



Deep Learning

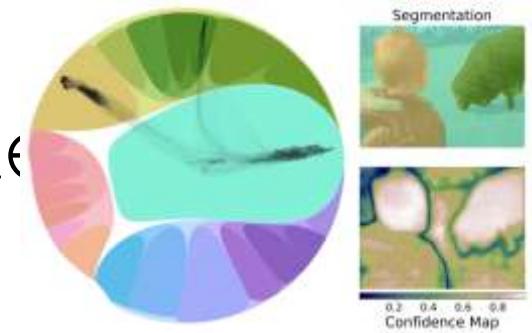
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2025-2026 – Pascal Mettes

Lecture 1

Introduction and history of deep learning

A warm welcome from me

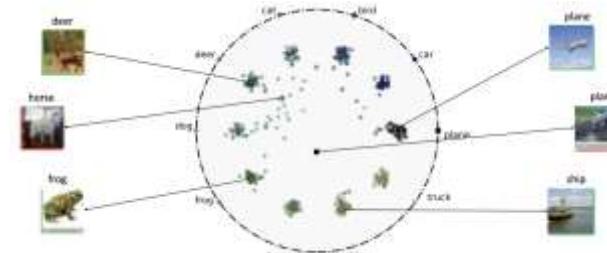


About me

Assistant Professor at *University of Amsterdam*

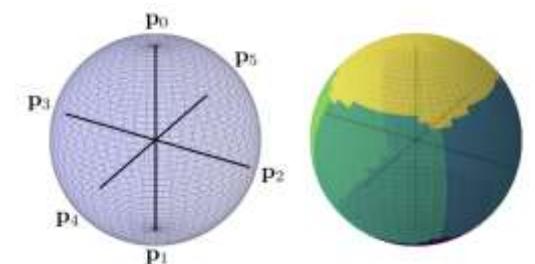
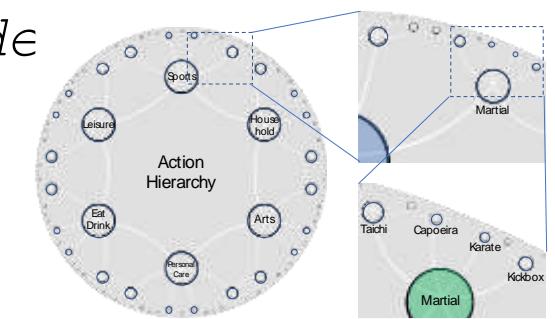
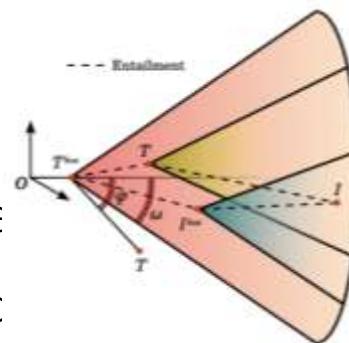
PI of *HypLab* (*Hyperbolic Deep Learning Lab*)

Scientific manager of *HAVA Lab* (*Human Aligned Video*)



Our research mission

We question the geometric foundation of deep learning and we are leading a new direction of deep learning in hyperbolic spaces.



A warm welcome from our team



What is the course about?

Lecture	Title	Lecture	Title
1	Intro and history of deep learning	2	AutoDiff
3	Deep learning optimization I	4	Deep learning optimization II
5	Convolutional deep learning	6	Attention-based deep learning
7	Graph deep learning	8	From supervised to unsupervised deep learning
9	Multi-modal deep learning	10	Generative deep learning
11	What doesn't work in deep learning	12	Non-Euclidean deep learning
13	Q&A	14	Deep learning for videos

My goals with this course

Provide an intuitive foundation for understanding deep learning.

Challenge you to dive into the topic and learning by interacting and doing.

Give you the best starting point for following courses and the thesis.

Look at deep learning critically and understand what works and what doesn't.

Prerequisites

Machine Learning 1

Calculus and Linear Algebra

- Derivatives, integrals
- Matrix operations
- Computing lower bounds, limits

Some Probability Theory and Statistics

Advanced programming

Reading materials

Textbooks (most available online)

- Deep Learning by I. Goodfellow, Y. Bengio, A. Courville, 2016
- Dive Into Deep Learning, by A. Zhang, Z. Lipton, M. Li, A. Smola, 2019
- Neural Networks and Deep Learning: A Textbook, by C. Aggarwal, 2018
- <https://udlbook.github.io/udlbook/> Understanding Deep Learning S.J.D. Prince 2022

Papers mentioned in the slides

At the end of each lecture, I list book chapters and papers to read

Tutorials

Alongside the lectures and the practicals, we have prepared tutorials.

In the tutorials we go step by step through fundamental concepts.

The tutorials include code, visualizations and explanations.

<https://uvadlc-notebooks.readthedocs.io/>

Held Tuesdays at 11:00-13:00.

Serves as extra service to you, to bridge theory and implementation.

Tutorial list

- 1: Intro to Snellius (!!!) and PyTorch
- 2: Activation functions + Tutorial 4: Optimization and Initialization
- 3: Inception, ResNet and DenseNet
- 4: Transformers and Multi-Head Attention
- 5: Graph Neural Networks
- 6: Self-Supervised Contrastive Learning with SimCLR
- 7: TBD

Exam and grading

Two parts: practicals (30%) + exam (70%).

Practicals grade = average grade of the three assignments.

Exam is classical written in-person assignment.

Practicals

Practical 1 [deadline: 9-11-2025]

Implement your own net modules, learn about core modules of deep learning.

Practical 2 [deadline: 30-11-2025]

Invariances in ConvNets, build your own nano-GPT, graph network theory.

Practical 3 [deadline: 14-12-2025]

Break networks with adversarial attacks and generative learning.

Vision of the practicals

Consists of both theory and implementation questions,
handled through ANS.

Complementary view and information stream to the lectures.

Both a hands-on view to the lectures and its own reading materials!

On purpose with a view different interpretation and more theoretical background.

Snellius

We have secured a healthy amount of computation units for Deep Learning 1.

Tutorial 1 will cover the essentials of Snellius.

Lab 1 will also partially cover doing AI on clusters.

On grades

6

8

10

On boredom

Plagiarism (standard slide)

Plagiarism **will not be** tolerated

- Academic discussions are encouraged, and you can help each other
- What is plagiarism? Copying from each other is plagiarism. Sharing is plagiarism. Seeing someone else's code and retyping is plagiarism. Copying ideas & structure. Copying from existing GitHub accounts is plagiarism. Of course, re-using past answers is plagiarism. You devalue your own diploma, you make no good use of your money, and you take time we spend from teaching and reporting to do something we don't enjoy

Previously suspected cases

- Most got assignment nullified, some lost this/next year exam opportunities
- We check answer sheets from previous years, existing GitHubs and code repos, each other's answer sheets and other resources (we also use **plagiarism-detection software**)

Asking questions

1. During and after lectures, tutorials, and especially labs.
2. On Canvas Ed Discussions.
3. In case of technical/grade issues: contact Alejandro.
4. In case of personal/ethical/large-scale issues: contact me.

About Ed Discussions

Learning involves not understanding.

Asking questions is key to understanding.

Use Ed discussions to ask AND answer each other's questions.

Multiples TAs will also check the platform regularly to answer questions.

Deep learning is an engineering science

This means:

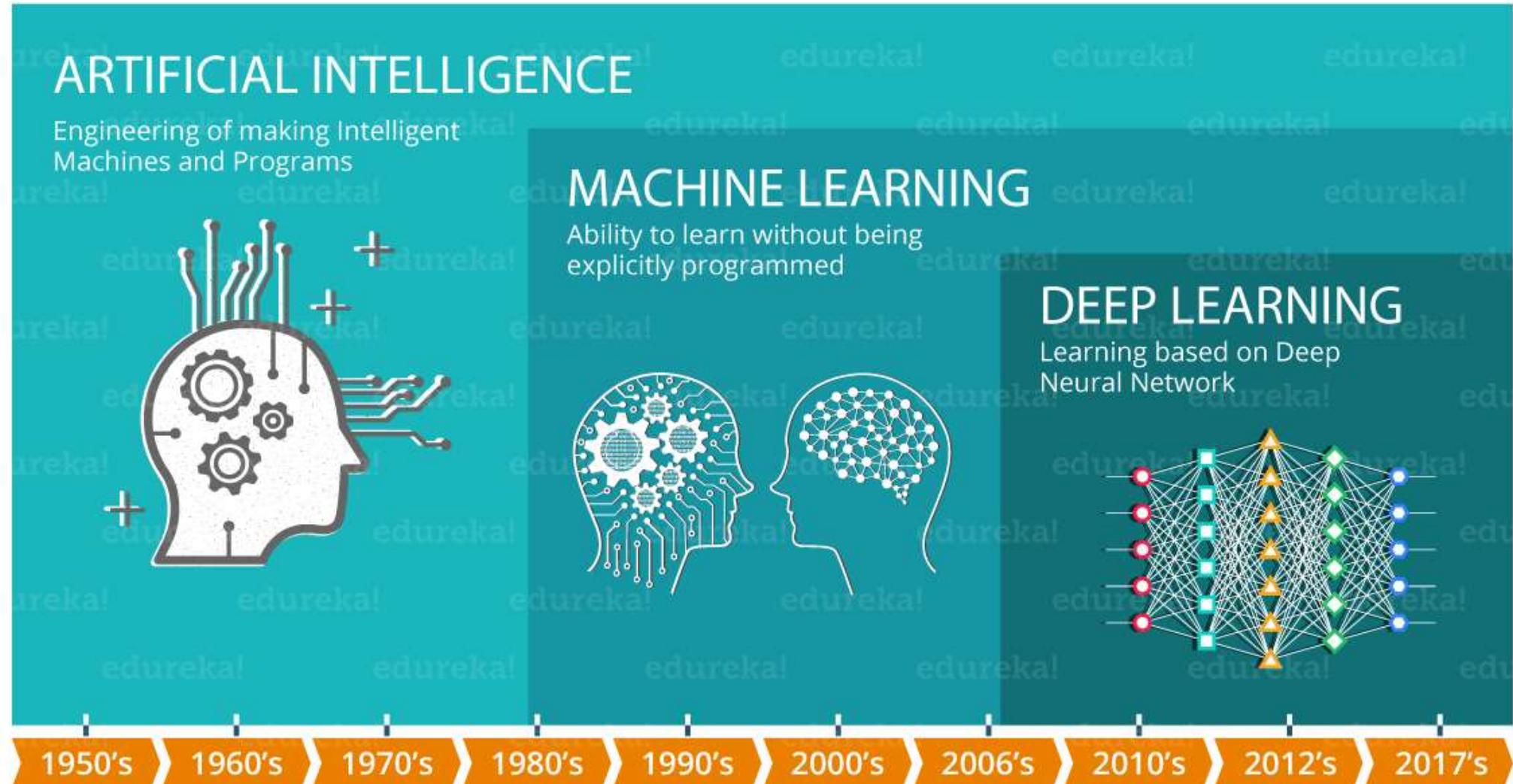
- We do not have fundamental & general theories for lots of areas.
- Plenty of hands-on experience will lead to better development of intuition.

The field moves quickly.

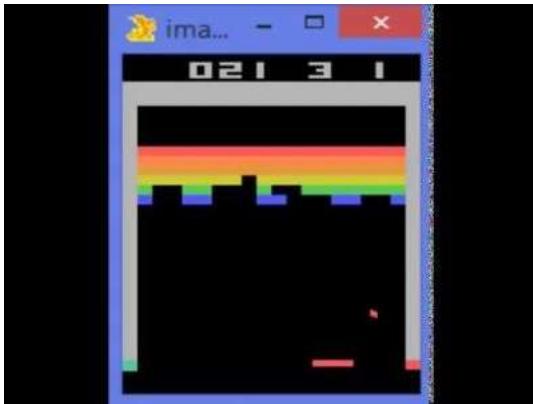
Here we teach fundamentals, but some will be outdated very soon.

