15.S14: Global Business of Artificial Intelligence (GBAIR)

Machine Learning: The Promise, Limitations, and Mystery of Thinking Machines

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https://lex.mit.edu

Artificial Intelligence Technology: Limited or Limitless?

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

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

Time → Today → *Future*

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

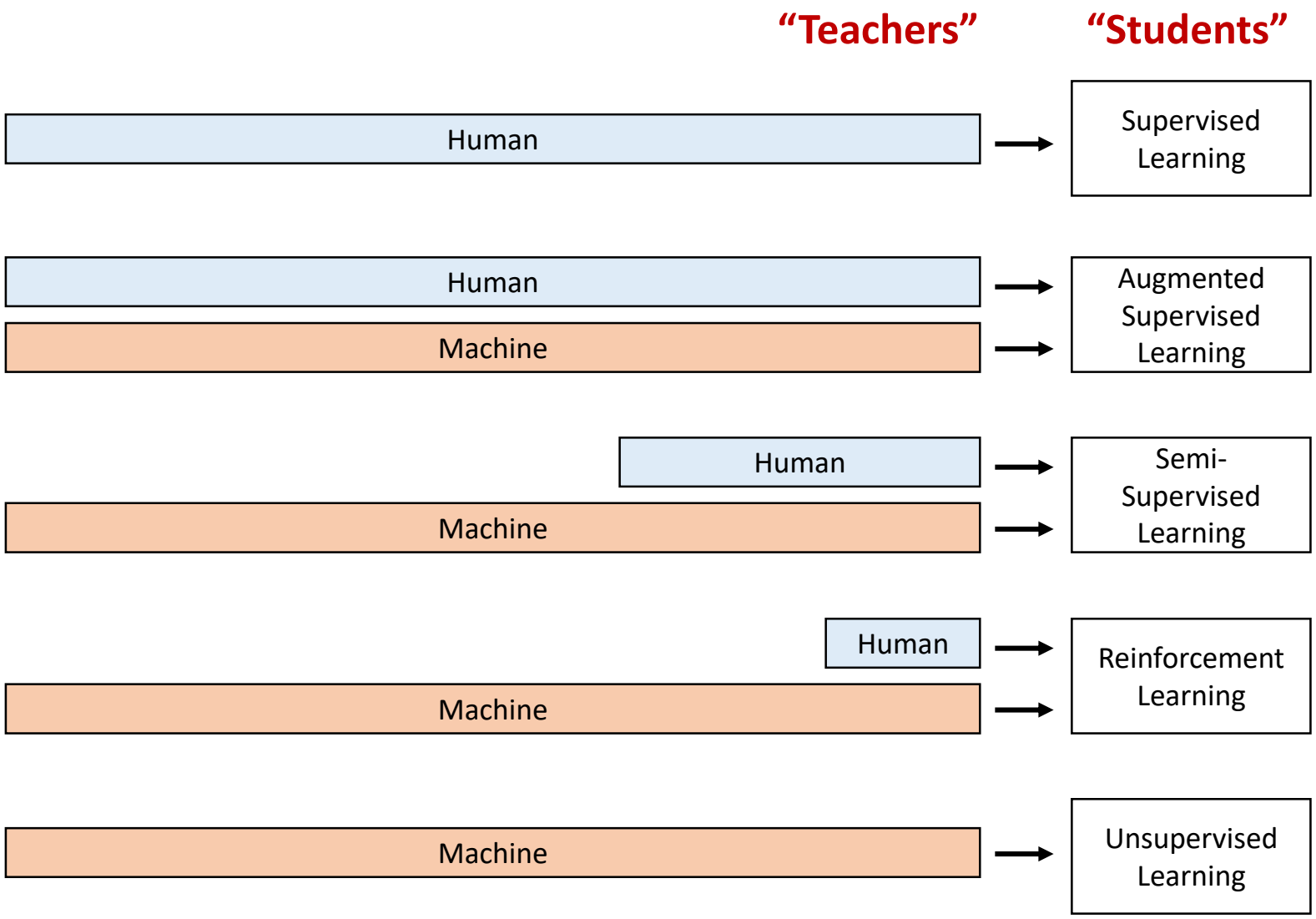
Takeaways

- **Limits:** Machine learning today and tomorrow.
  - Currently limited (data, compute, methods)
  - Potentially limitless (end-to-end general intelligence)

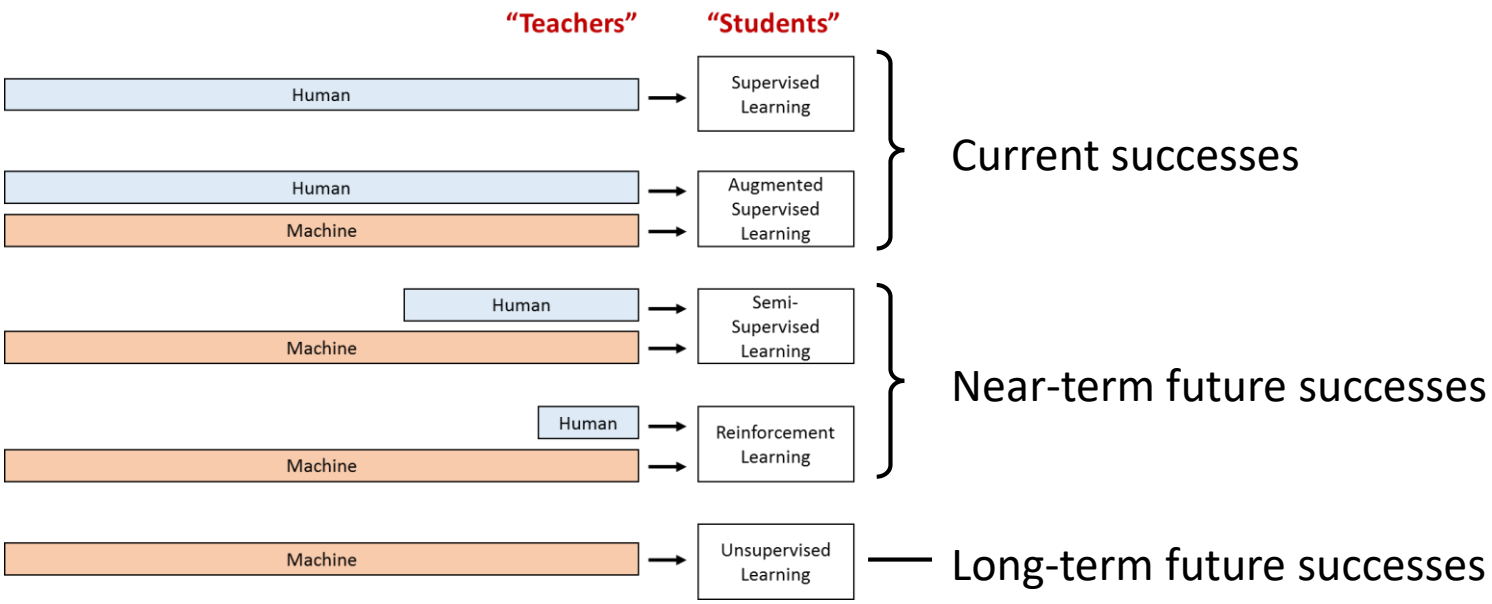
- **Data:**
  - Representation matters
    (deep learning > representation-agnostic learning)
  - Human annotation is needed
    (annotated data > big data)

- **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

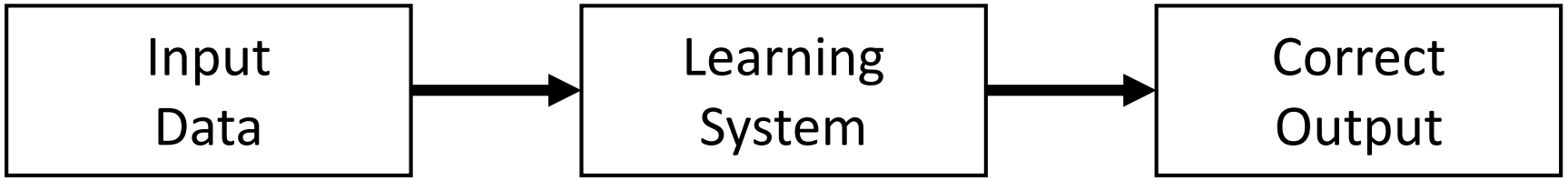


Better Question:

Machine Learning: Limited or Limitless?

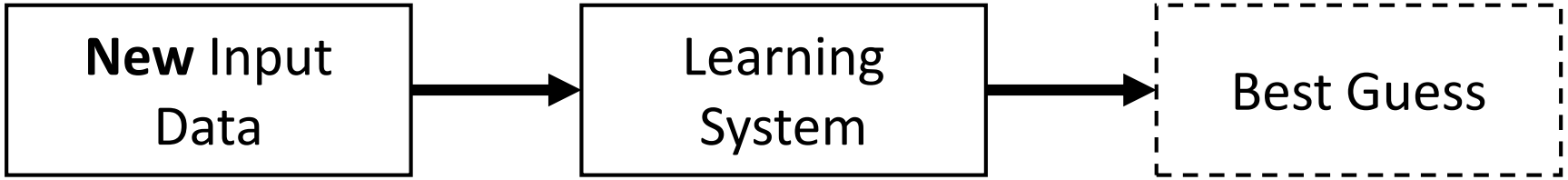
(PS: for now Machine Learning = Supervised Learning)

Training Stage:



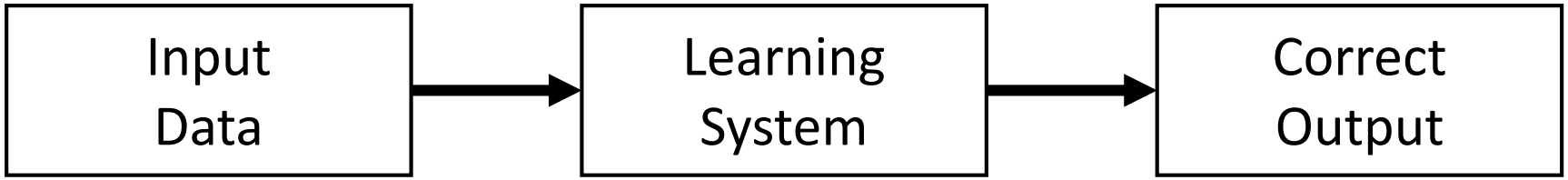
(aka "Ground Truth")

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

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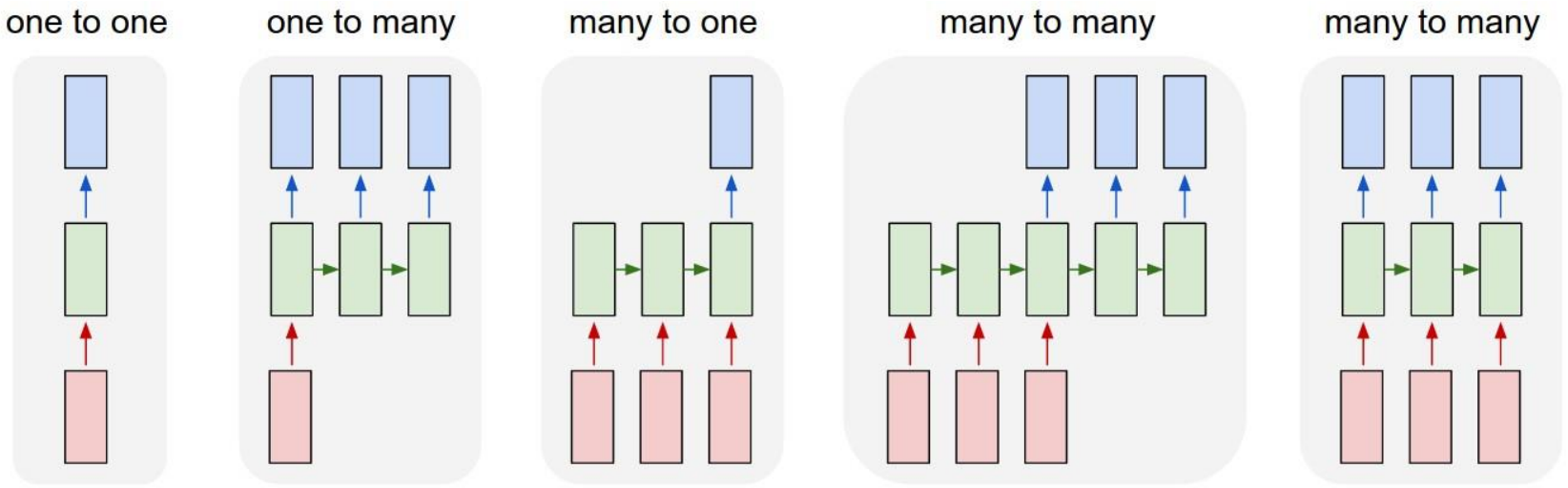
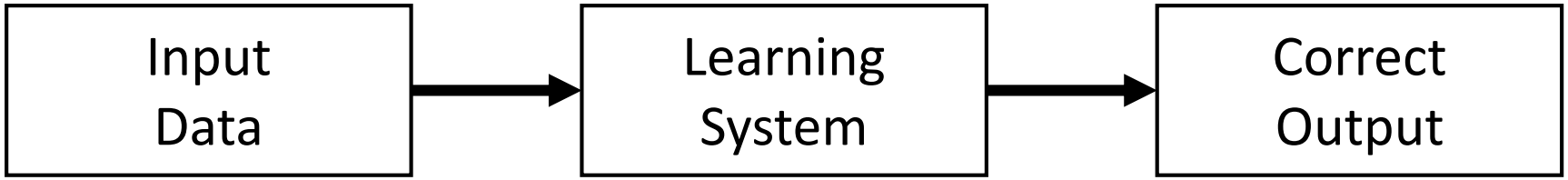


What can we do with Machine Learning?



- Images
  - Face
  - Medical
- Text
  - Conversations
  - Articles
  - Questions
- Sounds
  - Voice
- Time series
  - Financial
  - Physiological
- Physical world
  - Location of self
  - Actions of others

…

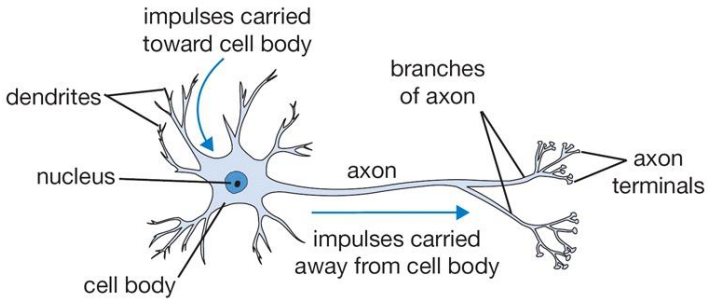
- Nearest Neighbor
- Naïve Bayes
- Support Vector Machines
- Hidden Markov Models
- Ensemble of Methods
- Neural Networks
  (aka Deep Learning)

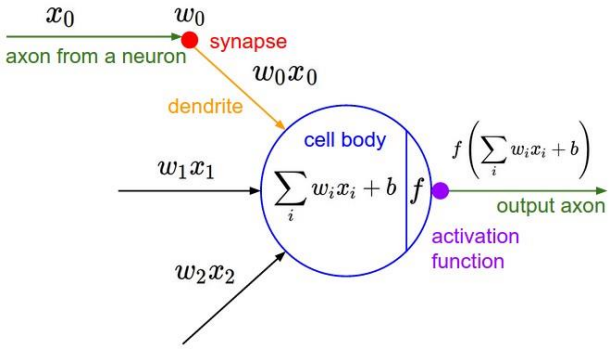
…

- Classification
- Regression
- Sequences
- Text
- Images
- Audio
- Actions

…

Neuron: Biological Inspiration for Computation



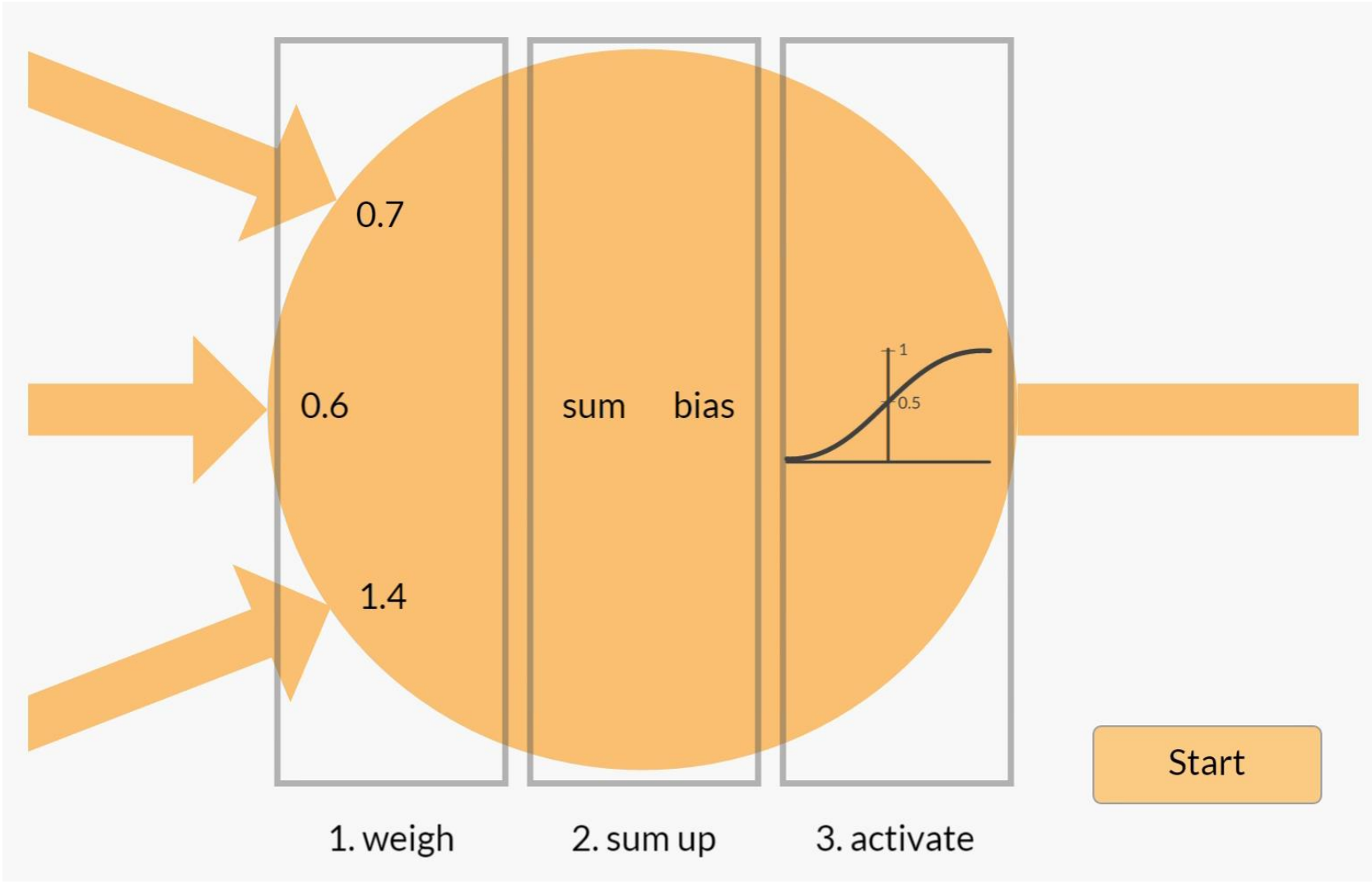


- **Neuron:** computational building block for the brain
- Human brain:
  - ~100-1,000 trillion synapses

