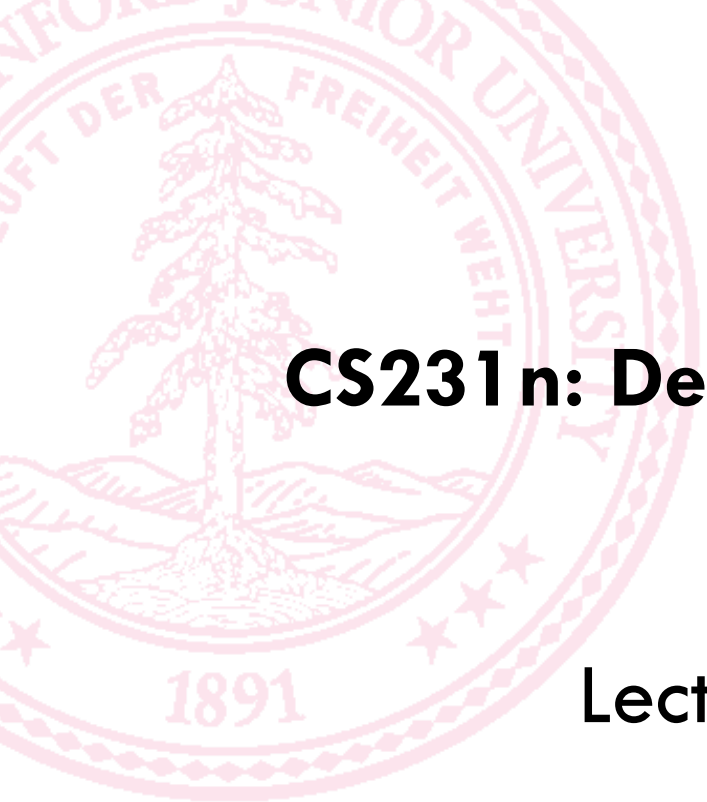
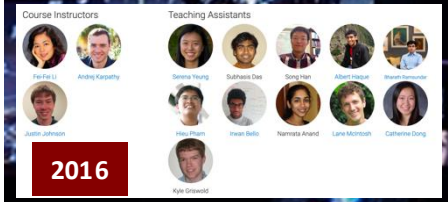


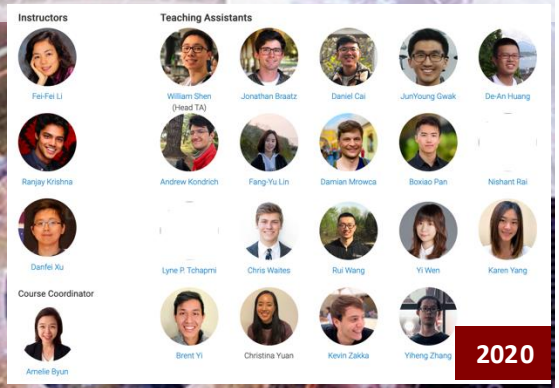
CS231n: Deep Learning for Computer Vision

