



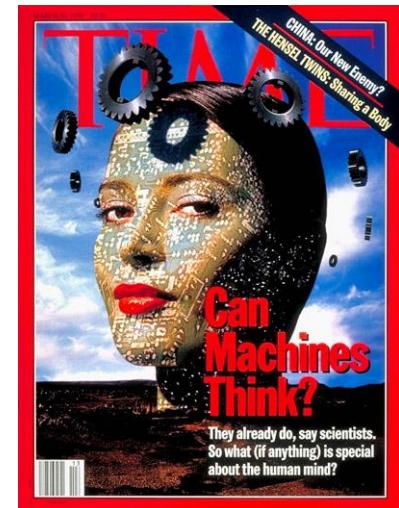
15.S14: Global Business of Artificial Intelligence (GBAIR) Machine Learning: The Promise, Limitations, and Mystery of Thinking Machines

Lex Fridman

<https://lex.mit.edu>



Artificial Intelligence Technology: Limited or Limitless?



Special Purpose:

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

Time →

Today

Future

General Purpose:

Can it achieve poorly-defined unconstrained set of goals?

Today's Lecture:

1. Overview current **approaches**
2. Highlight **limitations**
3. Discuss the **potential**
(and marvel at the mystery)

Best current answer:

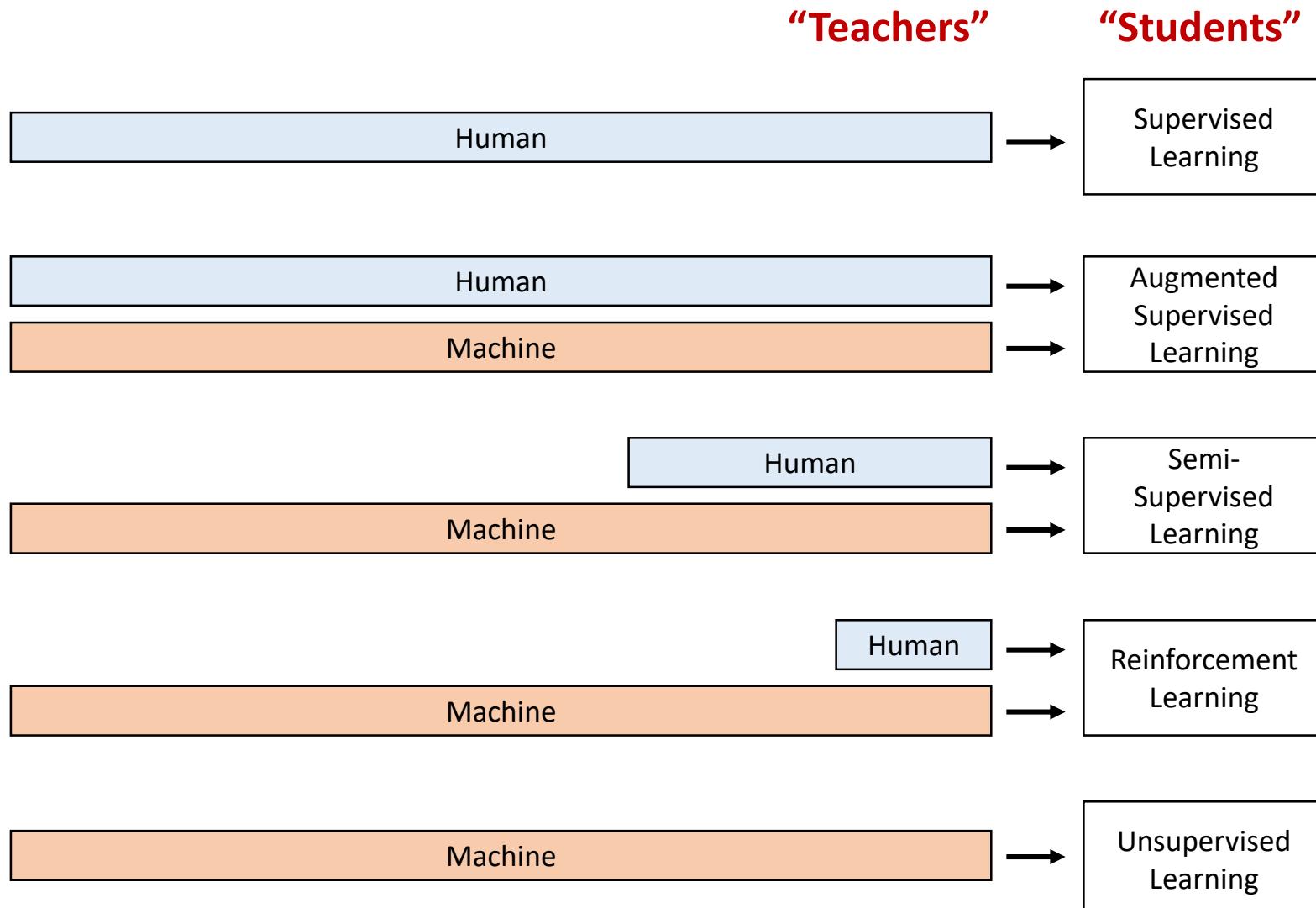
We Don't Know

Takeaways

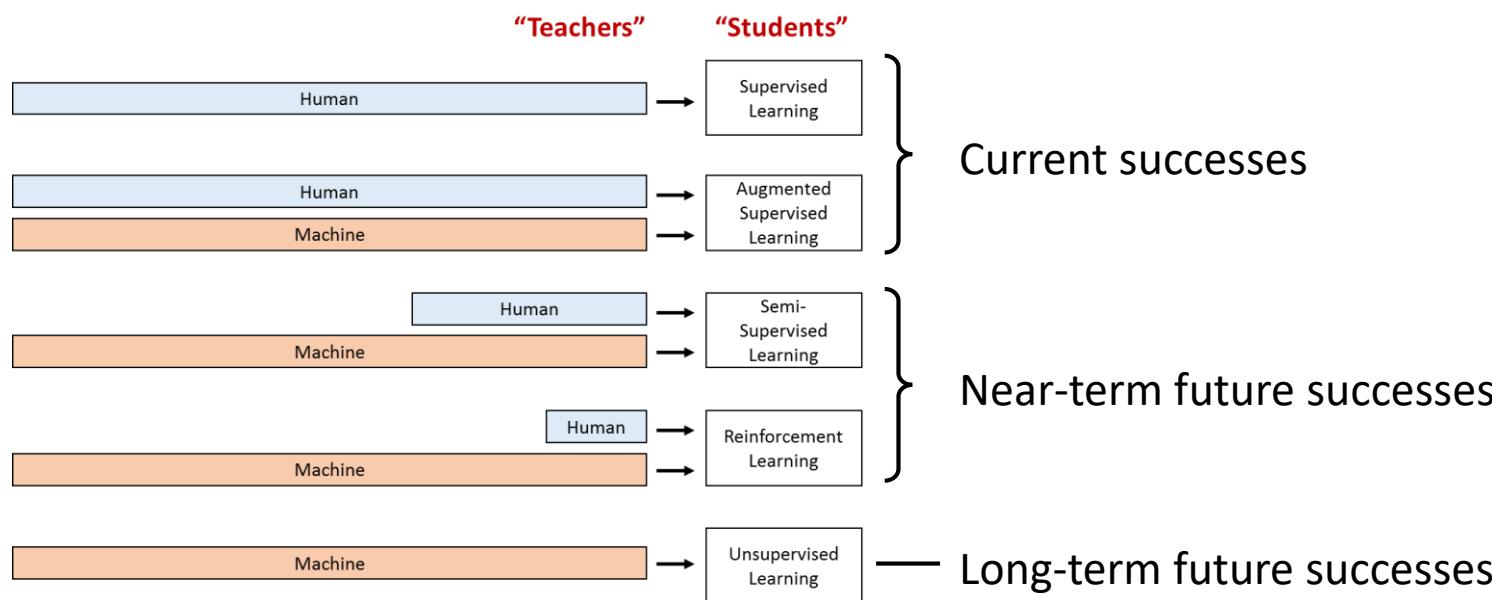
- **Limits:** Machine learning today and tomorrow.
 - Currently **limited** (data, compute, methods)
 - Potentially **limitless** (end-to-end general intelligence)
- **Data:**
 - Representation matters
(deep learning > representation-agnostic learning)
 - Human annotation is needed
(annotated data > big data)
- **Impact:**

Rule of thumb for real-world machine learning:
“If it takes one grad student one month to build a good software prototype,
you can make a product out of it. Otherwise, it’s still research.”

Machine Learning from Human and Machine



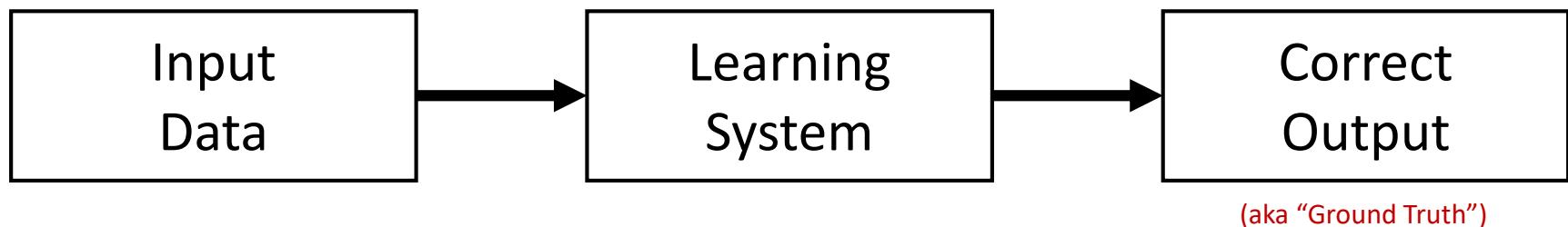
Machine Learning from Human and Machine



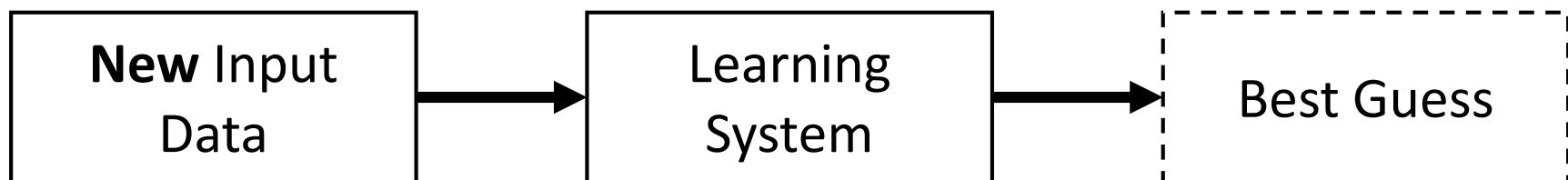
Better Question: Machine Learning: Limited or Limitless?

(PS: for now Machine Learning = Supervised Learning)

Training Stage:

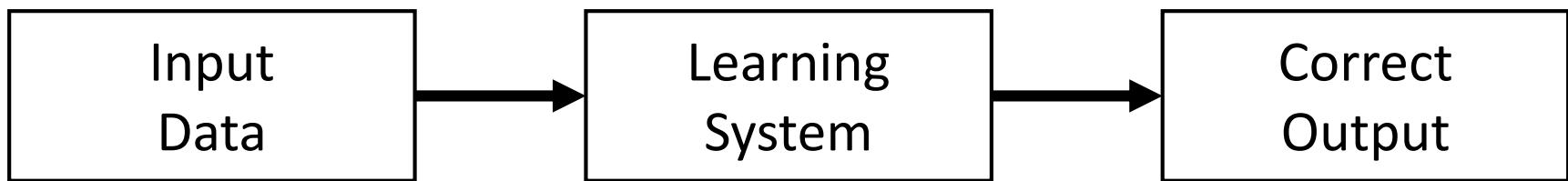


Training Stage:



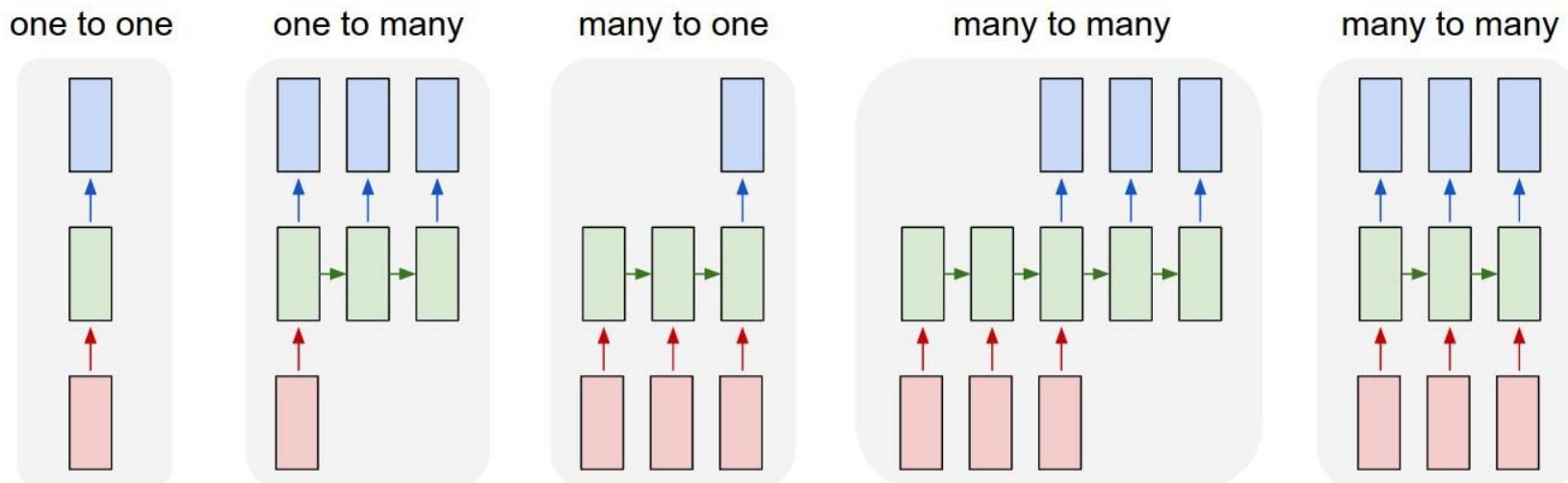
Open Question: What can't be learned in this way?

What can we do with Machine Learning?

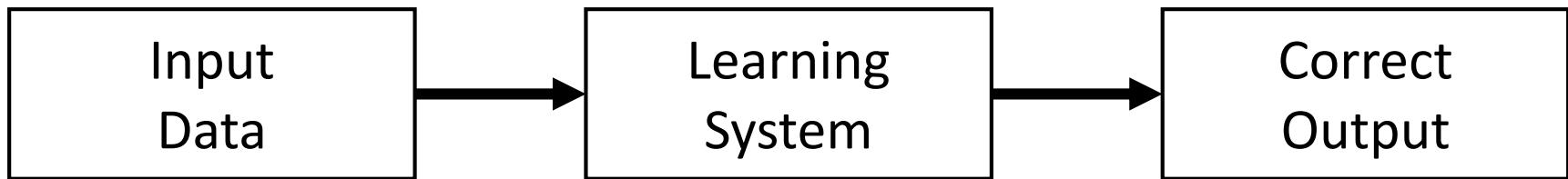


- Number
- Vector of numbers
- Sequence of numbers
- Sequence of vectors of numbers

- Number
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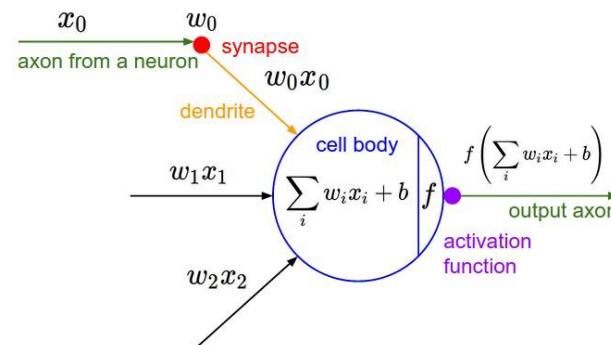
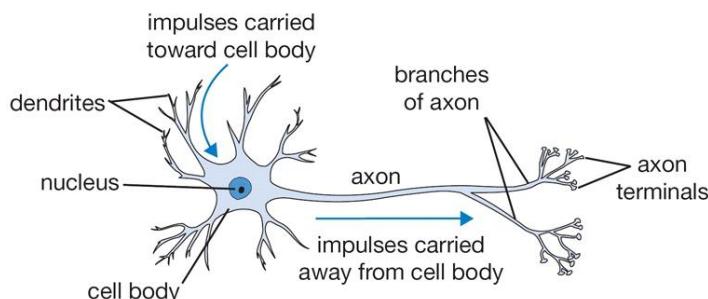


What can we do with Machine Learning?



- Images
 - Face
 - Medical
 - Text
 - Conversations
 - Articles
 - Questions
 - Sounds
 - Voice
 - Time series
 - Financial
 - Physiological
 - Physical world
 - Location of self
 - Actions of others
- ...
- Nearest Neighbor
 - Naïve Bayes
 - Support Vector Machines
 - Hidden Markov Models
 - Ensemble of Methods
 - Neural Networks
(aka Deep Learning)
- ...
- Classification
 - Regression
 - Sequences
 - Text
 - Images
 - Audio
 - Actions
- ...

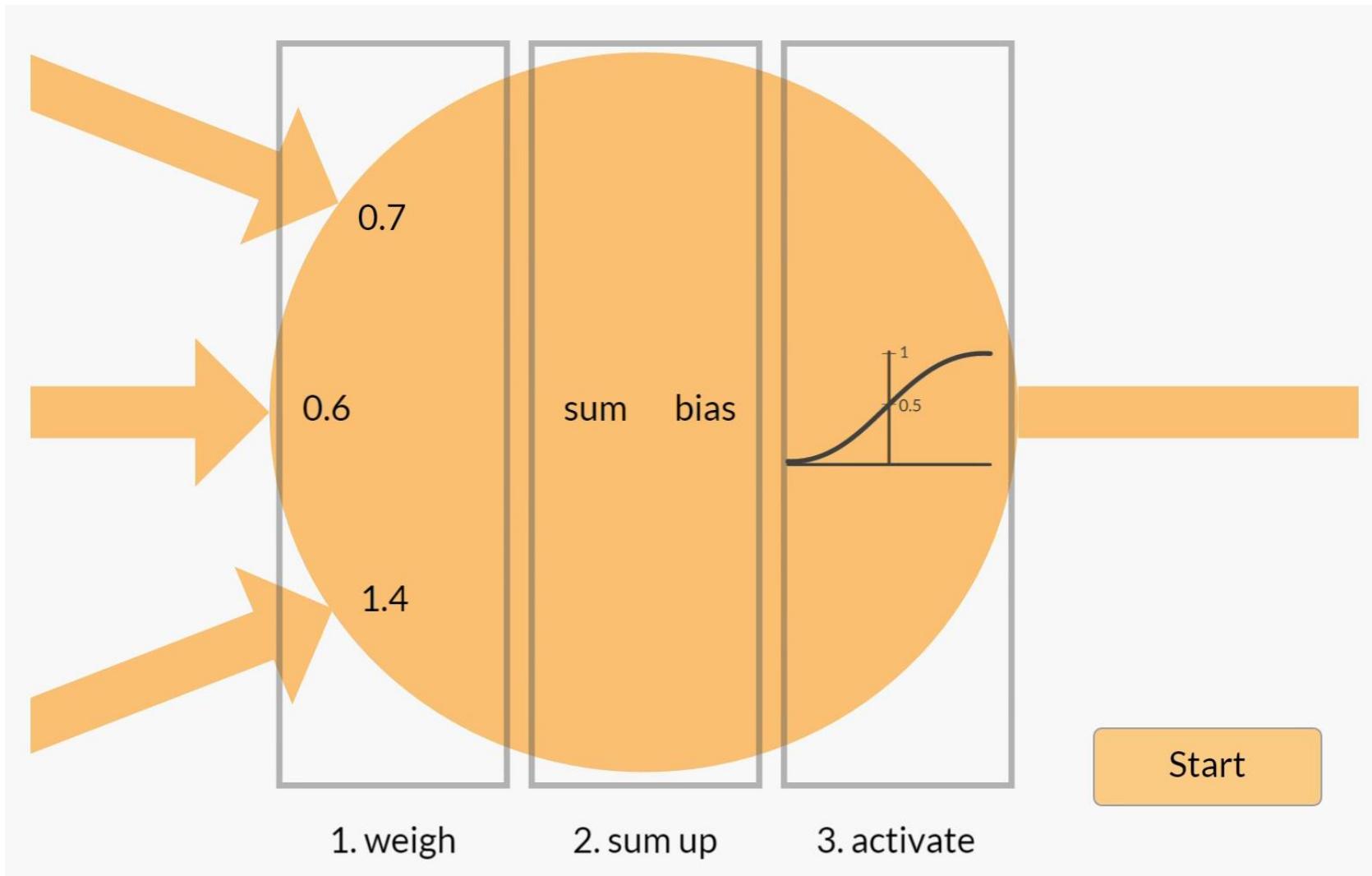
Neuron: Biological Inspiration for Computation



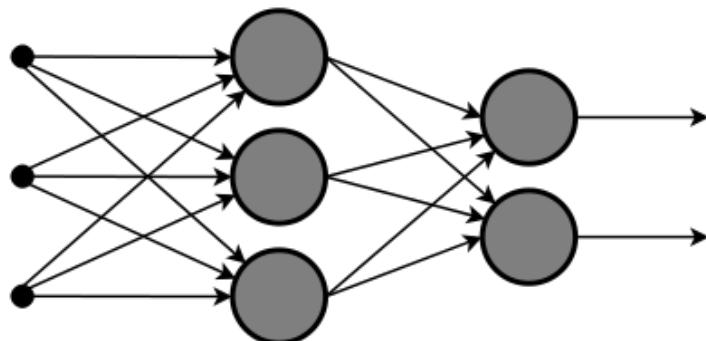
- **Neuron:** computational building block for the brain
- Human brain:
 - ~100-1,000 trillion synapses
- **(Artificial) Neuron:** computational building block for the “neural network”
- **(Artificial) neural network:**
 - ~1-10 billion synapses

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

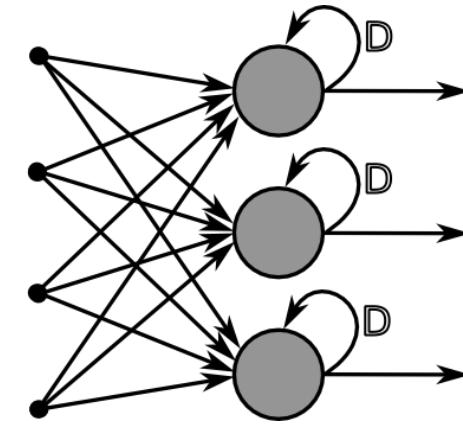
Neuron: Forward Pass



Combining Neurons into Layers



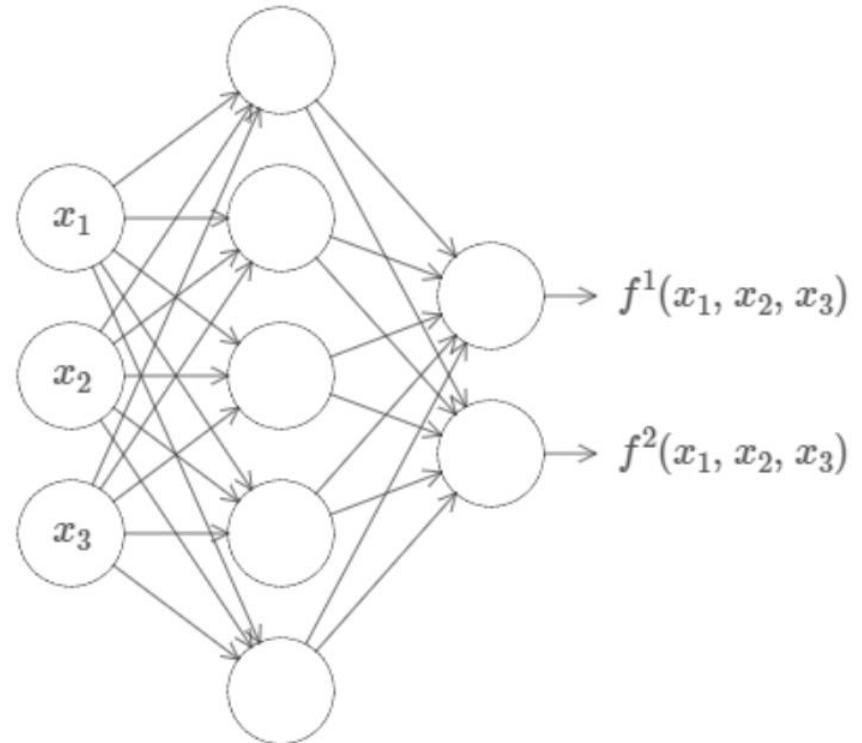
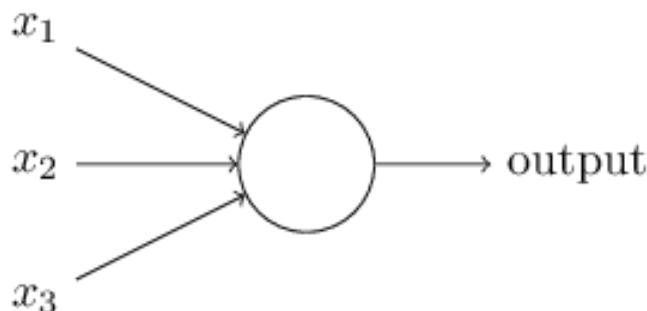
Feed Forward Neural Network



Recurrent Neural Network

- Have state memory
- Are hard to train

Neural Networks are Amazing



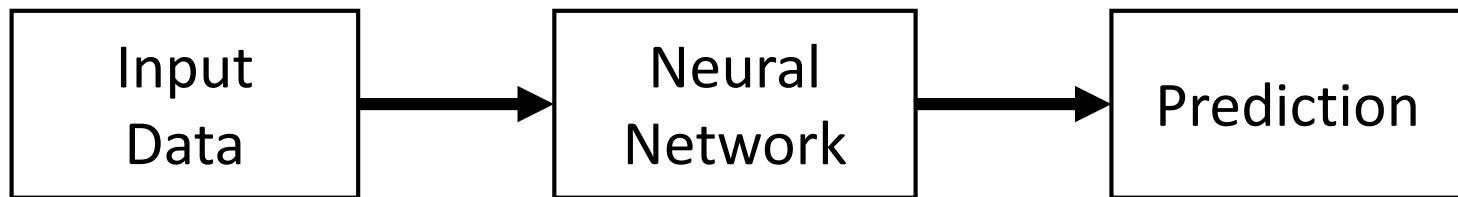
Universality: For any arbitrary function $f(x)$, there exists a neural network that closely approximate it for any input x

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

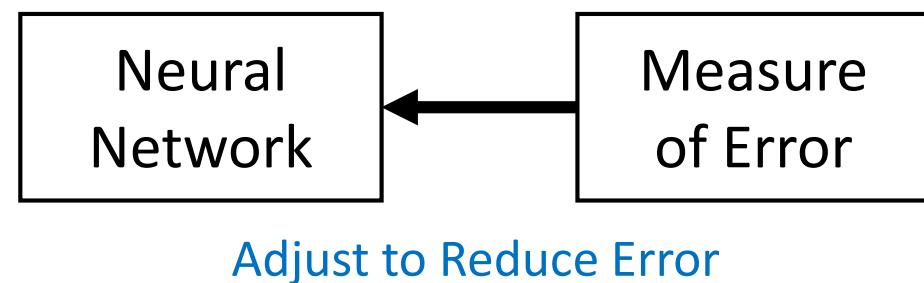
* Given that we have good algorithms for training these networks.

