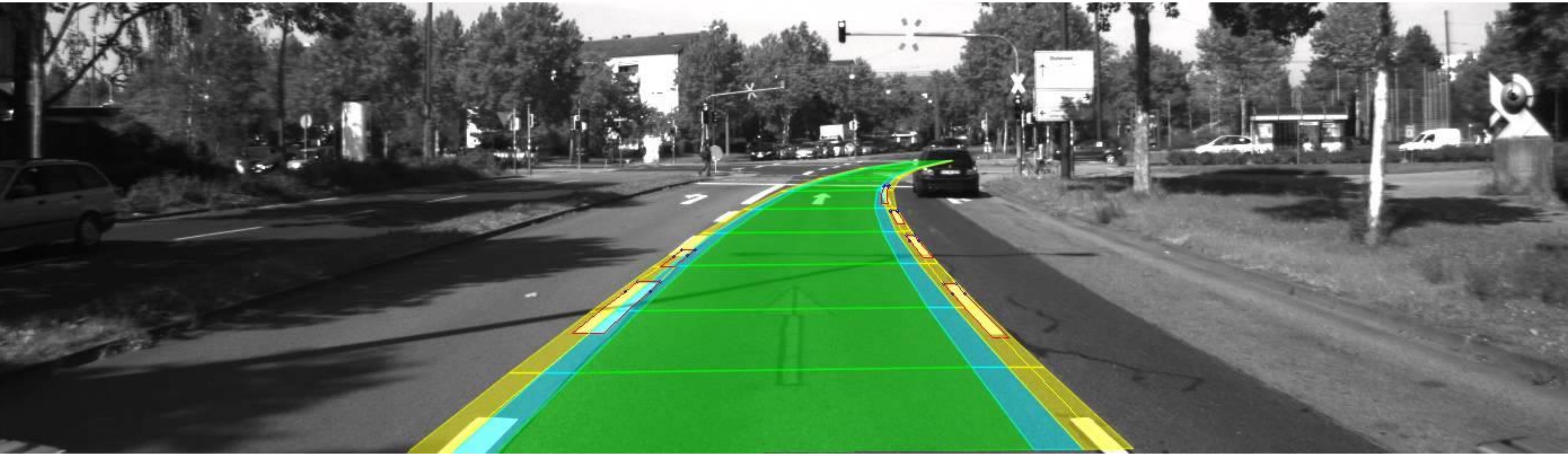
6.S094: Deep Learning for Self-Driving Cars

Lecture 1: Introduction to Deep Learning and Self-Driving Cars

cars.mit.edu



Administrative

- **Website:** cars.mit.edu
- **Contact Email:** deepcars@mit.edu
- **Required:**
  - Create an account on the website.
  - Follow the tutorial for each of the 2 projects.
- **Recommended:**
  - Ask questions
  - Win competition!

Lex Fridman

Instructor

Benedikt Jenik

TA

William Angell

TA

Spencer Dodd

TA

Dan Brown

TA

Target Audience

You may be:

- New to programming
- New to machine learning
- New to robotics

What you will learn:

- An overview of deep learning methods:
  - Deep Reinforcement Learning
  - Convolutional Neural Networks
  - Recurrent Neural Networks
- How deep learning can help improve each component of autonomous driving: perception, localization, mapping, control, planning, driver state

Target Audience

Not many equation slides like the following:

Lemma 0.1. *Let $\mathcal{C}$ be a set of the construction.*

Let $\mathcal{C}$ be a gerber covering. Let $\mathcal{F}$ be a quasi-coherent sheaves of $\mathcal{O}$-modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

.

Proof. This is an algebraic space with the composition of sheaves $\mathcal{F}$ on $X_{\acute{e}tale}$ we have

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where $\mathcal{G}$ defines an isomorphism $\mathcal{F} \to \mathcal{F}$ of $\mathcal{O}$-modules. $\square$

* Though it would be more efficient, since the above is LaTeX code automatically generated character by character with Recurrent Neural Networks (RNNs)

[35] Andrej Karpathy. "The Unreasonable Effectiveness of Recurrent Neural Networks." (2015).

Guest Speakers

Mapping, Localization, and the Challenge of Autonomous Driving

John Leonard

Professor, MIT

Past, Present, and Future of Motion Planning in a Complex World

Sertac Karaman

Professor, MIT

From Research to Reality: Testing Self-Driving Cars on Boston Public Roads

Karl Iagnemma

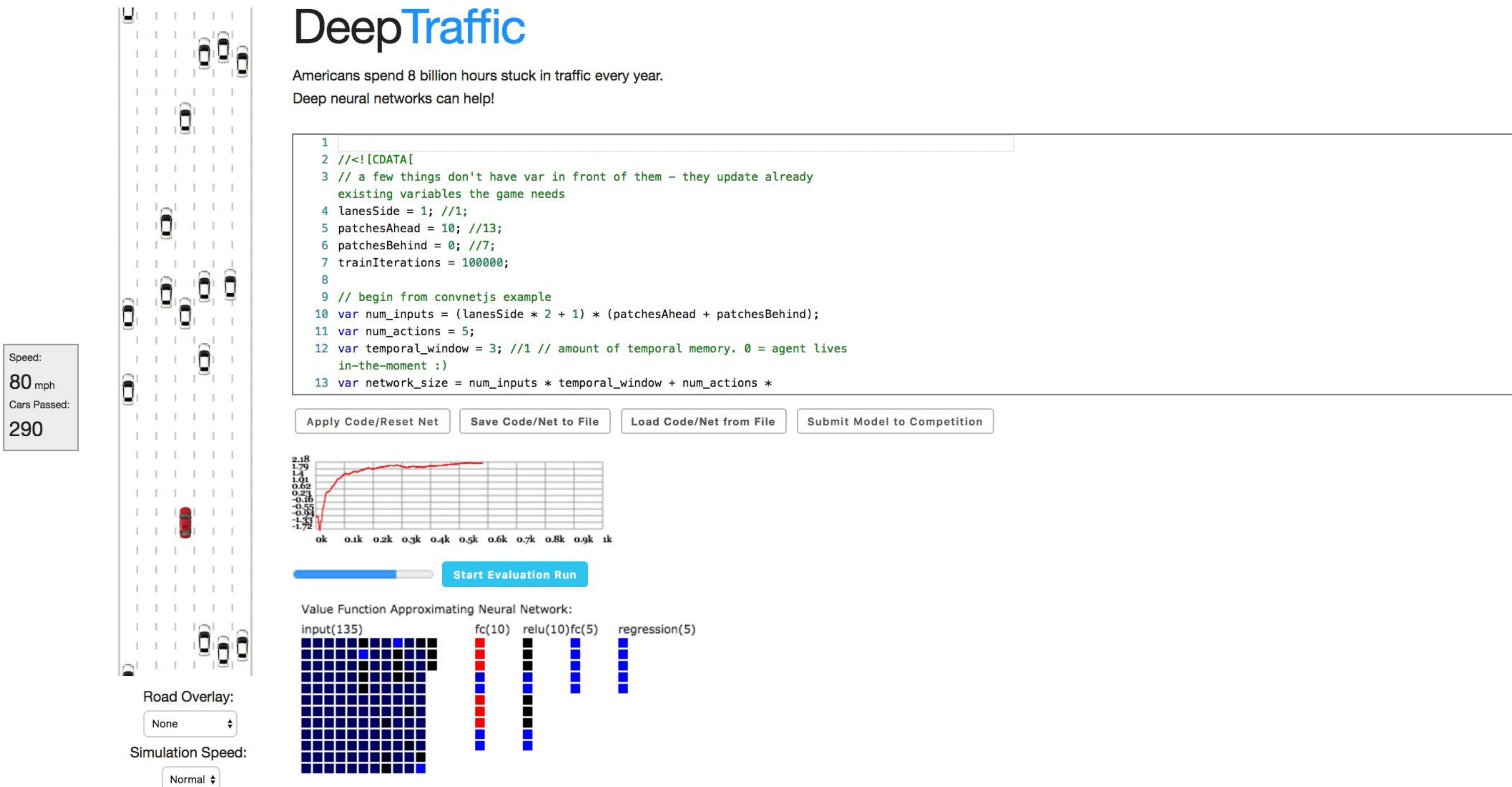
CEO, nuTonomy and Research Scientist, MIT

TBD

Chris Gerdes

Professor, Stanford

Project: **DeepTraffic**



Project: **DeepTesla**

Schedule

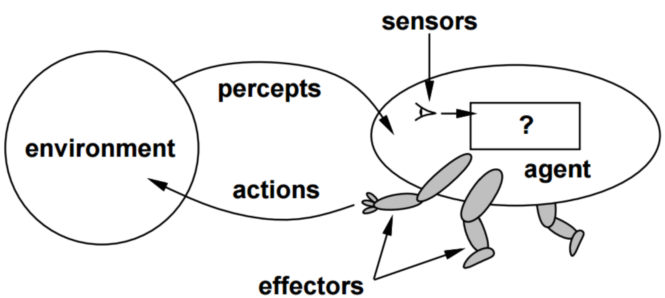
Mon, Jan 9	Introduction to Deep Learning and Self Driving Cars
Tue, Jan 10	**Learning to Move:** Reinforcement Learning for Motion Planning
	DeepTraffic: Solving Traffic with Deep Reinforcement Learning
Wed, Jan 11	**Learning to Drive:** End-to-End Learning for the Full Driving Task
	DeepTesla: End-to-End Learning from Human and Autopilot Driving
Thu, Jan 12	**Karl Iagnemma:** From Research to Reality: Testing Self-Driving Cars on Boston Public Roads
Fri, Jan 13	**John Leonard:** Mapping, Localization, and the Challenge of Autonomous Driving
Tue, Jan 17	**Chris Gerdes:** TBD
Wed, Jan 18	**Sertac Karaman:** Past, Present, and Future of Motion Planning in a Complex World
Thu, Jan 19	**Learning to Share:** Driver State Sensing and Shared Autonomy
Fri, Jan 20	**Eric Daimler:** The Future of Artificial Intelligence Research and Development
	Learning to Think: The Road Ahead for Human-Centered Artificial Intelligence

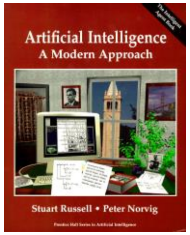
Defining (Artificial) Intelligence

March 25, 1996

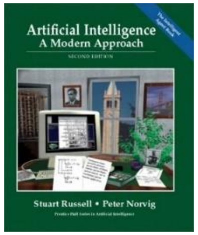
Special Purpose:
Can it achieve a well-defined finite set of goals?

General Purpose:
Can it achieve poorly-defined unconstrained set of goals?

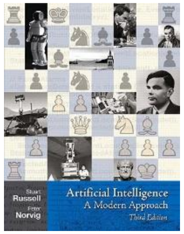




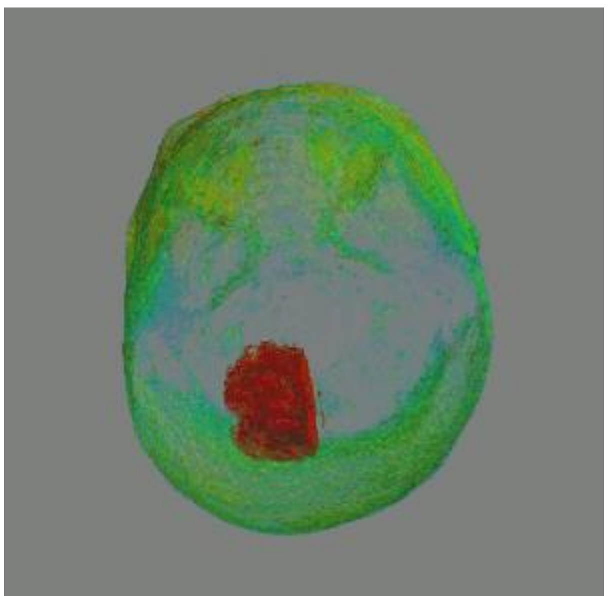
(1995)



(2002)



(2009)



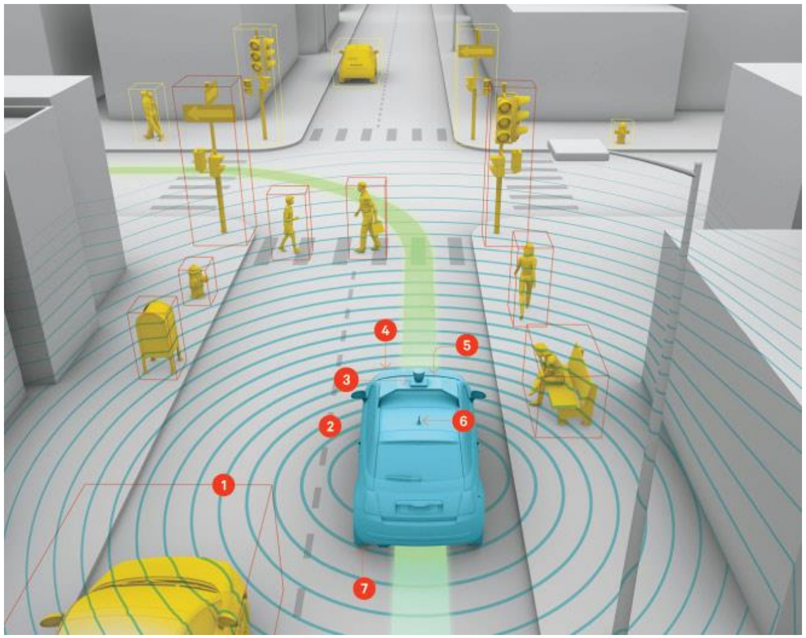
- **Formal tasks:** Playing board games, card games. Solving puzzles, mathematical and logic problems.
- **Expert tasks:** Medical diagnosis, engineering, scheduling, computer hardware design.
- **Mundane tasks:** Everyday speech, written language, perception, walking, object manipulation.

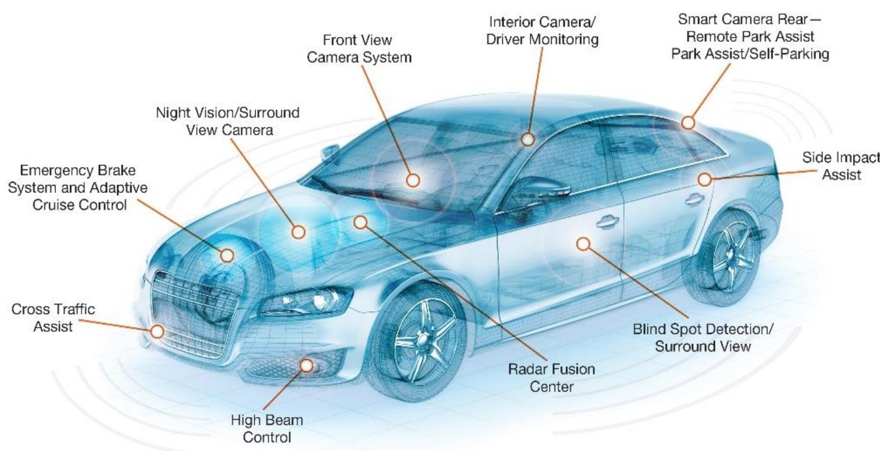
How Hard is Driving?

Open Question:

Is driving closer to **chess** or to **everyday conversation**?

Chess Pieces: Self-Driving Car Sensors





External

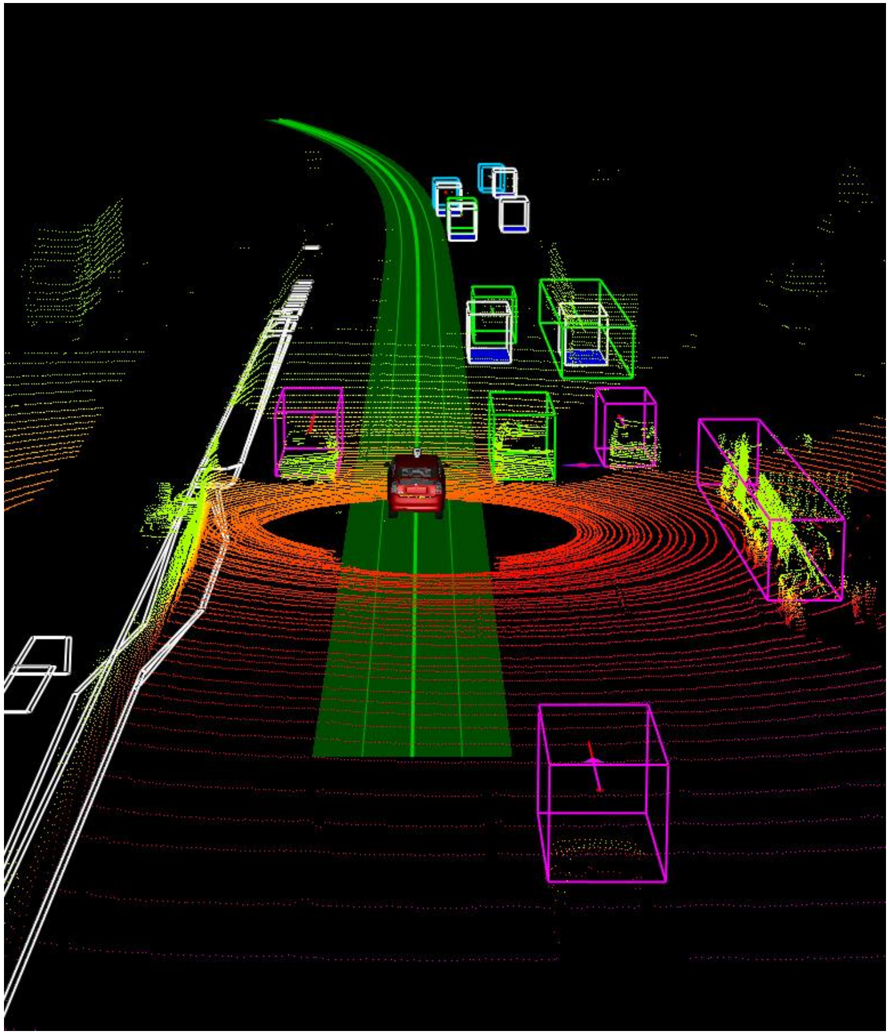
1. Radar
2. Visible-light camera
3. LIDAR
4. Infrared camera
5. Stereo vision
6. GPS/IMU
7. CAN
8. Audio

Internal

1. Visible-light camera
2. Infrared camera
3. Audio

Chess Pieces: Self-Driving Car Tasks

- **Localization and Mapping:**
  Where am I?
- **Scene Understanding:**
  Where is everyone else?
- **Movement Planning:**
  How do I get from A to B?
- **Driver State:**
  What's the driver up to?



References: [71]

DARPA Grand Challenge II (2006)

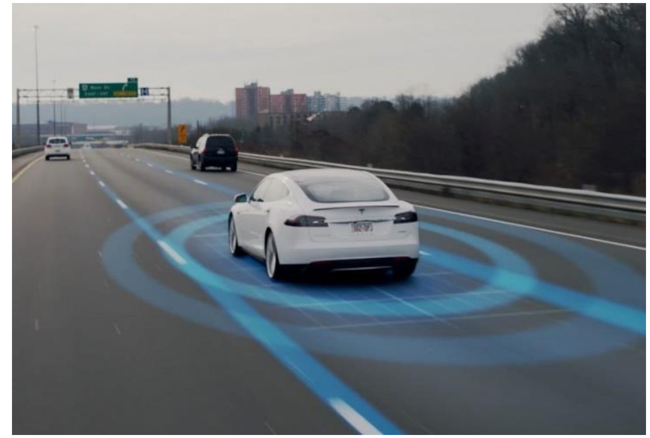
Result: Stanford's Stanley wins

DARPA Urban Challenge (2007)

Result: CMU's Boss (Tartan Racing) wins

Industry Takes on the Challenge

Waymo / Google Self-Driving Car



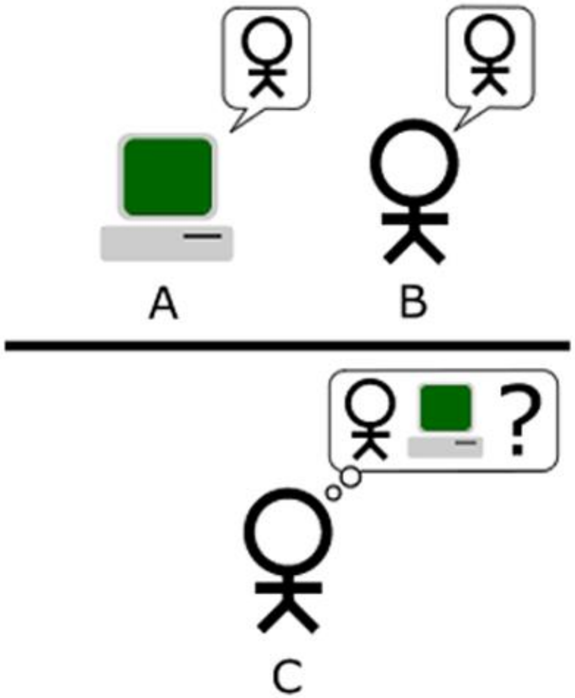
Tesla Autopilot

Uber

nuTonomy

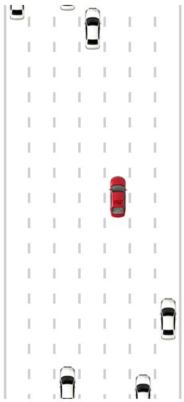
If Driving is a Conversation:

How Hard is it to Pass the Turing Test?