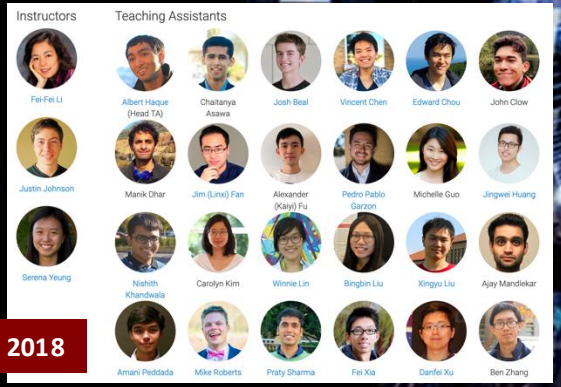
Lecture 1: Introduction

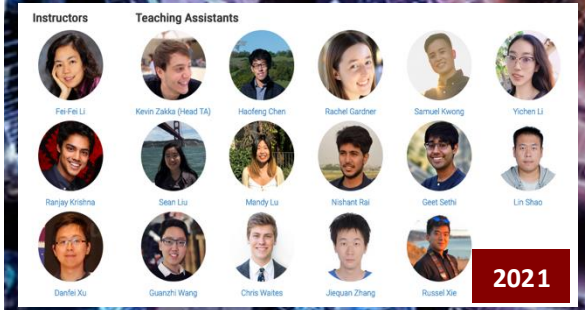
Welcome to CS231n

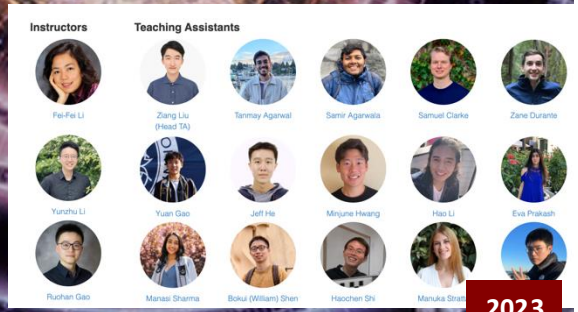
Welcome to CS231n



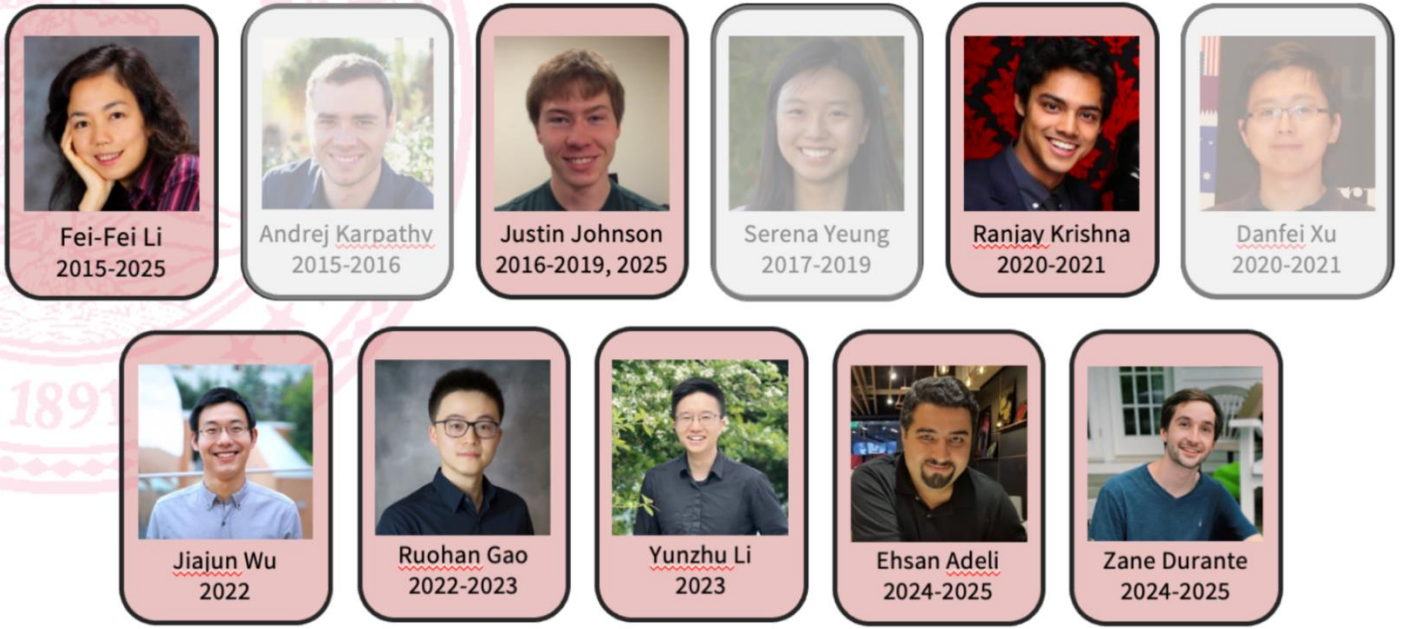


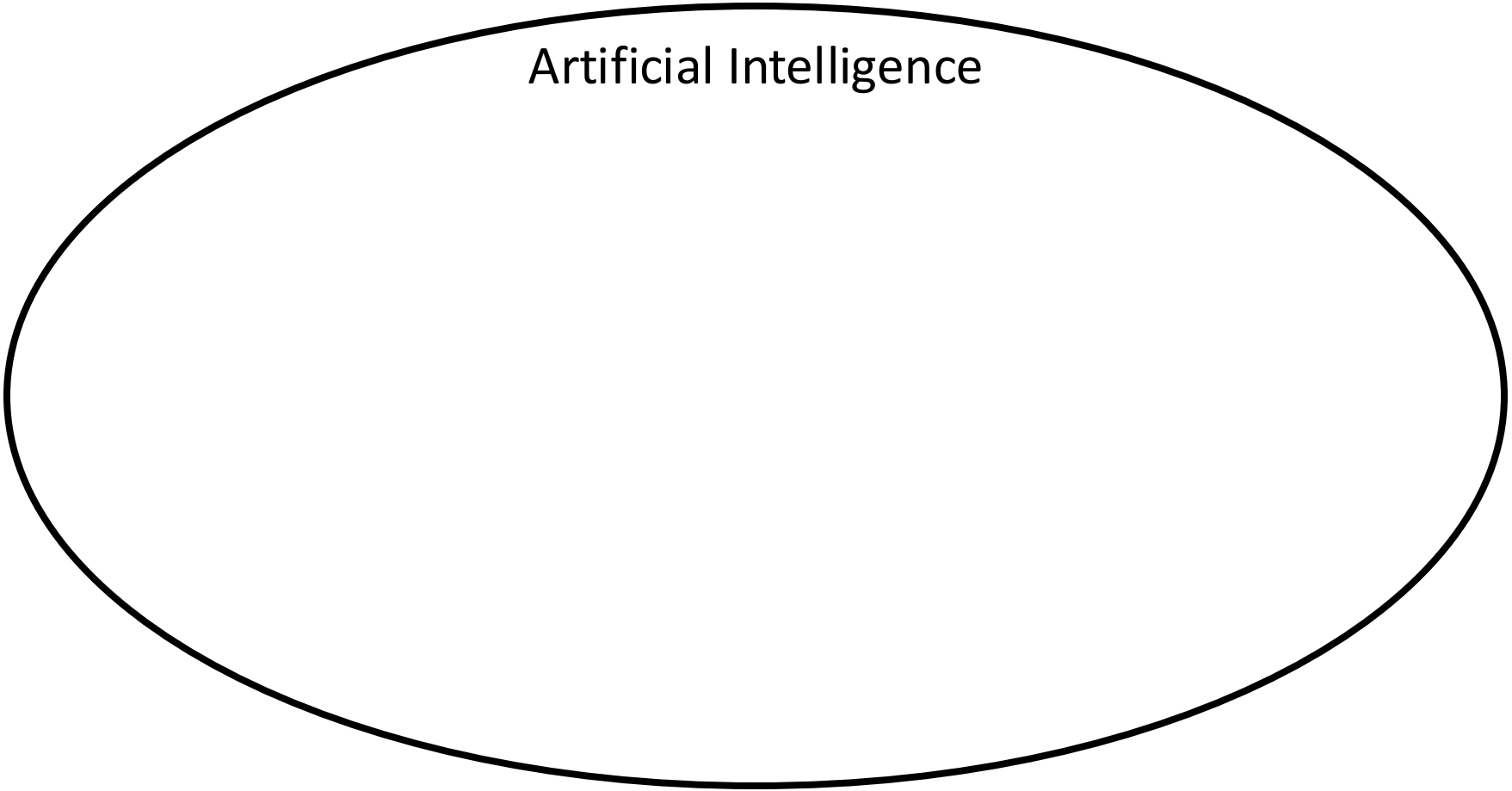




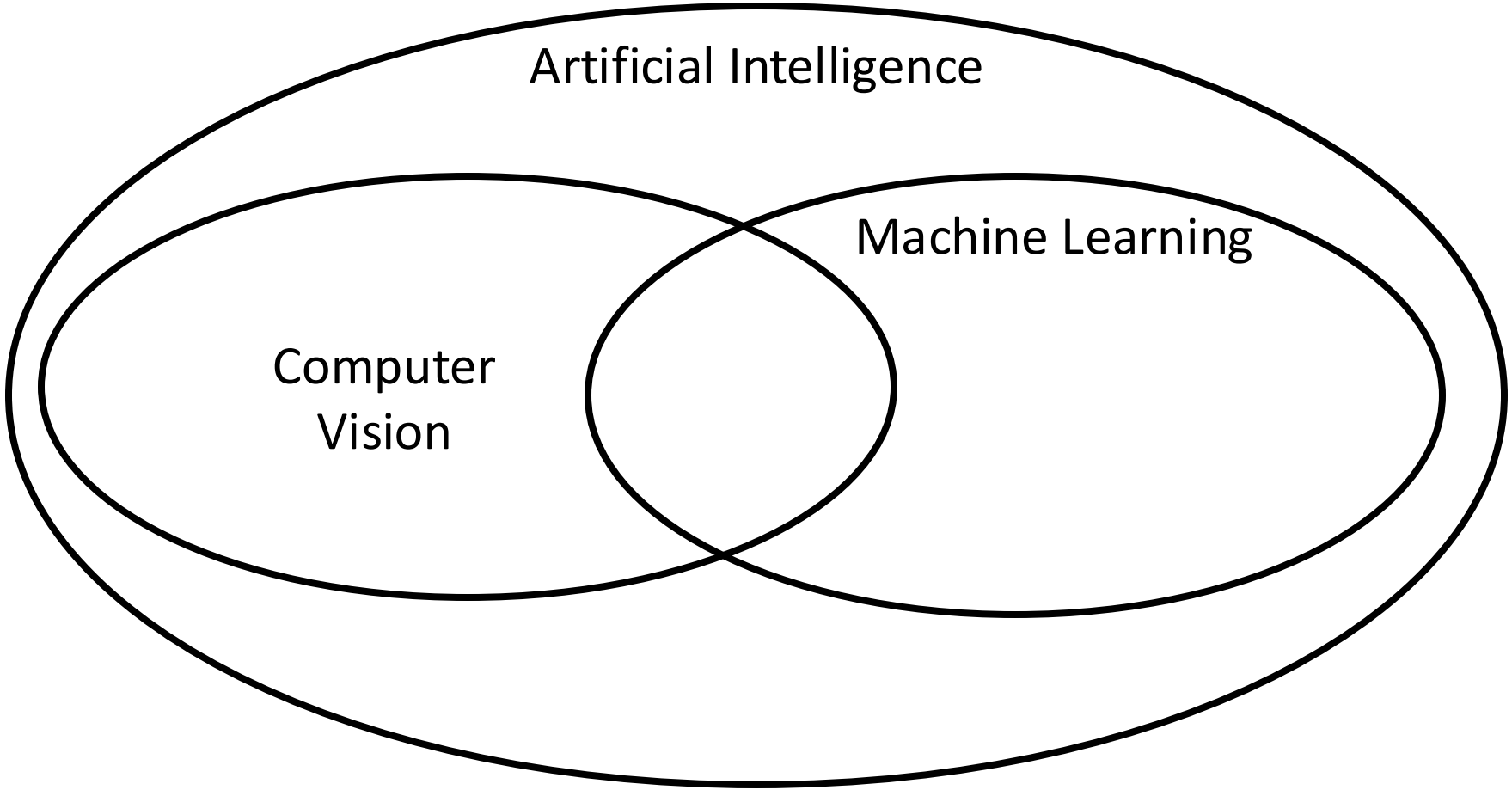


CS231n's Ten Year Anniversary: Returning Lecturers

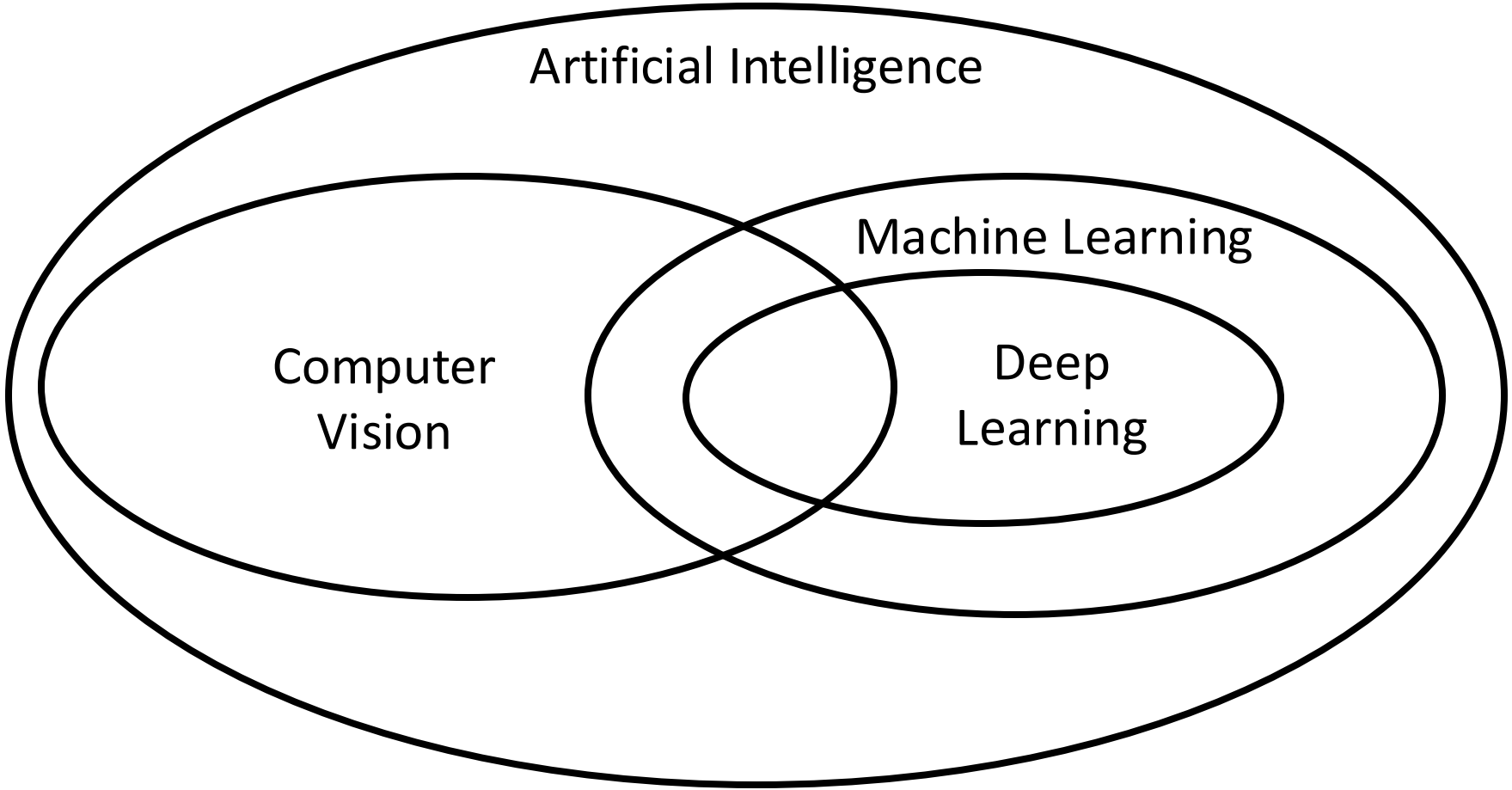




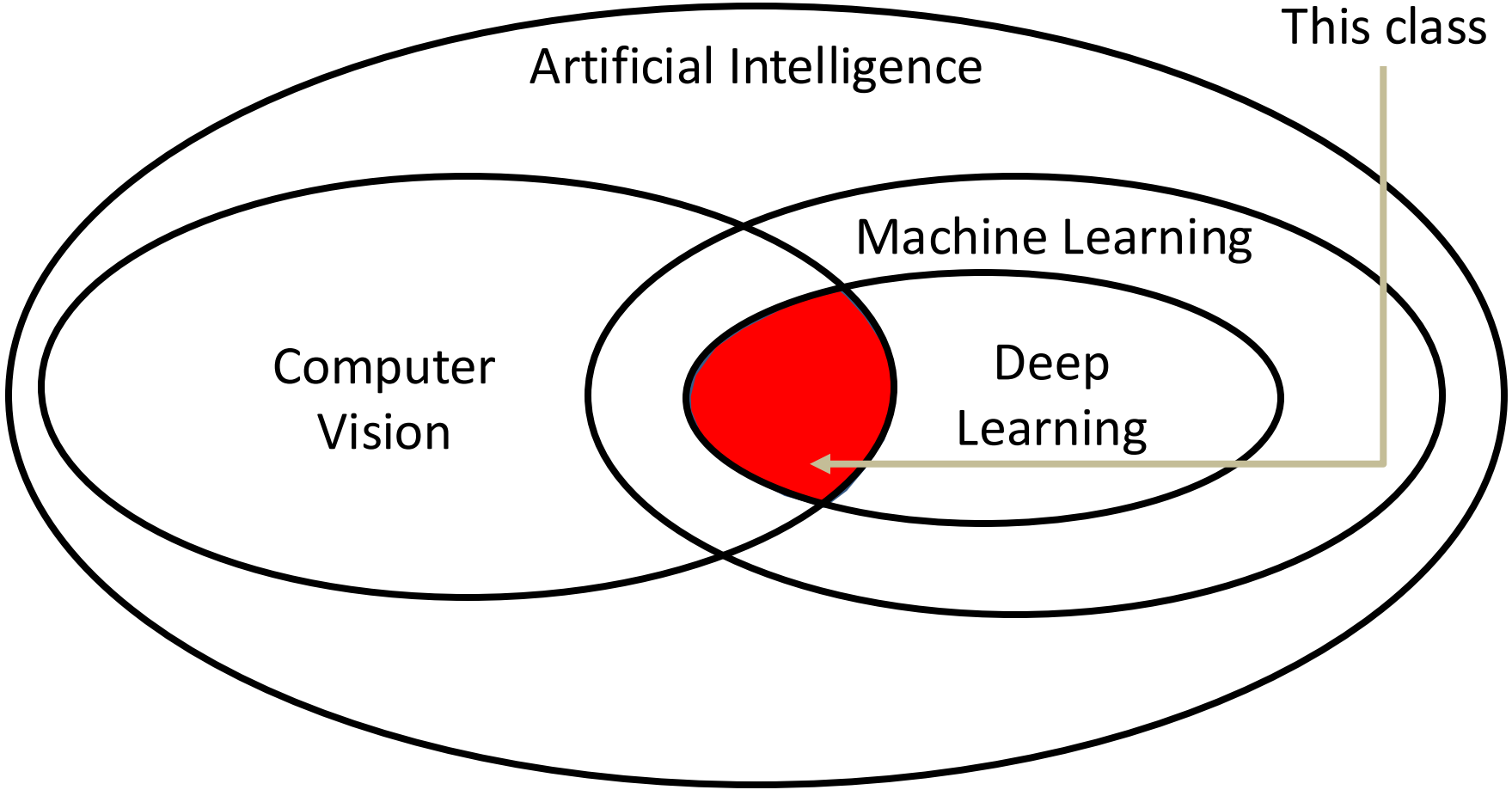
Slide inspiration: Justin Johnson



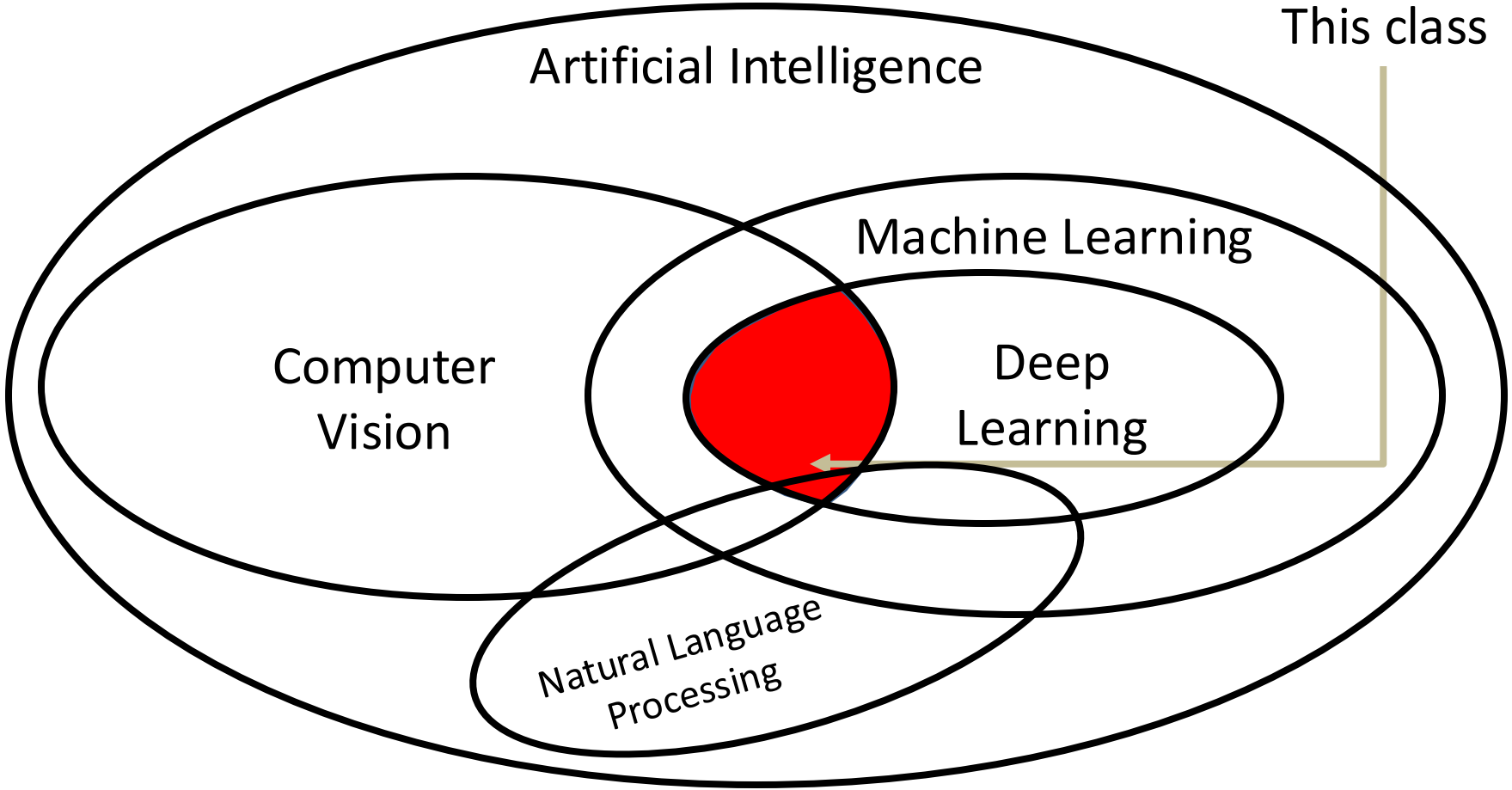
Slide inspiration: Justin Johnson



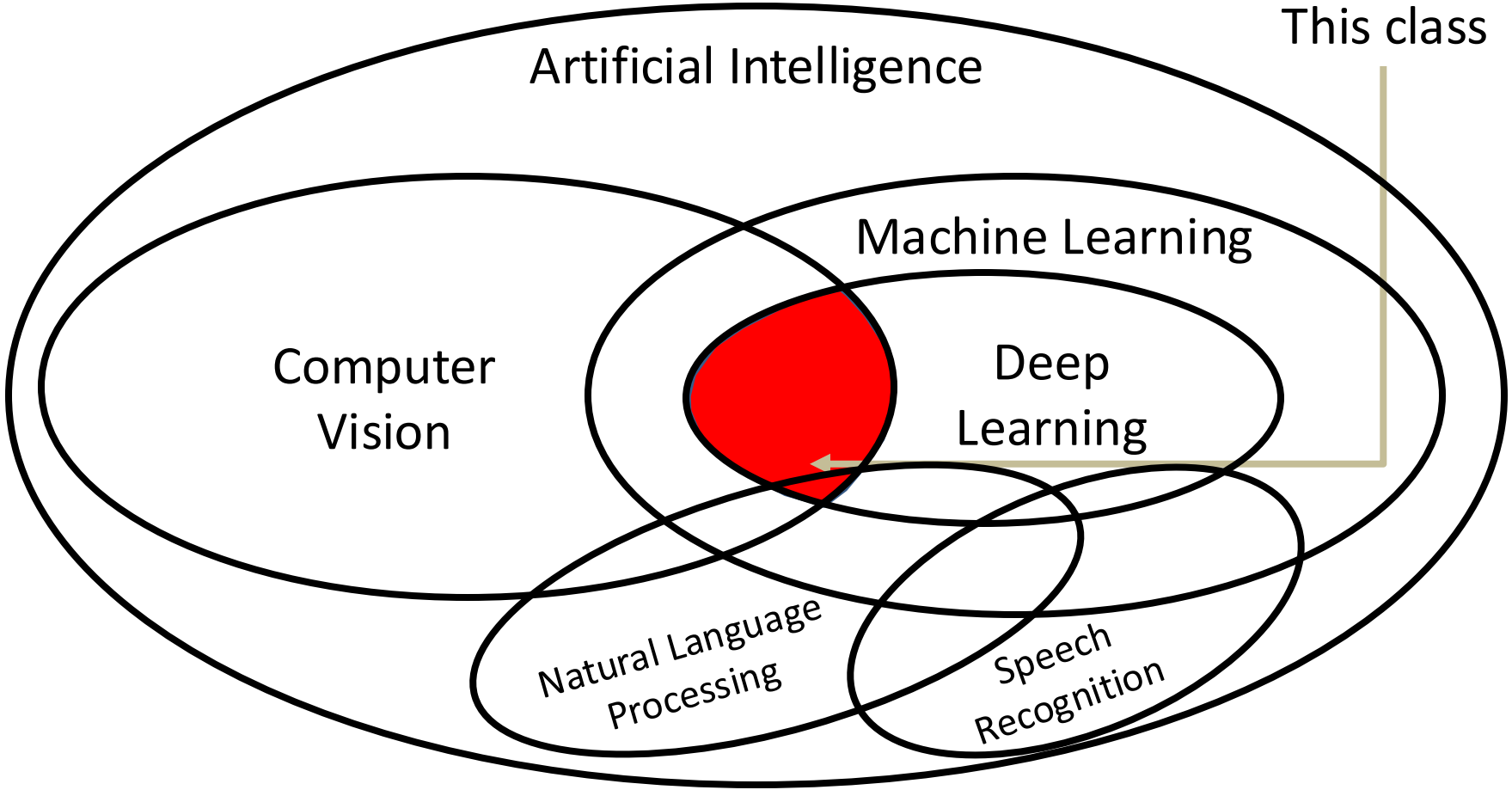
Slide inspiration: Justin Johnson



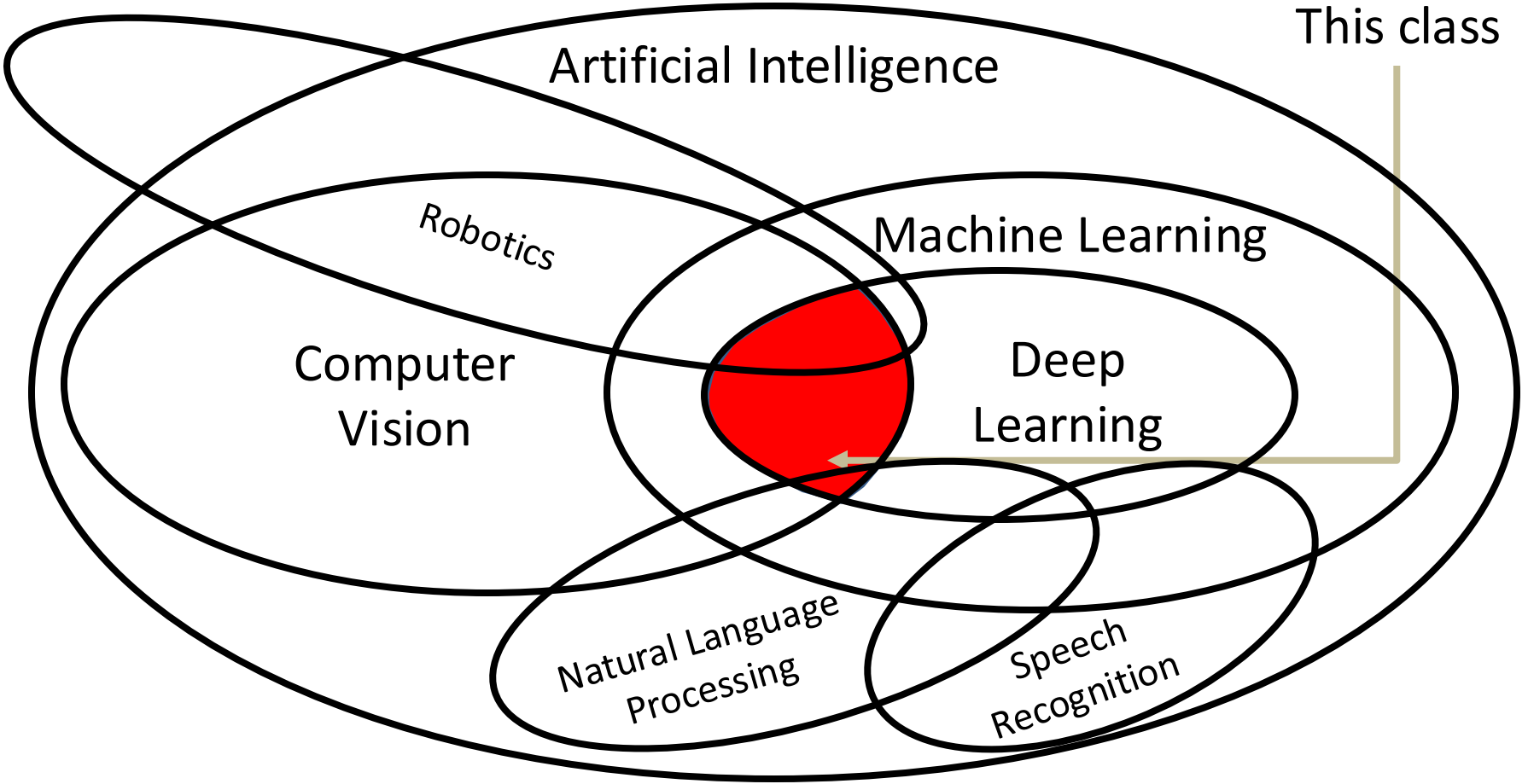
Slide inspiration: Justin Johnson



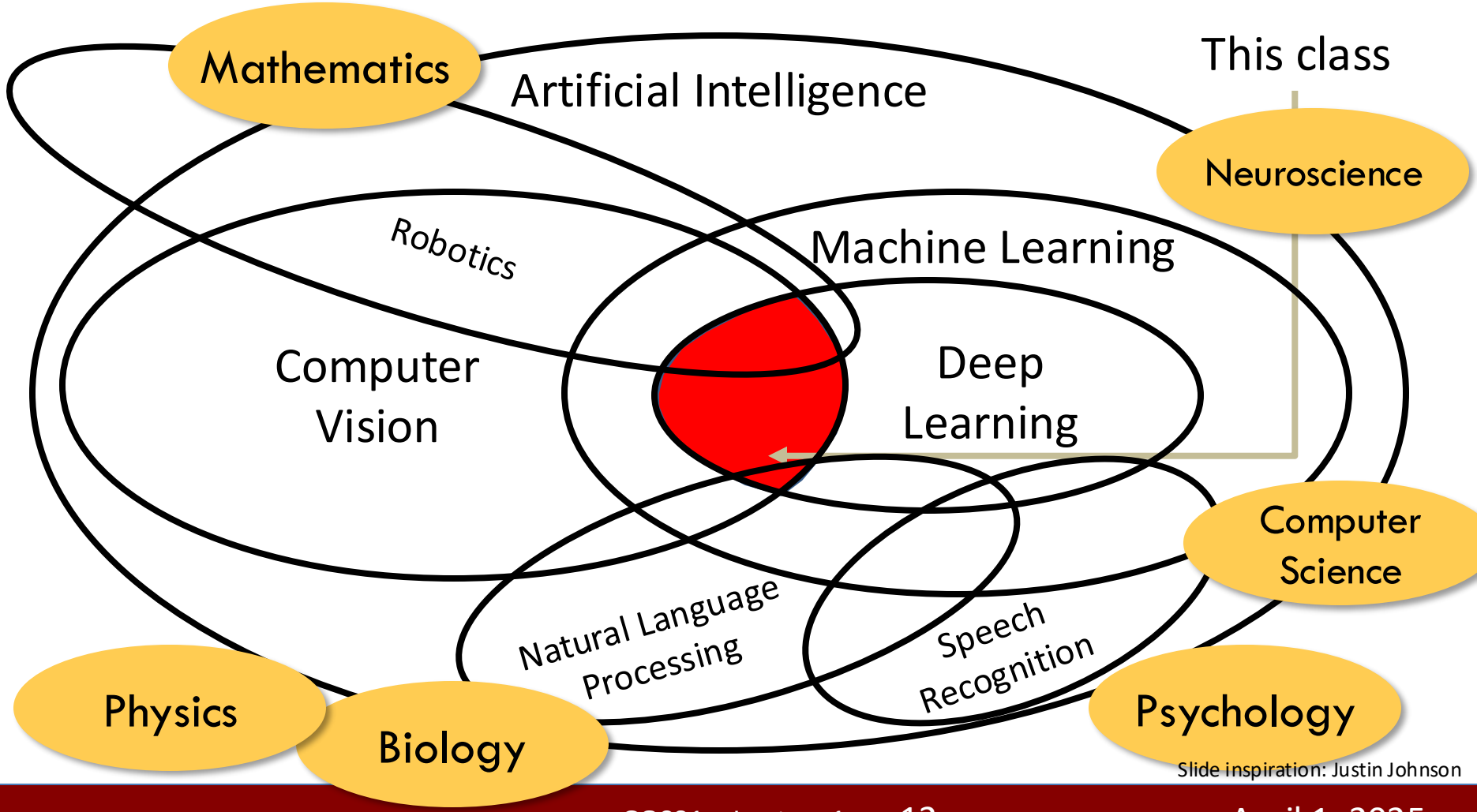
Slide inspiration: Justin Johnson



Slide inspiration: Justin Johnson



Slide inspiration: Justin Johnson

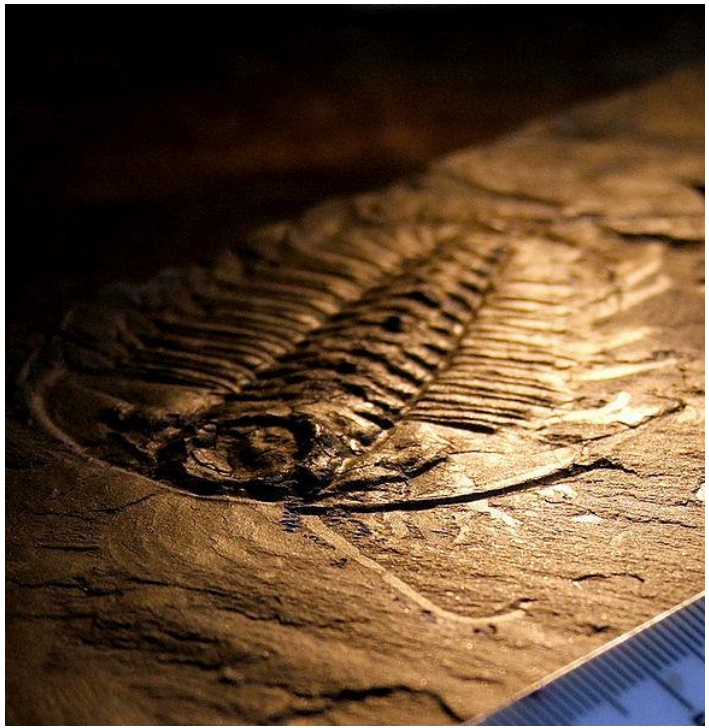


Slide inspiration: Justin Johnson

Today's agenda

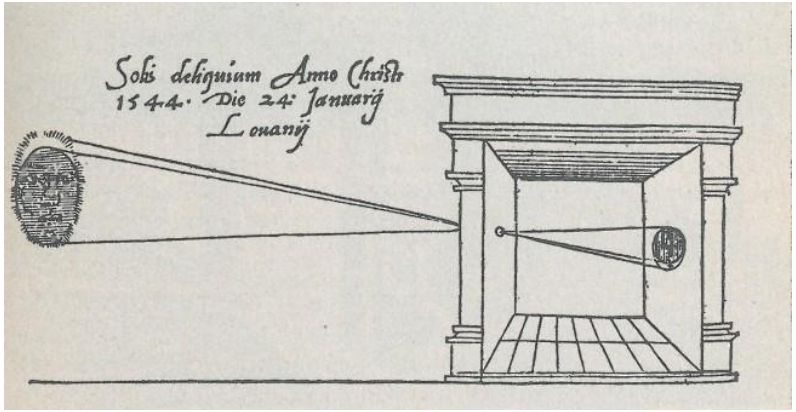
- A brief history of computer vision and deep learning
- CS231n overview

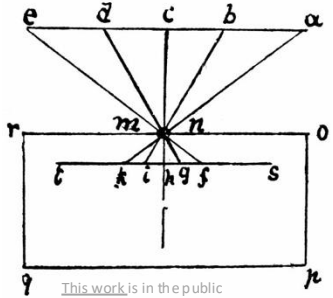
Evolution's Big Bang:
Cambrian Explosion, 530-540million years, B.C.



Camera Obscura

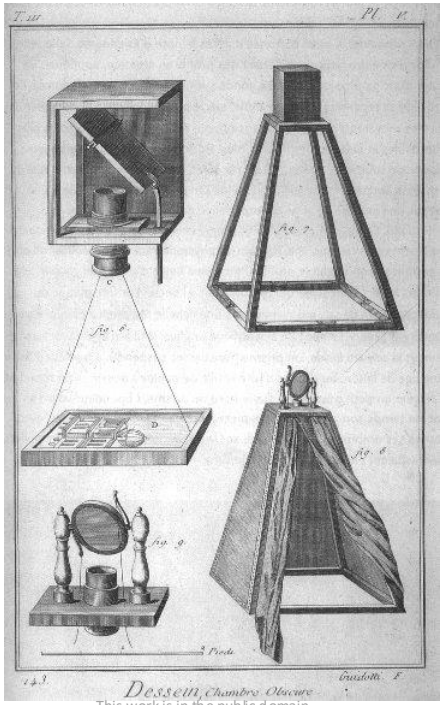
Gemma Frisius, 1545





Leonardo da Vinci,
16th Century AD

Encyclopedia, 18th Century



Computer Vision is everywhere!



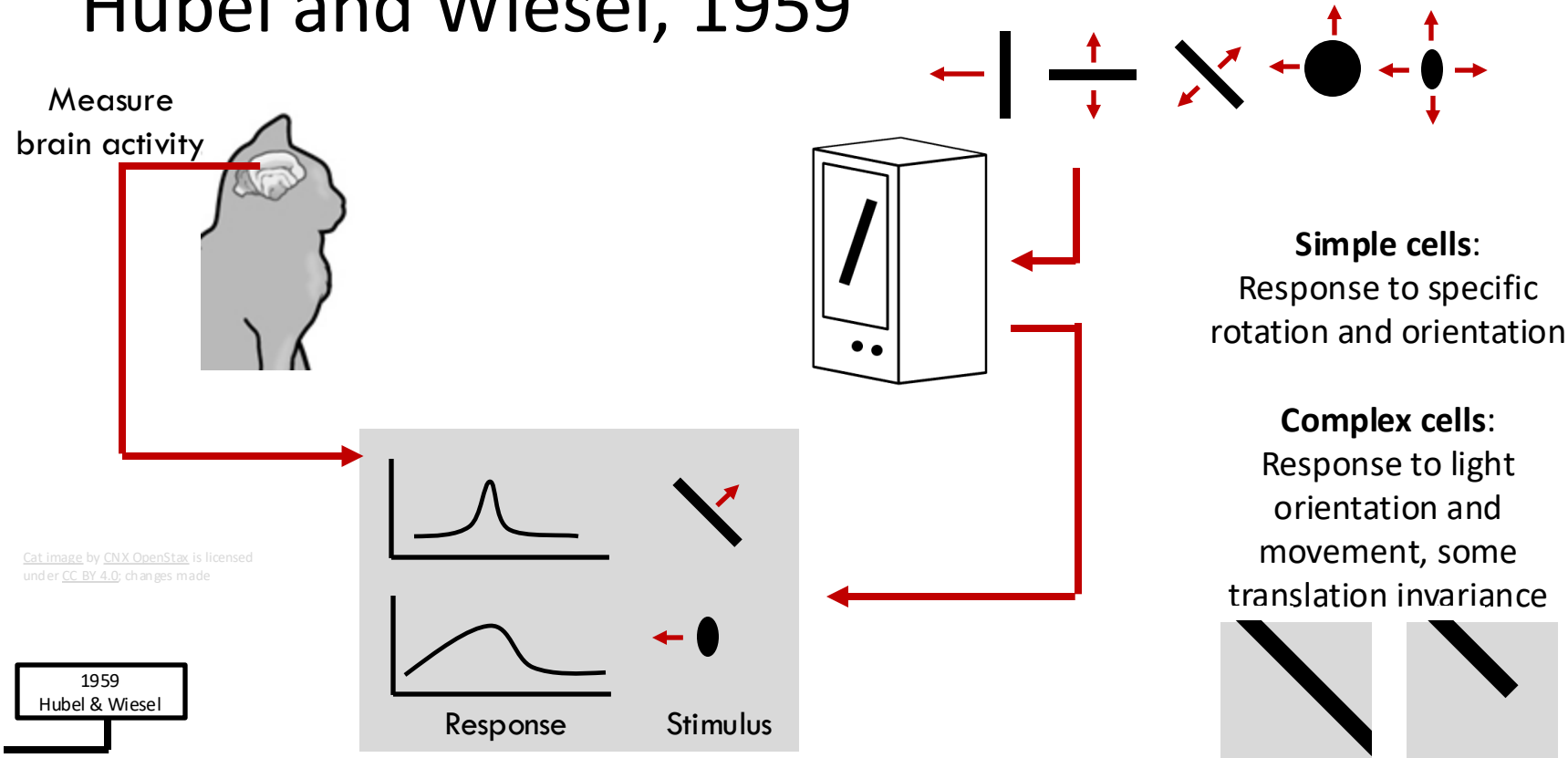







Where did we come from?

Hubel and Wiesel, 1959



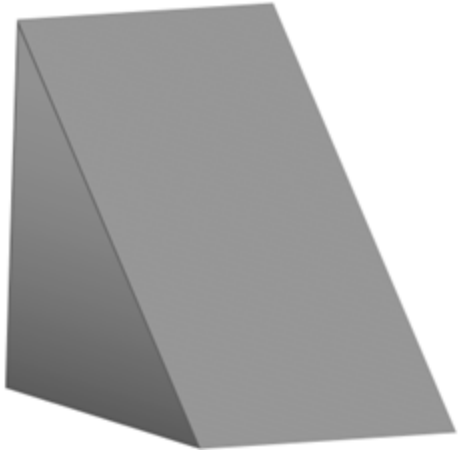
Simple cells:
Response to specific rotation and orientation

Complex cells:
Response to light orientation and movement, some translation invariance

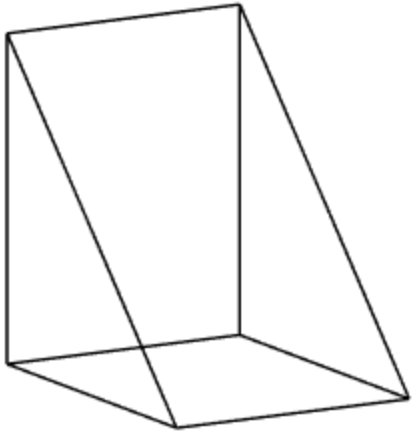
No response

Slide inspiration: Justin Johnson

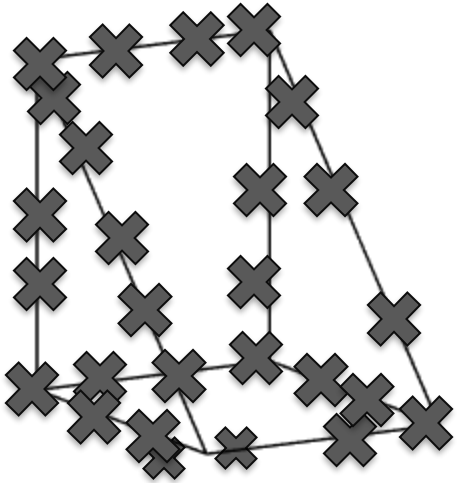
Larry Roberts, 1963



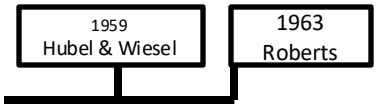
(a) Original picture