How Neural Networks Learn: Backpropagation

Forward Pass:

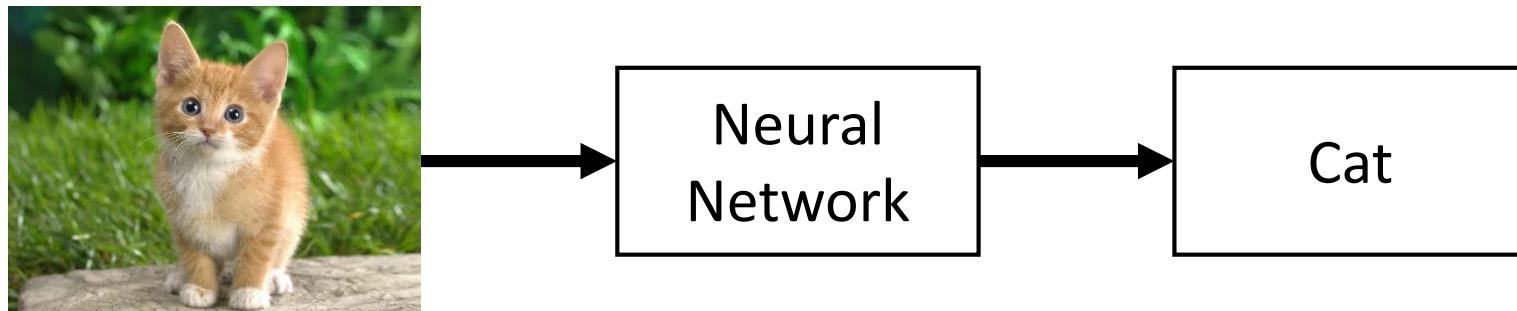


Backward Pass (aka Backpropagation):

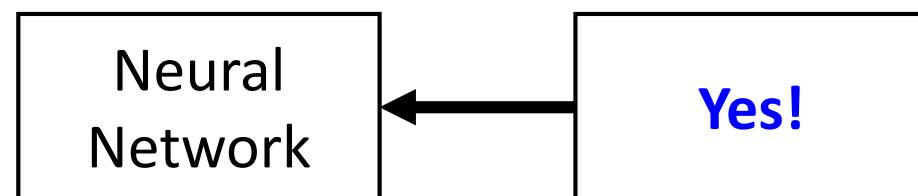


How Neural Networks Learn: Backpropagation

Forward Pass:

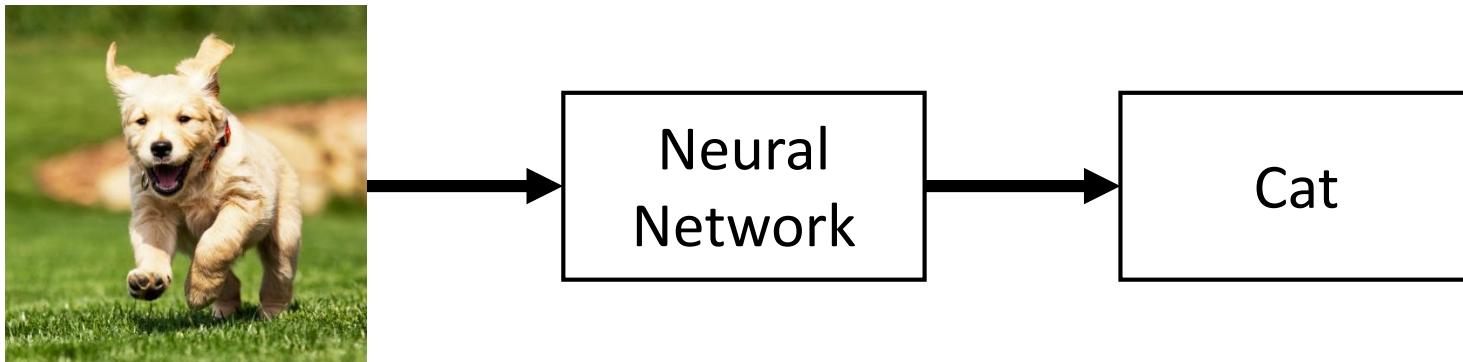


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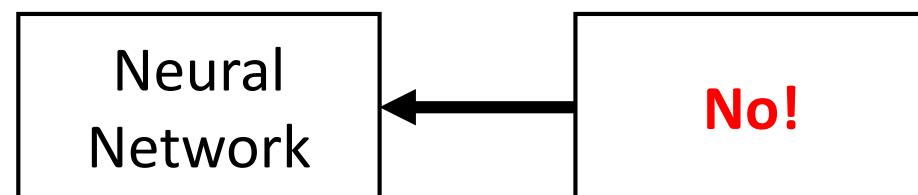


How Neural Networks Learn: Backpropagation

Forward Pass:

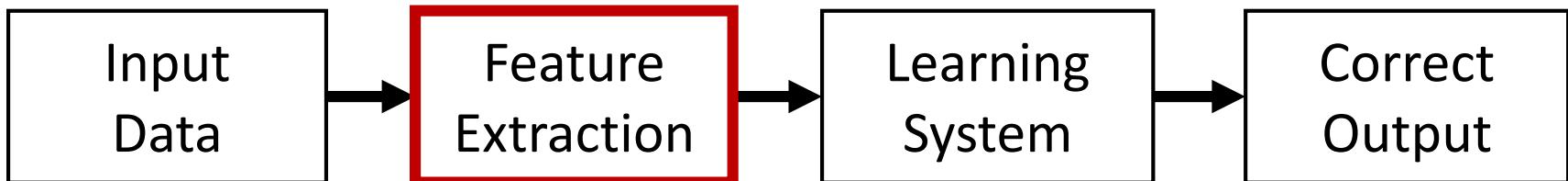


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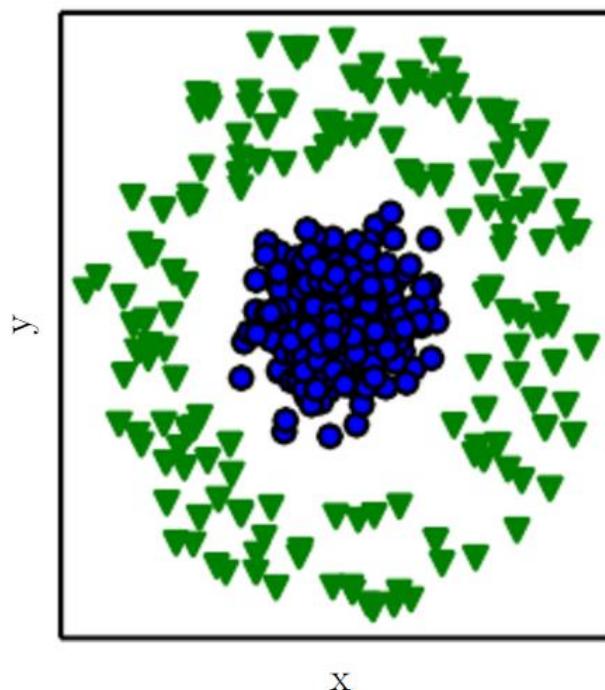


Representation Matters!

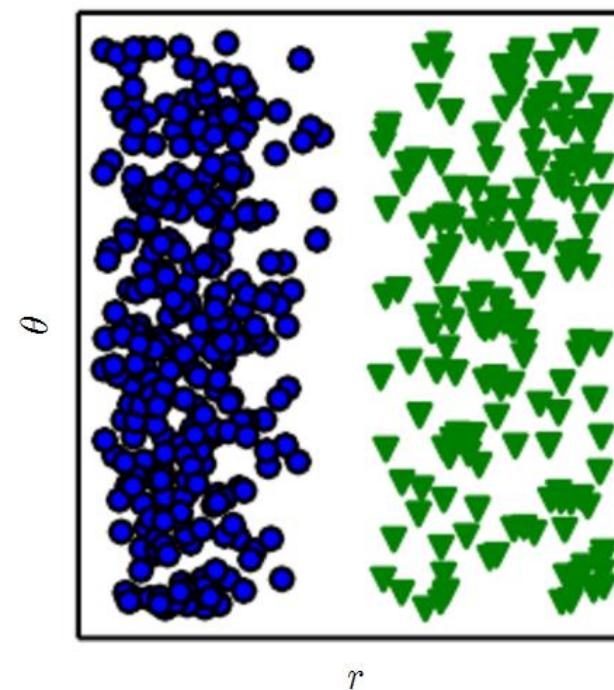
(Representation aka Features)



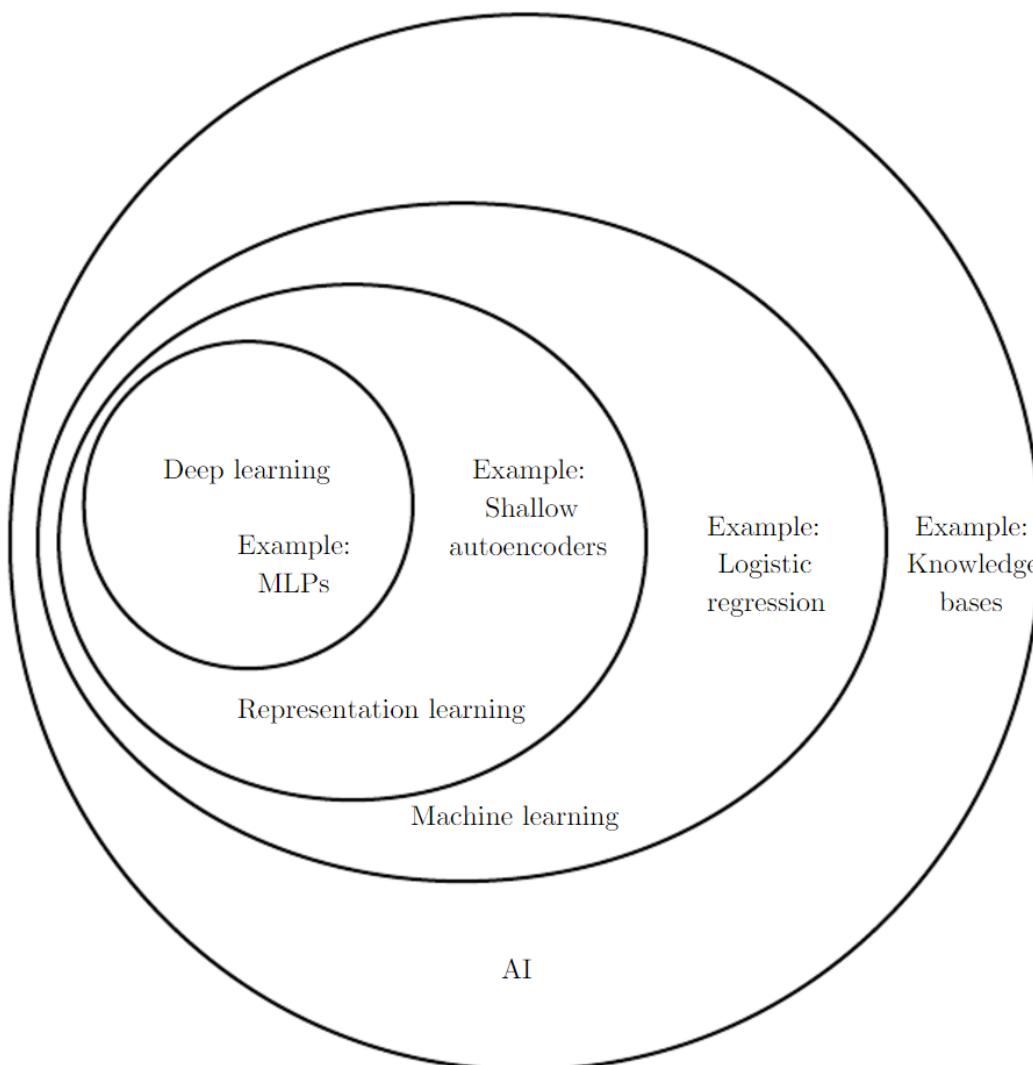
Cartesian coordinates



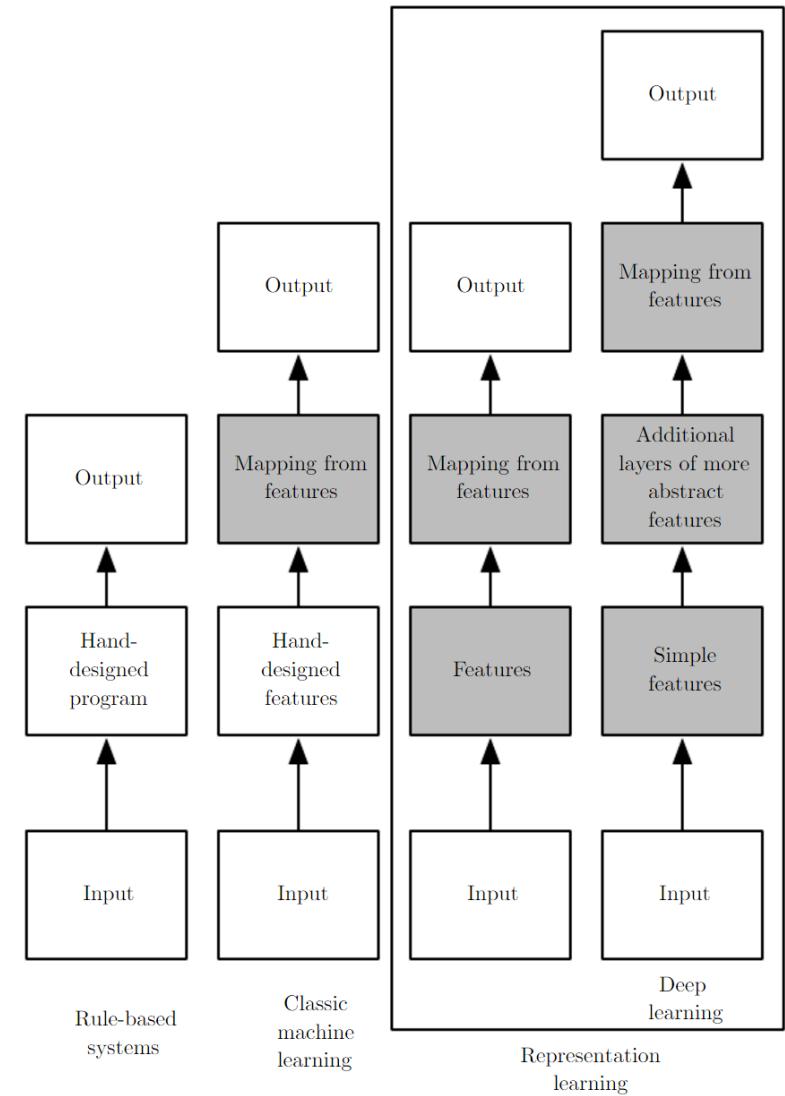
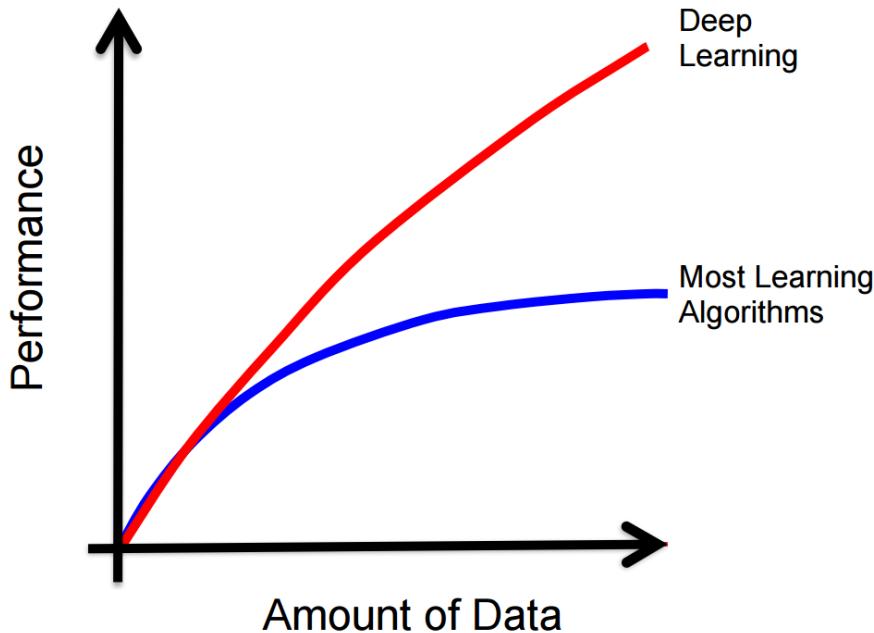
Polar coordinates



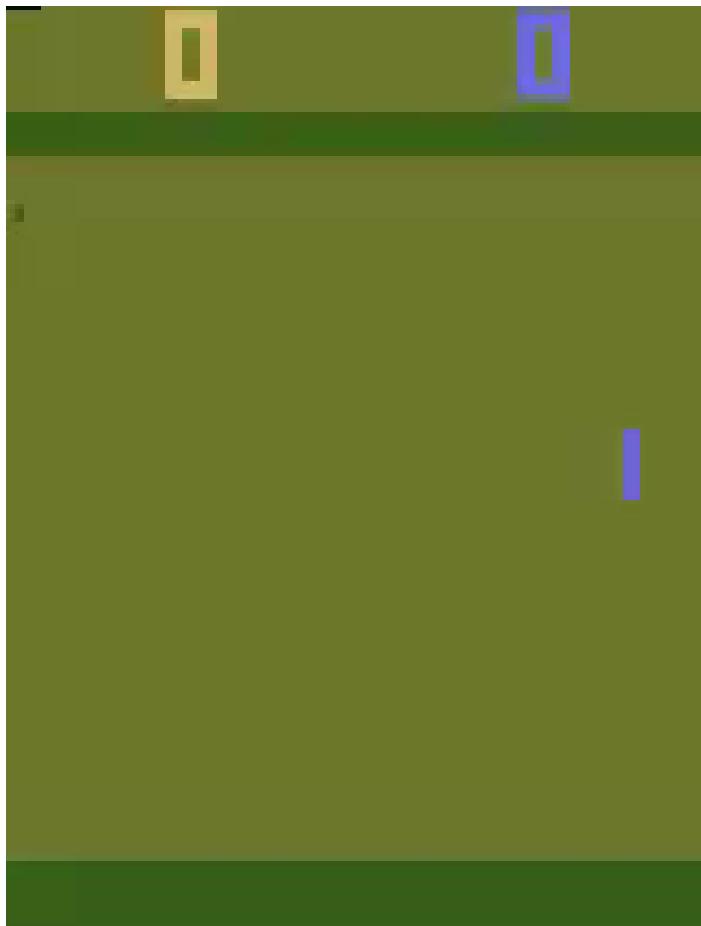
Deep Learning is Representation Learning



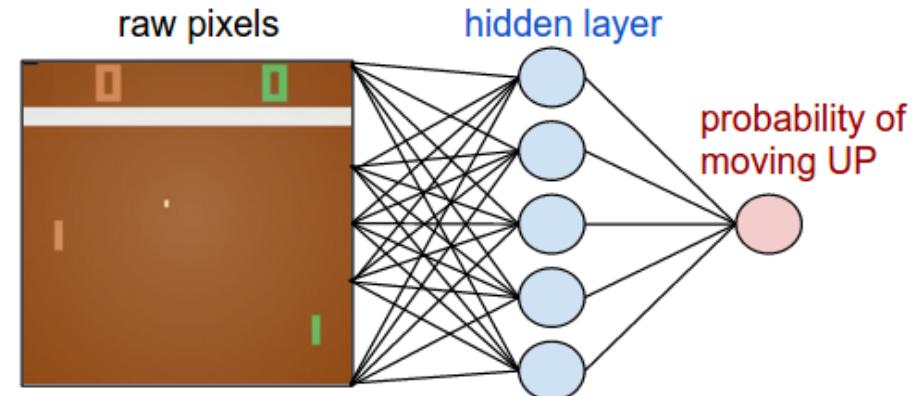
Deep Learning: Scalable Machine Learning



Neural Networks are Amazing: General Purpose Intelligence



Policy Network:

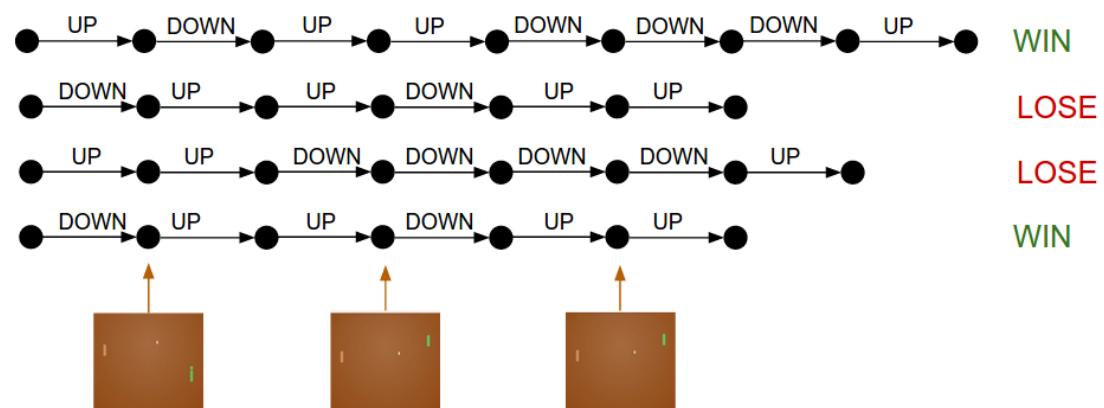


- 80x80 image (difference image)
- 2 actions: up or down
- 200,000 Pong games

**This is a step towards general purpose
artificial intelligence!**

Andrej Karpathy. “Deep Reinforcement Learning: Pong from Pixels.” 2016.

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...

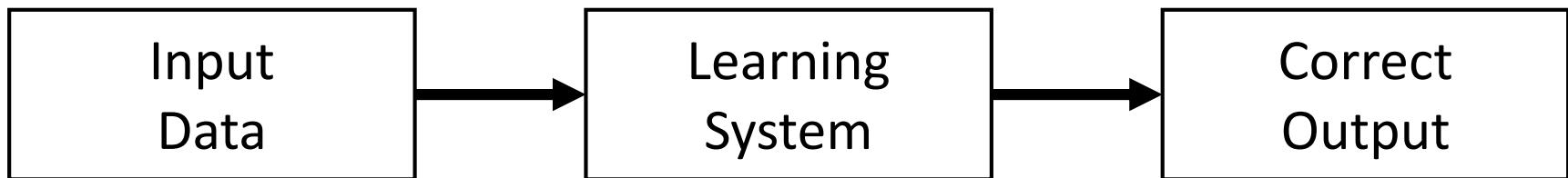
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What can we do with Machine Learning?

