UMassAmherst | Manning College of Information & Computer Sciences

682: Neural Networks: A Modern Introduction

Lecture 1: Introduction

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Who are we?

TAs

Subhransu Maji
CV
[Ecology, Remote Sensing, Astronomy, Material Science]

Rangel Daroya
CV, Remote Sensing, Ecology

Max Hamilton
CV, Astronomy, Ecology

Check course page for our office hours

https://cvl-umass.github.io/compsci682-spring-2026

Raise your hand if you are …

- First year student?
- Taking the first AI course?
- Interested in
    - Computer vision
    - Natural language processing
    - Robotics
    - Applications (remote sensing, medical imaging, climate change, etc.)
    - System building
    - Theory
    - Philosophy
    - …

Today's agenda

- 682 overview

- A brief history of computer vision and deep learning

Course page

https://cvl-umass.github.io/compsci682-spring-2026/

UMassAmherst | Home | Lectures | Notes | Assignments | Policies | Project | Office Hours

COMPSCI 682 Neural Networks: A Modern Introduction

Note

- This is a tentative class outline and is subject to change throughout the semester.
- Regular lectures will be Tue & Th 4:00PM - 5:15PM, Computer Science Labs E110 (new CS building).
- Slides will be finalized after the lecture and echo360 recordings (if available) accessible via Canvas.

Event Type	Date	Description	Course Materials
Lecture	Thursday, Jan 29	Course logistics and overview Historical context	[slides] [python/numpy tutorial] [software setup for assignments]
Lecture	Tuesday, Feb 3	Image classification and the data-driven approach • K-nearest neighbor • Linear classification Optimization	

Topics

- Intro to supervised learning
  - k-nearest neighbors, Support vector machines, Logistic regression for classification
- Feedforward neural nets
  - Network architecture, backpropagation, optimization, regularization, speed, etc
- Convolutional neural nets
- Beyond classification
  - Detection, segmentation, 3D understanding
- Visualization and understanding neural nets
- Other topics: generative AI, RNNs/Transformers, graphics, robotics, …
  - Will have some guest lectures

682 Neural Networks: A Modern Introduction

- Balance of theory vs. practice
    - Heavily tilted toward practice.
    - Examples:
        - Regularization will be used, but not much theory of it.
        - No proofs of convergence
    - Instead:
        - Develop applications “from scratch”
        - Build “layered” architectures from scratch so new models can be easily assembled
        - Implement popular add-ons such as batch normalization
        - Learn techniques for training and setting hyperparameters.

Topics

- Applications
  - Mostly **Computer Vision**: Object recognition in particular.
  - However, can easily be applied to other domains.
    - You will learn what you need to know to apply neural nets broadly.
  - Will cover some **Natural Language Processing** (or **Large Language Models**) this semester.

Topics

- What this course is *not*:
  - General course on machine learning
  - General course on graphical models
  - Not even a general class on deep learning!!!
    - No Bayes Nets
    - No restricted Boltzmann machines or deep Boltzmann machines
  - Not a computer vision survey class
    - No tracking, stereo, depth estimation, etc., etc.

Grading

- Assignments: 3 in total, 15% each: 45%
- Midterm #1: 15% (Tuesday, March 10 in class)
- Midterm #2: 15% (Tuesday, April 28 in class)
- Project: 25% (teams of 2-3 members)
    - Proposal: 5%
    - Final write-up: 15%
    - Presentation: 5%

- We will have a lecture on project ideas and expectations later in the semester.

- Late Policy:
    - 7 free late days in total: use them as you see fit (no permission necessary)
    - Max 3 late days per homework.
    - Afterwards: 25% off per day late
    - Does not apply to the course project requirements (must be on time)
- Check course website for details and dates.

Assignment #1

- Will be posted next week on course website
- It includes:
- Write/train/evaluate a kNN classifier
- Write/train/evaluate a Linear Classifier (SVM and Softmax)
- Write/train/evaluate a 2-layer Neural Network (backpropagation!)
- Requires writing numpy/Python code

Compute: Use your own laptops. Talk to TA if you don't have your own computer.

Communication

- Piazza for questions, announcements, etc.
  - Do not email us except for personal reasons
- Course website for syllabus, links to assignment downloads
  - https://cvl-umass.github.io/compsci682-spring-2026/
- Gradescope for homework and project submission
  - We will automatically enroll you
  - Automatically tracks late days, deadlines, etc.
  - Do not email us the submissions
- Echo360 via Canvas
  - For watching recorded lectures
  - About 80% reliable — use this sparingly
- Canvas page — where you can find links to all of these

Guidelines on using AI

The use of generative AI tools (e.g., ChatGPT, Copilot, Gemini) is **generally not permitted**. The goal of the course is for you to develop a strong understanding of the material through direct engagement with lectures, readings, and problem sets.

The following uses **are permitted**:

- Clarifying terminology or definitions (e.g., "What does overfitting mean?")
- Reviewing prerequisite material not specific to the assignment (e.g., linear algebra or probability refreshers)
- High-level conceptual explanations that do not reference or solve a specific homework problem
- Editing for grammar or clarity of text you have already written, without changing technical content

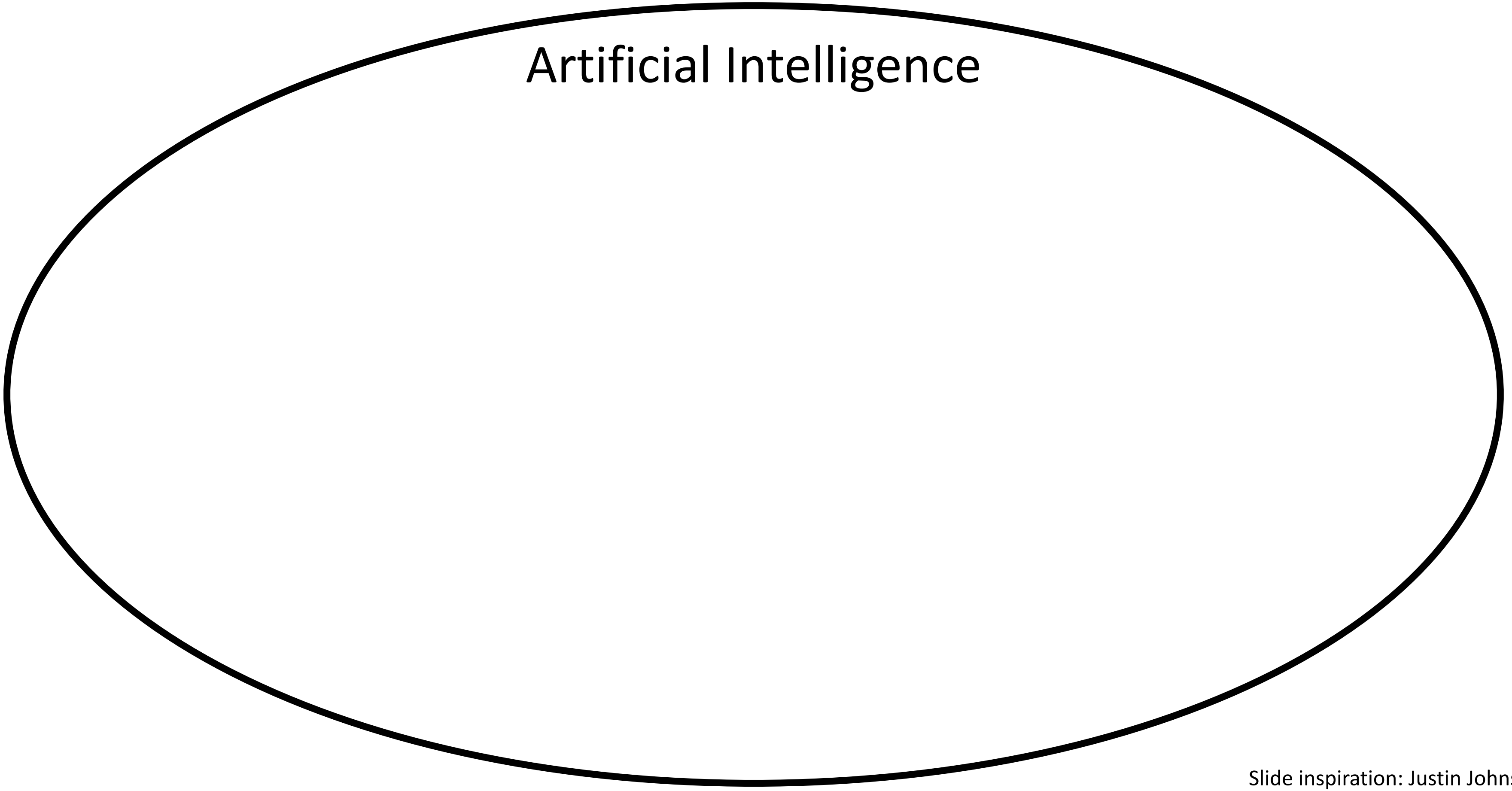
The following uses **are not permitted**:

- Asking AI to solve, complete, or substantially generate homework or projects
- Providing AI with assignment prompts or problem statements and requesting solutions, hints, or step-by-step reasoning
- Using AI-generated code, proofs, derivations, or explanations as your own work

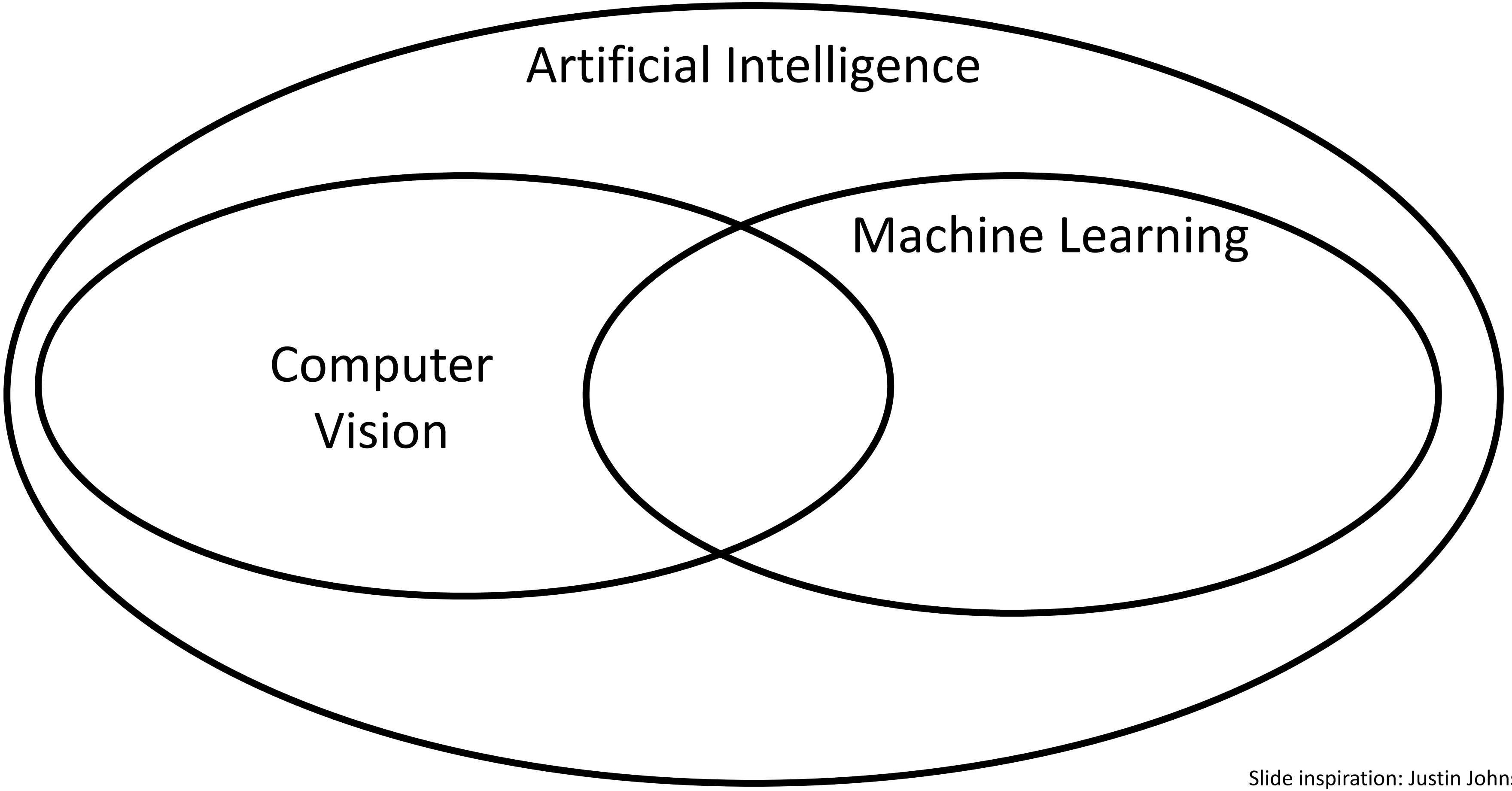
Your midterms will be **closed-book and AI-free**, and designed to test your understanding of the material and your performance on these exams will depend on how well you have engaged with and understood the homework problems.