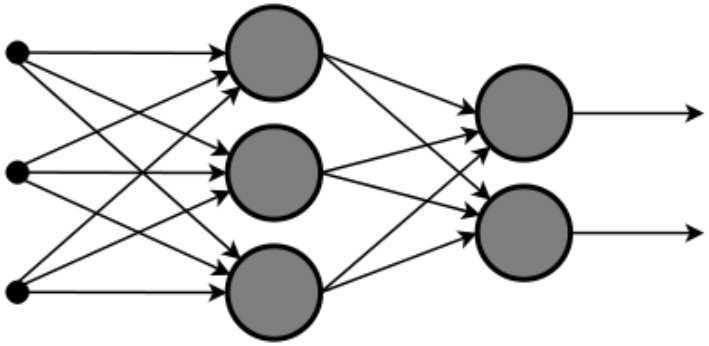
- **(Artificial) Neuron:** computational building block for the "neural network"
- (Artificial) neural network:
  - ~1-10 billion synapses

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

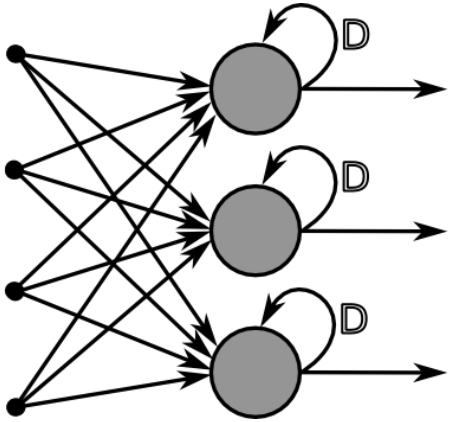
Neuron: Forward Pass



Combining Neurons into Layers



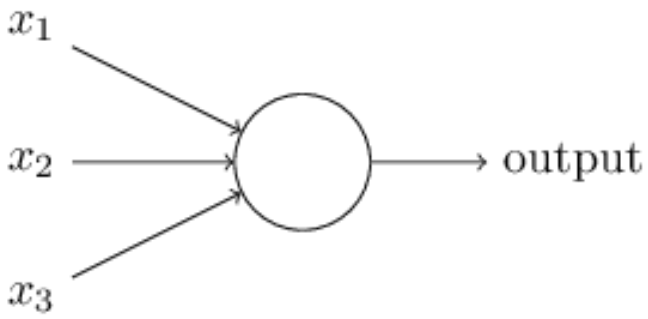
Feed Forward Neural Network

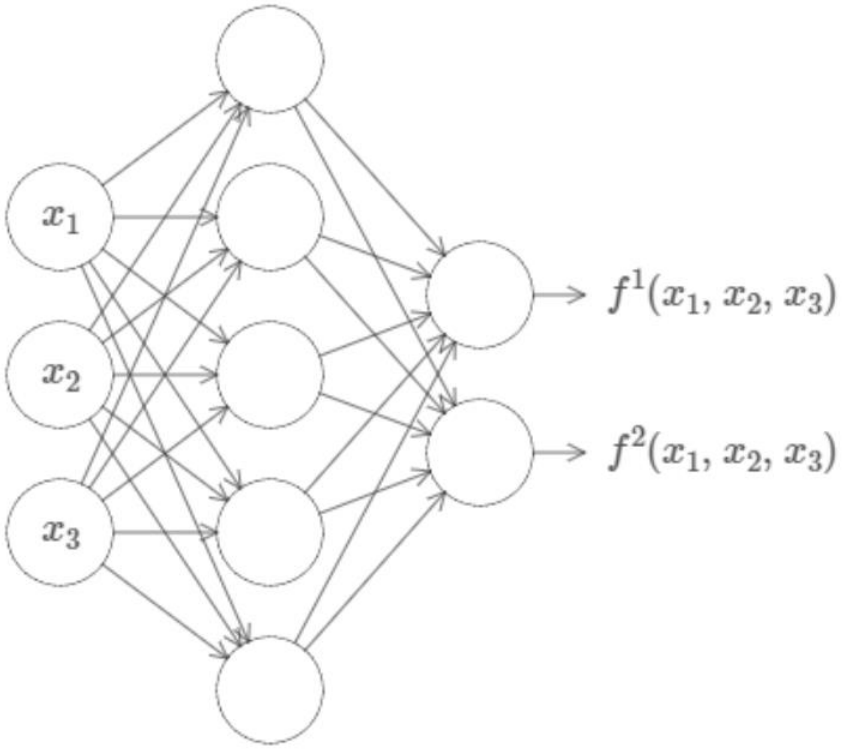


Recurrent Neural Network

- Have state memory
- Are hard to train

Neural Networks are Amazing





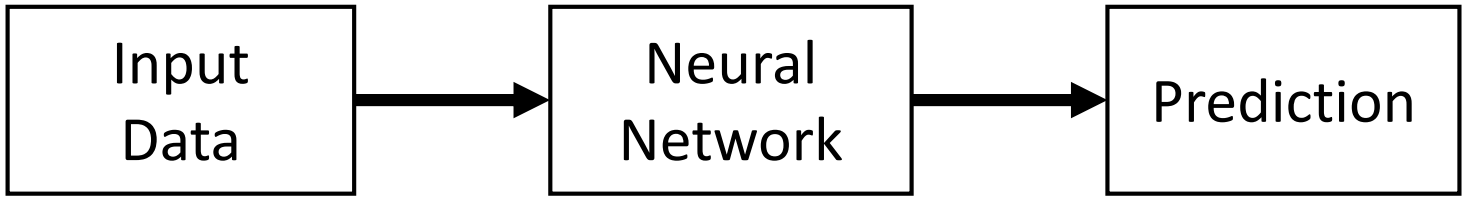
Universality: For any arbitrary function f(x), there exists a neural network that closely approximate it for any input x

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

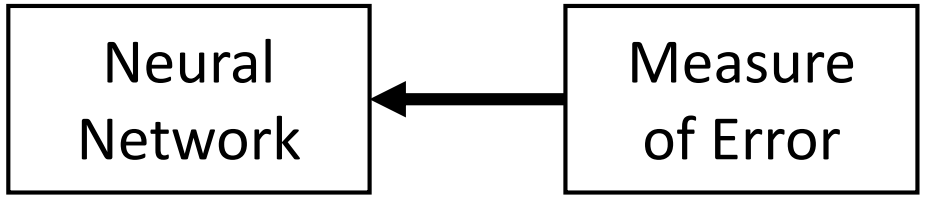
* Given that we have good algorithms for training these networks.

How Neural Networks Learn: Backpropagation

Forward Pass:



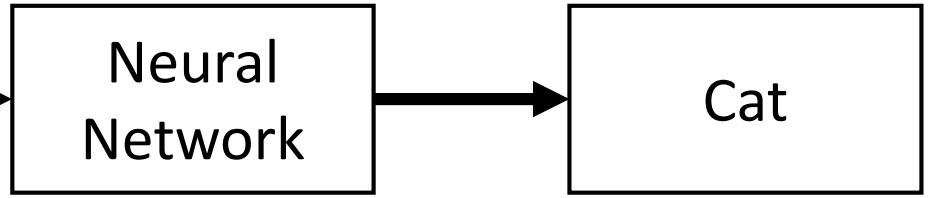
Backward Pass (aka Backpropagation):



Adjust to Reduce Error

How Neural Networks Learn: Backpropagation

Forward Pass:



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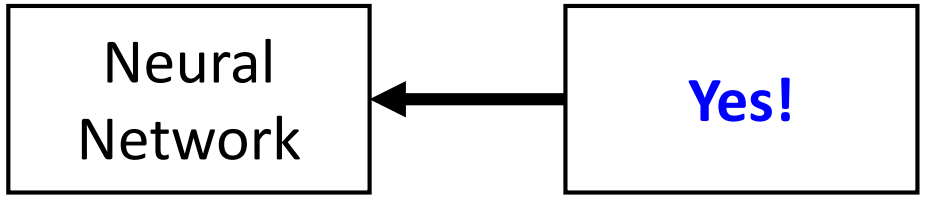

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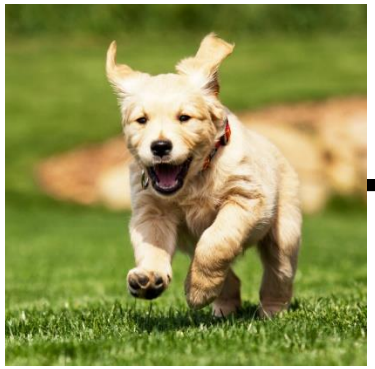

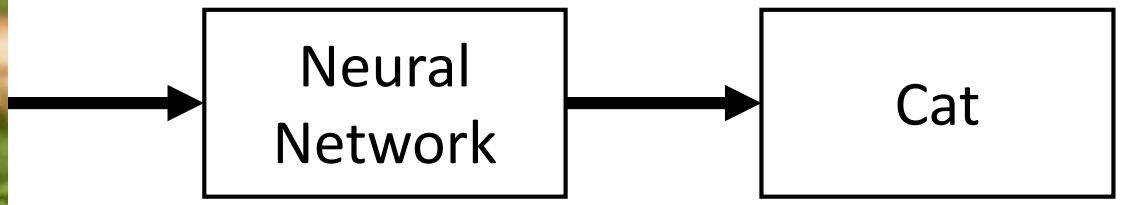

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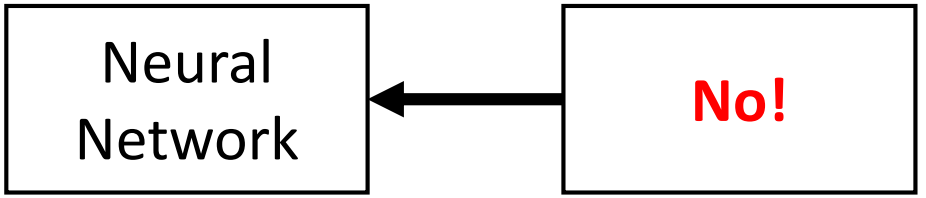
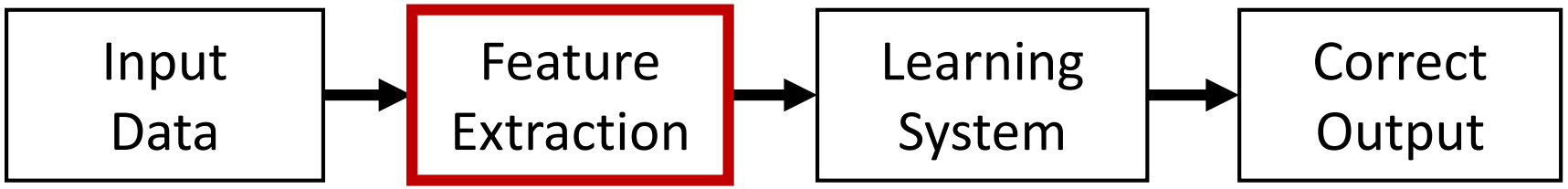
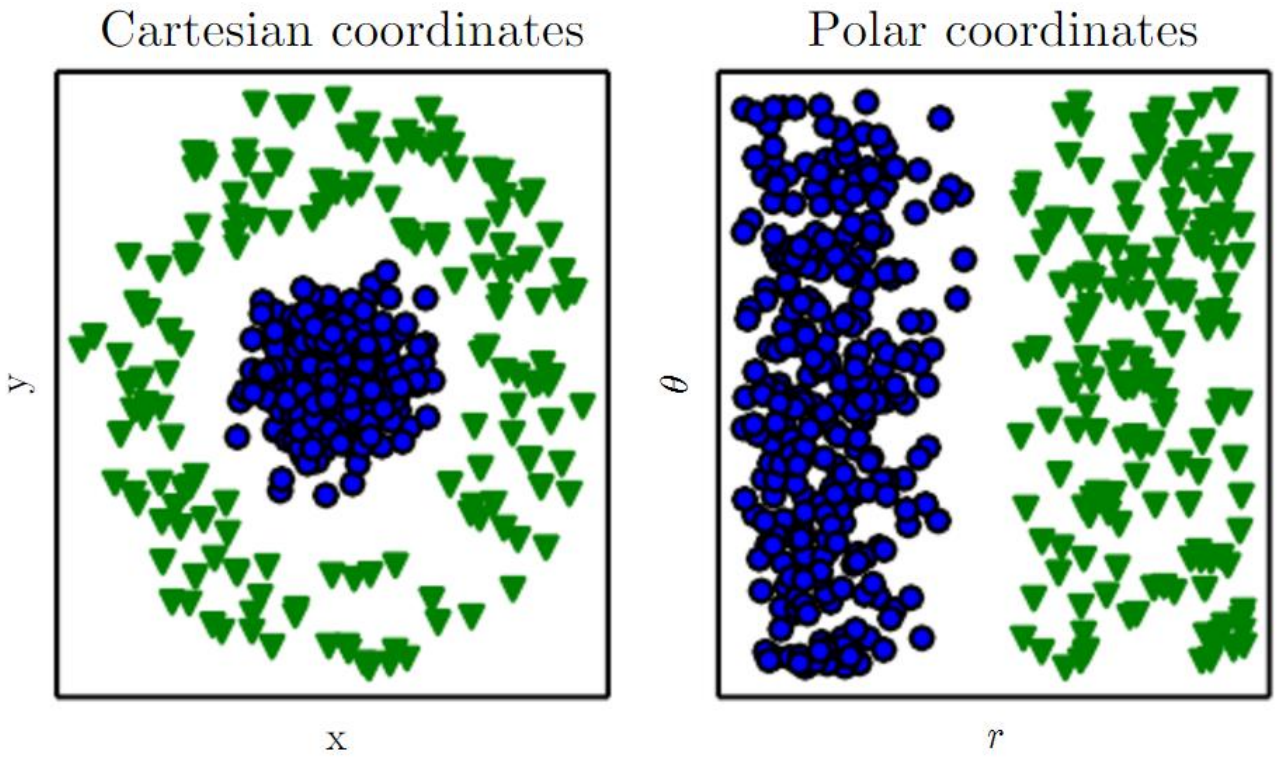


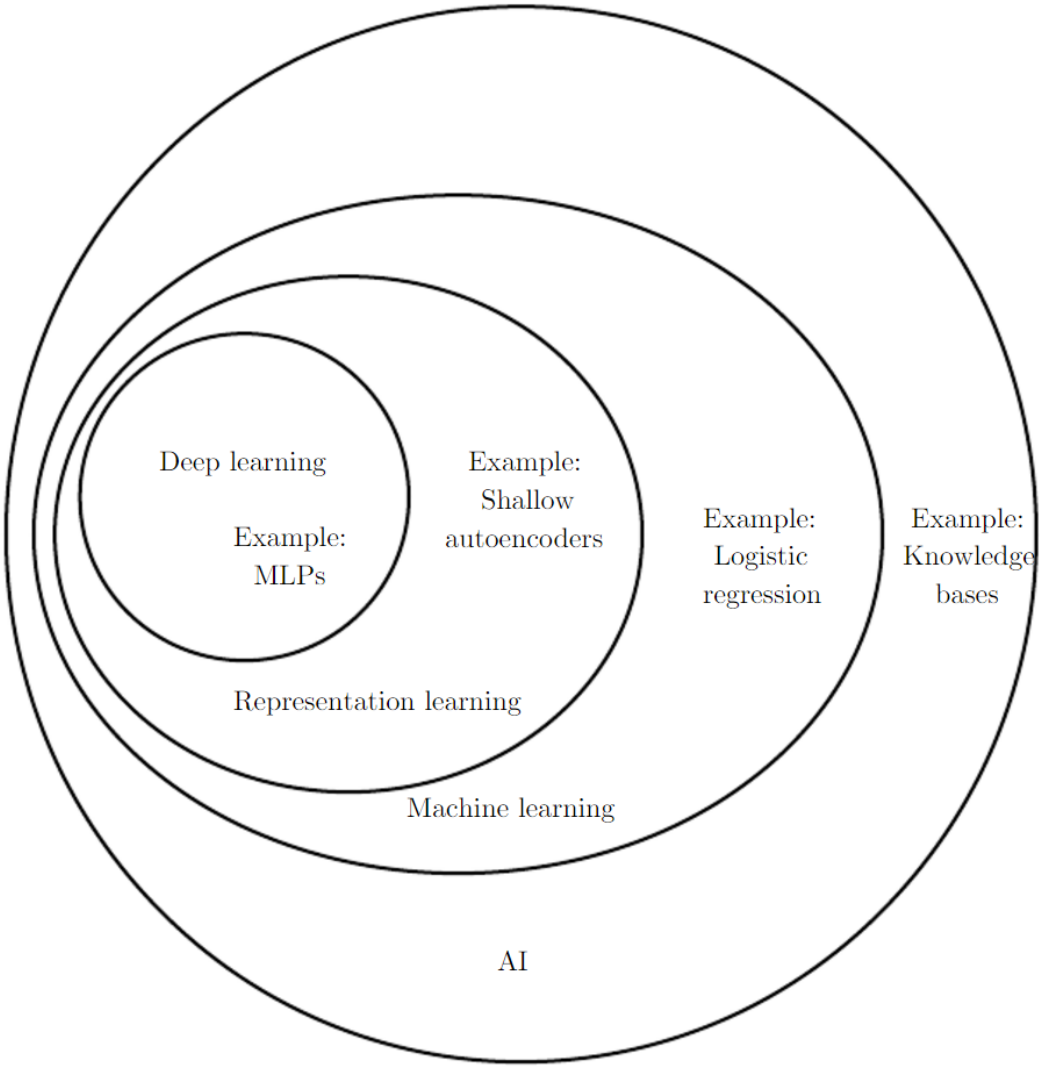
Representation Matters!