(b) Differentiated picture



(c) Feature points selected



Lawrence Gilman Roberts, "Machine Perception of Three-Dimensional Solids", 1963

Slide inspiration: Justin Johnson

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

PROJECT MAC

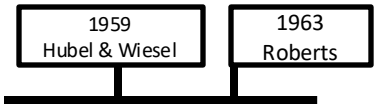
Artificial Intelligence Group
Vision Memo. No. 100.

July 7, 1966

THE SUMMER VISION PROJECT

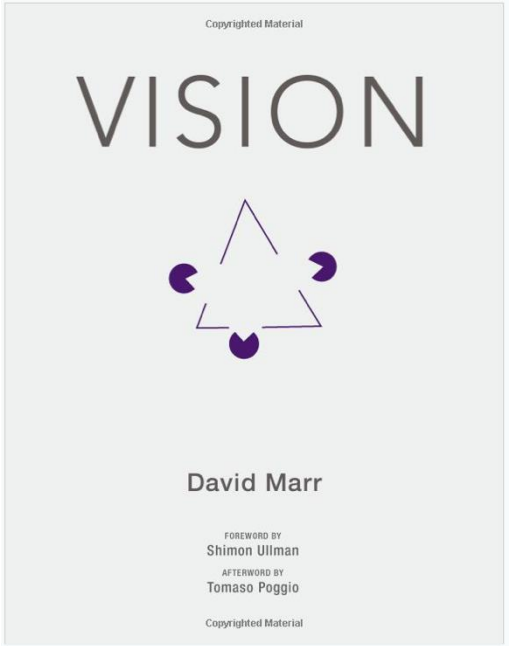
Seymour Papert

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".



https://dspace.mit.edu/handle/1721.1/6125

Slide inspiration: Justin Johnson



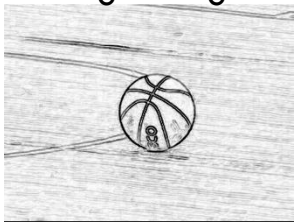
1959 Hubel & Wiesel

1963 Roberts

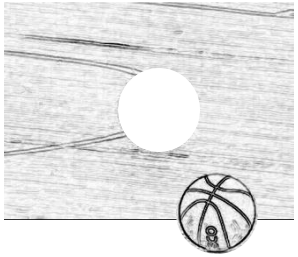
1970s David Marr

Input image

Edge image



2 ½-D sketch



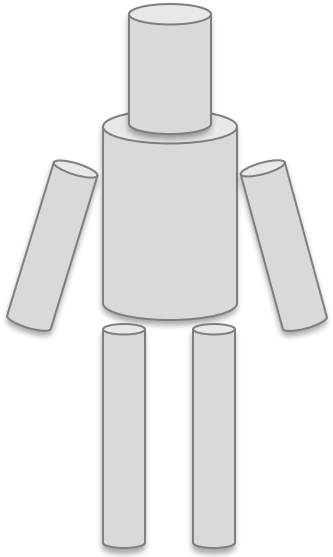
3-D model

Input Image	Primal Sketch	2 ½-D Sketch	3-D Model Representation
Perceived intensities	Zero crossings, blobs, edges, bars, ends, virtual lines, groups, curves boundaries	Local surface orientation and discontinuities in depth and in surface orientation	3-D models hierarchically organized in terms of surface and volumetric primitives

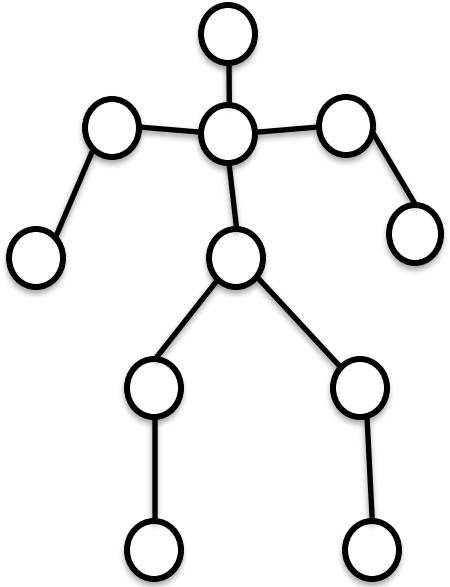
Stages of Visual Representation, David Marr, 1970s

Slide inspiration: Justin Johnson

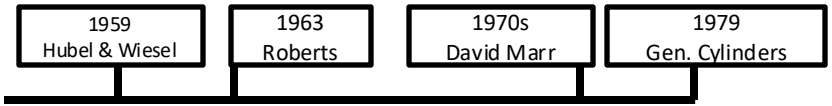
Recognition via Parts (1970s)



Generalized Cylinders,
Brooks and Binford,
1979

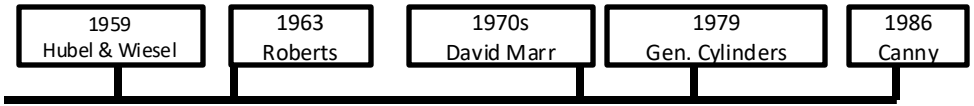


Pictorial Structures,
Fischler and Elshlager, 1973



Slide inspiration: Justin Johnson

Recognition via Edge Detection (1980s)

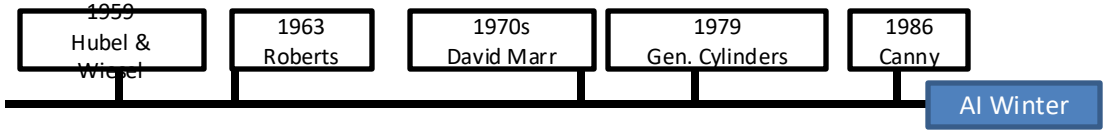


John Canny, 1986
David Lowe, 1987

Slide inspiration: Justin Johnson

Arriving at an “AI winter”

- Enthusiasm (and funding!) for AI research dwindled
- ”Expert Systems” failed to deliver on their promises
- But subfields of AI continues to grow
    - Computer vision, NLP, robotics, compbio, etc.