- Therefore, another goal of this course: develop tools/skillset to be able to independently delve into new topics.

What is deep learning?



Highlights from first DL1 iteration (2016)



Playing Atari with Deep Reinforcement Learning. Mnih et al. 2013



SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. Badrinarayanan et al. 2015



Large-scale Video Classification with Convolutional Neural Networks. Karpathy et al. 2014



<https://github.com/karpathy/neuraltalk> 2014

The 2024 physics laureates

The Nobel Prize in Physics 2024 was awarded to John J. Hopfield and Geoffrey E. Hinton "for foundational discoveries and inventions that enable machine learning with artificial neural networks."

John Hopfield created an associative memory that can store and reconstruct images and other types of patterns in data. Geoffrey Hinton invented a method that can autonomously find properties in data, and so perform tasks such as identifying specific elements in pictures.



John Hopfield and Geoffrey Hinton. Ill. Niklas Elmehed © Nobel Prize Outreach

The 2024 chemistry laureates

The Nobel Prize in Chemistry 2024 was awarded with one half to David Baker "for computational protein design" and the other half jointly to Demis Hassabis and John M. Jumper "for protein structure prediction".

Demis Hassabis and John Jumper have successfully utilised artificial intelligence to predict the structure of almost all known proteins. David Baker has learned how to master life's building blocks and create entirely new proteins.



David Baker, Demis Hassabis and John Jumper. Ill. Niklas Elmehed © Nobel Prize Outreach

THE TIMES

The AI revolution can supercharge learning in school

The classroom of the future has arrived, effectively offering pupils their digital personal tutor. As we begin the new term, schools must work hard to ensure our schools are built around the fact that will provide access having huge amounts of data gathered and stored about their children.

It's been a year since the first major breakthrough in artificial intelligence, when Google's DeepMind AI system beat the world's best human player at the ancient Chinese board game Go. Since then, AI has continued to make significant strides, particularly in the field of machine learning, which involves training computers to learn from data without being explicitly programmed. This has led to breakthroughs in areas such as image recognition, natural language processing, and robotics. In education, AI has the potential to transform the way we learn and teach. By providing personalized learning experiences, AI can help students learn at their own pace and in their own way. It can also help teachers identify areas where students may be struggling and provide targeted support. Additionally, AI can help schools manage resources more efficiently, such as by predicting student performance and identifying areas where resources are needed. Overall, the future of education looks bright, thanks to the power of AI.

"Each child has their own unique needs and talents, and it's up to the teacher or the educational institution to find the right approach for each individual."

AI: A force for social empowerment

It is committed to using AI to combat social inequality, while advancing privacy, ethical concerns

The world is facing a crisis of inequality, with many people struggling to make ends meet. This is particularly true for marginalized communities, who often lack access to basic necessities like food, water, and healthcare. In response, there is a growing movement to use artificial intelligence (AI) to empower these communities. One way AI can do this is by providing access to information and resources. For example, AI-powered search engines can help people find local food banks or medical clinics. Another way is by providing tools for advocacy and activism. For instance, AI can help track and analyze data on issues like climate change or discrimination, which can then be used to inform policy decisions. Additionally, AI can help people connect with others who share similar interests or challenges, creating a sense of community and support. Overall, AI has the potential to be a powerful tool for social empowerment, but it must be used ethically and responsibly to ensure it benefits everyone.



Wednesday November 27 2019 / 100 PAGES

Education is the cornerstone of a successful society. As we look towards the future, it's clear that AI will play a major role in shaping our education system. By providing personalized learning experiences, AI can help students learn at their own pace and in their own way. It can also help teachers identify areas where students may be struggling and provide targeted support. Additionally, AI can help schools manage resources more efficiently, such as by predicting student performance and identifying areas where resources are needed. Overall, the future of education looks bright, thanks to the power of AI.

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AI Holds Promise for Improving Diagnoses

With artificial intelligence, machines can see what many humans may have missed

BY NEIL PARMAR

RADIOLOGISTS can scrutinize hundreds of images before identifying an area of concern in a patient's body. Mark Michalski likens the process to "playing 'Where's Waldo?' on each of those images."

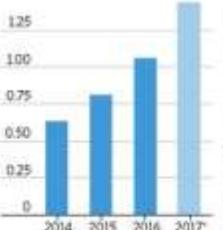
But a type of artificial intelligence known as deep learning could soon help medical experts pinpoint problems faster and more accurately, says Dr. Michalski, executive director of the Boston-based Center for Clinical Data Science at Massachusetts General Hospital and Brigham and Women's Hospital.

Deep learning includes algorithms, or computer programs, that search for, identify and analyze medicine without disease.

More Brainpower

Global spending on artificial intelligence and cognitive computing systems in health care

\$1.90 billion



*Projected

Source: Frost & Sullivan

THE WALL STREET JOURNAL



Mark Michalski works on a deep-learning algorithm for making diagnoses at Mass General.

PROFESSIONAL Outsourcing

Issue 25 Autumn 2016 | Artificial Intelligence | www.professionaloutsourcingmagazine.net

ARTIFICIAL INTELLIGENCE THE COMING WAVE

INCLUDING
What is AI?
Who's doing what and where

PLUS
Innovating for change
Time time again



»ARTIFICIAL INTELLIGENCE

The good, the bad, and the AV

From natural language and content creation, to advances in audio and the New Realities (augmented, virtual and mixed), AI in AV is here already, says Amelia Kallman.

» At its core AI is meant to solve problems, using machines to perform tasks that would traditionally be too time-consuming or complex for humans. A subset of AI machine learning can help us make sense of large data pools, recognising patterns and user intent. Machine learning only becomes AI when the machines start to carry out tasks and interact with humans. Deep learning is a kind of machine learning

that will need to be considered when integrating AI throughout businesses.

In retail we've been talking for years about how to bring together ecommerce and bricks-and-mortar, and AI integrated digital signage might be the key. Instead of pressing buttons to find your way, get price

checks, or learn about complementing products or competitive offers, a person can simply talk to a screen and get an instant informed reply. AI has instant access to backroom stock, other store locations and their stock, as well as the ability to recognise customers, either through facial recognition **»**

Artificial intelligence must not be allowed to hinder human rights

Jim GIBNEY

ROM time immemorial human beings have been interested in the world around them. Their curiosity has driven technological progress and led to a quality of life unimaginable even fifty years ago.

When my family arrived in Bryson Street in the Ballymacarrett-Short Strand area in 1963 there were three cars in the street of 50 houses, two telephones and a few televisions.

Forty years later members of my family had three cars in the driveway, several mobile phones in the house and a television in each room.

Technology has changed our lives – mostly, but not always – for the better.

The problem is not that technological advances are inherently bad. It is the way human beings use the advances which cause problems.

Nowhere can this be seen more clearly than in the threat to the planet's existence by global warming.

This existential threat forces us to review how humans should protect the planet and how they should change society, from an obsession with commodities as a benchmark of happiness, to a society which values human beings first and foremost.

It is around this notion of respect for human beings that a new society should be built, focused on human needs in areas such as health, education, economic security and human rights.

It is with this focus in mind that conversations about a new society, which harnesses human ingenuity and technological progress, should be conducted.

At this year's Féile an Phobail a fascinating lecture on the impact of rapid technological change, driven by developments in artificial intelligence (AI), examined the dilemma facing us today.

Unlike intelligence displayed by humans and animals AI is driven by computational power. It transforms input into output, and it advances

AI systems are also used at work. For example, they publicise human rights v

Al applications help to

and human rights activis

for justice and equality a

borders. But Dr Schippers emp

to address AI's cap

undermine and threaten.

A principal concern is

from human decision-ma

generated "automated

decisions. It undermines

accountability and respo

contrary to the right not

automated decision mak

There is a real worry t

making capacity by intell

systems will be used to u

won progress of long and

Campaigns that fought to

discrimination; the right

of expression, assembly:

The use of Al applica

boundaries between the

of democratic states and

interests of private comp

This is very worrying

used in sensitive areas su

security and intelligence.

It is particularly concer

systems are used to unde

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As Ms Schippers h

pointed out, human

technology are comp

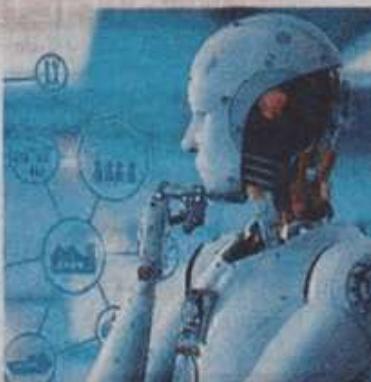
real need for robust and effective human

rights protection.

AI workforce to boom in future

KANIZA GARARI | DC
HYDERABAD, MAY 21

The demand for Artificial Intelligence professionals is expected to be 2,38,000 in the next three years in India according to National Association of Software and Service Companies analysis released