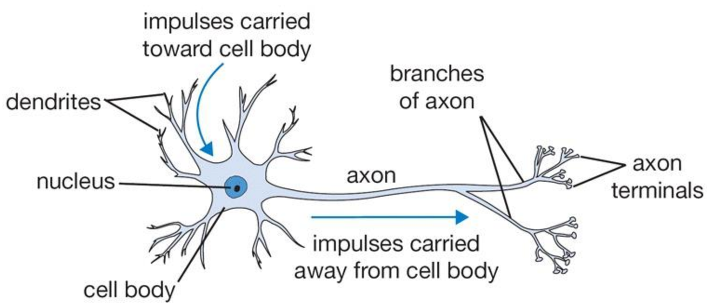


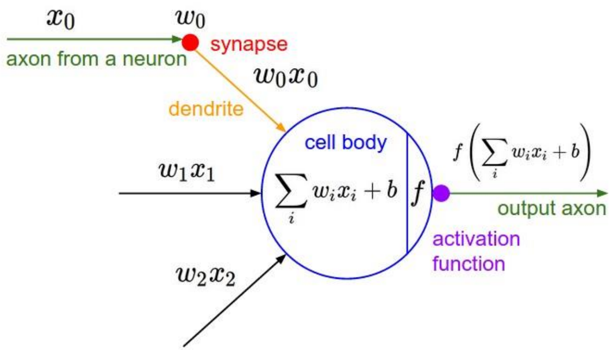
1. **Natural language processing** to enable it to communicate successfully
2. **Knowledge representation** to store information provided before or during the interrogation
3. **Automated reasoning** to use the stored information to answer questions and to draw new conclusions

Turing Test:
Can a computer be mistaken for a human more than 30% of the time?



Neuron: Biological Inspiration for Computation



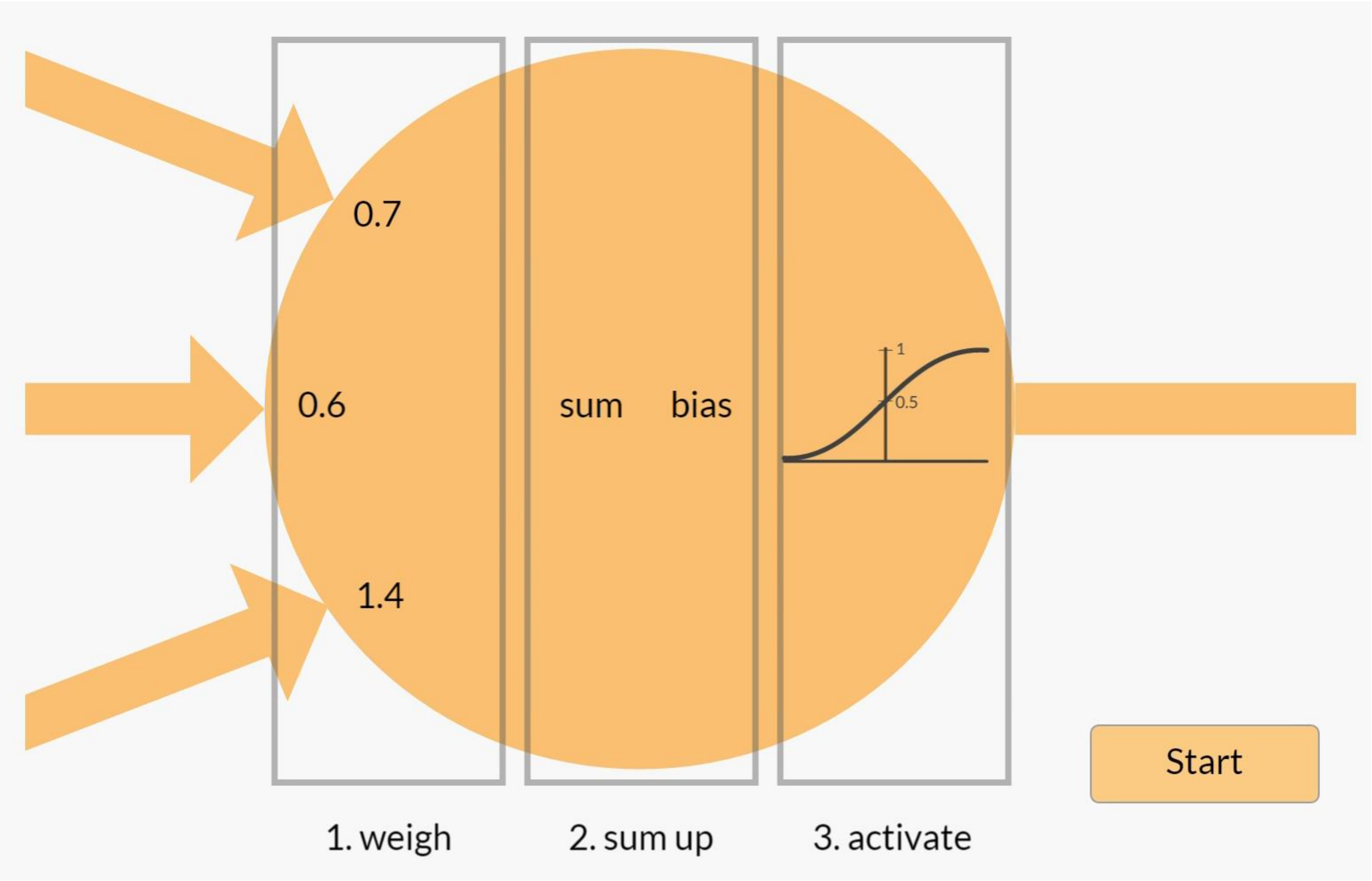


- **Neuron:** computational building block for the brain
- Human brain:
  - ~100-1,000 trillion synapses

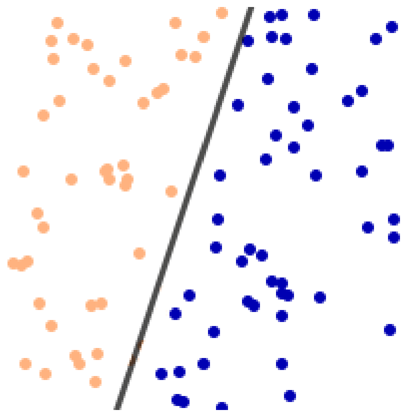
- **(Artificial) Neuron:** computational building block for the "neural network"
- (Artificial) neural network:
  - ~1-10 billion synapses

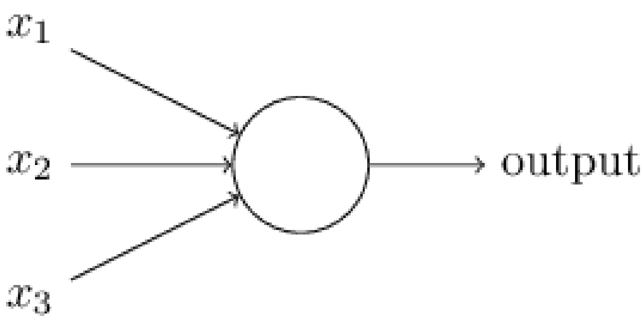
Human brains have ~10,000 computational power than computer brains.

Perceptron: Forward Pass



Perceptron Algorithm

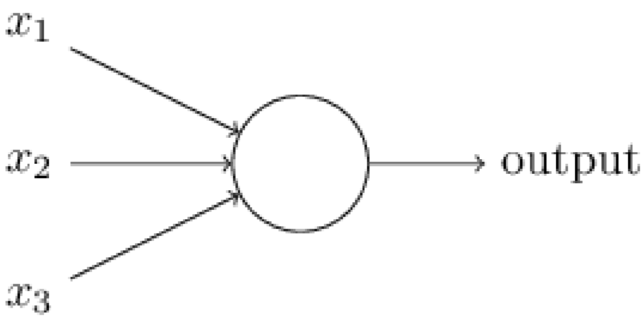


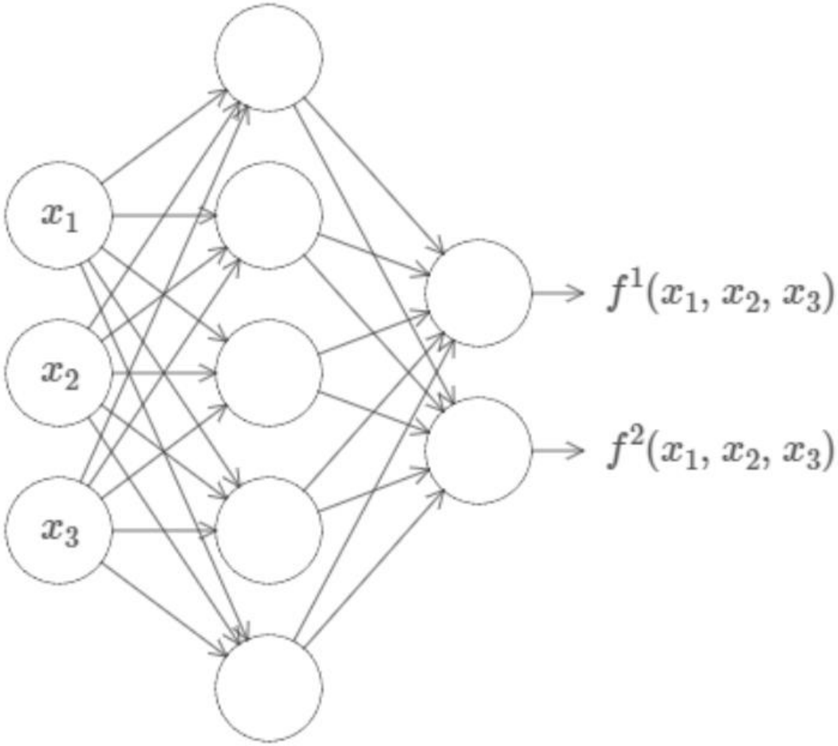


Provide training set of (input, output) pairs and run:

1. Initialize perceptron with random weights
2. For the inputs of an example in the training set, compute the Perceptron's output
3. If the output of the Perceptron does not match the output that is known to be correct for the example:
    1. If the output should have been 0 but was 1, decrease the weights that had an input of 1.
    2. If the output should have been 1 but was 0, increase the weights that had an input of 1.
4. Go to the next example in the training set and repeat steps 2-4 until the Perceptron makes no more mistakes

Neural Networks are Amazing



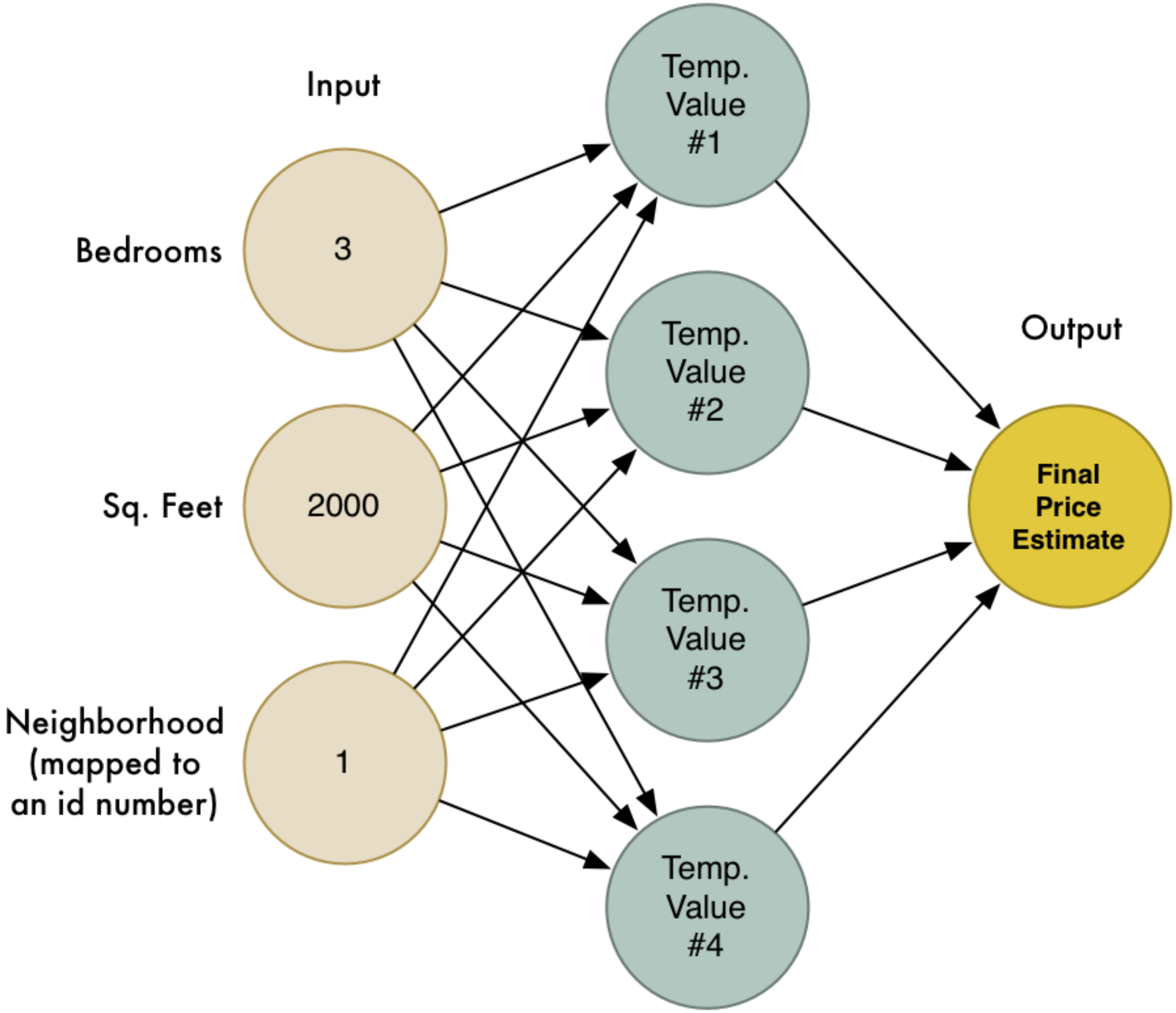


Universality: For any arbitrary function f(x), there exists a neural network that closely approximate it for any input x

Universality is an incredible property!* And it holds for just 1 hidden layer.

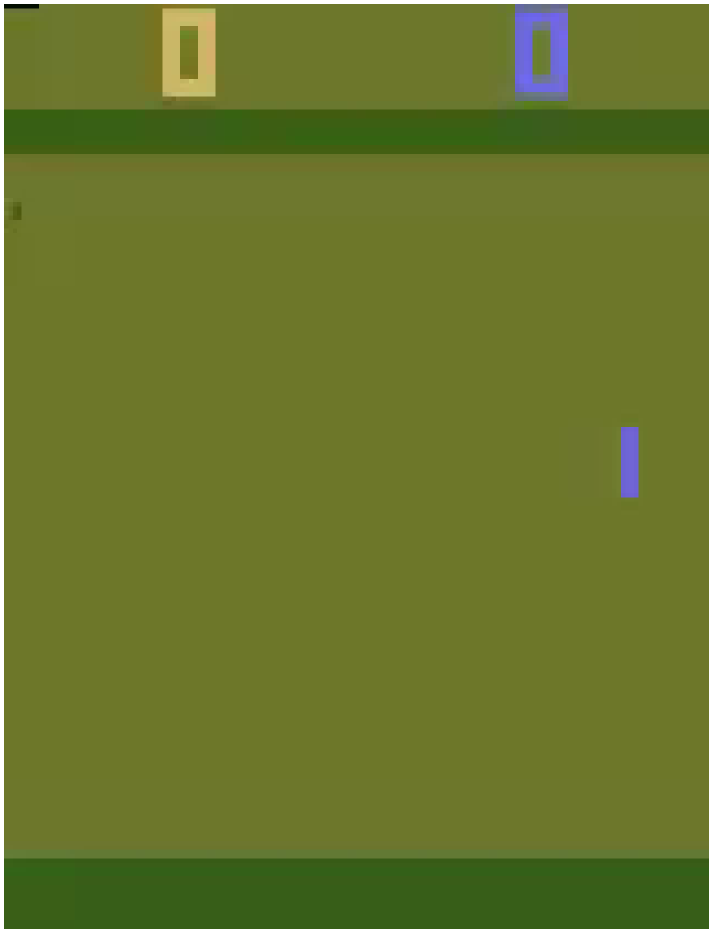
* Given that we have good algorithms for training these networks.

Special Purpose Intelligence



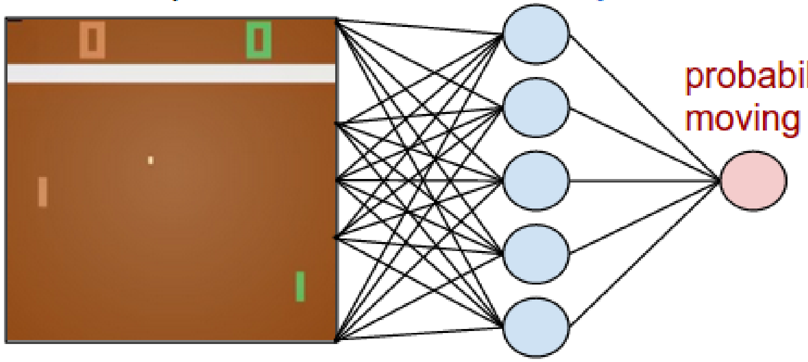
Neural Networks are Amazing:

General Purpose Intelligence



Andrej Karpathy. "Deep Reinforcement Learning: Pong from Pixels." 2016.