Object Recognition / Image Classification



mite

container ship

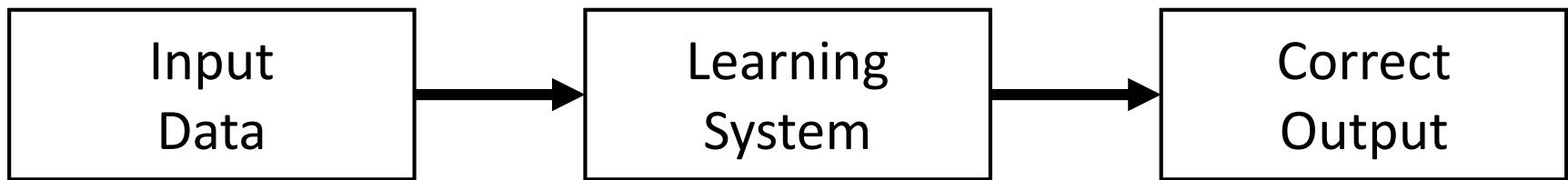
motor scooter

leopard

mite	container ship	motor scooter	leopard
black widow	lifeboat	motor scooter	leopard
cockroach	amphibian	go-kart	jaguar
tick	fireboat	moped	cheetah
starfish	drilling platform	bumper car	snow leopard
		golfcart	Egyptian cat

What can we do with Machine Learning?

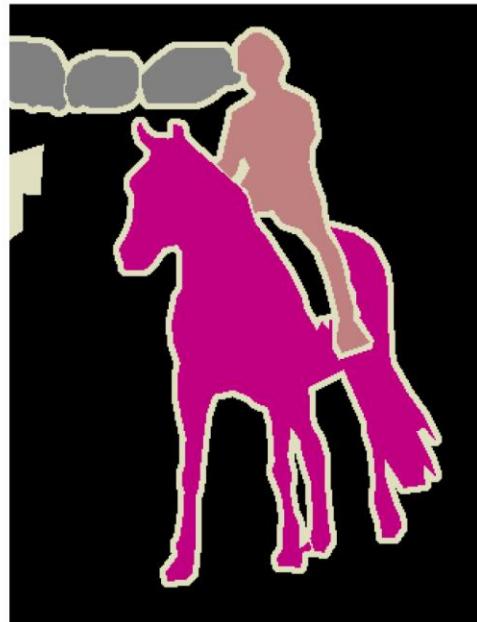
Image Segmentation



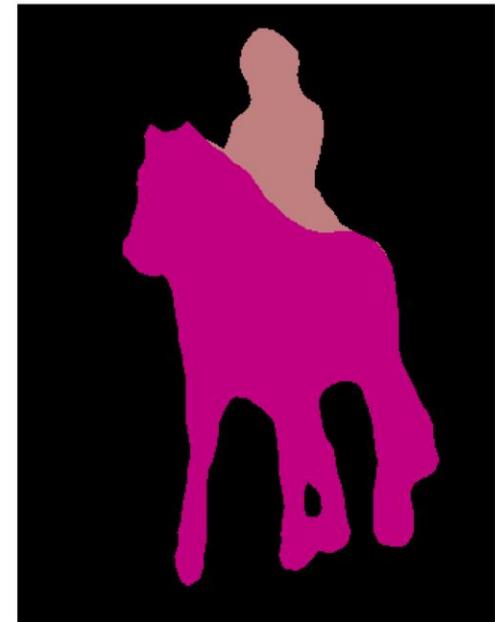
Original



Ground Truth

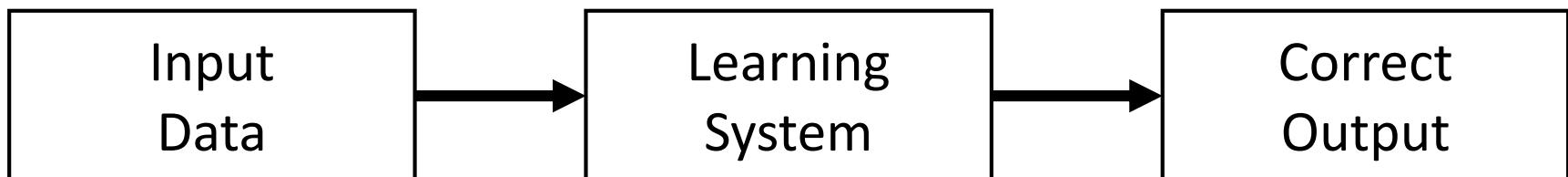


FCN-8



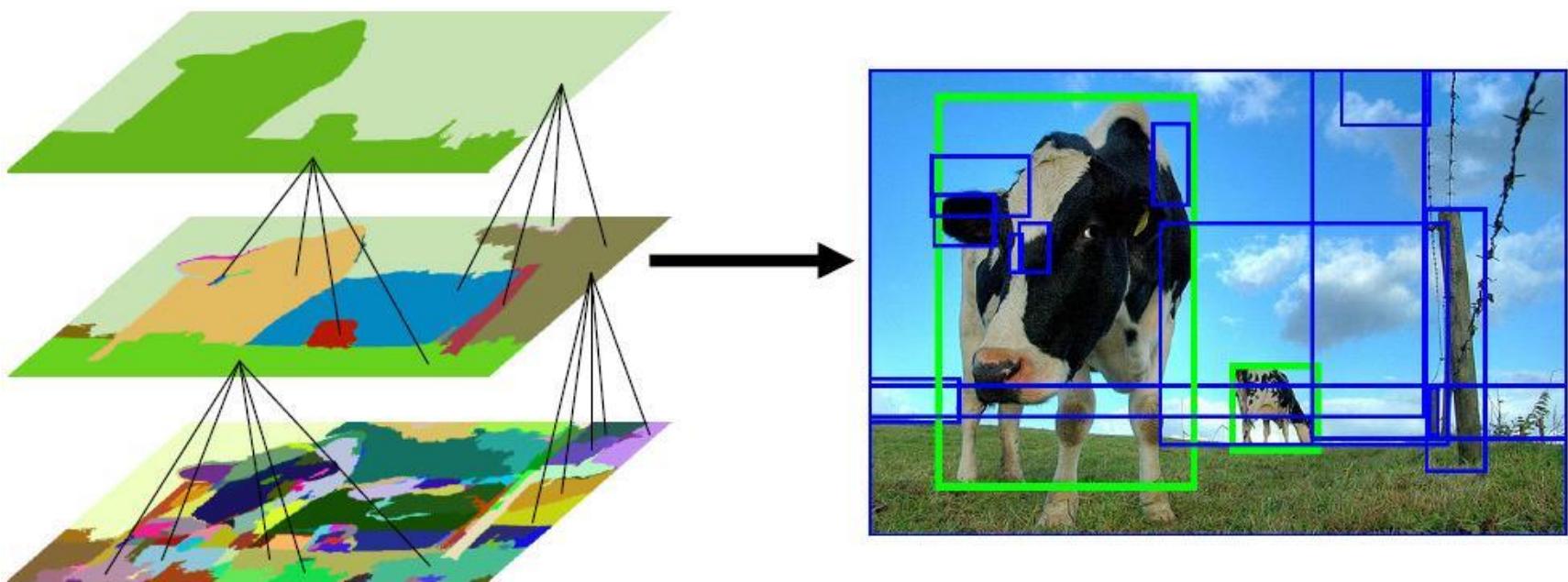
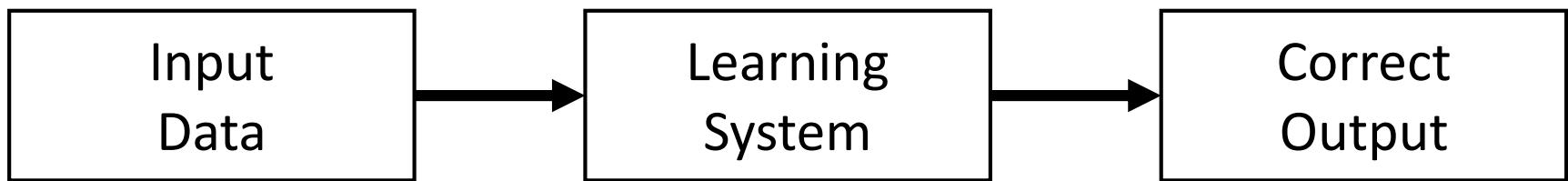
What can we do with Machine Learning?

Video Segmentation



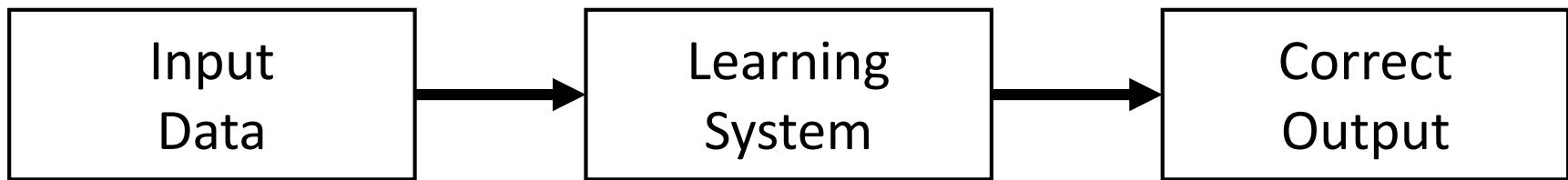
What can we do with Machine Learning?

Object Detection / Object Localization

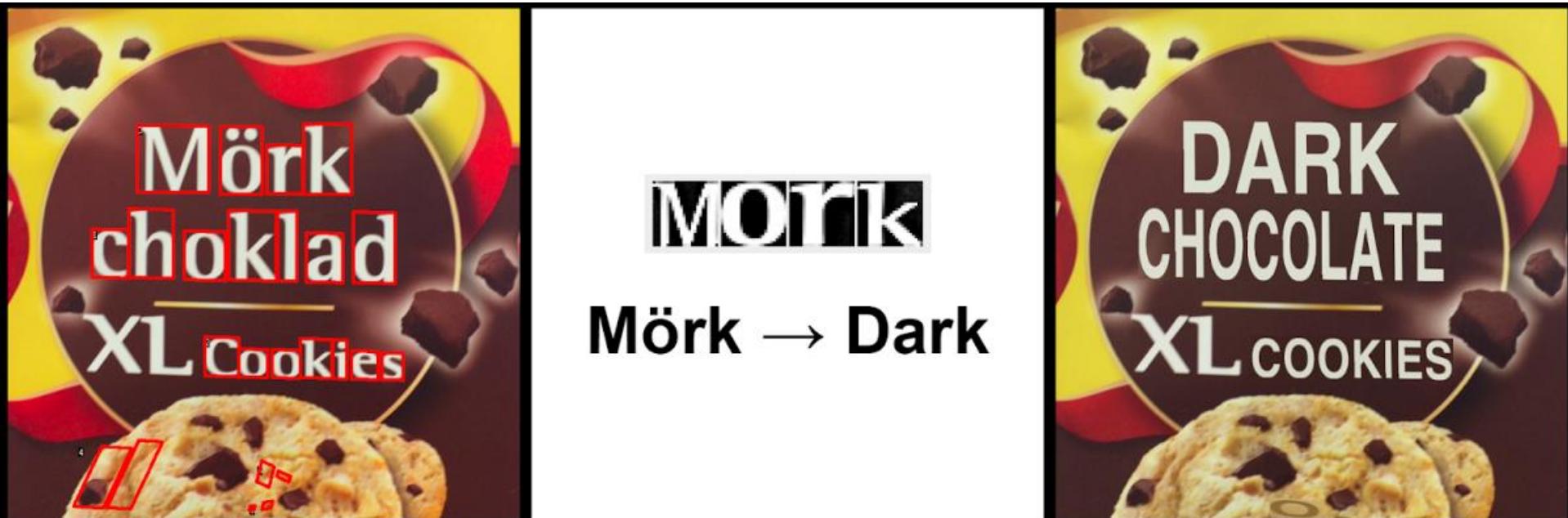
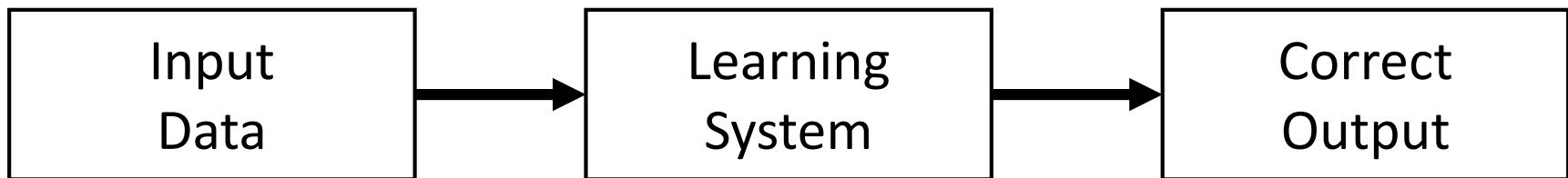


What can we do with Machine Learning?

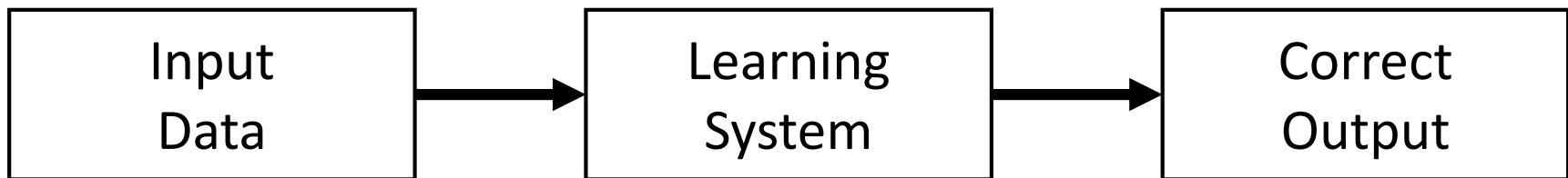
Colorization of Images



What can we do with Machine Learning? Automatic Translation of Text in Images



What can we do with Machine Learning? Handwriting Generation from Text

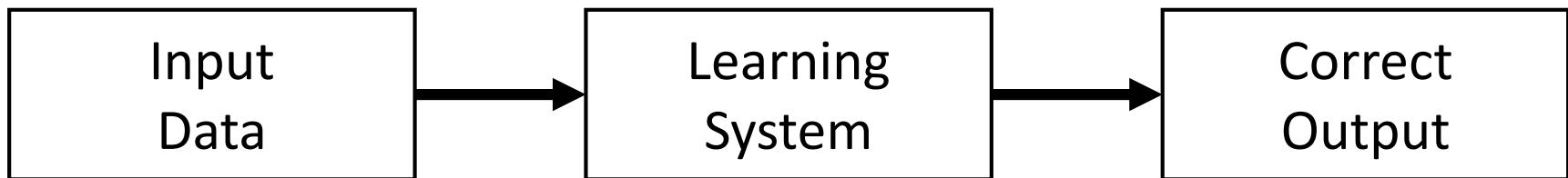


Text --- up to 100 characters, lower case letters work best

Global Business of Artificial Intelligence

What can we do with Machine Learning?

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

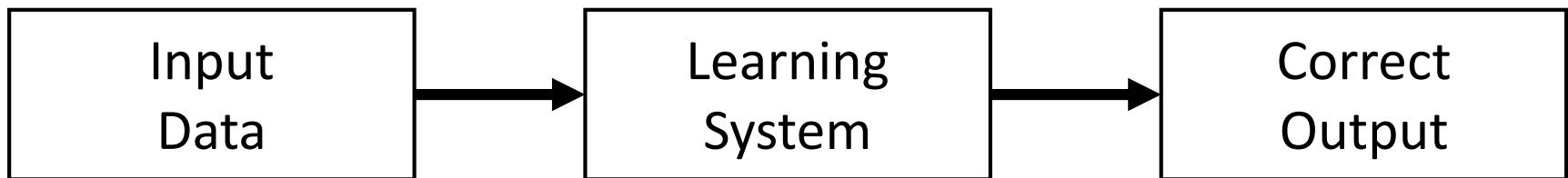
Life Is About The Truth Now

The meaning of life is literary recognition.

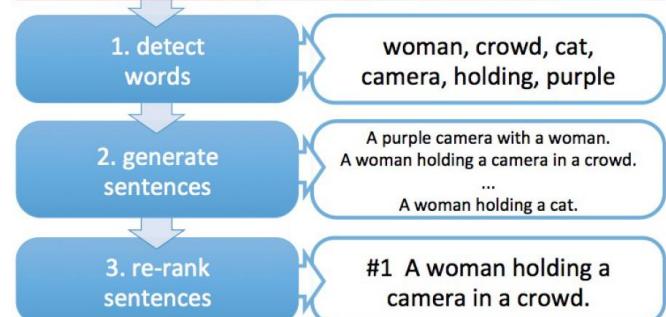
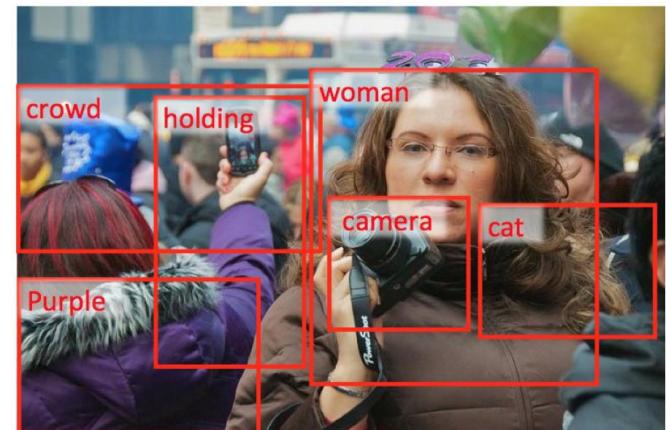
The meaning of life is the tradition of the ancient human reproduction

What can we do with Machine Learning?

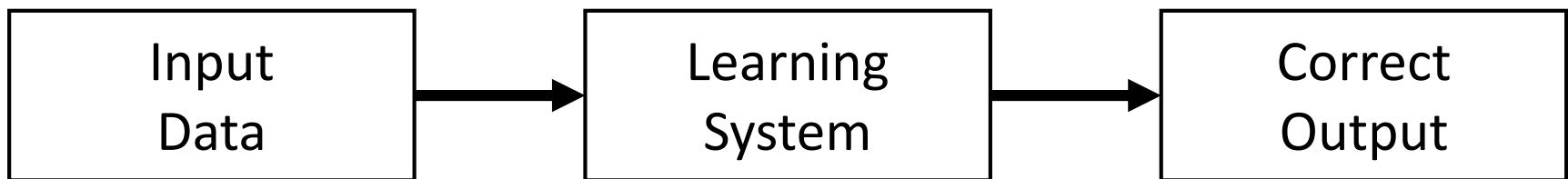
Image Caption Generation

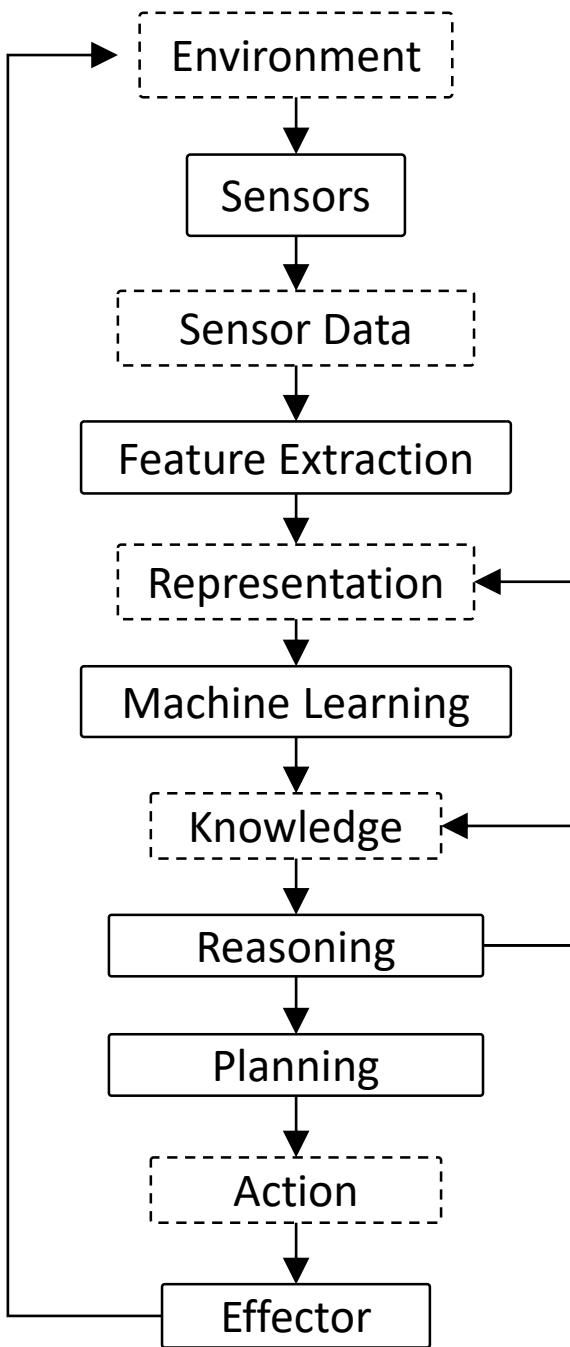


a man sitting on a couch with a dog
a man sitting on a chair with a dog in his lap

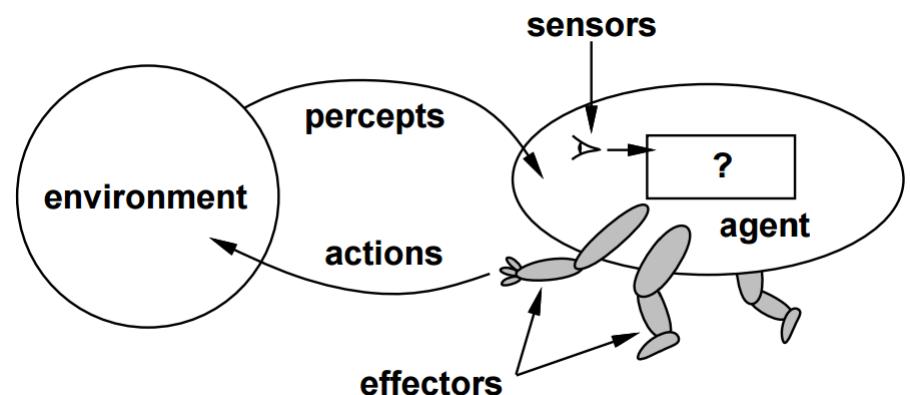


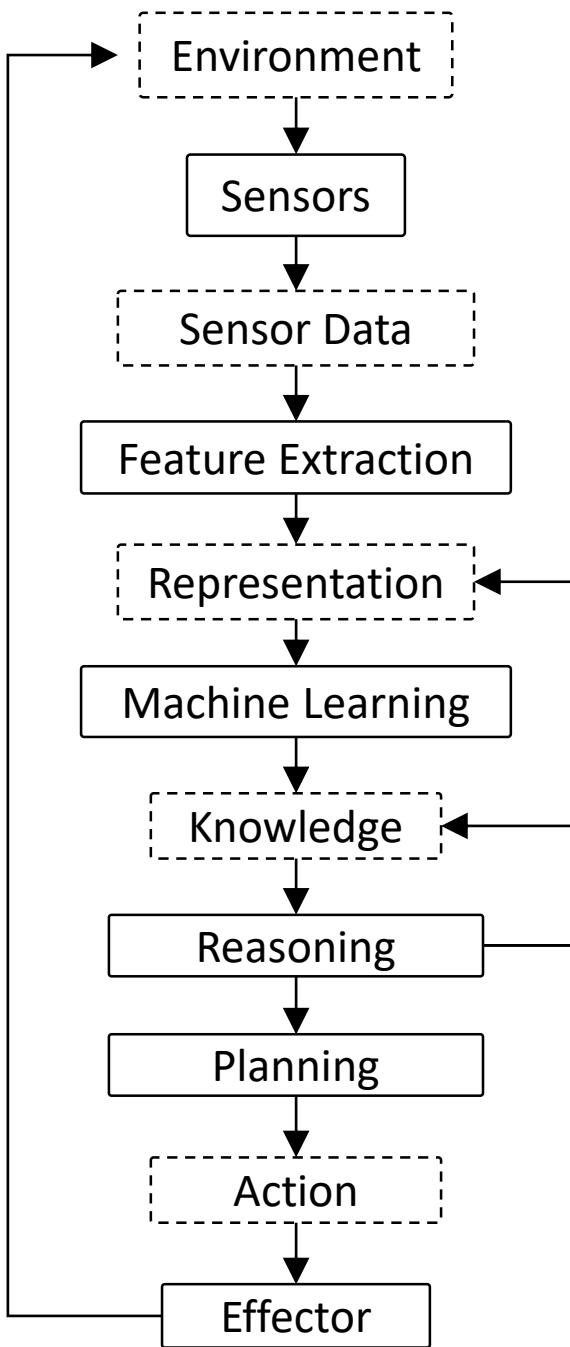
What can we do with Machine Learning? End-to-End Learning of the Driving Task



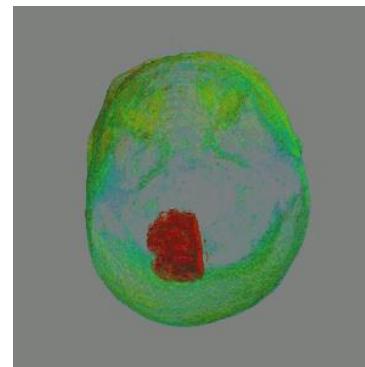


Open Question:
What can we **not** do with
Machine Learning?