a happy hippo flying through the sky





$\log(D(x)) = \mathbb{E}[\log D(x)]$

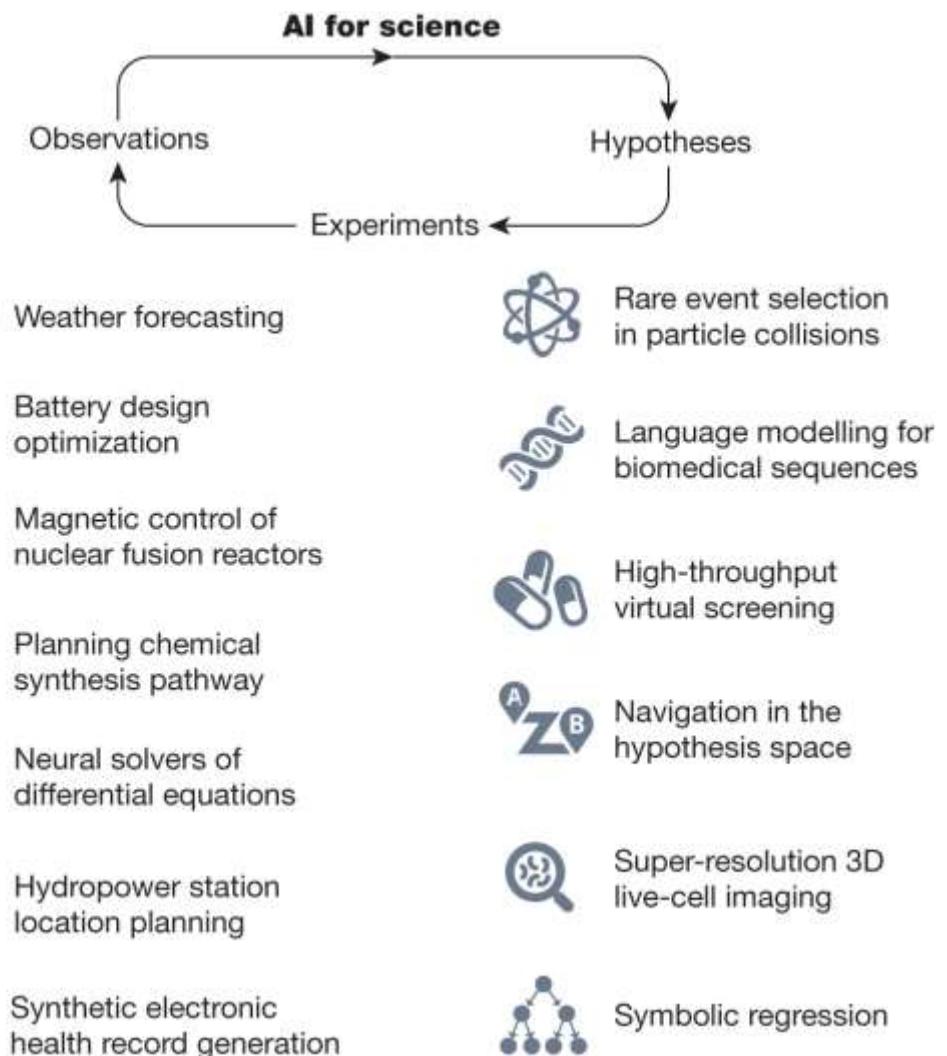
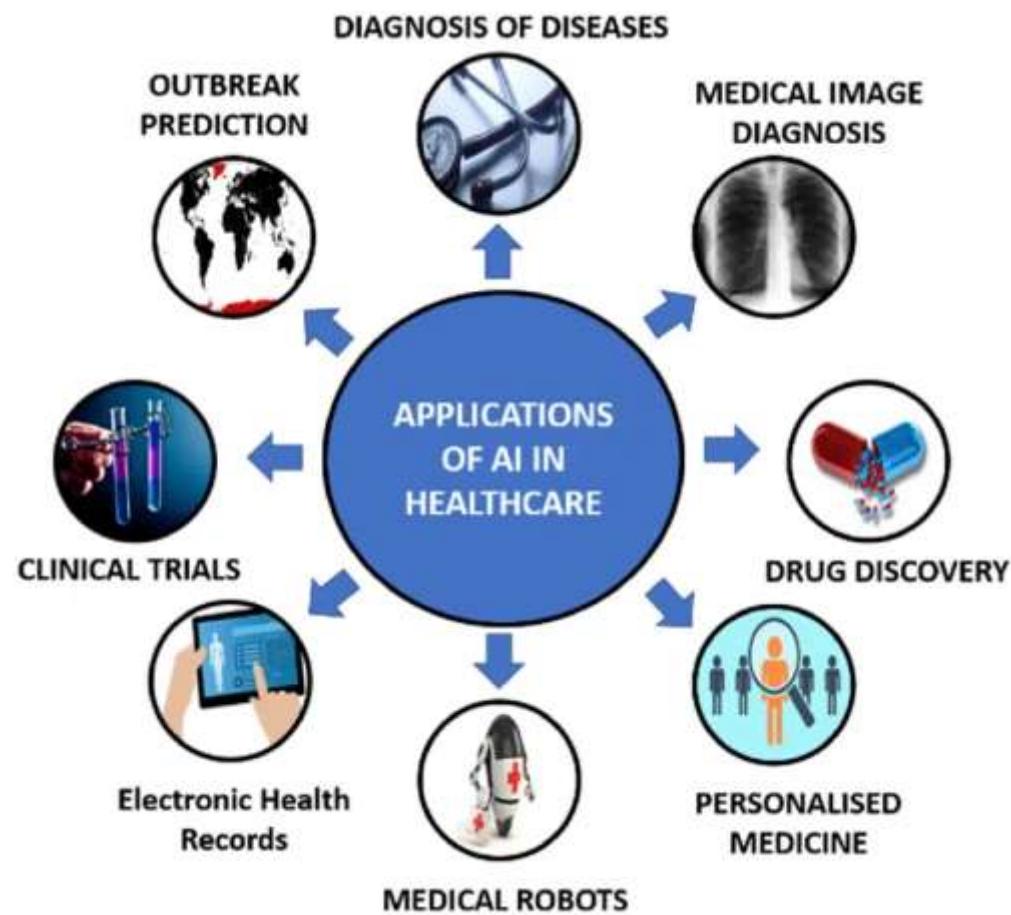


Jason Allen
Pueblo West
Théâtre D'opéra Spatial

\$750

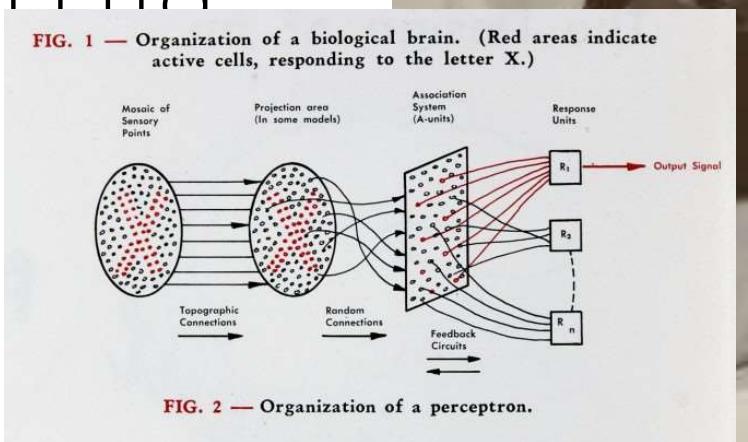
Colorado State Fair





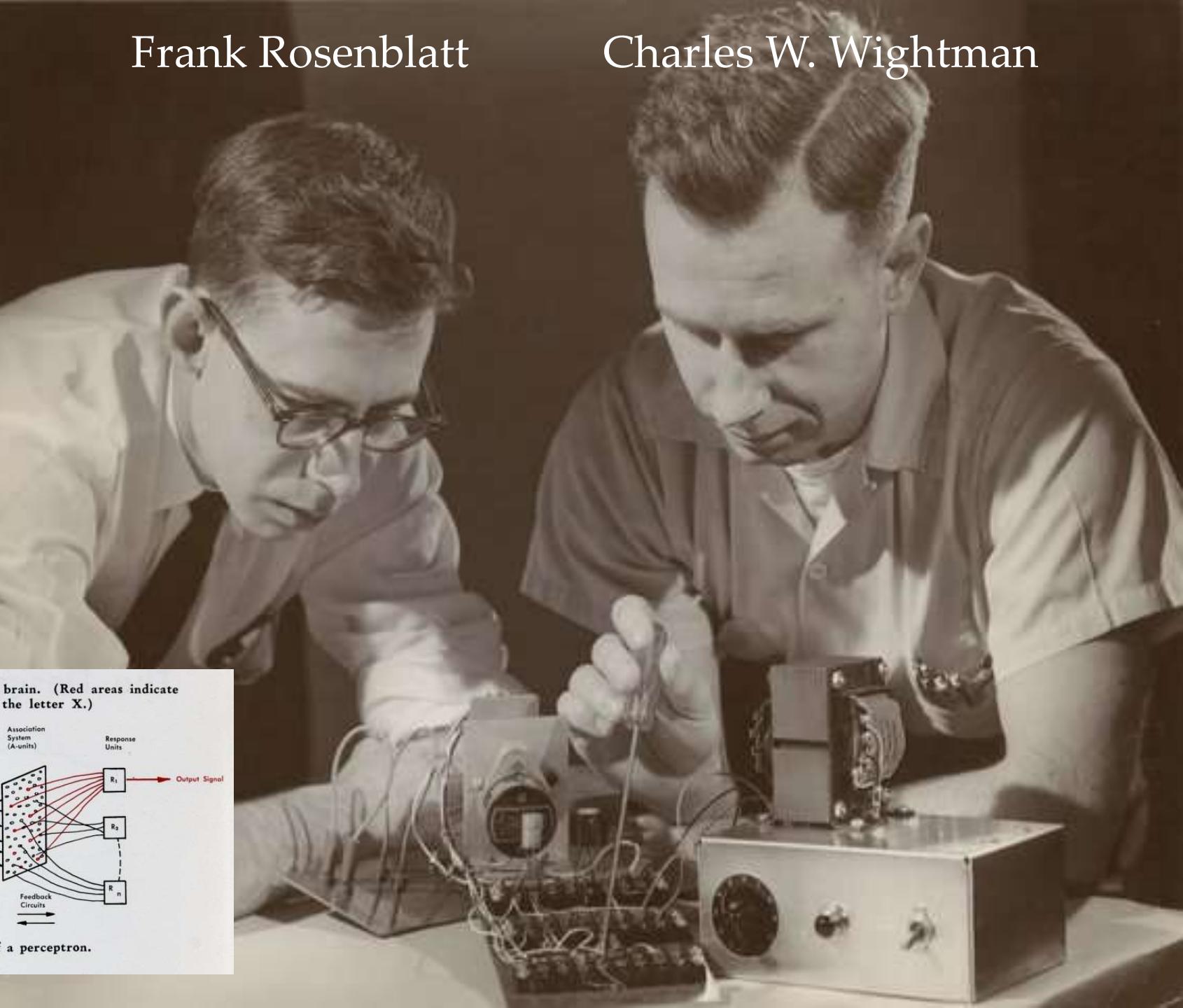


A brief history of deep learning



Frank Rosenblatt

Charles W. Wightman



Break



A brief history of deep learning

Frank Rosenblatt

Charles W. Wightman

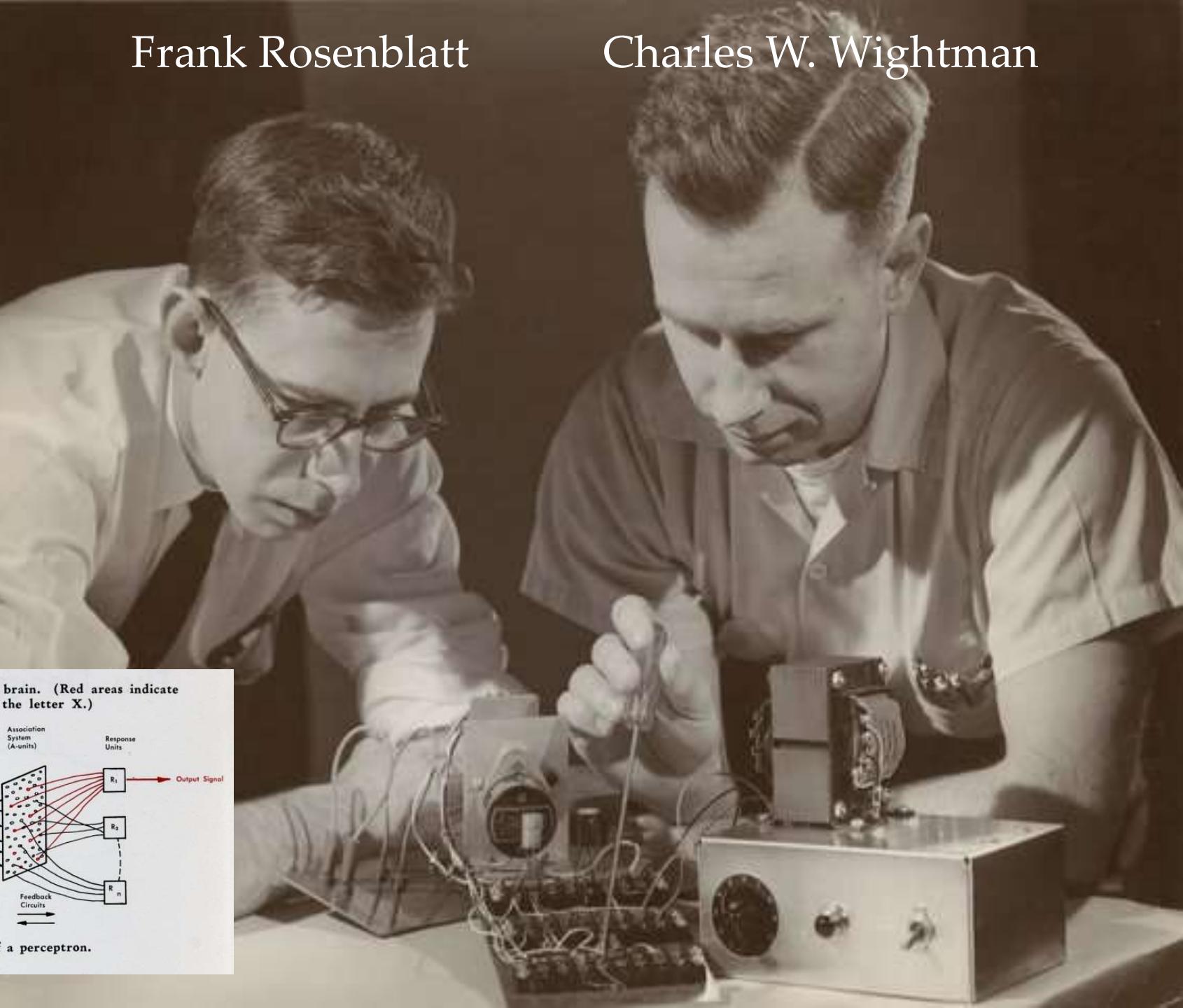


FIG. 1 — Organization of a biological brain. (Red areas indicate active cells, responding to the letter X.)