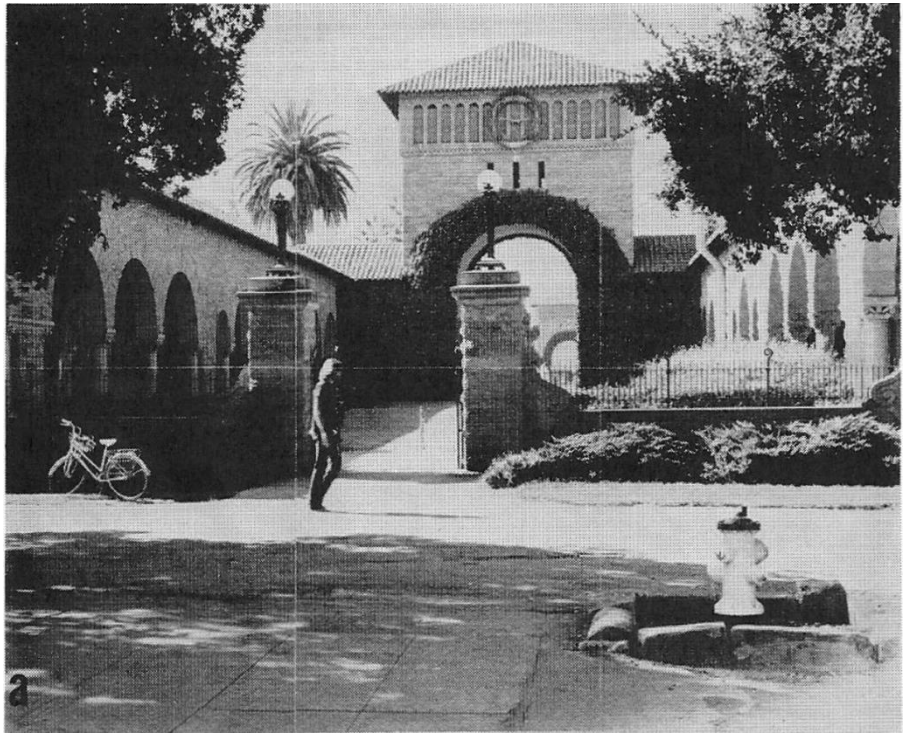


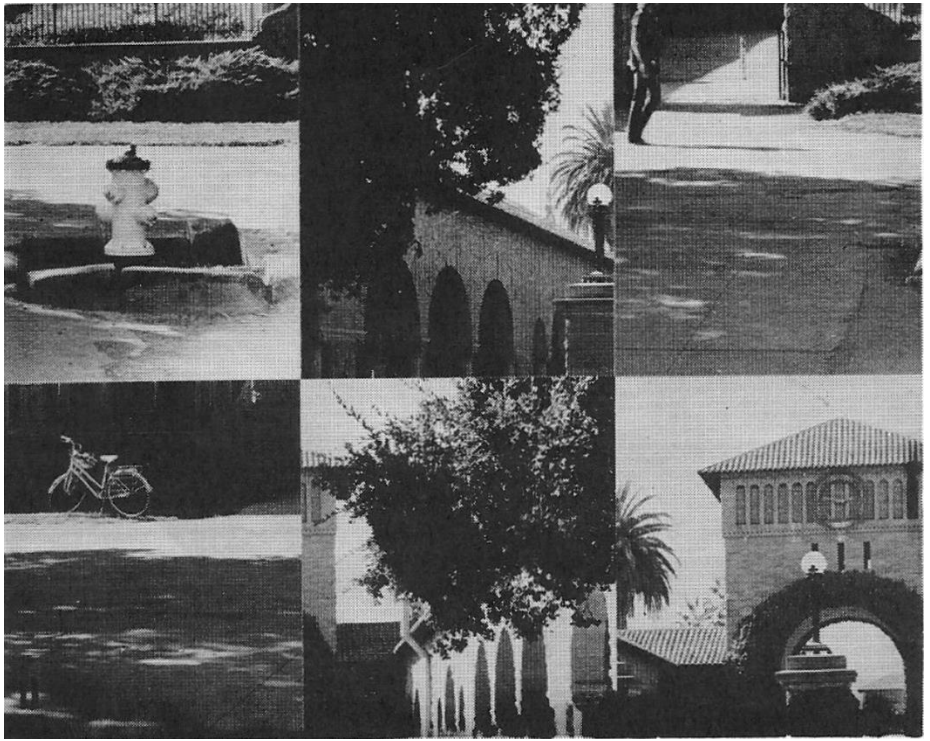
Slide inspiration: Justin Johnson

In the meantime…seminal work in cognitive and neuroscience

Perceiving Real-World Scenes

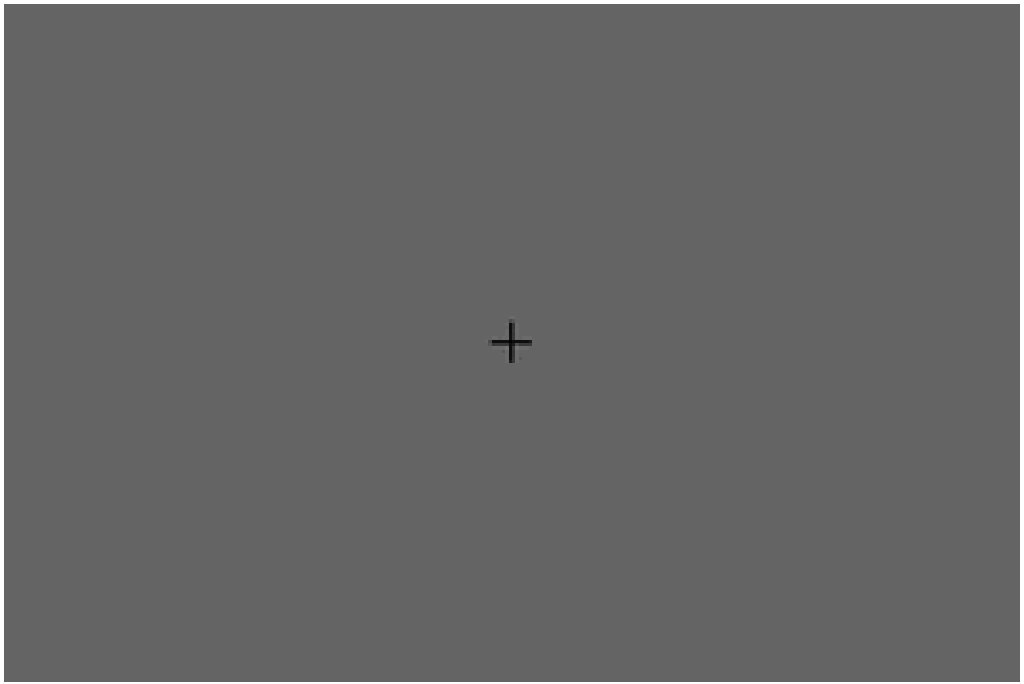
Irving Biederman





I. Biederman, *Science*, 1972

Rapid Serial Visual Perception (RSVP)



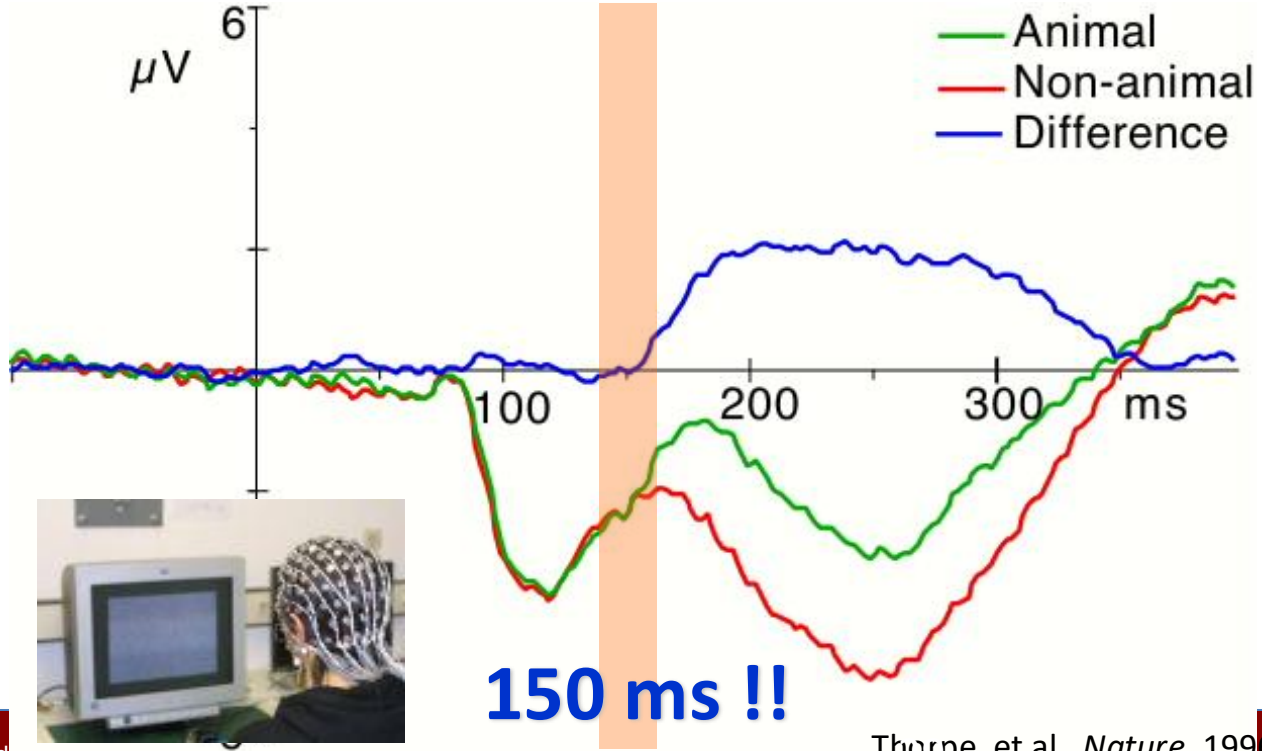
Potter, etc. 1970s






Speed of processing in the human visual system

Simon Thorpe, Denis Fize & Catherine Marlot

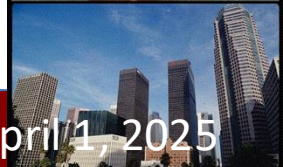


150 ms !!

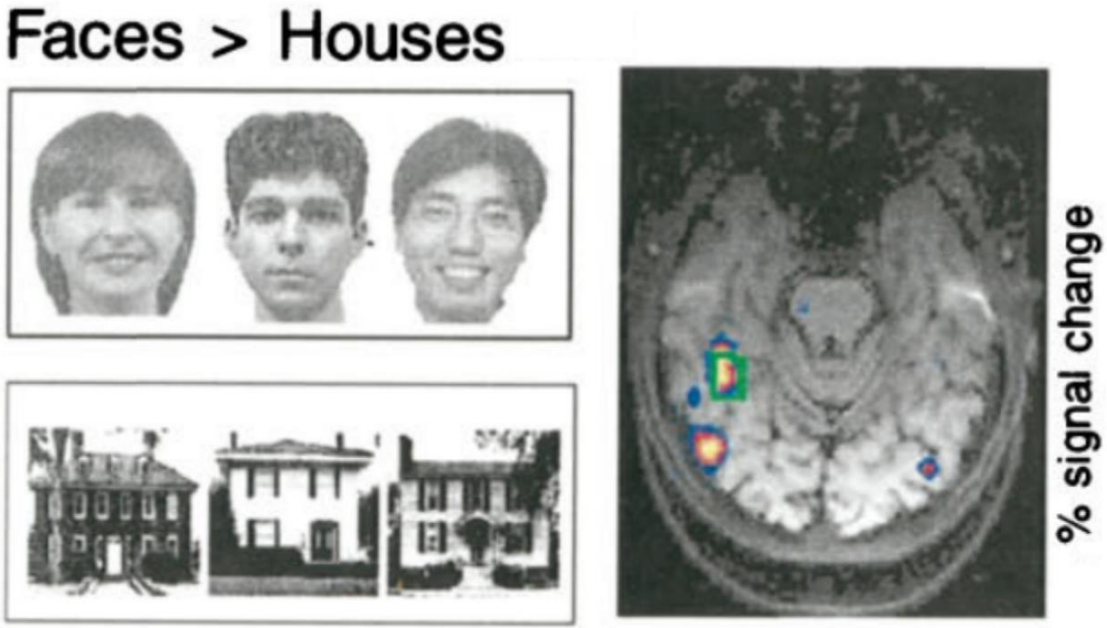
Thorpe, et al. *Nature*, 1996



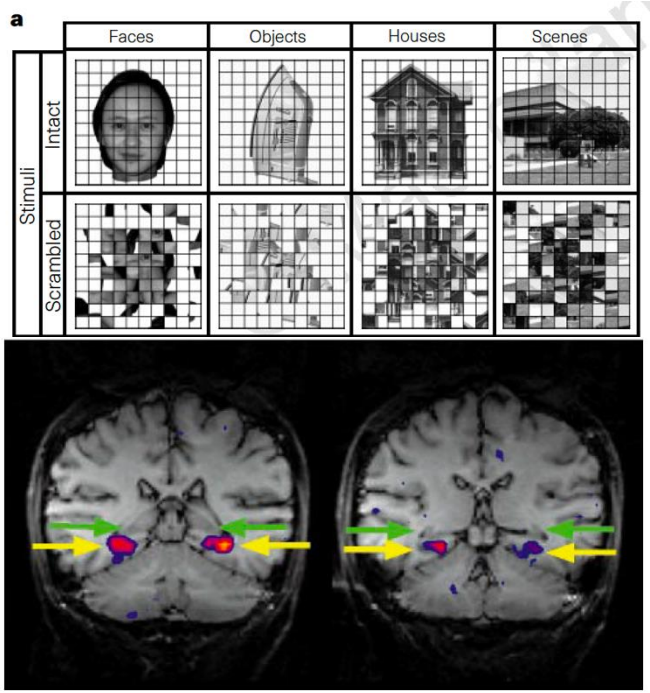




Neural correlates of object & scene recognition

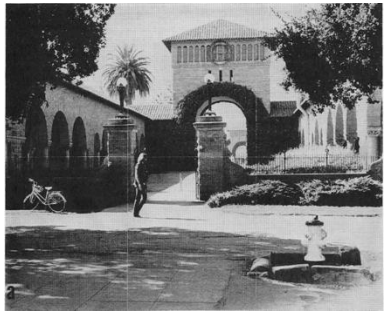


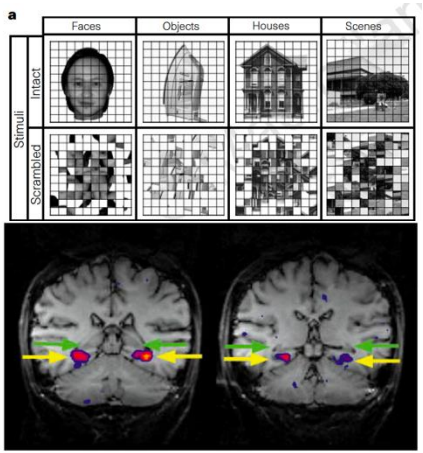
Kanwisher et al. J. Neuro. 1997



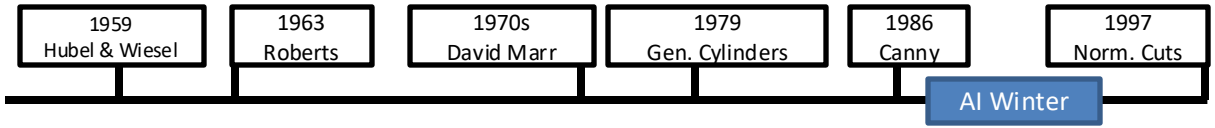
Epstein & Kanwisher, Nature, 1998

Visual recognition is a fundamental task for visual intelligence





Recognition via Grouping (1990s)



Normalized Cuts, Shi and Malik, 1997

Slide inspiration: Justin Johnson

Recognition via Matching (2000s)