Formal tasks: Playing board games, card games. Solving puzzles, mathematical and logic problems.



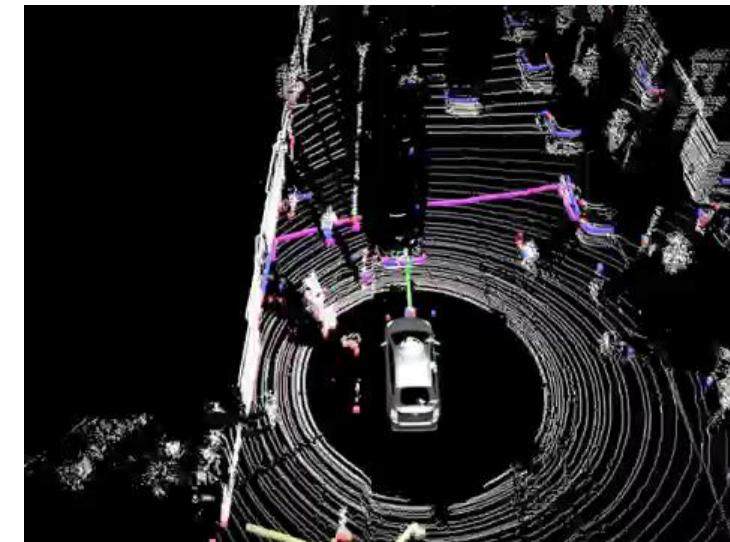
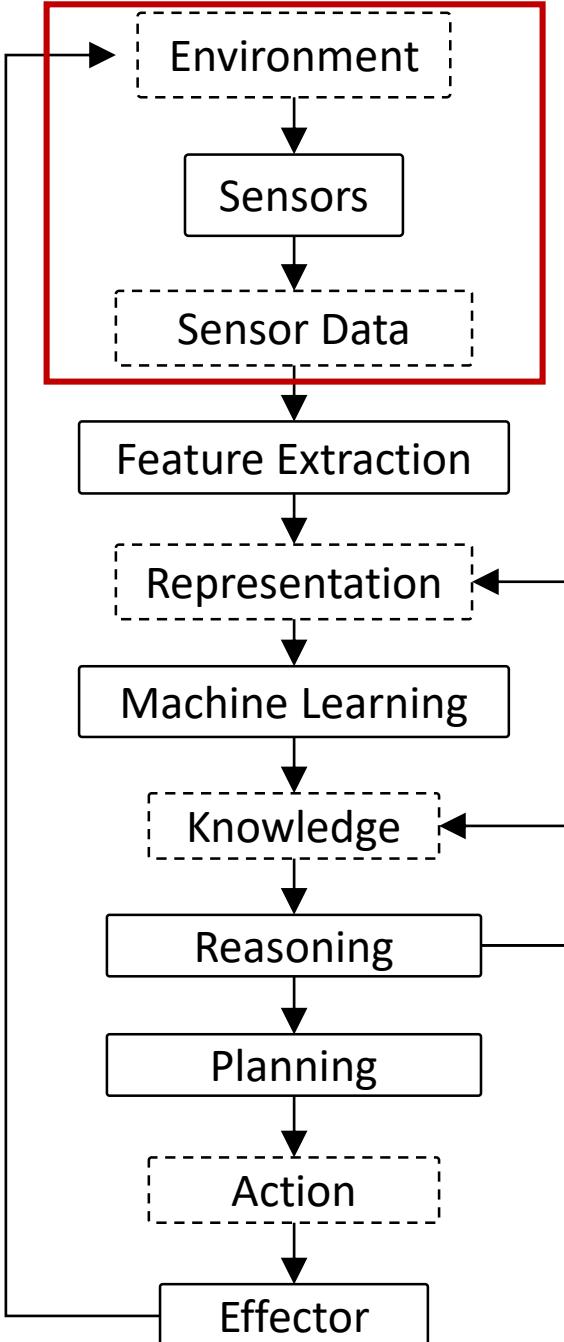
Expert tasks: Medical diagnosis, engineering, scheduling, computer hardware design.

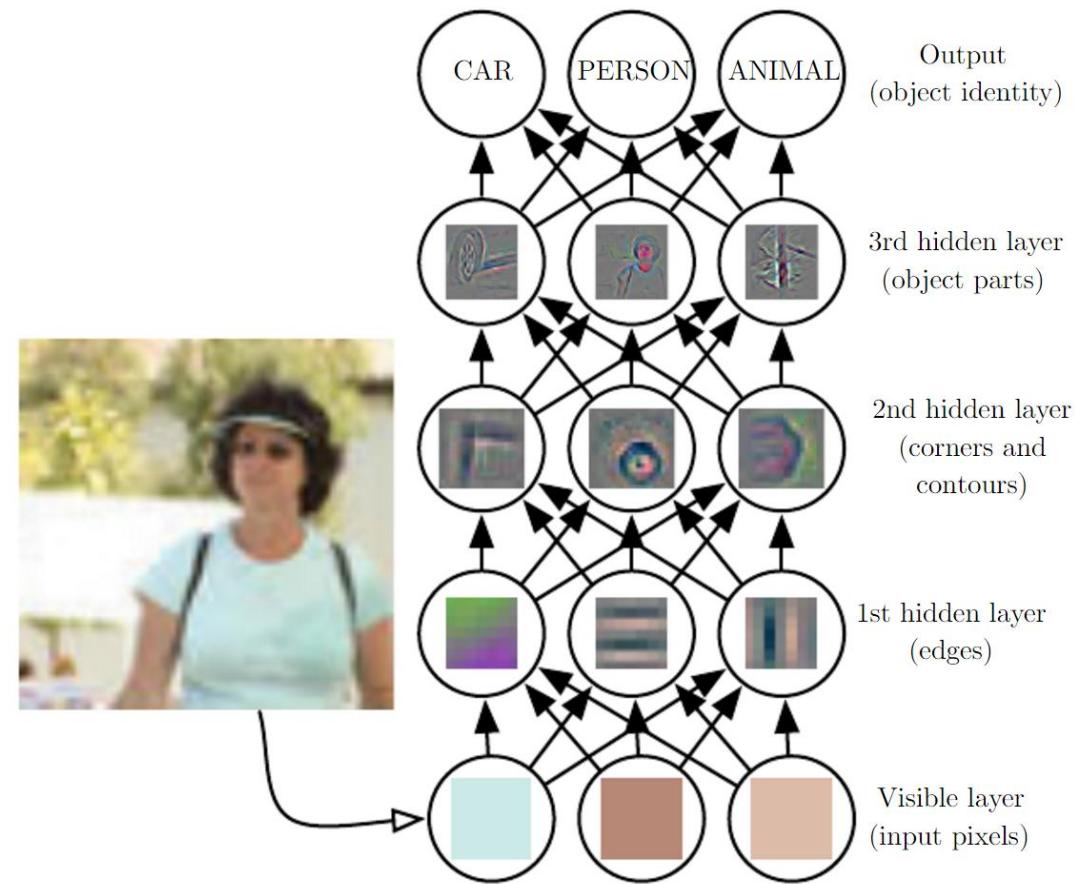
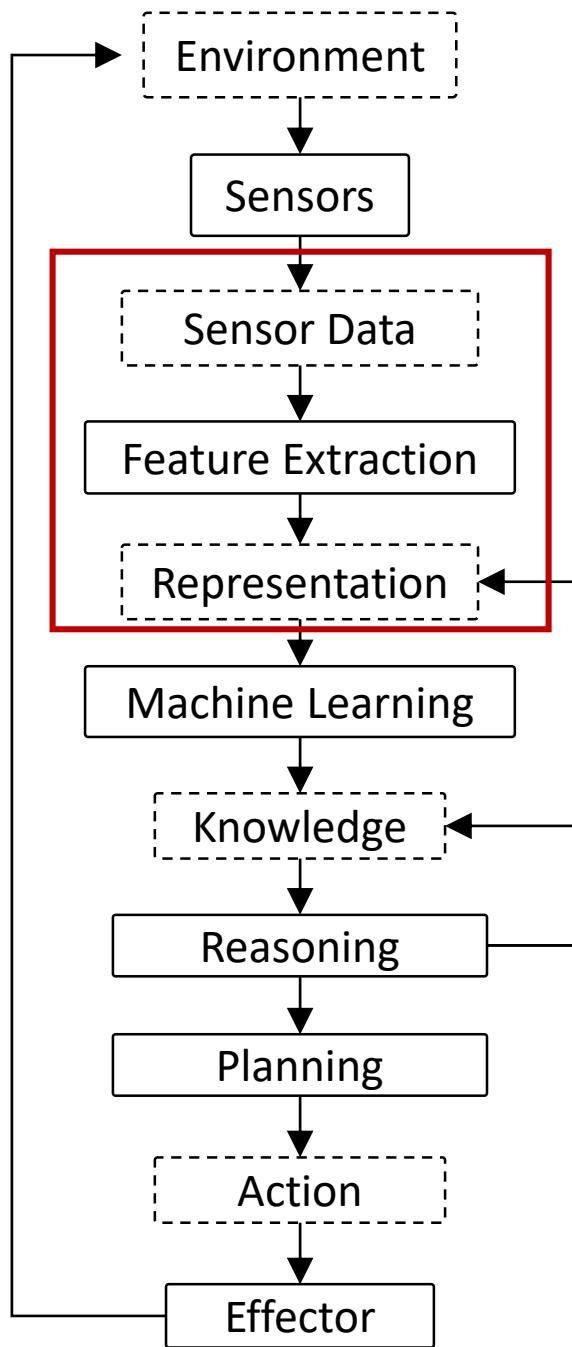


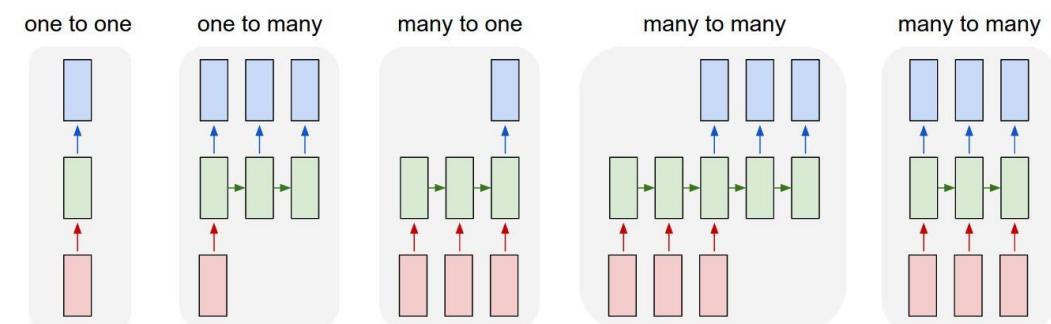
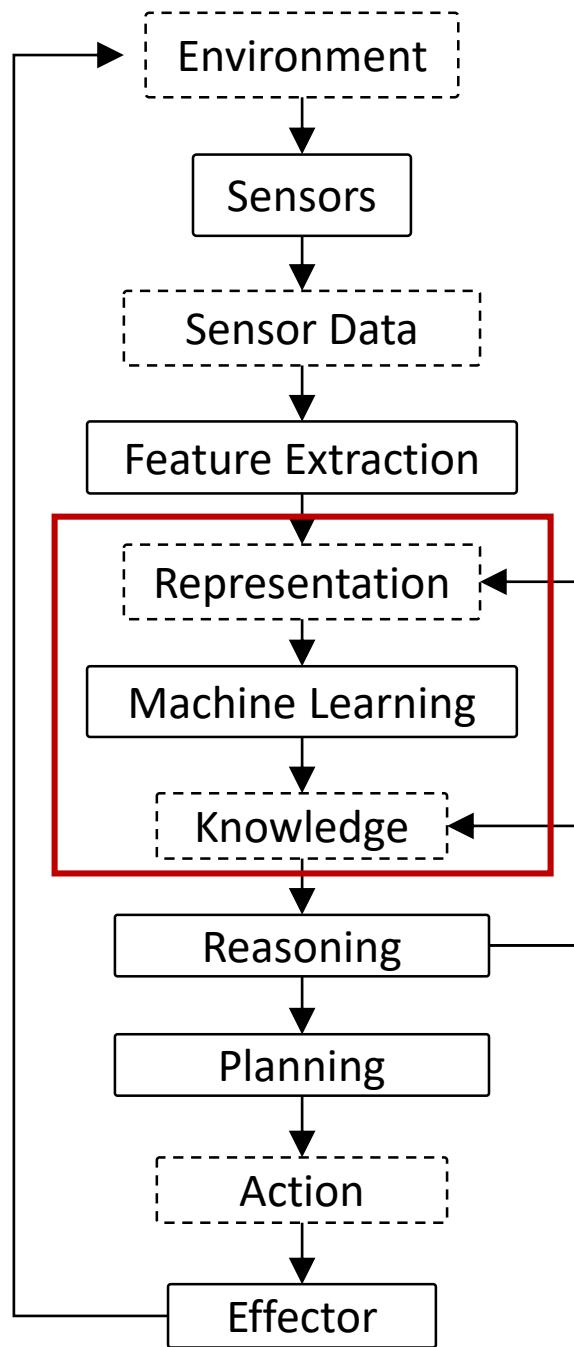
Mundane tasks: Everyday speech, written language, perception, walking, object manipulation.



Human tasks: Awareness of self, emotion, imagination, morality, subjective experience, high-level-reasoning, consciousness.







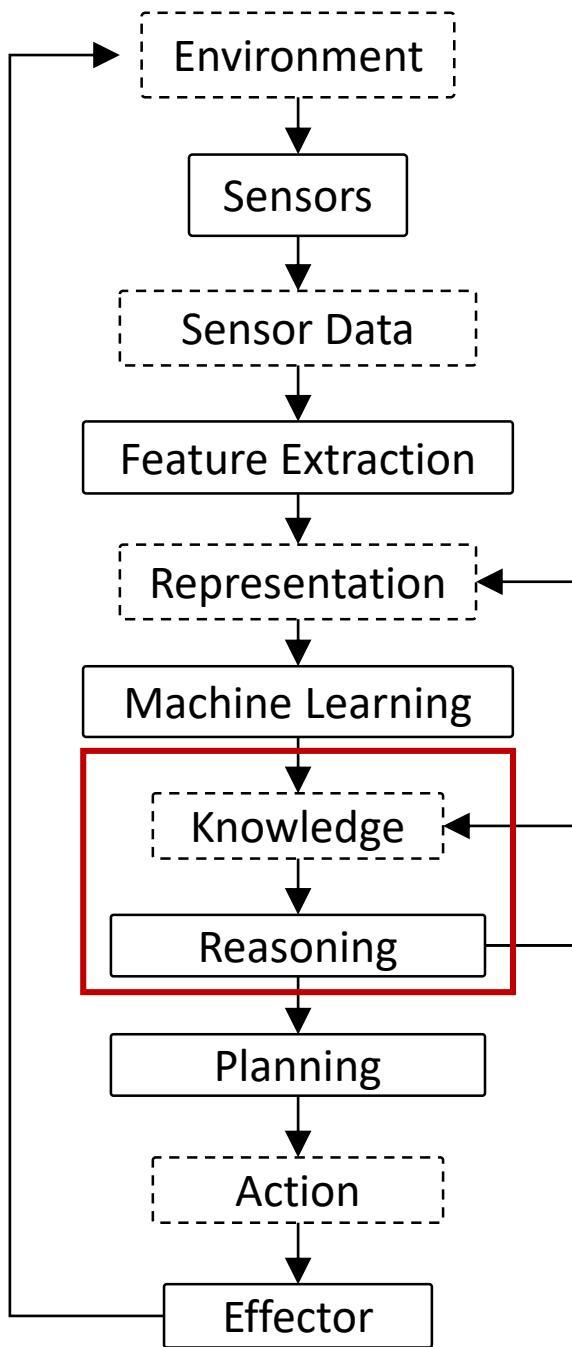


Image Recognition:
If it looks like a duck

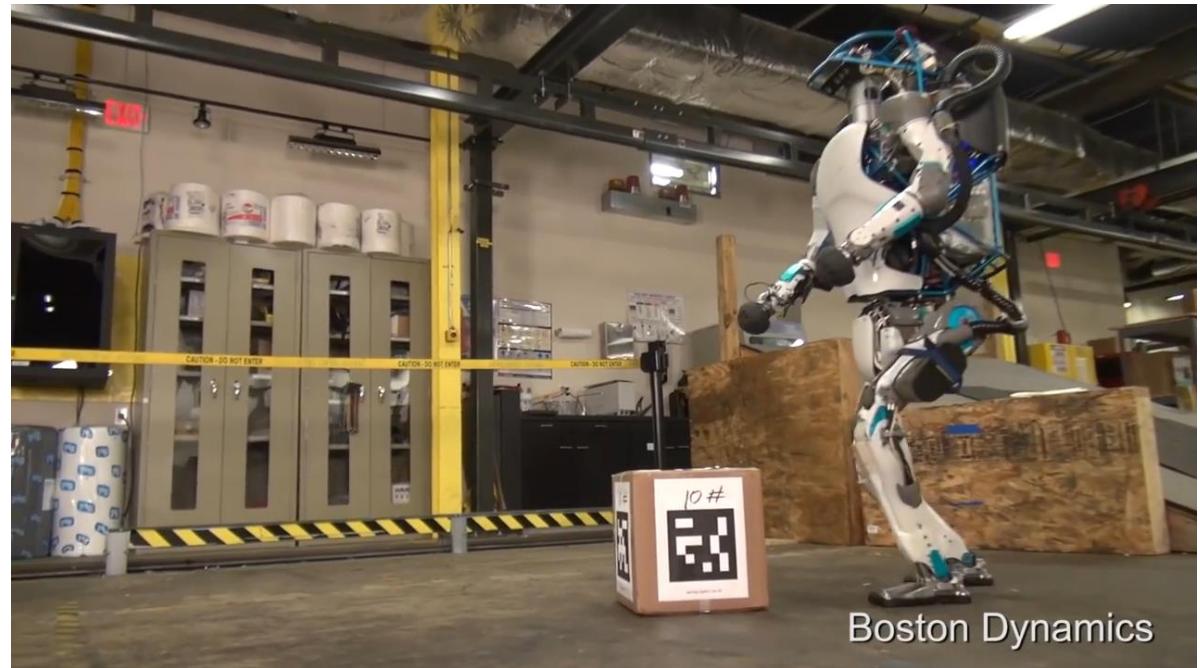
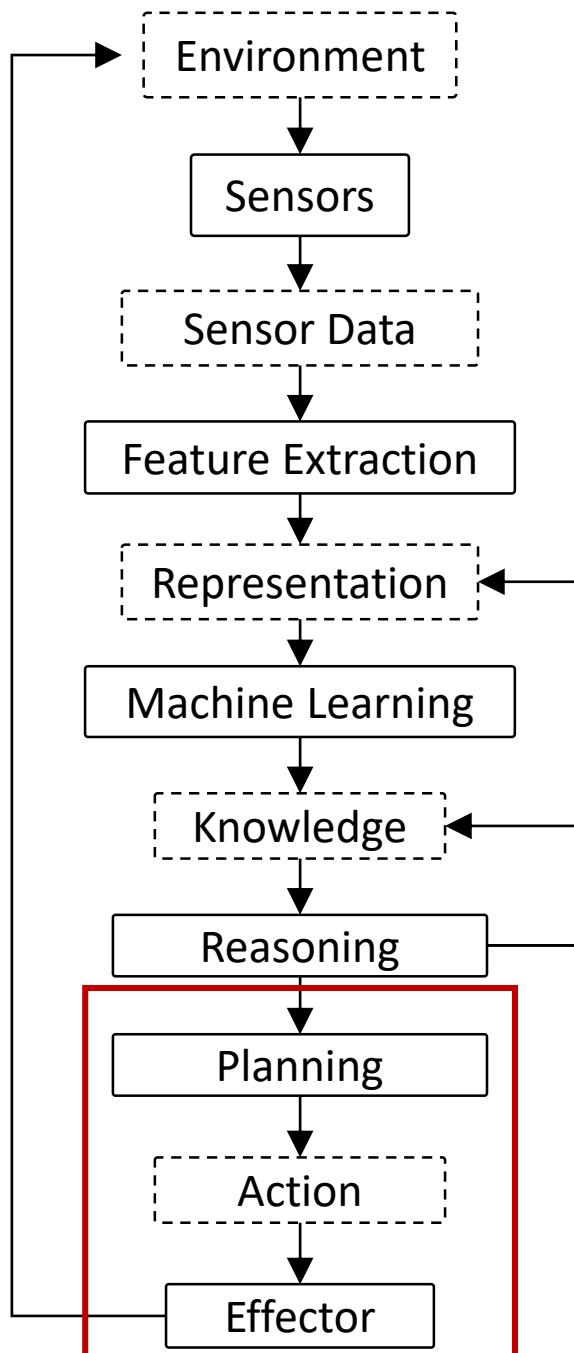