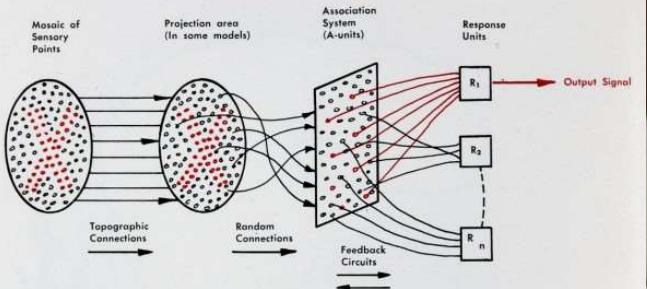


FIG. 2 — Organization of a perceptron.

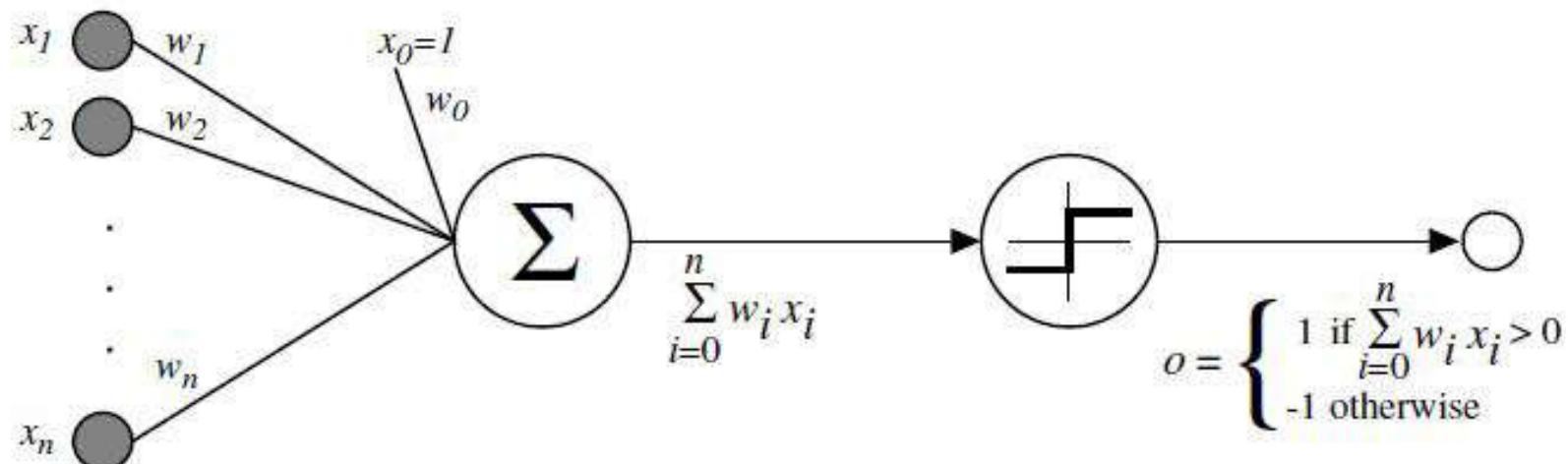
Origins



The perceptron

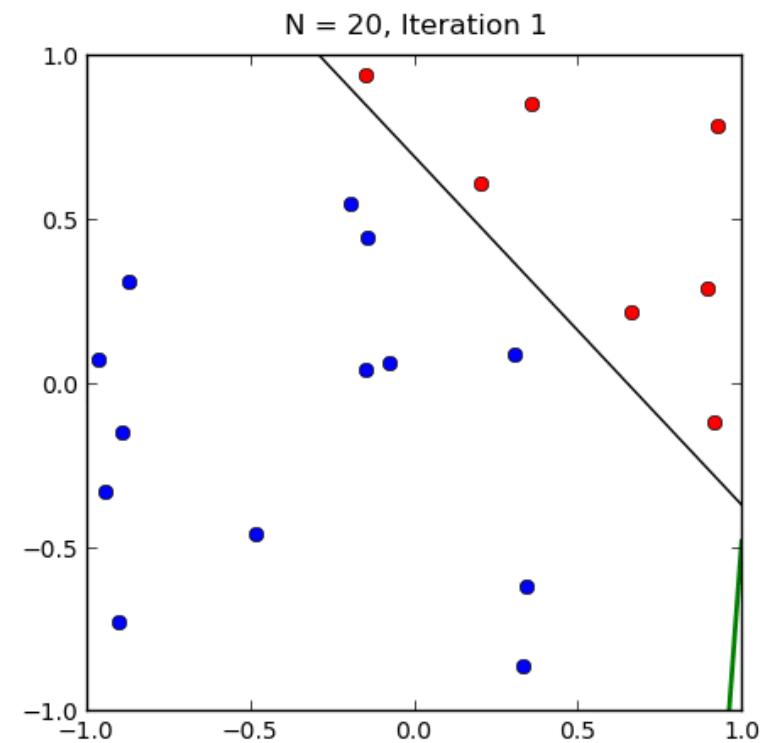
Single layer perceptron for binary classification.

- One weight w_i per input x_i
- Multiple each input with its weight, sum, and add bias
- If result larger than threshold, return 1, otherwise return 0



Training the perceptron

Perceptron learning algorithm	Comments
1. Set $w_j \leftarrow \text{random}$	
2. Sample new (x_i, l_i)	New train image, label
3. Compute $y_i = [\sum w_i x_i > 0]$	$[\cdot]$: indicator function
4. If $y_i < 0, l_i > 0 \rightarrow w_i = w_i + \eta \cdot x_i$	Score too low. Increase weights!
5. If $y_i > 0, l_i < 0 \rightarrow w_i = w_i - \eta \cdot x_i$	Score too high. Decrease weights!
6. Go to 2	Repeat till happy 😊



Hyping up the perceptron

FIG. 1 — Organization of a biological brain. (Red areas indicate active cells, responding to the letter X.)

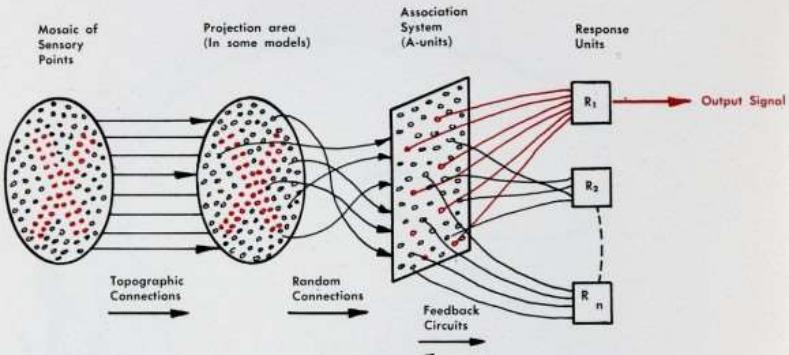
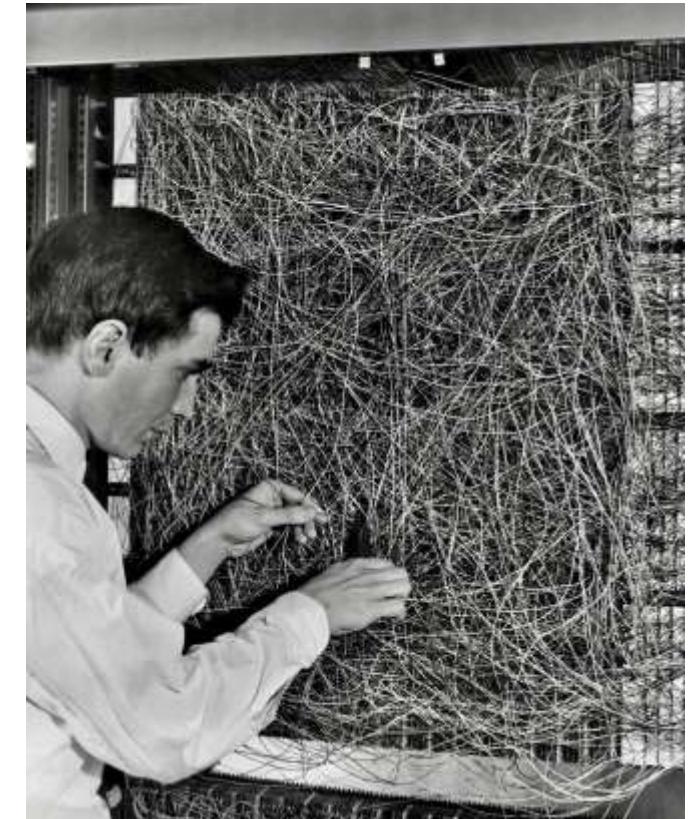


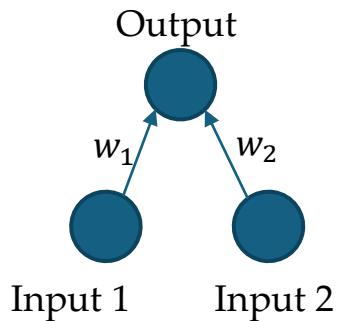
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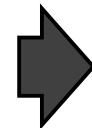
*"a machine which senses,
recognizes, remembers, and
responds like a human mind"*

XOR: The simplest hurdle

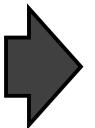
Input 1	Input 2	XOR
1	1	-1
1	0	+1
0	1	+1
0	0	-1



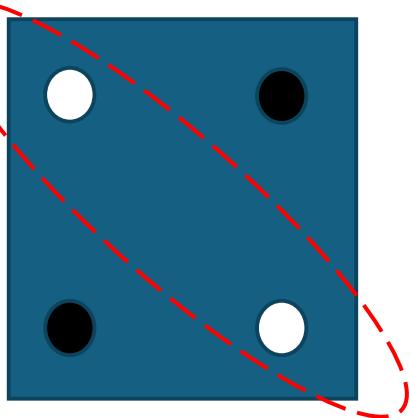
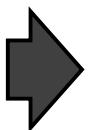
$$\begin{aligned}1 \cdot w_1 + 1 \cdot w_2 &< \tau \rightarrow w_1 + w_2 < \tau \\1 \cdot w_1 + 0 \cdot w_2 &> \tau \rightarrow w_1 > \tau \\0 \cdot w_1 + 1 \cdot w_2 &> \tau \rightarrow w_2 > \tau \\0 \cdot w_1 + 0 \cdot w_2 &< \tau \rightarrow 0 < \tau\end{aligned}$$



$$\begin{aligned}w_1 + w_2 &> 2\tau \\w_1 + w_2 &< \tau\end{aligned}$$



Inconsistent



No line can separate the white from the black

Moravec's paradox

Reasoning requires little computation, perception from sensors a lot.



MASSACHUSETTS INSTITUTE OF TECHNOLOGY
PROJECT MAC

Artificial Intelligence Group
Vision Memo. No. 100.

July 7, 1966

THE SUMMER VISION PROJECT
Seymour Papert

The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system. The particular task was chosen partly because it can be segmented into sub-problems which will allow individuals to work independently and yet participate in the construction of a system complex enough to be a real landmark in the development of "pattern recognition".

“AI Winter”



AI Winter

“If a perceptron cannot even solve XOR, why bother?”

Lack of funding due to overhyping.

Still, significant discoveries were made in this period

- Backpropagation → Learning algorithm for MLPs by Linnainmaa
- Recurrent networks → Varied-length inputs by Rumelhart
- CNNs → Neocognitron by Fukushima

The two paths of machine learning research

Path 1:

Fix perceptrons by making better features.

Path 2:

Fix perceptrons by making them more complex.