Image is public domain

Image is public domain

1959 Hubel & Wiesel
1963 Roberts
1970s David Marr
1979 Gen. Cylinders
1986 Canny
AI Winter
1997 Norm. Cuts
1999 SIFT

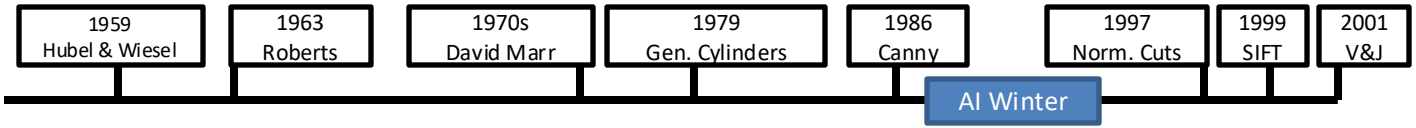
SIFT, David Lowe, 1999

Slide inspiration: Justin Johnson

Face Detection

Viola and Jones, 2001

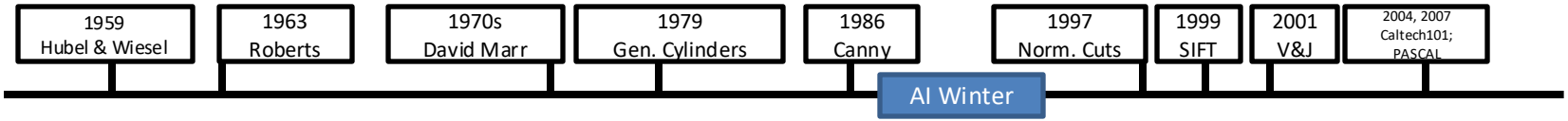
One of the first successful applications of machine learning to vision



Slide inspiration: Justin Johnson

Caltech 101 images

PASCAL Visual Object Challenge

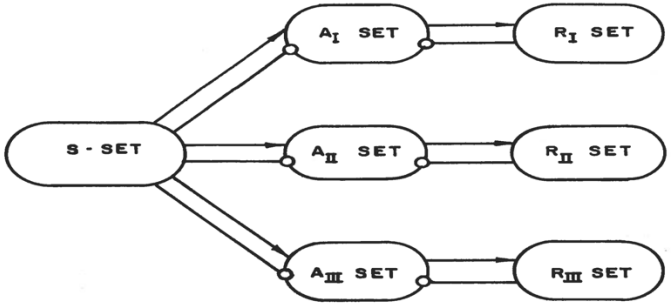


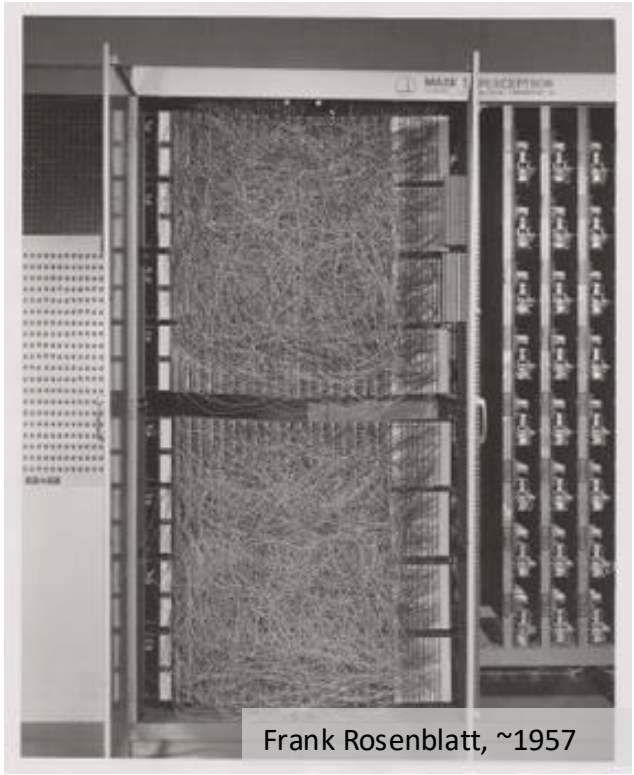
Slide inspiration: Justin Johnson

Learning representations by back-propagating errors

David E. Rumelhart*, Geoffrey E. Hinton† & Ronald J. Williams*

* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA



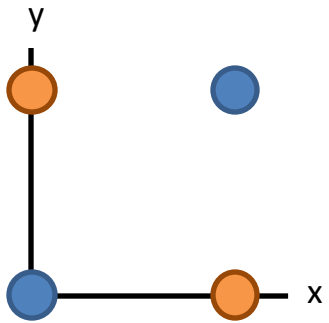

Frank Rosenblatt, ~1957

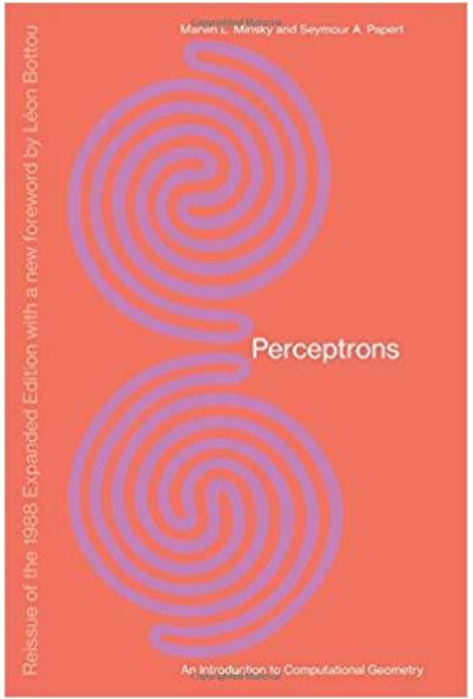
1958 Perceptron
1959 Hubel & Wiesel
1963 Roberts
1970s David Marr
1979 Gen. Cylinders
1986 Canny
AI Winter
1997 Norm. Cuts
1999 SIFT
2001 V&J
2004, 2007 Caltech101; PASCAL

Slide inspiration: Justin Johnson

Minsky and Papert, 1969

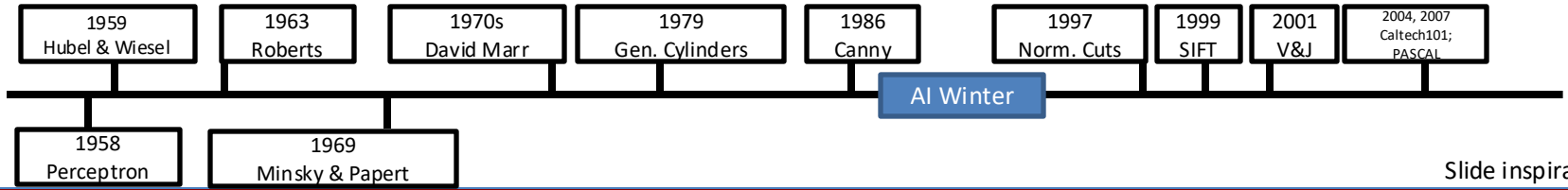
X	Y	F(x,y)
0	0	0
0	1	1
1	0	1
1	1	0





Showed that Perceptrons could not learn the XOR function

Caused a lot of disillusionment in the field



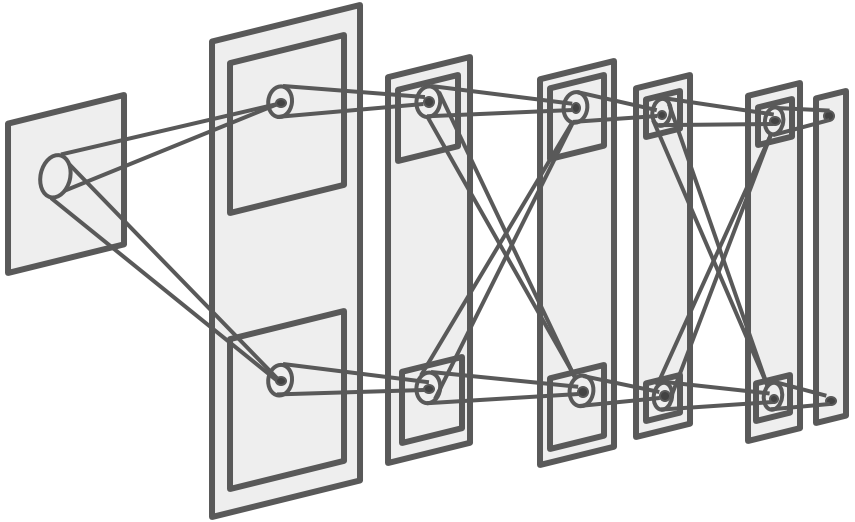
Slide inspiration: Justin Johnson

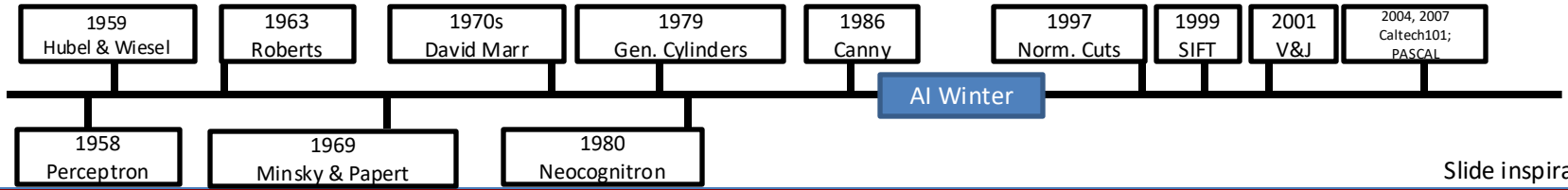
Neocognitron: Fukushima, 1980

Computational model the visual system, directly inspired by Hubel and Wiesel's hierarchy of complex and simple cells

Interleaved simple cells (convolution) and complex cells (pooling)

No practical training algorithm





Slide inspiration: Justin Johnson

Backprop: Rumelhart, Hinton, and Williams, 1986

Introduced backpropagation for computing gradients in neural networks

Successfully trained perceptrons with multiple layers

$$\frac{\partial E_p}{\partial w_{ji}} = \frac{\partial E_p}{\partial o_{pj}} \frac{\partial o_{pj}}{\partial w_{ji}}$$

recognizable math

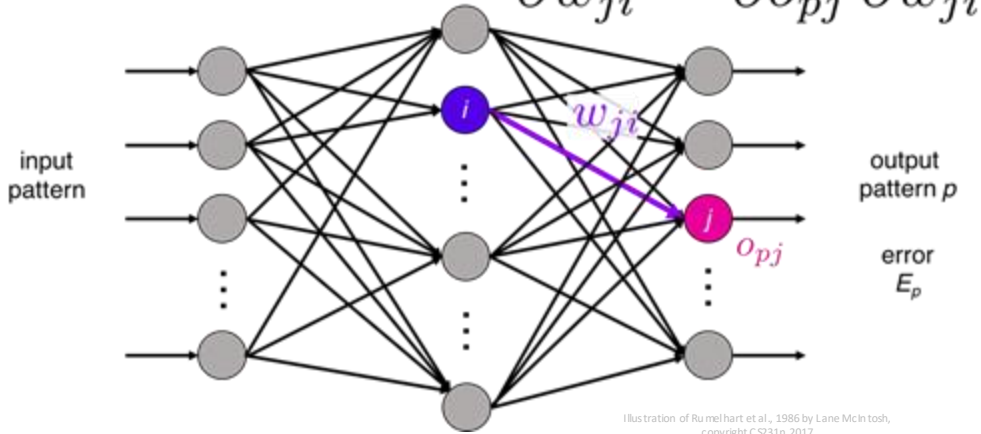
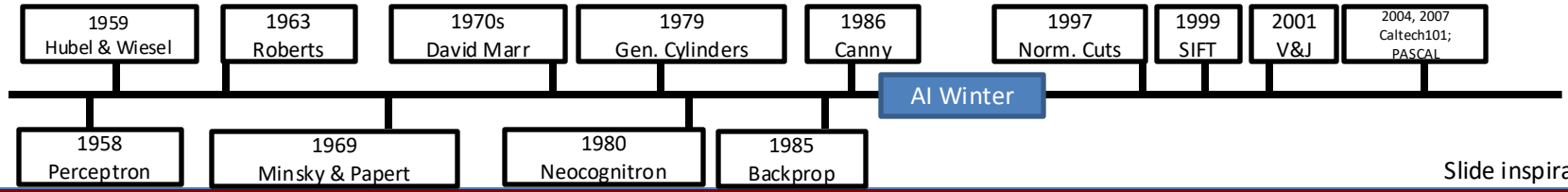
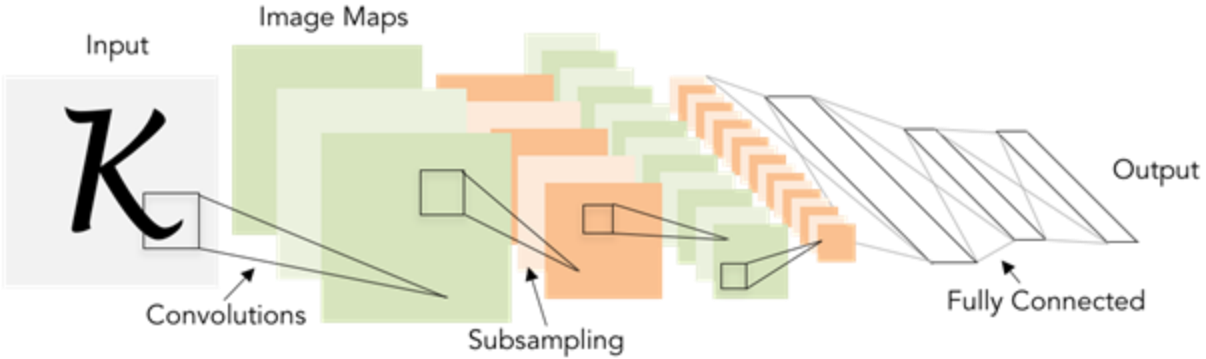


Illustration of Rumelhart et al., 1986 by Lane McIntosh, copyright CS231n 2017

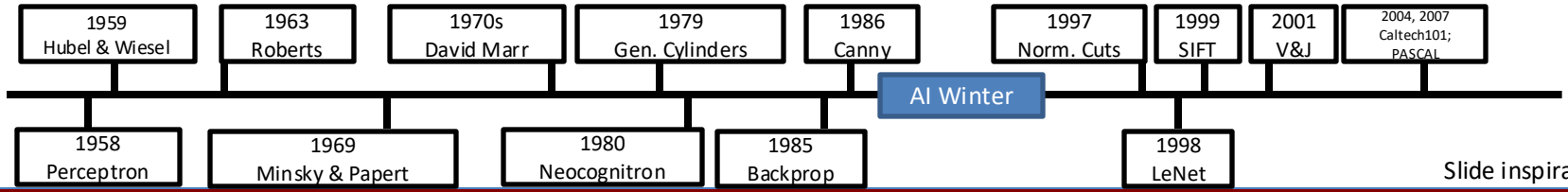


Slide inspiration: Justin Johnson

Convolutional Networks: LeCun et al, 1998



Applied backprop algorithm to a Neocognitron-like architecture
Learned to recognize handwritten digits
Was deployed in a commercial system by NEC, processed handwritten checks
Very similar to our modern convolutional networks!



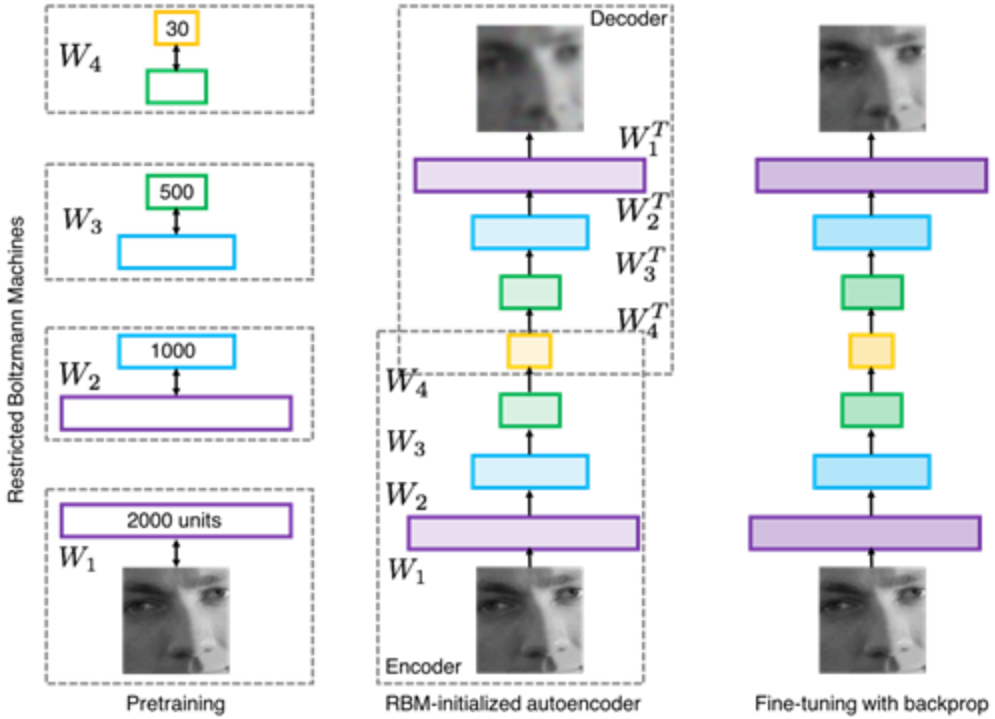
Slide inspiration: Justin Johnson

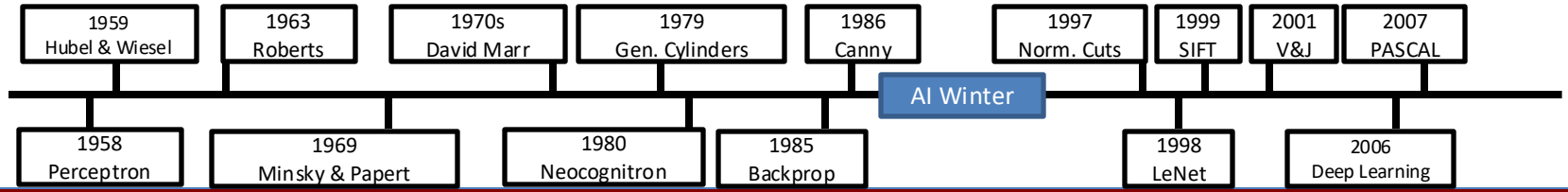
2000s: “Deep Learning”