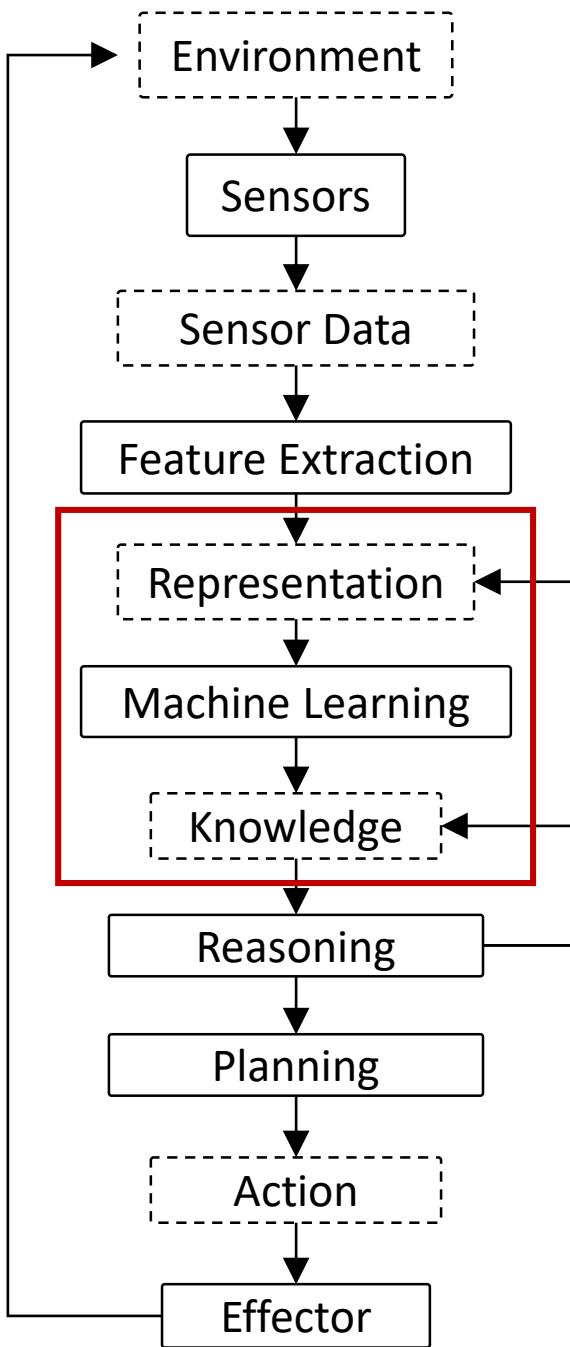
Audio Recognition:
Quacks like a duck



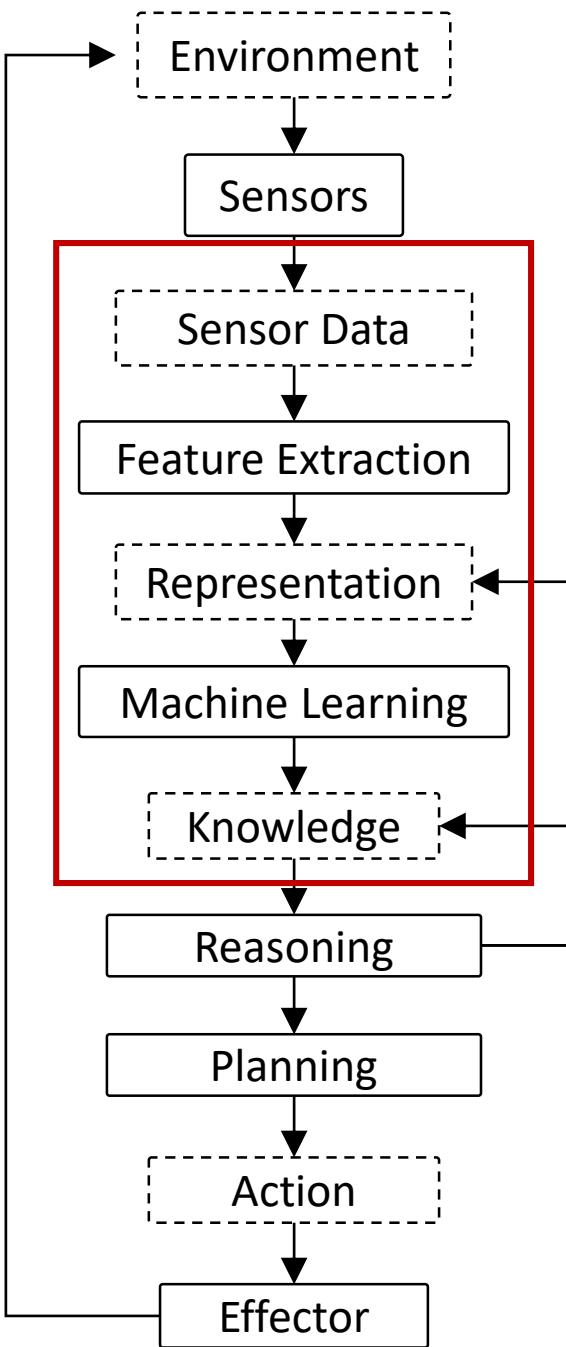
Activity Recognition:
Swims like a duck



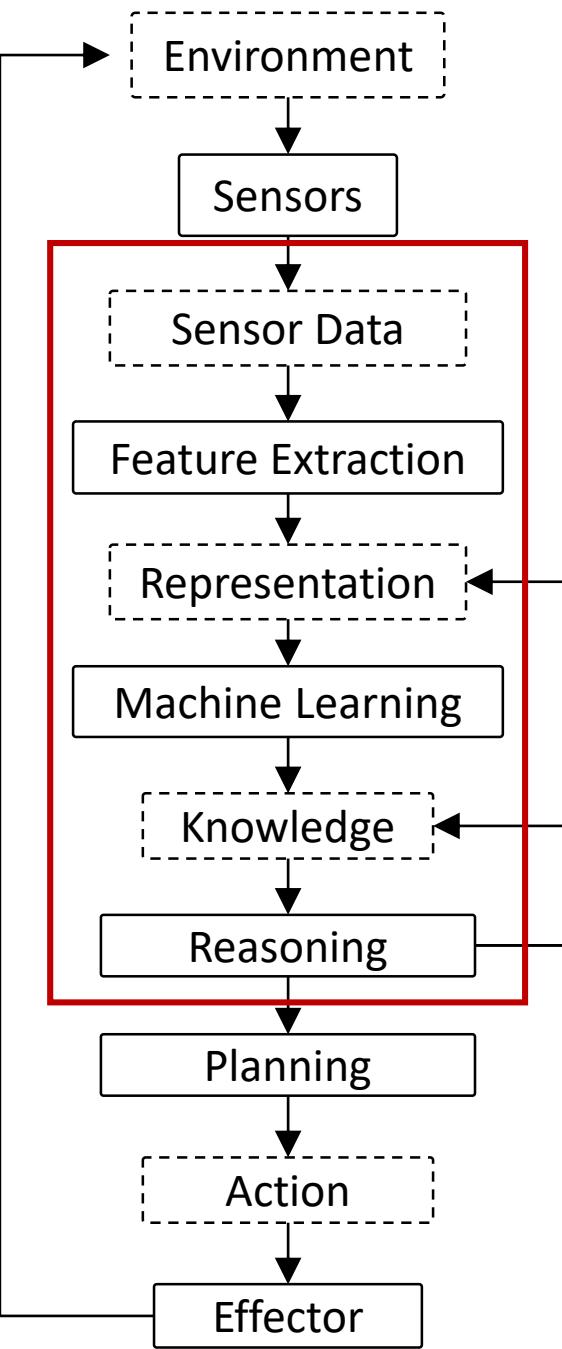




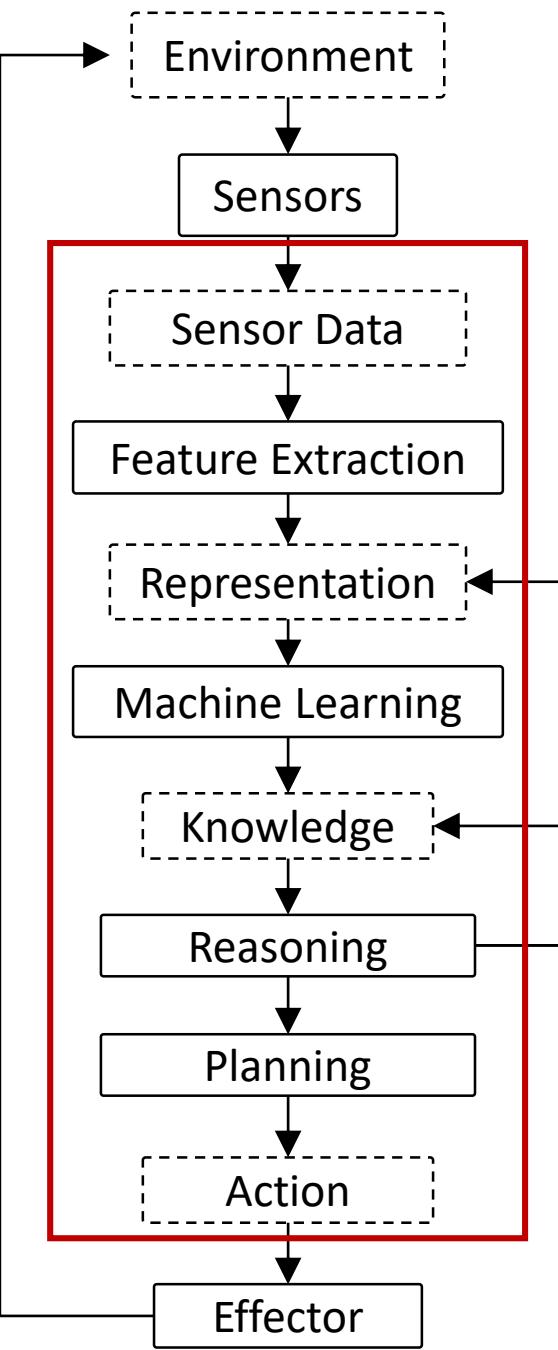
Open Question:
How much of this AI stack
can be **learned**?



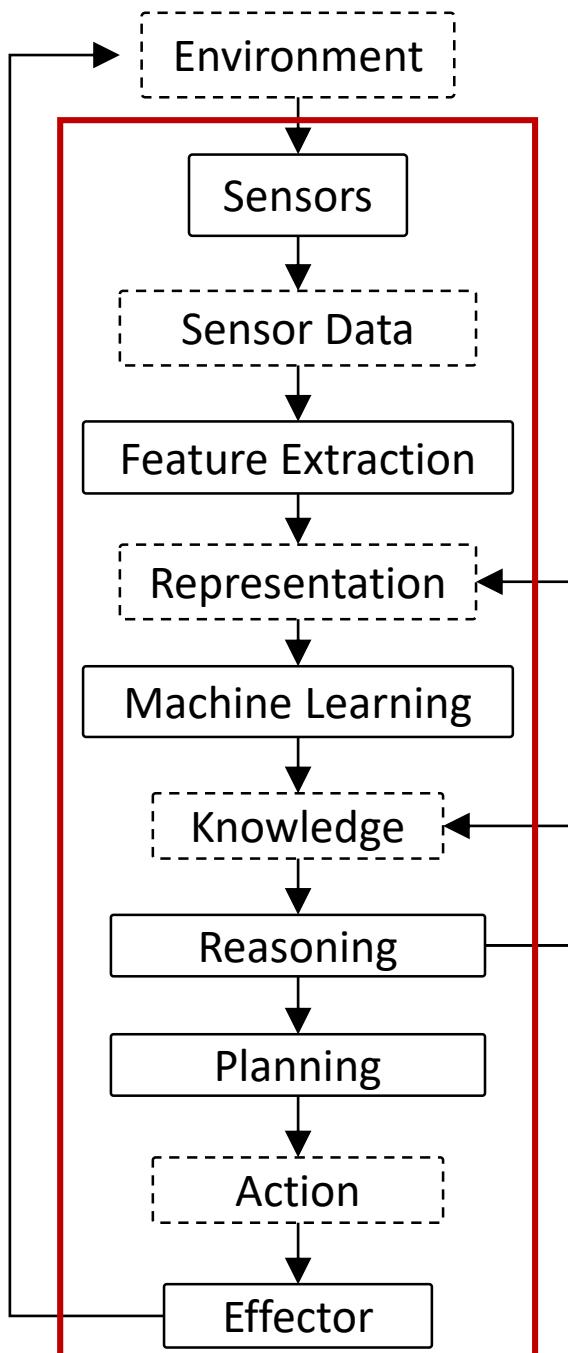
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Rule of thumb for real-world machine learning:
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you can make a product out of it. Otherwise, it’s still research.”

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."

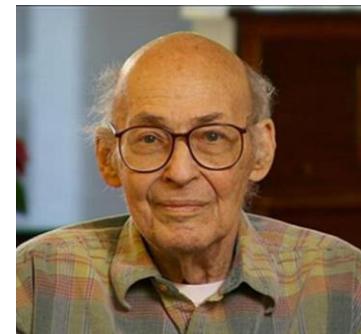
- Hans Moravec, *Mind Children* (1988)



Hans Moravec (CMU)



Rodney Brooks (MIT)



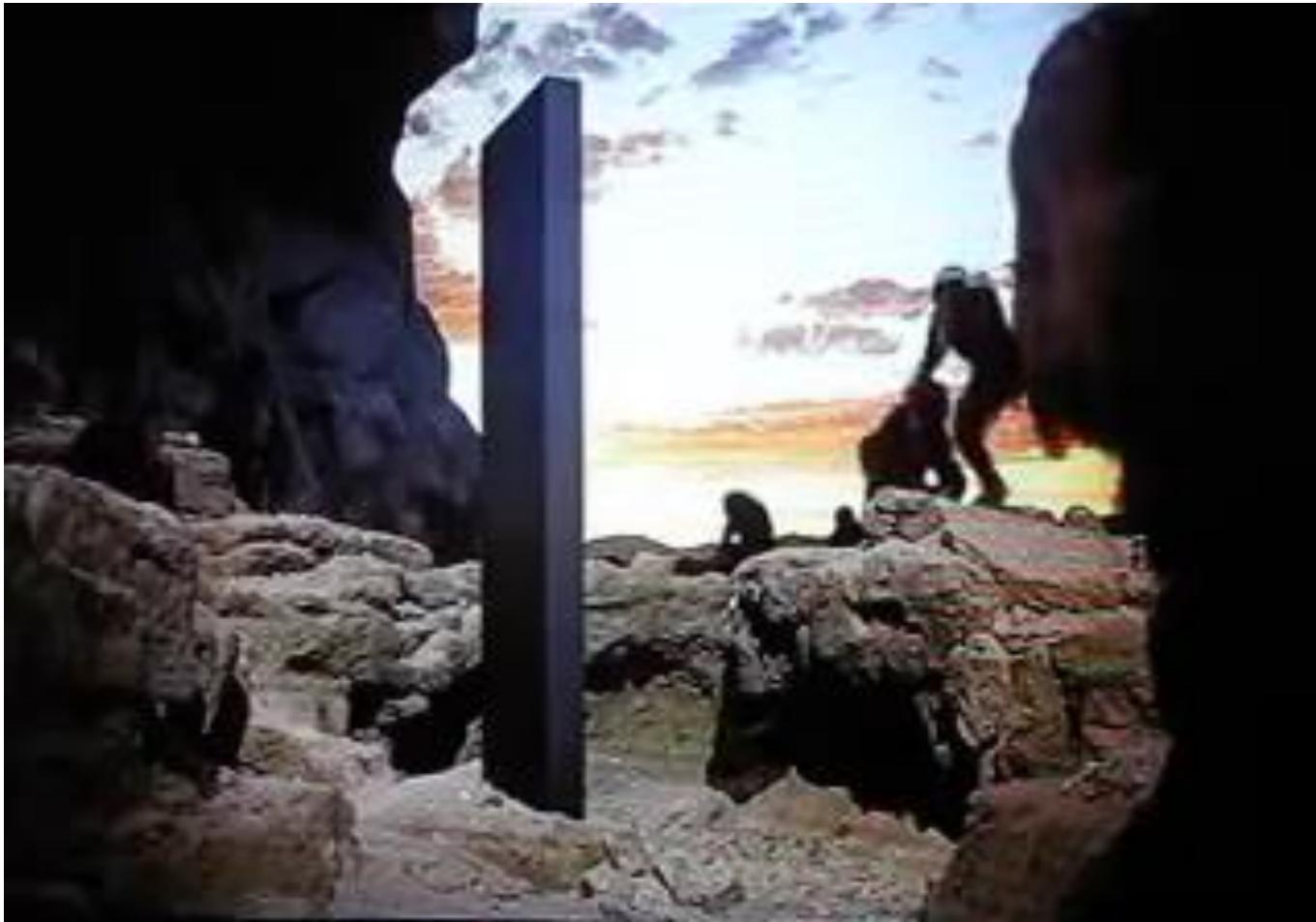
Marvin Minsky (MIT)

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



Soccer is harder than Chess

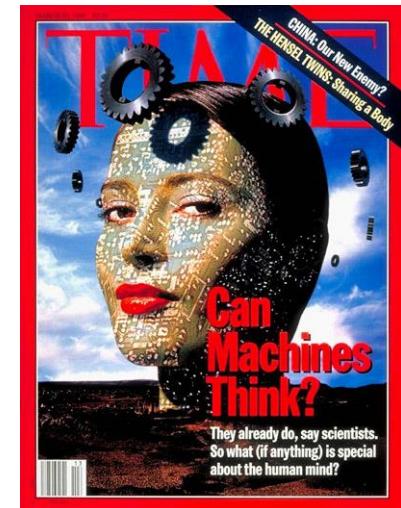




15.S14: Global Business of Artificial Intelligence (GBAIR)
Machine Learning: The Promise, Limitations, and Mystery of Thinking Machines
(Part 2)
Guest Lecture: [Lex Fridman](#)



Artificial Intelligence Technology: Limited or Limitless?



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Time →

Today

Future

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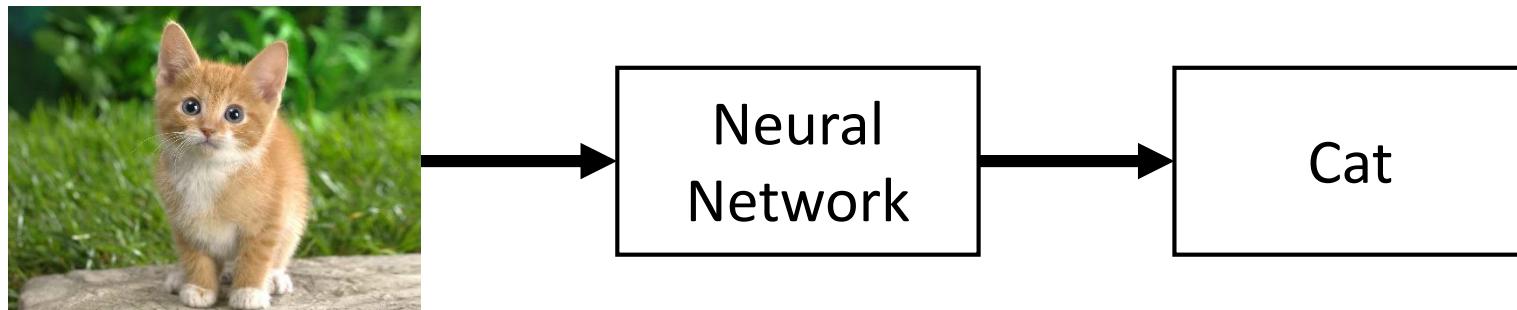
1. Overview current **approaches**
2. Highlight **limitations**
3. Discuss the **potential**
(and marvel at the mystery)

Best current answer:

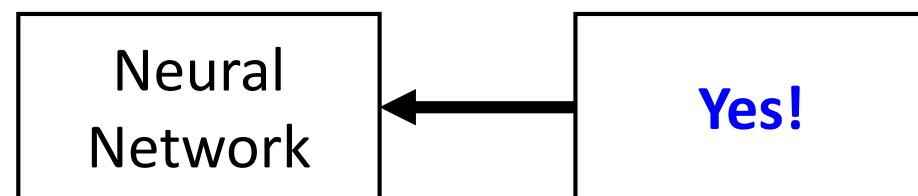
We Don't Know

How Neural Networks Learn: Backpropagation

Forward Pass:

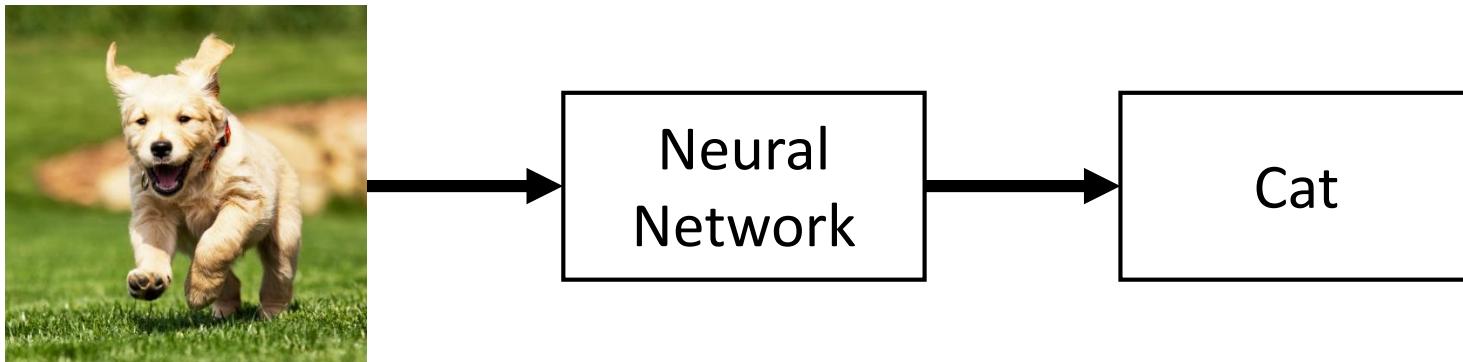


Backward Pass (aka Backpropagation):

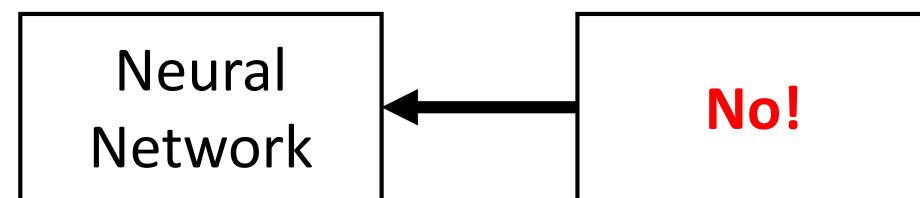


How Neural Networks Learn: Backpropagation

Forward Pass:

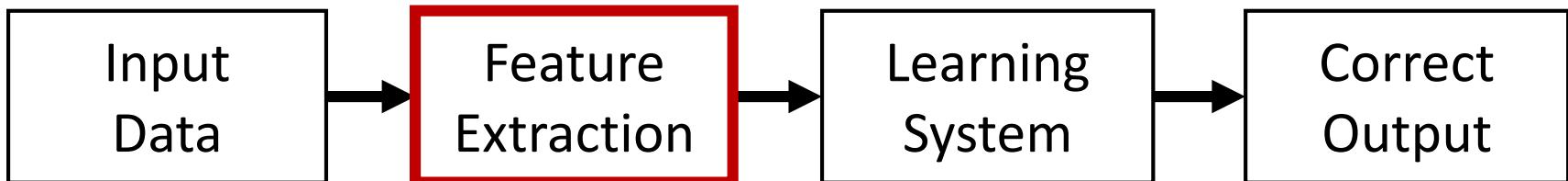


Backward Pass (aka Backpropagation):

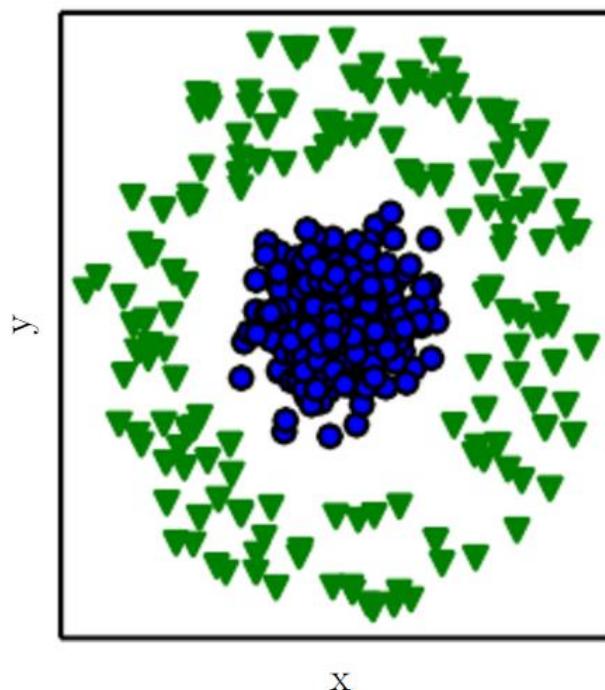


Representation Matters!

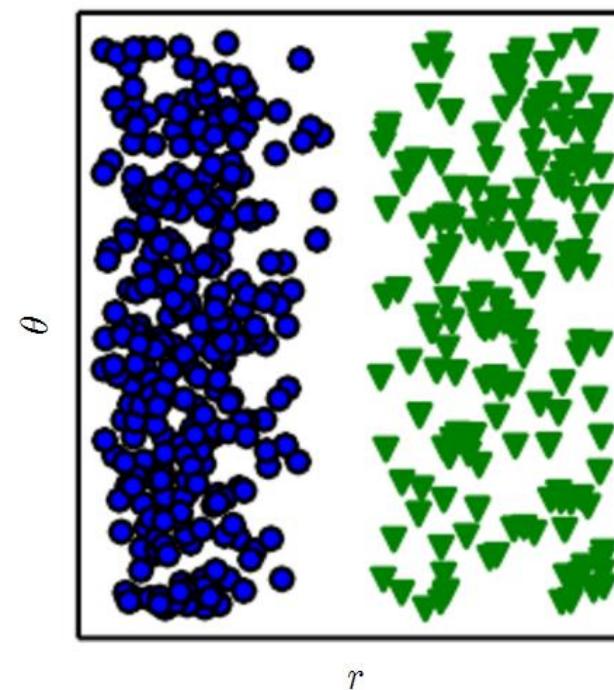
(Representation aka Features)



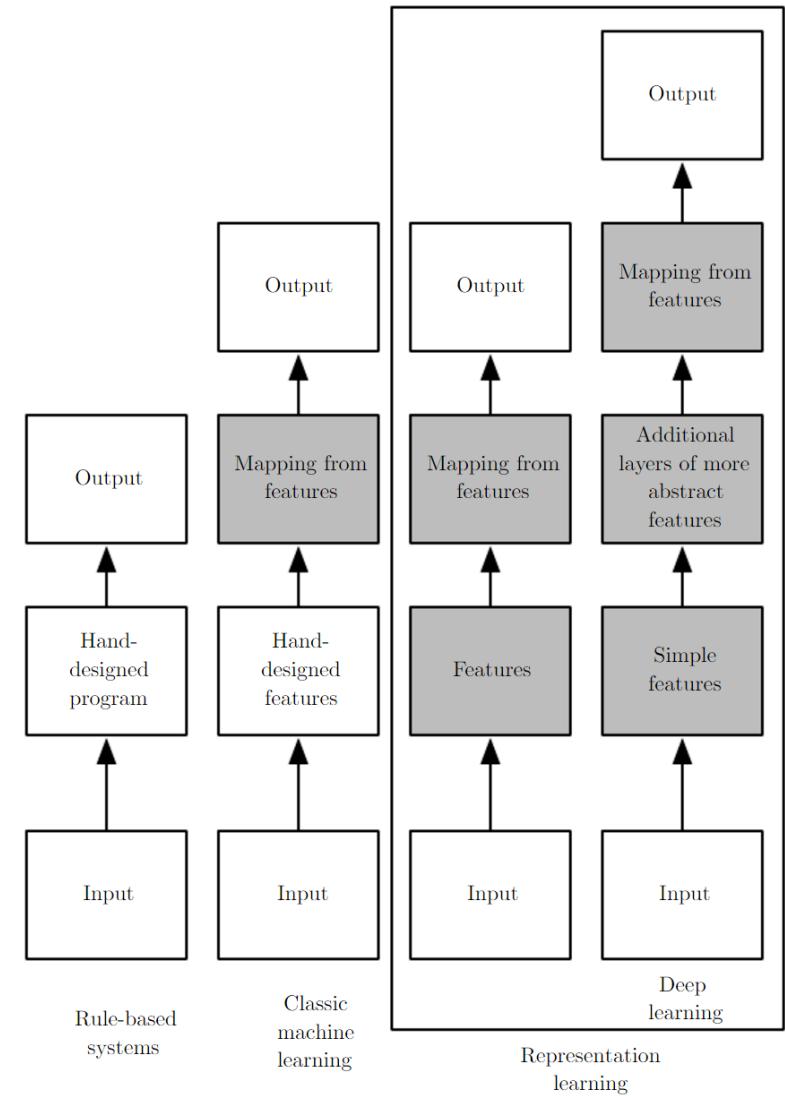
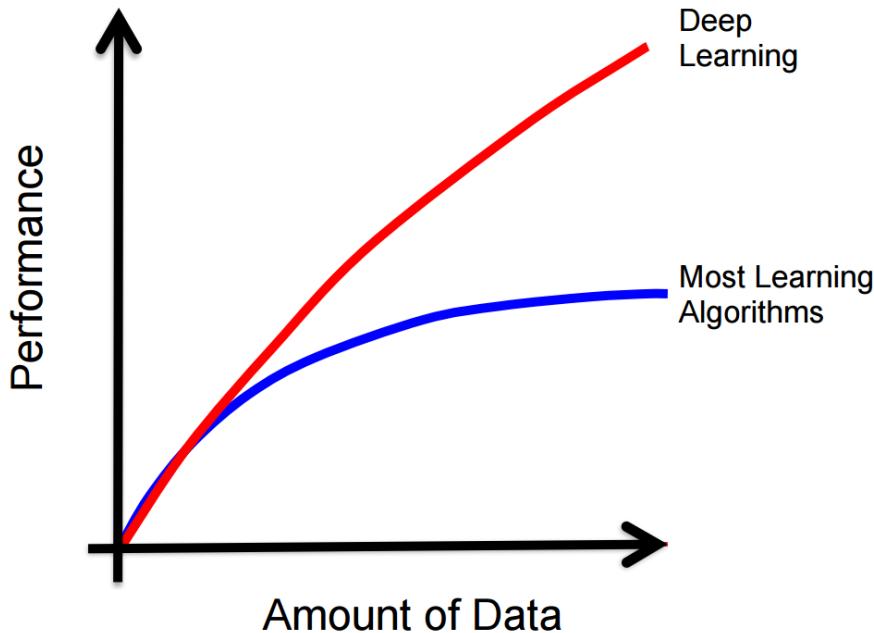
Cartesian coordinates