Today's agenda

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



Slide inspiration: Justin Johnson



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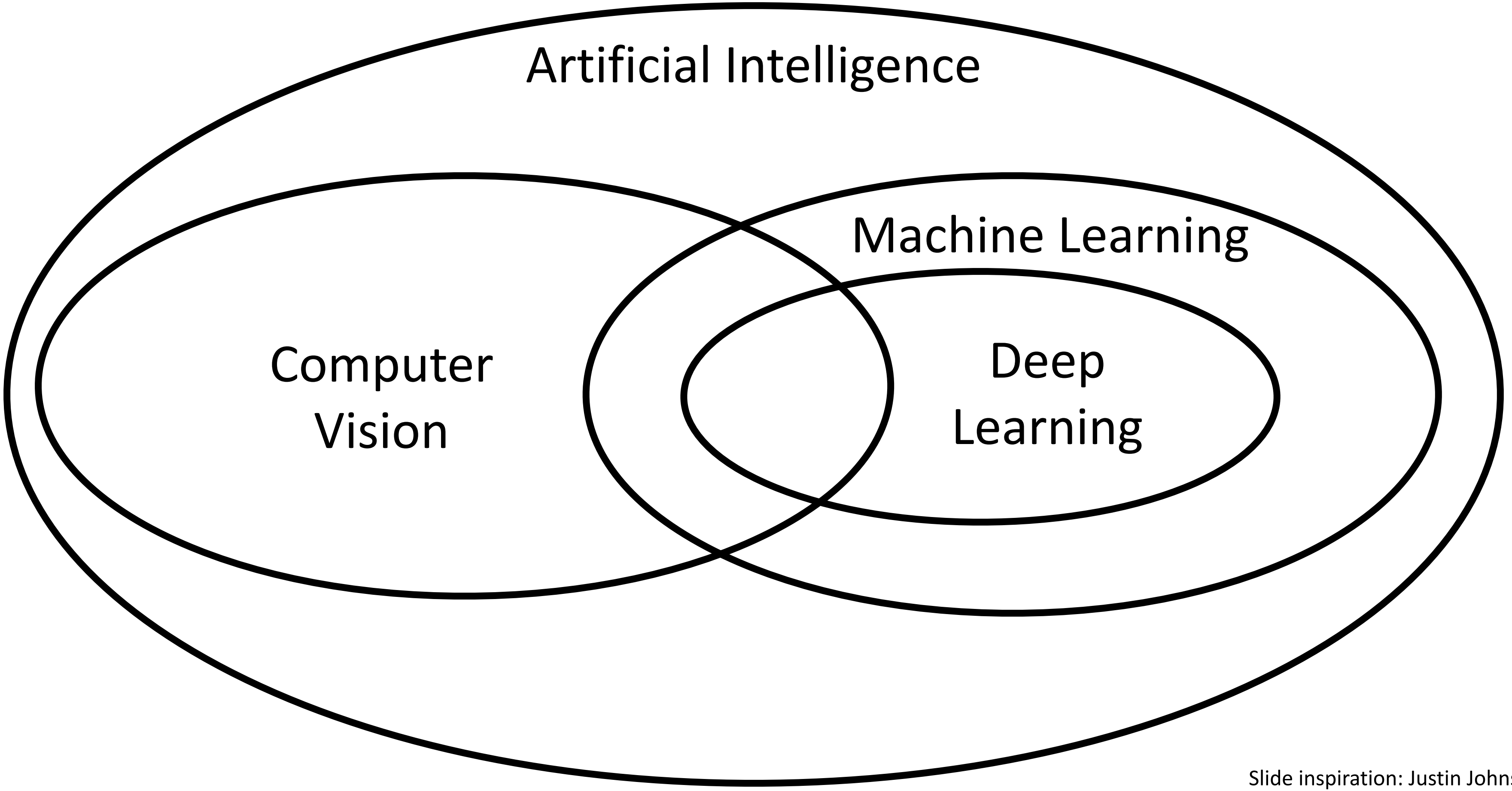
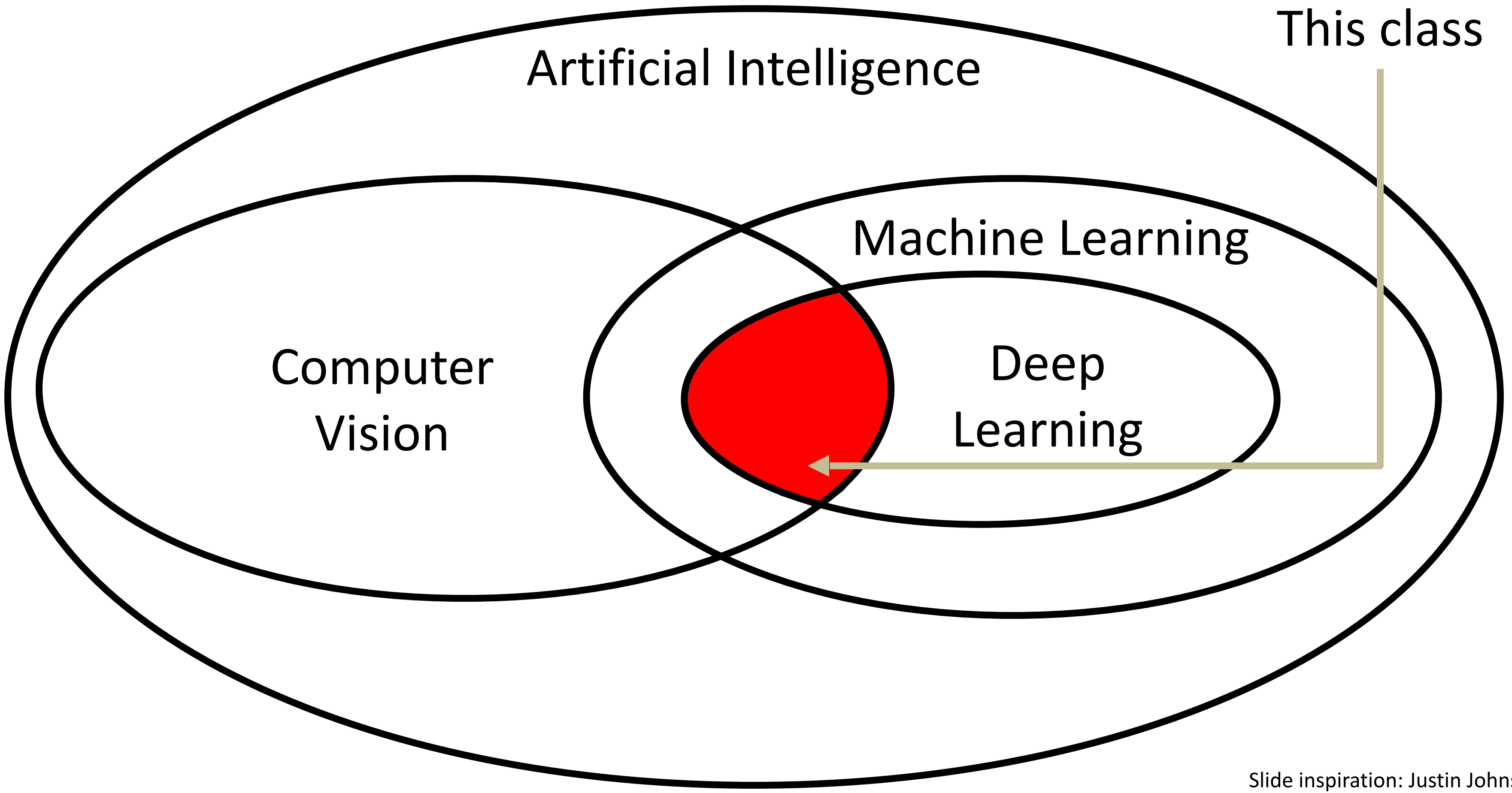
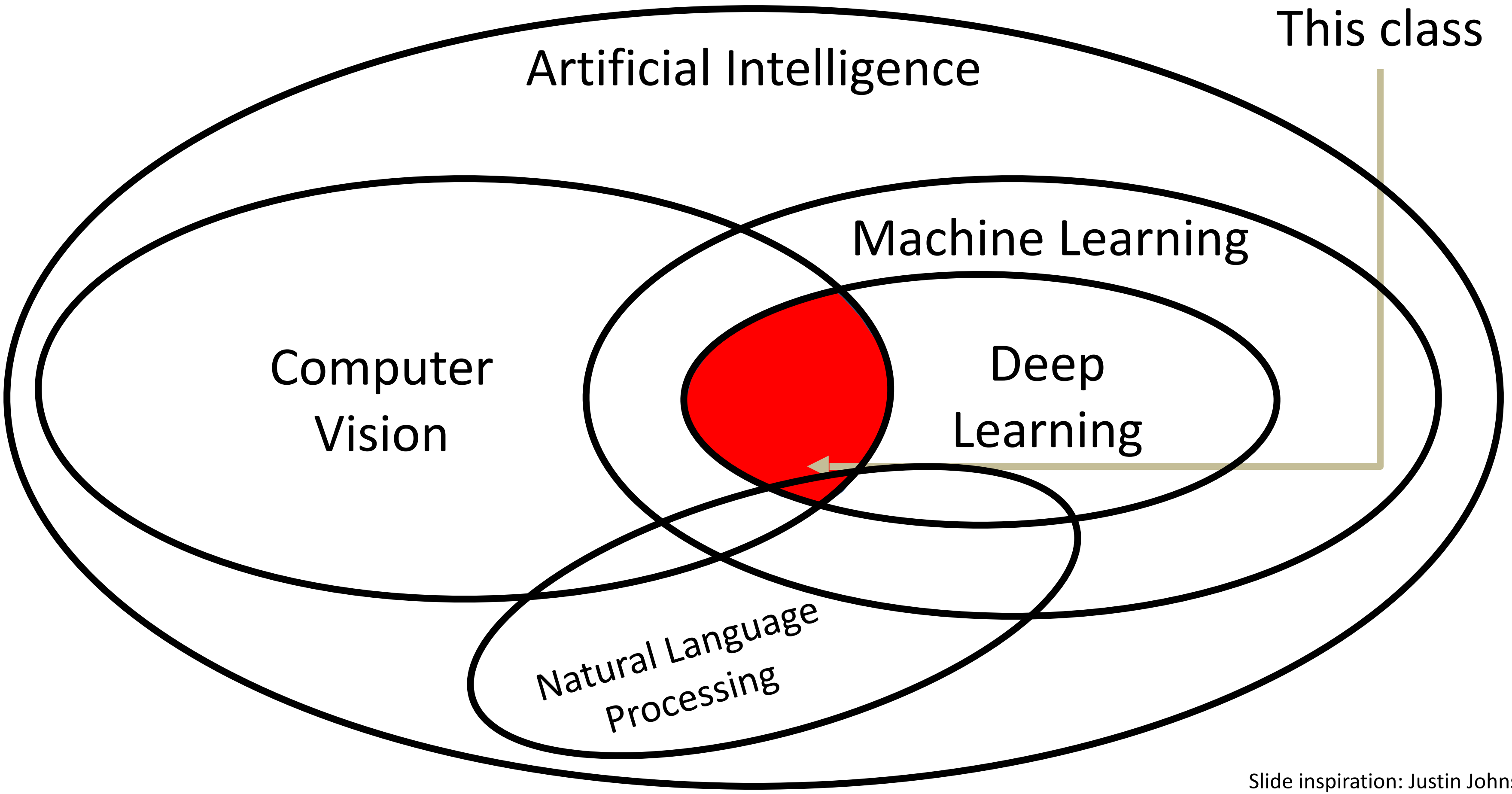