People tried to train neural networks that were deeper and deeper

Not a mainstream research topic at this time

Hinton and Salakhutdinov, 2006
Bengio et al, 2007
Lee et al, 2009
Glorot and Bengio, 2010





Slide inspiration: Justin Johnson

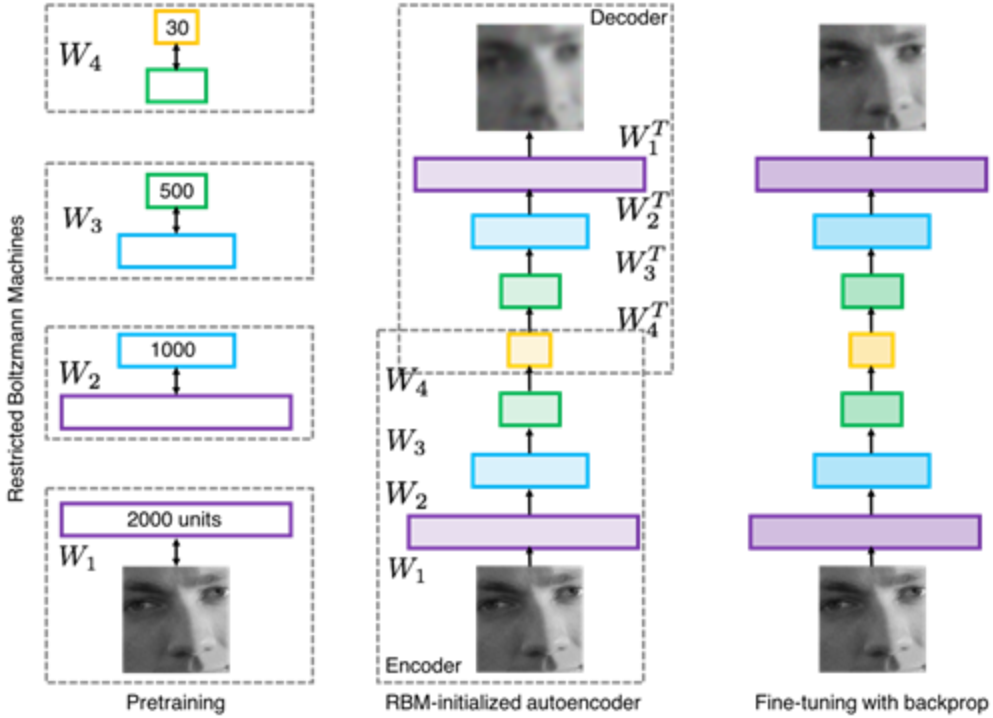
2000s: “Deep Learning”

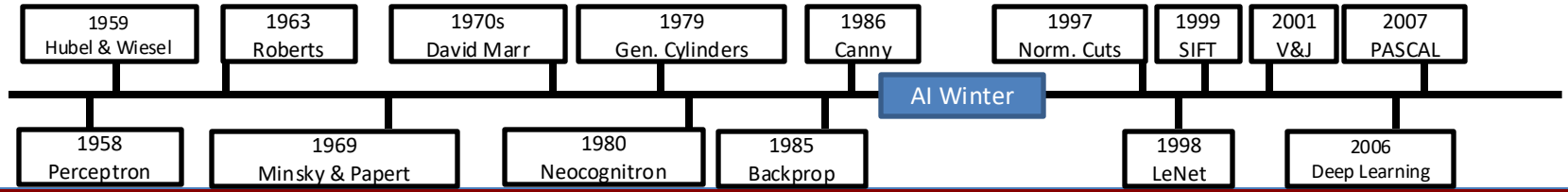
People tried to train neural networks that were deeper and deeper

Not a mainstream research topic at this time

No good dataset to work on

Hinton and Salakhutdinov, 2006
Bengio et al, 2007
Lee et al, 2009
Glorot and Bengio, 2010





Slide inspiration: Justin Johnson

IMAGENET Large Scale Visual Recognition Challenge

The Image Classification Challenge:

1,000 object classes

1,431,167 images

Output:

Scale

T-shirt

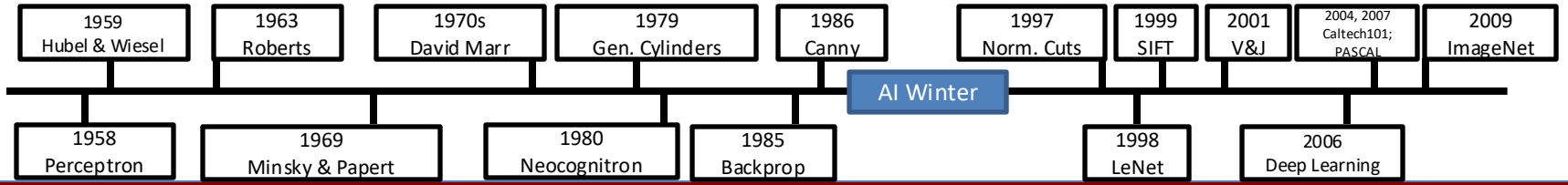
Steel drum

Drumstick

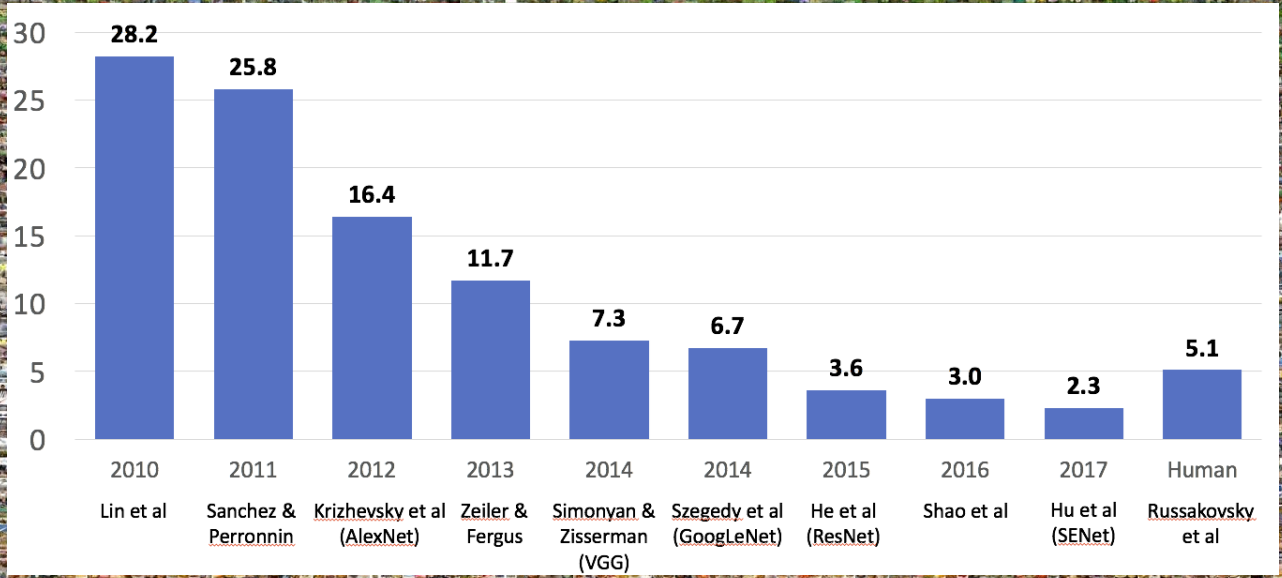
Mud turtle

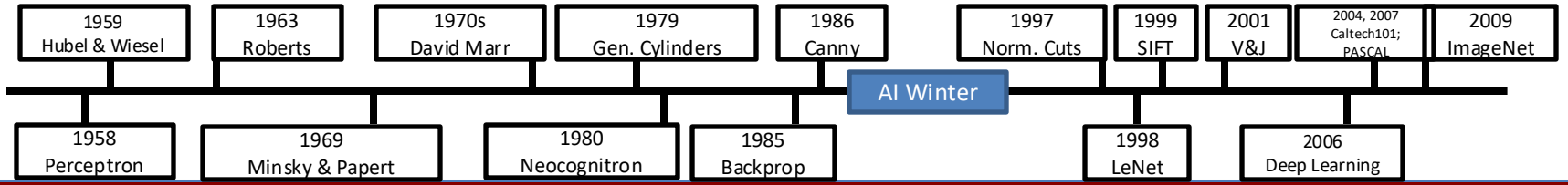
Deng et al, 2009

Russakovsky et al. IJCV 2015

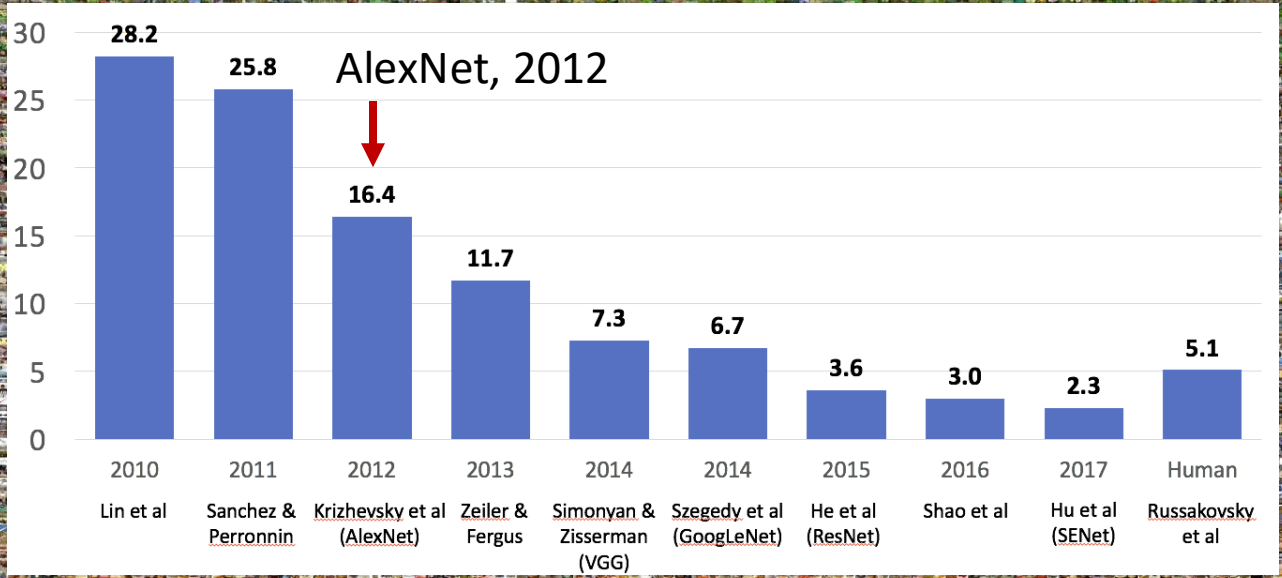


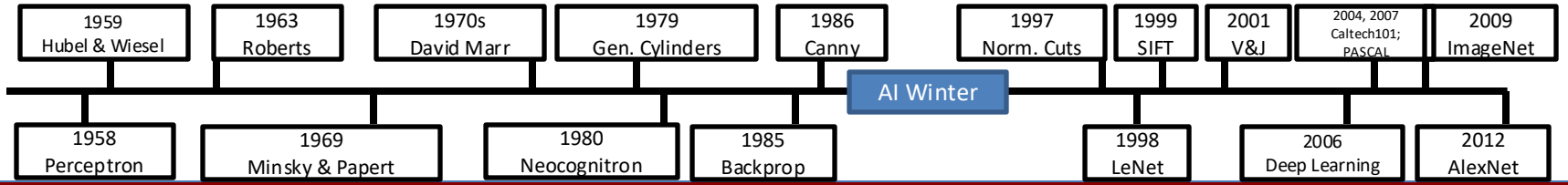
IMAGENET Large Scale Visual Recognition Challenge



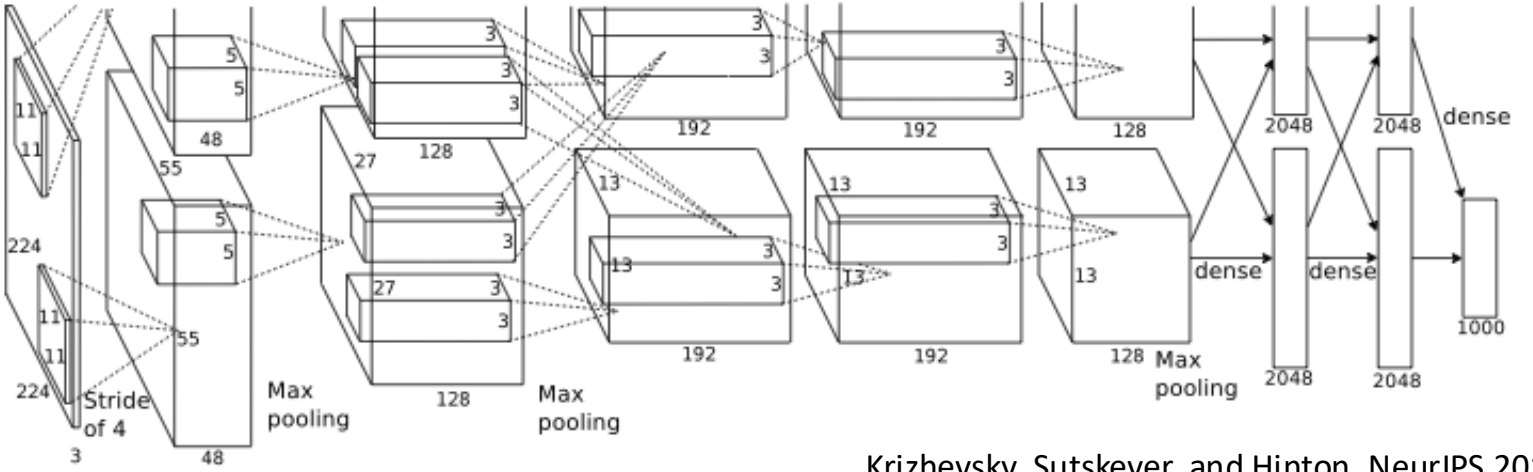


IMAGENET Large Scale Visual Recognition Challenge

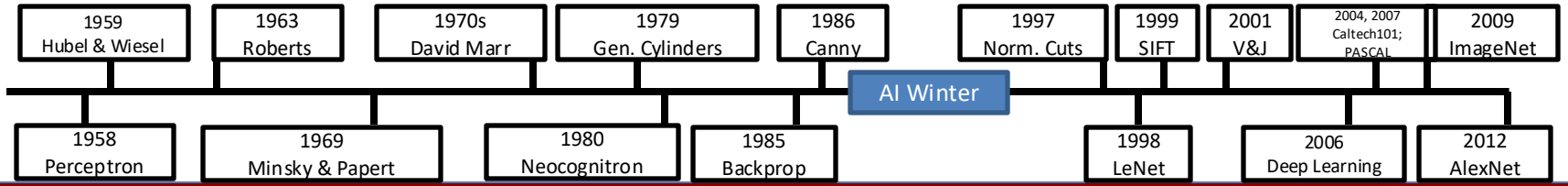




AlexNet: Deep Learning Goes Mainstream

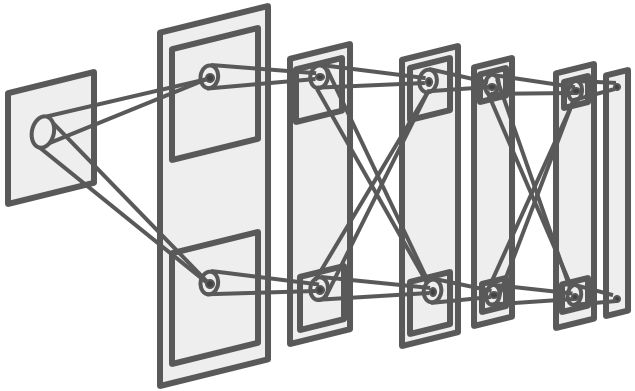


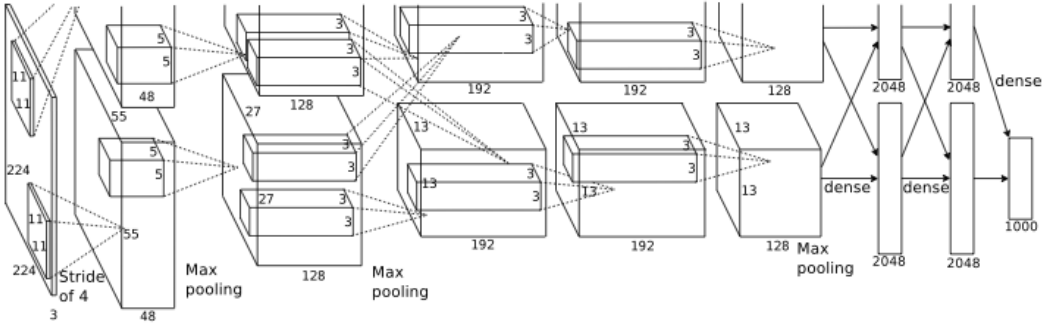
Krizhevsky, Sutskever, and Hinton, NeurIPS 2012