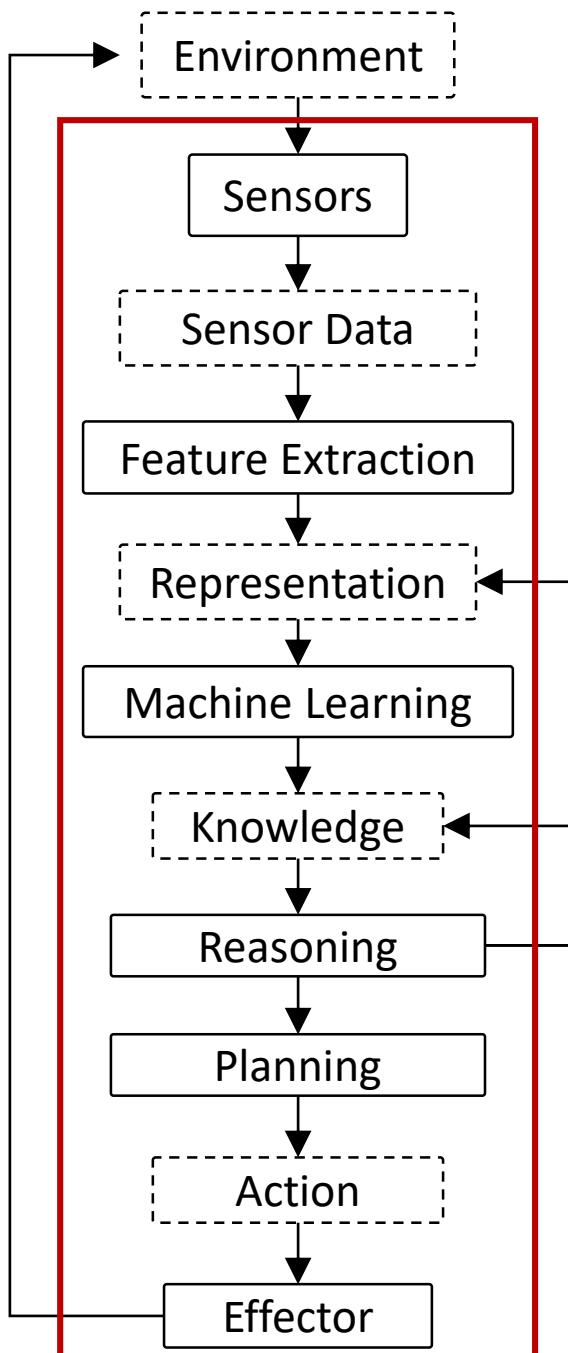


Polar coordinates



Deep Learning: Scalable Machine Learning





Open Question:
How much of this AI stack
can be **learned**?

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."

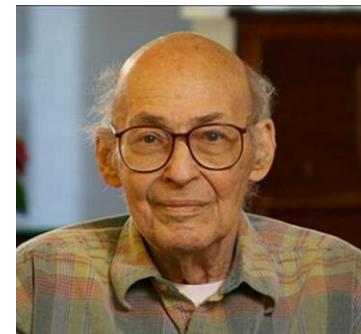
- Hans Moravec, *Mind Children* (1988)



Hans Moravec (CMU)

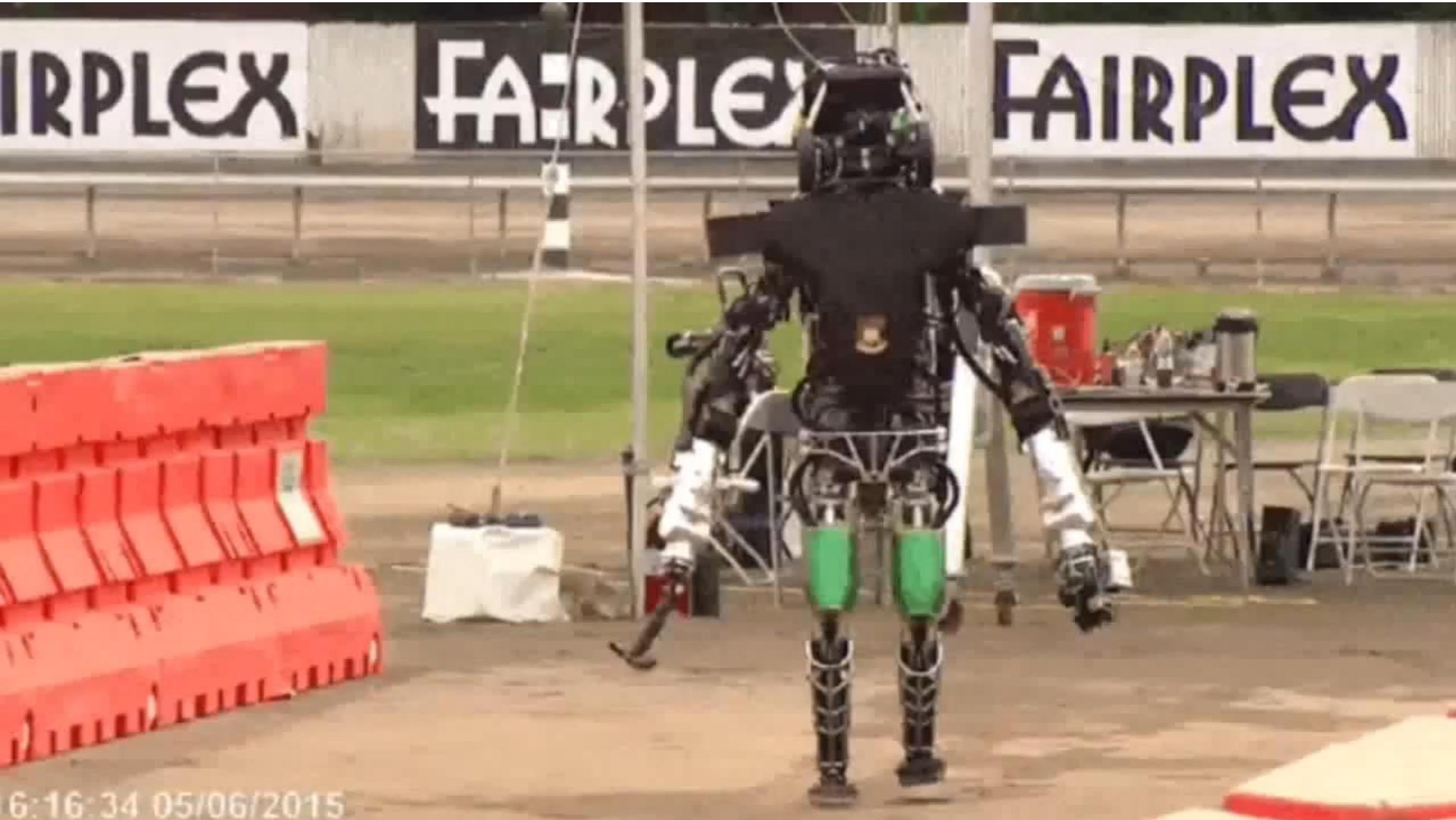


Rodney Brooks (MIT)



Marvin Minsky (MIT)

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



Challenge and Opportunity:

Real World Application

(Robustness)

Computer Vision for Intelligent Systems



3D Scene

Feature Extraction

Texture

Color

Optical Flow

Stereo Disparity

Grouping

Surfaces

Bits of objects

Sense of depth

Motion patterns

Interpretation

Objects

Agents and goals

Shapes and properties

Open paths

Words

Action

Walk, touch, contemplate, smile, evade, read on, pick up, ...

Images are Numbers



08	02	22	97	38	15	00	40	00	75	04	05	07	18	52	12	50	77	91	00
49	49	99	40	17	81	18	57	60	87	17	40	98	43	69	46	04	56	62	00
81	49	31	73	55	79	14	29	93	71	40	67	51	88	30	03	49	13	36	65
52	70	95	23	04	60	11	42	62	21	68	86	01	32	56	71	37	02	36	91
22	31	16	71	51	67	03	89	41	92	36	54	22	40	40	28	66	33	13	80
24	47	38	00	99	03	45	02	44	75	33	53	78	36	84	20	35	17	12	50
32	98	81	28	64	23	67	10	26	38	40	67	59	54	70	66	18	38	64	70
67	26	20	68	02	62	12	20	95	63	94	39	63	08	40	91	66	49	94	21
24	55	58	05	66	73	99	26	97	17	78	78	96	83	14	88	34	89	63	72
21	36	23	09	75	00	76	44	20	45	35	14	00	61	33	97	34	31	33	95
78	17	53	28	22	75	31	67	15	94	03	80	04	62	16	14	09	53	56	92
16	39	05	42	96	35	31	47	55	58	88	24	00	17	54	24	36	29	85	57
86	56	00	48	35	71	89	07	05	44	44	37	44	60	21	58	51	54	17	58
19	80	81	68	05	94	47	69	28	73	92	13	86	52	17	77	04	89	55	40
04	52	08	83	97	35	99	16	07	97	57	32	16	26	26	79	33	27	98	66
63	36	68	87	57	62	20	72	03	46	33	67	46	55	12	32	63	93	53	69
04	42	16	73	38	26	39	11	24	94	72	18	08	46	29	32	40	62	76	36
20	69	36	41	72	30	23	88	31	68	99	69	82	67	59	85	74	04	36	16
20	73	35	29	78	31	90	01	74	31	49	71	93	54	61	16	23	57	05	54
01	70	84	71	83	51	54	69	16	92	33	48	61	43	52	01	89	23	67	48

What the computer sees

image classification

82% cat
15% dog
2% hat
1% mug

Computer Vision is Hard

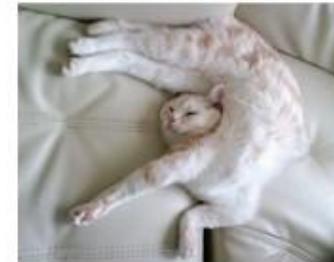
Viewpoint variation



Scale variation



Deformation



Occlusion



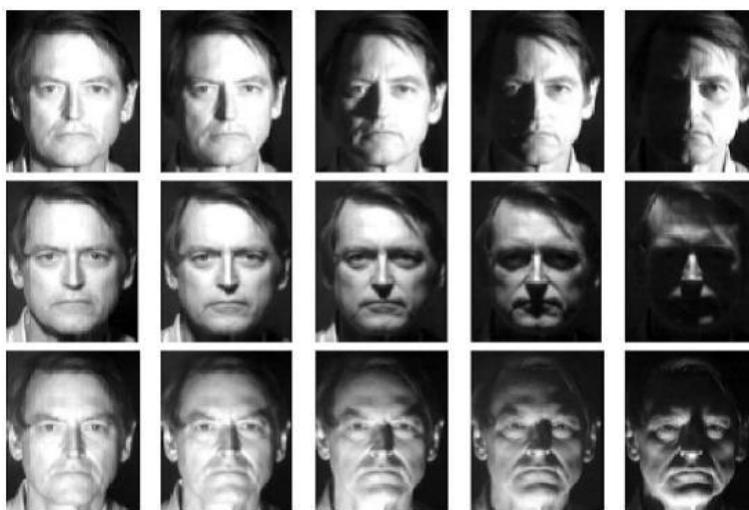
Illumination conditions



Background clutter



Intra-class variation



Object Classification Challenge: Occlusion



Object Classification Challenge: Occlusion



Object Classification Challenge: Occlusion



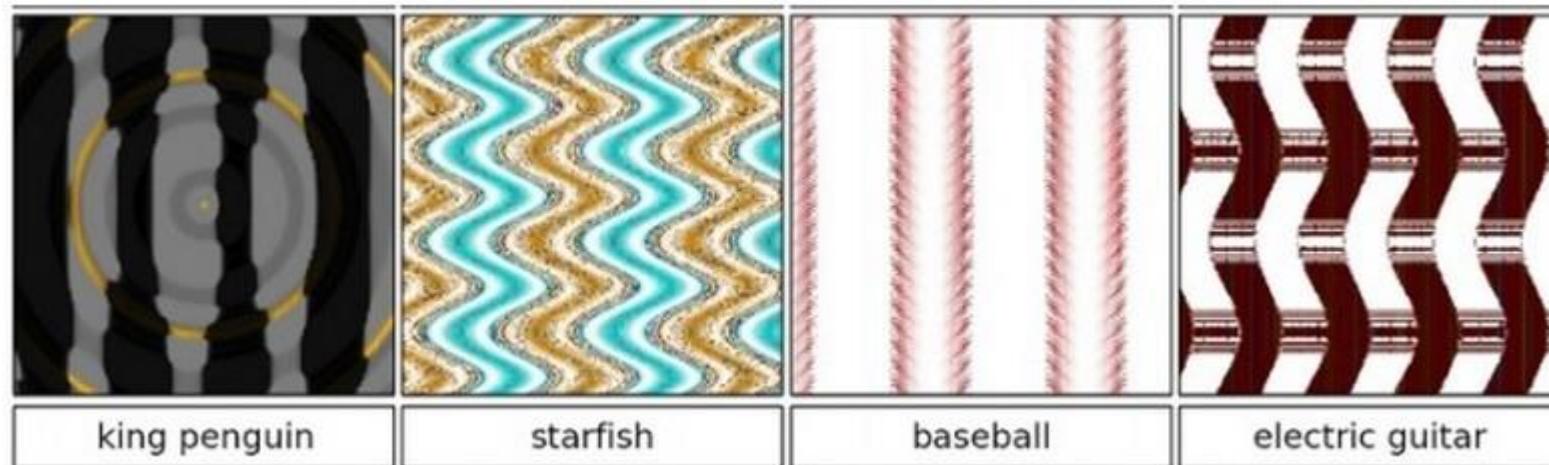
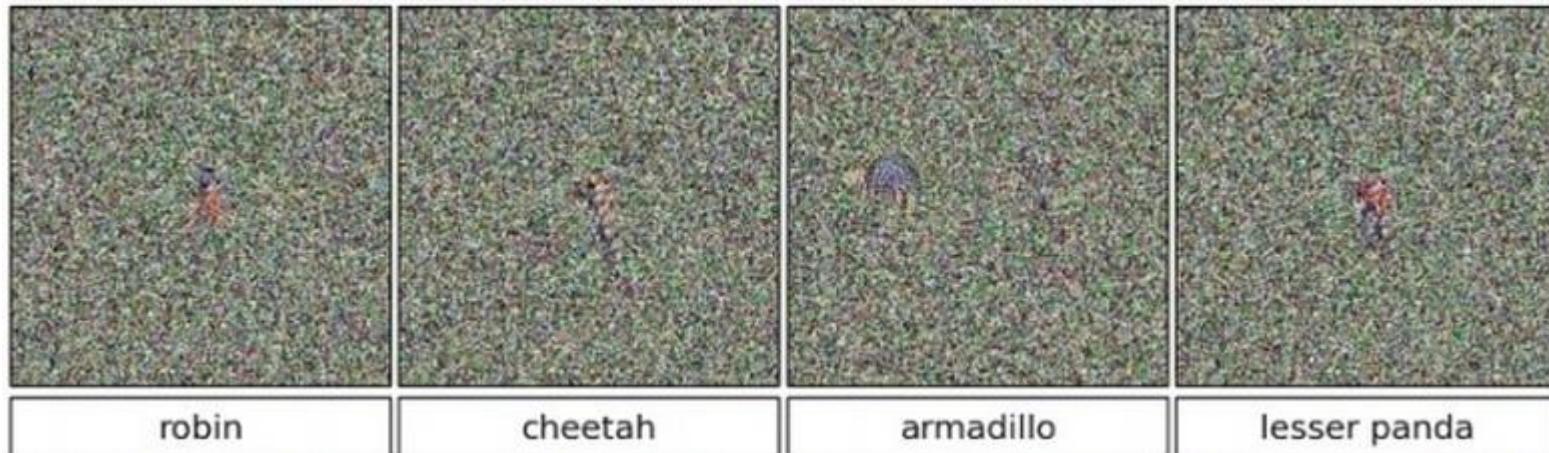
Object Classification Challenge: Occlusion



Object Classification Challenge: Occlusion



Robustness: >99.6% Confidence in the Wrong Answer



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

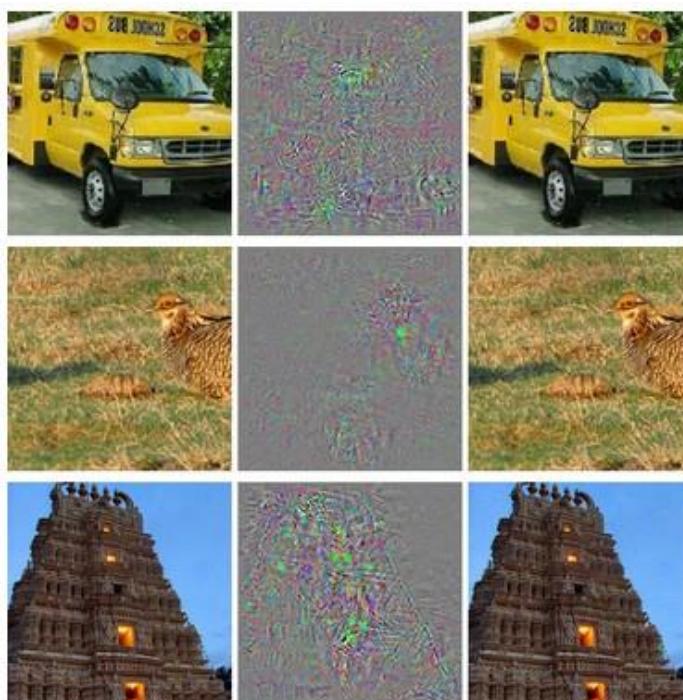
Robustness: Fooled by a Little Distortion



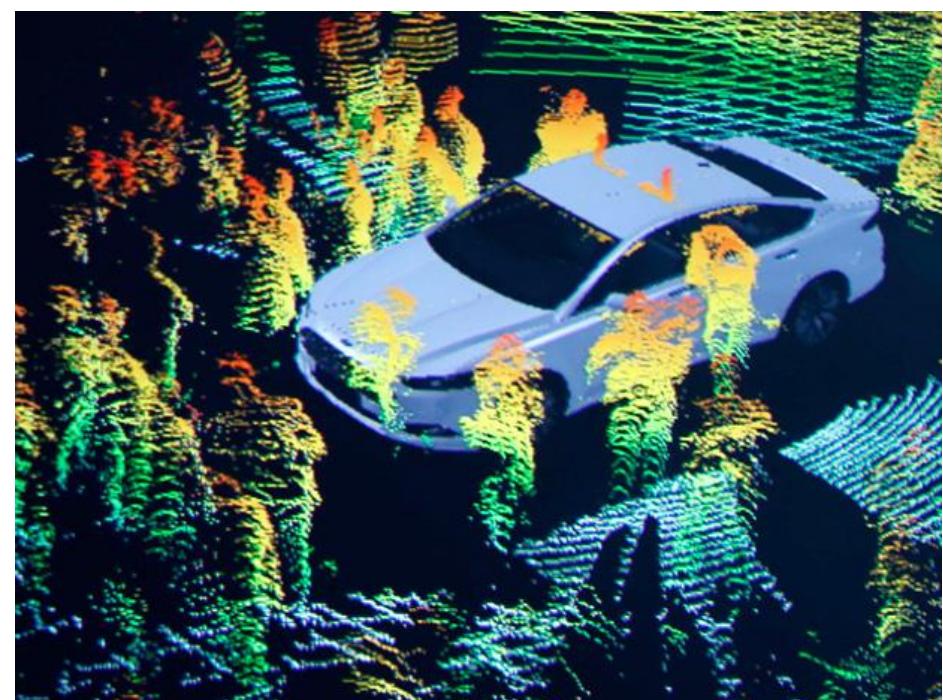
Szegedy et al. "Intriguing properties of neural networks." 2013.

