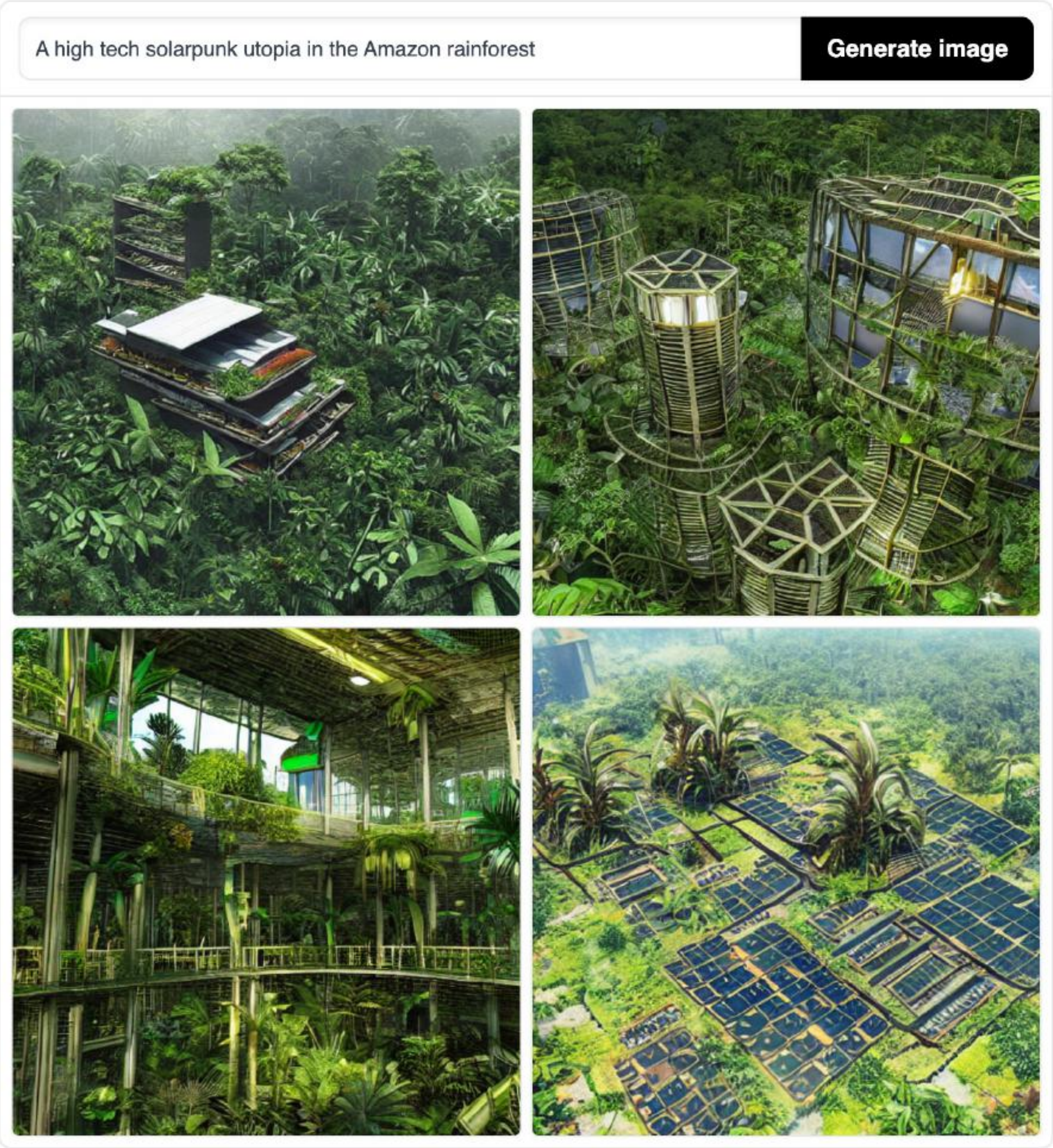
Image synthesis is one of the computer vision fields with the most spectacular recent development, but also among those with the greatest computational demands. Especially high-resolution synthesis of complex, natural scenes is presently dominated by scaling up likelihood-based models, potentially containing billions of parameters in autoregressive (AR) transformers [64, 65]. In contrast, the promising results of GANs [3, 26, 39] have been revealed to be mostly confined to data with comparably limited variability as their adversarial learning procedure does not easily scale to modeling complex, multi-modal distributions. Recently, diffusion models [79], which are built from a hierarchy of denoising autoencoders, have shown to achieve impressive