(Representation aka Features)

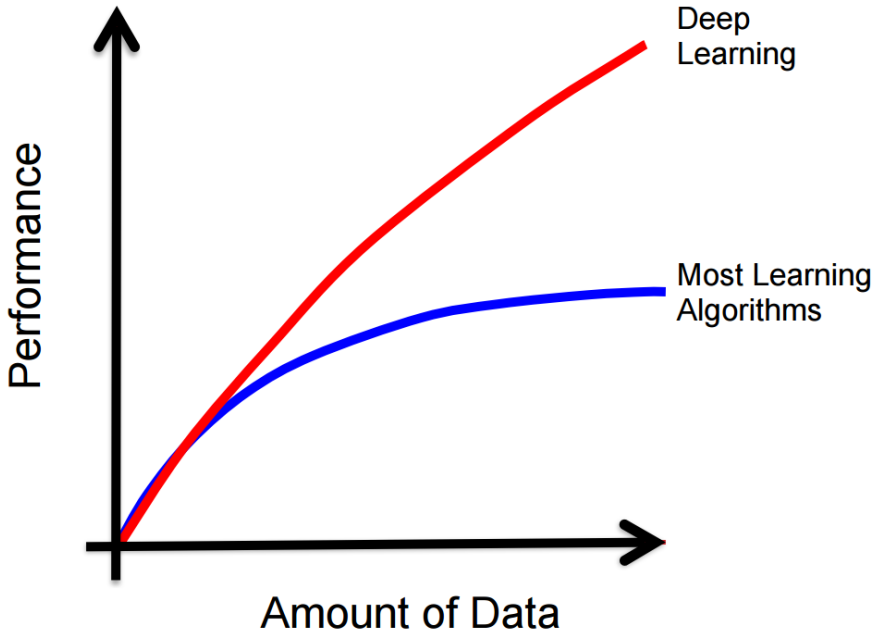


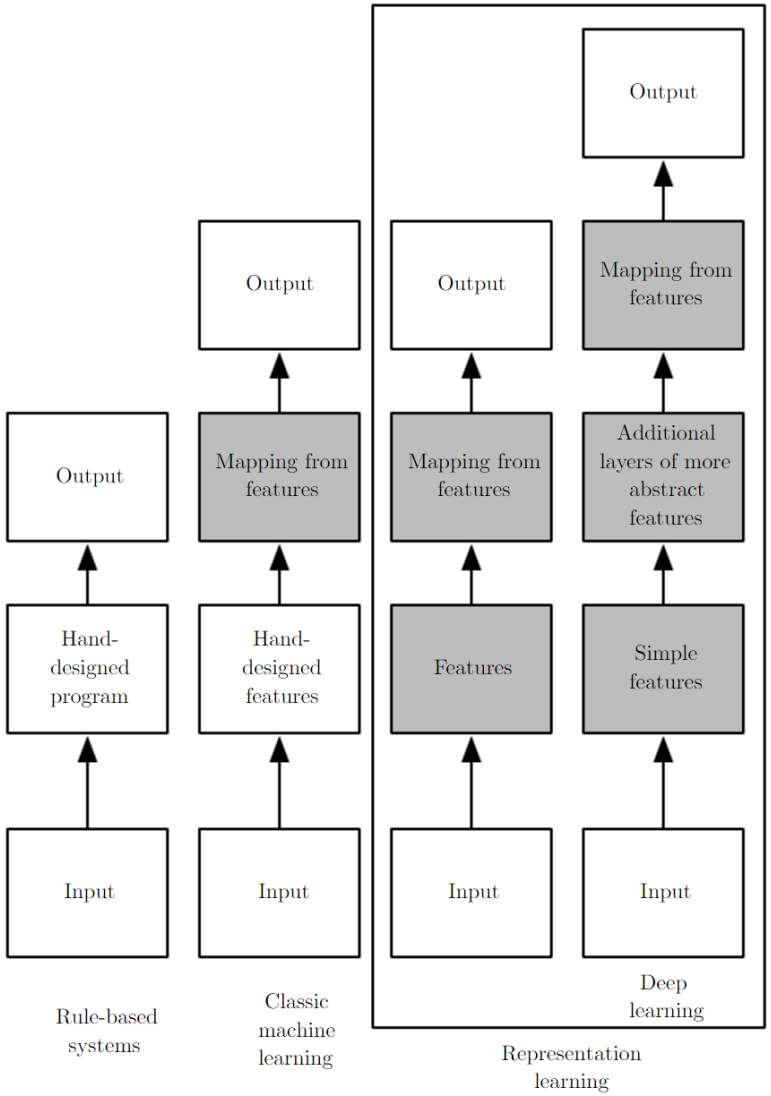


Deep Learning is **Representation Learning**



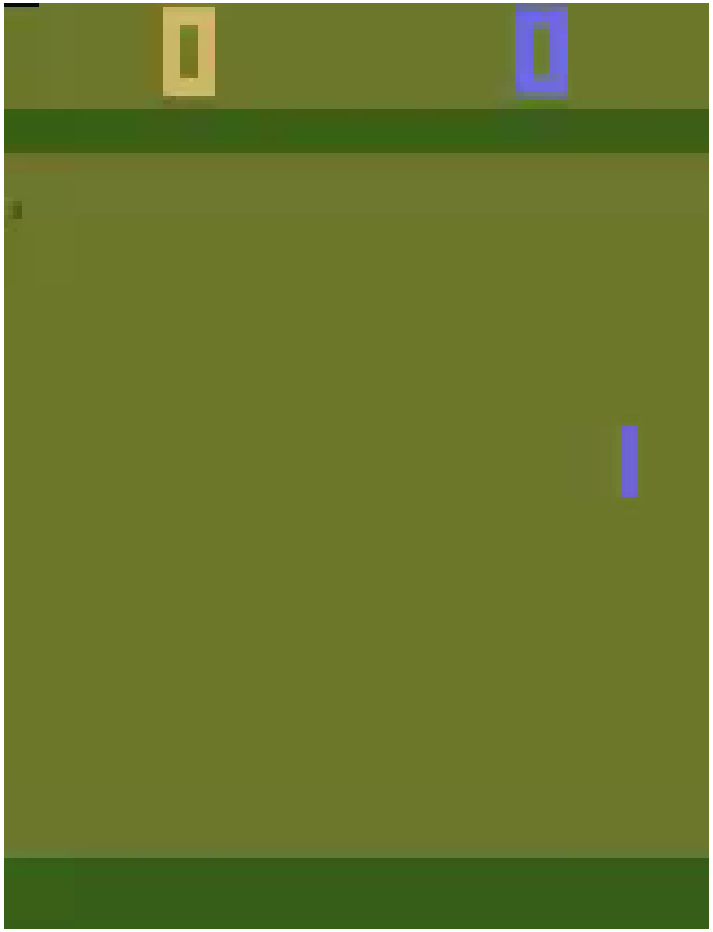
Deep Learning: **Scalable** Machine Learning





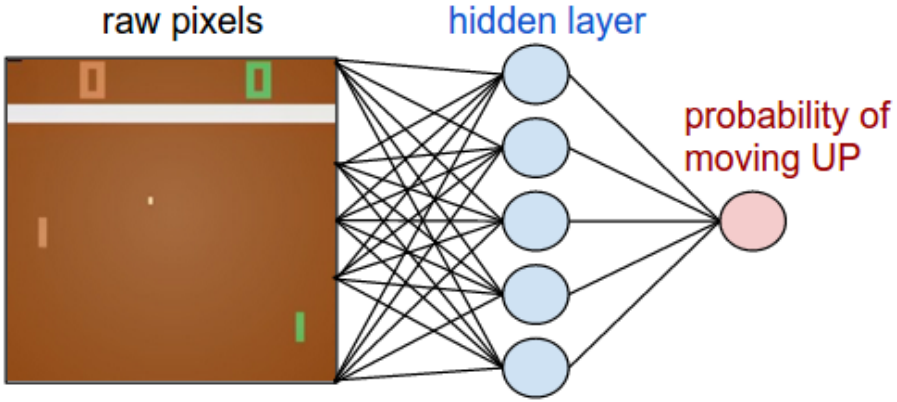
Neural Networks are Amazing:

General Purpose Intelligence



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

Policy Network:

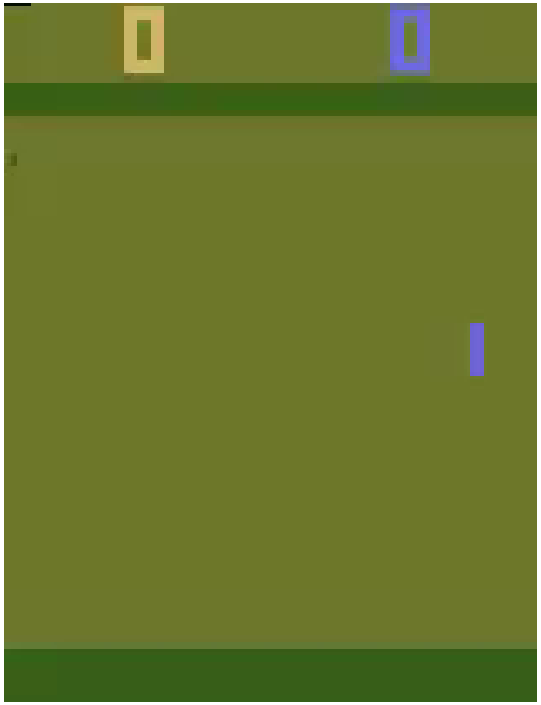


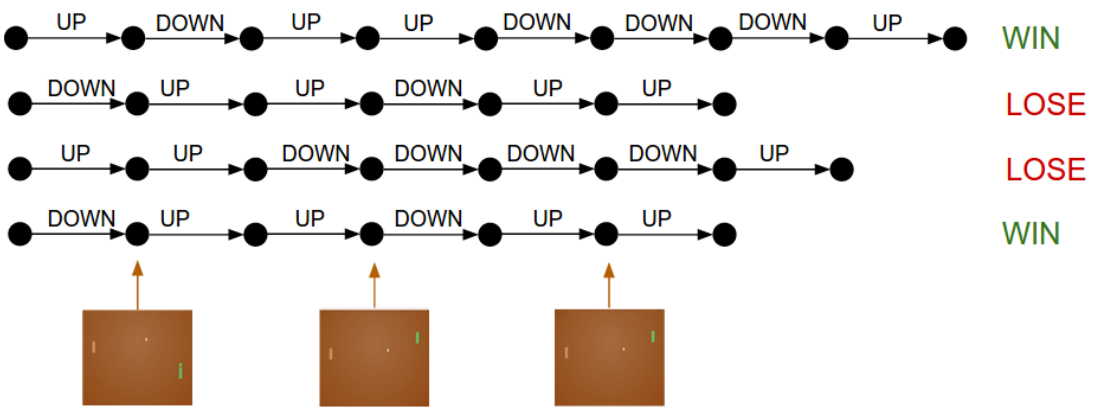
- 80x80 image (difference image)
- 2 actions: up or down
- 200,000 Pong games

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…

Takeaways

- **Limits:** Machine learning today and tomorrow.
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- **Data:**
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  Rule of thumb for real-world machine learning:
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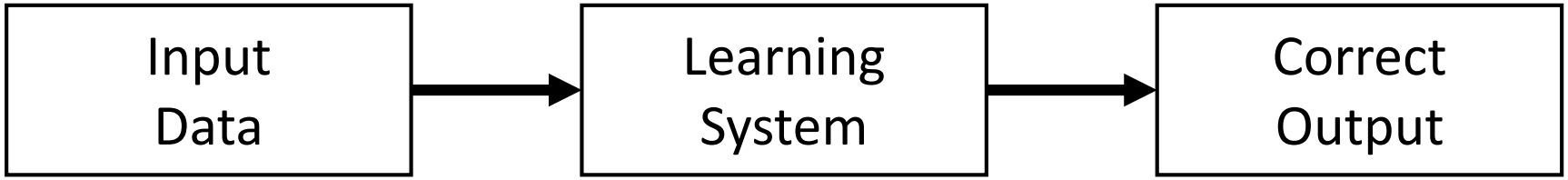
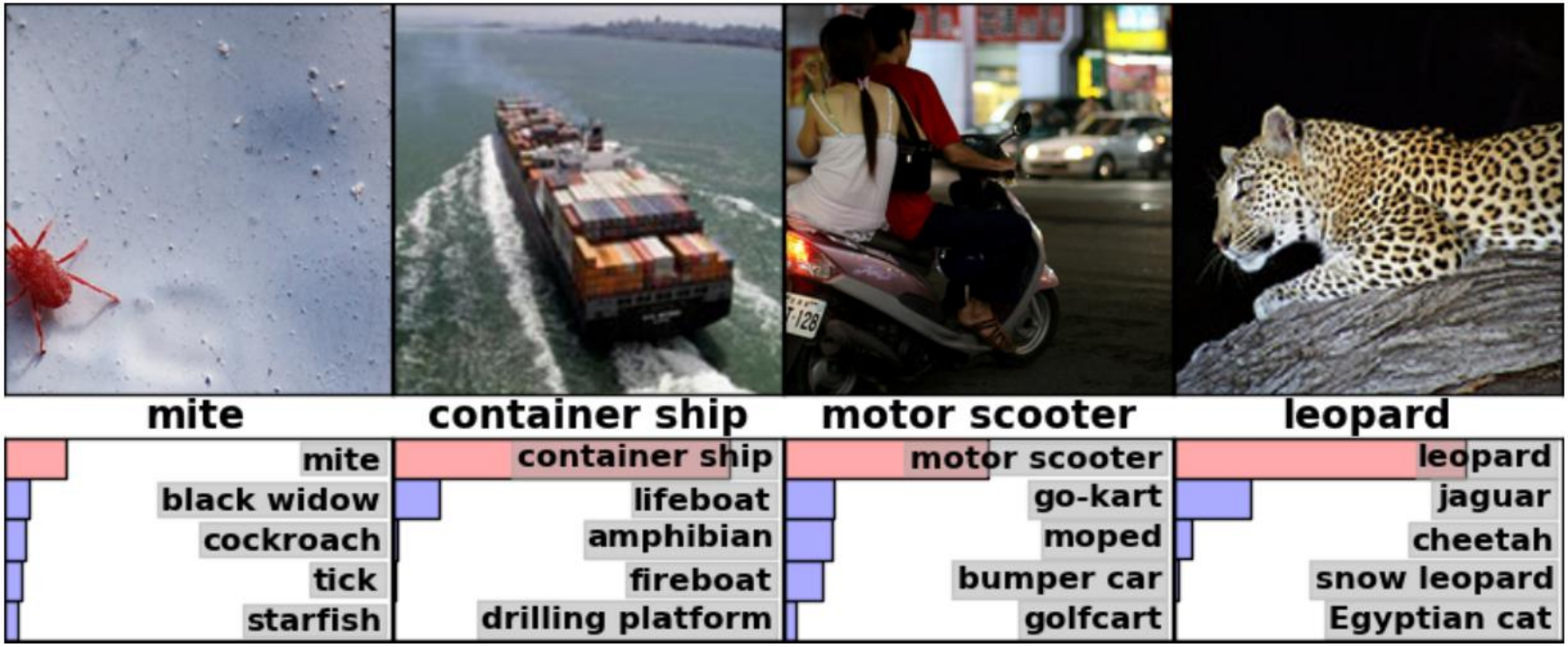
What can we do with Machine Learning?

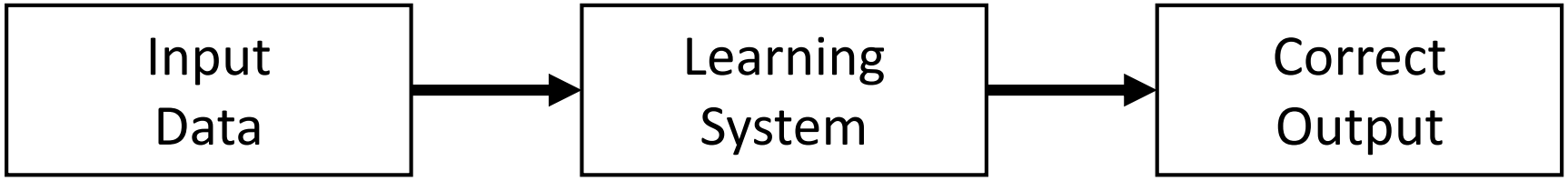
Object Recognition / Image Classification





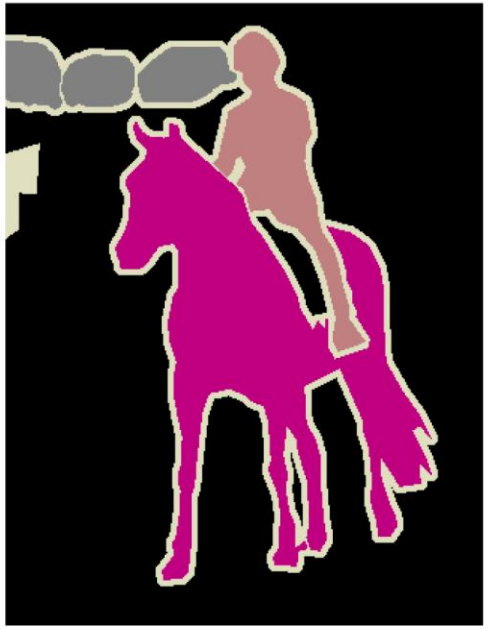
What can we do with Machine Learning?

Image Segmentation

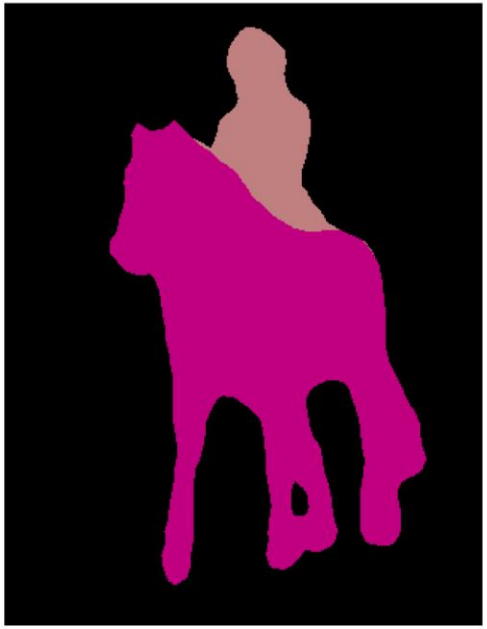


Original

Ground Truth

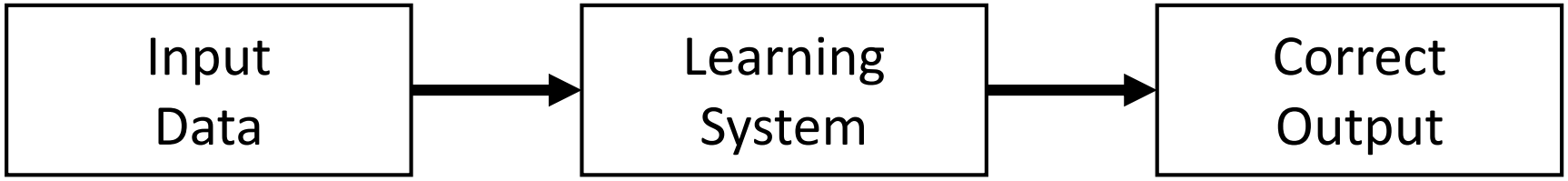


FCN-8



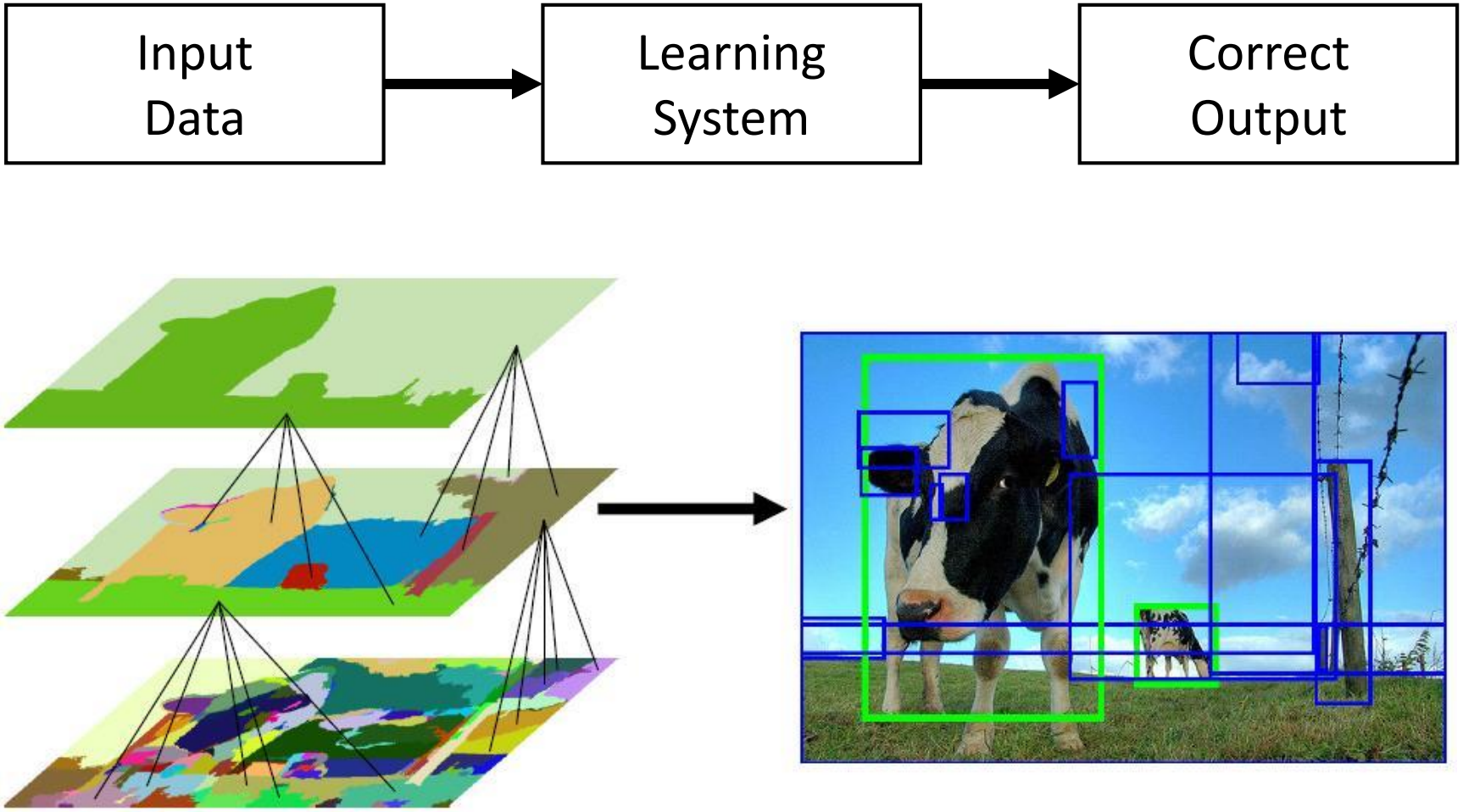
What can we do with Machine Learning?