Sensor Spoofing

Camera Spoofing



LIDAR Spoofing



Challenge and Opportunity:

Sparsely-Labeled Data

Current Challenges

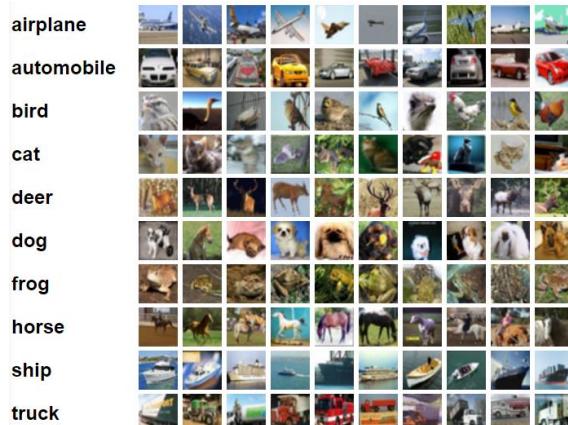
- **Lacks Reasoning:**
Unable to build unconstrained knowledge graphs from small human-defined seed graphs
- **Inefficient Learners:**
Every “concept” needs a lot of examples
- **Label Cost:**
Supervised data is costly

Supervised Data Example: Computer Vision Datasets

9 3 1 9 7 2 4 5 1 0 3 2 4 3 7 5 9 0 3 4 9
3 0 2 4 2 9 4 8 3 2 0 1 3 5 3 5 7 4 6 8 5
2 8 2 3 2 3 8 2 4 9 8 2 9 1 3 9 1 1 1 9 9
6 3 6 9 0 3 6 0 3 0 1 1 3 9 3 1 5 0 4 9 6
3 3 8 0 7 0 5 6 9 8 8 4 1 4 4 4 6 9 5 3 3
1 1 9 5 8 0 4 3 7 7 5 0 5 4 2 0 9 8 1 2 4
9 5 0 0 5 1 1 1 7 4 7 7 2 6 5 1 8 2 4 1 1
0 2 1 6 1 7 0 9 5 6 3 2 6 6 7 1 5 2 3 2
9 4 3 2 1 0 0 2 0 8 7 4 0 9 7 9 3 6 9 3 4
5 5 1 6 6 2 7 6 7 5 6 6 5 8 1 6 8 7 1 0 5
7 1 7 5 9 2 3 9 4 3 0 4 5 8 0 0 4 0 4 6 6
1 6 7 9 6 4 1 1 4 1 3 1 2 3 4 8 1 5 5 0 7
0 1 6 1 6 7 5 5 5 6 6 8 8 1 7 2 8 3 7 6 5
6 4 6 8 7 7 1 3 0 7 3 8 6 9 1 6 7 3 6 4 8
7 9 7 3 1 3 9 7 9 3 6 2 4 9 2 1 4 5 0 3 8

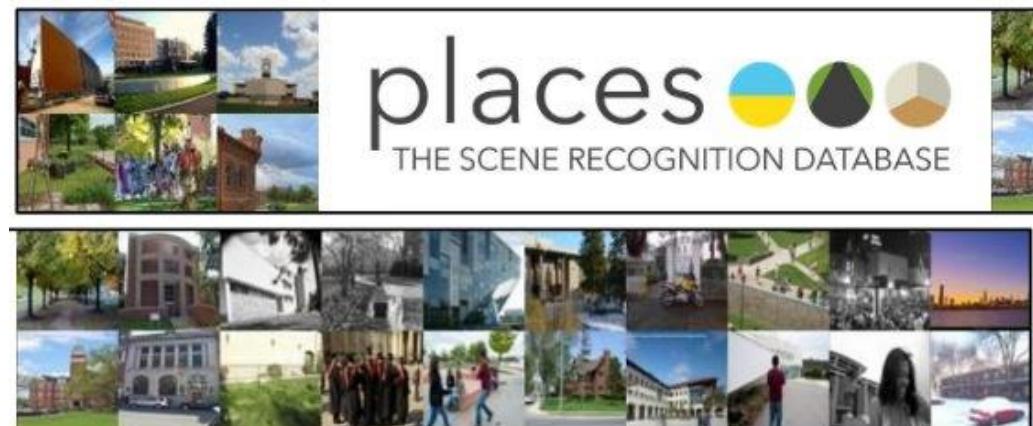
printer housing animal weight drop headquarters egg white
offspring teacher computer album garage down flower television
register measure court key structure light date spread breakfast
gallery horse press market lighter
king fireplace church concert pack
hotel road paper cup coffee
sport screen wall means fan hill can camp fish bathroom
sky plant tree file tower railcar
bread wine fox house school stock film
weapon table top man car gun
cloud cover top man car fly study
spring range leash van net button
descent fruit dog bed shop people sign
kitchen train kit roll goal
engine camera memoriesieve cell bar watch
chain stone boat tea overall sleeve center step
dinner apple girl flat stand student
home room office rule hall
flag bank valley cross chair mine castle club
radio beach support level line street golf
base library stage video food building
tool material player machine security call clock
football hospital match equipment cell phone mountain telephone
short circuit bridge scale gas pedal microphone recording crowd

MNIST: handwritten digits



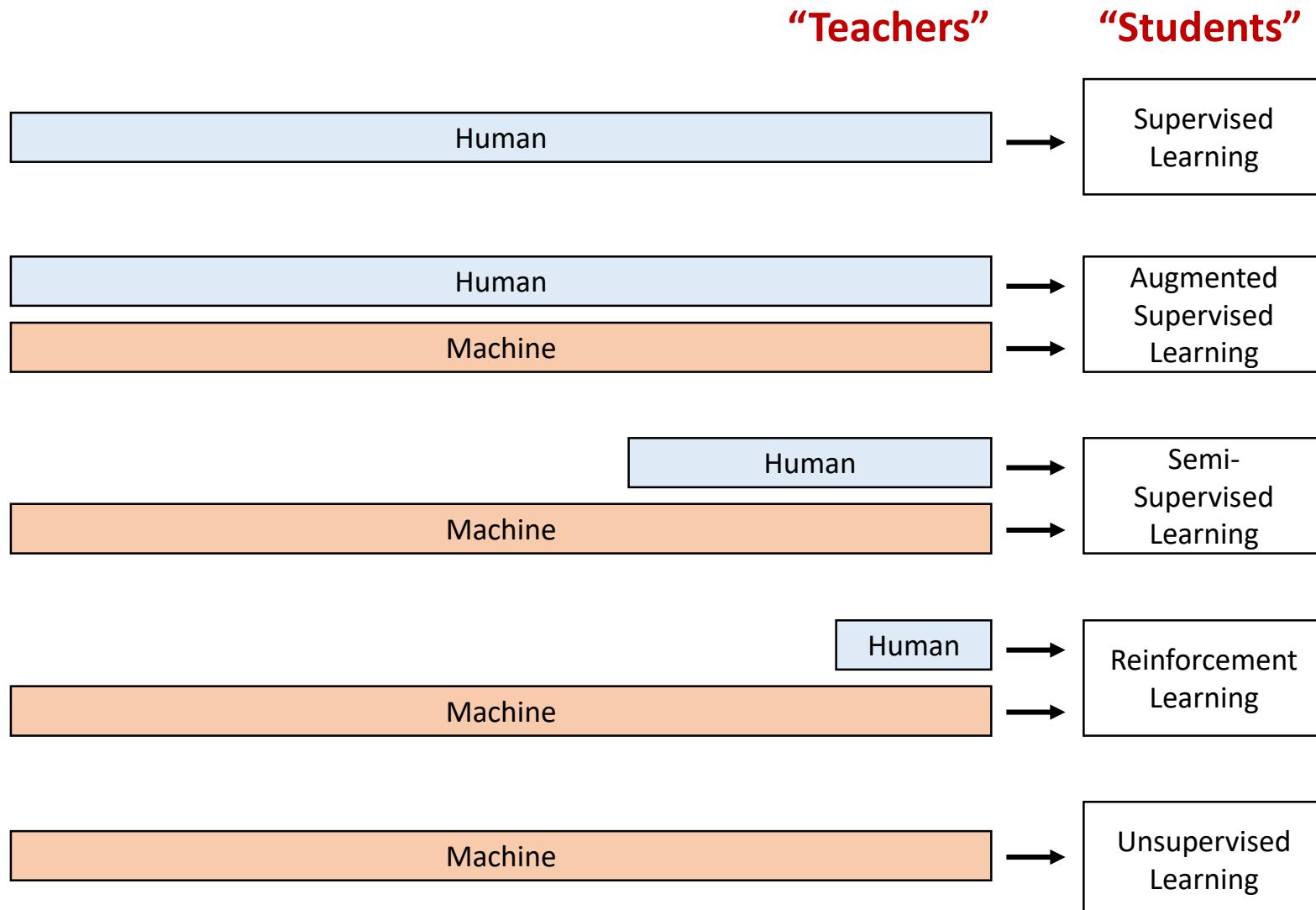
CIFAR-10(0): tiny images

ImageNet: WordNet hierarchy

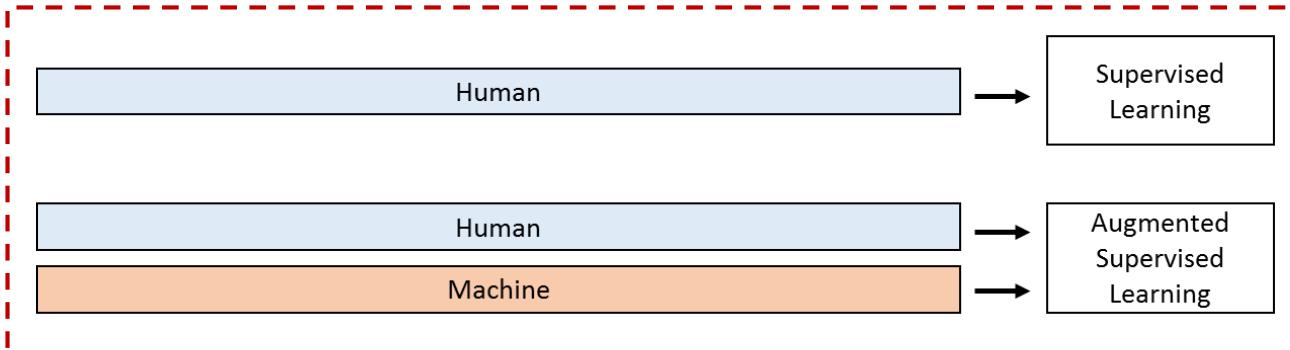


Places: natural scenes

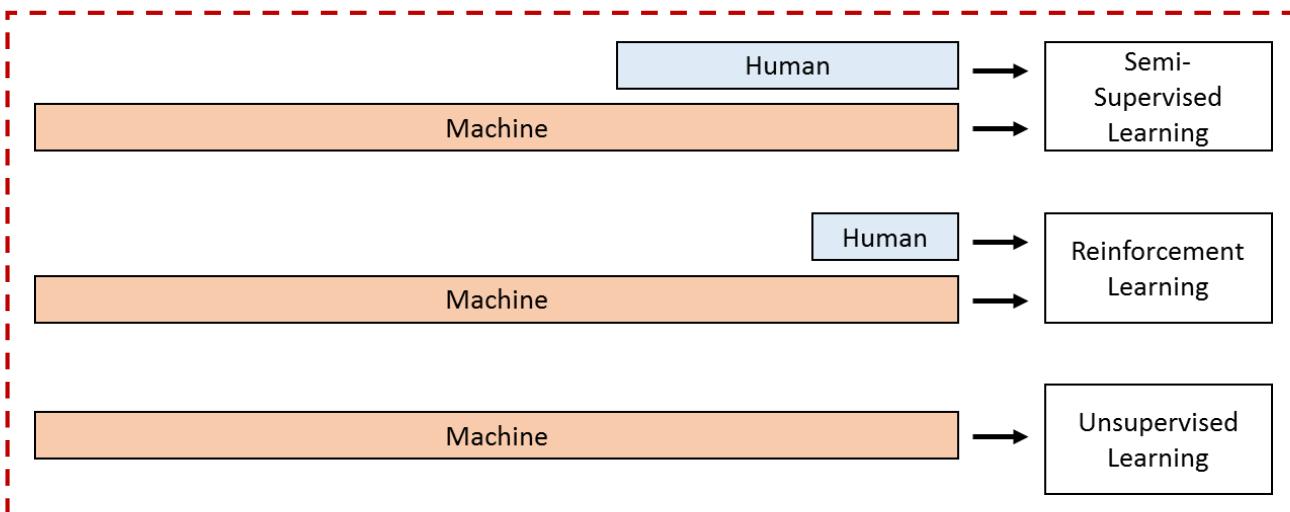
Machine Learning from Human and Machine



Machine Learning from Human and Machine



Memorization



Understanding

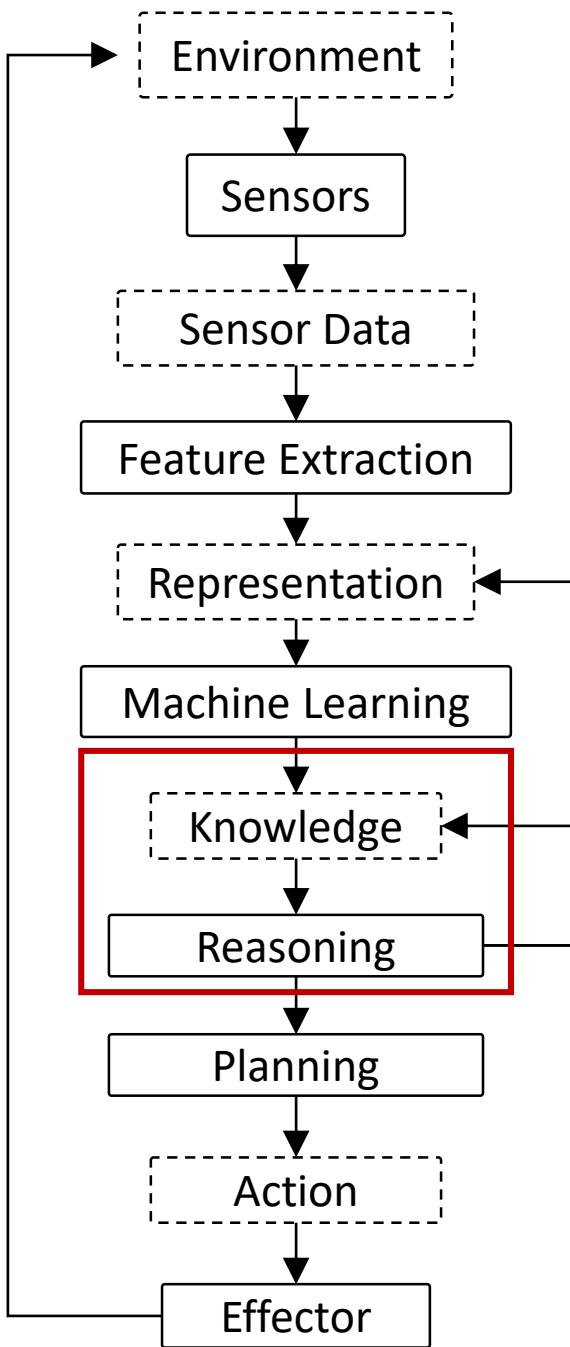


Image Recognition:
If it looks like a duck



Audio Recognition:
Quacks like a duck

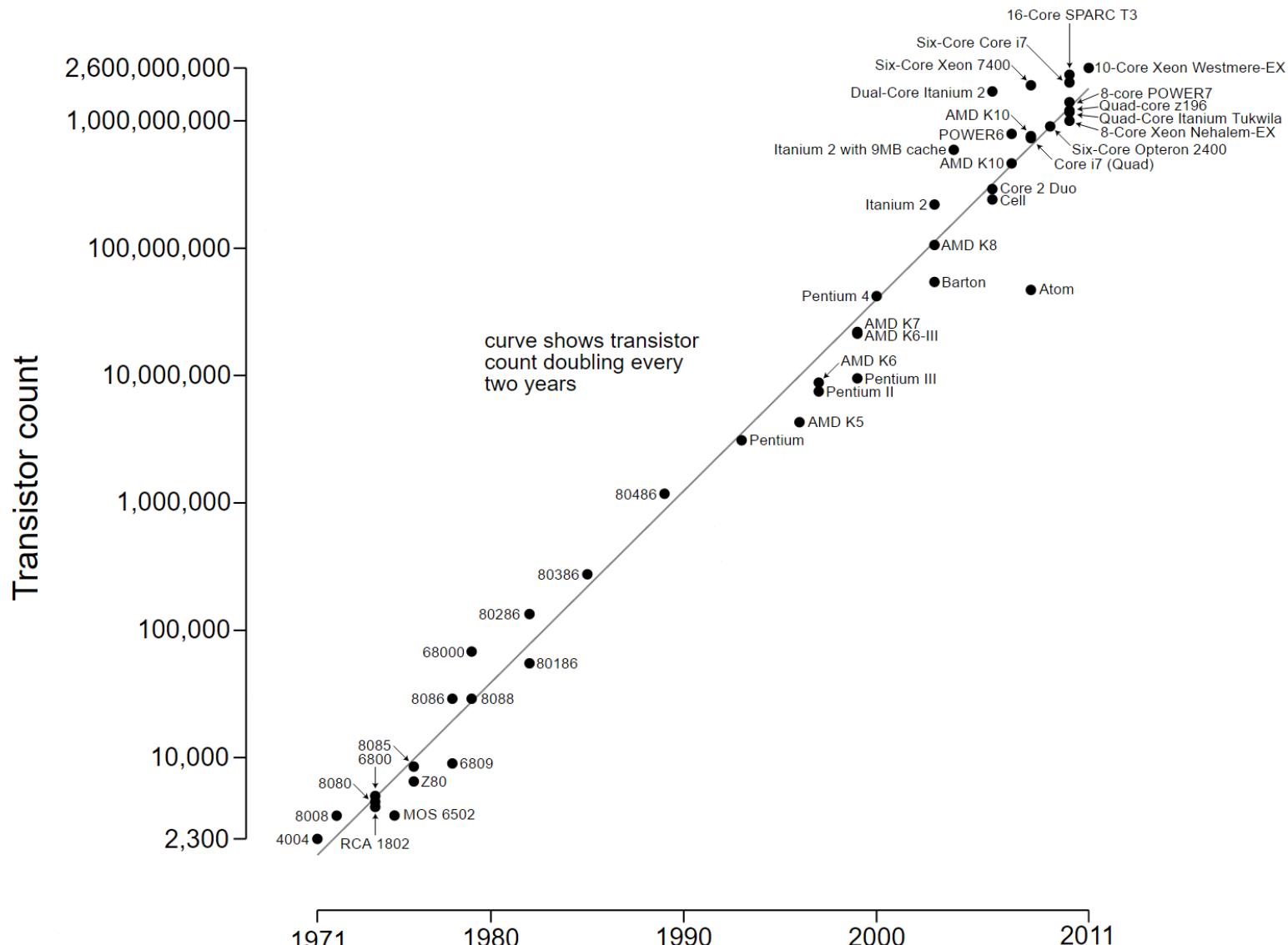


Activity Recognition:
Swims like a duck

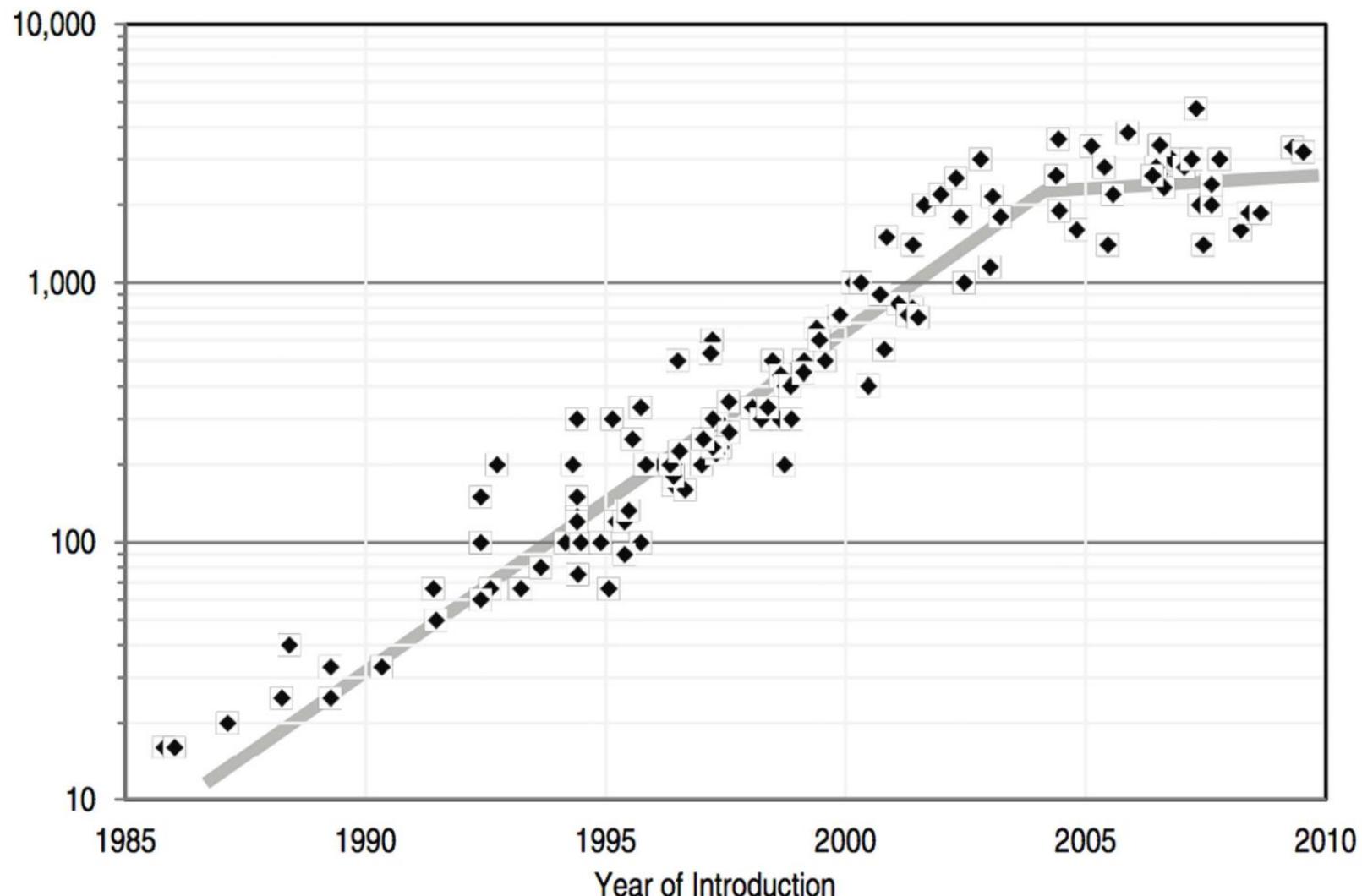


Challenge and Opportunity: Compute

Microprocessor Transistor Counts 1971-2011 & Moore's Law



National Academy of Sciences: Clock Speed (MHz) Scaling Hits a Wall



Intel: Innovation Continues

(Aggressively Solving Technical Challenges)

Innovation Enabled Technology Pipeline

Our Visibility Continues to Go Out ~10 Years

32nm
2009

22nm
2011

14nm
2013

10nm

7nm
2015+

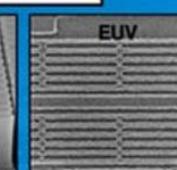
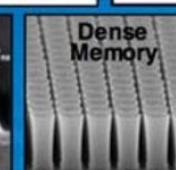
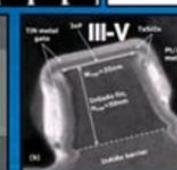
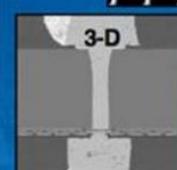
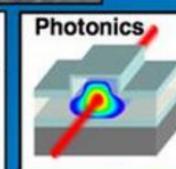
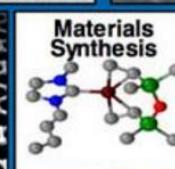
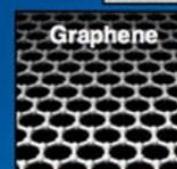
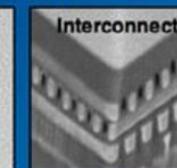
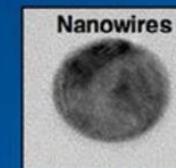
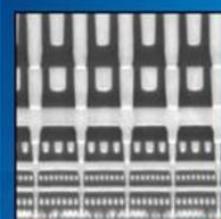
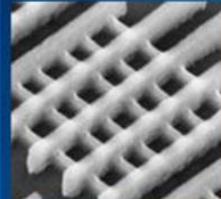
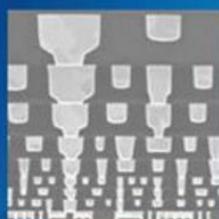
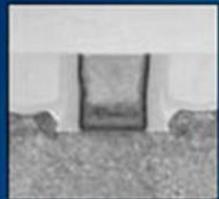
5nm

Manufacturing

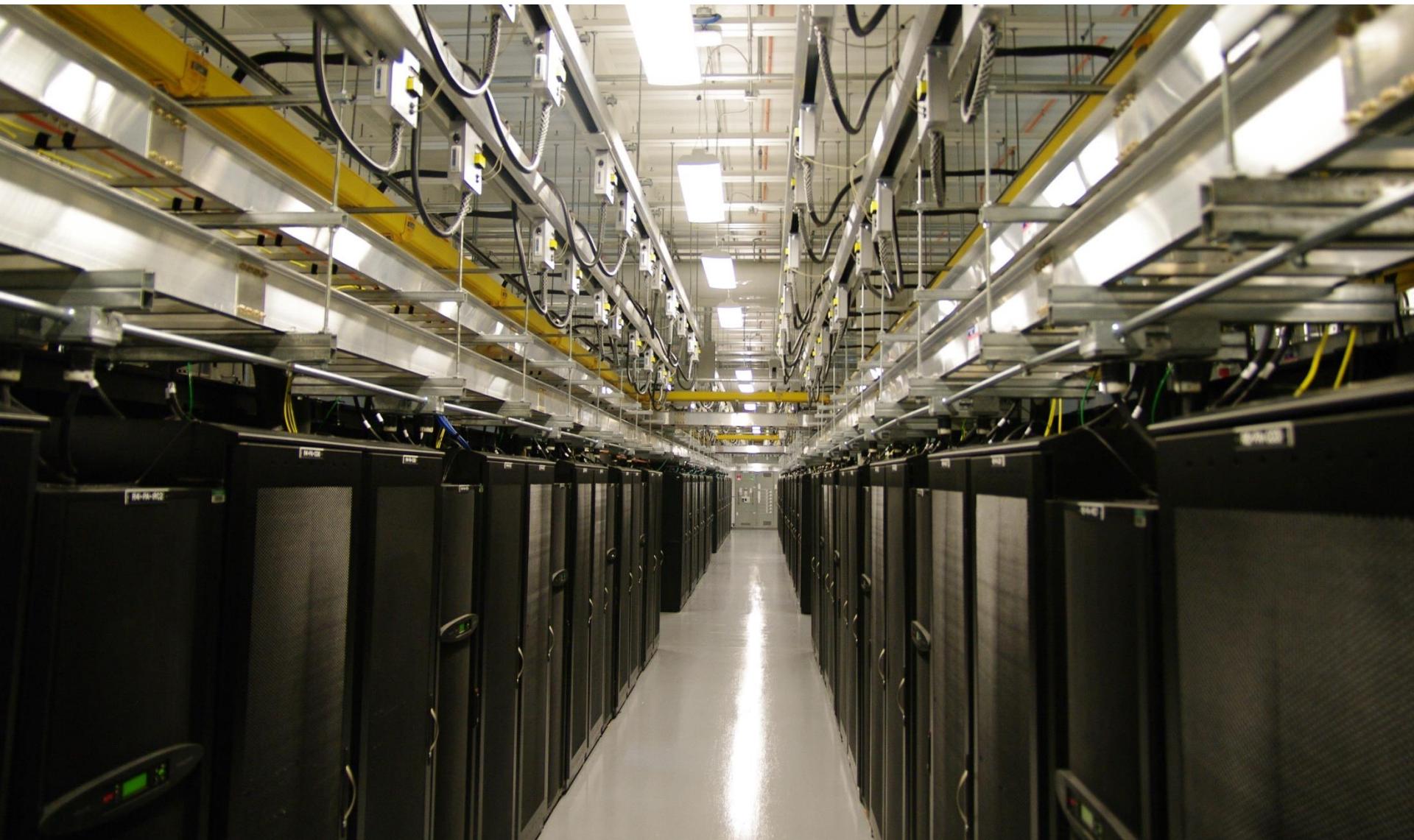
Development

Research

Future Options



Beyond Moore's Law: Machine Learning Massive Parallelism & Distributed Compute

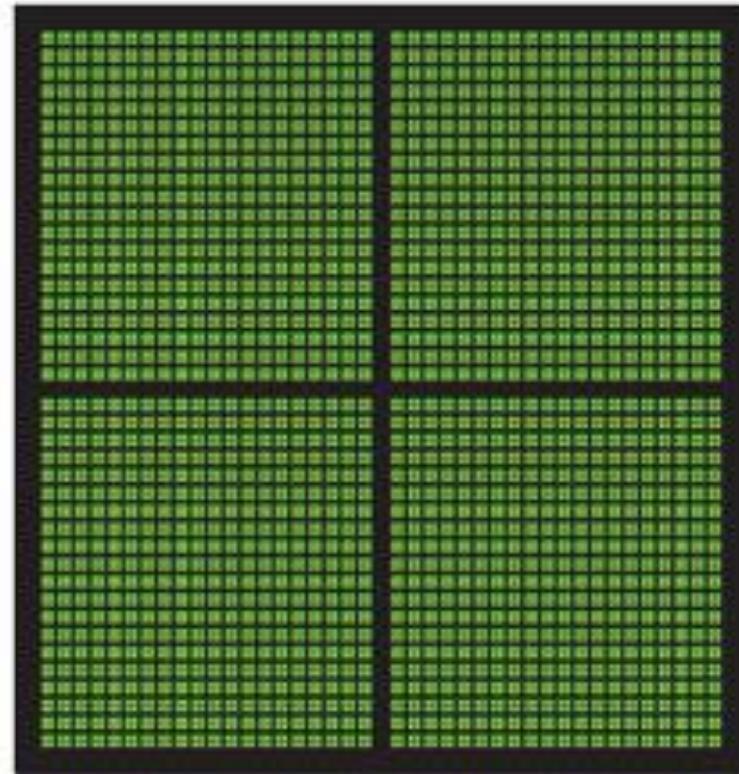


Beyond Moore's Law: Machine Learning

Graphics Processing Unit (GPU) Parallelism

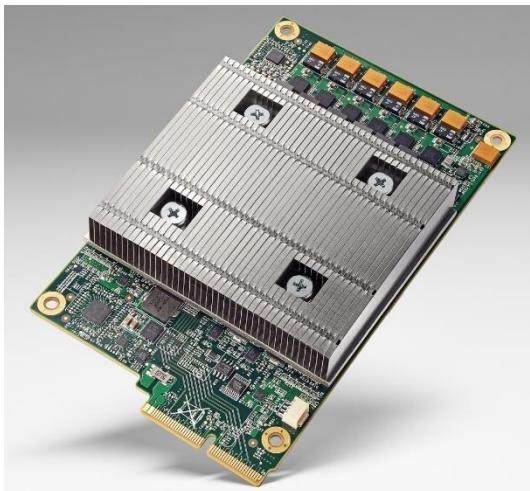


CPU
MULTIPLE CORES



GPU
THOUSANDS OF CORES

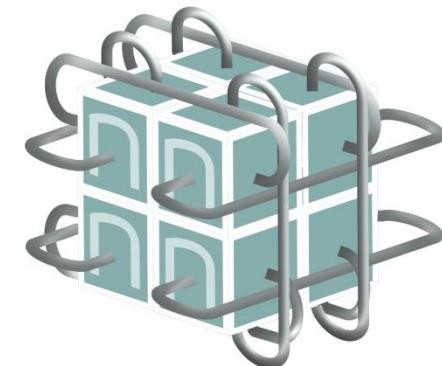
Beyond Moore's Law: Machine Learning Custom Deep Neural Network Chips