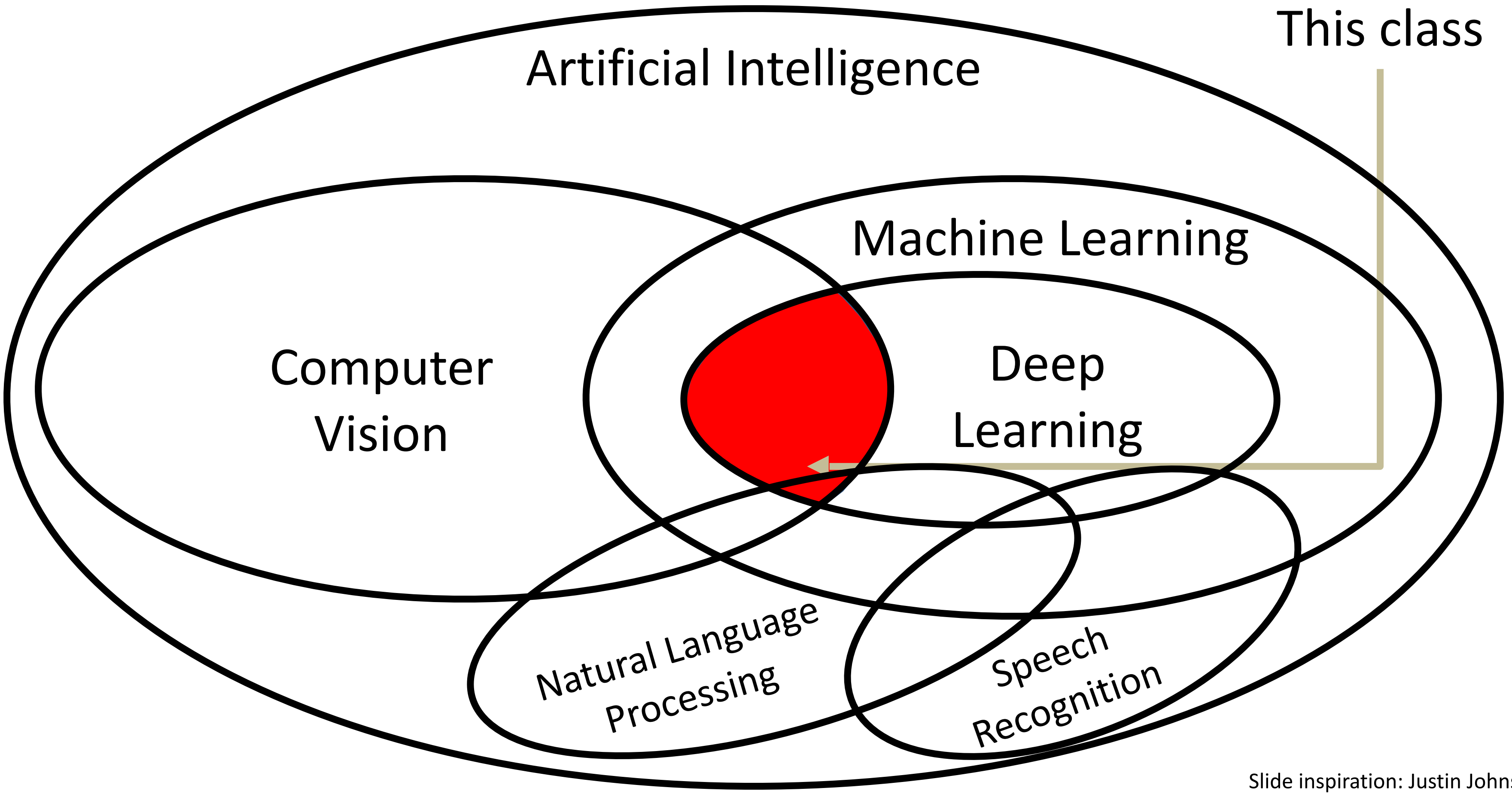
Slide inspiration: Justin Johnson



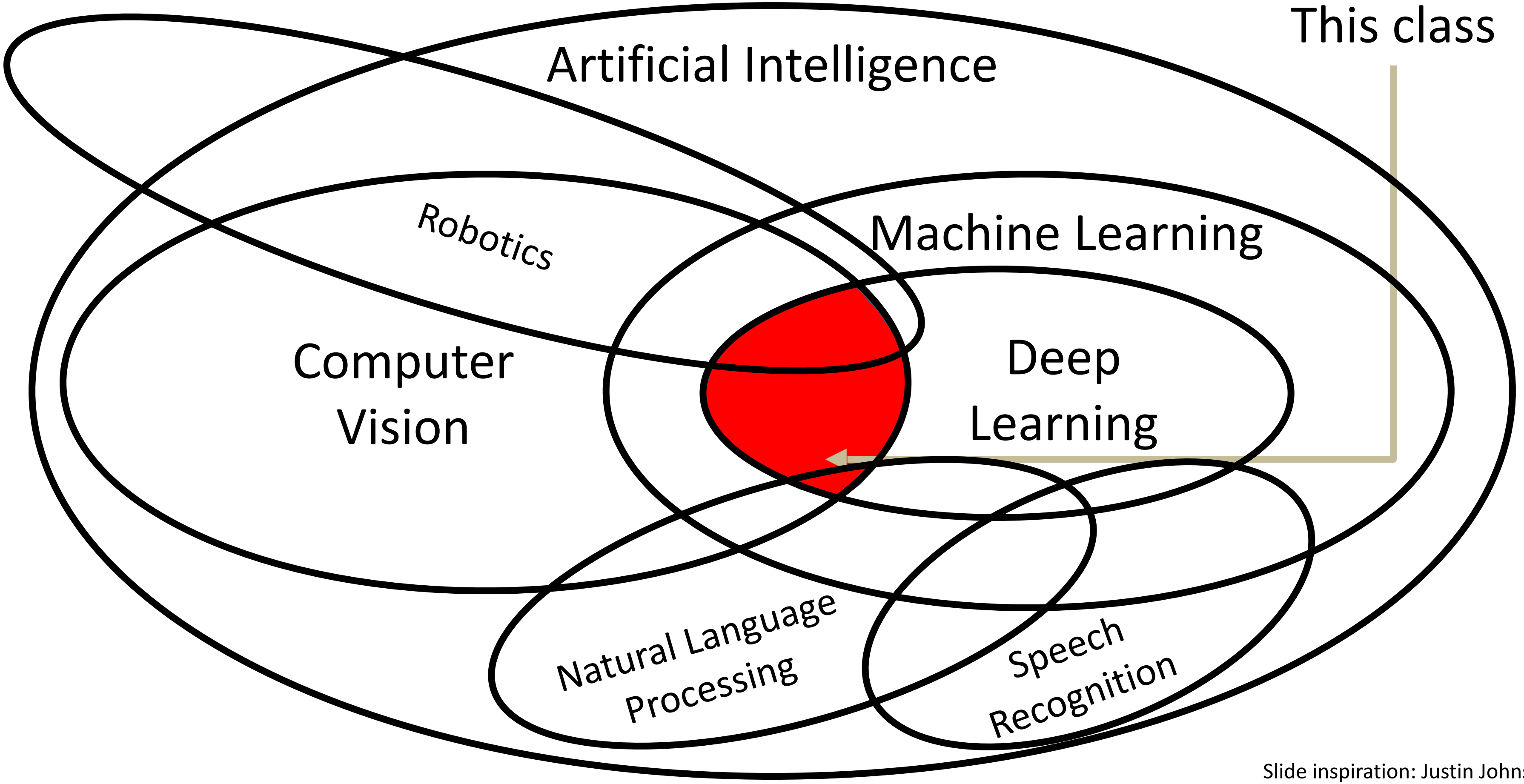
Slide inspiration: Justin Johnson



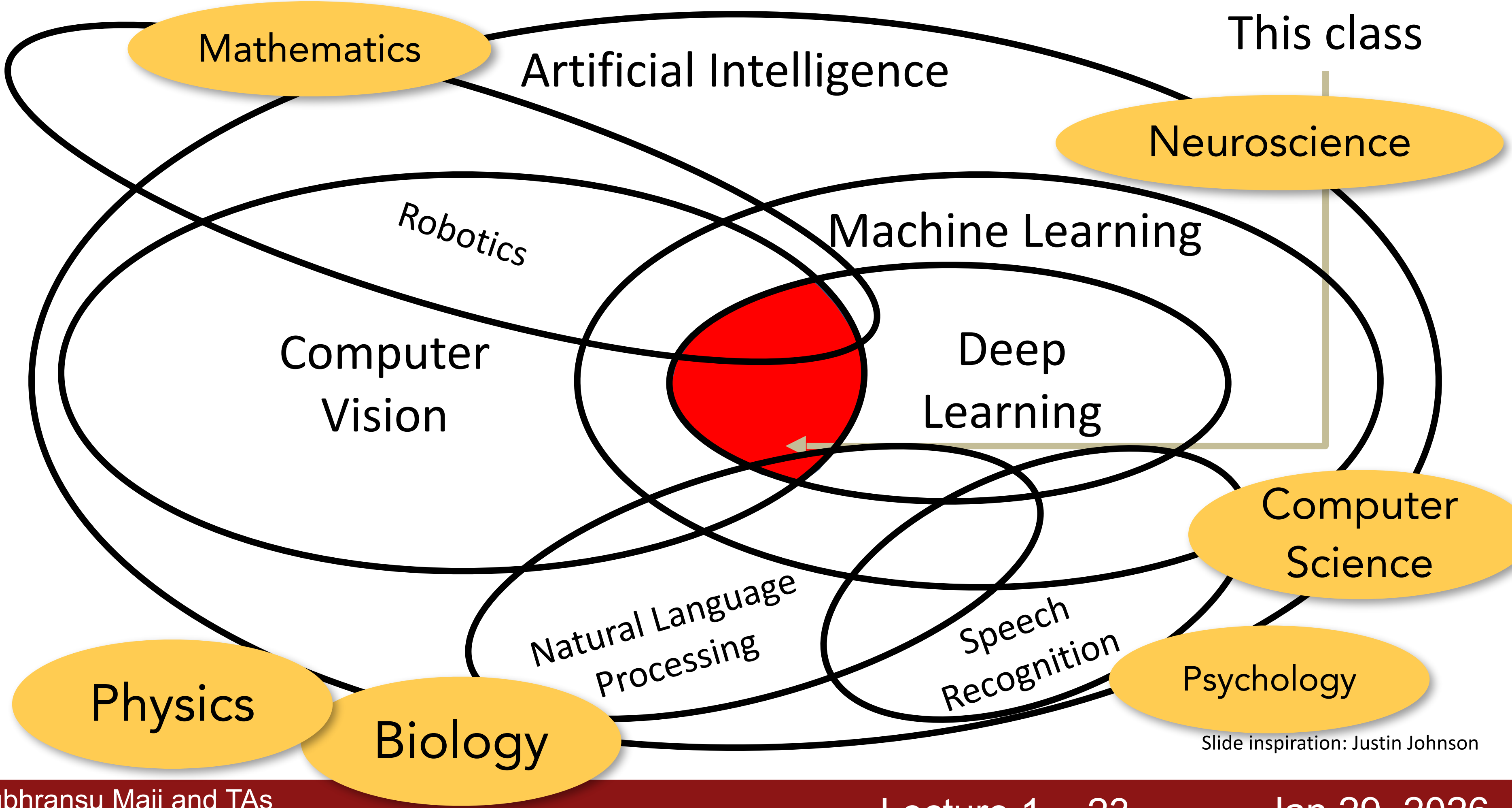
Slide inspiration: Justin Johnson



Slide inspiration: Justin Johnson



Slide inspiration: Justin Johnson



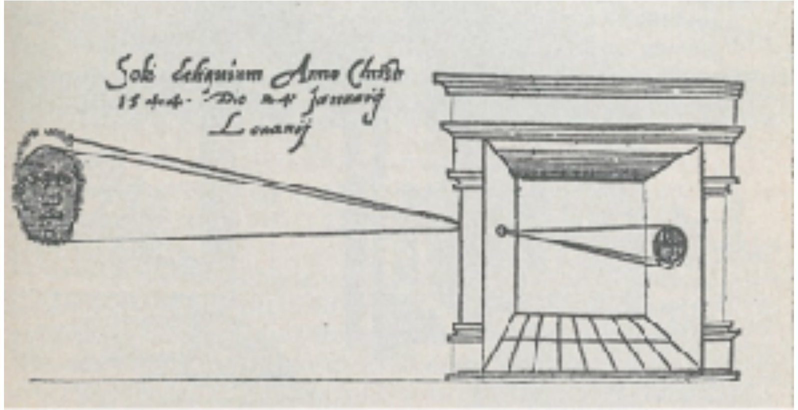
Slide inspiration: Justin Johnson

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




Camera Obscura

Gemma Frisius, 1545



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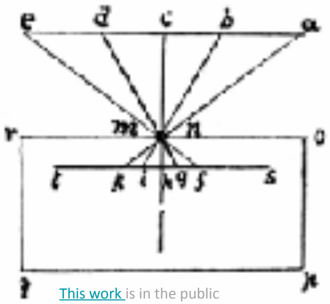

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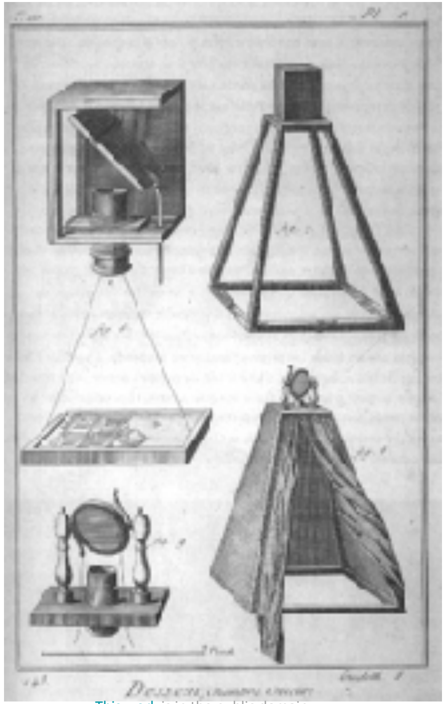
Leonardo da Vinci, 16th Century AD

Encyclopedia, 18th Century



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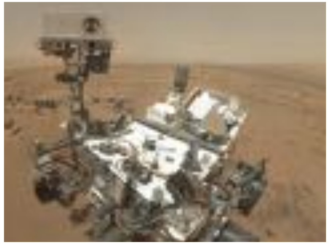
Computer Vision is everywhere!





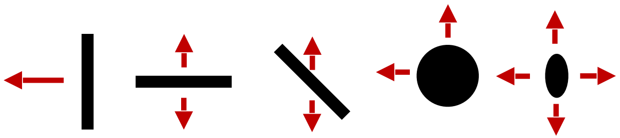





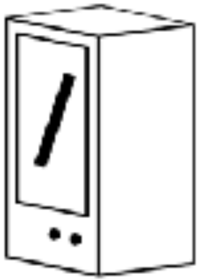


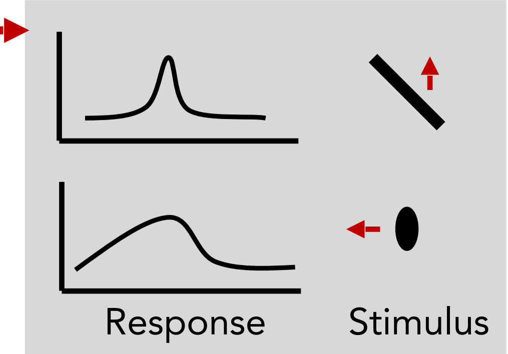
Where did we come from?

Hubel and Wiesel, 1959



Measure brain activity

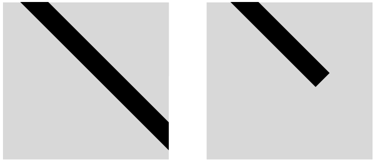




1959
Hubel & Wiesel

Simple cells:
Response to specific rotation and orientation

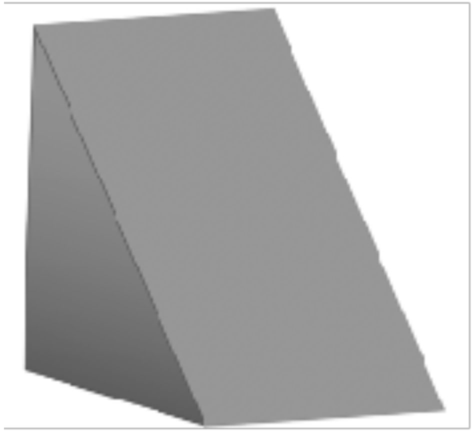
Complex cells:
Response to light orientation and movement, some translation invariance



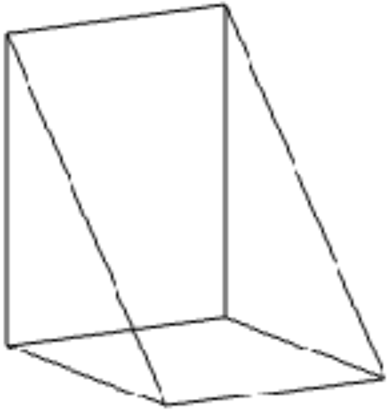
No response

Slide inspiration: Justin Johnson

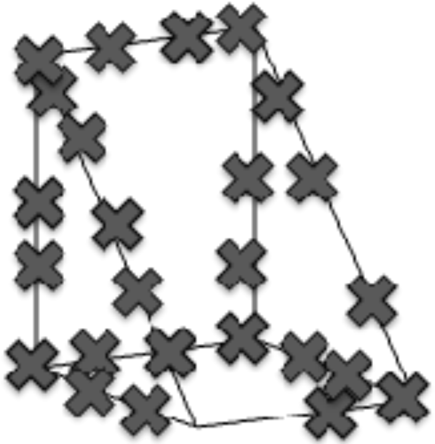
Larry Roberts, 1963



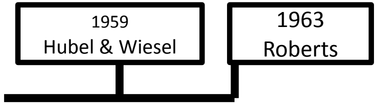
(a) Original picture



(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

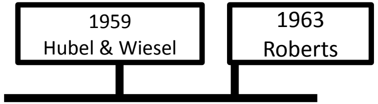
Artificial Intelligence Group | July 7, 1966

Vision Memo. No. 100.

THE SUMMER VISION PROJECT

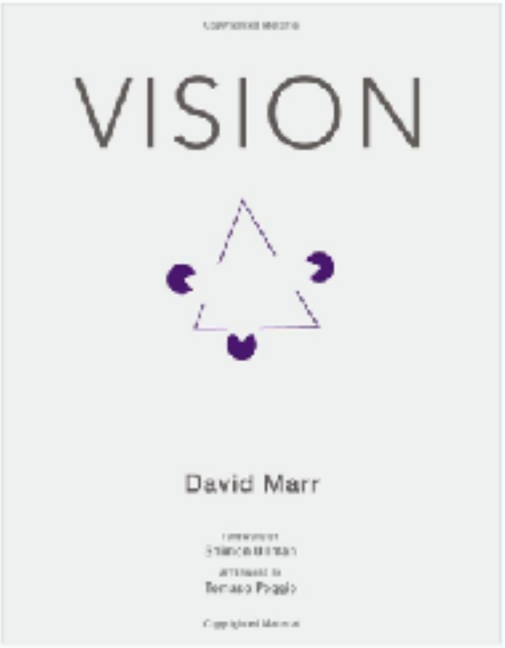
Seymour Papert

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".



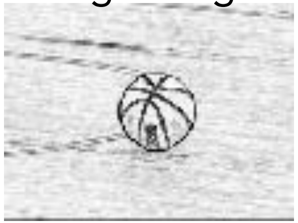
https://dspace.mit.edu/handle/1721.1/6125

Slide inspiration: Justin Johnson

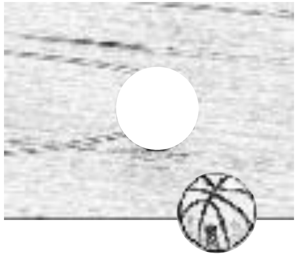


Input image

Edge image



2 ½-D sketch



3-D model

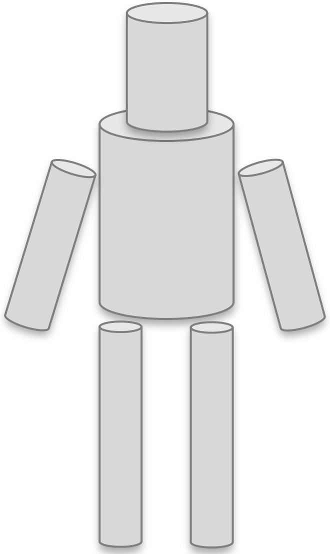
1959 Hubel & Wiesel	1963 Roberts	1970s David Marr

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

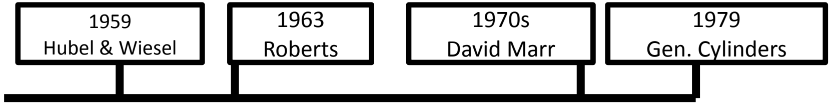
Stages of Visual Representation, David Marr, 1970s

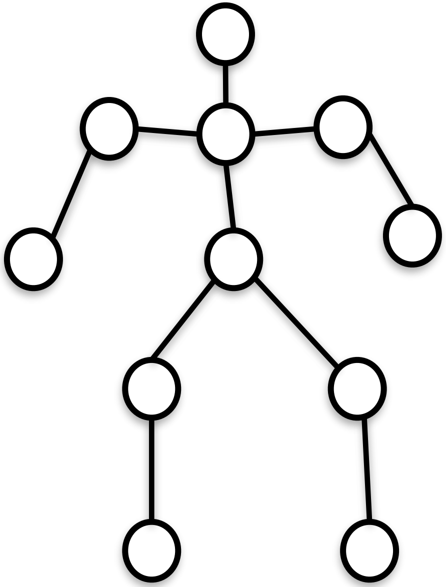
Slide inspiration: Justin Johnson

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)

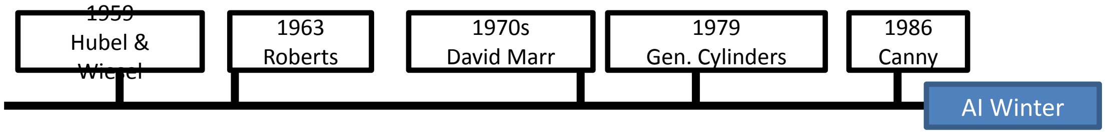
1959 Hubel & Wiesel | 1963 Roberts | 1970s David Marr | 1979 Gen. Cylinders | 1986 Canny

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.