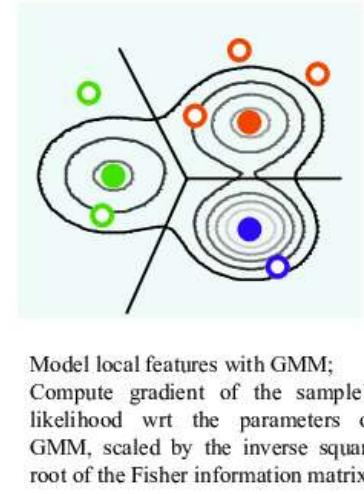
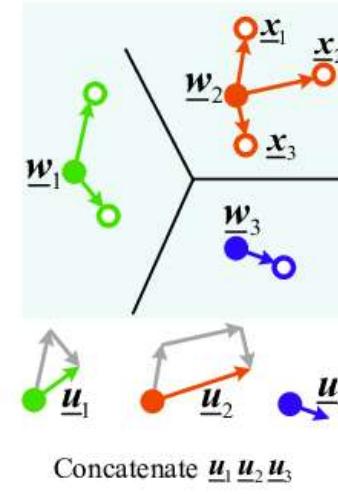
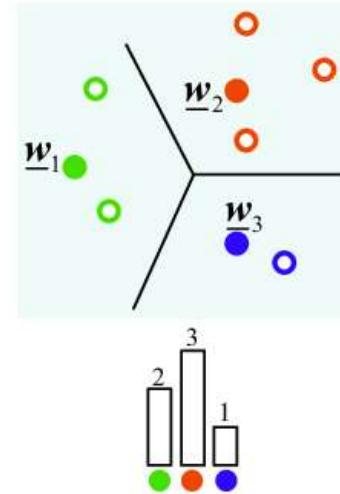
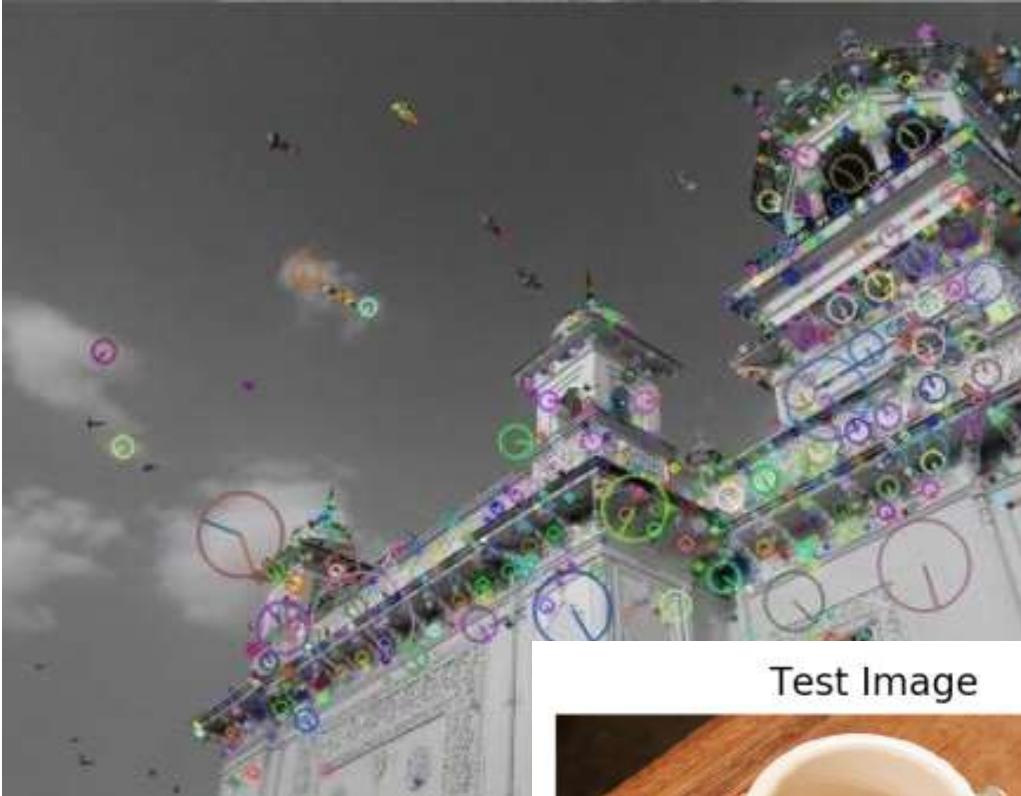
Path 1: Better inputs

Philosophy: encode domain knowledge to help machine learning algorithms.

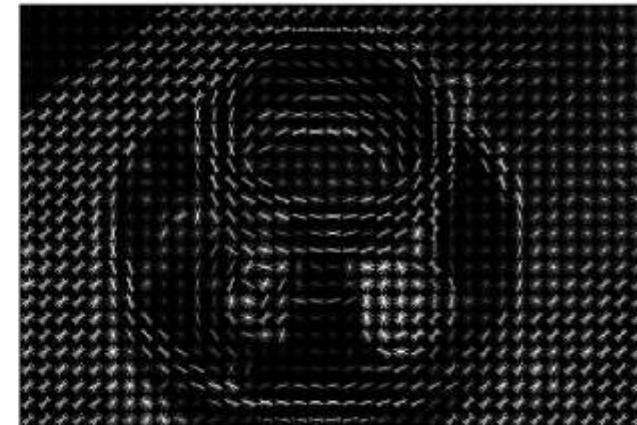
Classical image recognition pipeline:

1. Extract local features.
2. Aggregate local features over image.
3. Train classical models on aggregations.

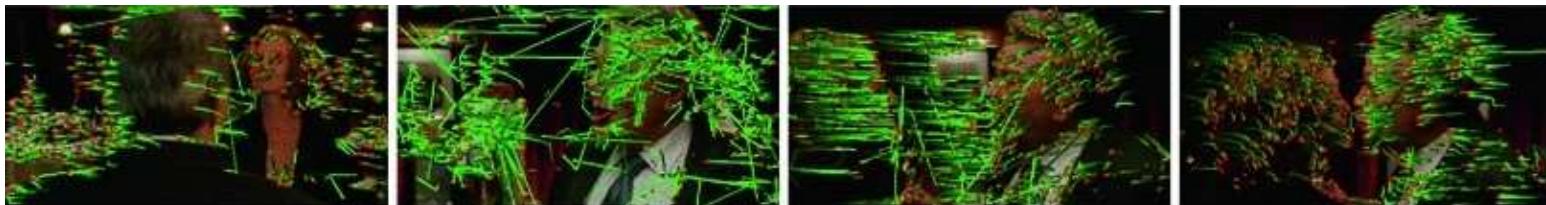
Feature engineering: image domain



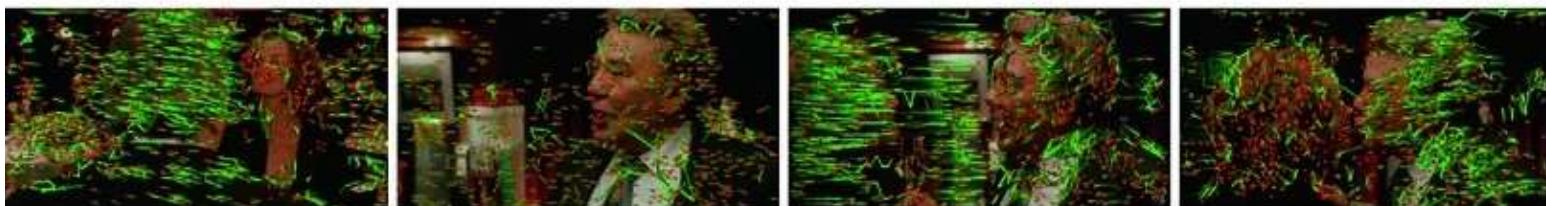
Histogram of Oriented Gradients



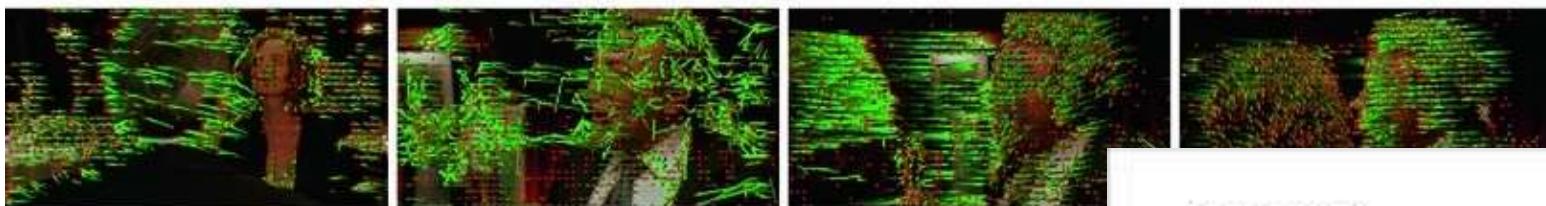
Feature engineering: video domain



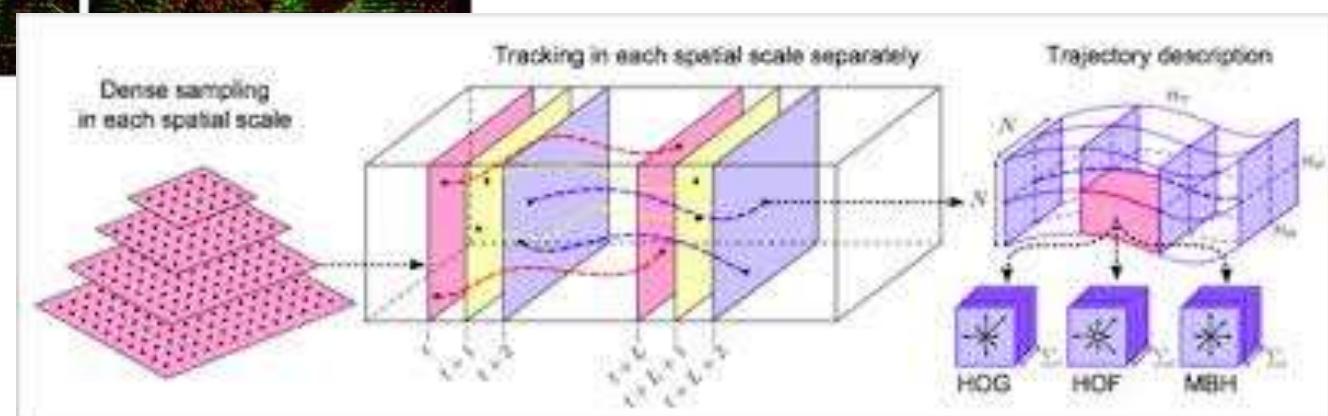
KLT trajectories



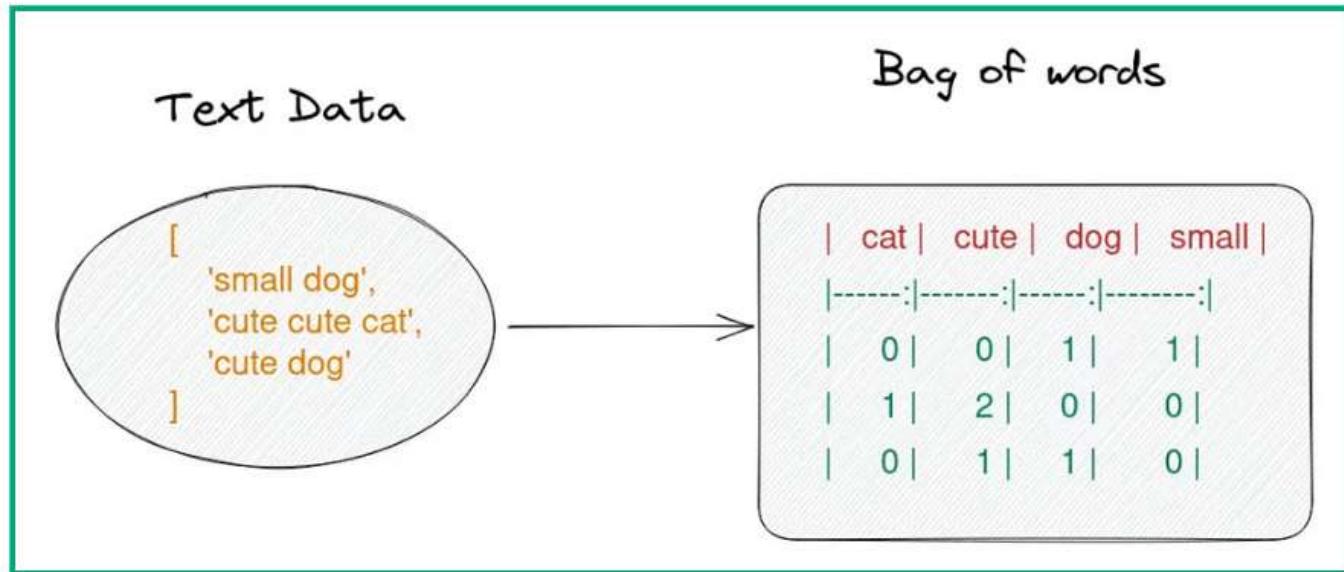
SIFT trajectories



Dense trajectories



Feature engineering: text domain

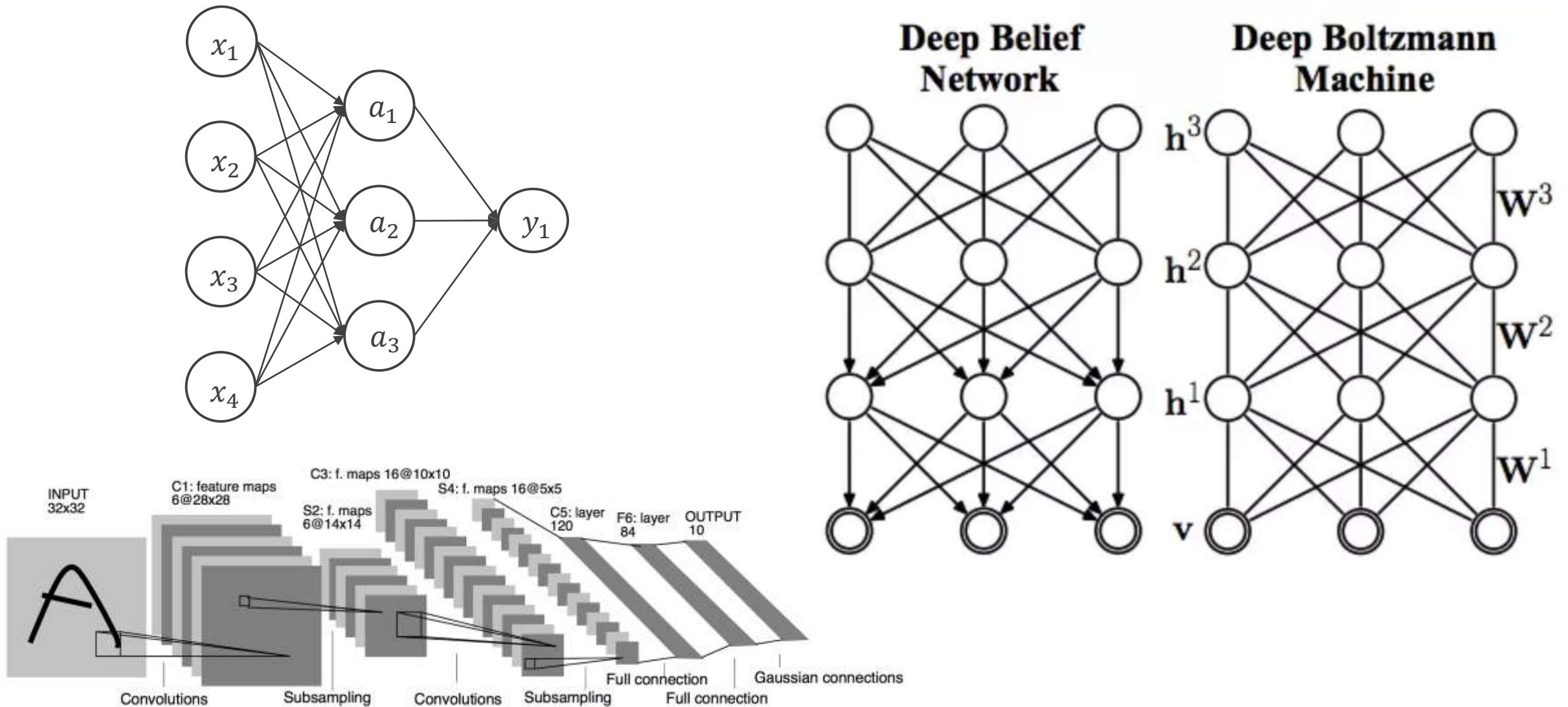


$$w_{x,y} = \text{tf}_{x,y} \times \log \left(\frac{N}{df_x} \right)$$

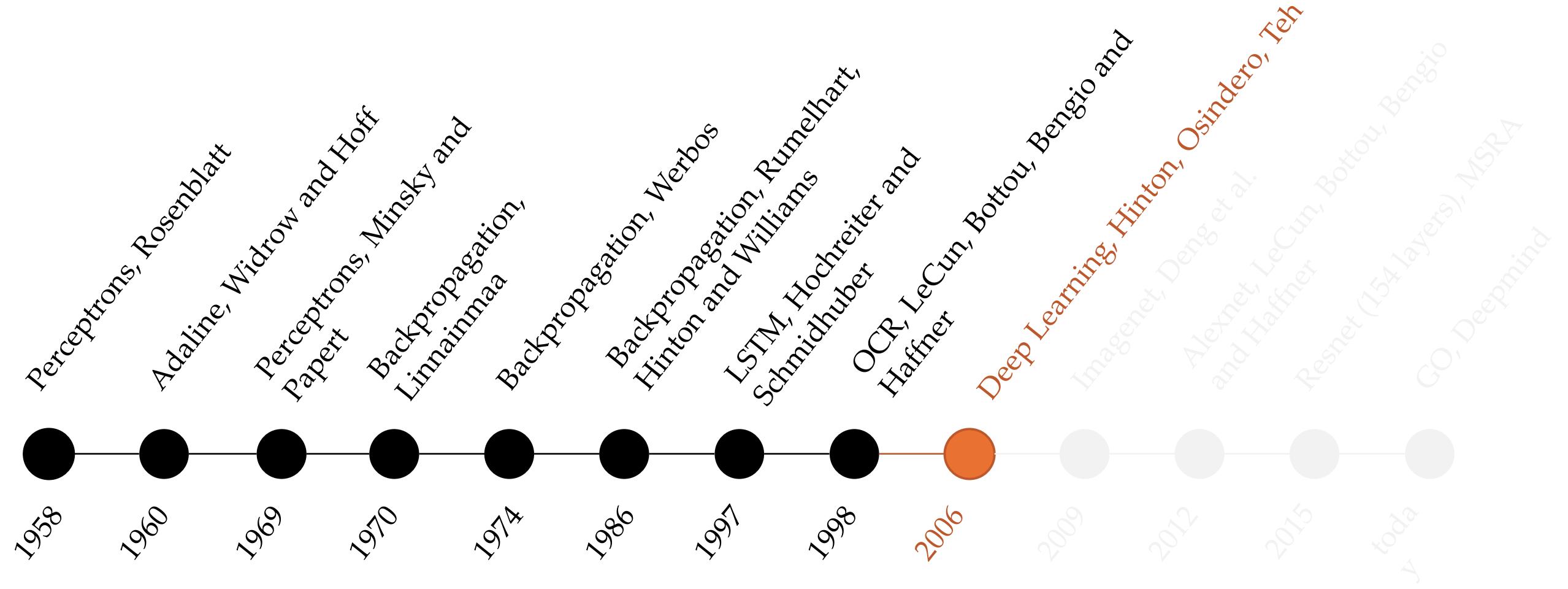
TF-IDF
Term x within document y

$\text{tf}_{x,y}$ = frequency of x in y
 df_x = number of documents containing x
 N = total number of documents

Path 2: Neural networks beyond a single layer



The thaw of AI Winter



Signs of life of deep neural networks...

In 2006, Hinton and Salakhutdinov found multi-layer feedforward neural networks can be pretrained layer by layer.

Fine-tuned by backpropagation

Deep Belief Nets (DBNs)
(based on Boltzmann machines)

LETTER Communicated by Yann Le Cun

A Fast Learning Algorithm for Deep Belief Nets

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We show how to use “complementary priors” to eliminate the explaining-away effects that make inference difficult in densely connected belief nets that have many hidden layers. Using complementary priors, we derive a fast, greedy algorithm that can learn deep, directed belief networks one layer at a time, provided the top two layers form an undirected associative memory. The fast, greedy algorithm is used to initialize a slower learning procedure that fine-tunes the weights using a contrastive version of the wake-sleep algorithm. After fine-tuning, a network with three hidden layers forms a very good generative model of the joint distribution of handwritten digit images and their labels. This generative model gives better digit classification than the best discriminative learning algorithms. The low-dimensional manifolds on which the digits lie are modeled by long ravines in the free-energy landscape of the top-level associative memory, and it is easy to explore these ravines by using the directed connections to display what the associative memory has in mind.

Deep learning arrives

Easier to train one layer at a time → Layer-by-layer training

Training multi-layered neural networks became easier

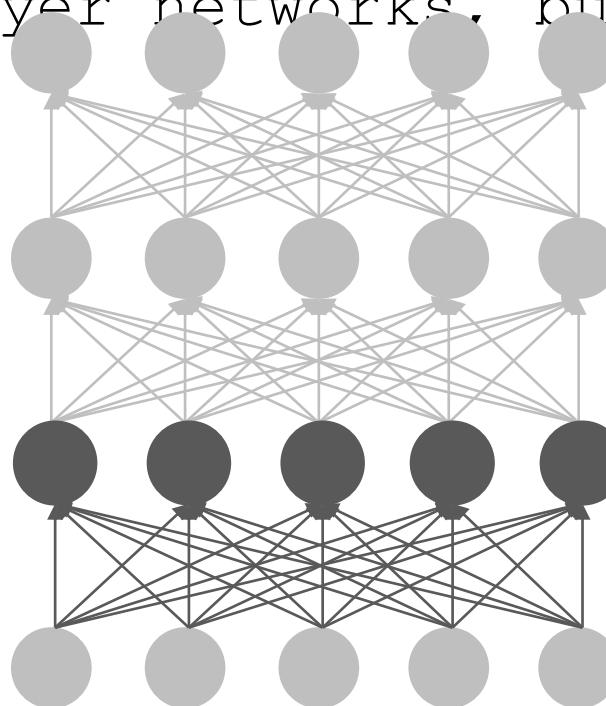
Benefits of multi-layer networks, but single-layer easy of training

Freeze layer 3

Freeze layer 2

Training layer 1

Input



Deep learning arrives

Easier to train one layer at a time → Layer-by-layer training

Training multi-layered neural networks became easier

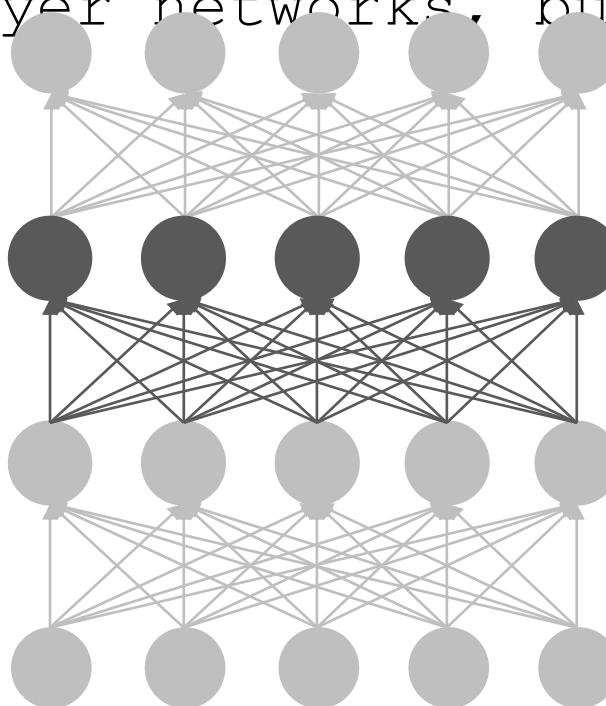
Benefits of multi-layer networks, but single-layer easy of training

Freeze layer 3

Freeze layer 2

Training layer 1

Input



Deep learning arrives

Easier to train one layer at a time → Layer-by-layer training.