Policy Network:

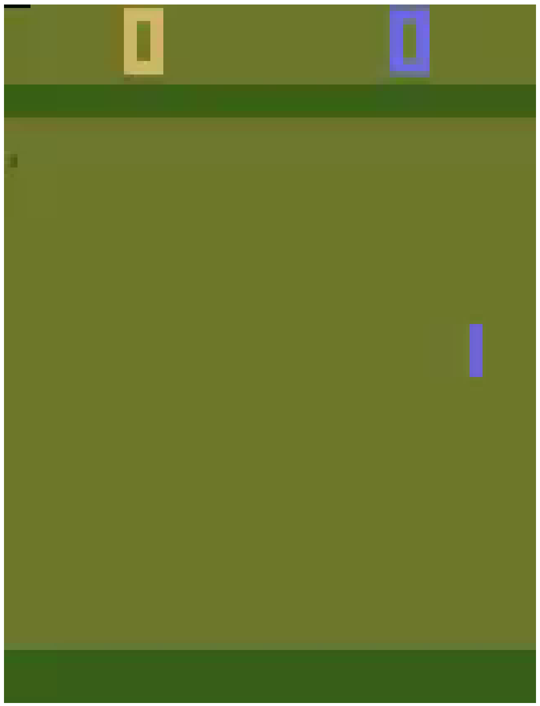


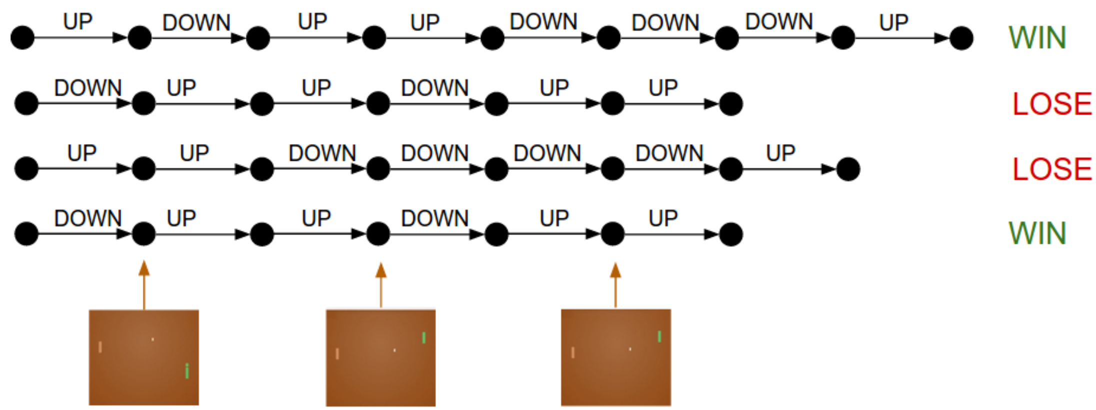
- 80x80 image (difference image)
- 2 actions: up or down
- 200,000 Pong games

This is a step towards general purpose artificial intelligence!

Neural Networks are Amazing:

General Purpose Intelligence





- Every (state, action) pair is **rewarded** when the final result is a **win**.
- Every (state, action) pair is **punished** when the final result is a **loss**.

The fact that this works at all is amazing!

It could be called “general intelligence” but not yet “human-level” intelligence…

Current Drawbacks

- Lacks Reasoning:
  - Humans only need simple instructions:
    "You're in **control** of a paddle and you can move it up and down, and your task is to bounce the ball past the other player controlled by AI."
- Requires **big** data: inefficient at learning from data
- Requires **supervised** data: costly to annotate real-world data
- Need to manually select network structure
- Needs hyperparameter tuning for training:
  - Learning rate
  - Loss function
  - Mini-batch size
  - Number of training iterations
  - Momentum: gradient update smoothing
  - Optimizer selection
- Defining a good reward function is difficult…

References: [63, 64]

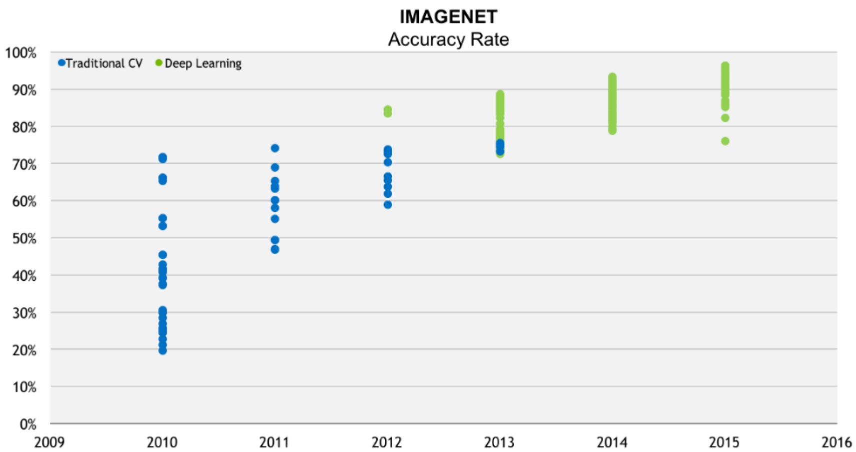
Current Drawbacks

Defining a good reward function is difficult… **Coast Runners:** Discovers local pockets of high reward ignoring the “implied” bigger picture goal of finishing the race.

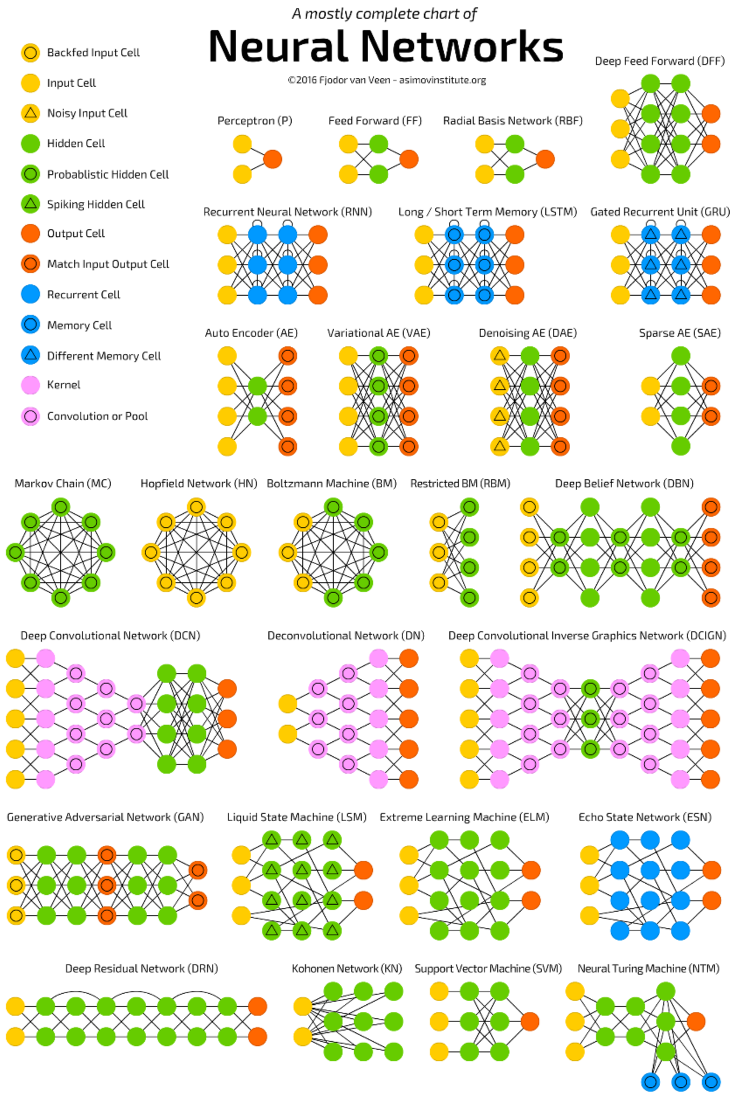
In addition, specifying a reward function for self-driving cars raises ethical questions…

Deep Learning Breakthroughs: What Changed?

- **Compute**
  CPUs, GPUs, ASICs
- **Organized large(-ish) datasets**
  Imagenet
- **Algorithms and research:**
  Backprop, CNN, LSTM
- **Software and Infrastructure**
  Git, ROS, PR2, AWS, Amazon Mechanical Turk, TensorFlow, …
- **Financial backing of large companies**
  Google, Facebook, Amazon, …



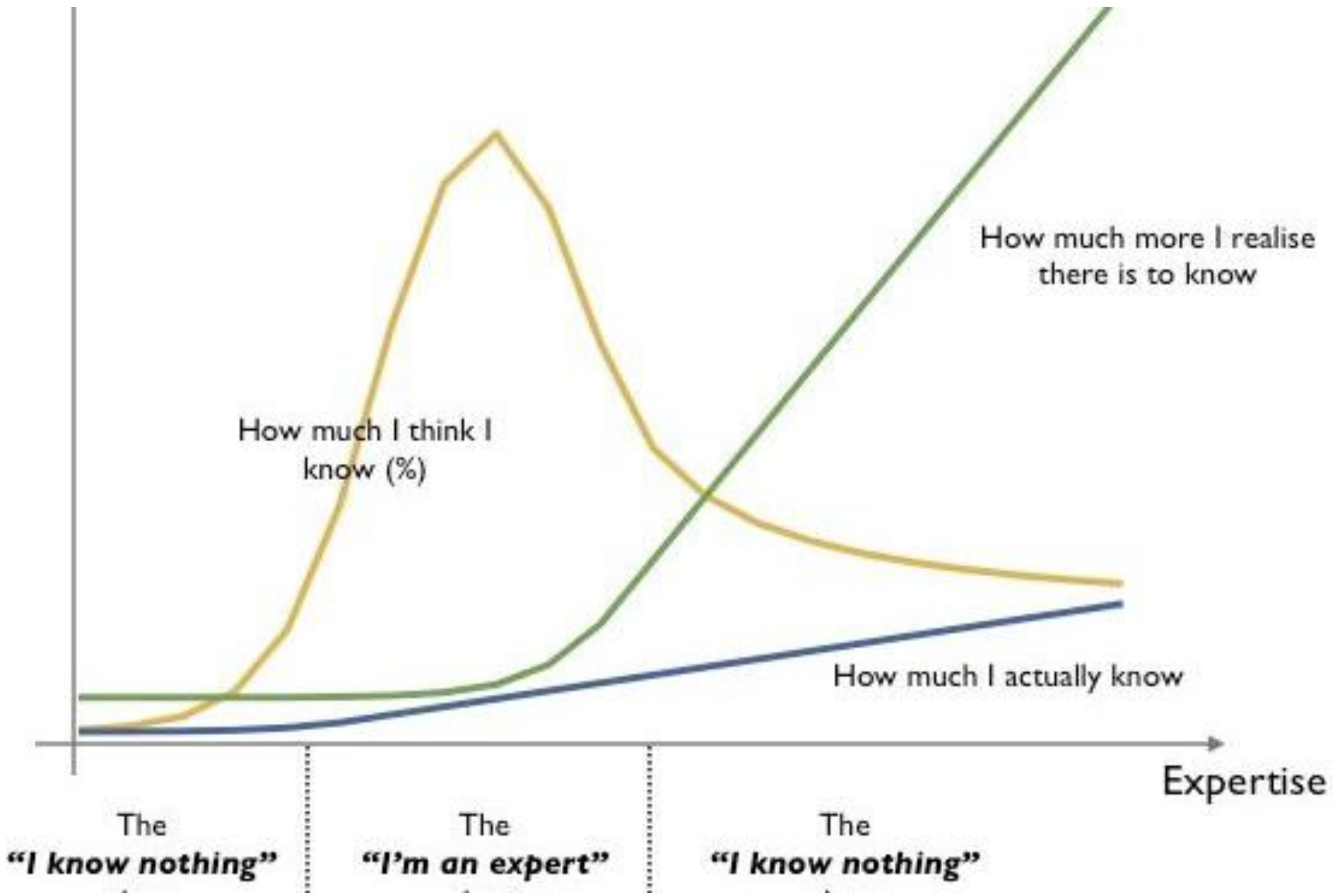
Useful Deep Learning Terms



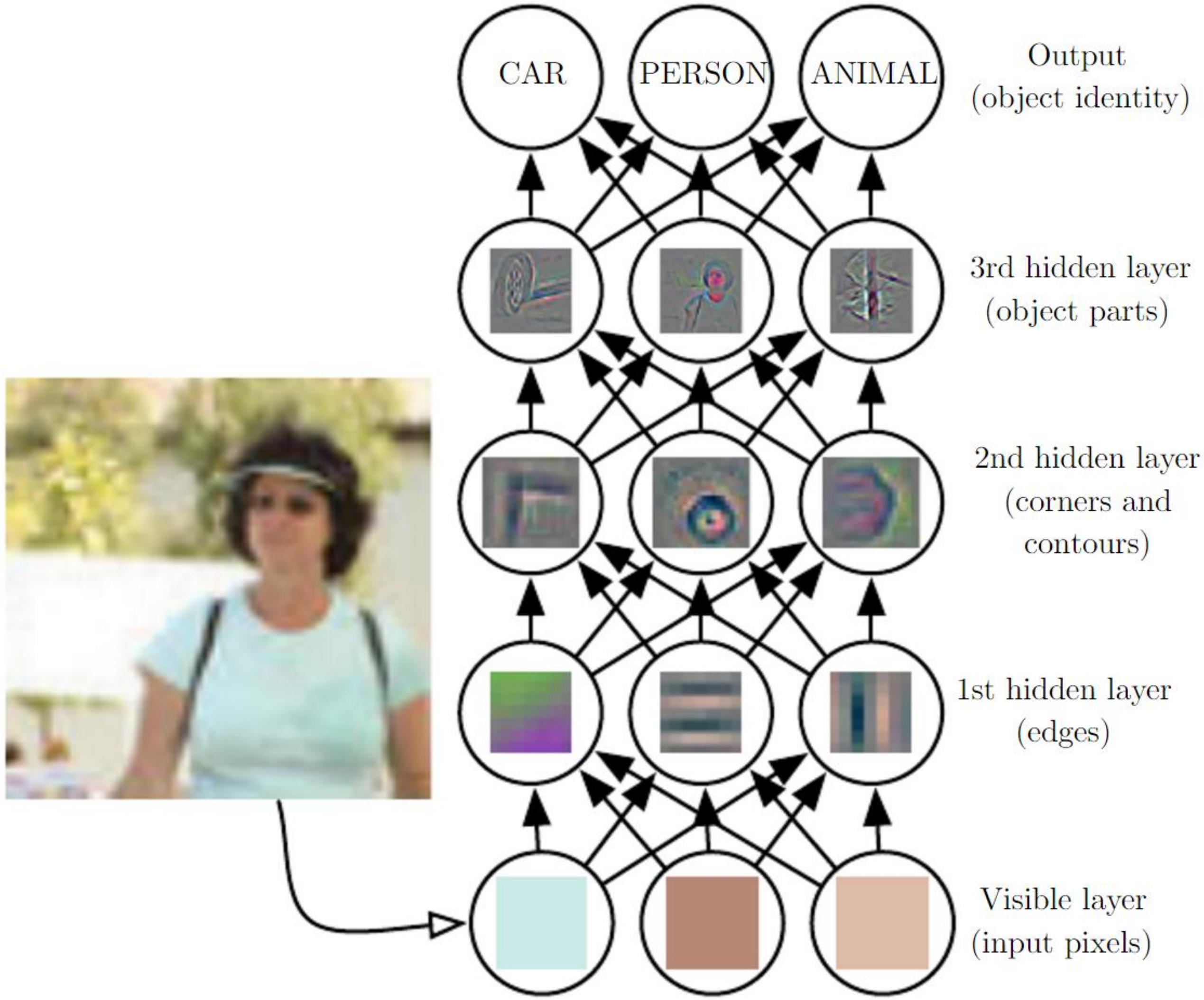
- Basic terms:
  - **Deep Learning = Neural Networks**
  - **Deep Learning** is a subset of **Machine Learning**
- Terms for neural networks:
  - **MLP:** Multilayer Perceptron
  - **DNN:** Deep neural networks
  - **RNN:** Recurrent neural networks
    - **LSTM:** Long Short-Term Memory
  - **CNN or ConvNet:** Convolutional neural networks
  - **DBN:** Deep Belief Networks
- Neural network operations:
  - Convolution
  - Pooling
  - Activation function
  - Backpropagation

Asimov Institute. “A mostly complete chart of neural networks.”

Neural Networks: Proceed with Caution

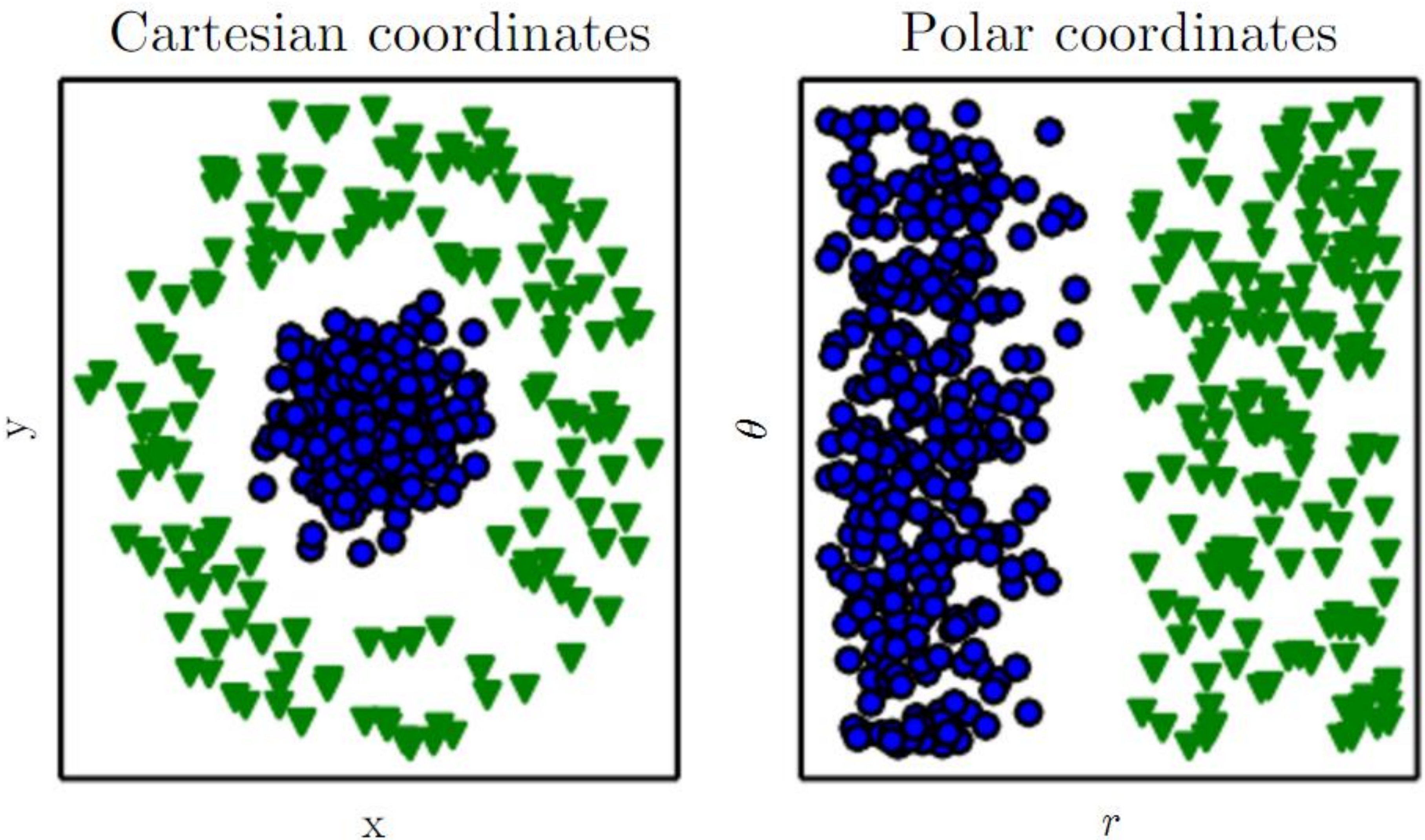


Deep Learning is **Representation Learning**

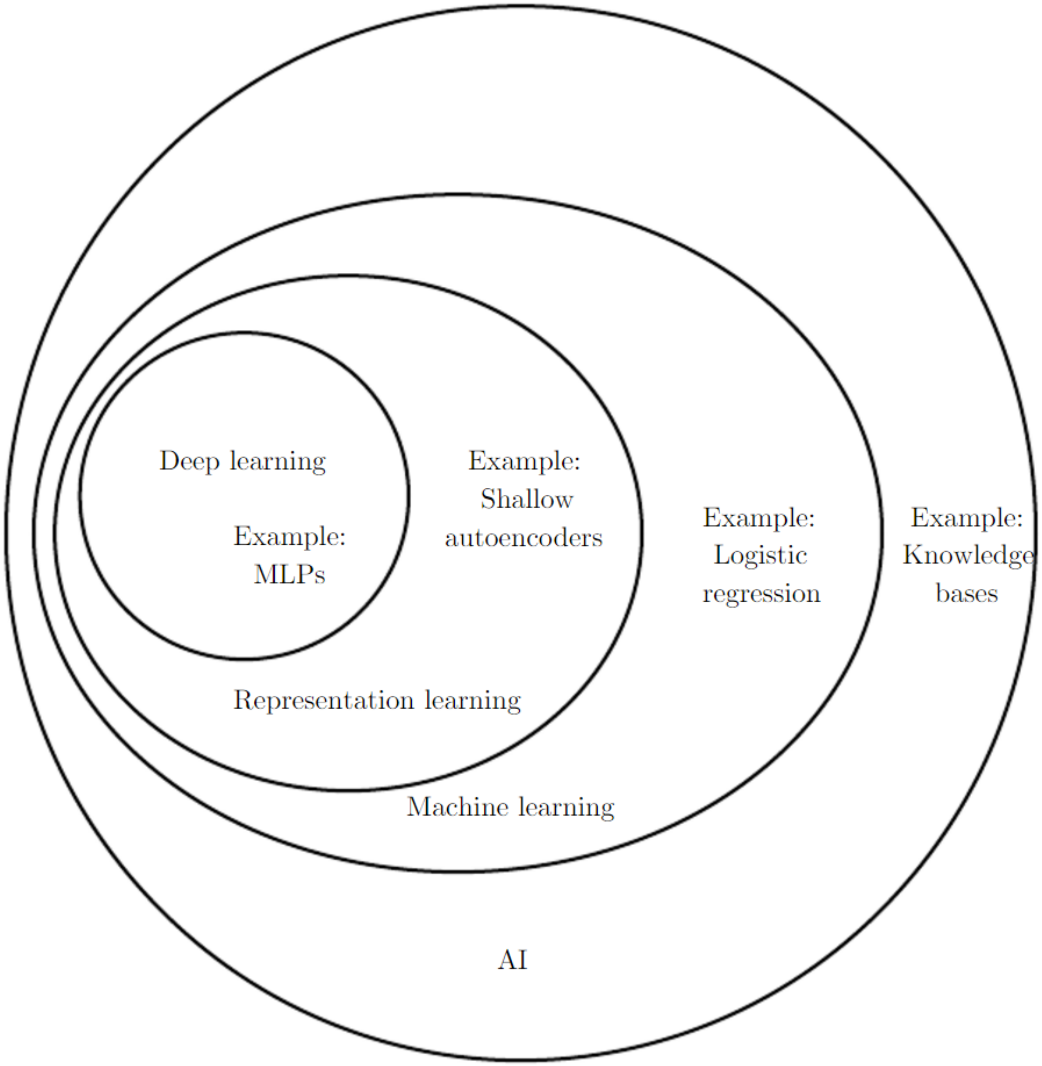


[20] Goodfellow et al. "Deep learning." (2017).