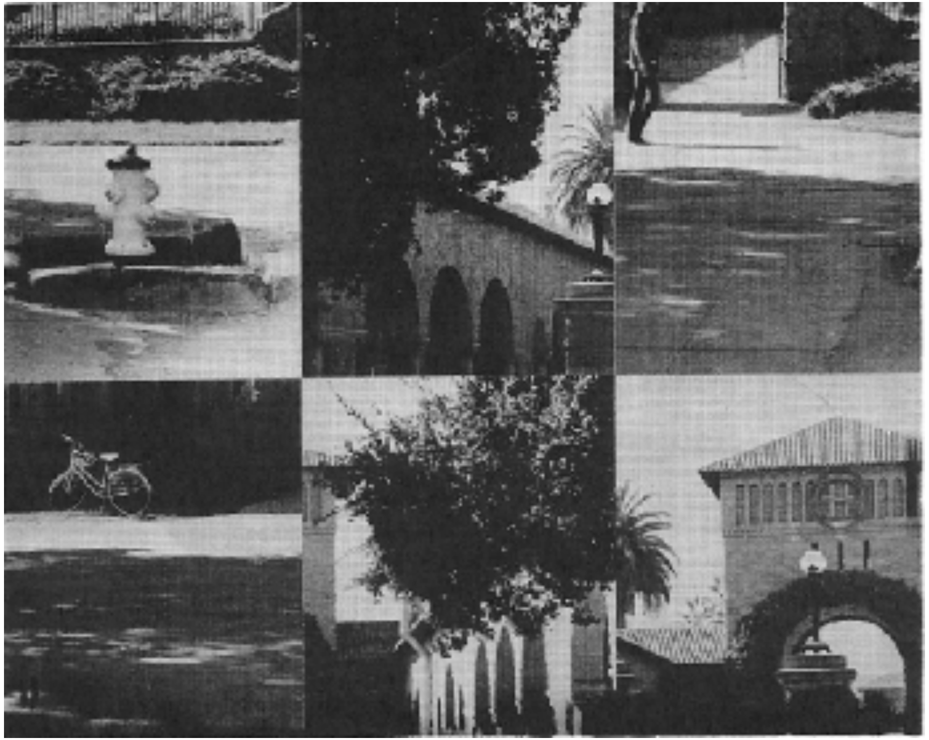


Slide inspiration: Justin Johnson

In the meantime…seminal work in cognitive and neuroscience

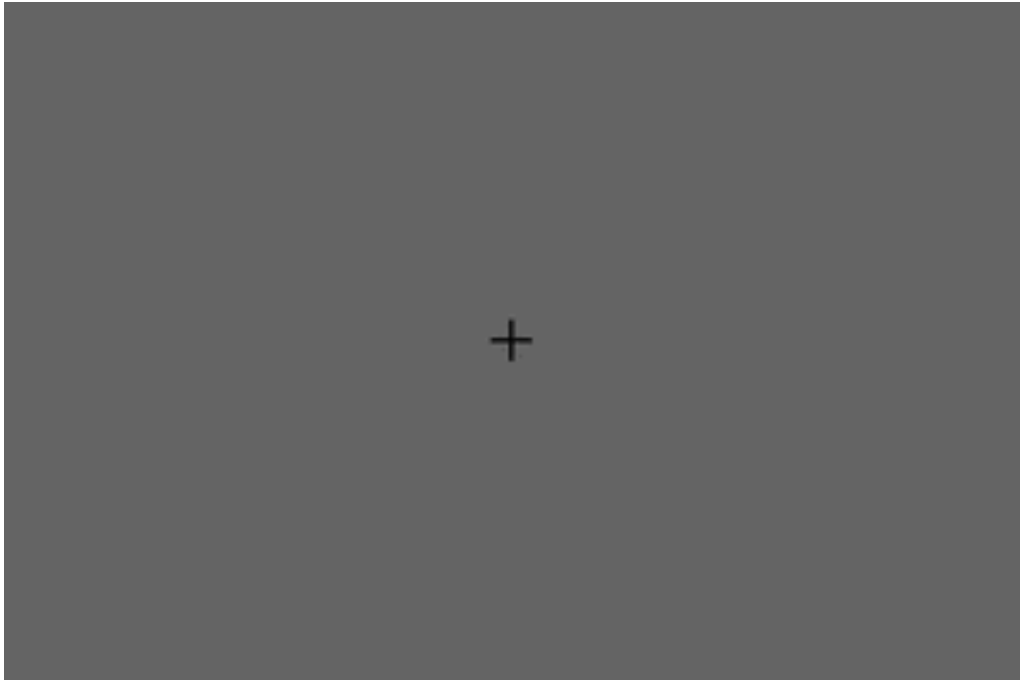
Perceiving Real-World Scenes

Irving Biederman



I. Biederman, *Science*, 1972

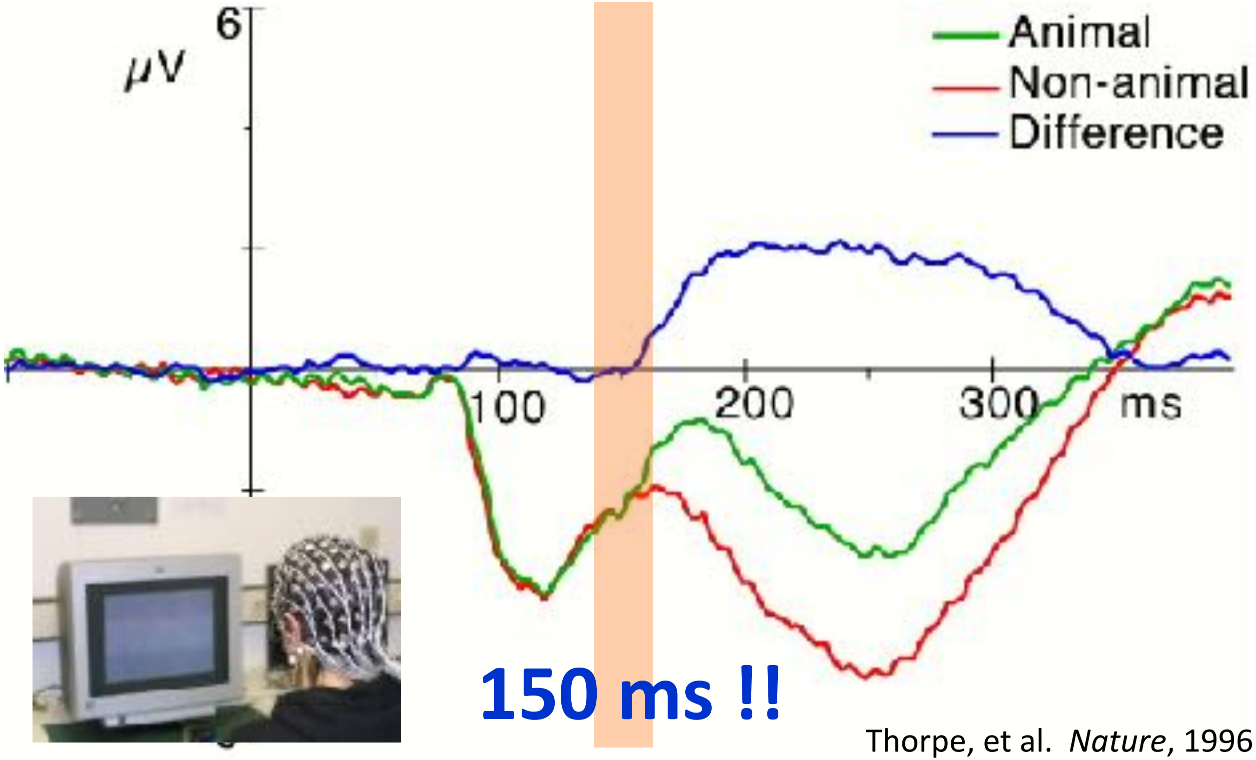
Rapid Serial Visual Perception (RSVP)



Potter, etc. 1970s

Speed of processing in the human visual system

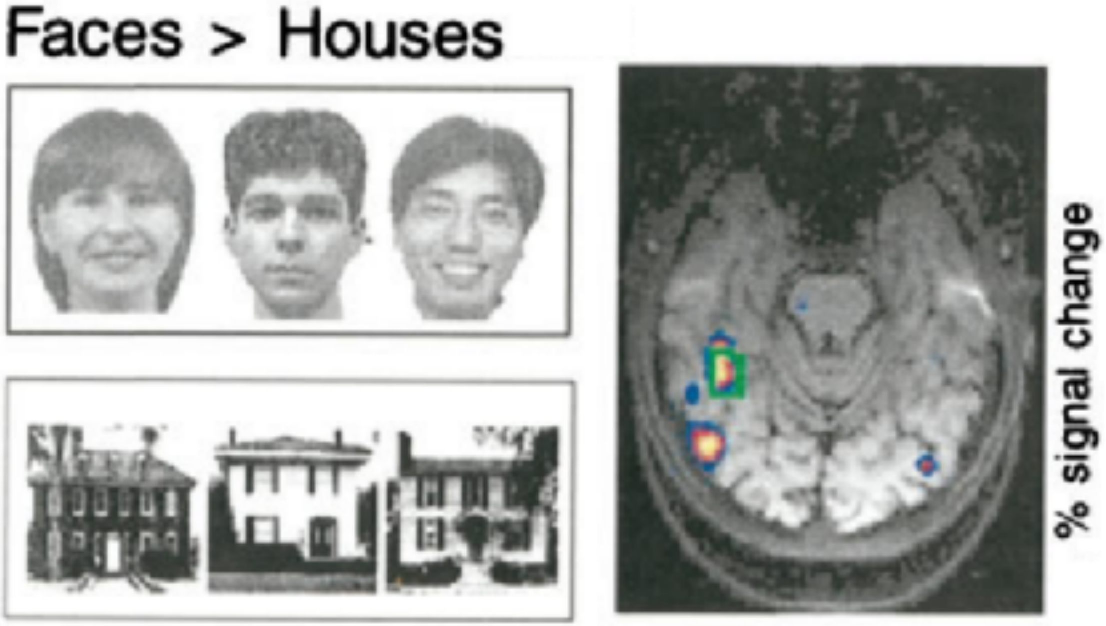
Simon Thorpe, Denis Fize & Catherine Marlot



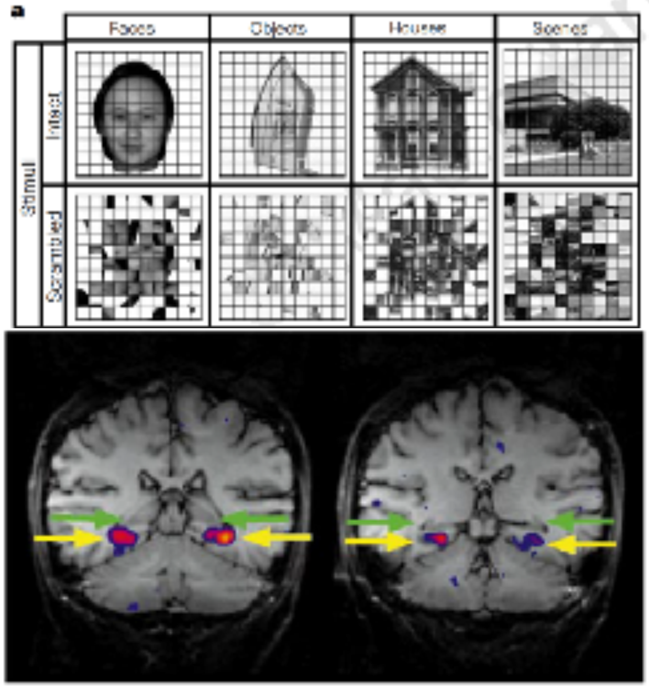
150 ms !!

Thorpe, et al. *Nature*, 1996

Neural correlates of object & scene recognition

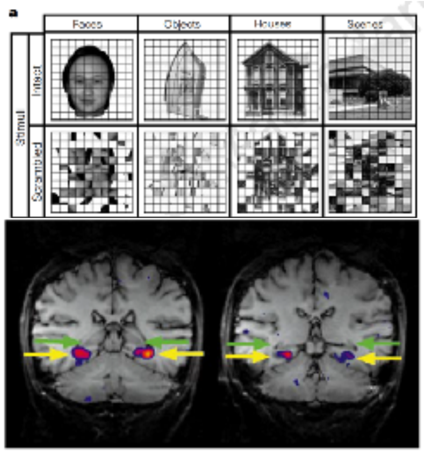


Kanwisher et al. J. Neuro. 1997

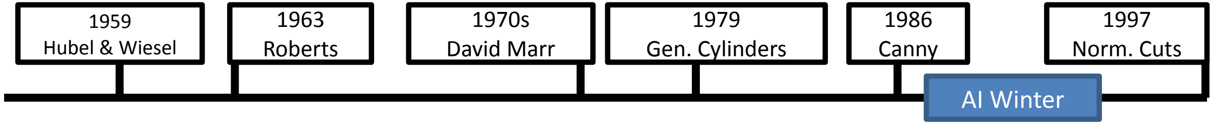


Epstein & Kanwisher, Nature, 1998

Visual recognition is a fundamental task for visual intelligence



Recognition via Grouping (1990s)



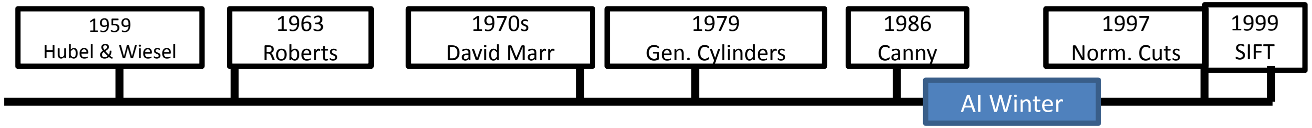
Normalized Cuts, Shi and Malik, 1997

Slide inspiration: Justin Johnson

Recognition via Matching (2000s)

Image is public domain

Image is public domain



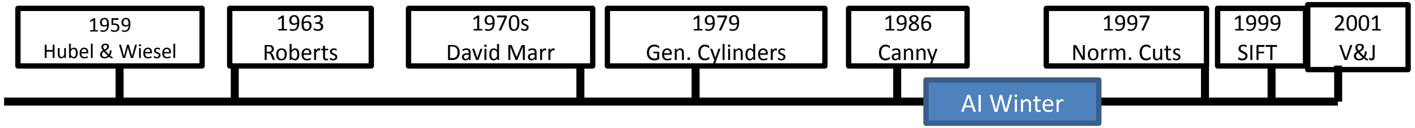
SIFT, David Lowe, 1999

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

PASCAL Visual Object Challenge

Caltech 101 images

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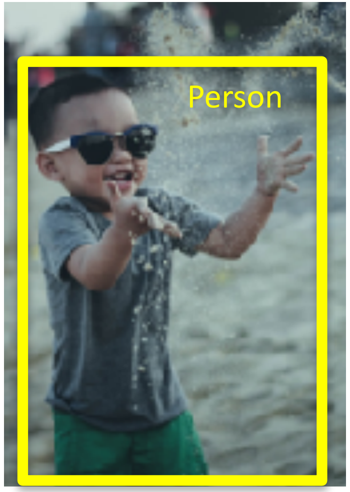