Video Segmentation



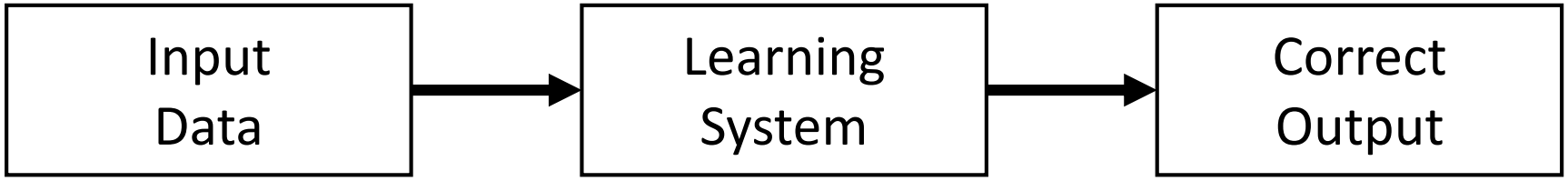
What can we do with Machine Learning?

Object Detection / Object Localization



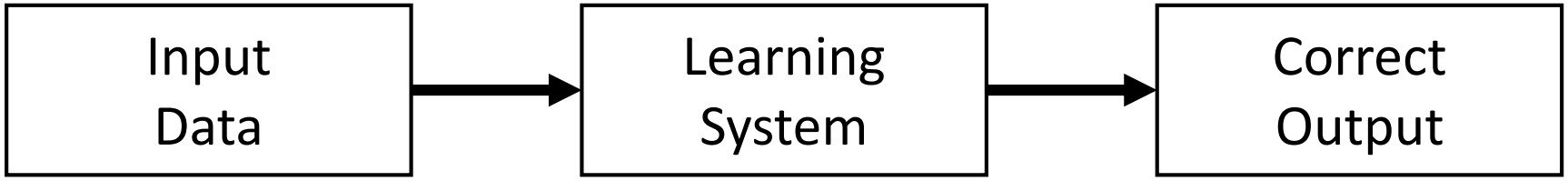
What can we do with Machine Learning?

Colorization of Images



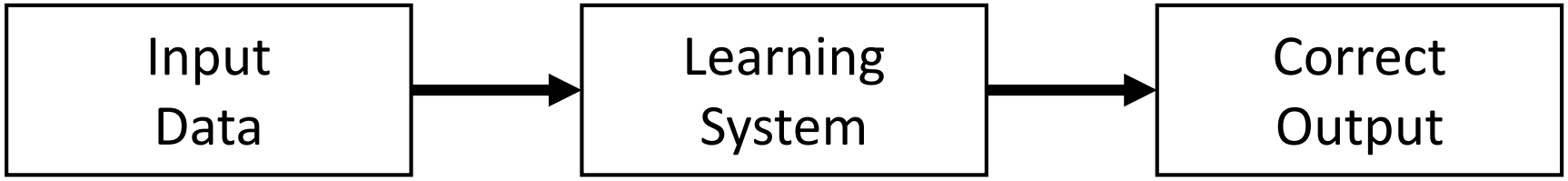
What can we do with Machine Learning?

Automatic Translation of Text in Images



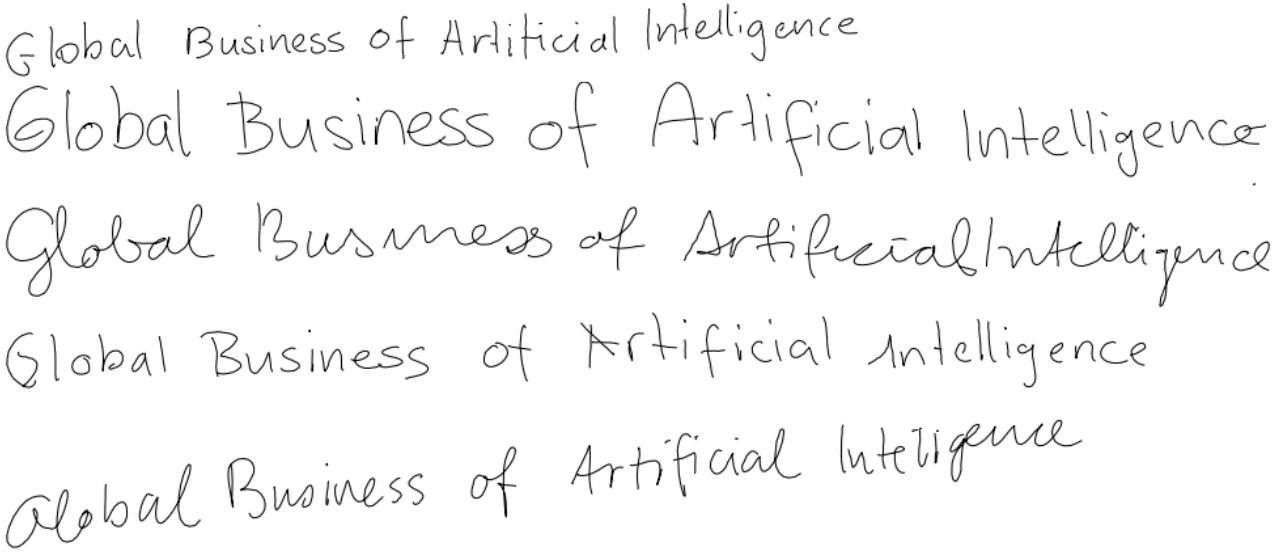
What can we do with Machine Learning?

Handwriting Generation from Text



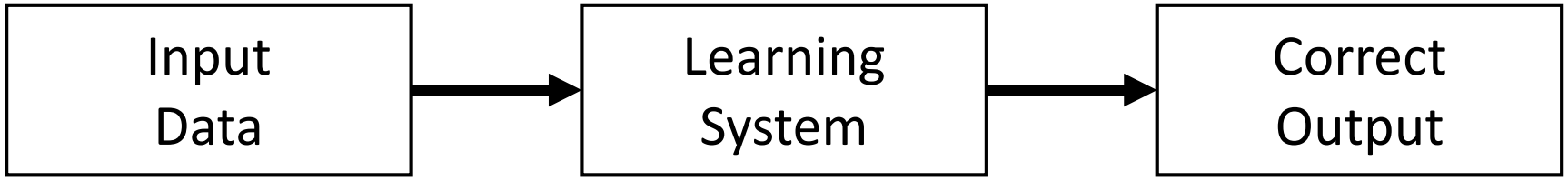
Text --- up to 100 characters, lower case letters work best

Global Business of Artificial Intelligence



What can we do with Machine Learning?

Character-Level Text Generation

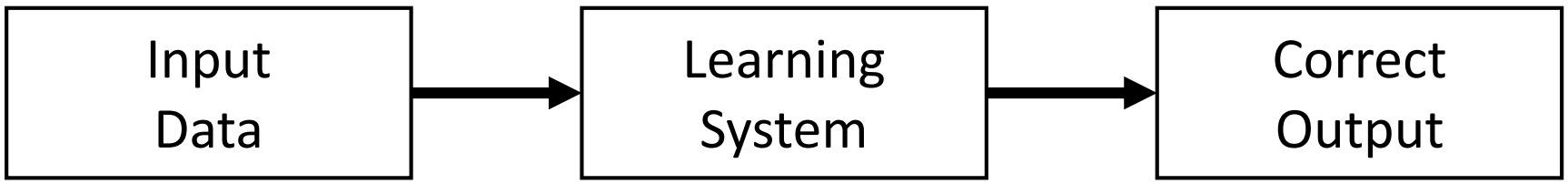


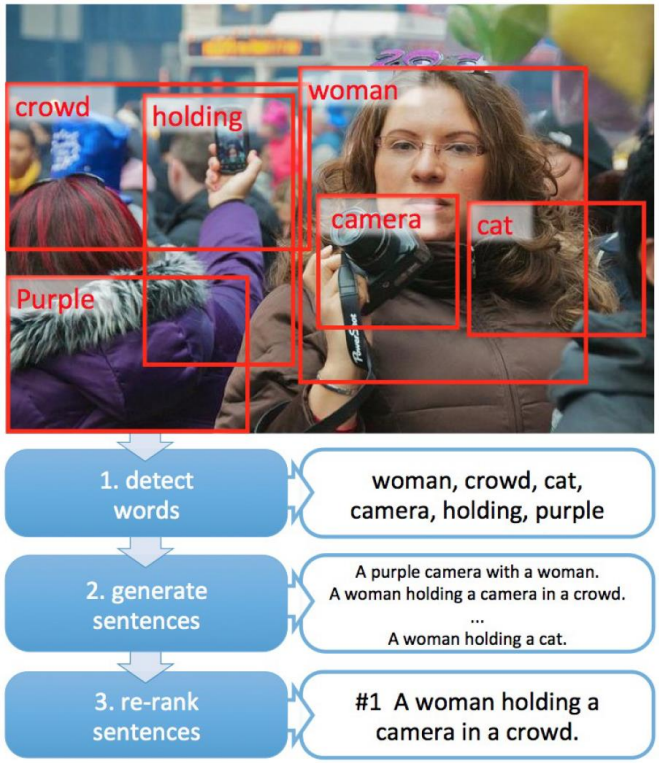
Life Is About The Weather!
Life Is About The (Wild) Truth About Human-Rights
Life Is About The True Love Of Mr. Mom
Life Is About Where He Were Now
Life Is About Kids
Life Is About What It Takes If Being On The Spot Is Tough
Life Is About… An Eating Story
Life Is About The Truth Now

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?

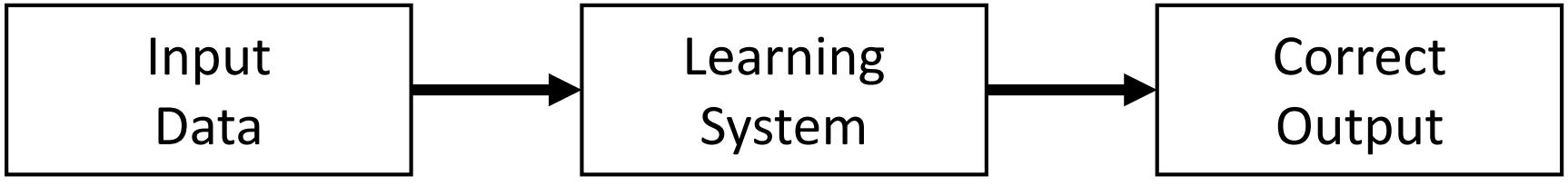
Image Caption Generation

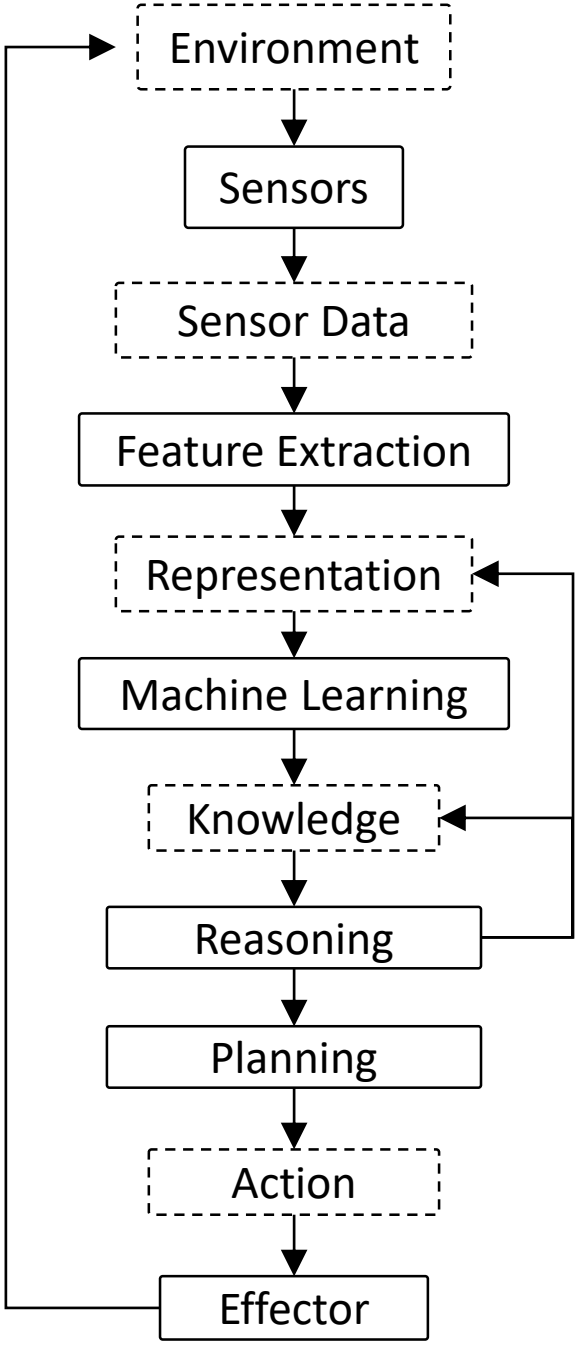




What can we do with Machine Learning?

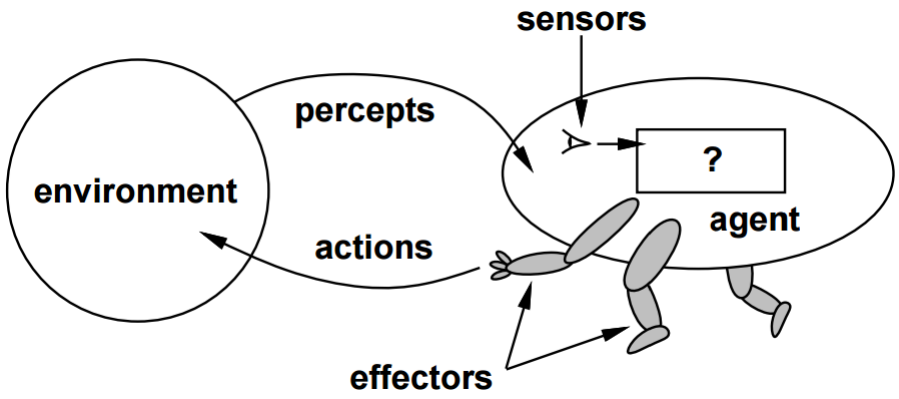
End-to-End Learning of the Driving Task

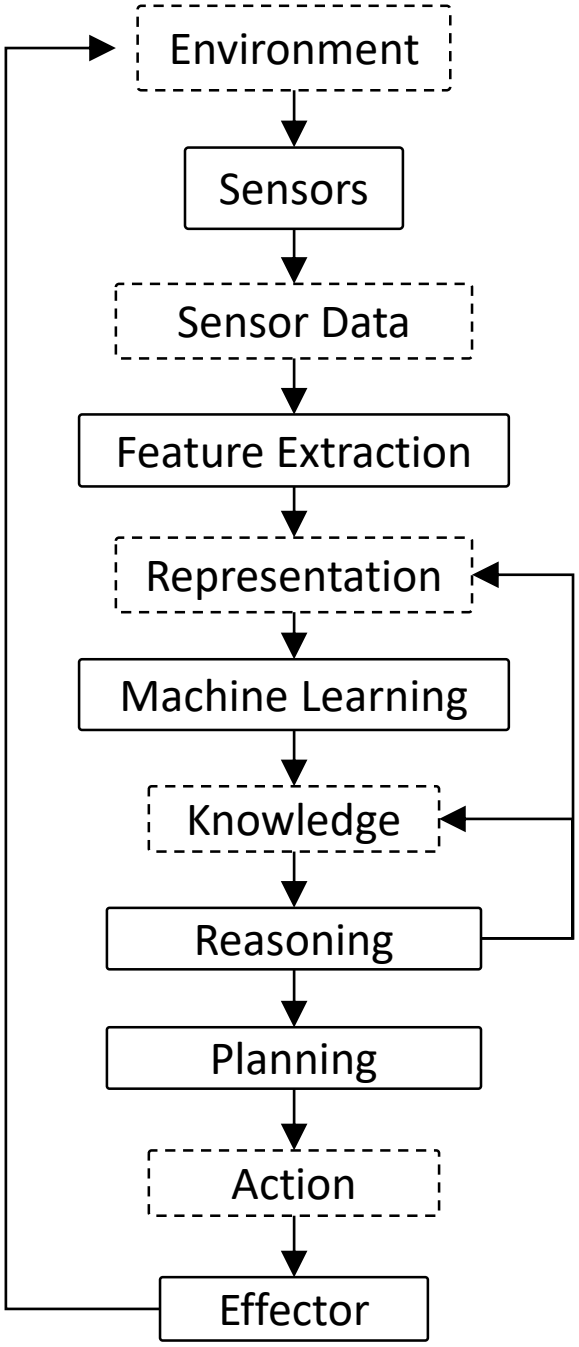




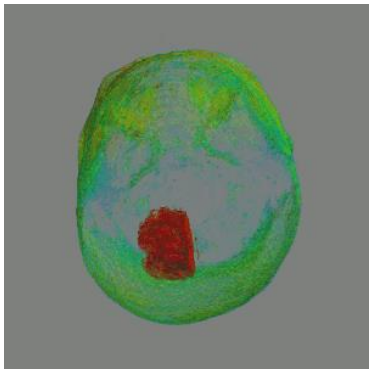
Open Question:

What can we **not** do with Machine Learning?