*The first two authors contributed equally to this work.

Figure 1. Boosting the upper bound on achievable quality with less agressive downsampling. Since diffusion models offer excellent inductive biases for spatial data, we do not need the heavy spatial downsampling of related generative models in latent space, but can still greatly reduce the dimensionality of the data via suitable autoencoding models, see Sec. 3. Images are from the DIV2K [1] validation set, evaluated at 512^2 px. We denote the spatial downsampling factor by f. Reconstruction FIDs [28] and PSNR are calculated on ImageNet-val. [12]; see also Tab. 8.

results in image synthesis [29, 82] and beyond [7, 44, 47, 56], and define the state-of-the-art in class-conditional image synthesis [15, 30] and super-resolution [70]. Moreover, even unconditional DMs can readily be applied to tasks such as inpainting and colorization [82] or stroke-based synthesis [52], in contrast to other types of generative models [19, 45, 67]. Being likelihood-based models, they do not exhibit mode-collapse and training instabilities as GANs and, by heavily exploiting parameter sharing, they can model highly complex distributions of natural images without involving billions of parameters as in AR models [65].

Democratizing High-Resolution Image Synthesis DMs belong to the class of likelihood-based models, whose mode-covering behavior makes them prone to spend excessive amounts of capacity (and thus compute resources) on modeling imperceptible details of the data [16, 71]. Although the reweighted variational objective [29] aims to address this by undersampling the initial denoising steps, DMs are still computationally demanding, since training and evaluating such a model requires repeated function evaluations (and gradient computations) in the high-dimensional space of RGB images. As an example, training the most powerful DMs often takes hundreds of GPU days (*e.g.* 150 - 1000 V100 days in [15]) and repeated evaluations on a noisy version of the input space render also inference expensive,