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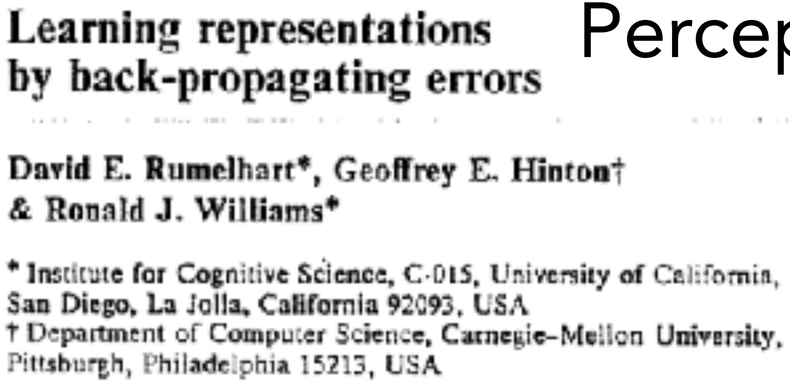
1959 Hubel & Wiesel | 1963 Roberts | 1970s David Marr | 1979 Gen. Cylinders | 1986 Canny | AI Winter | 1997 Norm. Cuts | 1999 SIFT | 2001 V&J | 2004, 2007 Caltech101; PASCAL

Slide inspiration: Justin Johnson

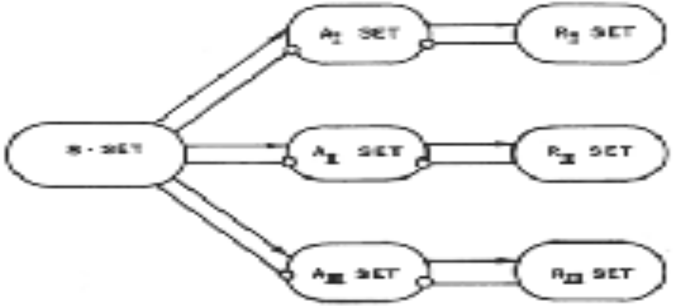
Perceptron

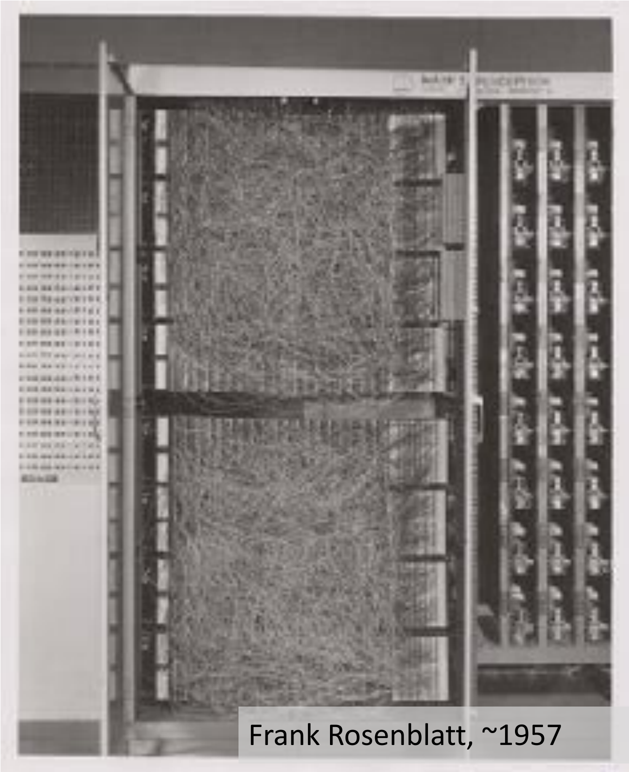


Learning representations by back-propagating errors

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





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

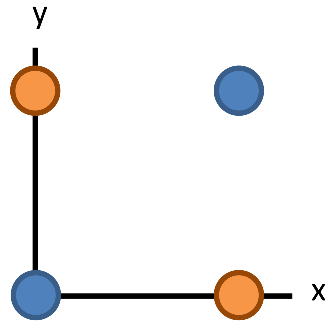
AI Winter

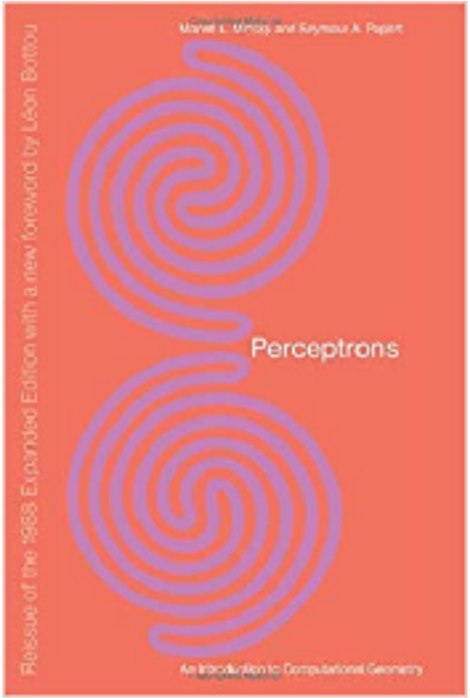
1958 Perceptron

Slide inspiration: Justin Johnson

Minsky and Papert, 1969

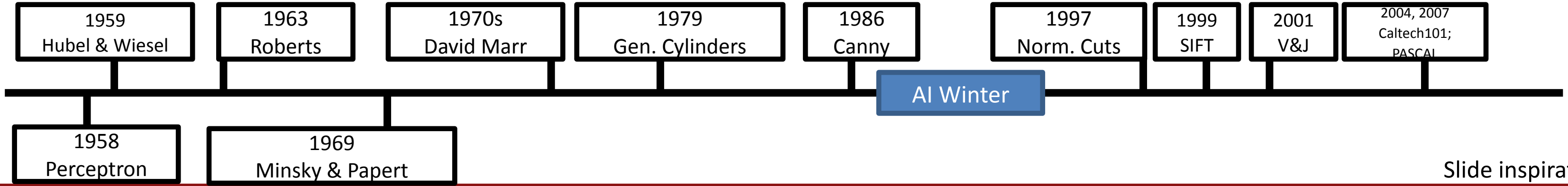
X	Y	F(x,y)
0	0	0
0	1	1
1	0	1
1	1	0





Showed that Perceptrons could not learn the XOR function

Caused a lot of disillusionment in the field



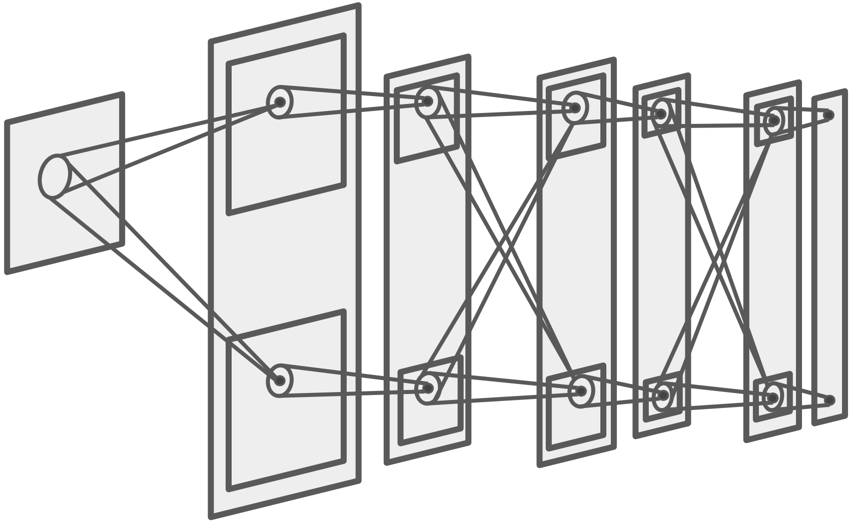
Slide inspiration: Justin Johnson

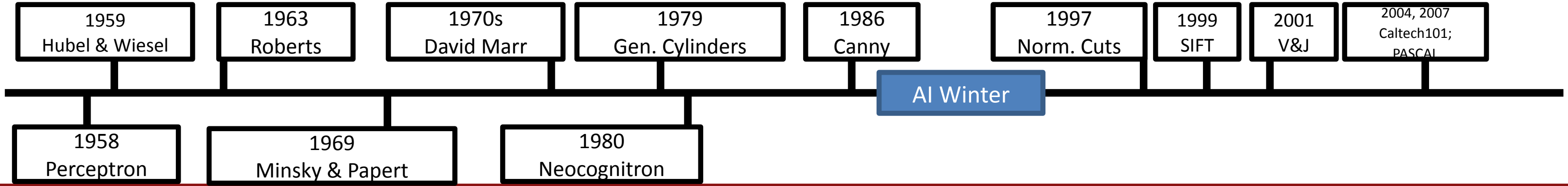
Neocognitron: Fukushima, 1980

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





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

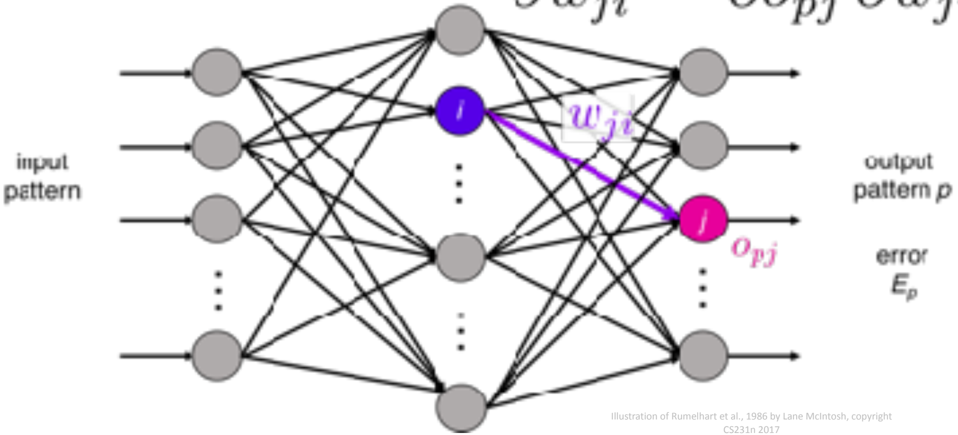
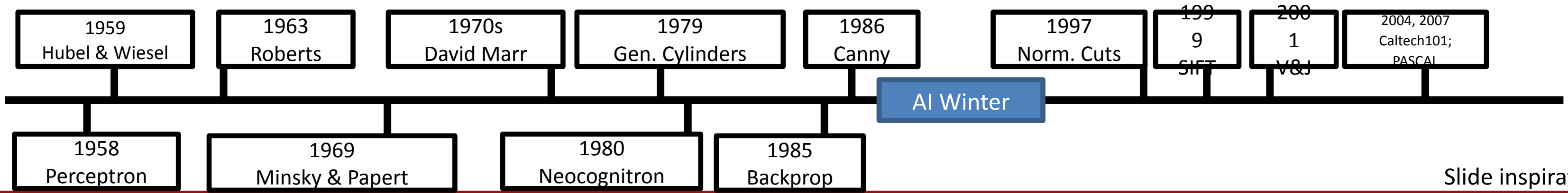
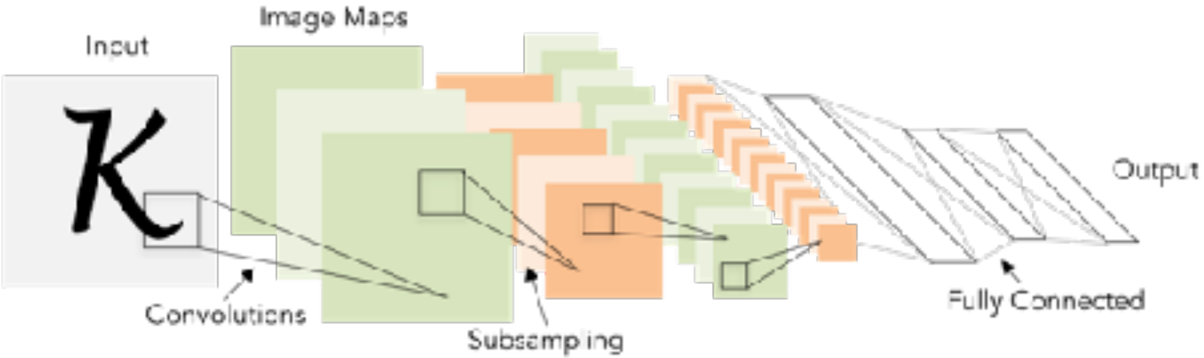


Illustration of Rumelhart et al., 1986 by Lane McIntosh, copyright CS231n 2017



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!

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

AI Winter

1958 Perceptron
1969 Minsky & Papert
1980 Neocognitron
1985 Backprop
1998 LeNet

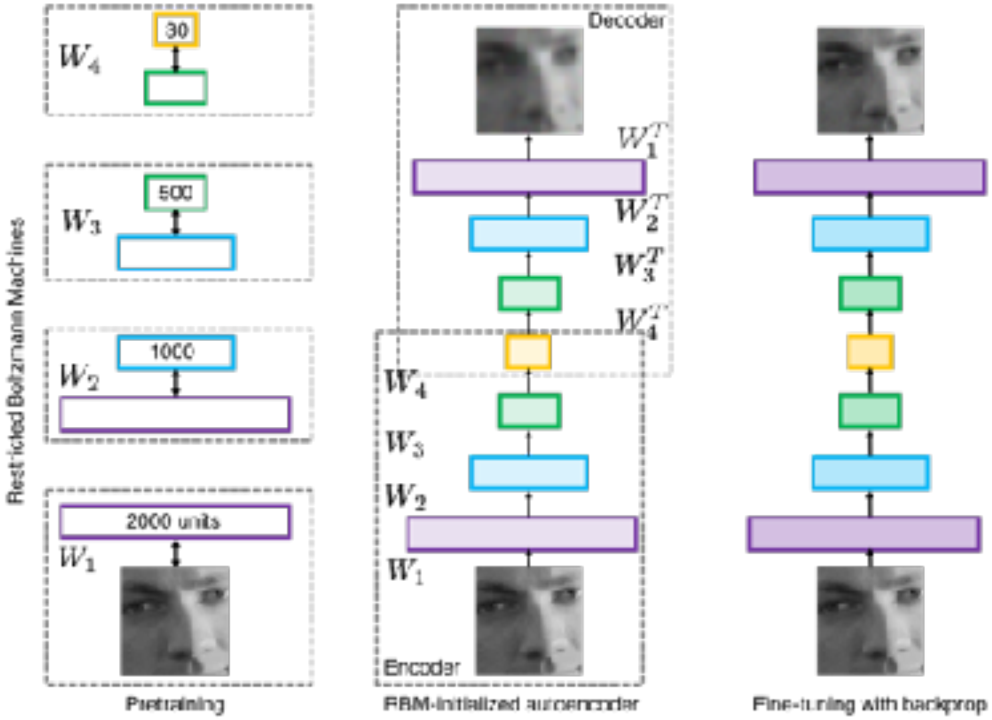
Slide inspiration: Justin Johnson

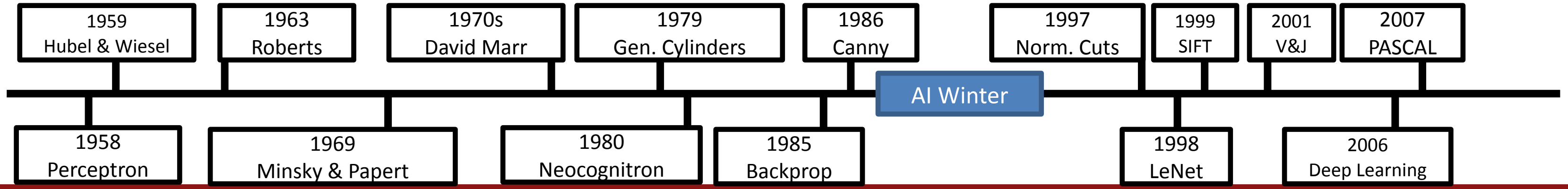
2000s: “Deep Learning”