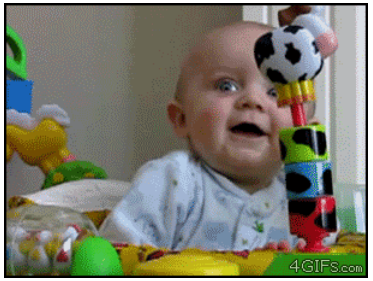


Formal tasks: Playing board games, card games. Solving puzzles, mathematical and logic problems.

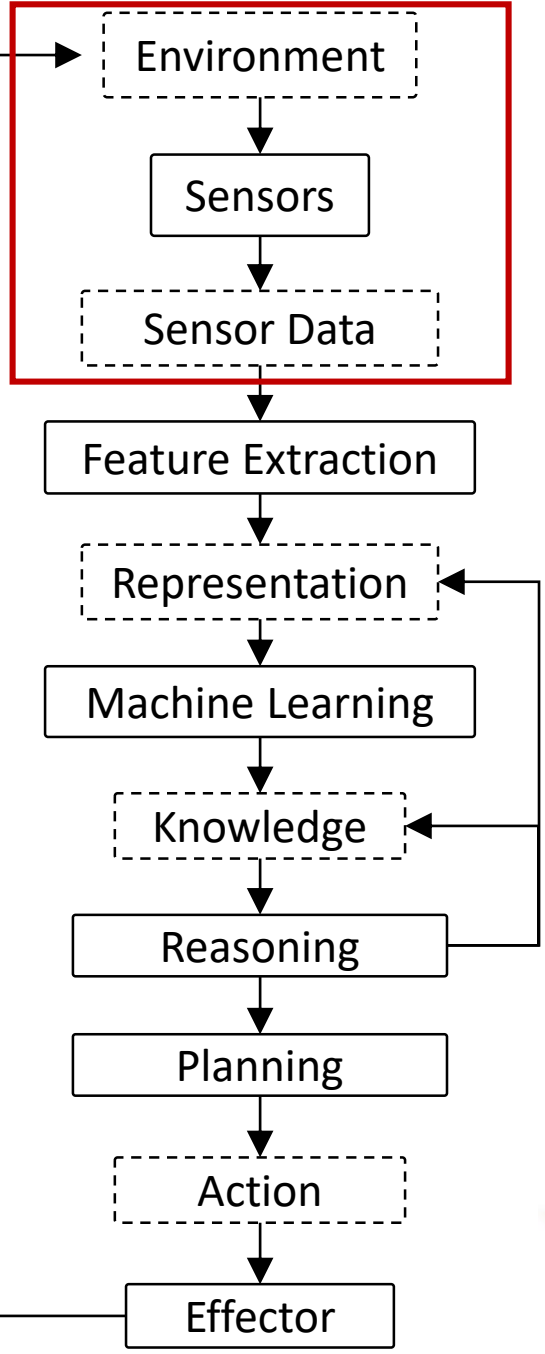


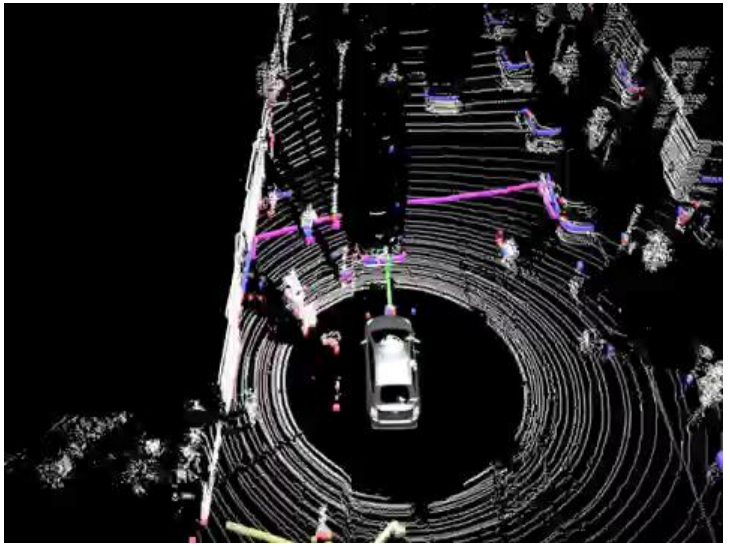
Expert tasks: Medical diagnosis, engineering, scheduling, computer hardware design.

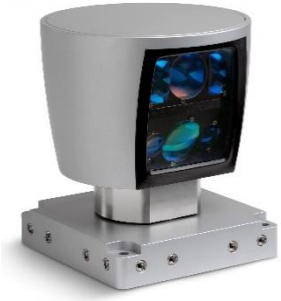
Mundane tasks: Everyday speech, written language, perception, walking, object manipulation.



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







Lidar

Camera
(Visible, Infrared)

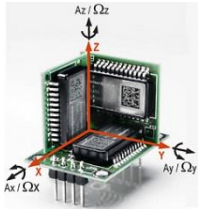
Radar

GPS

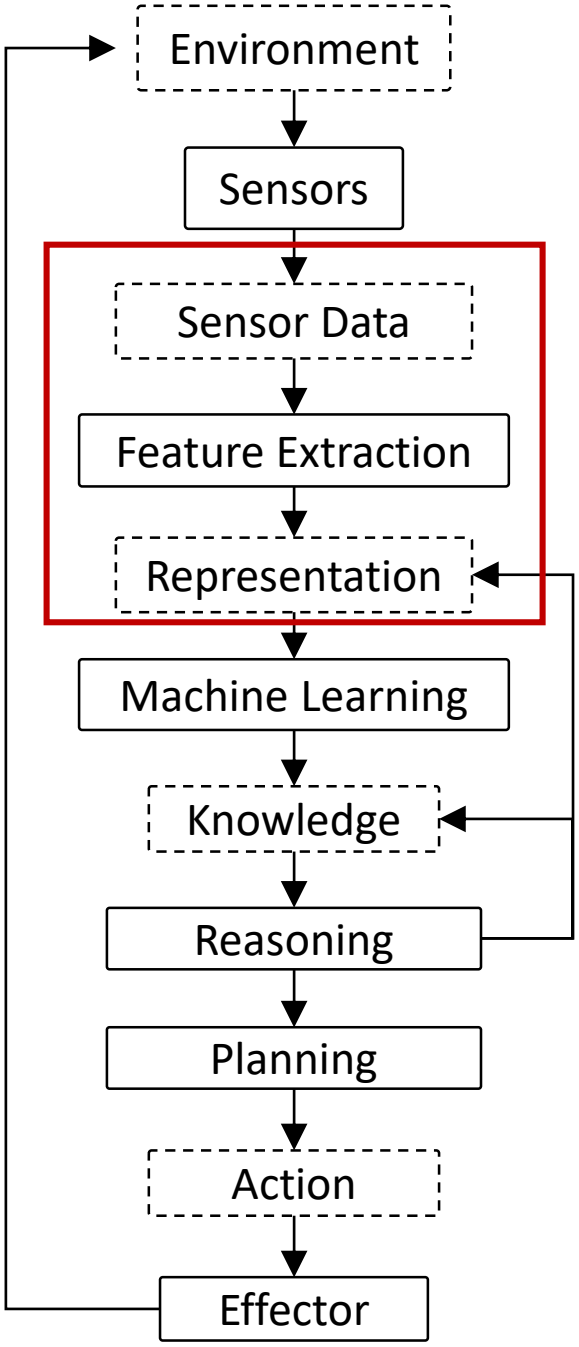
Stereo Camera

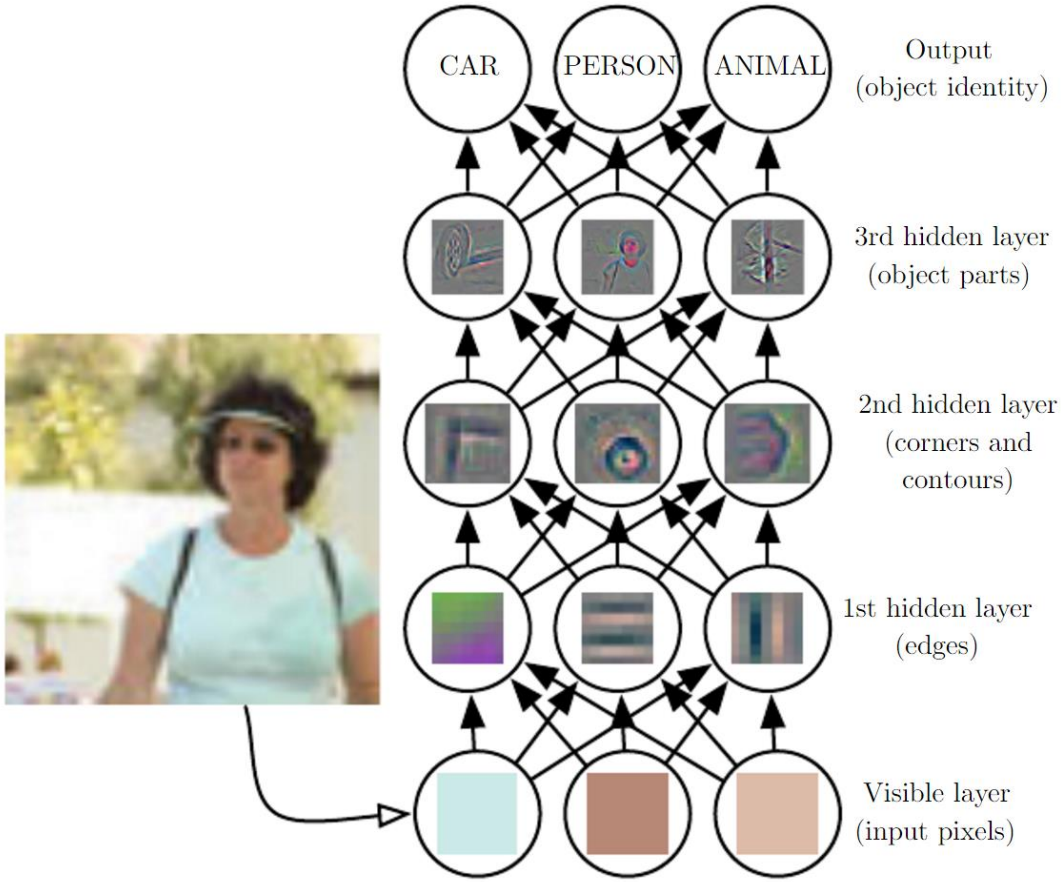
Microphone

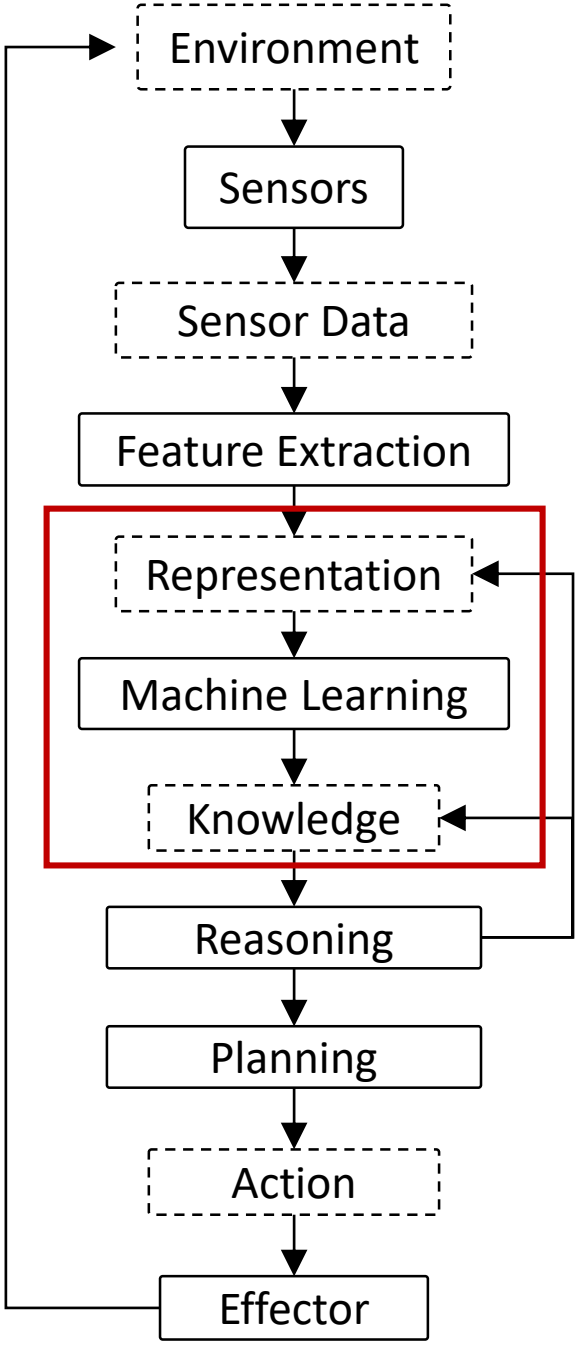
Networking
(Wired, Wireless)



IMU


Environment
Sensors
Sensor Data
Feature Extraction
Representation
Machine Learning
Knowledge
Reasoning
Planning
Action
Effector


CAR
PERSON
ANIMAL
Output
(object identity)
3rd hidden layer
(object parts)
2nd hidden layer
(corners and
contours)
1st hidden layer
(edges)
Visible layer
(input pixels)


Environment
Sensors
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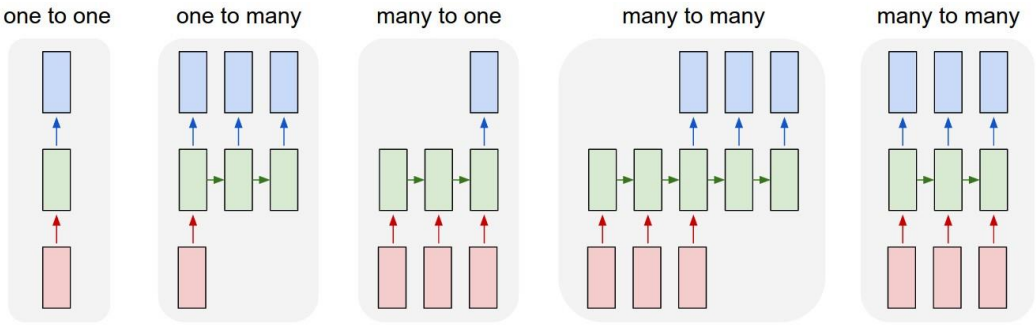

one to one
one to many
many to one
many to many
many to many

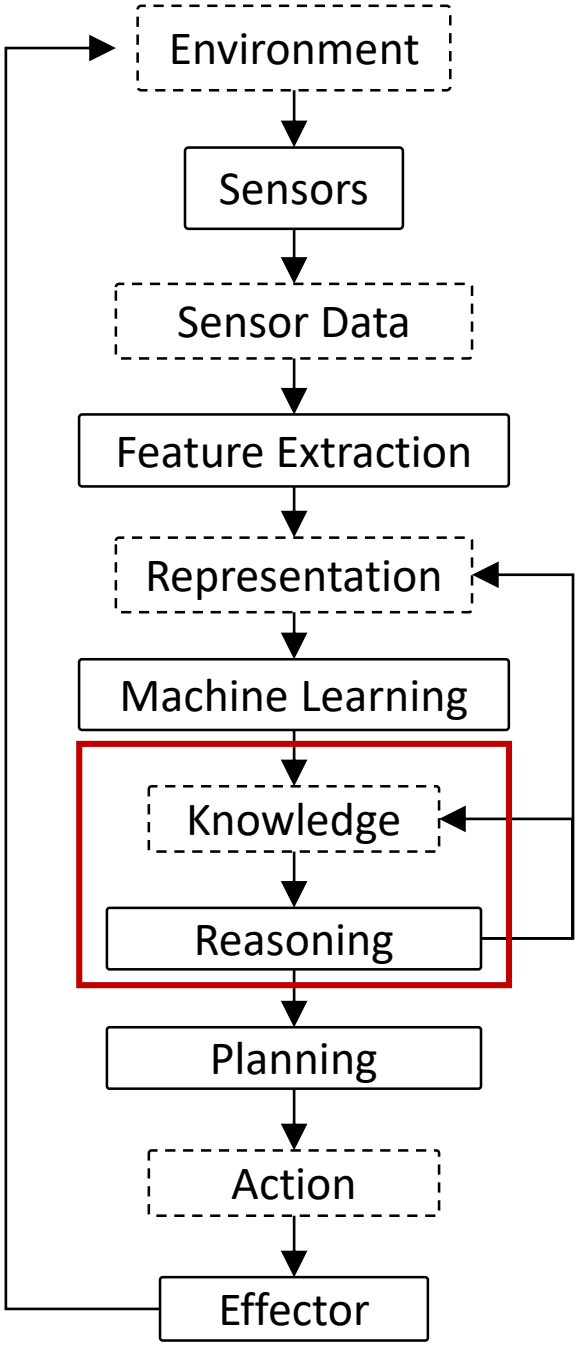
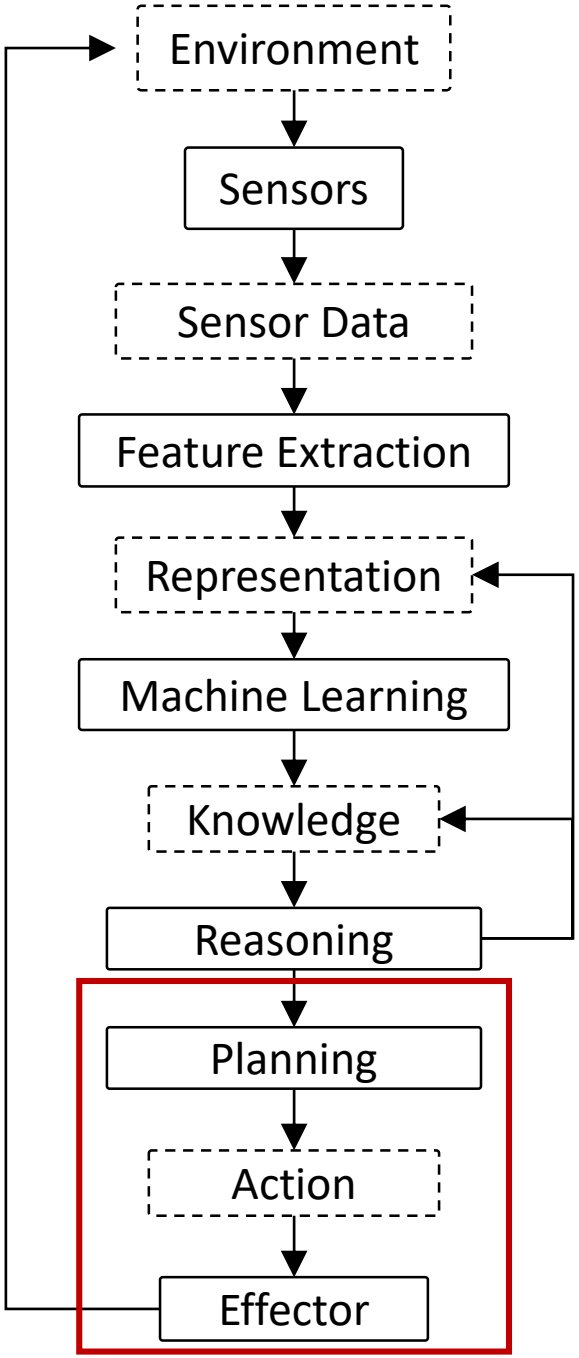