Stable Diffusion

High-Resolution Image Synthesis with Latent Diffusion Models

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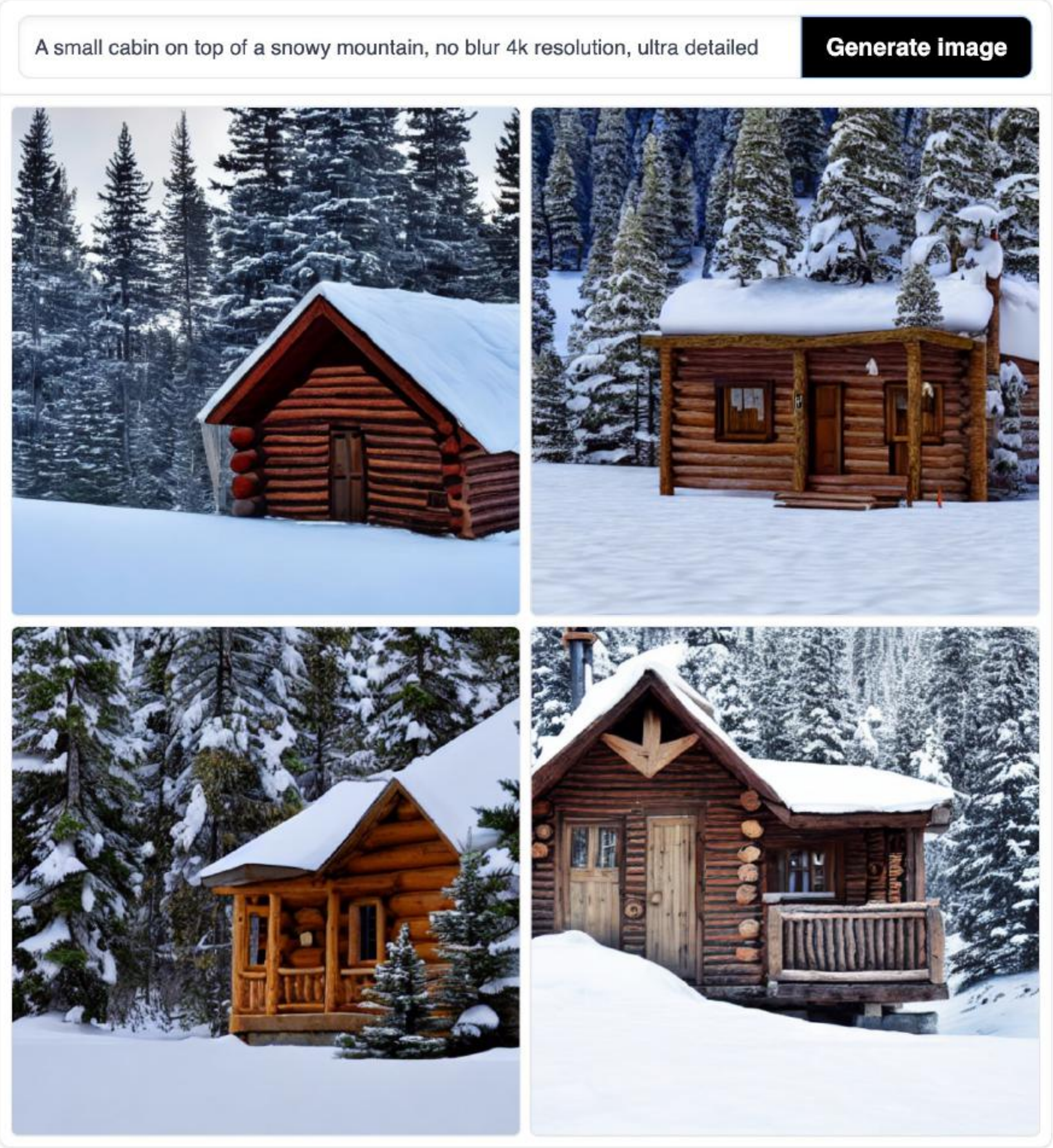


Tomer Ullman
@TomerUllman

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

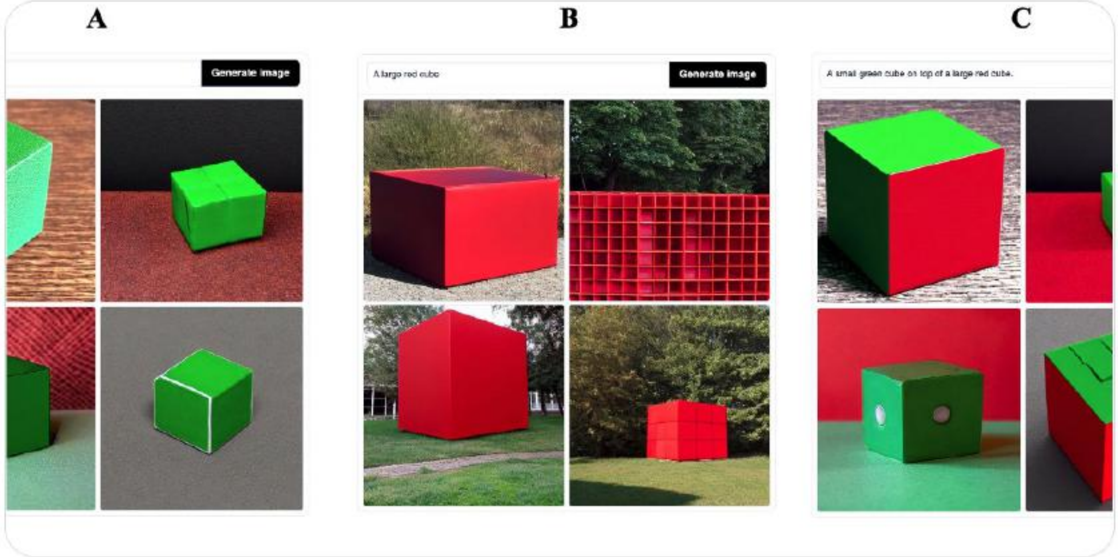

"A spoon in a cup"
"A cup on a spoon"