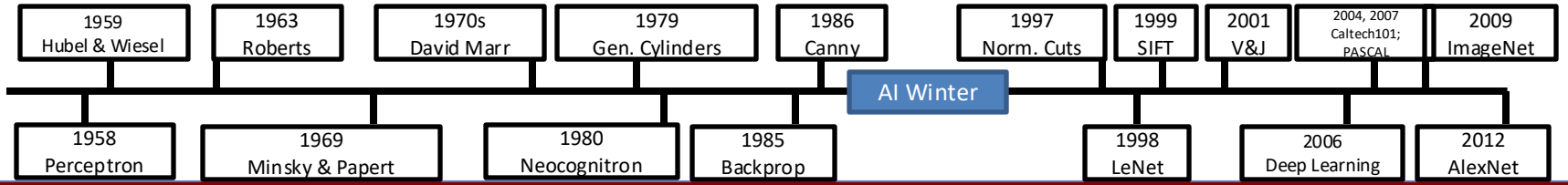


Slide inspiration: Justin Johnson

AlexNet vs. Neocognitron: 32 years apart

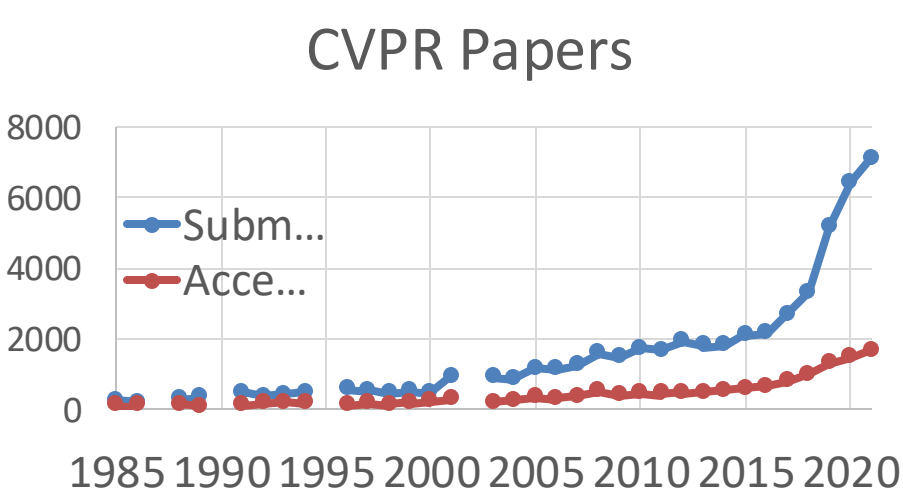




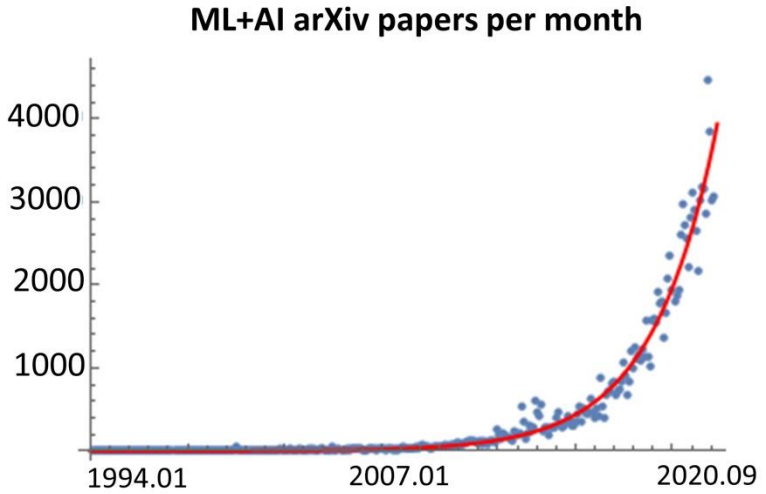


Slide inspiration: Justin Johnson

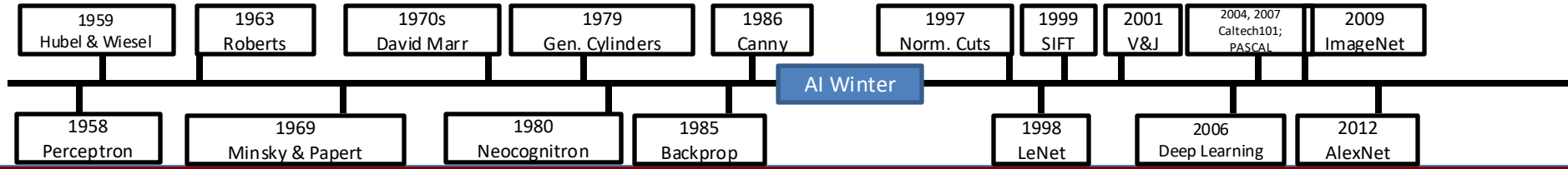
2012 to Present: Deep Learning Explosion



Publications at top Computer Vision conference



arXiv papers per month (source)



Slide inspiration: Justin Johnson

2012 to Present: Deep Learning is Everywhere

Year 2010

NEC-UIUC

Dense descriptor grid: HOG, LBP

Coding: local coordinate, super-vector

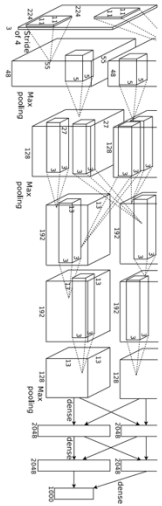
Pooling, SPM

Linear SVM

[Lin CVPR 2011]

Year 2012

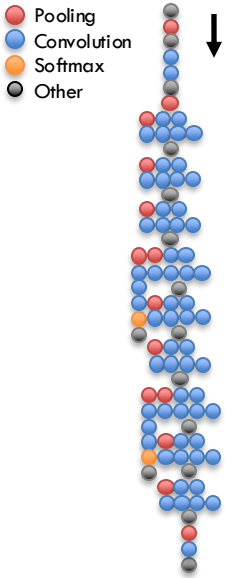
SuperVision



[Krizhevsky NIPS 2012]

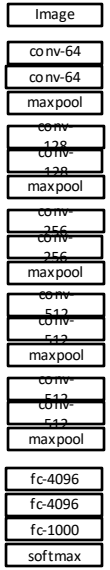
Year 2014

GoogLeNet



[Szegedy arxiv 2014]

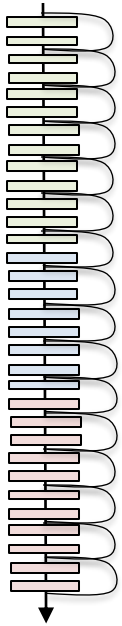
VGG



[Simonyan arxiv 2014]

Year 2015

MSRA



[He ICCV 2015]

2012 to Present: Deep Learning is Everywhere

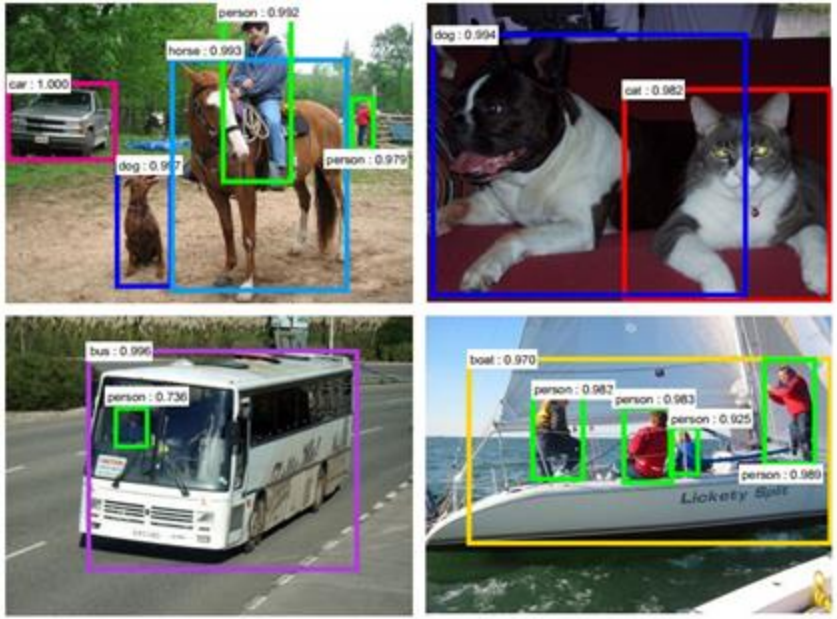
Image Classification

Image Retrieval

Slide inspiration: Justin Johnson

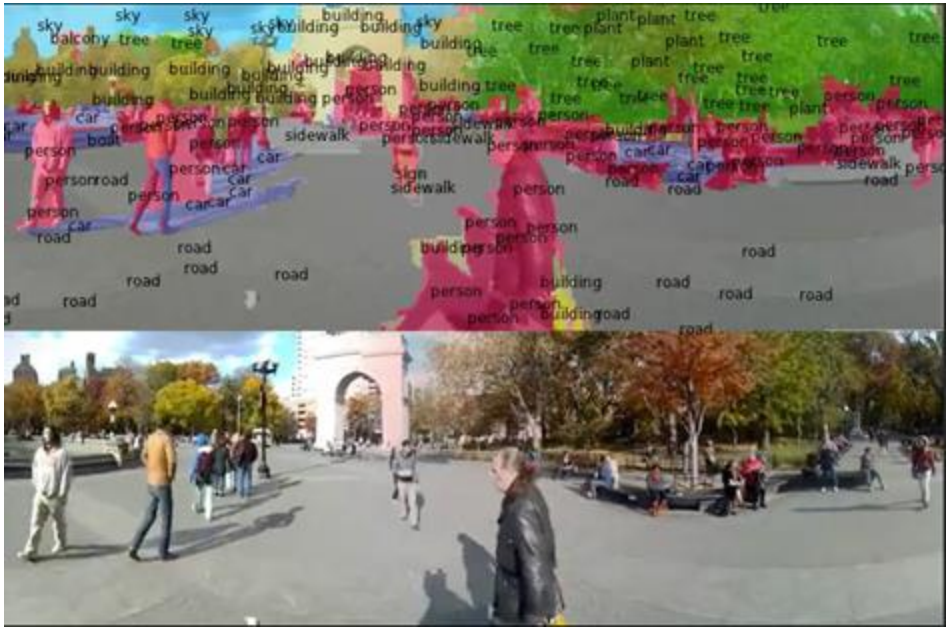
2012 to Present: Deep Learning is Everywhere

Object Detection



Ren, He, Girshick, and Sun, 2015

Image Segmentation

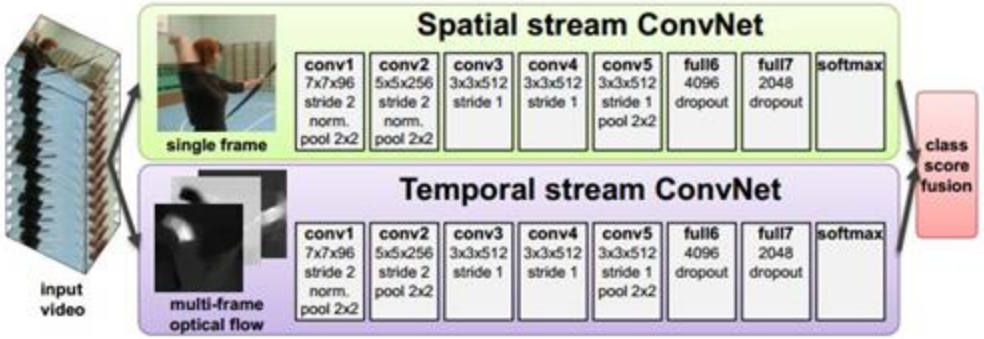


Fabaret et al, 2012

Slide inspiration: Justin Johnson

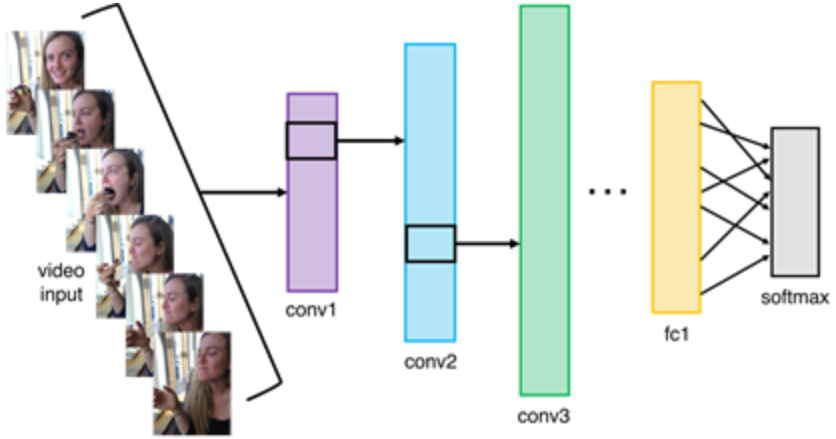
2012 to Present: Deep Learning is Everywhere

Video Classification



Simonyan et al, 2014

Activity Recognition

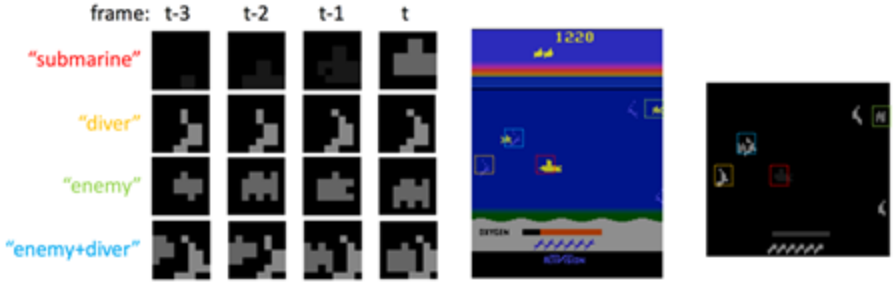


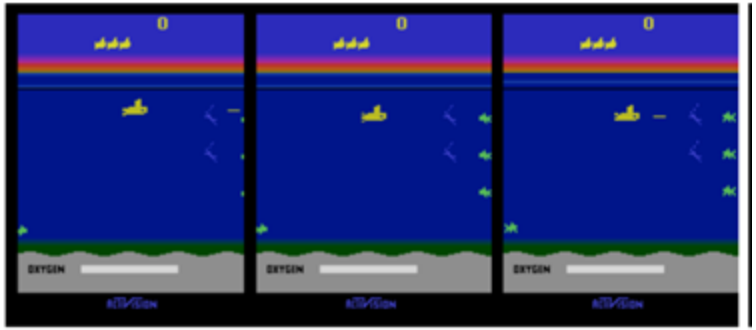
Slide inspiration: Justin Johnson

2012 to Present: Deep Learning is Everywhere

Pose Recognition (Toshev and Szegedy, 2014)

Playing Atari games (Guo et al, 2014)

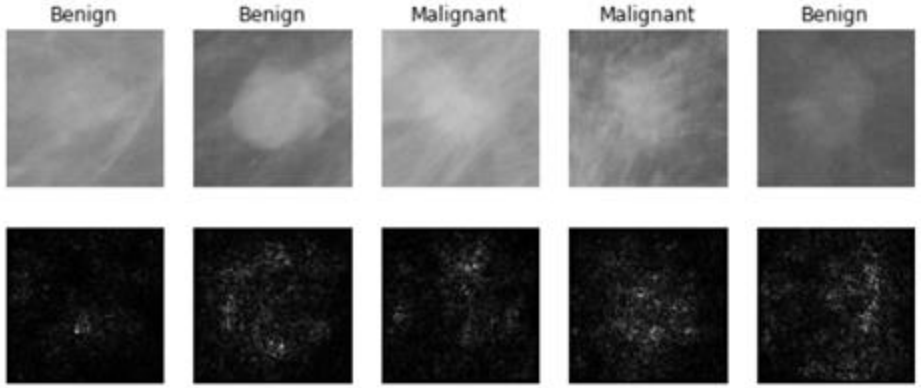




Slide inspiration: Justin Johnson

2012 to Present: Deep Learning is Everywhere

Medical Imaging



Levy et al, 2016 Figure reproduced with permission

Galaxy Classification

Dieleman et al, 2014

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Whale recognition

Kaggle Challenge

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Slide inspiration: Justin Johnson

2012 to Present: Deep Learning is Everywhere

Image Captioning

Vinyals et al, 2015
Karpathy and Fei-Fei, 2015

A white teddy bear sitting in the grass

A man in a baseball uniform throwing a ball

A woman is holding a cat in her hand

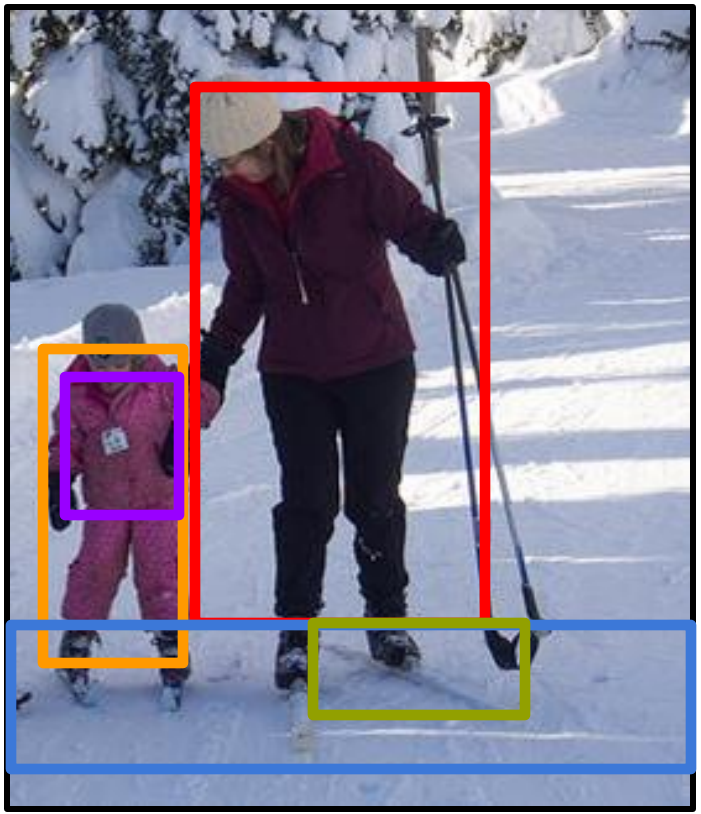
A man riding a wave on top of a surfboard