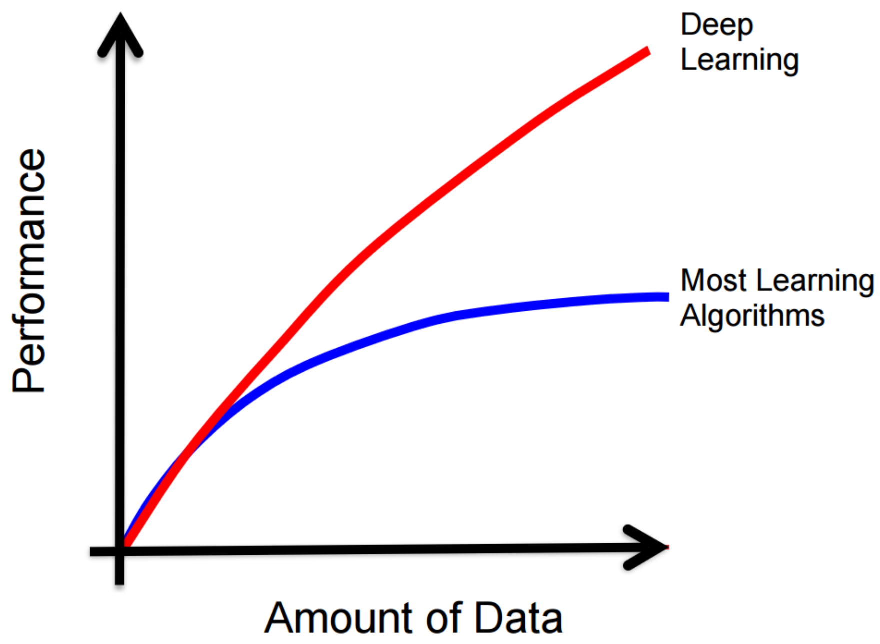
Representation Matters

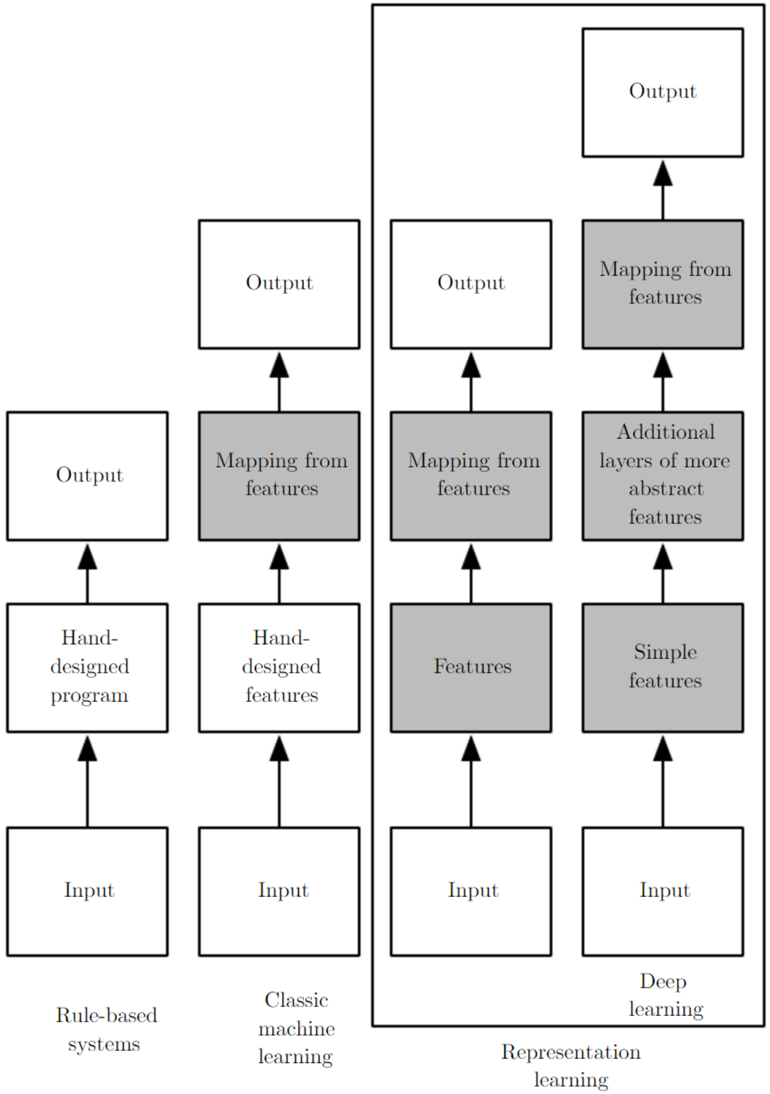


Deep Learning is **Representation Learning**

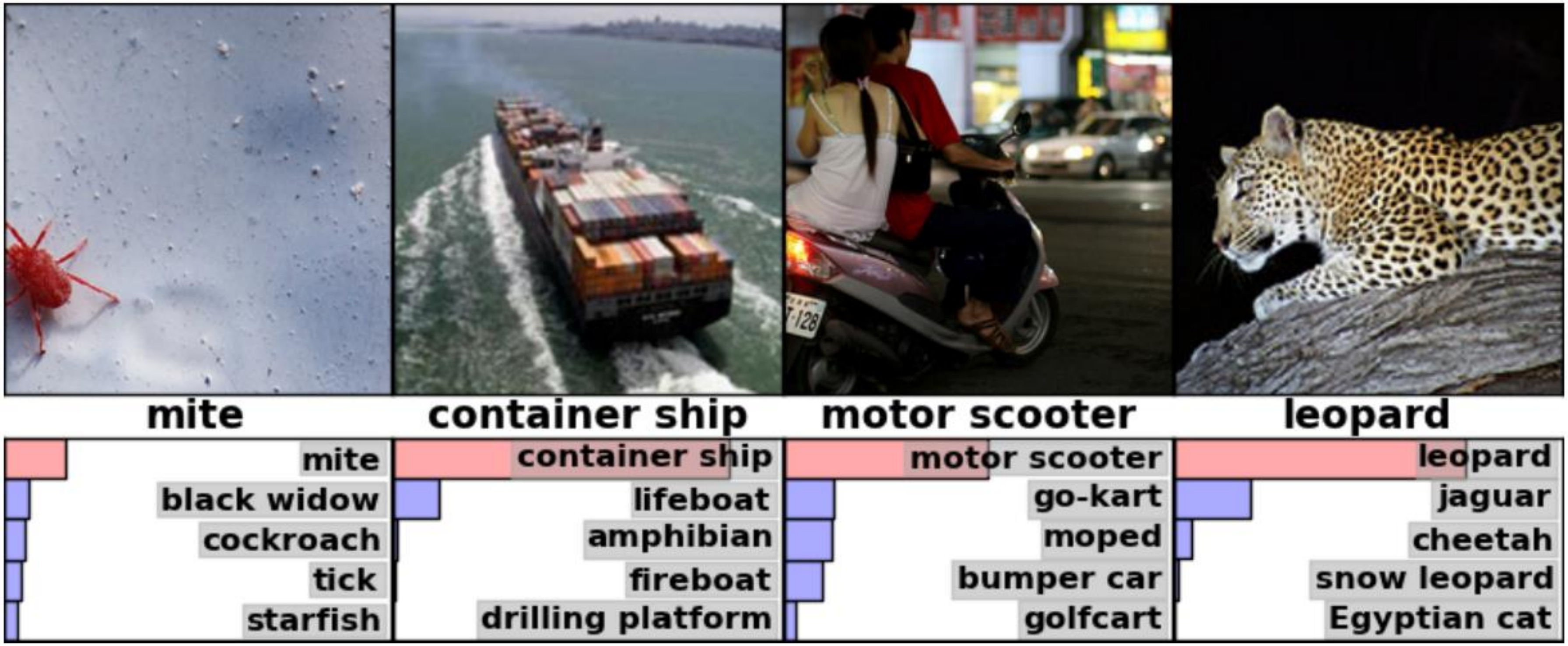


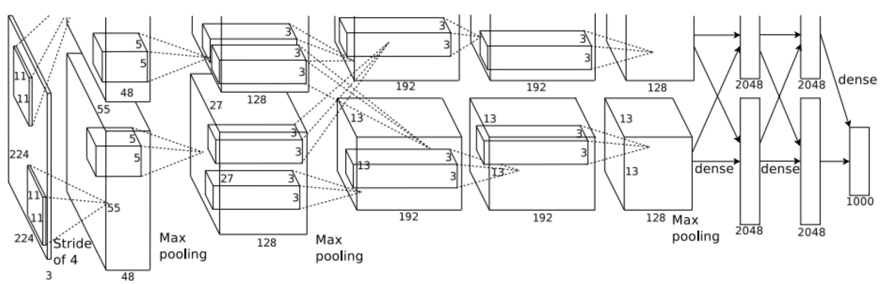
Deep Learning: **Scalable** Machine Learning





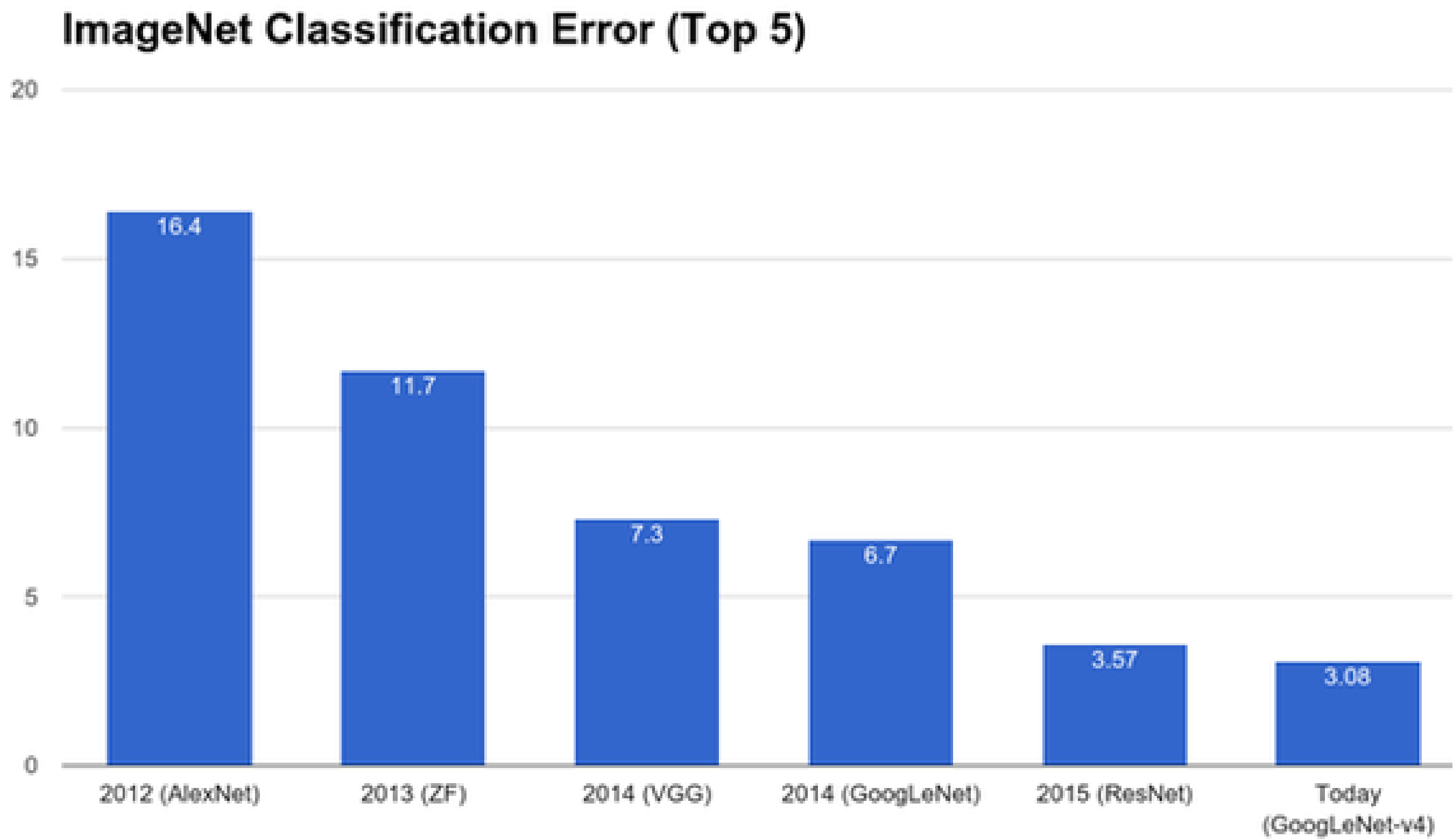
Applications: Object Classification in Images





Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. **"Imagenet classification with deep convolutional neural networks."** Advances in neural information processing systems. 2012.

Pause: Progress on ImageNet



Computer Vision is Hard:

Illumination Variability

Computer Vision is Hard:

Pose Variability and Occlusions

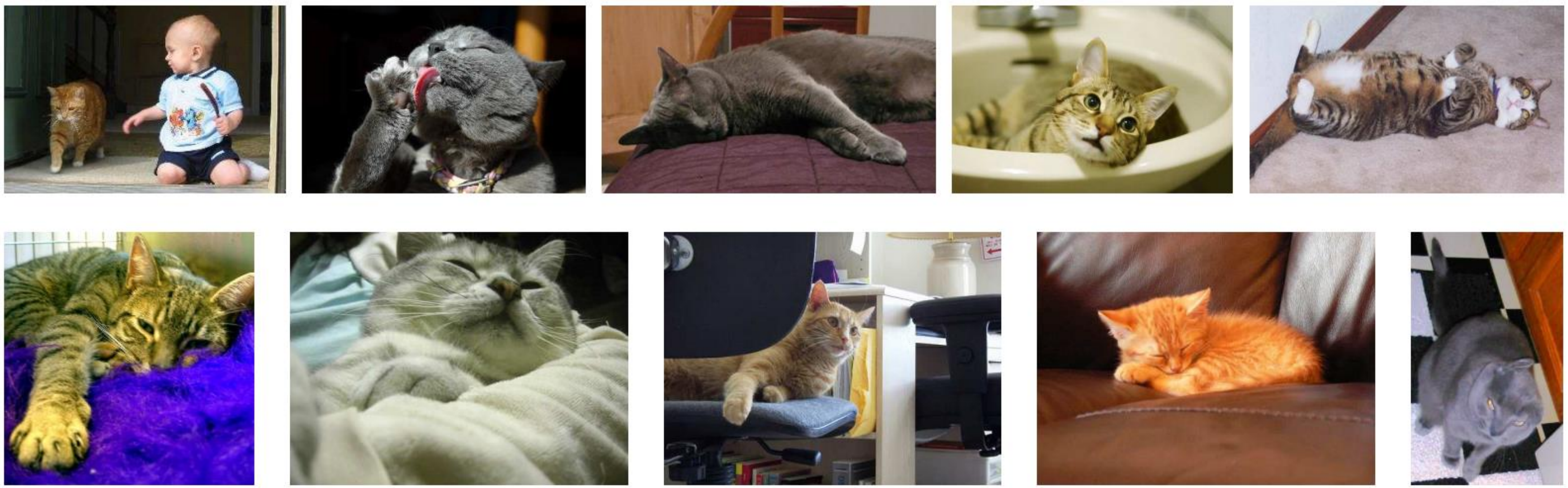
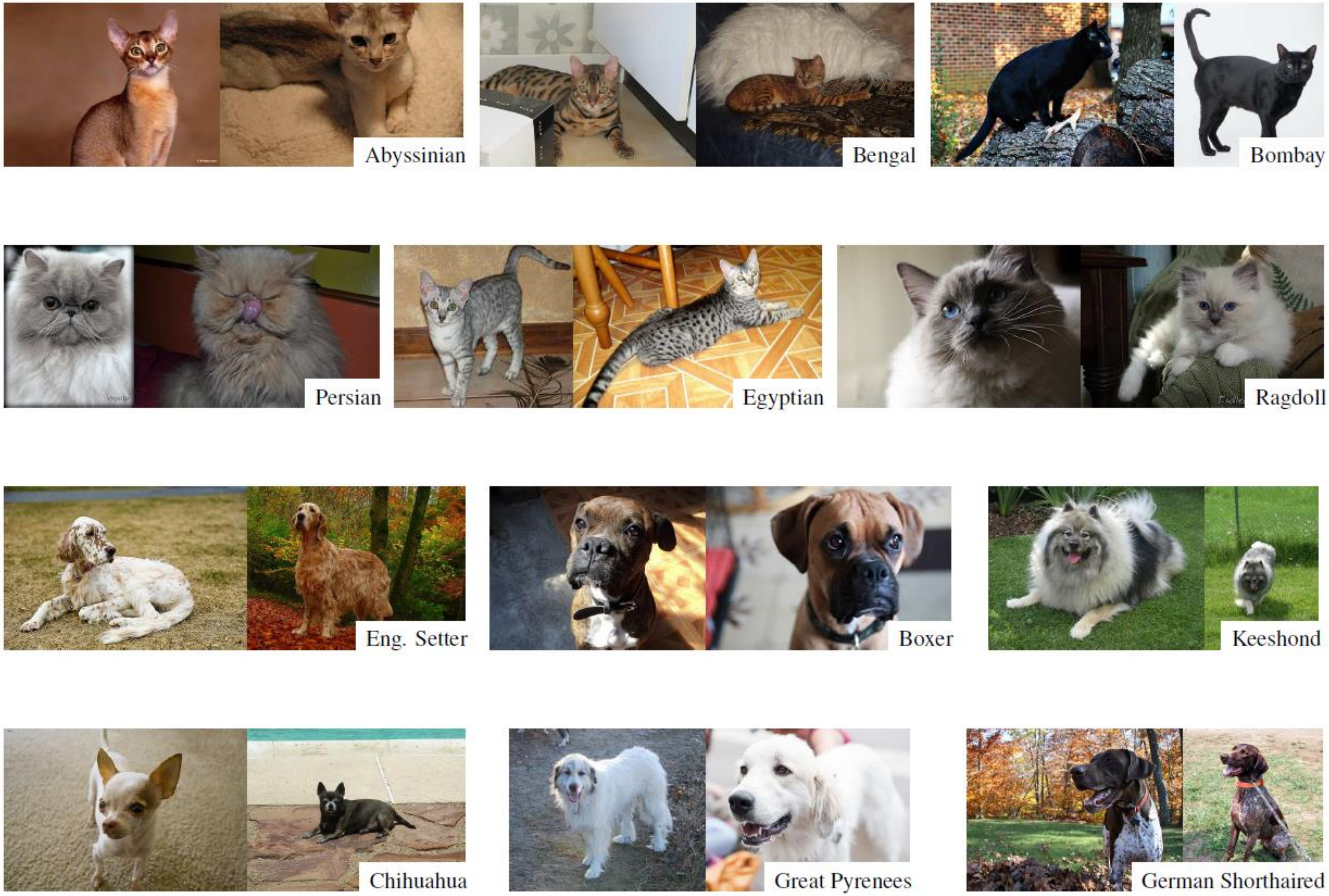


Figure 1. **The deformable and truncated cat.** Cats exhibit (al-

Parkhi et al. "The truth about cats and dogs.“ 2011.