Melanie Mitchell
@MelMitchell1

Prepositions are hard.

Stable diffusion demo (huggingface.co/spaces/stabili…)

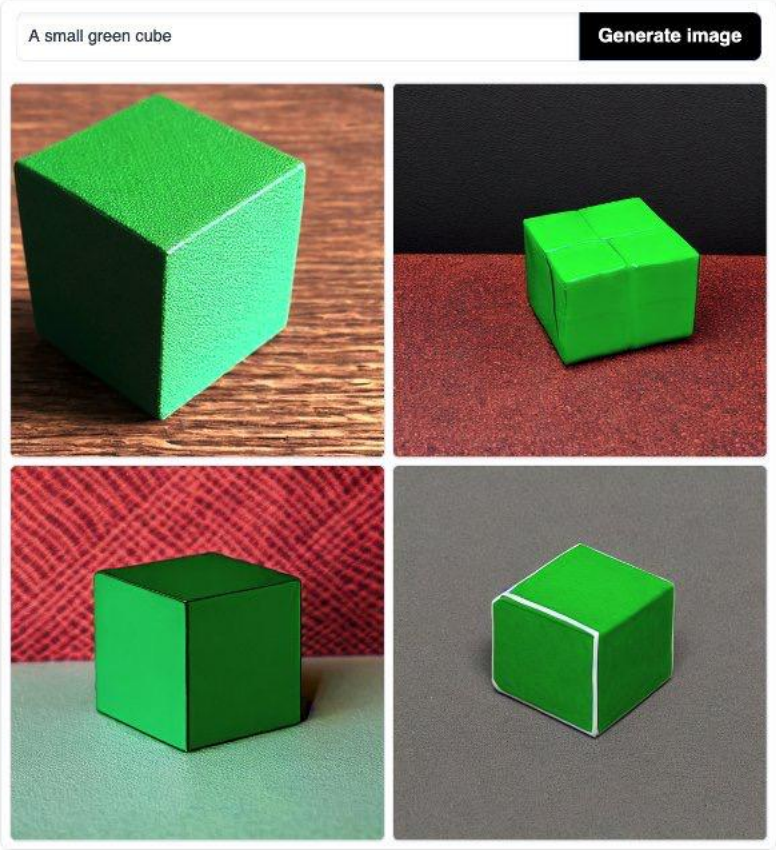
Prompt A: A small green cube
Prompt B: A large red cube
Prompt C: A small green cube on top of a large red cube