A cat sitting on a suitcase on the floor

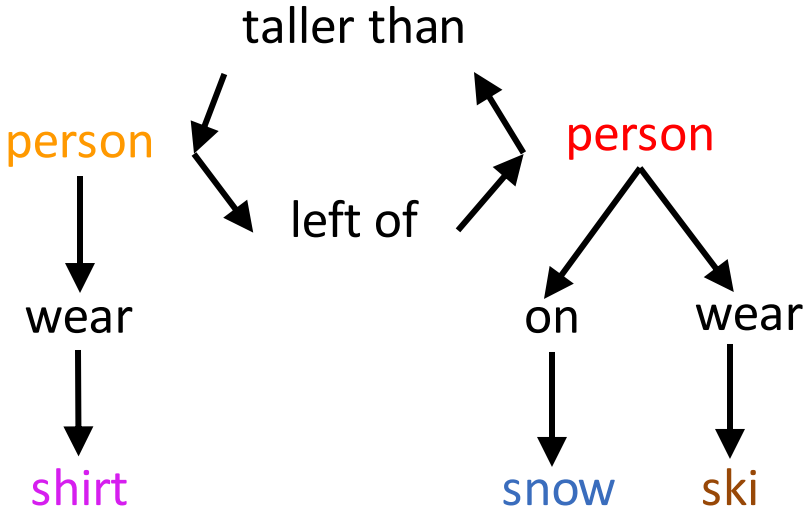
A woman standing on a beach holding a surfboard

Slide inspiration: Justin Johnson

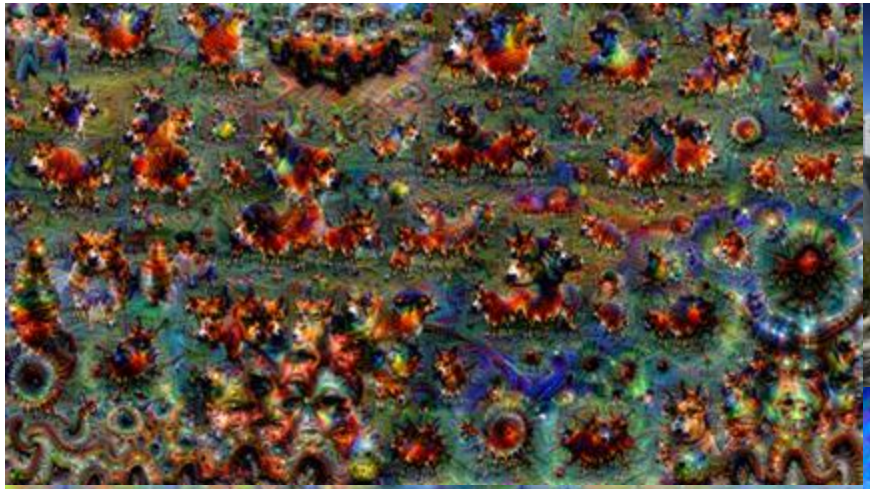
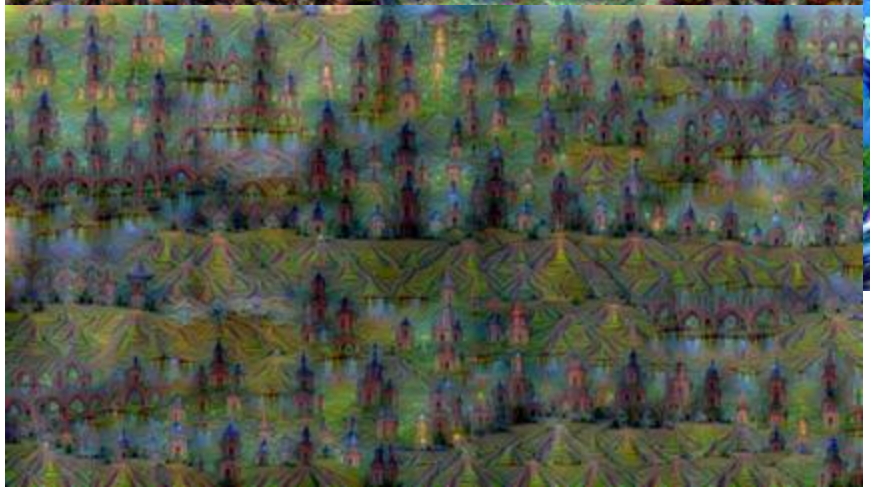
2012 to Present: Deep Learning is Everywhere



Results:
spatial, comparative, asymmetrical, verb, prepositional



Krishna*, Lu*, Bernstein, Fei-Fei, *ECCV* 2016





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Starry Night and Tree Roots by Van Gogh are in the public domain
Bolshoi image is in the public domain
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Mordvinsev et al, 2015
Gatys et al, 2016

Slide inspiration: Justin Johnson

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2012 to Present: Deep Learning is Everywhere

Karras et al, “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

Slide inspiration: Justin Johnson

2012 to Present: Deep Learning is Everywhere

TEXT PROMPT

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

AI-GENERATED IMAGES

Slide inspiration: Justin Johnson

Ramesh et al, "DALL·E: Creating Images from Text", 2021. https://openai.com/blog/dall-e/

2012 to Present: Deep Learning is Everywhere

TEXT PROMPT

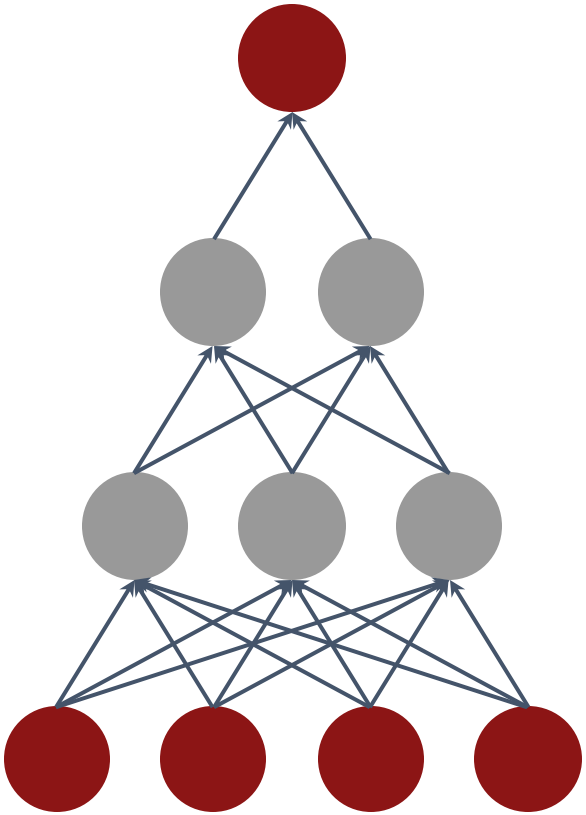
an armchair in the shape of a peach. an armchair imitating a peach.

AI-GENERATED IMAGES

Ramesh et al, "DALL·E: Creating Images from Text", 2021. https://openai.com/blog/dall-e/

Slide inspiration: Justin Johnson

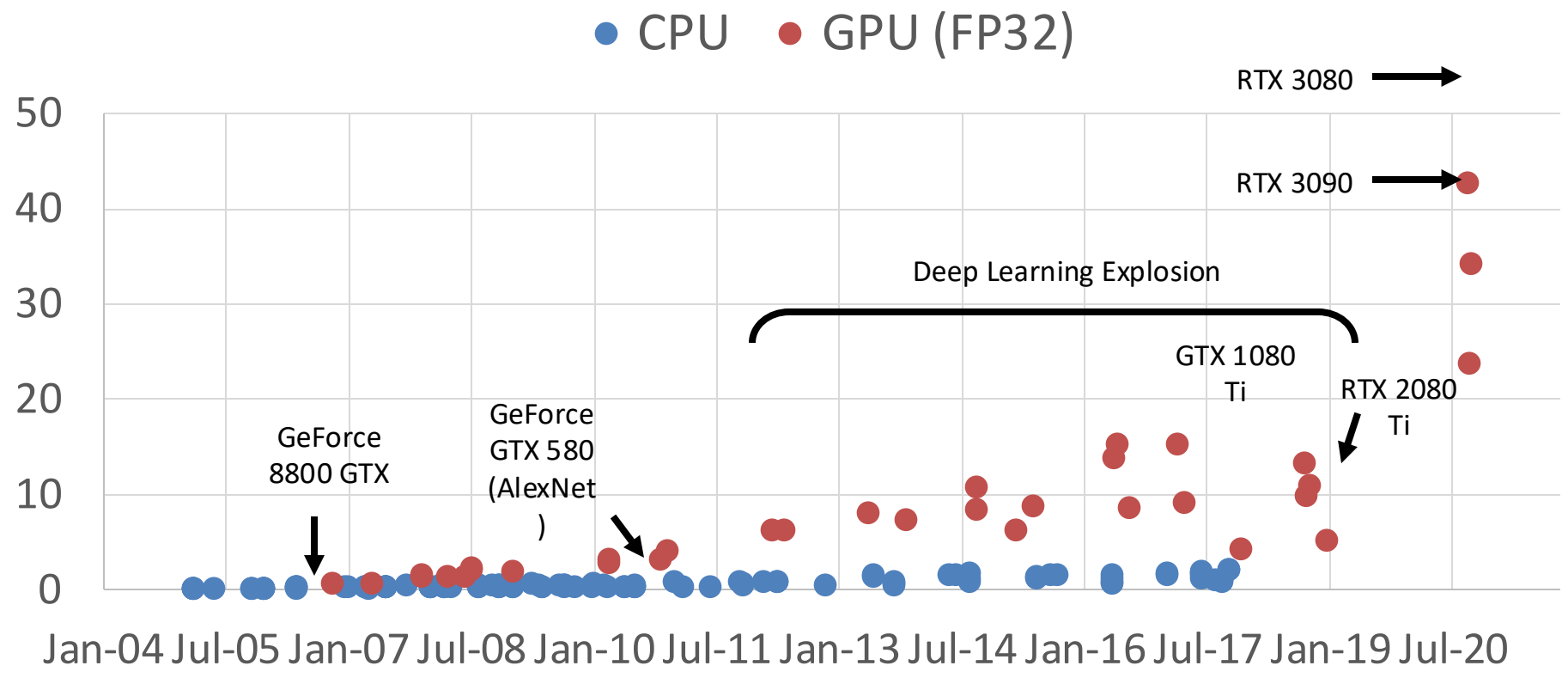
Computation



Algorithms

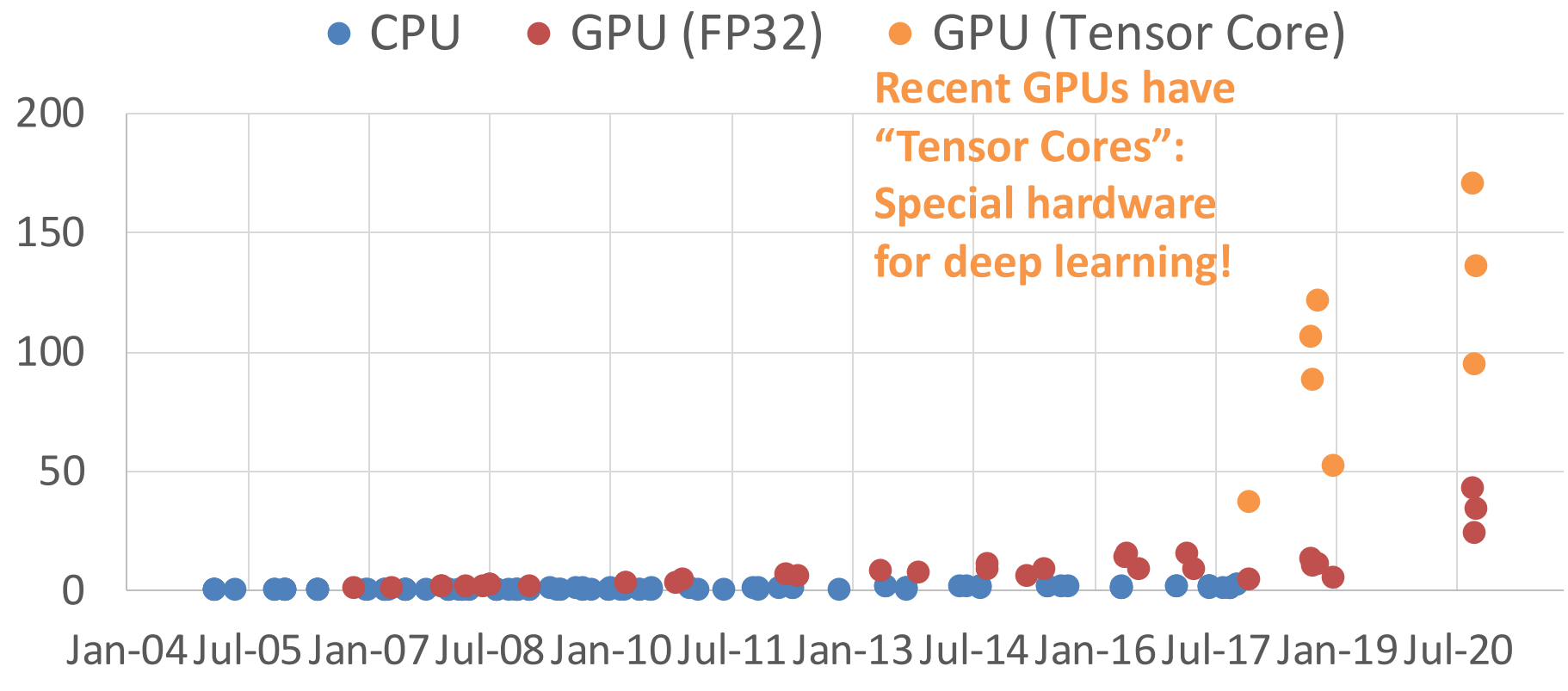
Data

GFLOP per Dollar



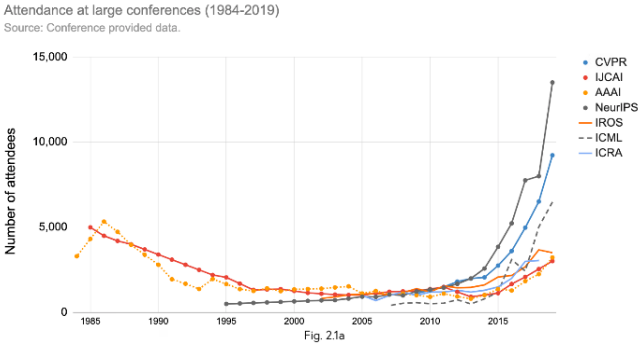
Slide inspiration: Justin Johnson

GFLOP per Dollar



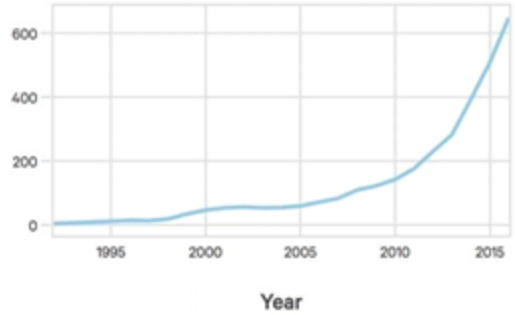
Slide inspiration: Justin Johnson

AI's Explosive Growth & Impact



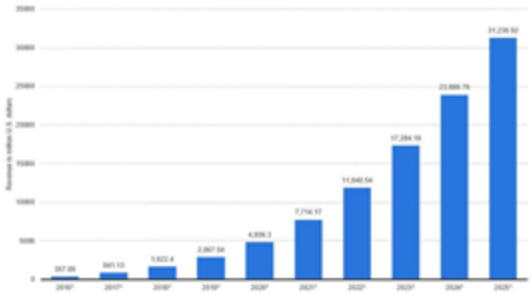
Number of attendance At AI conferences

Source: The Gradient



Startups Developing AI Systems

Source: Crunchbase, VentureSource, Sand Hill Econometrics



Enterprise Application AI Revenue

Source: Statista

Despite the successes, computer vision still has a long way to go

Computer Vision Can Cause Harm

Harmful Stereotypes

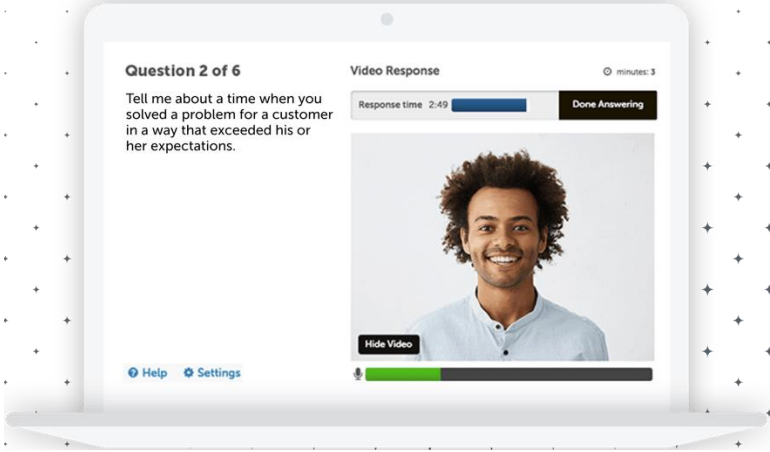
Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%

Affect people's lives

Technology

A face-scanning algorithm increasingly decides whether you deserve the job

HireVue claims it uses artificial intelligence to decide who's best for a job. Outside experts call it 'profoundly disturbing.'



Source: https://www.washingtonpost.com/technology/2019/10/22/ai-hiring-face-scanning-algorithm-increasingly-decides-whether-you-deserve-job/
https://www.hirevue.com/platform/online-video-interviewing-software

Example Credit: Timnit Gebru

Computer Vision Can Save Lives

Slide inspiration: Justin Johnson

And there is a lot we don't know how to do

https://fedandfit.com/wp-content/uploads/2020/06/summer-activities-for-kids_optimized-scaled.jpeg

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Slide inspiration: Andrej Karpathy

Today's agenda

- A brief history of computer vision & deep learning

- CS231n overview