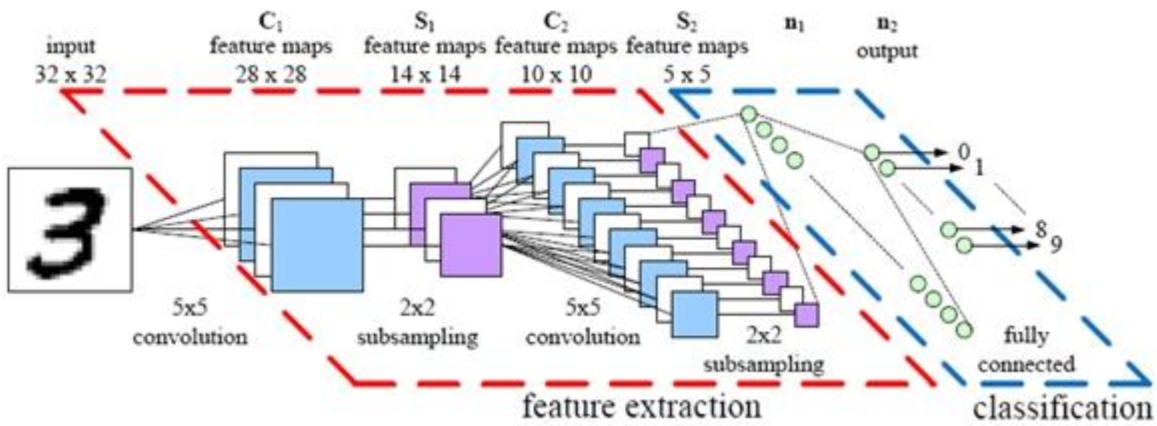
Computer Vision is Hard:

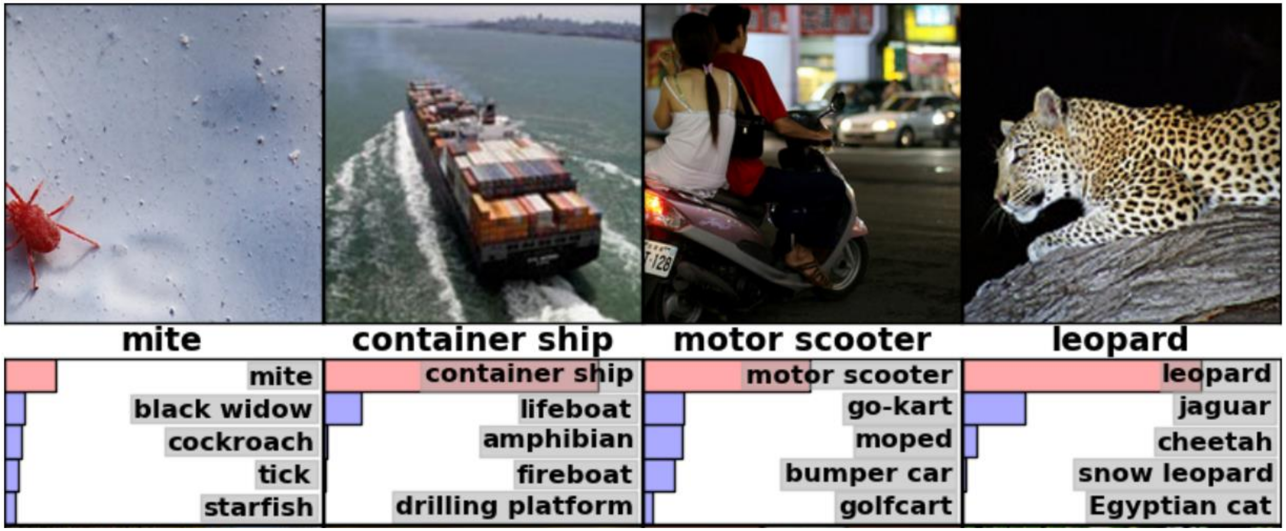
Intra-Class Variability



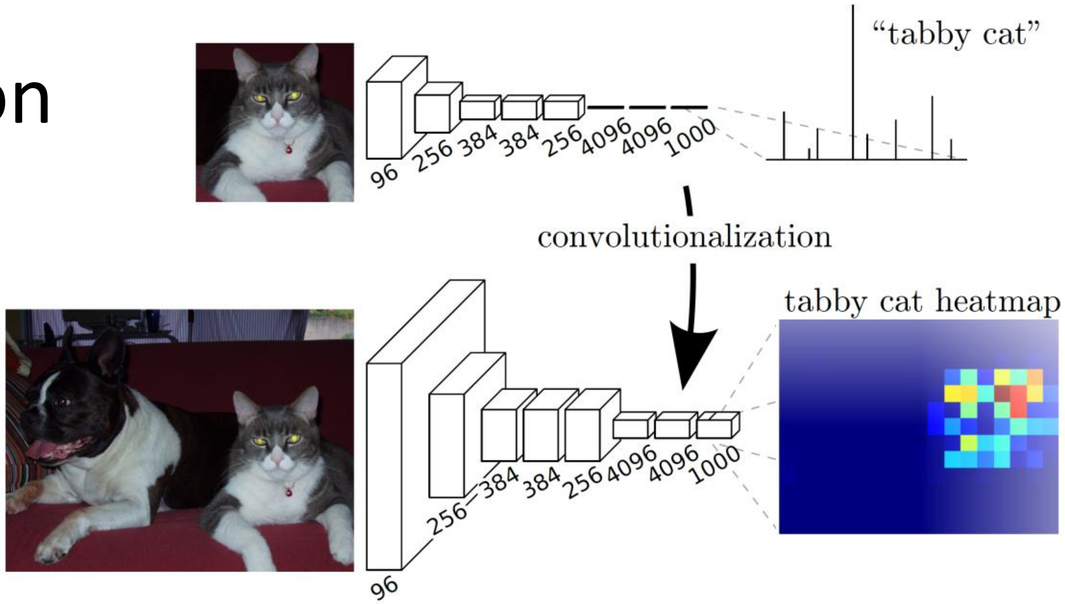
Parkhi et al. "Cats and dogs." 2012.

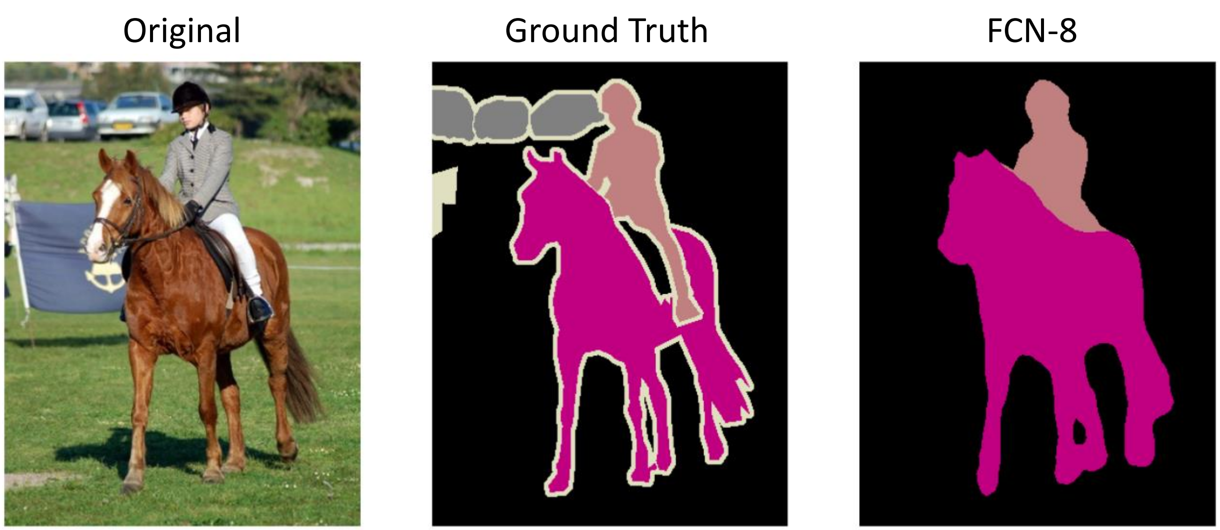
Pause: Object Recognition / Classification





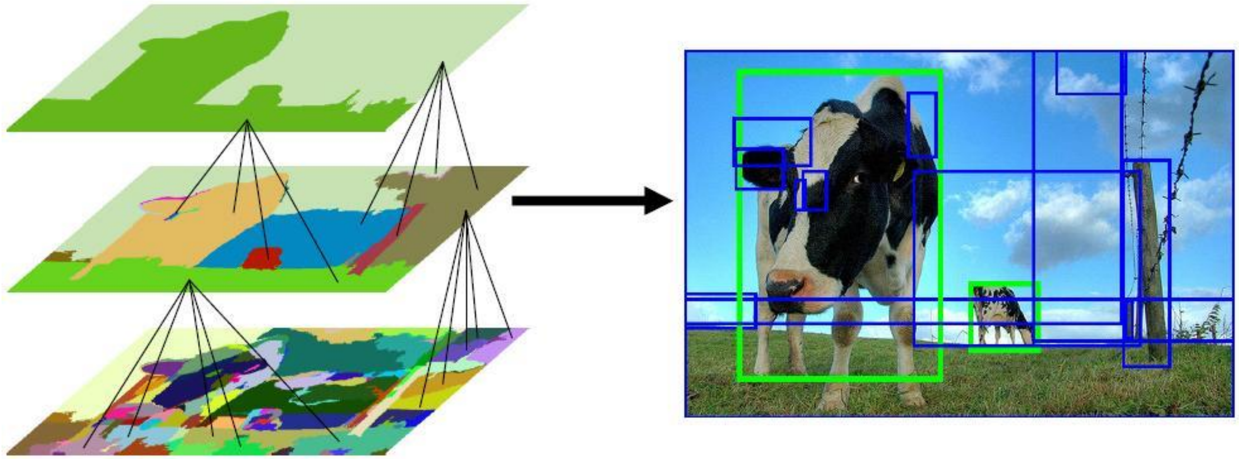
Pause: Segmentation

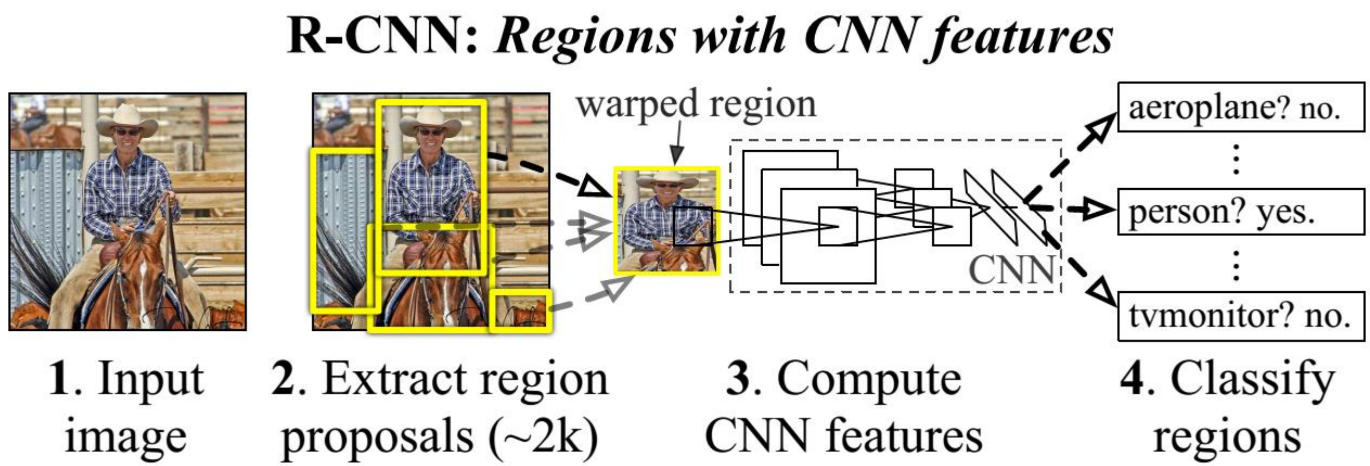




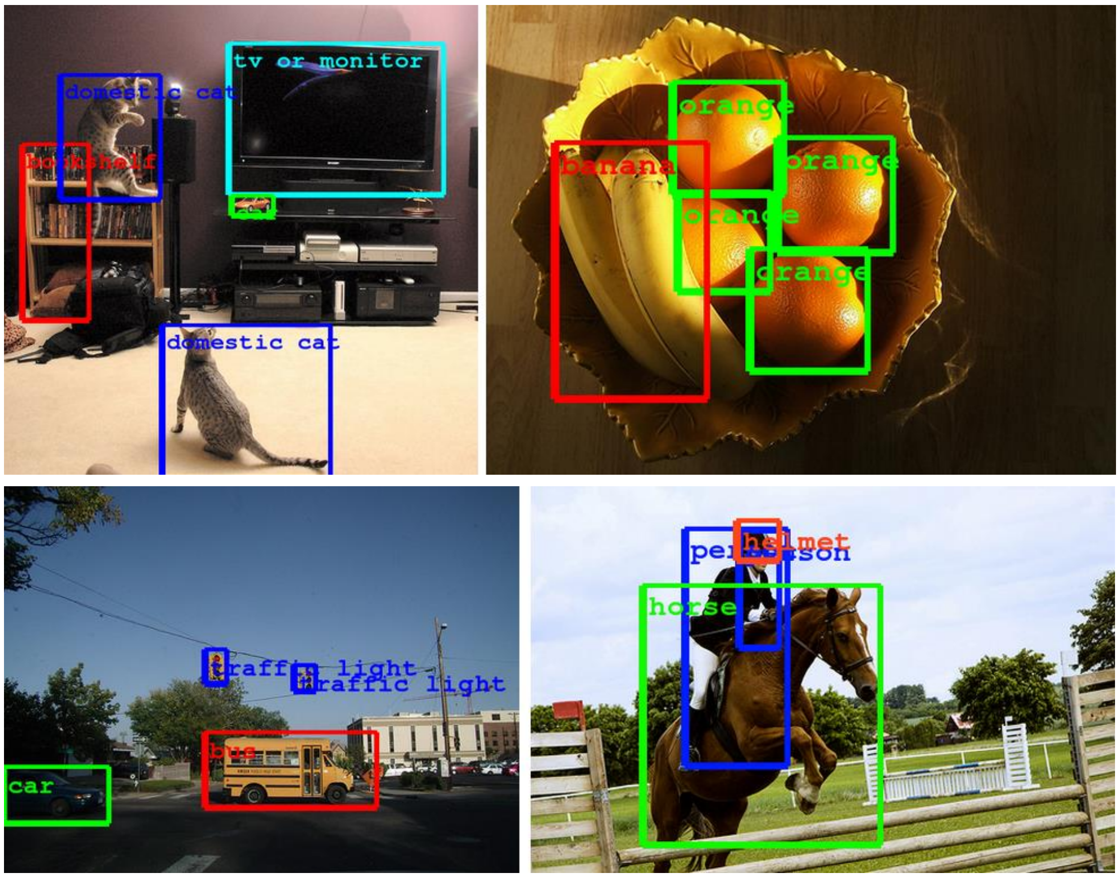
Source: Long et al. Fully Convolutional Networks for Semantic Segmentation. CVPR 2015.

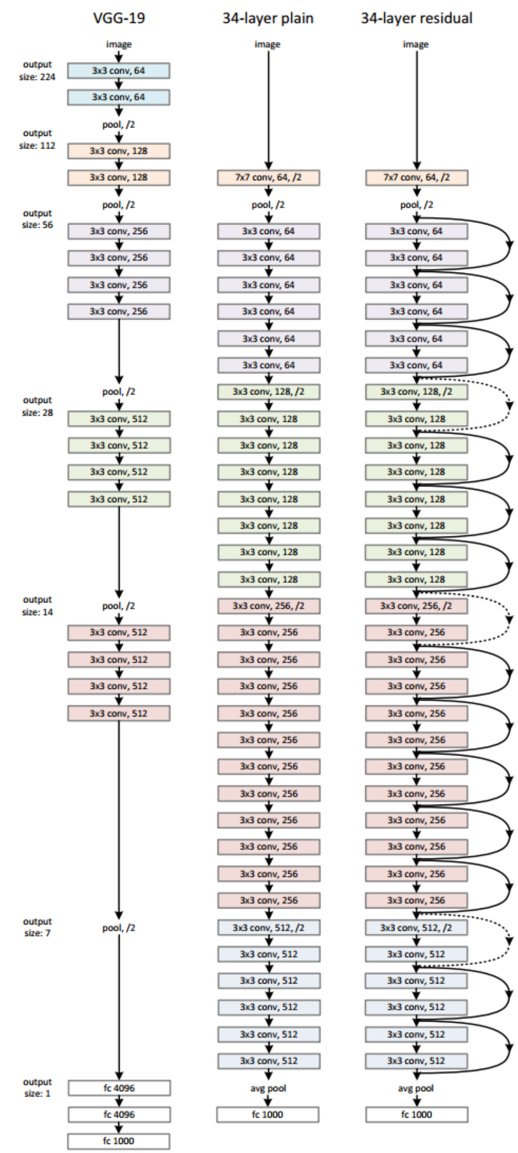
Pause: Object Detection





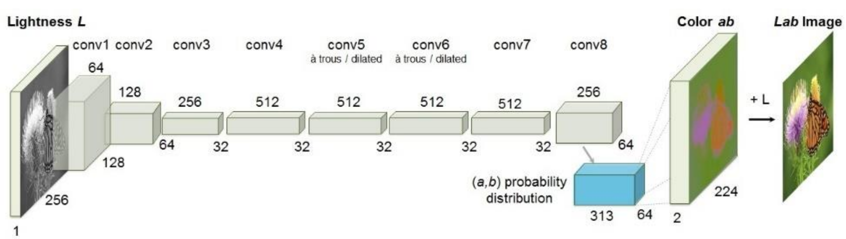
Applications: Object Detection and Localization in Images





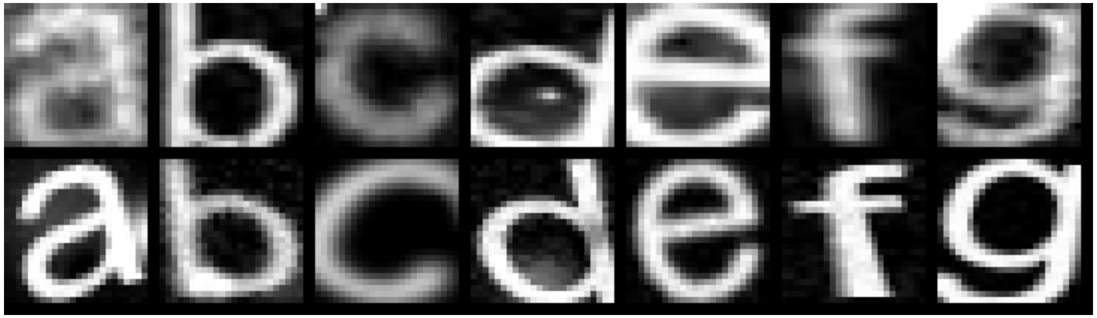
He Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Su. **"Deep residual learning for image recognition."** (2015).