Image Recognition:
If it looks like a duck

Audio Recognition:
Quacks like a duck

Activity Recognition:
Swims like a duck


Environment
Sensors
Sensor Data
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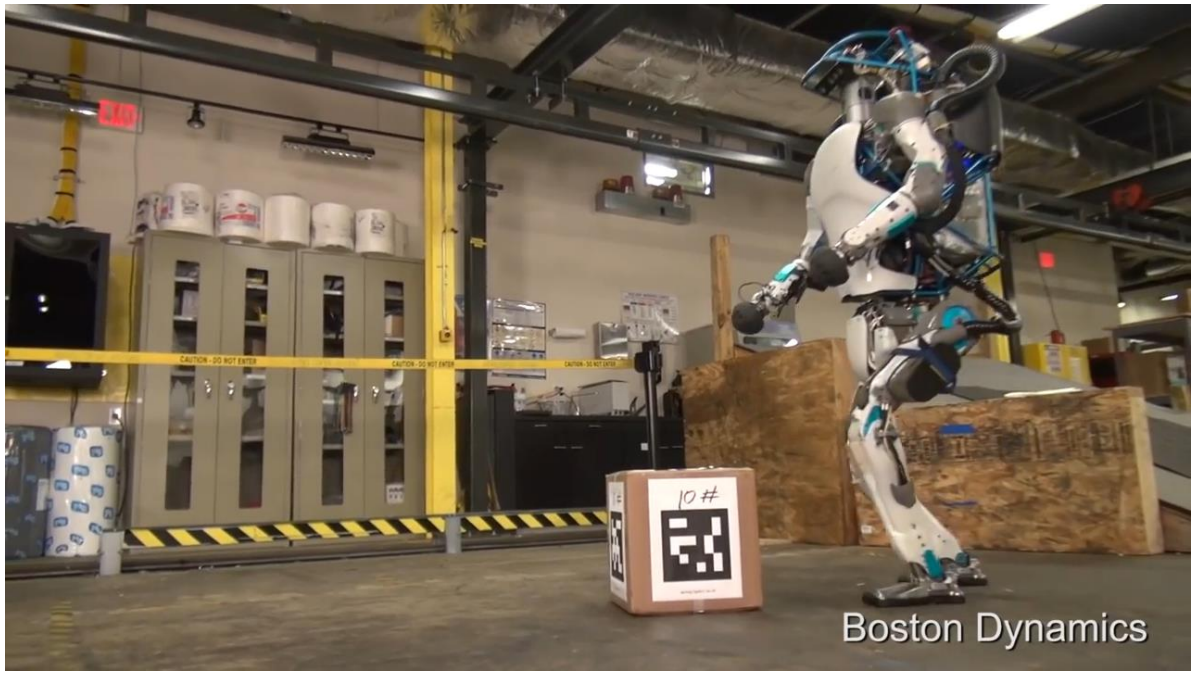
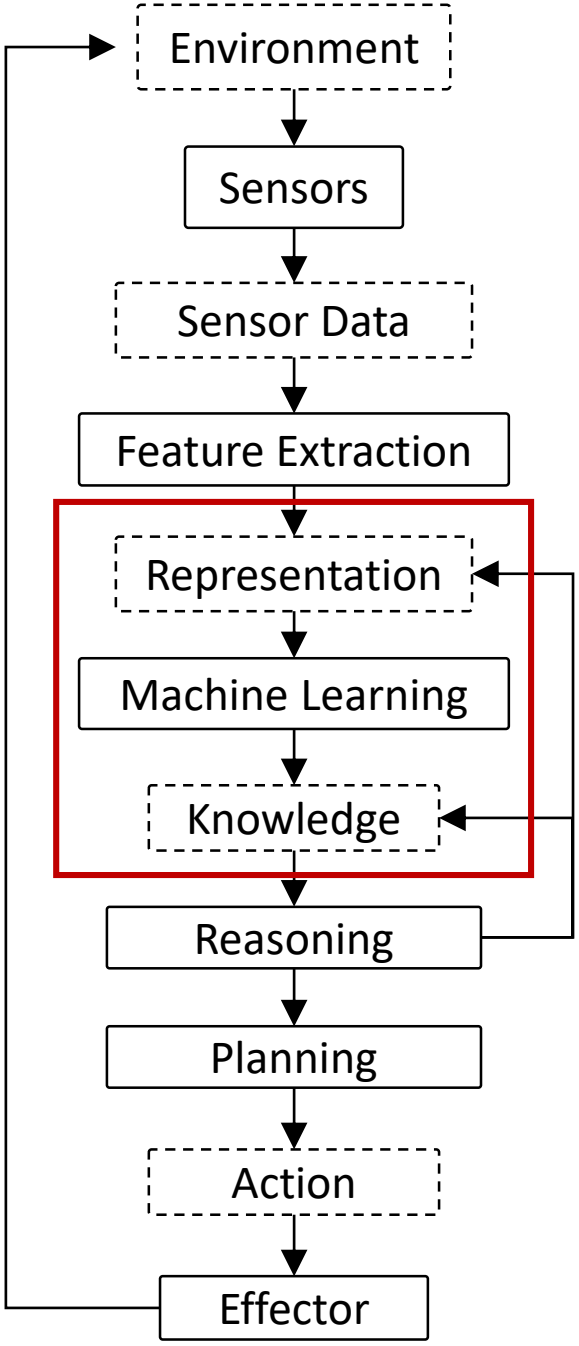
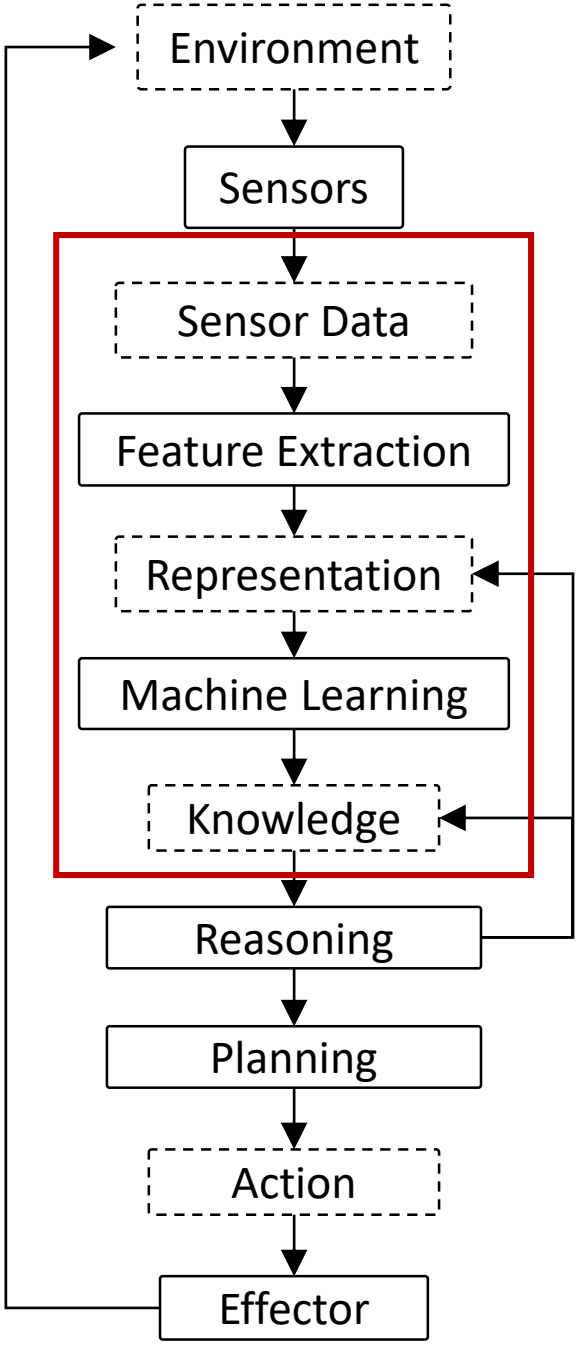

Boston Dynamics



Open Question:

How much of this AI stack can be **learned**?



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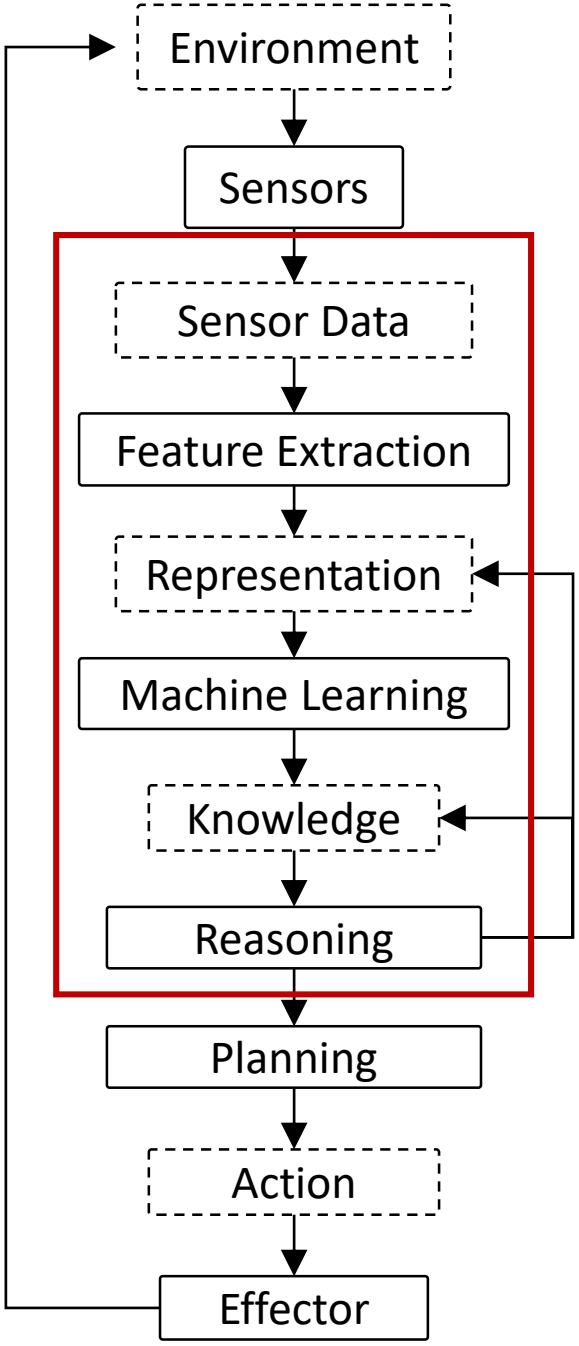

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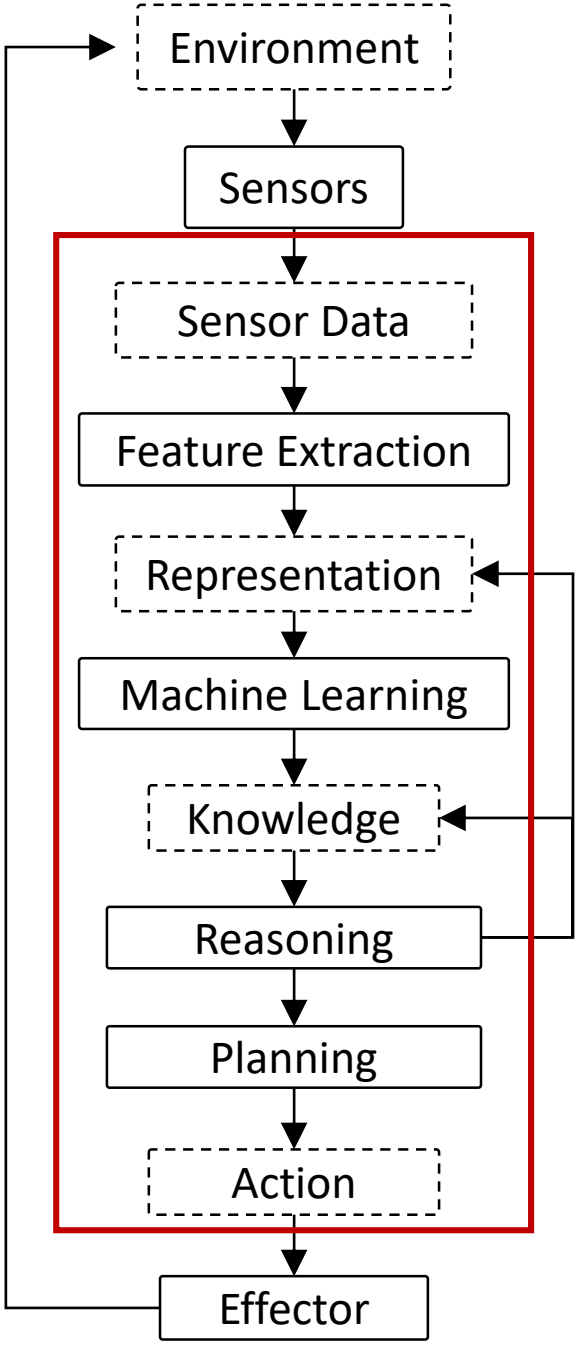

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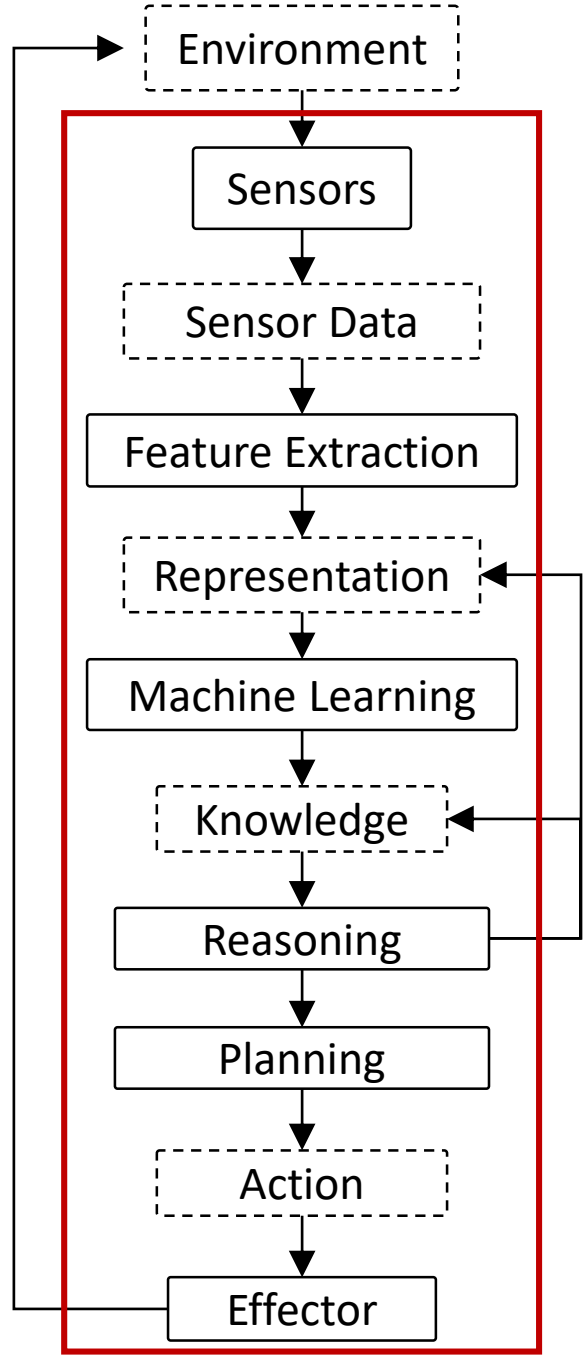


Open Question:

How much of this AI stack can be **learned**?

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."

Question: Why? **Answer:** Data

Visual perception: 540 millions years of data

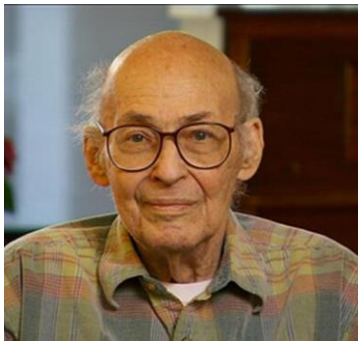
Bipedal movement: 230+ million years of data

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?

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

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

Time → Today → *Future*

Today's Lecture:

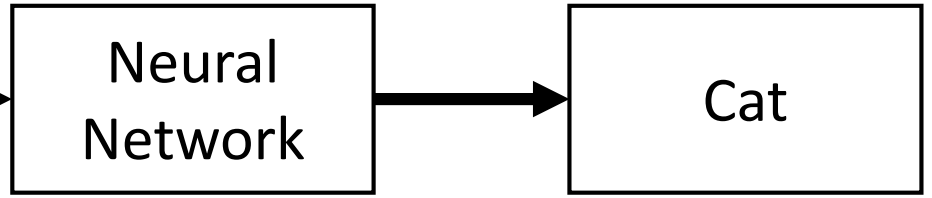
1. Overview current **approaches**
2. Highlight **limitations**
3. Discuss the **potential**
   (and marvel at the mystery)

Best current answer:

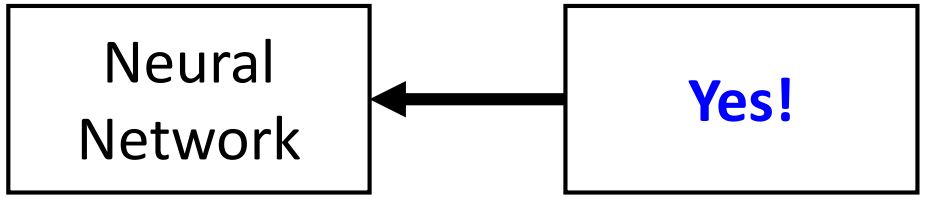
We Don't Know

How Neural Networks Learn: Backpropagation

Forward Pass:



Backward Pass (aka Backpropagation):



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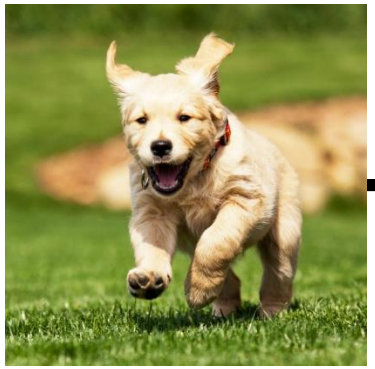