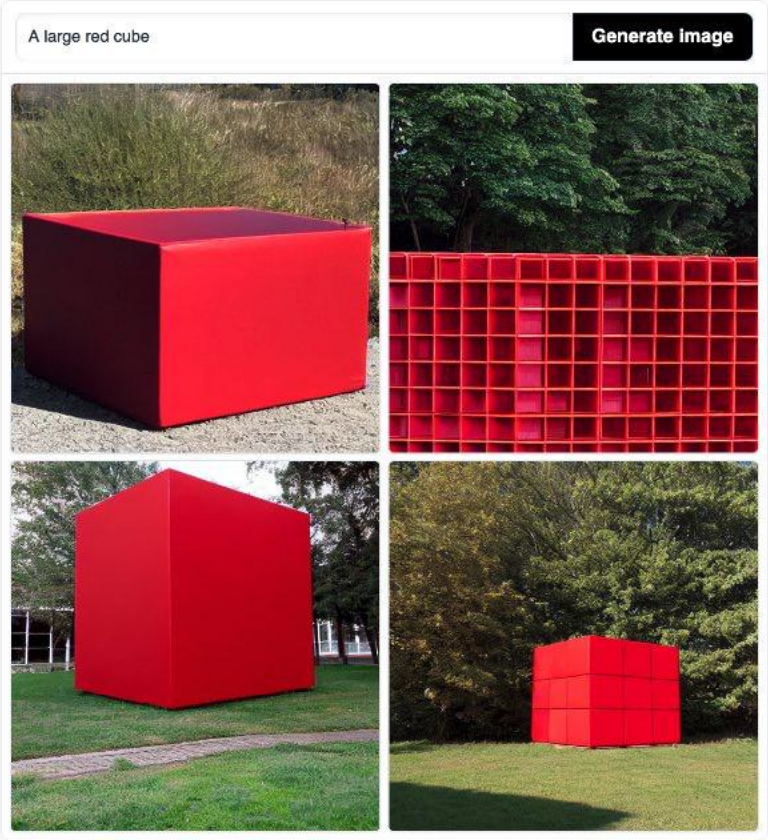
6:10 PM · Aug 23, 2022 · Twitter Web App