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

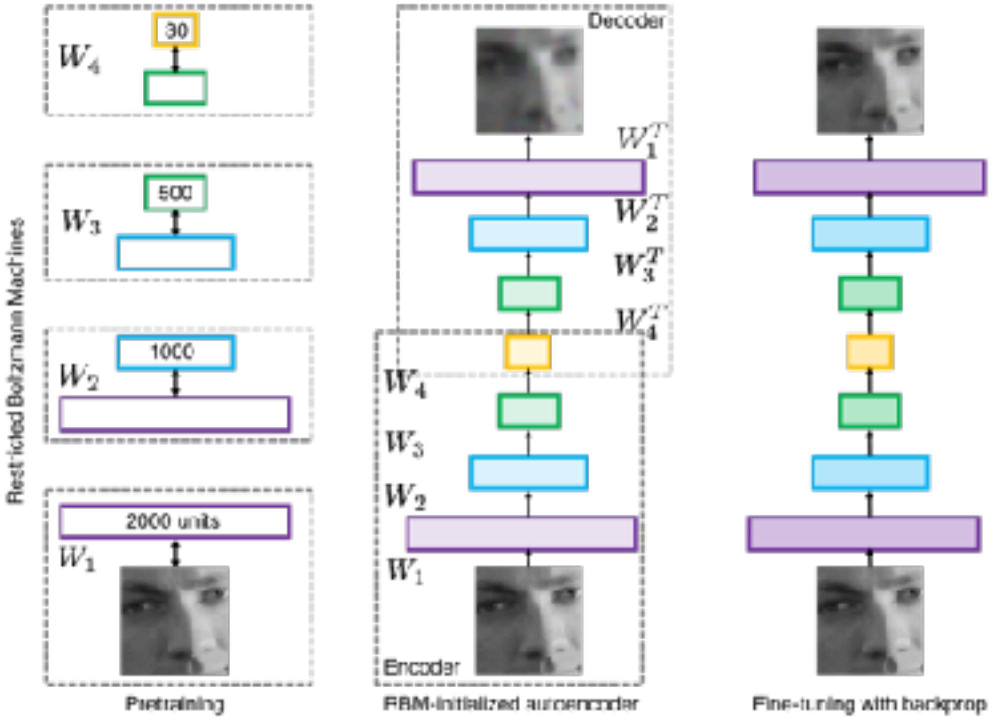
2000s: “Deep Learning”

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



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AI Winter

1958 Perceptron
1969 Minsky & Papert
1980 Neocognitron
1985 Backprop
1998 LeNet
2006 Deep Learning

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

1959 Hubel & Wiesel
1963 Roberts
1970s David Marr
1979 Gen. Cylinders
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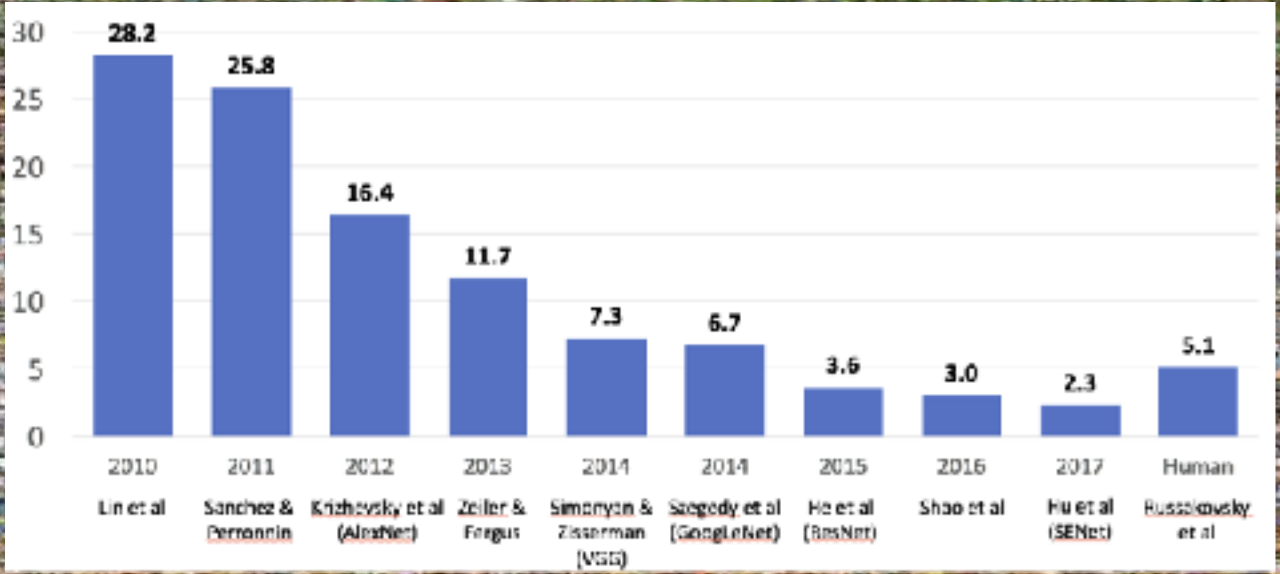
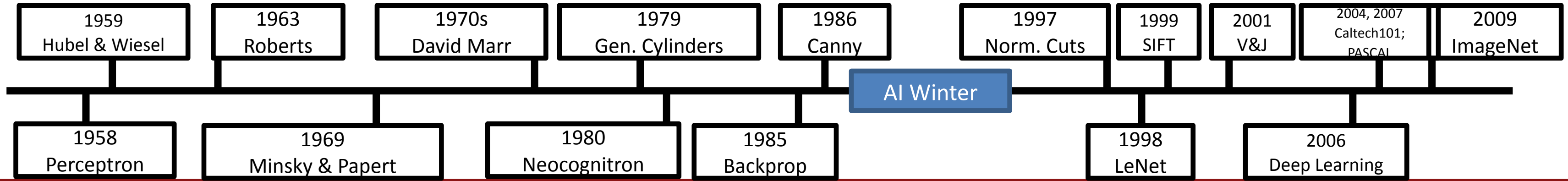
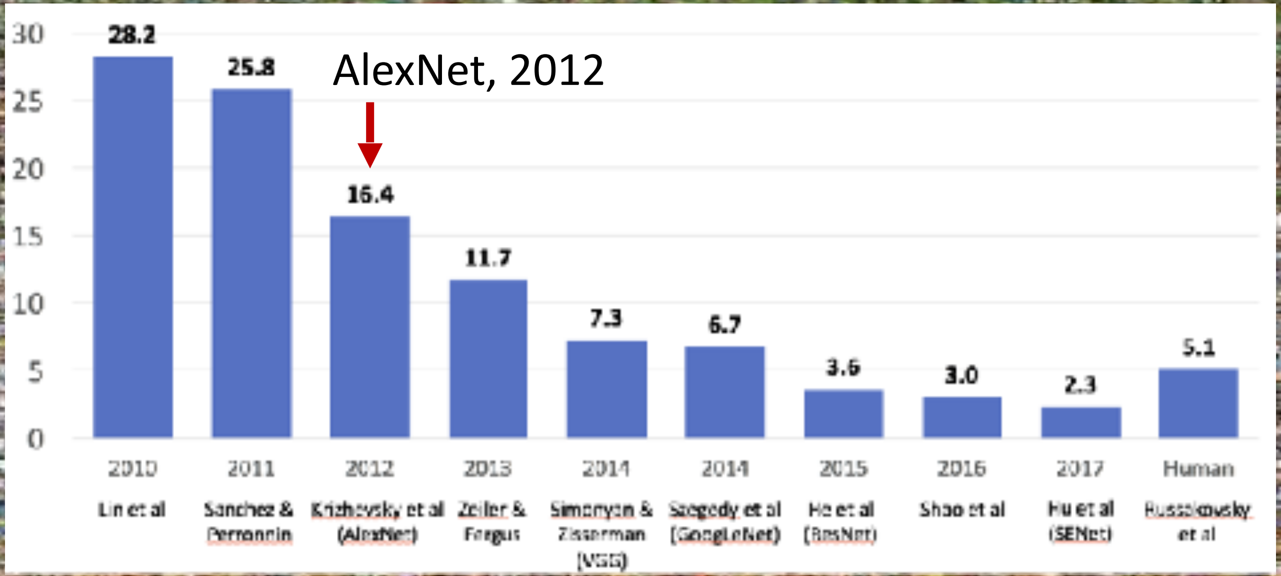
IMAGENET Large Scale Visual Recognition Challenge





IMAGENET Large Scale Visual Recognition Challenge



- 1958 Perceptron
- 1959 Hubel & Wiesel
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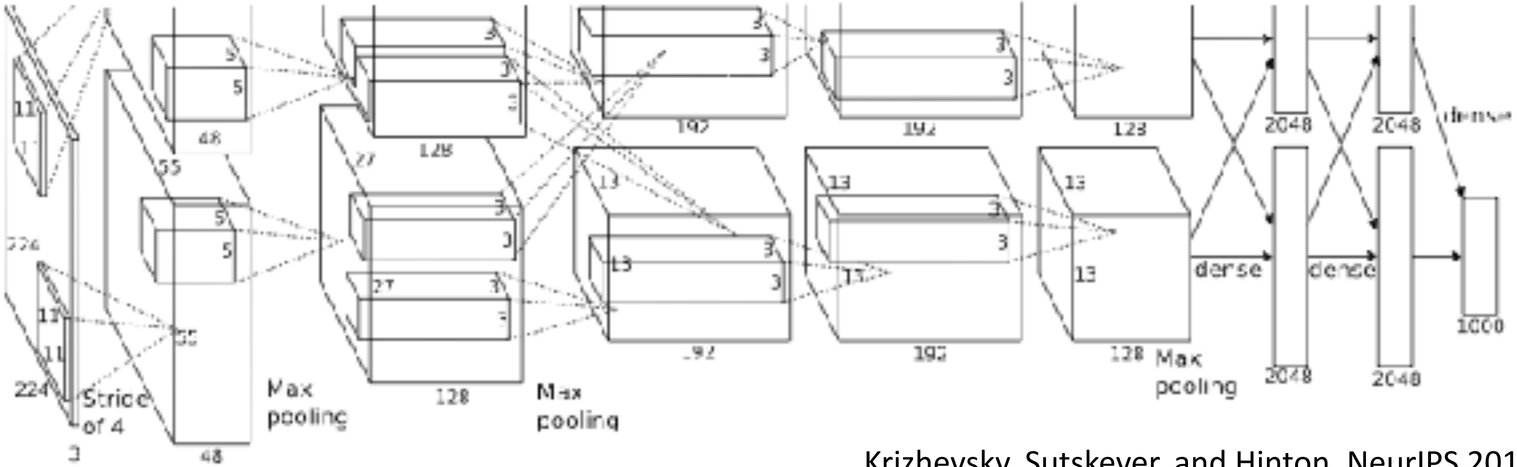
- 1998 LeNet
- 1999 SIFT
- 2001 V&J
- 2004, 2007 Caltech101; PASCAL
- 2006 Deep Learning
- 2009 ImageNet
- 2012 AlexNet

AlexNet: Deep Learning Goes Mainstream



Krizhevsky, Sutskever, and Hinton, NeurIPS 2012

1959 Hubel & Wiesel
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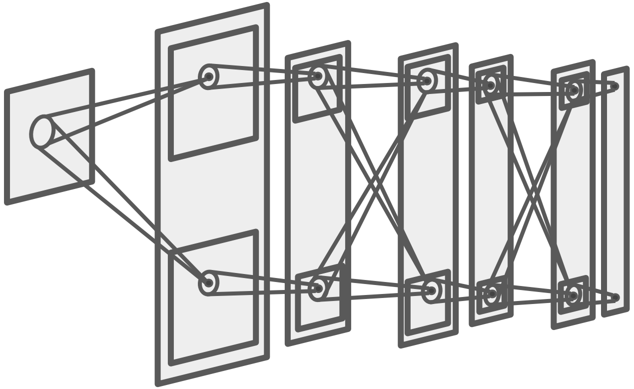
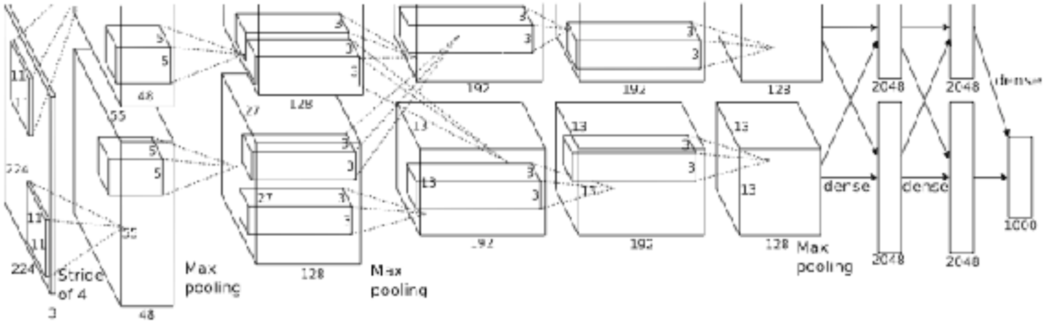
AI Winter

1958 Perceptron
1969 Minsky & Papert
1980 Neocognitron
1985 Backprop
1998 LeNet
2006 Deep Learning
2012 AlexNet

Slide inspiration: Justin Johnson

AlexNet vs. Neocognitron: 32 years apart





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AI Winter

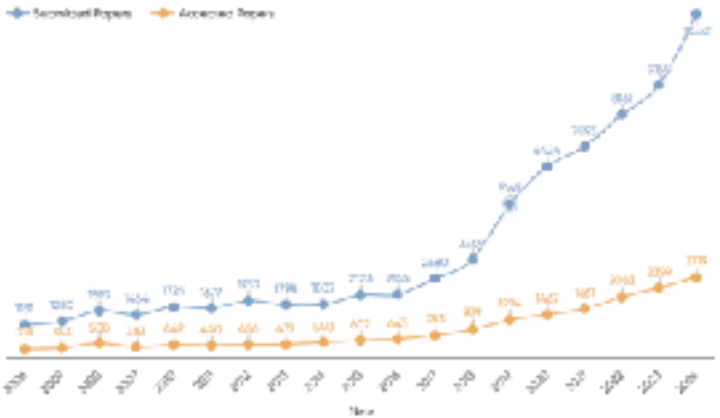
1958 Perceptron | 1969 Minsky & Papert | 1980 Neocognitron | 1985 Backprop | 1998 LeNet | 2006 Deep Learning | 2012 AlexNet

Slide inspiration: Justin Johnson

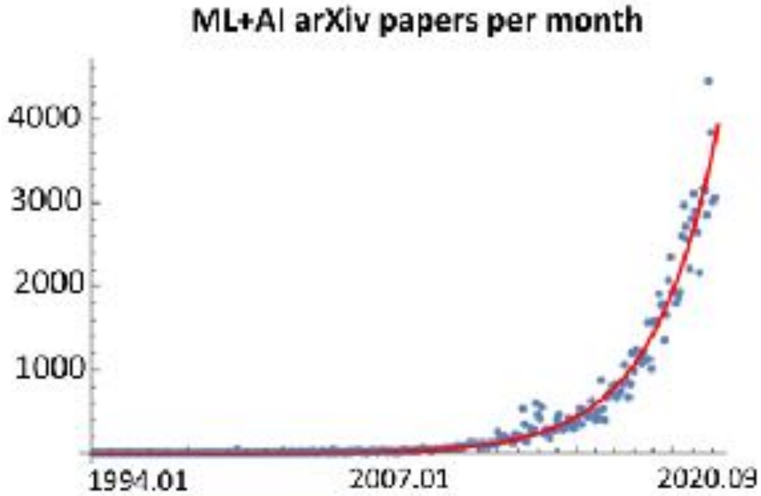
The AI winter thawed,
deep learning revolution arrived