Applications: Colorization of Images



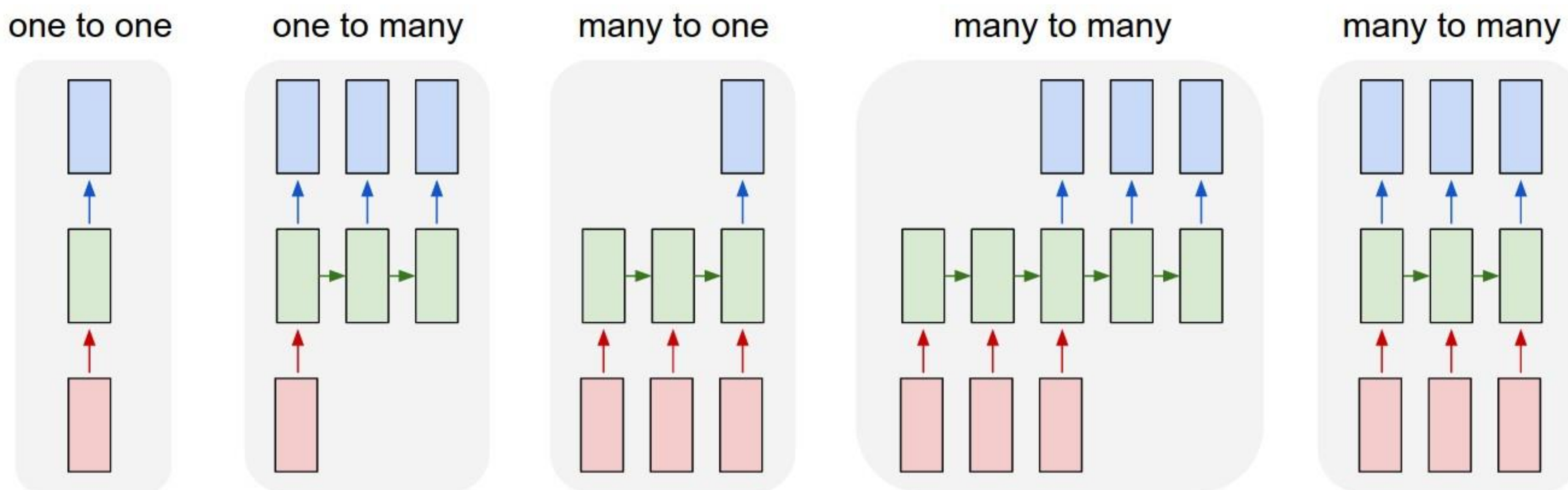
Zhang, Richard, Phillip Isola, and Alexei A. Efros. **"Colorful Image Colorization."** (2016).

Applications: Automatic Translation of Text in Images



Google Translate

(Pause…) Flavors of Neural Networks



"Vanilla" Neural Networks

Recurrent Neural Networks

Andrej Karpathy. **"The Unreasonable Effectiveness of Recurrent Neural Networks."** (2015).

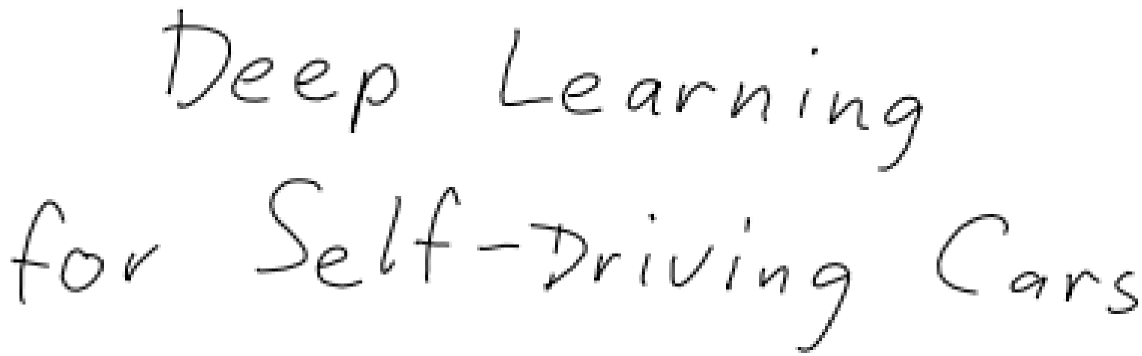
Applications: Handwriting Generation from Text

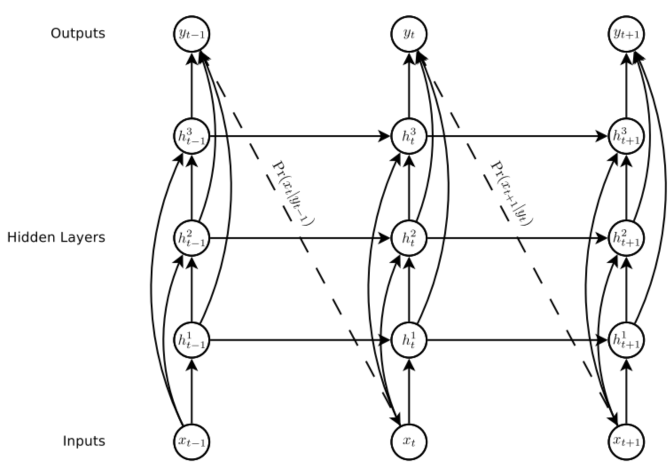
Input:

Text --- up to 100 characters, lower case letters work best

Deep Learning for Self Driving Cars

Output:

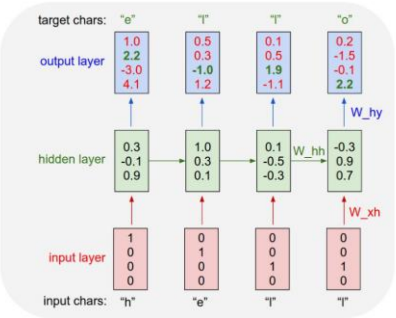




Alex Graves. **"Generating sequences with recurrent neural networks."** (2013).

Applications: Character-Level Text Generation

Naturalism and decision for the majority of Arab countries' capitalide was grounded by the Irish language by [[John Clair]], [[An Imperial Japanese Revolt]], associated with Guangzham's sovereignty. His generals were the powerful ruler of the Portugal in the [[Protestant Immineners]], which could be said to be directly in Cantonese Communication, which followed a ceremony and set inspired prison, training.



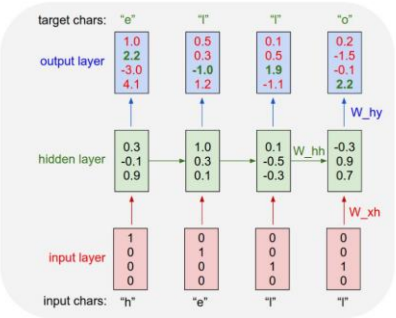
Andrej Karpathy. "The Unreasonable Effectiveness of Recurrent Neural Networks." (2015).

Code: https://github.com/karpathy/char-rnn

Applications: Character-Level Text Generation

Life Is About The Weather!
Life Is About The (Wild) Truth About Human-Rights
Life Is About The True Love Of Mr. Mom
Life Is About Where He Were Now
Life Is About Kids
Life Is About What It Takes If Being On The Spot Is Tough
Life Is About… An Eating Story
Life Is About The Truth Now

The meaning of life is literary recognition.
The meaning of life is the tradition of the ancient human reproduction

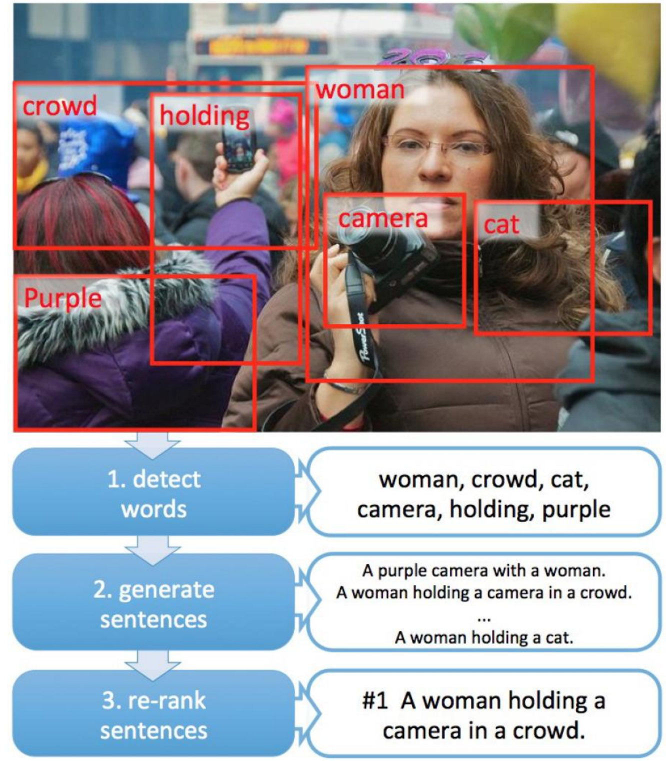


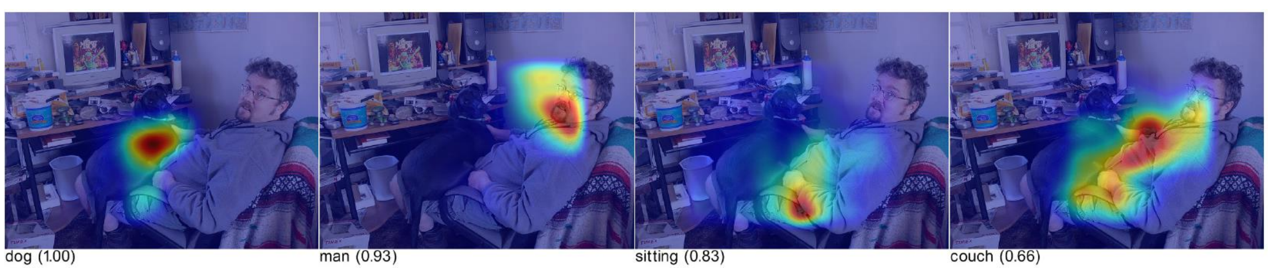
Andrej Karpathy. "The Unreasonable Effectiveness of Recurrent Neural Networks." (2015).

Code: https://github.com/karpathy/char-rnn

Applications: Image Caption Generation

a man sitting on a couch with a dog
a man sitting on a chair with a dog in his lap

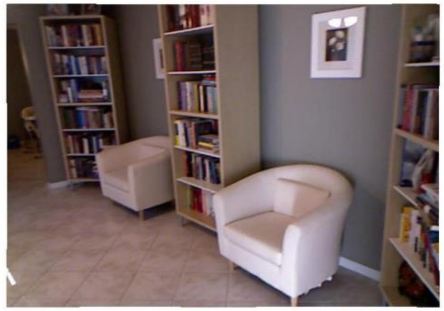




Applications: Image Question Answering

COCOQA 33827
What is the color of the cat?
Ground truth: black
IMG+BOW: black (0.55)
2-VIS+LSTM: black (0.73)
BOW: gray (0.40)

COCOQA 33827a
What is the color of the couch?
Ground truth: red
IMG+BOW: red (0.65)
2-VIS+LSTM: black (0.44)
BOW: red (0.39)



DAQUAR 1522
How many chairs are there?
Ground truth: two
IMG+BOW: four (0.24)
2-VIS+BLSTM: one (0.29)
LSTM: four (0.19)

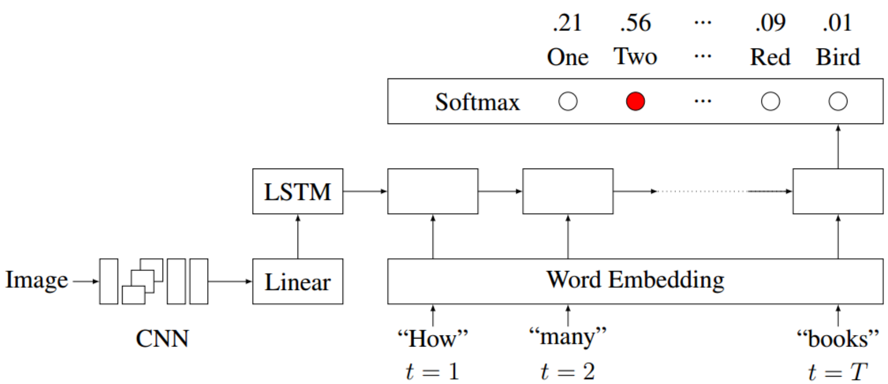
DAQUAR 1520
How many shelves are there?
Ground truth: three
IMG+BOW: three (0.25)
2-VIS+BLSTM: two (0.48)
LSTM: two (0.21)

COCOQA 14855
Where are the ripe bananas sitting?
Ground truth: basket
IMG+BOW: basket (0.97)
2-VIS+BLSTM: basket (0.58)
BOW: bowl (0.48)

COCOQA 14855a
What are in the basket?
Ground truth: bananas
IMG+BOW: bananas (0.98)
2-VIS+BLSTM: bananas (0.68)
BOW: bananas (0.14)

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

DAQUAR 585a
Where is the pillow found?
Ground truth: chair
IMG+BOW: bed (0.13)
2-VIS+BLSTM: chair (0.17)
LSTM: cabinet (0.79)



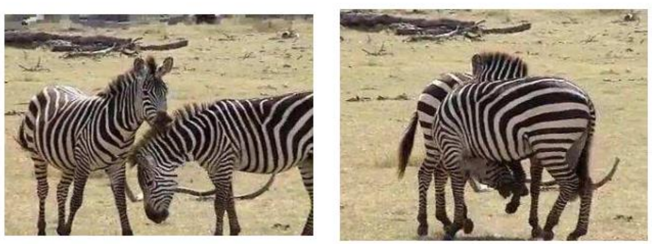
Ren et al. "Exploring models and data for image question answering." 2015.

Code: https://github.com/renmengye/imageqa-public

Applications: Video Description Generation

Correct descriptions.

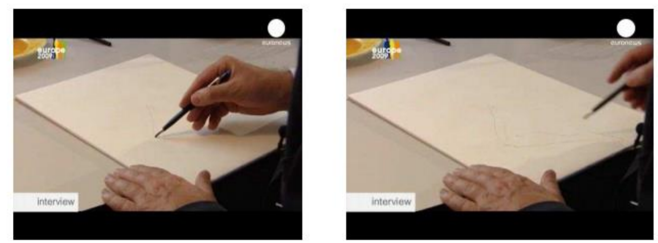
S2VT: A man is doing stunts on his bike.



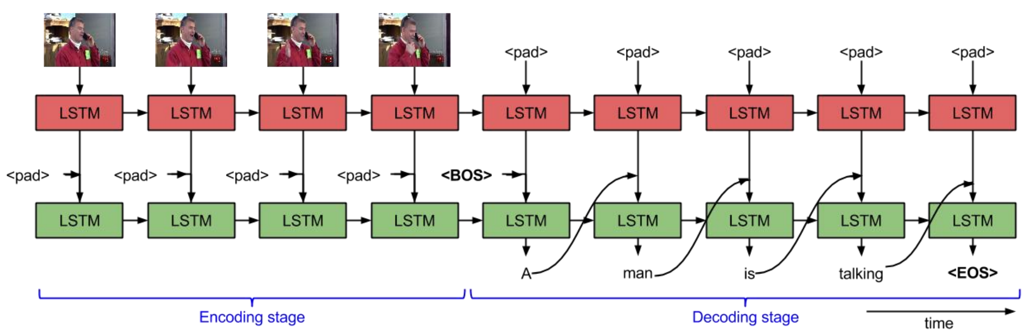
S2VT: A herd of zebras are walking in a field.

Relevant but incorrect descriptions.

S2VT: A small bus is running into a building.



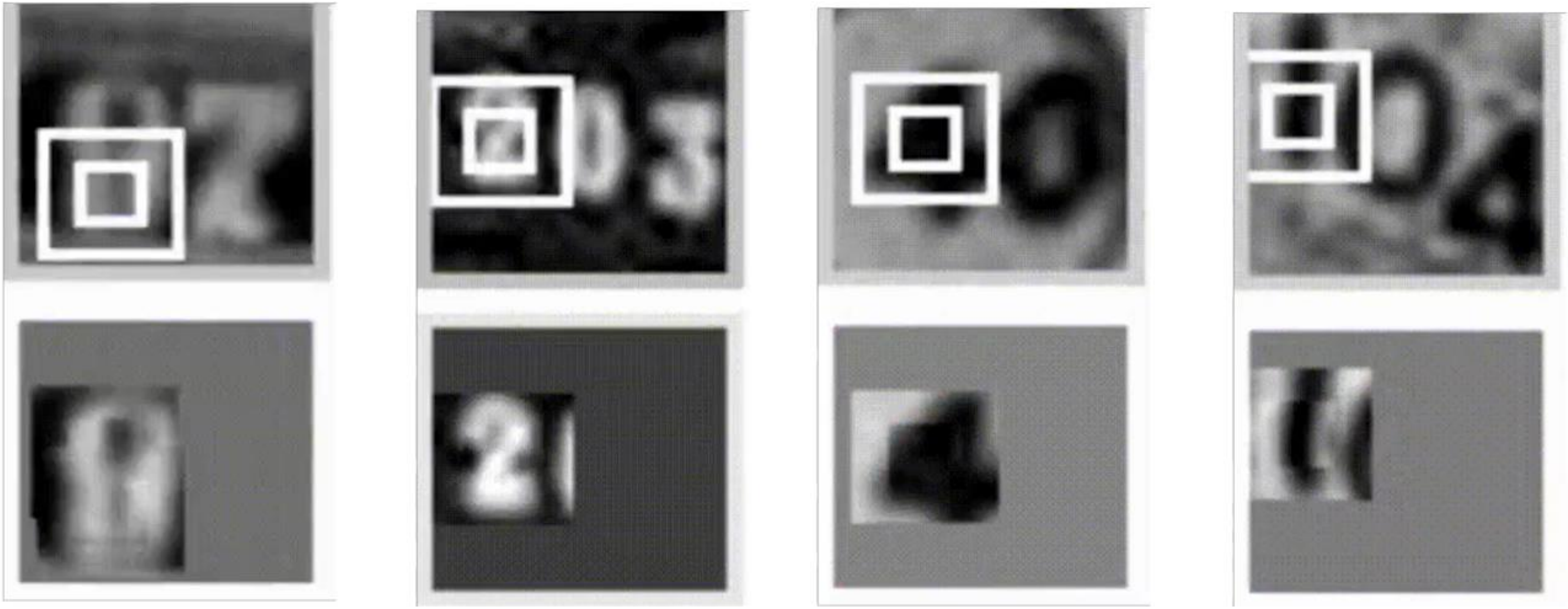
S2VT: A man is cutting a piece of a pair of a paper.

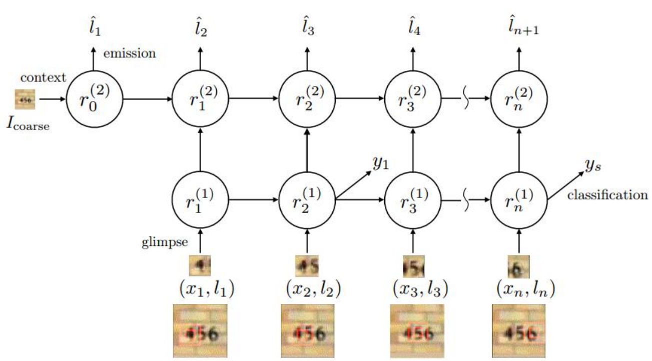


Venugopalan et al.
"Sequence to sequence-video to text." 2015.