Training multi-layered neural networks became easier.

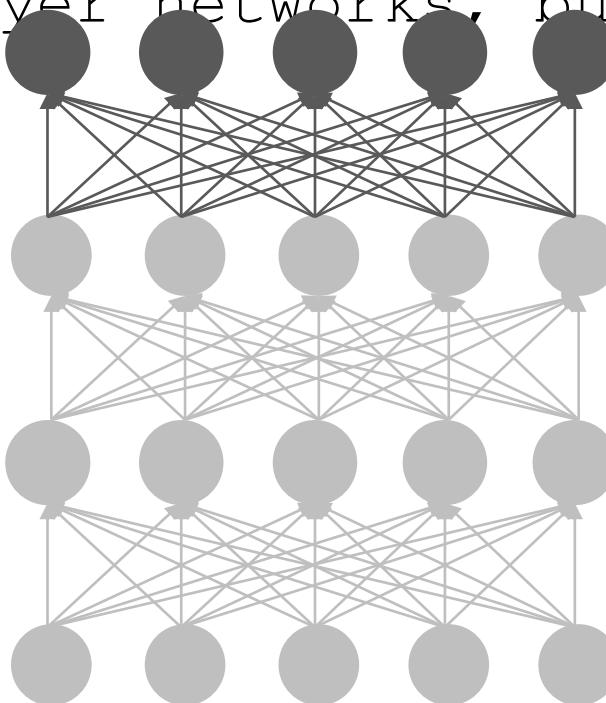
Benefits of multi-layer networks, but single-layer ease of training.

Freeze layer 3

Freeze layer 2

Training layer 1

Input



Challenges of neural networks then

Lack of processing power

Lack of data

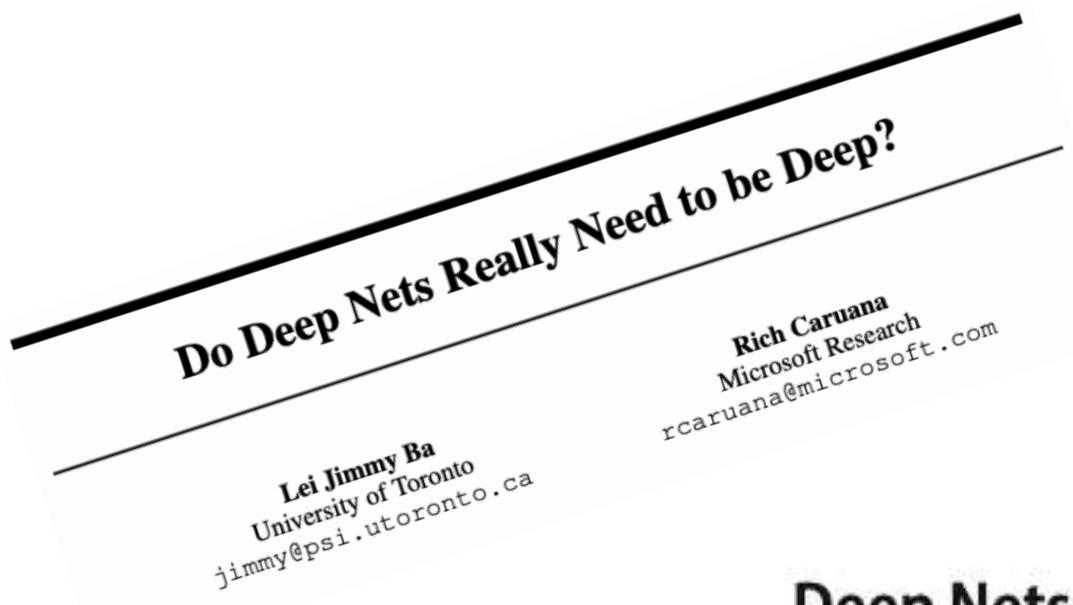
Overfitting

Vanishing gradients

Experimentally, training multi-layer perceptrons was not that useful

“Are 1-2 hidden layers the best neural networks can do?”

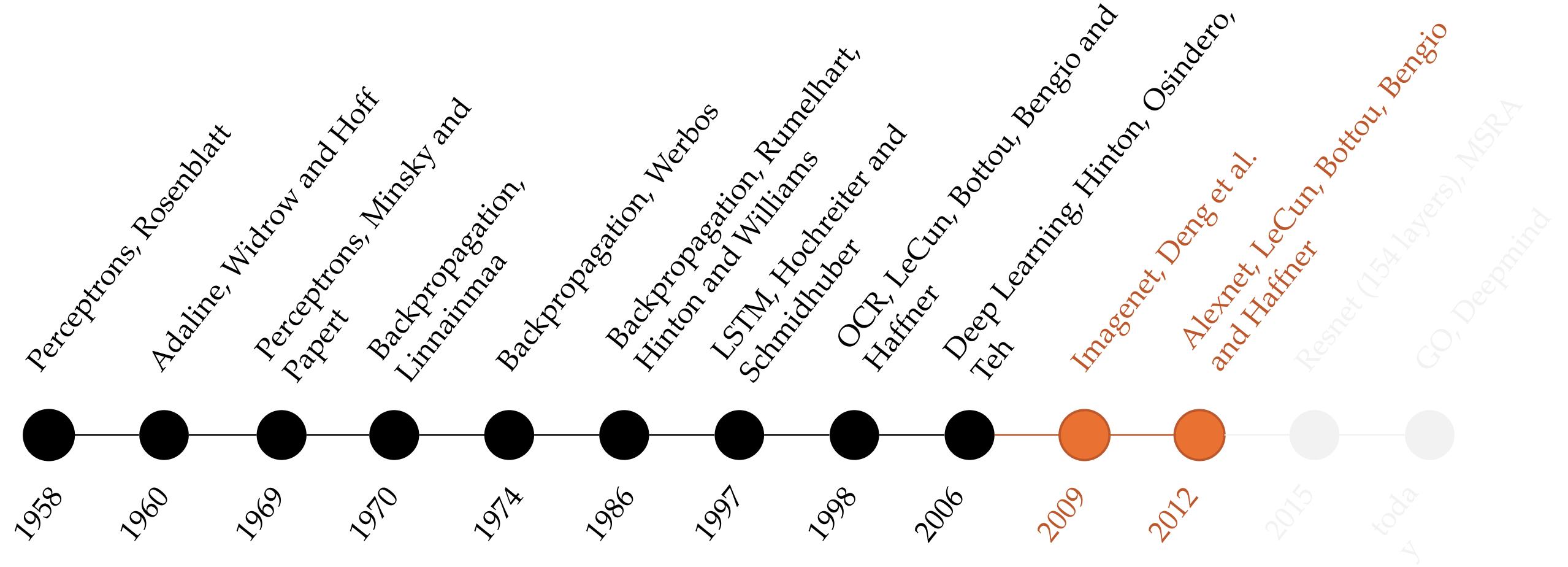
...hence many skeptics remain



Deep Nets: What have They Ever Done for Vision?

Alan L. Yuille¹ · Chenxi Liu¹ 

Deep learning arrives



Turns out that deep learning is data hungry

In 2009 the ImageNet dataset was published [Deng et al., 2009]

- Collected images for all 100K terms in Wordnet (16M images in total)
- Terms organized hierarchically:
“Vehicle” → “Ambulance”

ImageNet Large Scale Visual Recognition Challenge
(ILSVRC)

- 1 million error measure and top-1

2012 Teams	%error	2013 Teams	%error	2014 Teams	%error
Supervision (Toronto)	15.3	Clarifai (NYU spinoff)	11.7	GoogLeNet	6.6
ISI (Tokyo)	26.1	NUS (singapore)	12.9	VGG (Oxford)	7.3
VGG (Oxford)	26.9	Zeiler-Fergus (NYU)	13.5	MSRA	8.0
XRCE/INRIA	27.0	A. Howard	13.5	A. Howard	8.1
UvA (Amsterdam)	29.6	OverFeat (NYU)	14.1	DeeperVision	9.5
INRIA/LEAR	33.4	UvA (Amsterdam)	14.2	NUS-BST	9.7
		Adobe	15.2	TTIC-ECP	10.2
		VGG (Oxford)	15.2	XYZ	11.2
		VGG (Oxford)	23.0	UvA	12.1

CNN based, non-CNN based

ImageNet 2012 winner: AlexNet

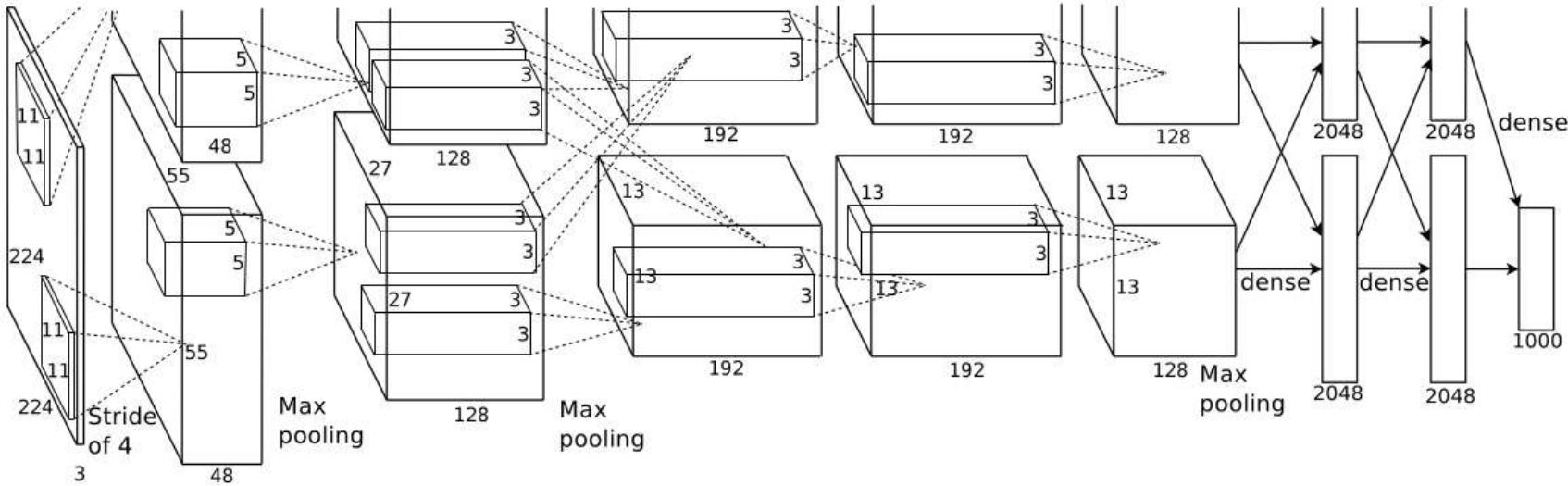


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

ImageNet



Most commonly used version: ImageNet-12: 1K categories, ~1.3M images, ~150GB.
From Fei-Fei Li

Explore them here: <https://knowyourdata-tfds.withgoogle.com/#tab=STATS&dataset=imagenet2012>

(Important! Also check out "see" the ~~the~~ genealogy of machine learning datasets neural network at it!) ImageNet. De

Evolution of scale

Evolution of Computer Power/Cost

MIPS per \$1000 (1997 Dollars)