2012 to Present: Deep Learning Explosion

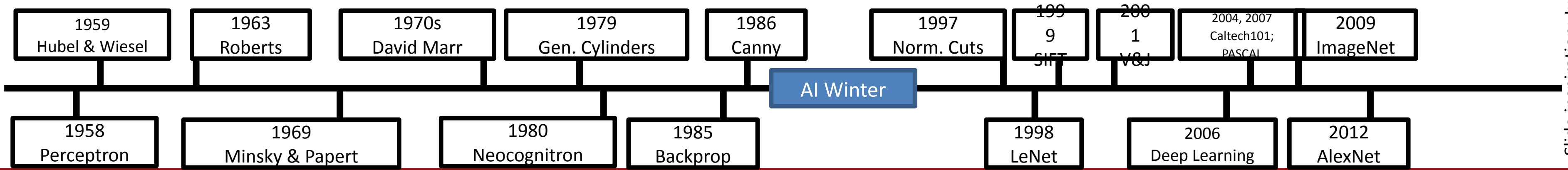
CVPR



Top computer vision conference (source)



arXiv papers per month (source)

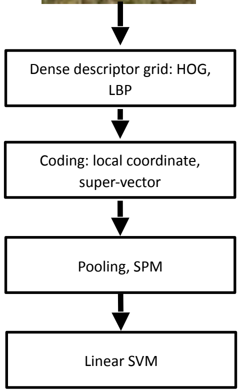


Slide inspiration: Justin Johnson

2012 to Present: Deep Learning is Everywhere

Year 2010

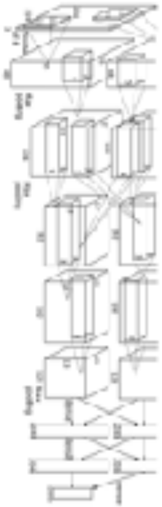
NEC-UIUC



[Lin CVPR 2011]

Year 2012

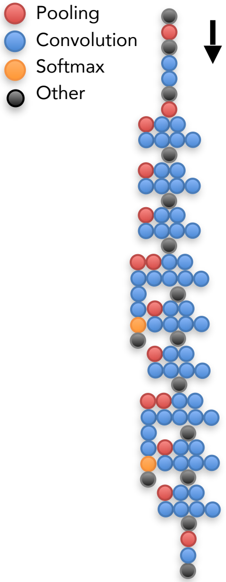
SuperVision



[Krizhevsky NIPS 2012]

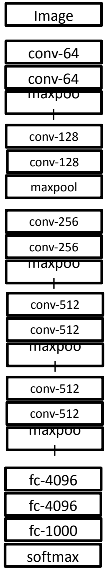
Year 2014

GoogLeNet



[Szegedy arxiv 2014]

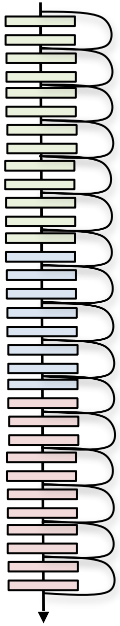
VGG



[Simonyan arxiv 2014]

Year 2015

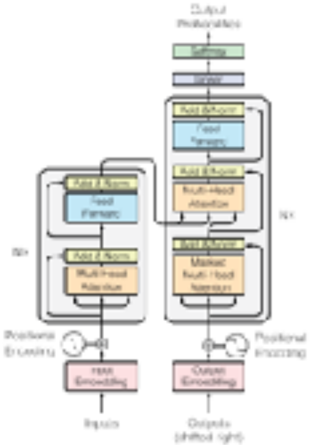
MSRA



[He ICCV 2015]

Year 2017

Transformers



[Vaswani NeurIPS 2017]

2012 to Present: Deep Learning is Everywhere

Image Classification

Image Retrieval

Figures copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

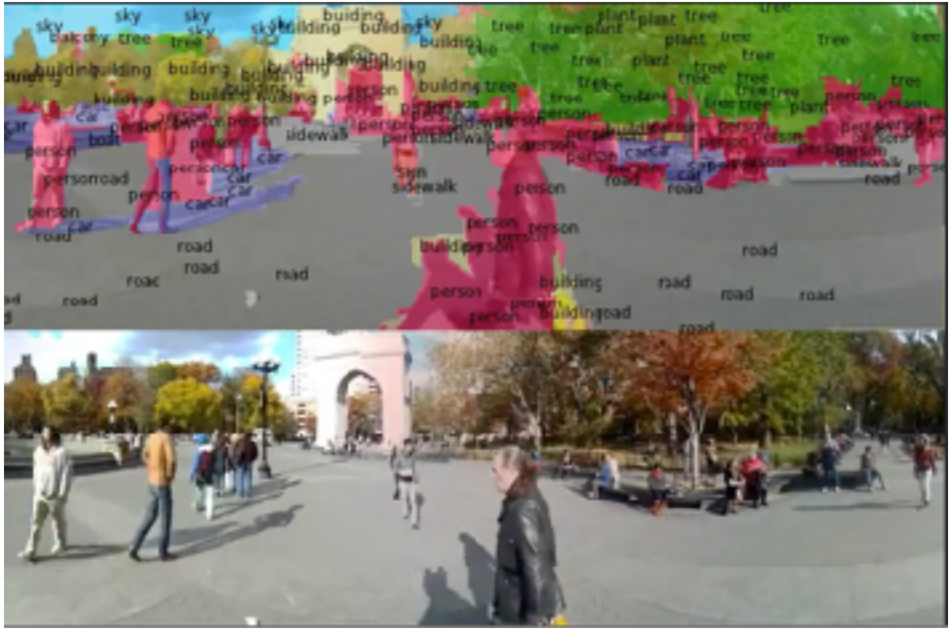
Slide inspiration: Justin Johnson

2012 to Present: Deep Learning is Everywhere

Object Detection

Ren, He, Girshick, and Sun, 2015

Image Segmentation

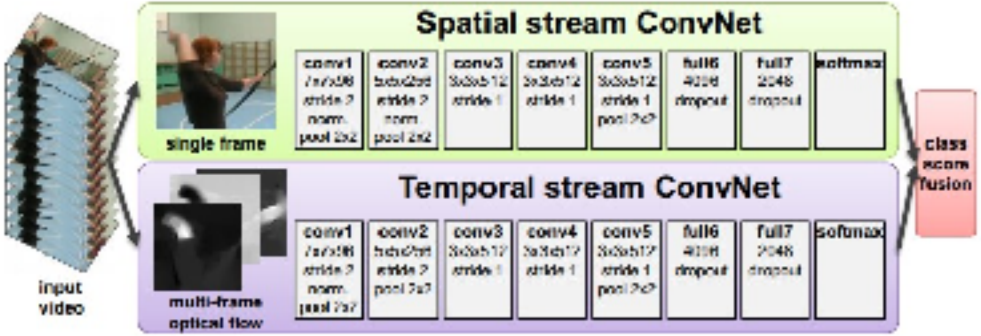


Fabaret et al, 2012

Slide inspiration: Justin Johnson

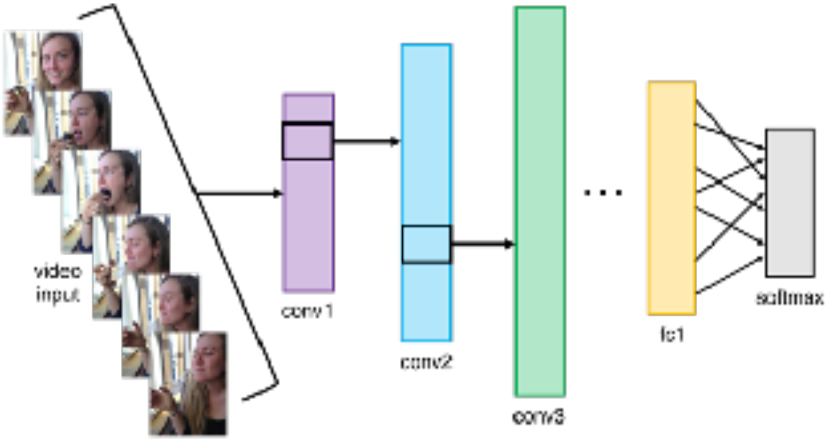
2012 to Present: Deep Learning is Everywhere

Video Classification



Simonyan et al, 2014

Activity Recognition

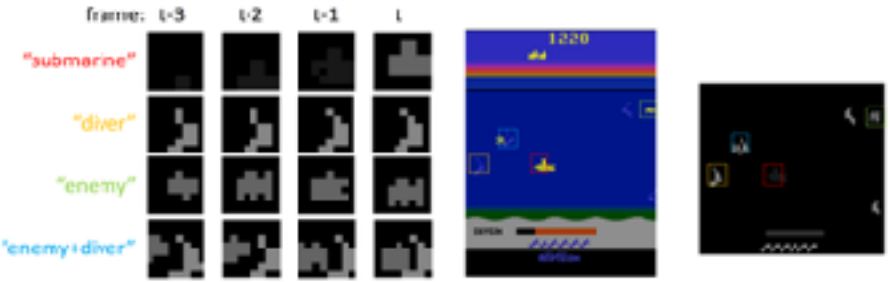


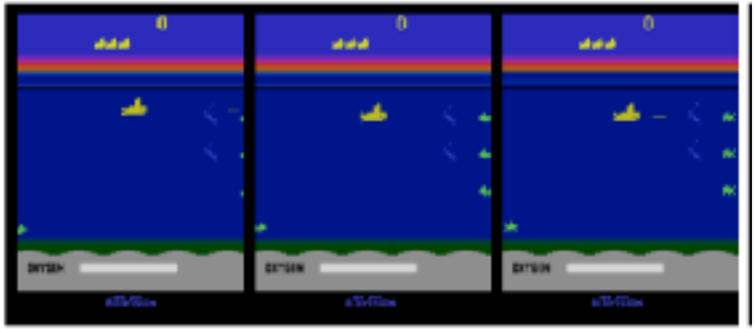
Slide inspiration: Justin Johnson

2012 to Present: Deep Learning is Everywhere

Pose Recognition (Toshev and Szegedy, 2014)

Playing Atari games (Guo et al, 2014)

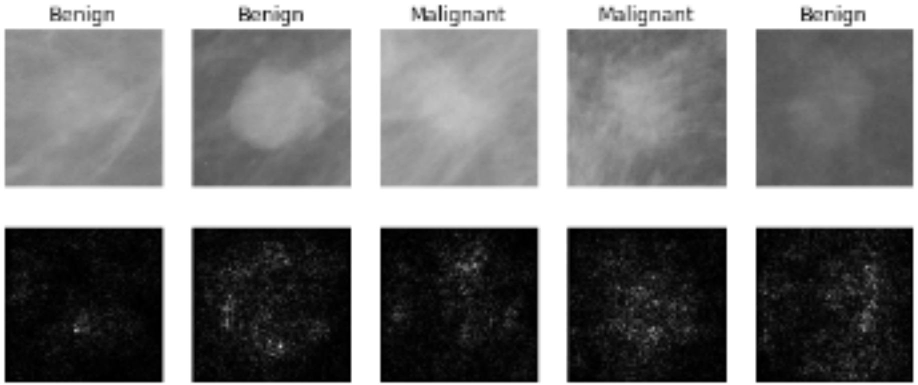




Slide inspiration: Justin Johnson

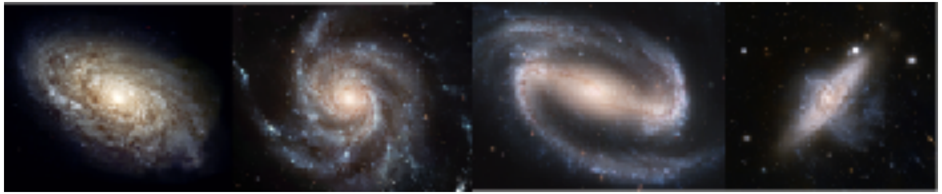
2012 to Present: Deep Learning is Everywhere

Medical Imaging



Levy et al, 2016 Figure reproduced with permission

Galaxy Classification



Dieleman et al, 2014

Whale recognition

Kaggle Challenge

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

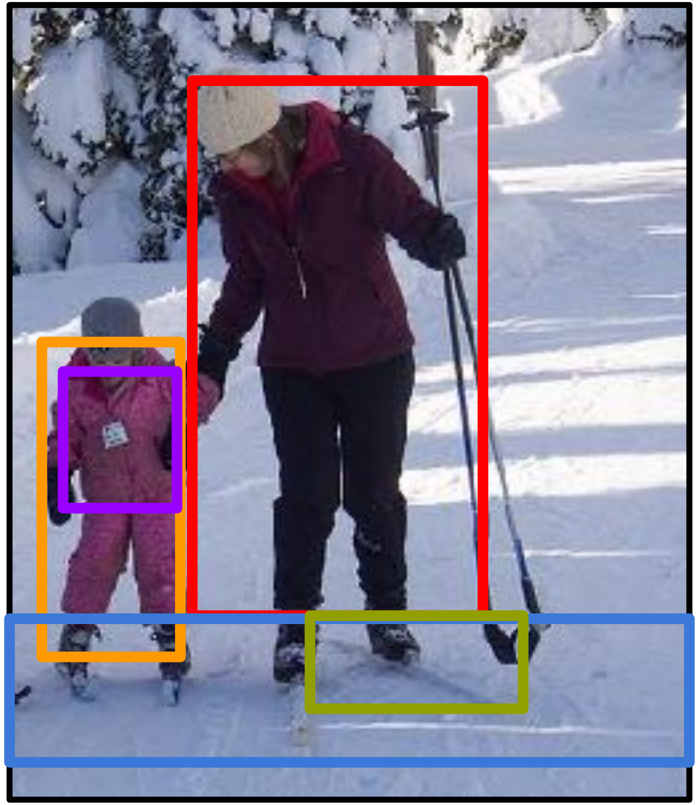
A cat sitting on a suitcase on the floor