Code: https://vsubhashini.github.io/s2vt.html

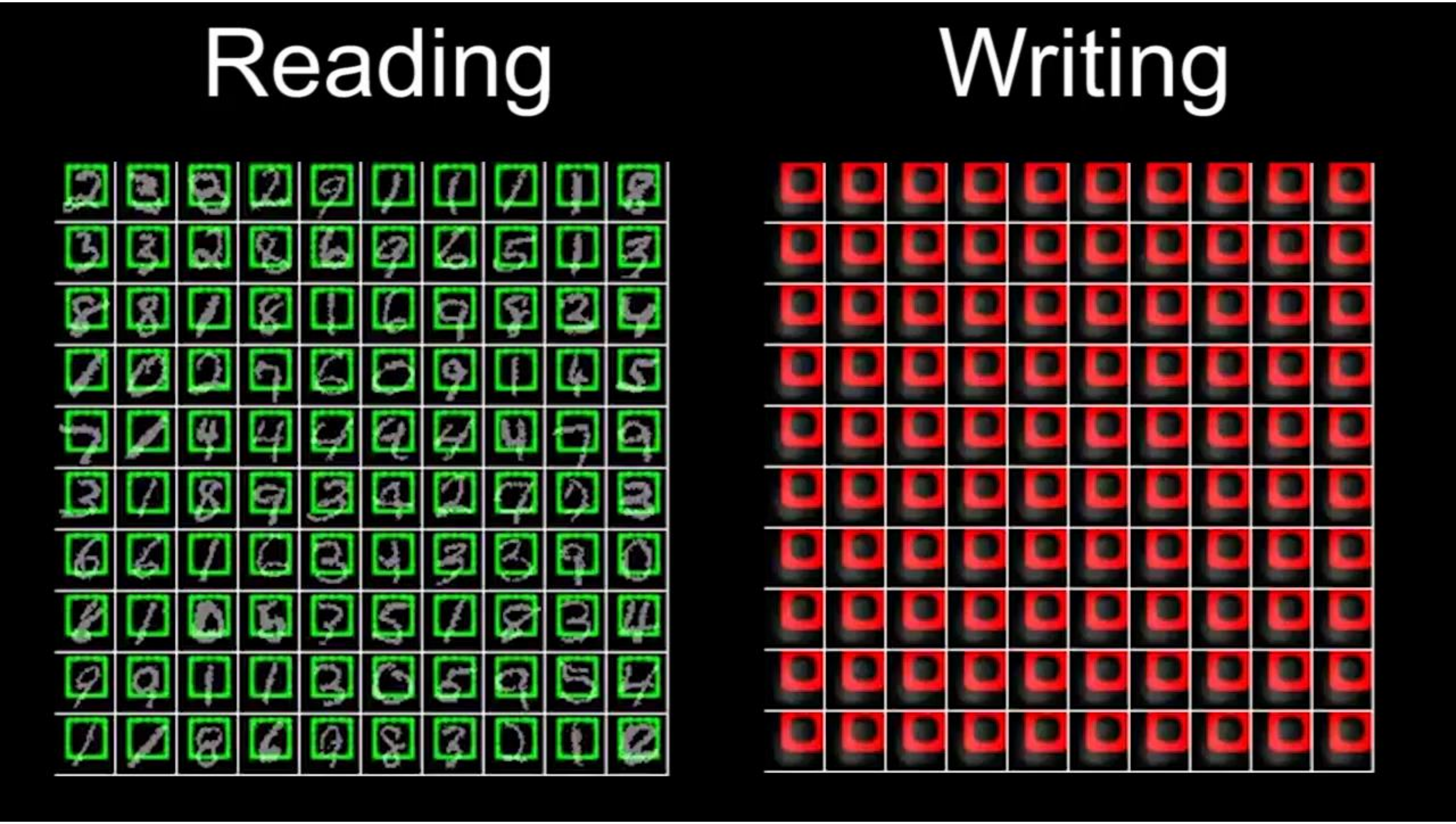
Applications: Modeling Attention Steering





Jimmy Ba, Volodymyr Mnih, and Koray Kavukcuoglu. **"Multiple object recognition with visual attention."** (2014).

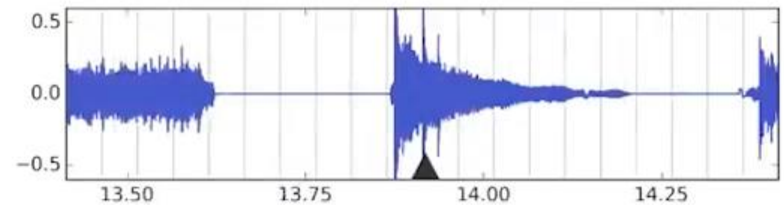
Applications: Drawing with Selective Attention



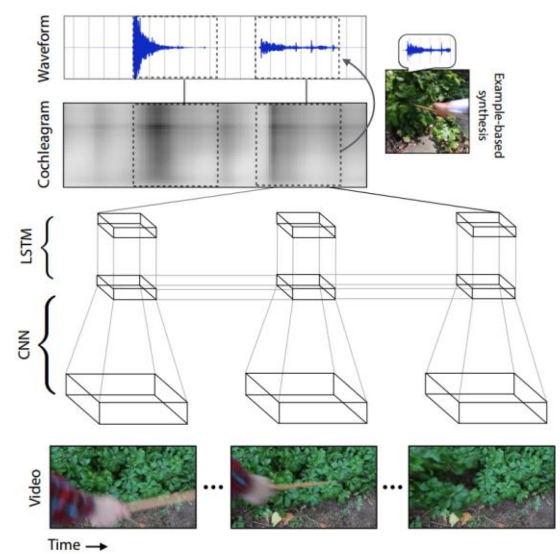
Gregor et al. "DRAW: A recurrent neural network for image generation." (2015). Code: https://github.com/ericjang/draw

Applications: Adding Audio to Silent Film

Silent video



Predicted soundtrack



Owens, Andrew, Phillip Isola, Josh McDermott, Antonio Torralba, Edward H. Adelson, and William T. Freeman. **"Visually Indicated Sounds."** (2015).

Moravec’s Paradox: The “Easy” Problems are Hard

Soccer is harder than **Chess**

Moravec's Paradox: The "Easy" Problems are Hard

Question: Why? **Answer:** Data

Visual perception: 540 millions years of data

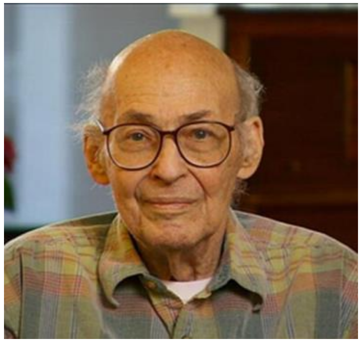
Bipedal movement: 230+ million years of data

Abstract thought: 100 thousand years of data

"Encoded in the large, highly evolved sensory and motor portions of the human brain is a **billion years of experience** about the nature of the world and how to survive in it.... Abstract thought, though, is a new trick, perhaps less than **100 thousand years** old. We have not yet mastered it. It is not all that intrinsically difficult; it just seems so when we do it."
- *Hans Moravec, Mind Children (1988)*

Hans Moravec (CMU)

Rodney Brooks (MIT)



Marvin Minsky (MIT)

Walking is Hard. How Hard is Driving?

Human performance: 1 fatality per 100,000,000 miles

Error rate for AI to improve on: 0.000001%

Challenges:

- Snow
- Heavy rain
- Big open parking lots
- Parking garages
- Any pedestrian behaving irresponsibly or just unpredictably
- Reflections, dynamics blinding ones
- Merging into a high-speed stream of oncoming traffic

Google Self-Driving Car: Driver Disengagements

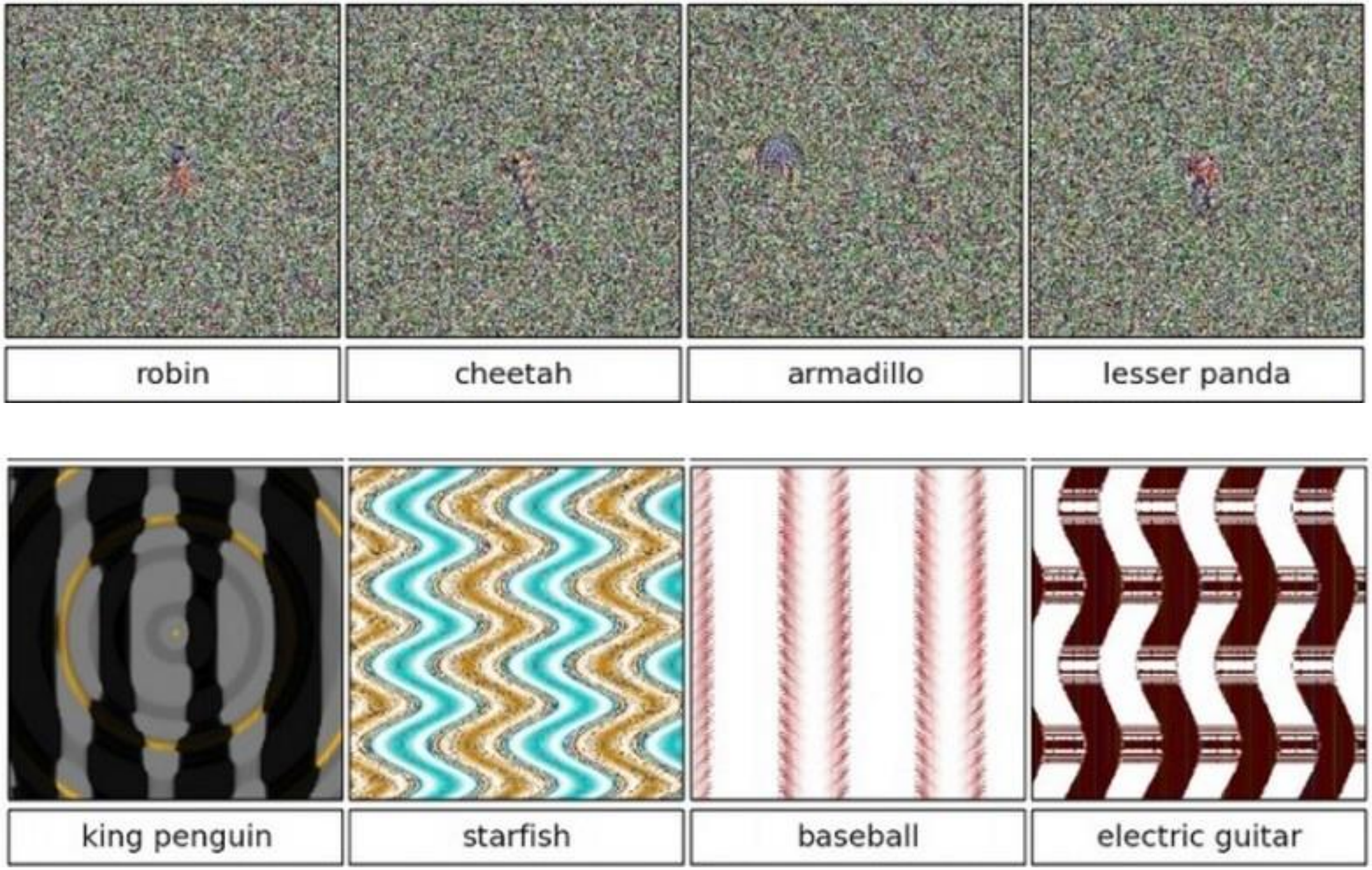
Month	Number Disengages	Autonomous miles on public roads
2014/09	2	4207.2
2014/10	19	23971.1
2014/11	21	15836.6
2014/12	43	9413.1
2015/01	53	18192.1
2015/02	14	18745.1
2015/03	30	22204.2
2015/04	51	31927.3
2015/05	13	38016.8
2015/06	11	42046.6
2015/07	29	34805.1
2015/08	7	38219.8
2015/09	16	36326.6
2015/10	16	47143.5
2015/11	16	43275.9
Total	341	424331

Google Self-Driving Car: Driver Disengagements

Cause	Sep 2014	Oct 2014	Nov 2014	Dec 2014	Jan 2015	Feb 2015	Mar 2015	Apr 2015	May 2015	Jun 2015	Jul 2015	Aug 2015	Sep 2015	Oct 2015	Nov 2015	Total
disengage for weather conditions during testing	0	0	0	0	1	5	0	6	0	0	0	0	0	0	1	**13**
disengage for a recklessly behaving road user	1	0	1	1	1	3	3	7	0	0	0	2	1	0	3	**23**
disengage for hardware discrepancy	0	1	0	0	2	1	0	1	0	5	8	1	8	8	4	**39**
disengage for unwanted maneuver of the vehicle	0	3	6	14	15	1	3	2	1	0	3	2	0	3	2	**55**
disengage for a perception discrepancy	1	2	3	18	19	2	20	30	4	4	8	0	4	3	1	**119**
disengage for incorrect behavior prediction of other traffic participants	0	2	2	0	1	0	2	0	0	0	0	0	0	1	0	**8**
disengage for a software discrepancy	0	11	9	9	14	2	1	5	8	2	9	2	3	1	4	**80**
disengage for construction zone during testing	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	**3**
disengage for emergency vehicle during testing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**
Total	**2**	**19**	**21**	**43**	**53**	**14**	**30**	**51**	**13**	**11**	**29**	**7**	**16**	**16**	**16**	**341**

References: [77]

Robustness:
>99.6% Confidence in the Wrong Answer



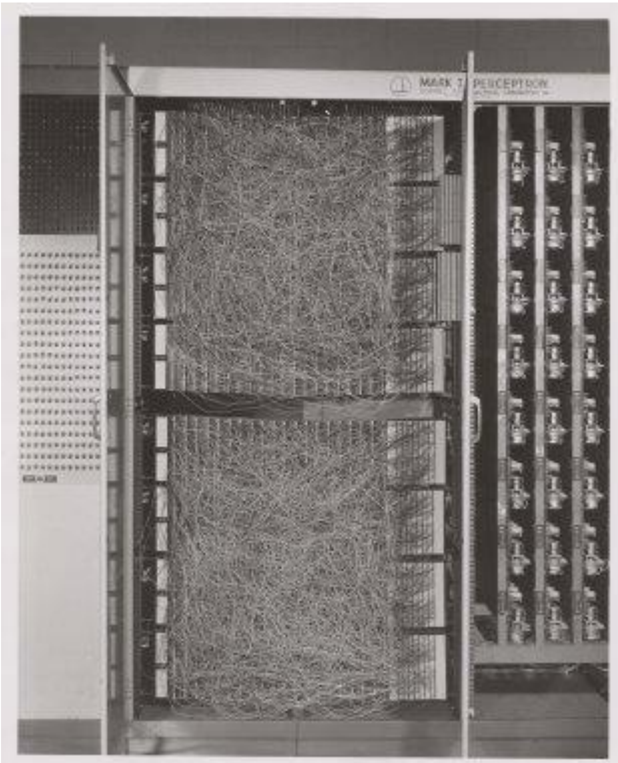
Nguyen et al. "Deep neural networks are easily fooled: High confidence predictions for unrecognizable images." 2015.

Robustness:

Fooled by a Little Distortion

Szegedy et al. "Intriguing properties of neural networks." 2013.

Mark I Perceptron



- Frank Rosenblatt
- 400 pixel image input
- Weights encoded in potentiometers
- Weight updated by electric motors

The New York Times

NEW NAVY DEVICE LEARNS BY DOING

July 8, 1958

"The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence… Dr. Frank Rosenblatt, a research psychologist at the Cornell Aeronautical Laboratory, Buffalo, said Perceptrons might be fired to the planets as mechanical space explorers"

AI Winters

Two major episodes:

- 1974-80
- 1987-93

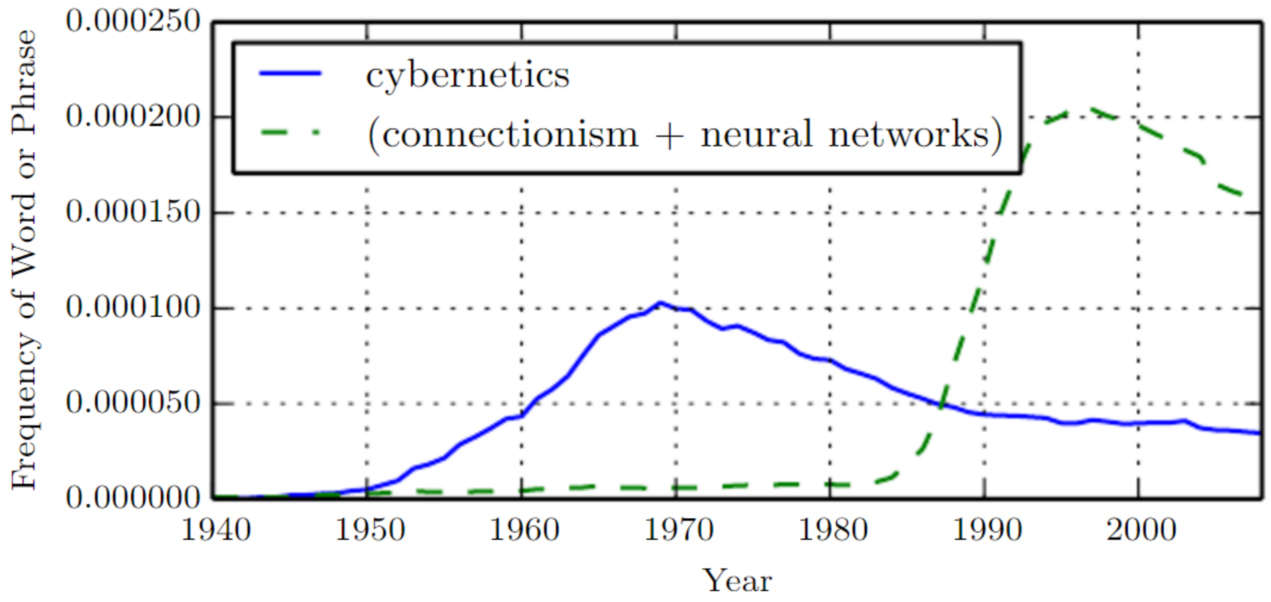
Smaller episodes:

- 1966: the failure of machine translation
- 1970: the abandonment of connectionism
- 1971-75: DARPA's frustration with the Speech Understanding Research program
- 1973: the large decrease in AI research in the UK in response to the Lighthill report.
- 1973–74: DARPA's cutbacks to academic AI research in general
- 1987: the collapse of the Lisp machine market
- 1988: the cancellation of new spending on AI by the Strategic Computing Initiative
- 1993: expert systems slowly reaching the bottom
- 1990s: the quiet disappearance of the fifth-generation computer project's original goals.