Million

Object recognition with CNN

1000

OCR with CNN

1

Backpropagation

1000

Perceptron

1. Better hardware

1 Million

1 Billion

1900

1920

1940

1960

1980

2000

2020

Year

Brain Power Equivalent per \$1000 of Computer

Human

Monkey

Mouse

Lizard

Spider

Nematode

Worm

Bacterium

Manual Calculation

Imagenet: 1000 classes from real images, 1M images



Results:
• Perceptron 0.2505
• Convolutional 0.2505
• Gated conv 0.2506
• Residual 0.2506

2345

Bank cheques

X1	X2	X3	Y
0	0	0	True
0	0	1	False
0	1	0	False
0	1	1	True
1	0	0	False
1	0	1	True
1	1	0	True
1	1	1	False

Parity, negation problems

**3. Better algorithms**

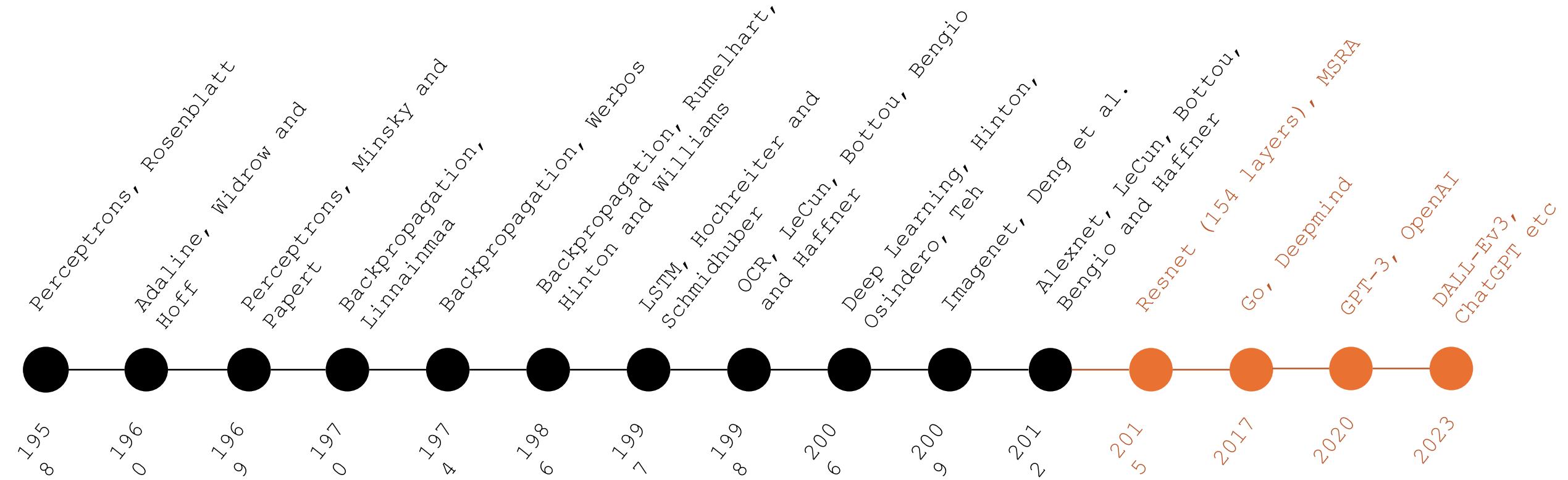
Mark I Perceptron



Potentiometers

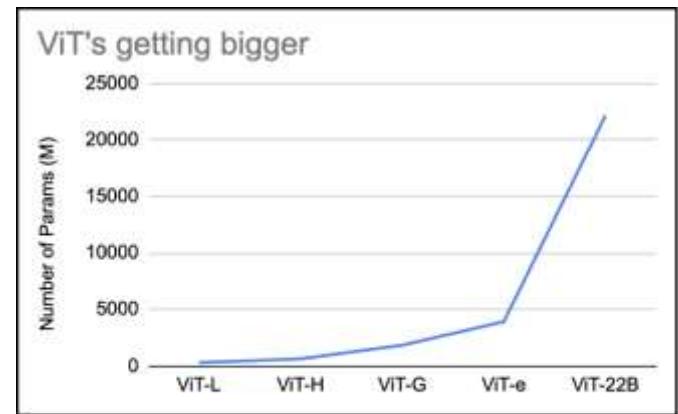
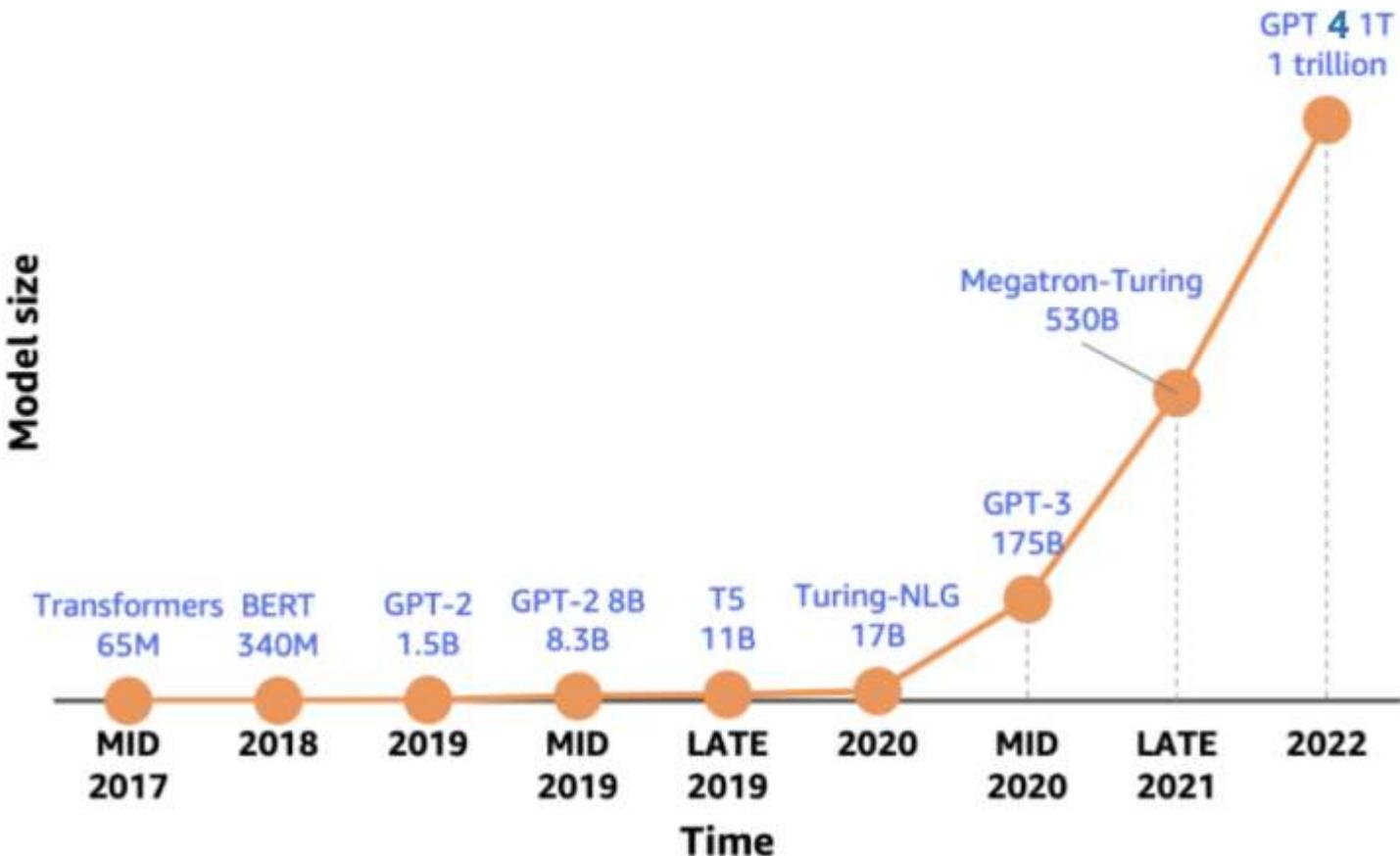
2. Bigger data

Golden era of deep learning



Scale, scale, scale

15,000x increase in 5 years



"Compute Requirements: ViT-22B was trained on 1024 TPU V4 chips [...]"

Current scaling of models

BERT model (354M parameters) ~ now \$2K

RoBERTa (1000 GPUs for a week) ~ now \$350K

GPT-3 (175B parameters, 1500 GPUs for 2 months) ~ \$3M

...

PaLM

- 6144 TPUs, ~\$25M
- 3.2 million kWh ~~1000 Households for a year



Is deep learning ready for the
real world?





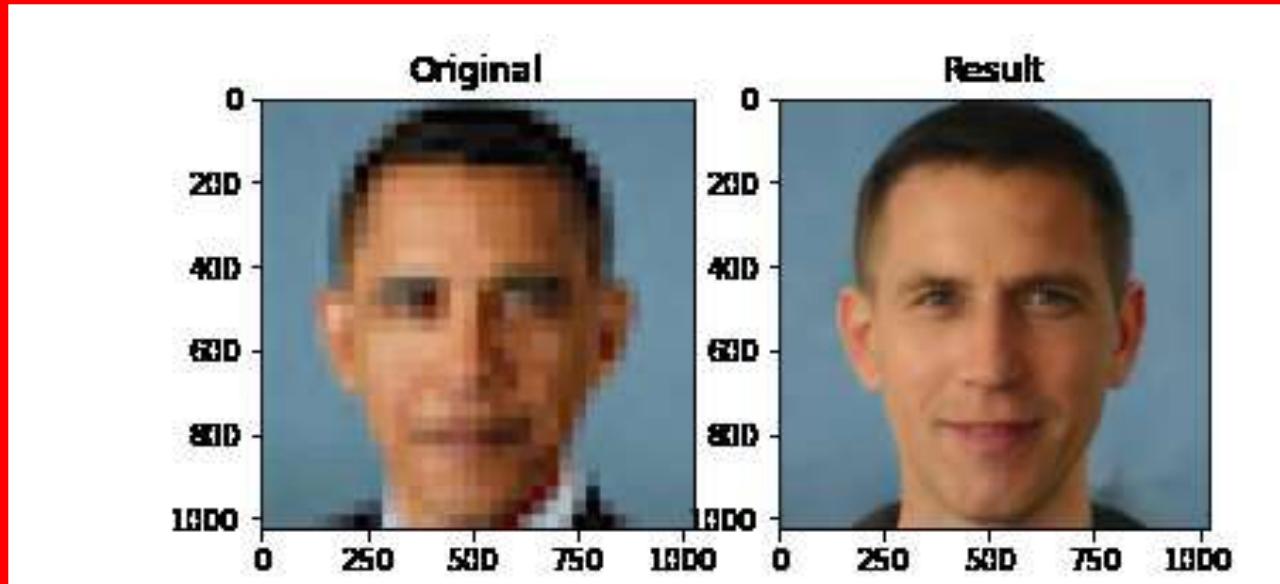
Deadly accidents



Surveillance concerns



Misinformation



Bias

Deep learning: an ongoing effort

Rapid advances and quick strides.

AI is already assisting us with many basic efforts.

Many fundamental issues remain:

Causality, generalization, robustness, hierarchies,
facts/knowledge, continuality, alignment,
sustainability, ...

Is AI only deep learning?



Recap

Course overview

History of deep learning

Future of deep learning

Learning and reflection

Understanding Deep Learning: Chapter 1

Annotated History of Modern AI and Deep Learning –
Jürgen Schmidhuber

All reading is in "Reading Materials" under "Modules" in Canvas

Next lecture

Lecture	Title	Lecture	Title
1	Intro and history of deep learning	2	AutoDiff
3	Deep learning optimization I	4	Deep learning optimization II
5	Convolutional deep learning	6	Attention-based deep learning
7	Graph deep learning	8	From supervised to unsupervised deep learning
9	Multi-modal deep learning	10	Generative deep learning
11	What doesn't work in deep learning	12	Non-Euclidean deep learning
13	Q&A	14	Deep learning for videos