Google Tensor
Processing Unit



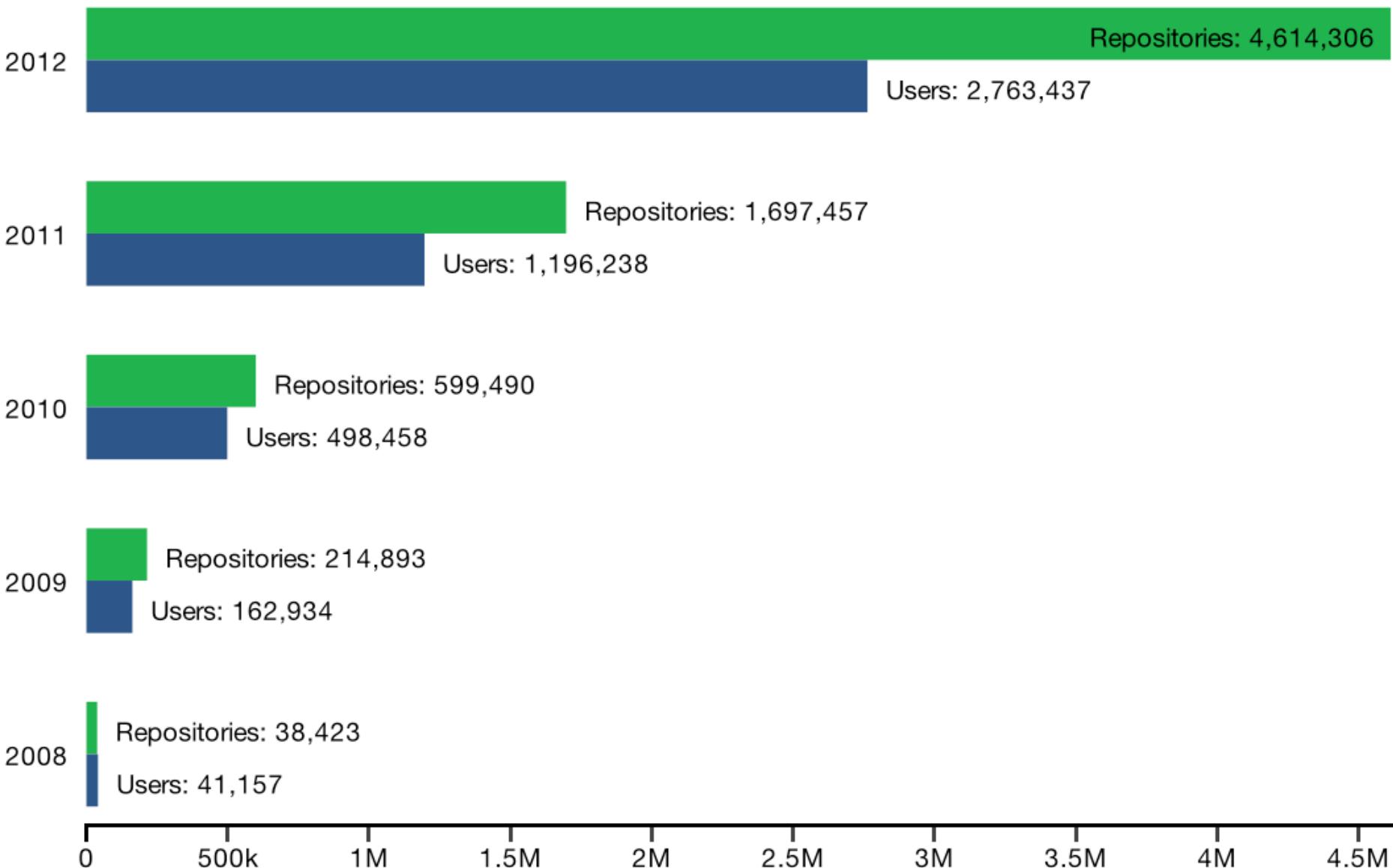
IBM True North
(Brain-Inspired Chip)



Intel Deep Learning Chip
(Nervana Acquisition)

Challenge and Opportunity: Community

GitHub Growth

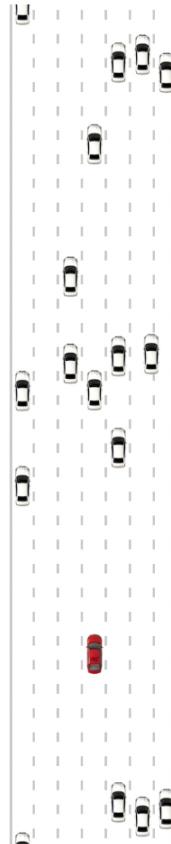


DeepTraffic

Americans spend 8 billion hours stuck in traffic every year.

Deep neural networks can help!

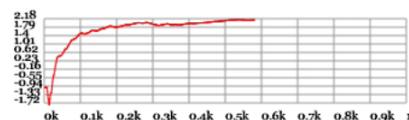
Speed:
80 mph
Cars Passed:
290



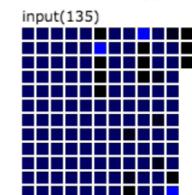
Road Overlay:

Simulation Speed:

```
1 //<![CDATA[
2 // a few things don't have var in front of them - they update already
3 // existing variables the game needs
4 lanesSide = 1; //1;
5 patchesAhead = 10; //13;
6 patchesBehind = 0; //7;
7 trainIterations = 100000;
8
9 // begin from convnetjs example
10 var num_inputs = (lanesSide * 2 + 1) * (patchesAhead + patchesBehind);
11 var num_actions = 5;
12 var temporal_window = 3; //1 // amount of temporal memory. 0 = agent lives
in-the-moment :)
13 var network_size = num_inputs * temporal_window + num_actions *
```



Value Function Approximating Neural Network:

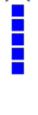
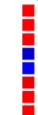
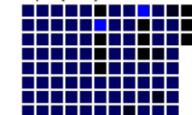


fc(10)

relu(10)

fc(5)

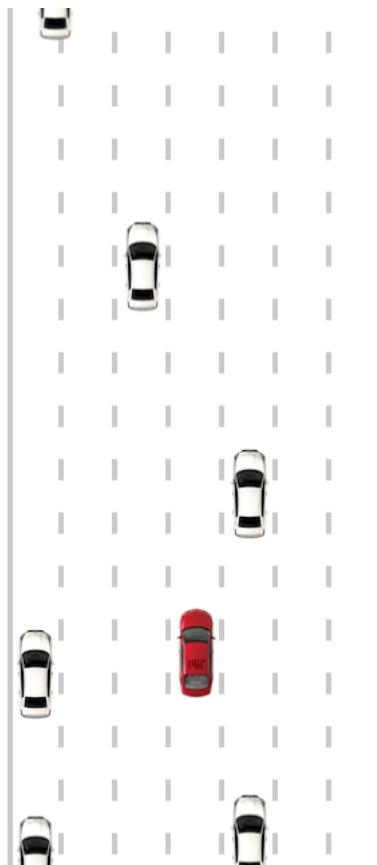
regression(5)



<http://cars.mit.edu>

The Road, The Car, The Speed

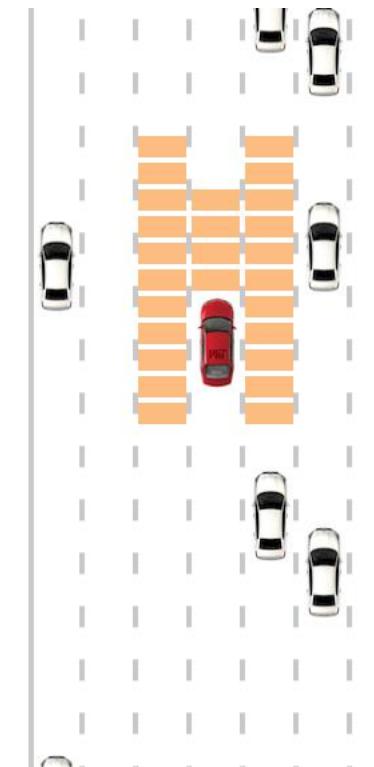
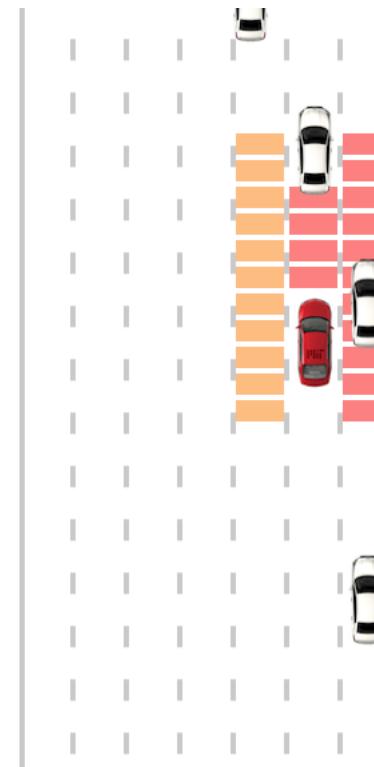
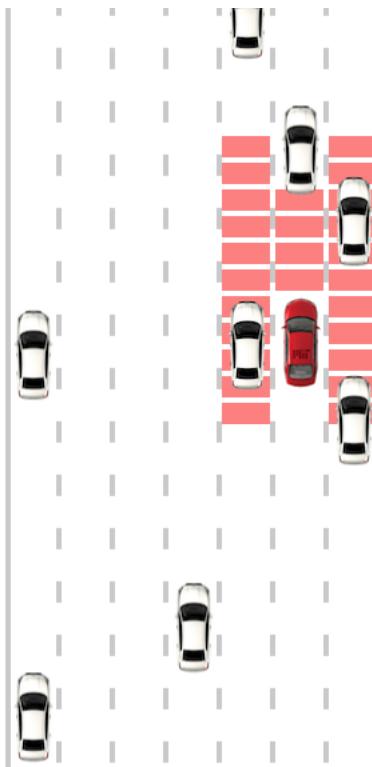
Speed:
47 mph
Cars Passed:
5



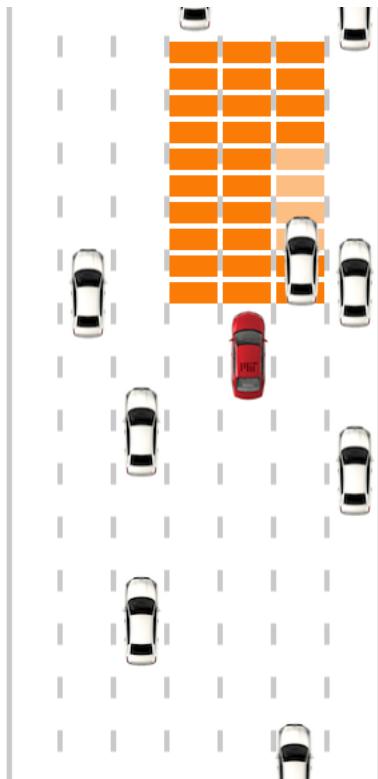
State Representation:



“Safety System”



Learning Input

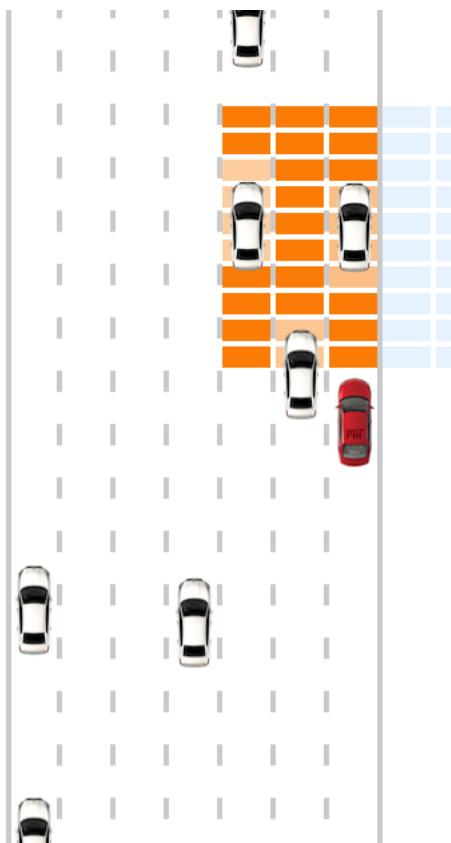


Road Overlay:

Learning Input ▾

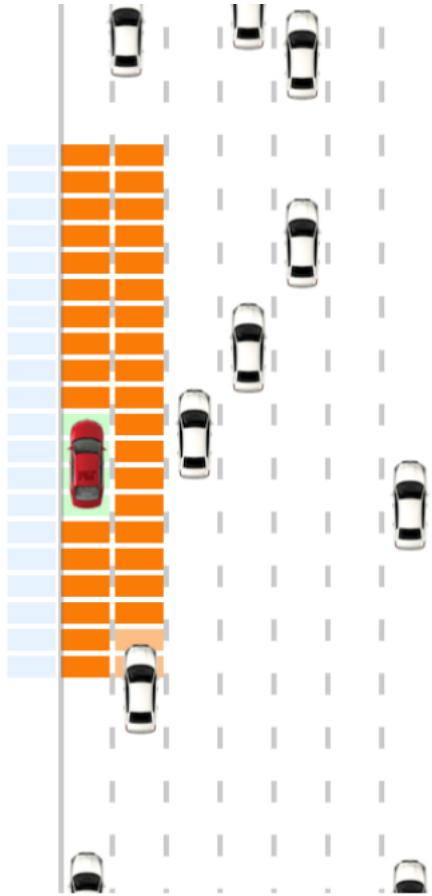
```
lanesSide = 1;  
patchesAhead = 10;  
patchesBehind = 0;
```

Learning Input



```
lanesSide = 2;  
patchesAhead = 10;  
patchesBehind = 0;
```

Learning Input

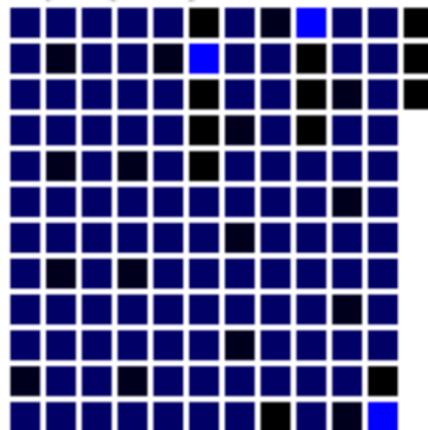


```
lanesSide = 1;  
patchesAhead = 10;  
patchesBehind = 10;
```

Deep RL: Q-Function Learning Parameters

Value Function Approximating Neural Network:

input(135)



fc(10)



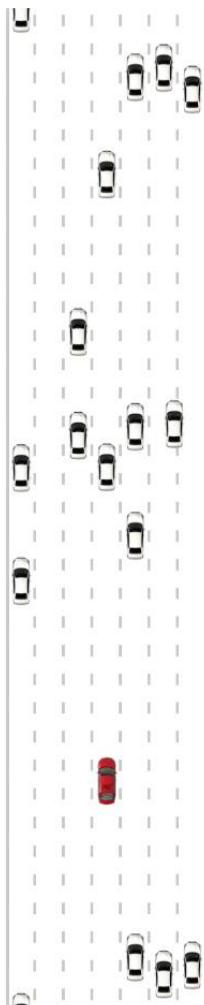
relu(10)fc(5)



regression(5)



```
var num_inputs = (lanesSide * 2 + 1) * (patchesAhead + patchesBehind);
var num_actions = 5;
var temporal_window = 3;
var network_size = num_inputs * temporal_window + num_actions *
temporal_window + num_inputs;
```



DeepTraffic

<http://cars.mit.edu>

We ran a competition, and in one month:

- 250 submission from MIT
- 10,000+ submissions from outside MIT

DeepTraffic

<http://cars.mit.edu>

In MIT



Purnawirman (74.48 mph)

Winnings: [Deep Learning book \(Goodfellow et al.\)](#)

Comment: "I used a single hidden layer. I also used a learning rate of 0.001. I initialized the weights with a uniform distribution between -0.1 and 0.1. I used a window size of 5. I set the learning rate to 0.001. I spent some time on hyperparameters, because the test scores have a big impact on the final result."



Michael Gump (74.04 mph)

Winnings: [Udacity Self-Driving Car Engineering Nanodegree](#)

Comment: "I mainly played around with the network architecture. I found that a simple fully connected network with two layers would get stuck in suboptimal strategies. I eventually added a convolutional layer to the network, which improved the performance significantly."



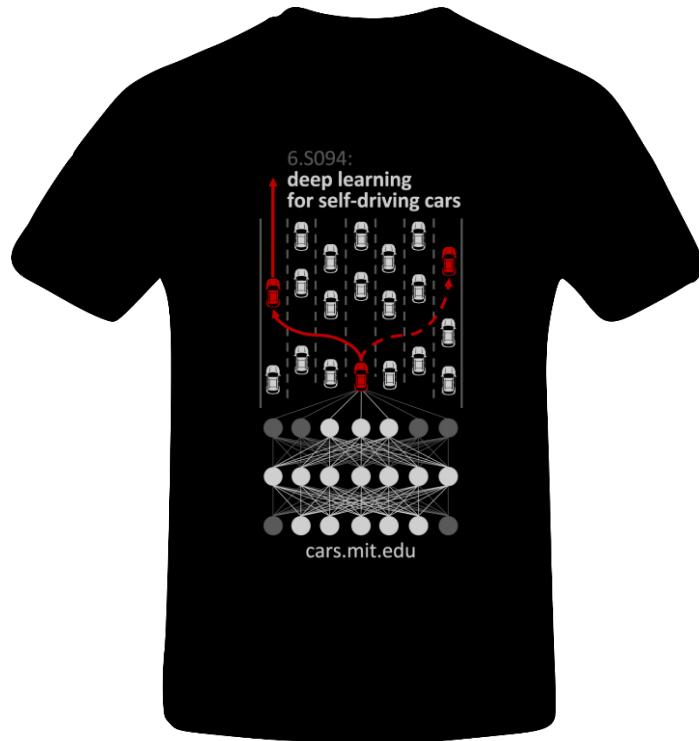
Jeffrey Hu (73.59 mph)

Winnings: [Udacity Self-Driving Car Engineering Nanodegree](#)

Comment: "I preprocessed the input images by resizing them to 64x64 pixels. I then used a two-layer fully connected network. Then I tried different activation functions and loss functions to get the network to converge."

Outside MIT

User	MPH
Hoan Nguyen	76.29
Jorcus96	76.16
leiming yu	75.97
jordan ott	75.86
Nándor Kedves	75.83
3upperm2n	75.80
Mark S.	75.73
Diego Rojo U-tad	75.69
katypiano	75.62



DeepTraffic

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Challenge to GBAIR Students:
Make a neural network
that travels 70+ mph.

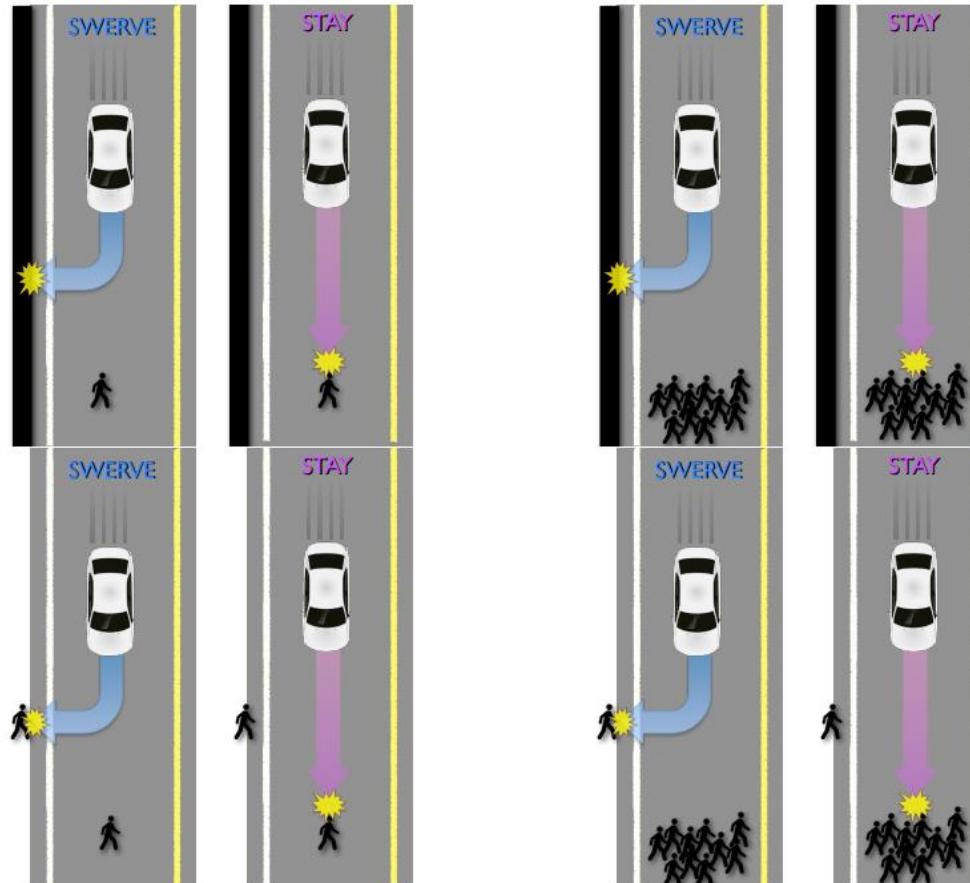
Challenge and Opportunity:

Reward Function

(aka Ethics)

Defining a Good Reward Function is Difficult

This example is popular but is not an engineering challenge as it's faced by both humans and machines alike.



Instead, we want to answer the engineering question...



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.

All references cited in this presentation are listed in the following Google Sheets file: <https://goo.gl/wDHwnU>

Question?