Melanie Mitchell
@MelMitchell1

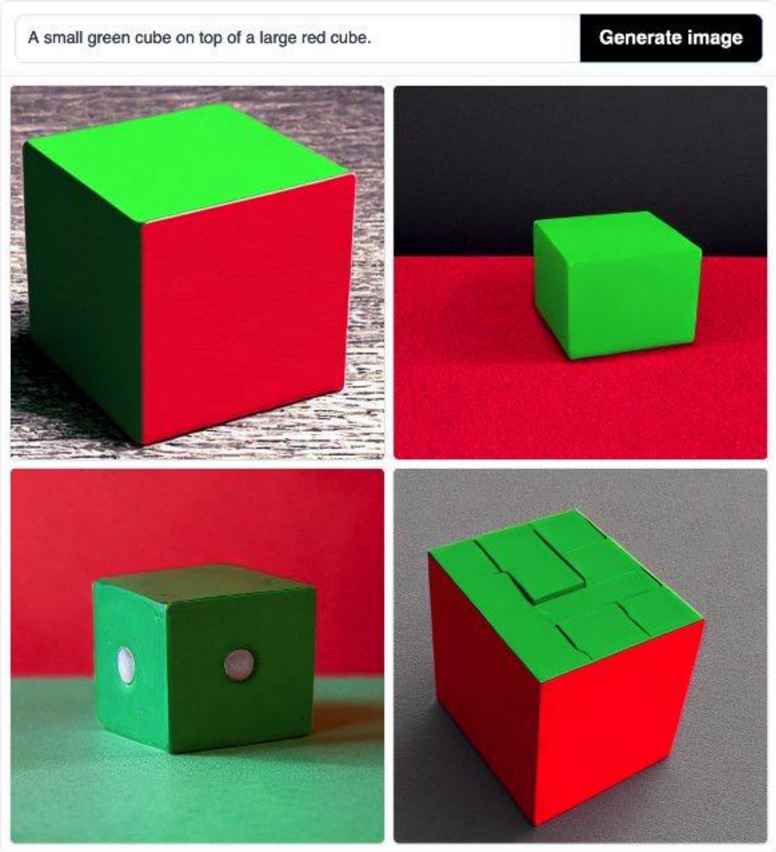
A



B



C



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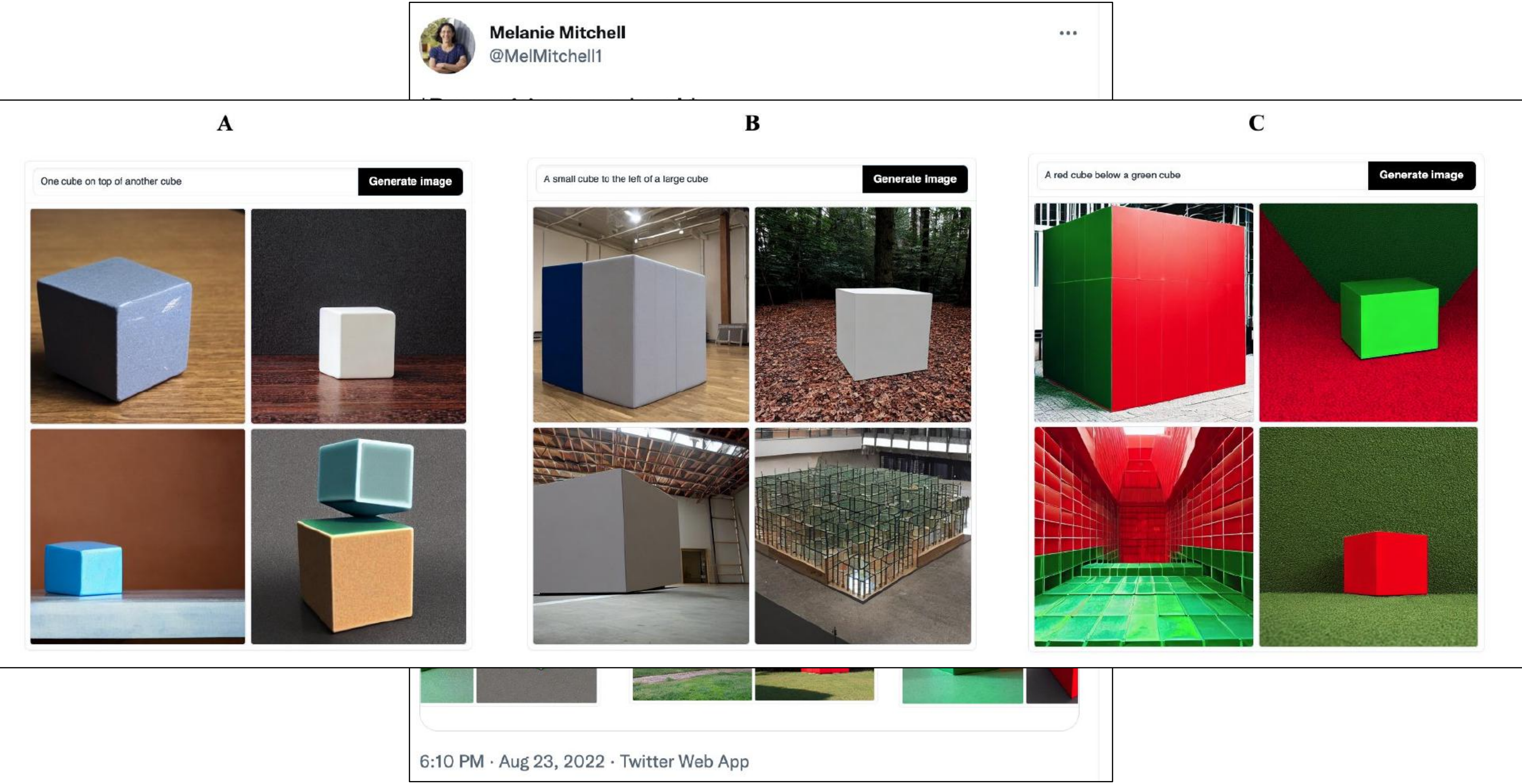
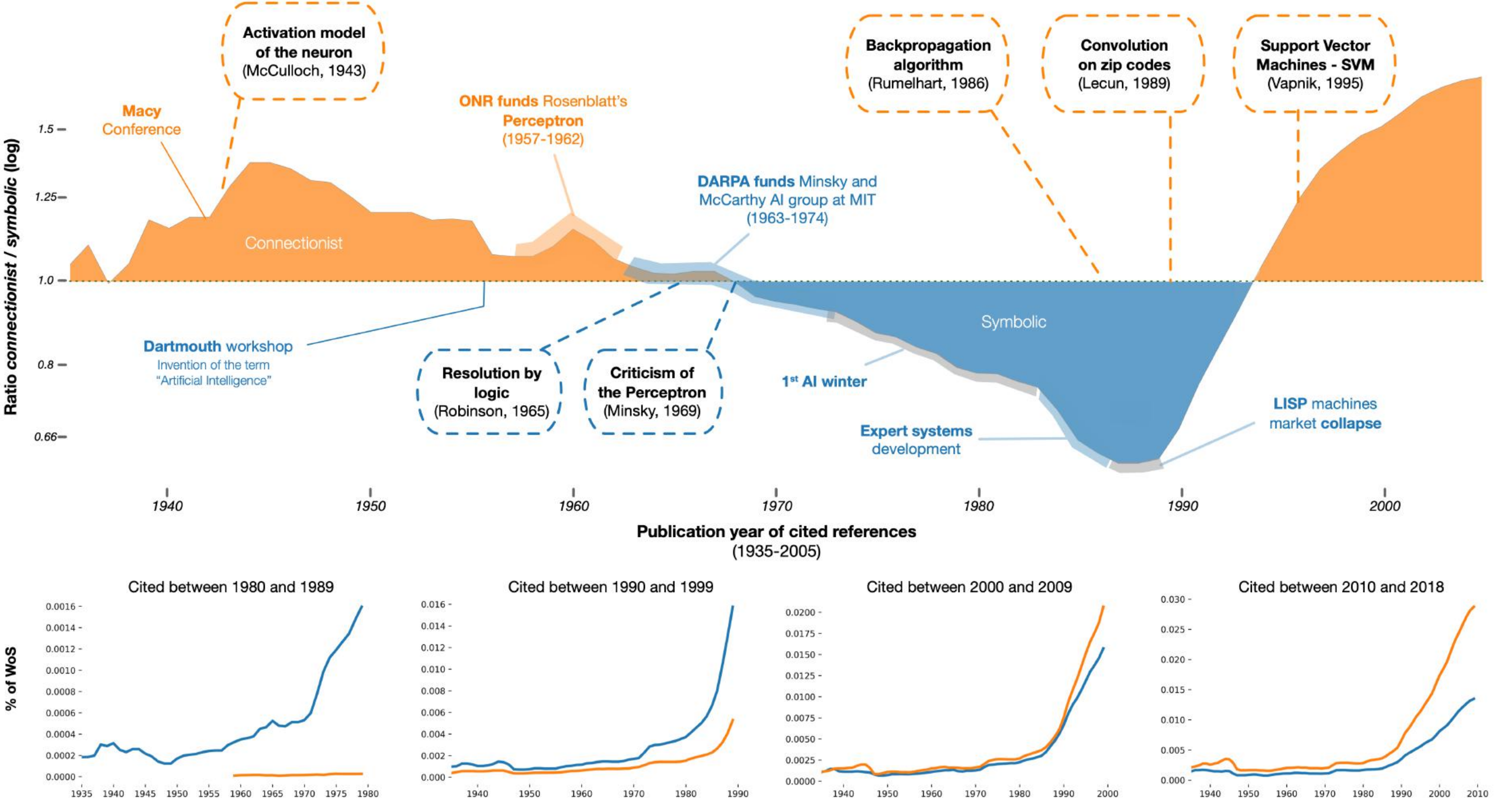


Melanie Mitchell
@MelMitchell1
A
One cube on top of another cube
Generate image
B
A small cube to the left of a large cube
Generate image
C
A red cube below a green cube
Generate image
6:10 PM · Aug 23, 2022 · Twitter Web App



D. Cardon et al. "**Neurons spike back: The Invention of Inductive Machines and the AI Controversy**", Réseaux n°211/2018

AI DEBATE : YOSHUA BENGIO | GARY MARCUS

Gary Marcus

—

Yoshua Bengio

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

Montréal.AI

Next Lecture:
Machine Learning Overview