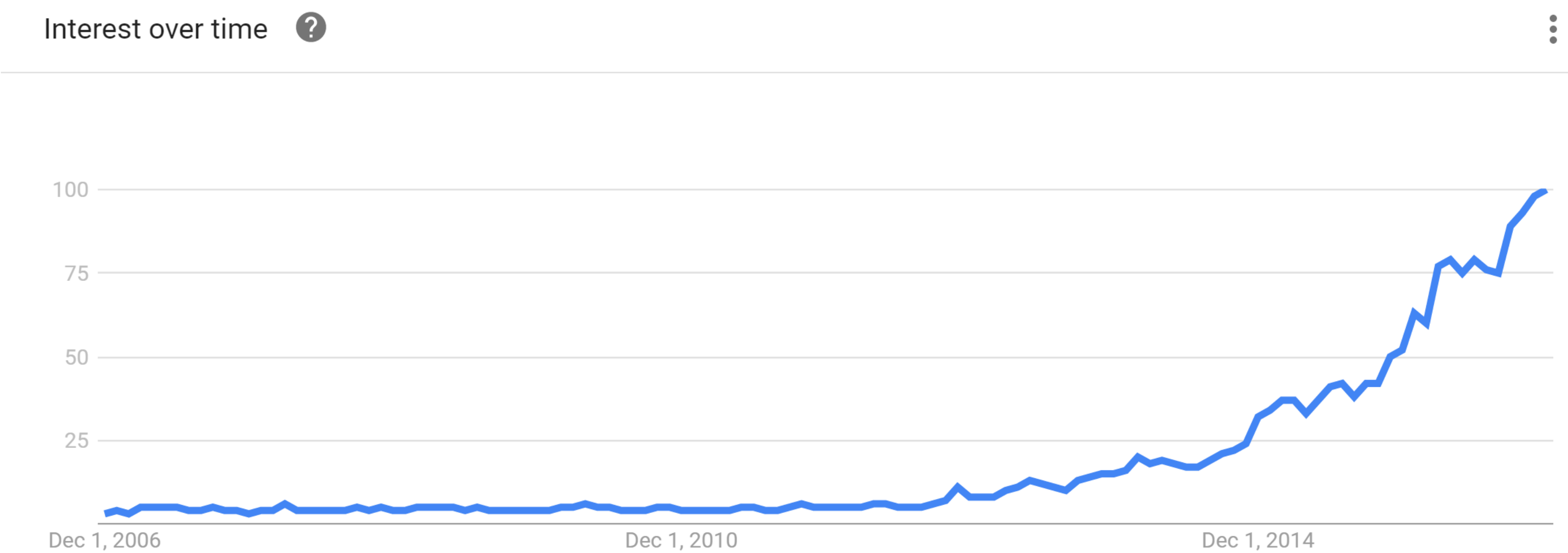
"In no part of the field have discoveries made so far produced the major impact that was then promised."

The Seasons of Deep Learning

- 1940s-1960s: Cybernetics
  - Biological learning (1943)
  - Perceptron (1958)
- 1980s-1990s: Connectionism
  - Backpropagation
- 2006-: Deep Learning



3rd Summer of Deep Learning



Google trends: “Deep Learning”

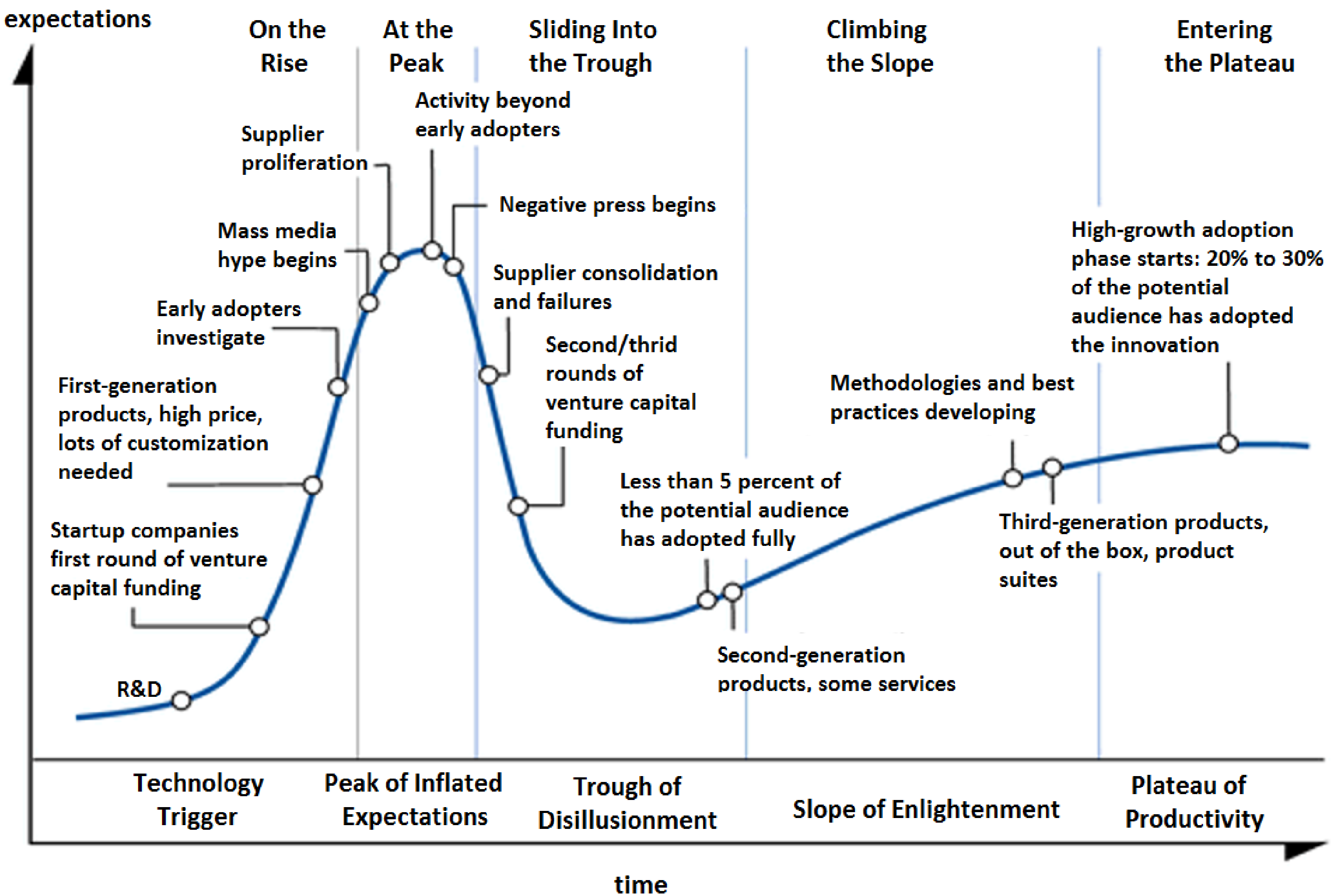
Proceed with Caution: What's Next for Deep Learning?

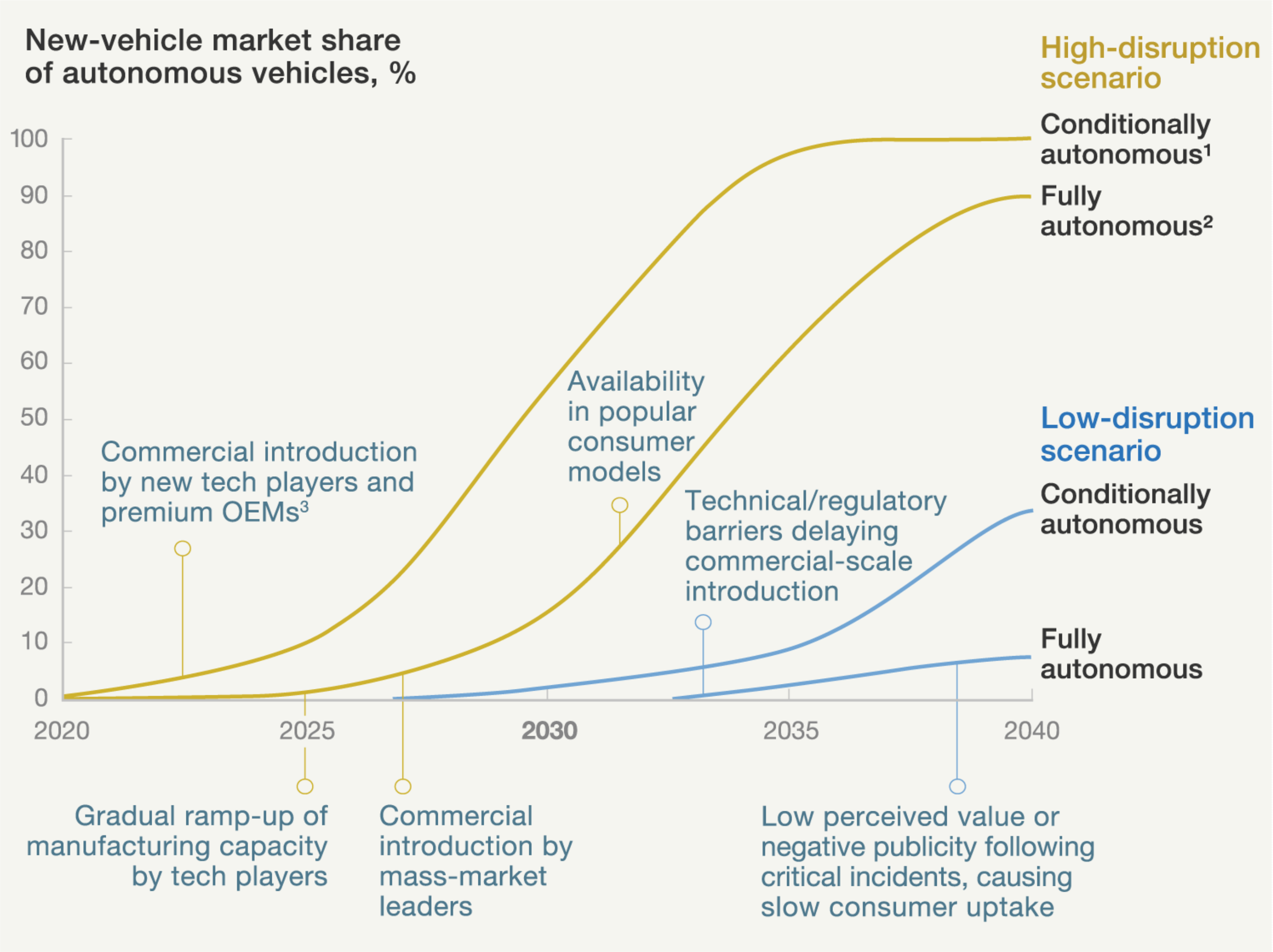
(5 year vision)

- Ilya Sutskever, Research Director of OpenAI:
  Deeper models, models that need fewer examples for training.
- Christian Szegedy, Senior Research Scientist at Google:
  Become so efficient that they will be able to **run on cheap mobile devices**.
- Pieter Abbeel, Associate Professor in Computer Science at UC Berkeley:
  Significant advances in deep unsupervised learning and deep **reinforcement learning**.
- Ian Goodfellow, Senior Research Scientist at Google:
  Neural networks that **can summarize what happens in a video clip**, and will be able to generate short videos. Neural networks that model the behavior of genes, drugs, and proteins and then used to design new medicines.
- Koray Kavukcuoglu & Alex Graves, Research Scientists at Google DeepMind:
  An increase in **multimodal learning**, and a stronger focus on learning that persists **beyond individual datasets**.
- Charlie Tang, Machine Learning group, University of Toronto:
  Deep learning algorithms ported to **commercial products**, much like how the face detector was incorporated into consumer cameras in the past 10 years.

References: [58]

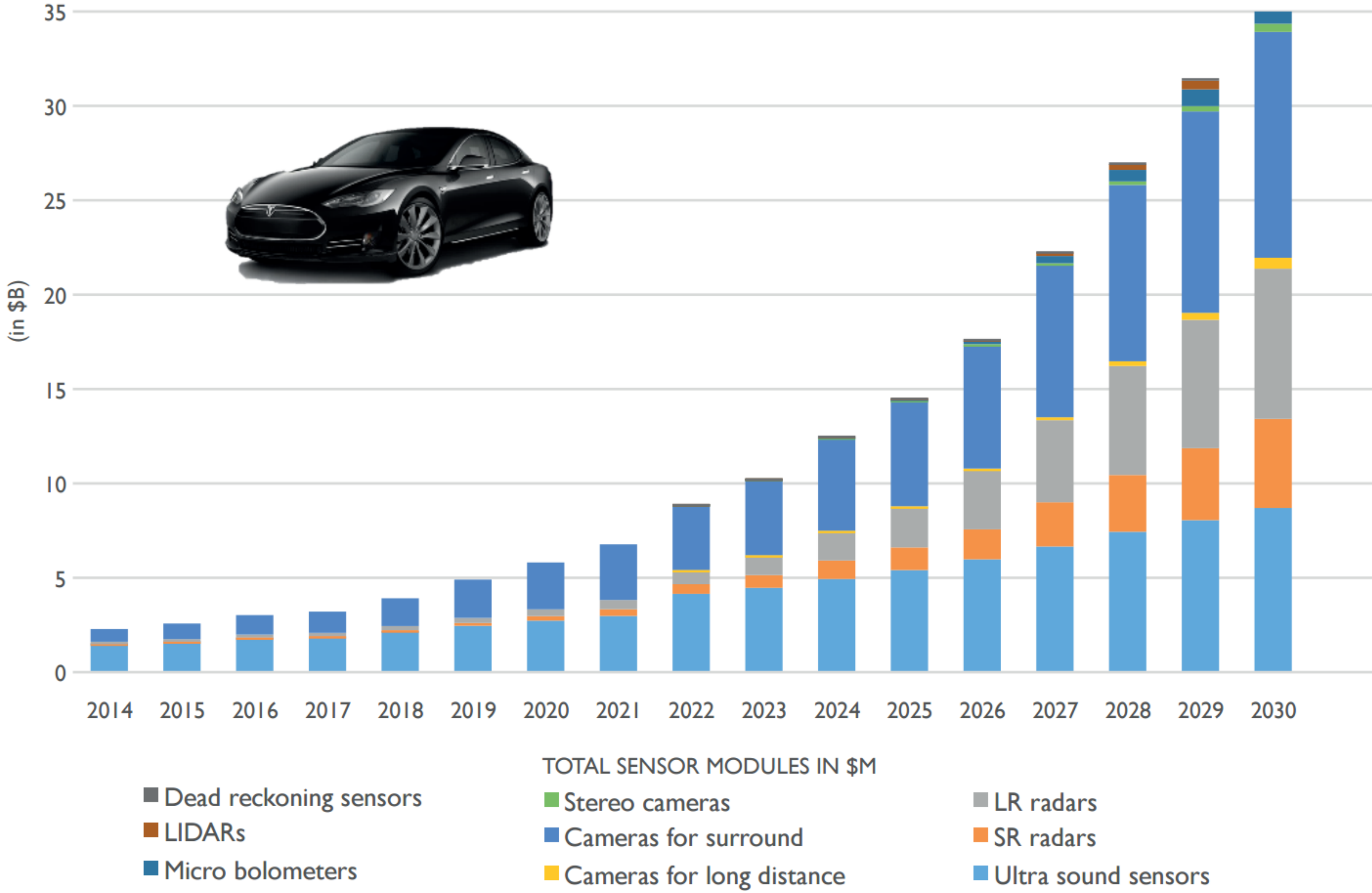
Gartner Hype Cycle





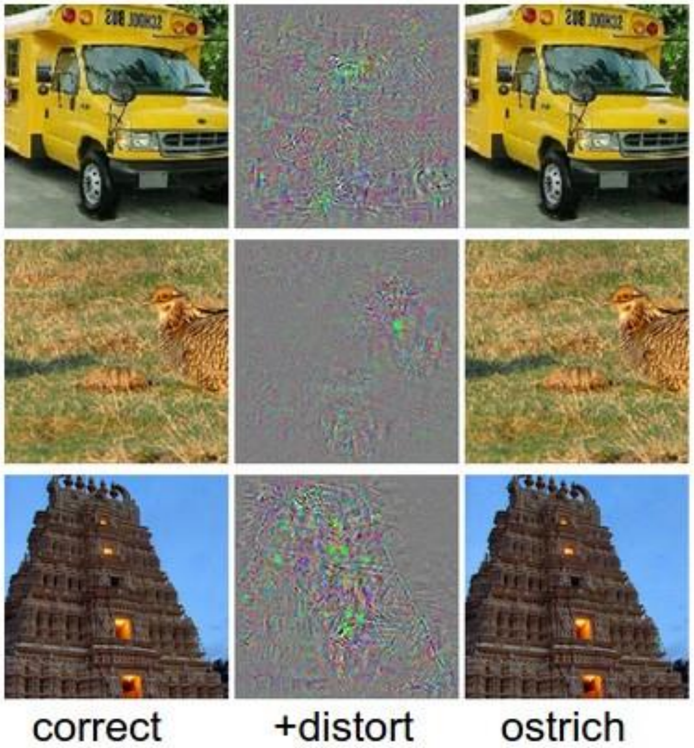
Factors in disruption scenarios	High disruption	Low disruption
Regulatory challenges	Fast	Gradual
Safe, reliable technical solutions	Comprehensive	Incomplete
Consumer acceptance, willingness to pay	Enthusiastic	Limited

Sensor modules market value for autonomous cars from 2015 to 2030 (in $B)

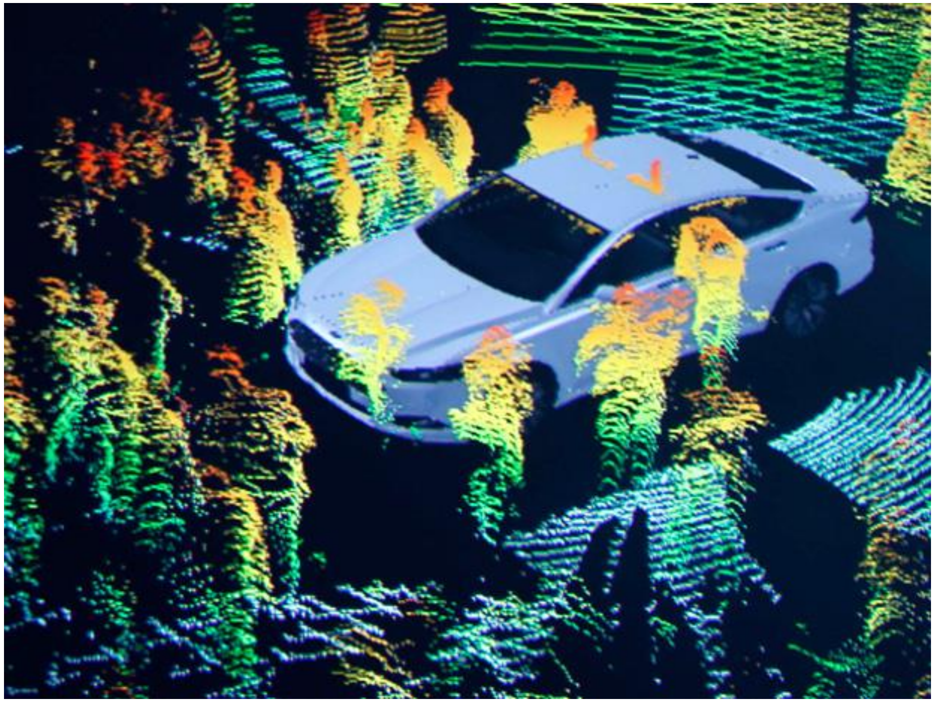


Attention to (AI) Drivers: Proceed with Caution

Camera Spoofing



LIDAR Spoofing



TensorFlow

- Interface: Python, (C++)
- Automatic Differentiation
- Multi GPU, Cluster Support
- Currently most popular

Google

Keras

- On top of Tensorflow (and Theano)
- Interface: Python
- Goal: provide a simplified interface

- **Also:** TF Learn, TF Slim

Torch

- Used by researchers doing lower level (closer to the details) neural net work
- Interface: Lua
- Fragmented across different plugins

facebook

theano

- Interface: Python (tight NumPy integration)
- One of the earlier frameworks with GPU support
- Encourages low-level tinkering

Université de Montréal | Montreal Institute for Learning Algorithms

cuDNN

- The library that most frameworks use for doing the actual computation
- Implements primitive neural network functions in CUDA on the GPU

- Multi GPU Support (scales well)
- Interface: Python, R, Julia, Scala, Go, Javascript …

neon
framework by nervana

- Interface: Python
- Often best on benchmarks
- Nervana was working on a neural network chip
- Bought by Intel

intel®

Caffe

- Interface: C++, Python
- One of the earliest GPU supported
- Initial focus on computer vision (and CNNs)

Berkeley
Artificial Intelligence Research Laboratory

Microsoft Cognitive Toolkit (CNTK)

- Interface: Custom Language (BrainScript), Python, C++, C#
- Multi GPU Support (scales very well)
- Mostly used at MS Research

Microsoft

In the Browser

- Keras.js
  - GPU Support
  - Full sized networks
  - Can use trained Keras models

- ConvNetJS
  - Built by a Andrej Karpathy
  - Good for explaining neural network concepts
    - Fun to play around with
    - Very few requirements
  - Full CNN, RNN, Deep Q Learning

References

All references cited in this presentation are listed in the following Google Sheets file:

https://goo.gl/9Xhp2t