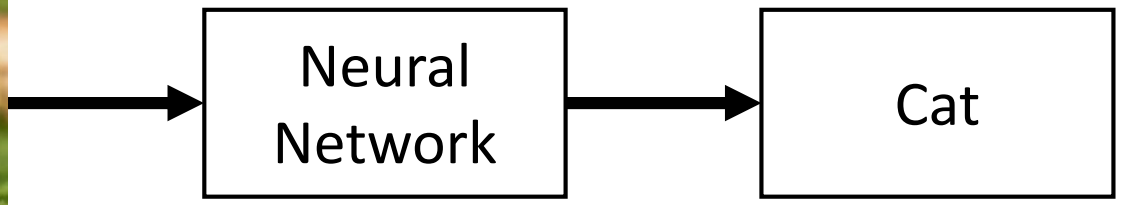

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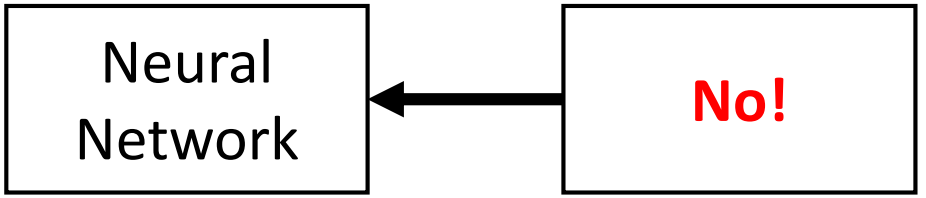
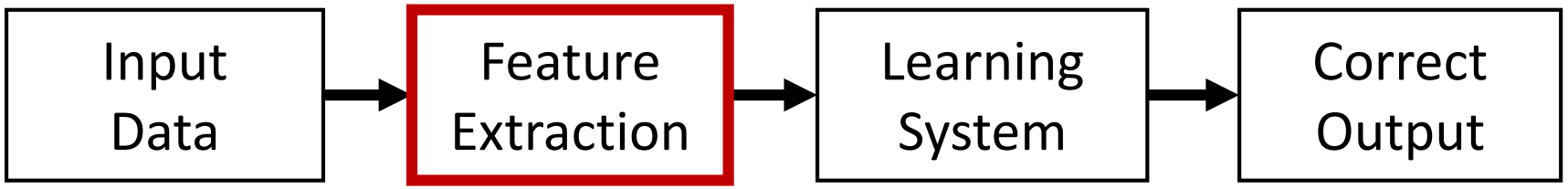
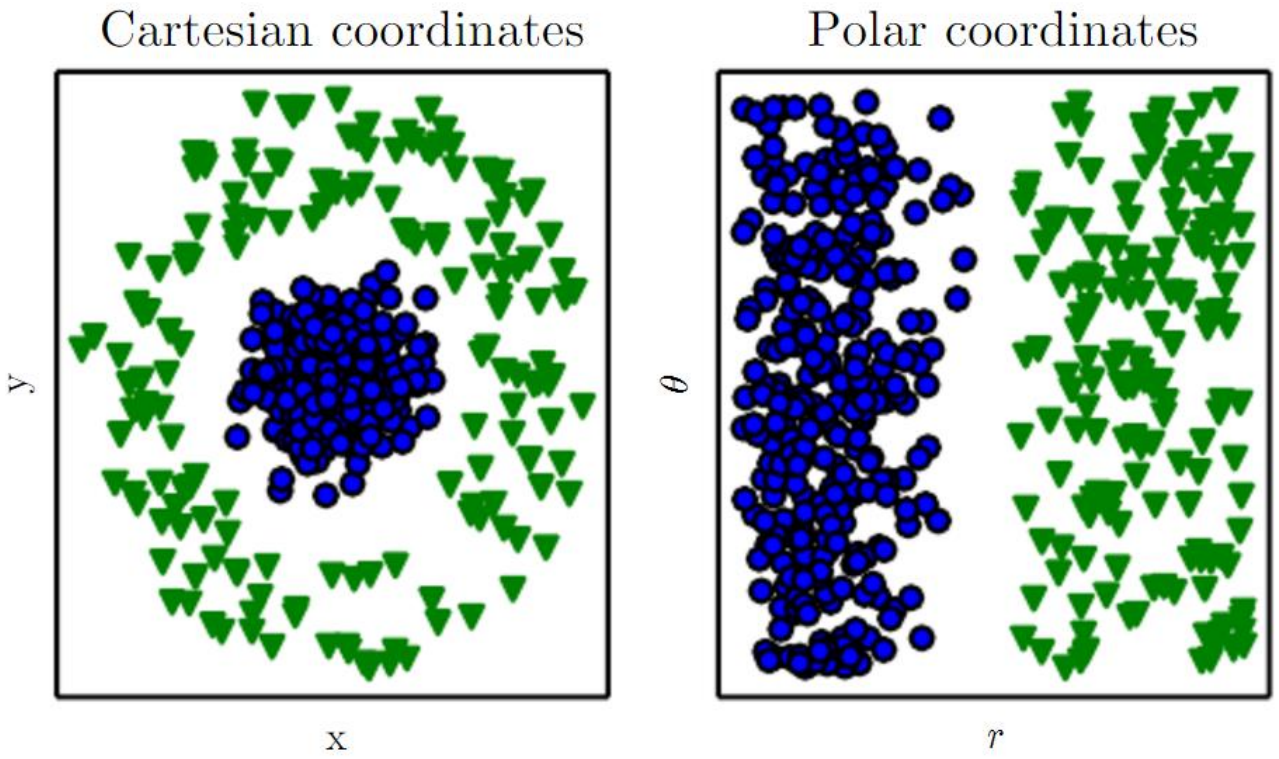


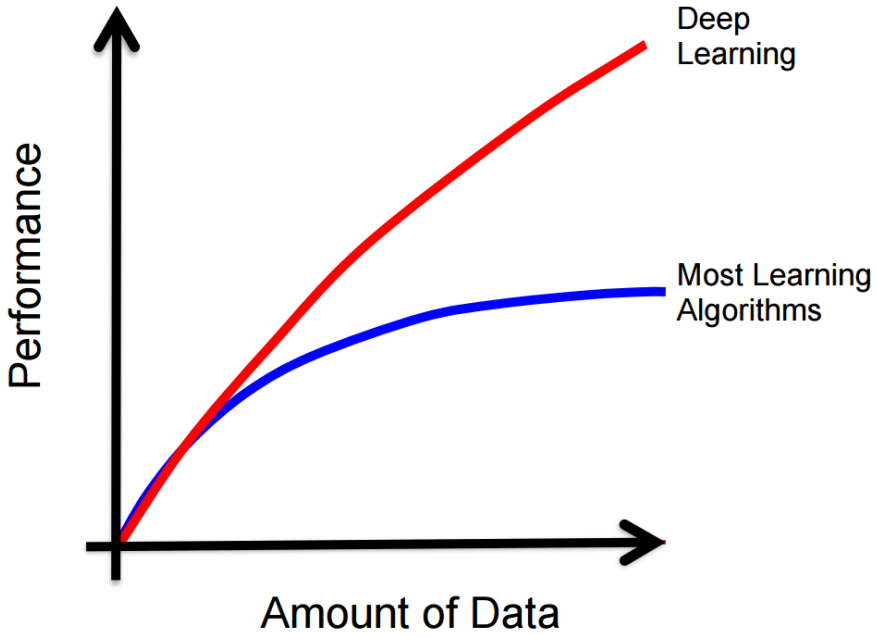
Representation Matters!

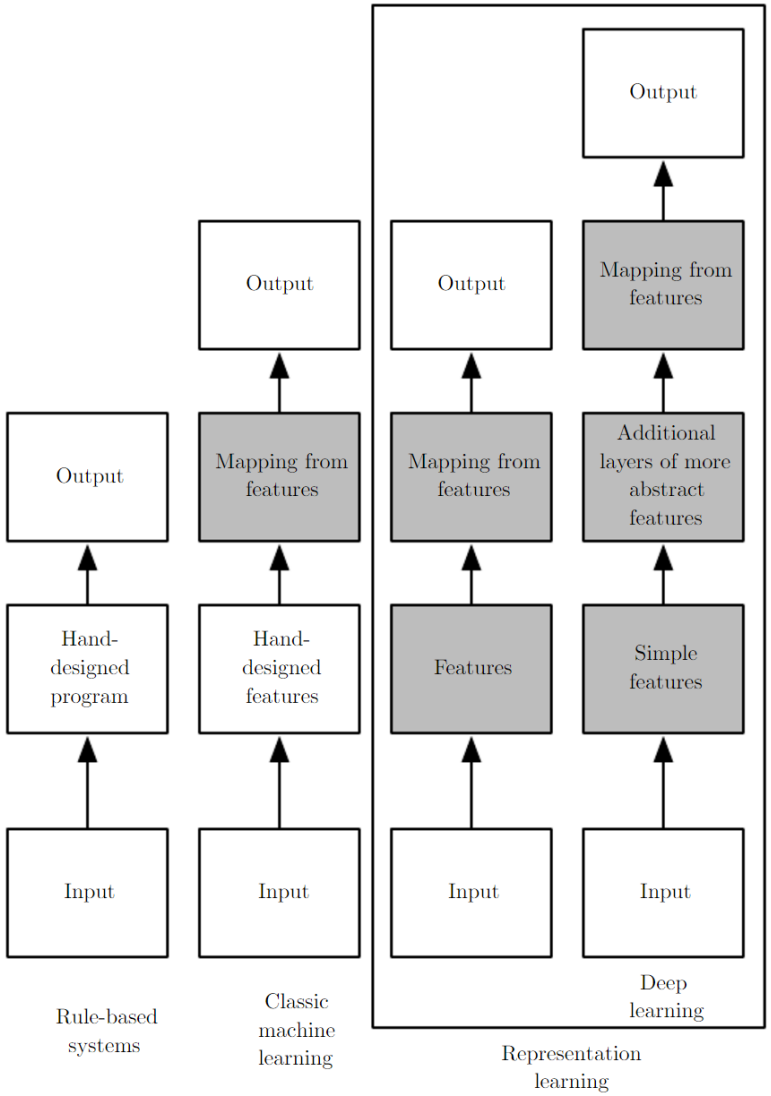
(Representation aka Features)

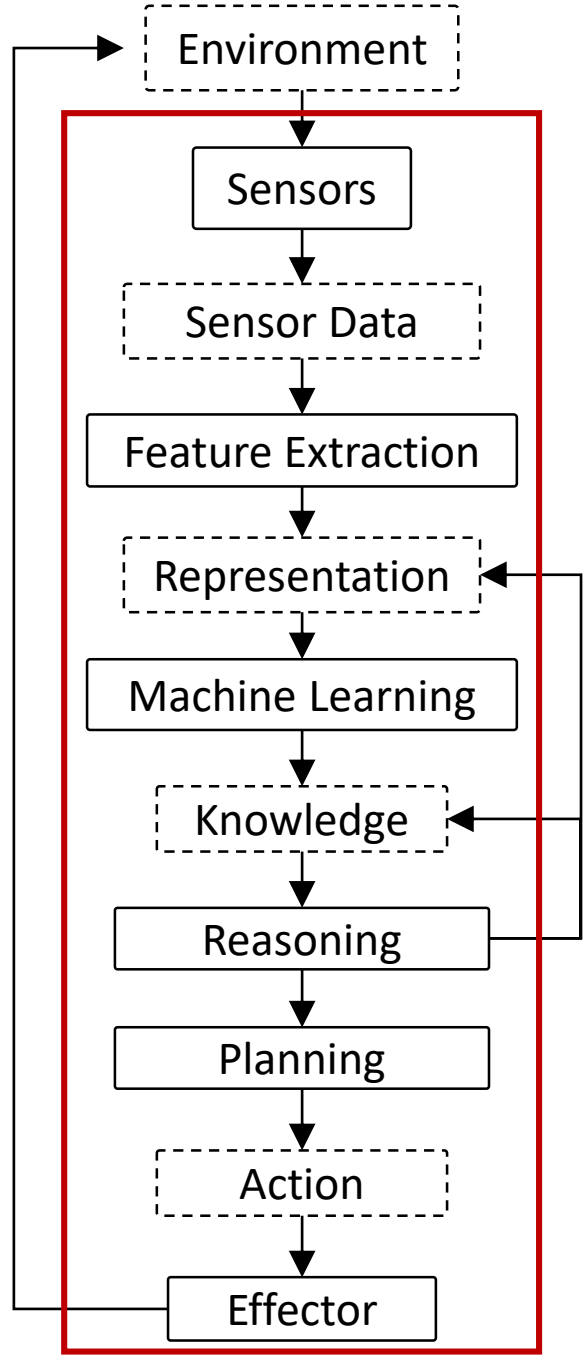




Deep Learning: **Scalable** Machine Learning







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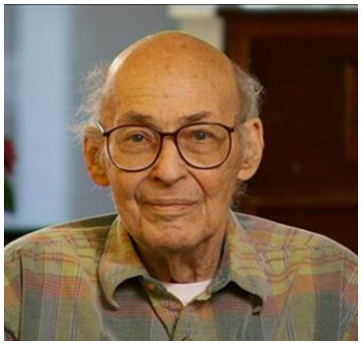


Marvin Minsky (MIT)

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

References: [8, 9]

Challenge and Opportunity:

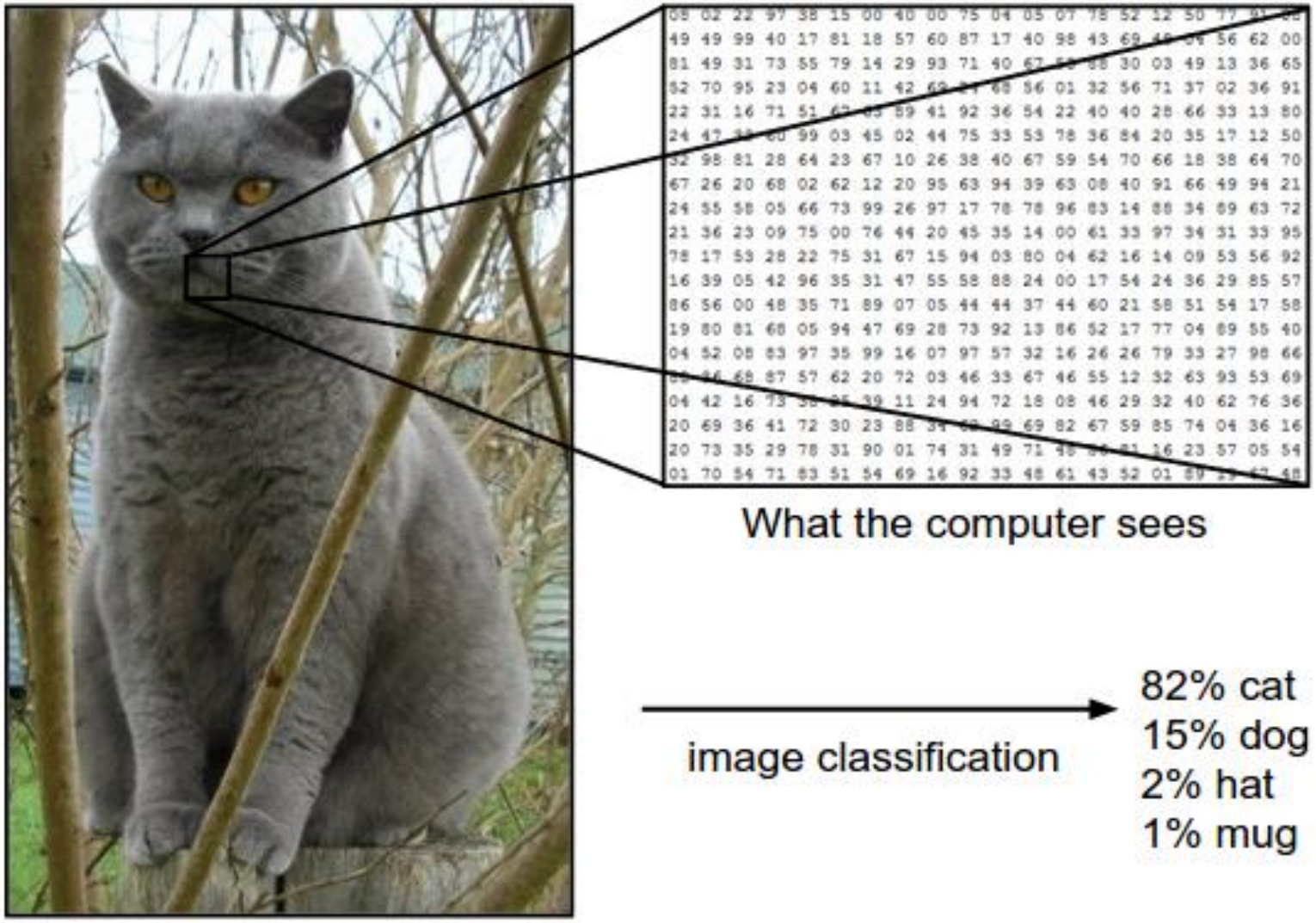
Real World Application

(Robustness)

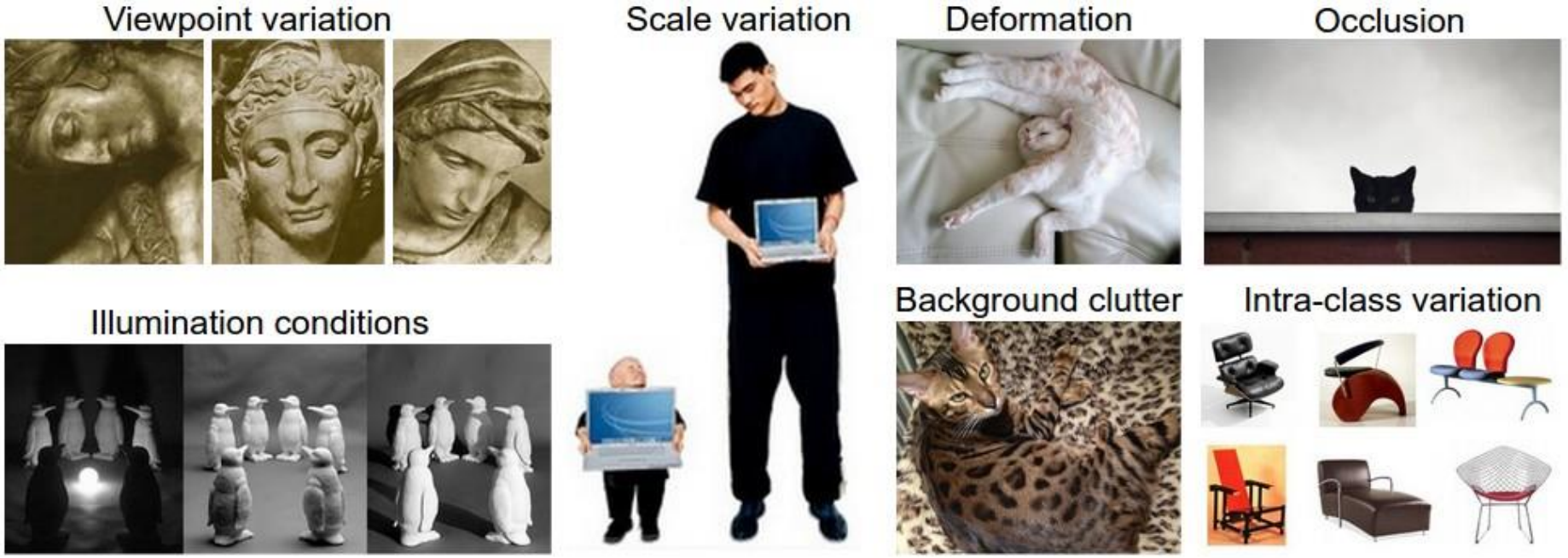
Computer Vision for Intelligent Systems

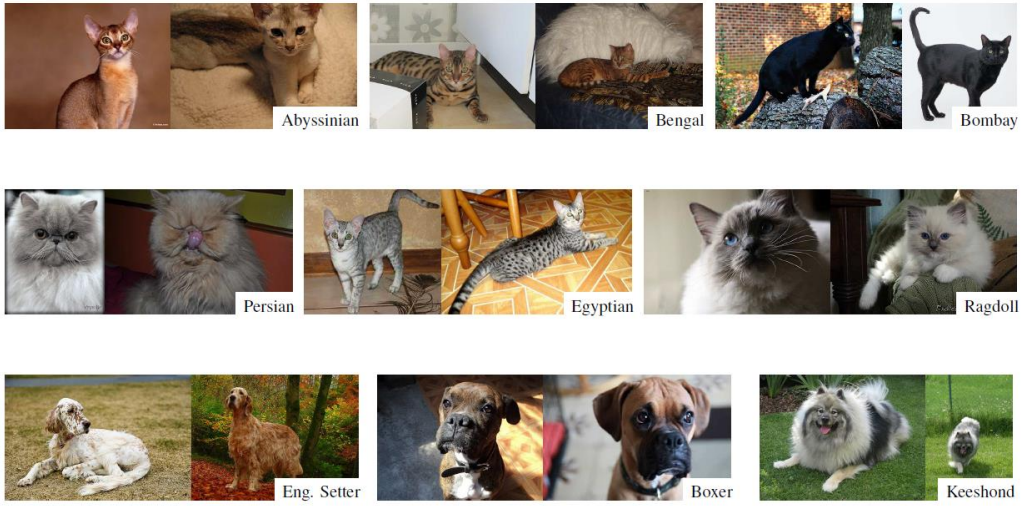
3D Scene	
Feature Extraction	Texture; Color; Optical Flow; Stereo Disparity
Grouping	Surfaces; Bits of objects; Sense of depth; Motion patterns
Interpretation	Objects; Agents and goals; Shapes and properties; Open paths; Words
Action	Walk, touch, contemplate, smile, evade, read on, pick up, …