A woman standing on a beach holding a surfboard

Captions generated by Justin Johnson using Neuraltalk2

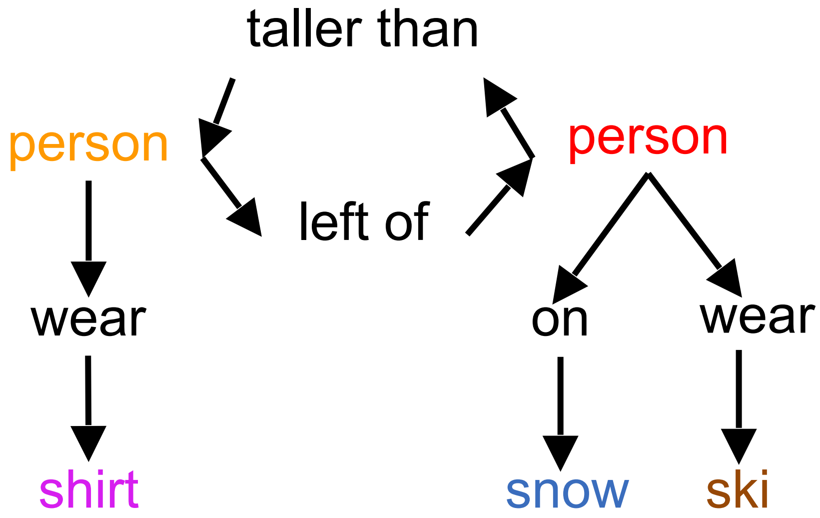
Slide inspiration: Justin Johnson

2012 to Present: Deep Learning is Everywhere

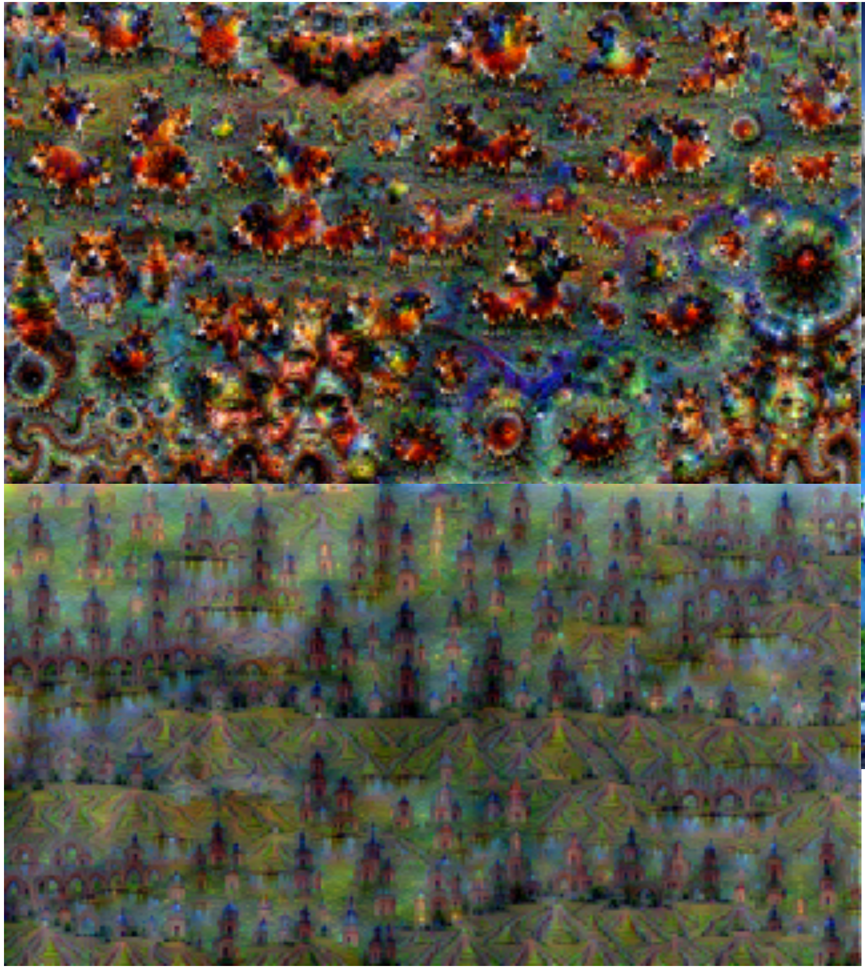


Results:

spatial, comparative, asymmetrical, verb, prepositional



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



Figures copyright Justin Johnson, 2015. Reproduced with permission. Generated using the Inceptionism approach from a blog post by Google Research.

Mordvinsev et al, 2015
Gatys et al, 2016

Slide inspiration: Justin Johnson

2012 to Present: Deep Learning is Everywhere

A Dutch still life of an arrangement of tulips in a fluted vase. The lighting is subtle, casting gentle highlights on the flowers and emphasizing their delicate details and natural beauty.

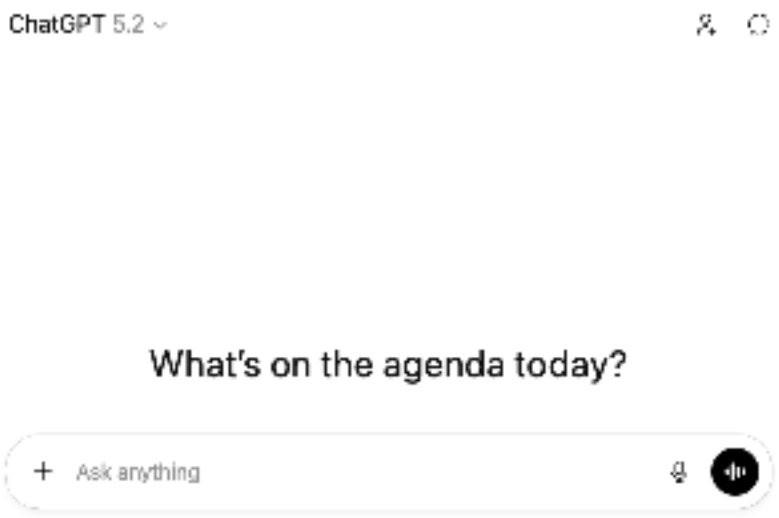
Slide inspiration: Justin Johnson

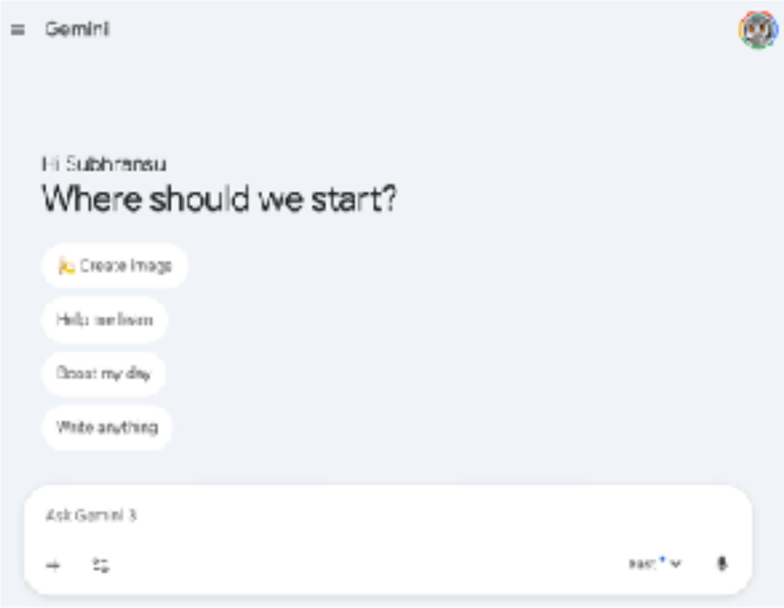
2012 to Present: Deep Learning is Everywhere

A 2D animation of a folk music band composed of anthropomorphic autumn leaves, each playing traditional bluegrass instruments, amidst a rustic forest setting dappled with the soft light of a harvest moon.

Slide inspiration: Justin Johnson

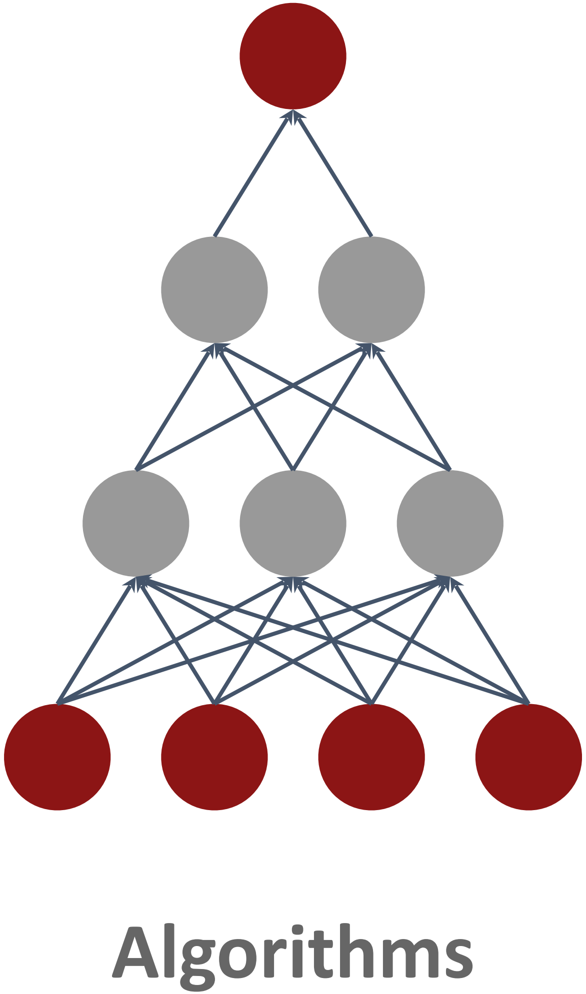
2012 to Present: Deep Learning is Everywhere





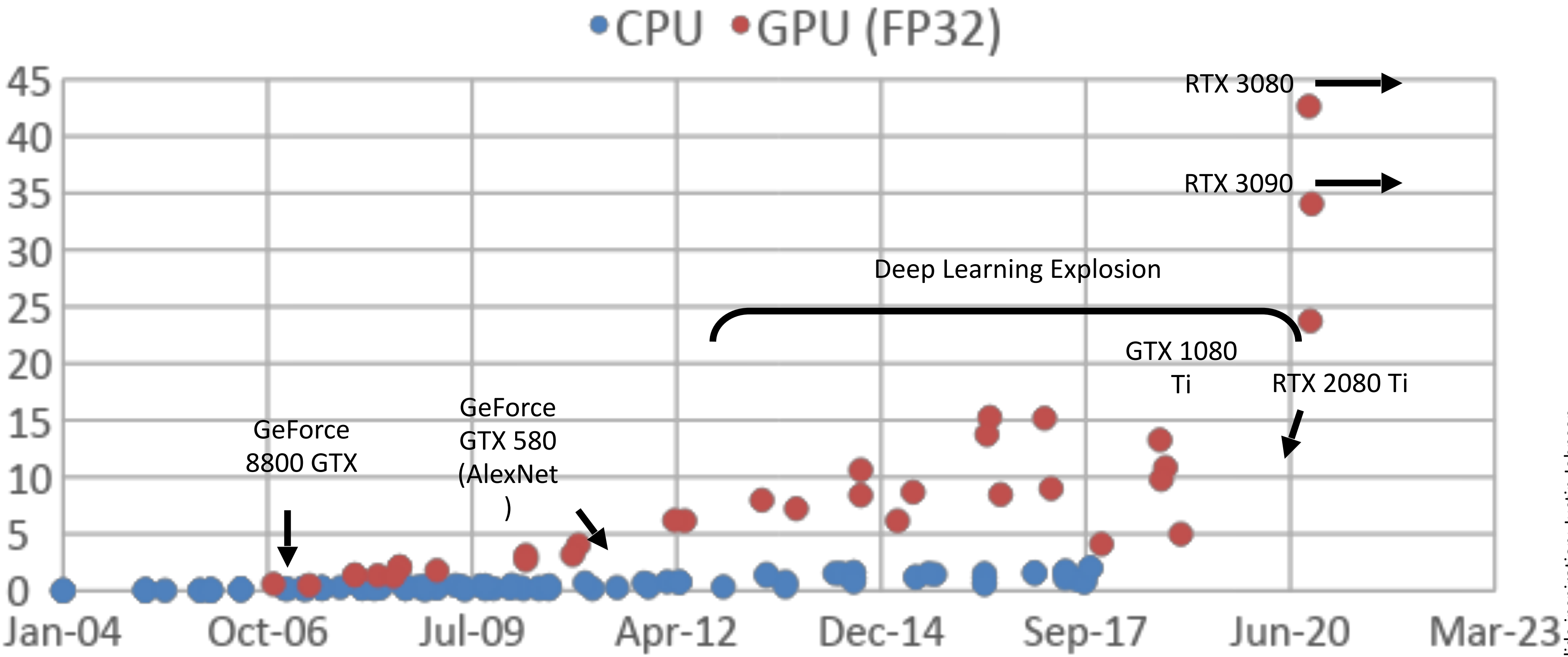
Slide inspiration: Justin Johnson


Computation


Algorithms

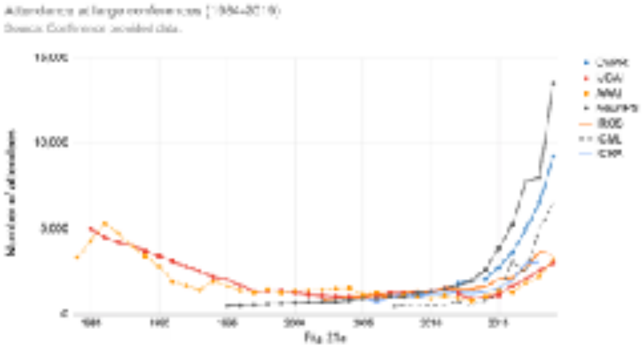

Data

GFLOP per Dollar



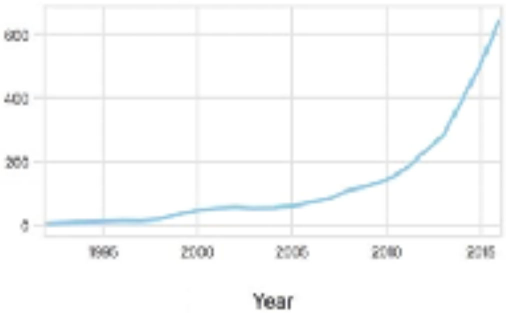
Slide inspiration: Justin Johnson

AI's Explosive Growth & Impact



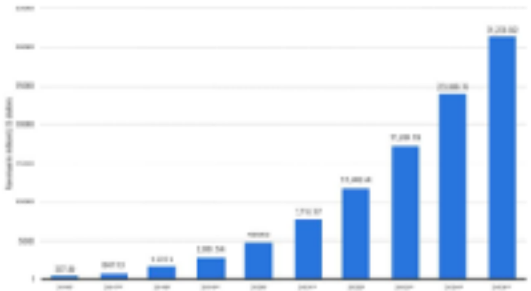
Number of attendance At AI conferences

Source: The Gradient



Startups Developing AI Systems

Source: Crunchbase, VentureSource, Sand Hill Econometrics



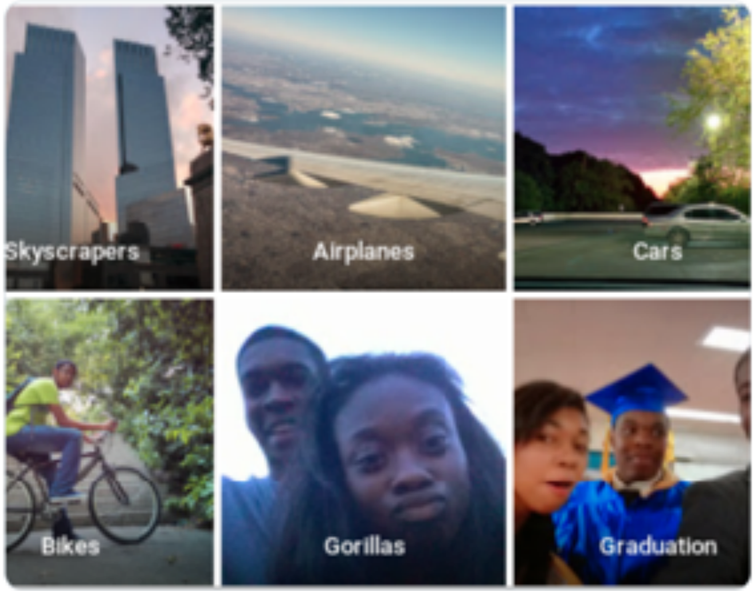
Enterprise Application AI Revenue

Source: Statista

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

Computer Vision Can Cause Harm

Harmful Stereotypes



Barocas et al, "The Problem With Bias: Allocative Versus Representational Harms in Machine Learning", SIGCIS 2017
Kate Crawford, "The Trouble with Bias", NeurIPS 2017 Keynote
Source: https://twitter.com/jackyalcine/status/615329515909156865 (2015)

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

CV and AI in General Can Cause Harm

- Opacity and loss of accountability — who is responsible?
- Misinformation at scale
- Loss of agency and autonomy — future of work
- Concentration of power

- These aren’t technical problems alone—they’re **social and governance problems**.

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

Slide inspiration: Andrej Karpathy

Next lecture: Image Classification: A core task in Computer Vision

(assume given set of discrete labels)
{dog, cat, truck, plane, ...}

→ cat