Images are Numbers



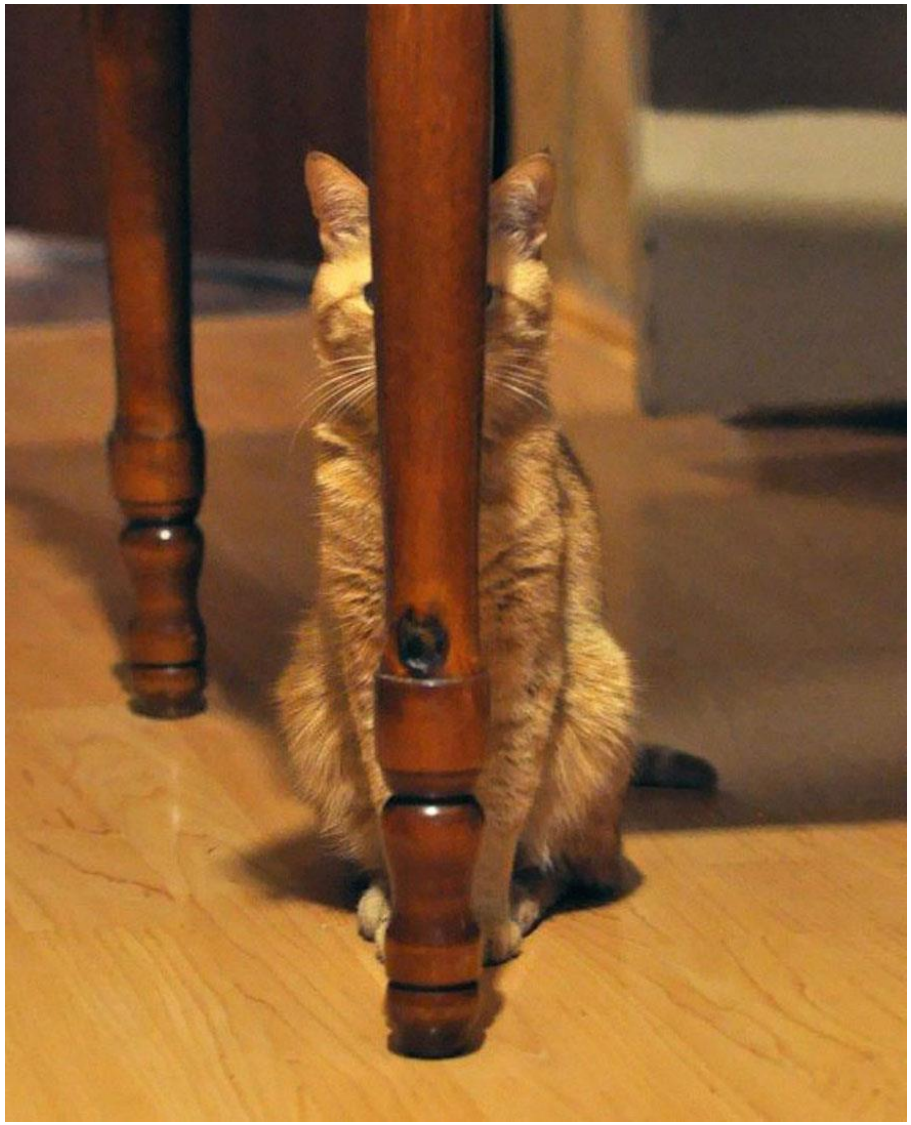
Computer Vision is Hard





References: [66, 69, 89]

Object Classification Challenge: Occlusion



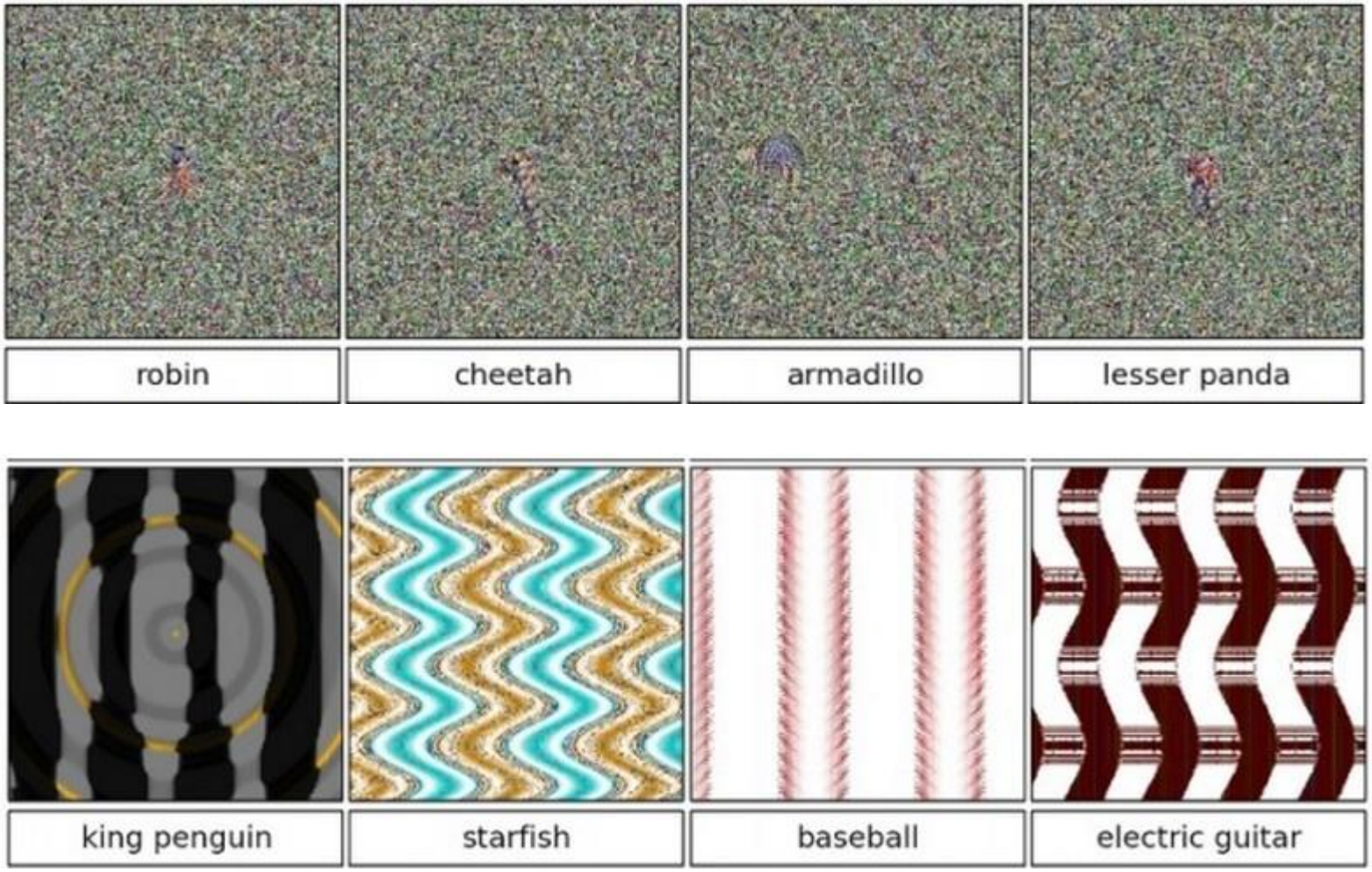
Object Classification Challenge: Occlusion

Object Classification Challenge: Occlusion

Object Classification Challenge: Occlusion

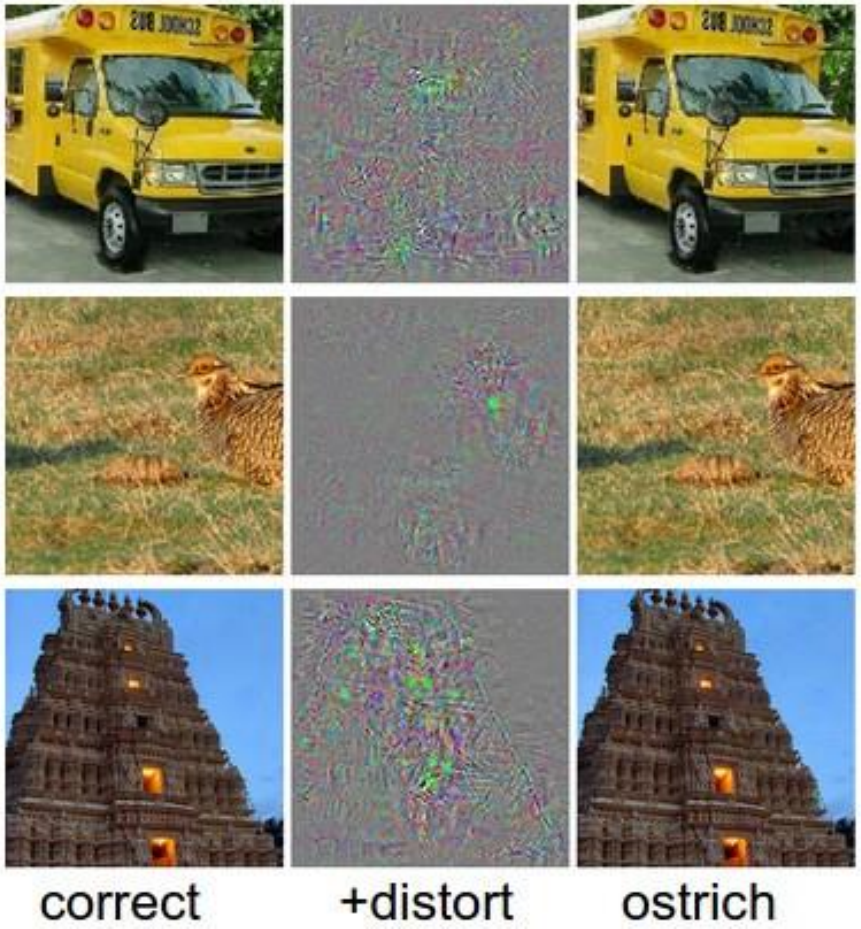
Object Classification Challenge: Occlusion

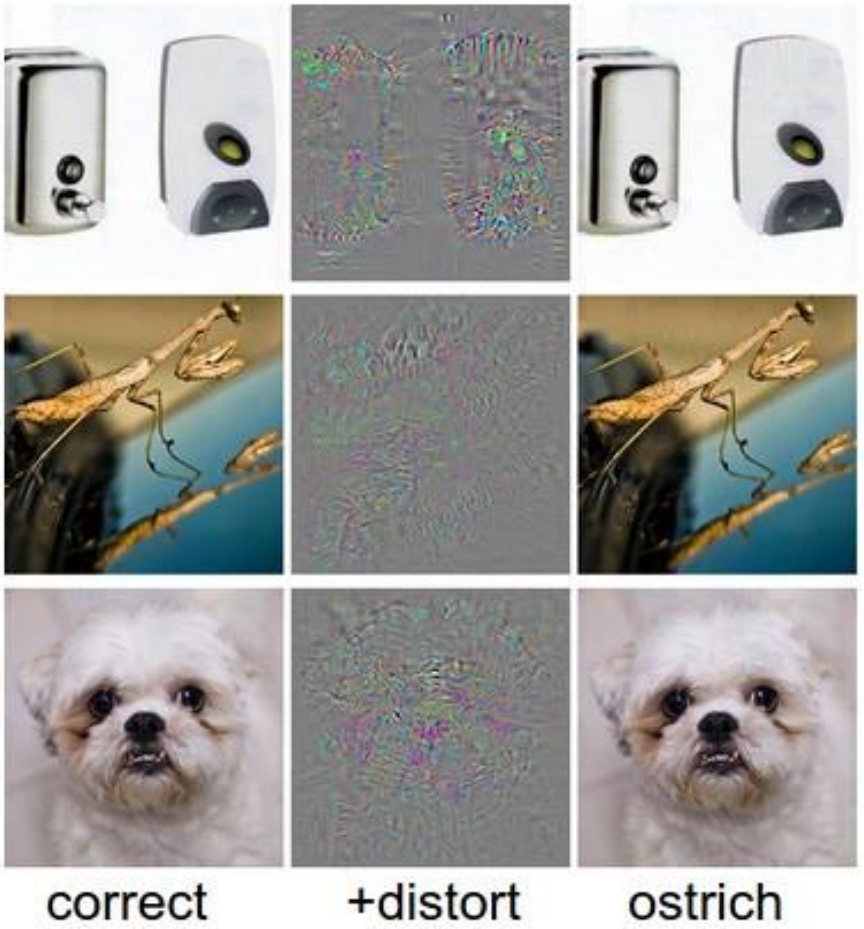
Robustness:
>99.6% Confidence in the Wrong Answer



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

Robustness:
Fooled by a Little Distortion

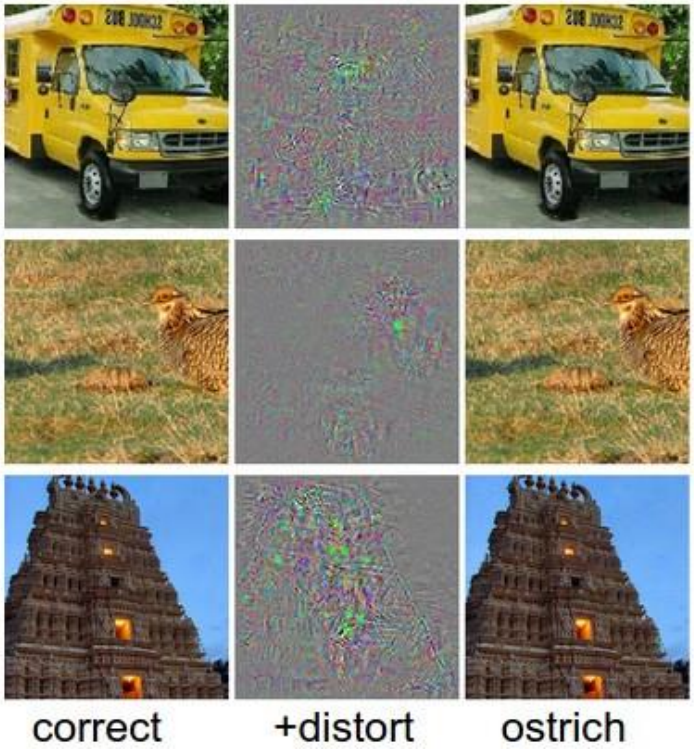




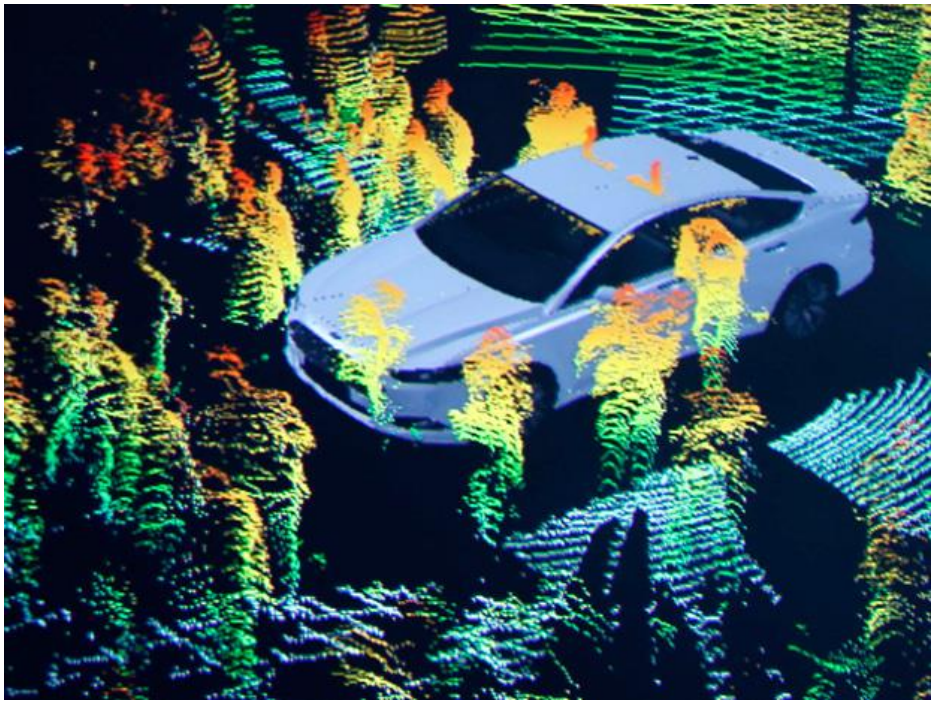
Szegedy et al. "Intriguing properties of neural networks." 2013.

Sensor Spoofing

Camera Spoofing



LIDAR Spoofing



References: [68, 72]

Challenge and Opportunity:

Sparsely-Labeled Data

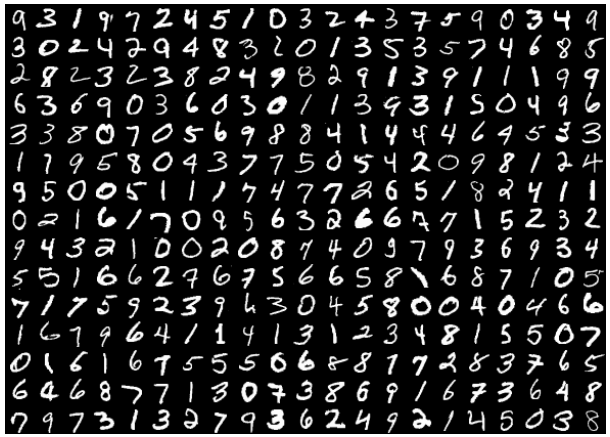
Current Challenges

- **Lacks Reasoning:**
  Unable to build unconstrained knowledge graphs from small human-defined seed graphs

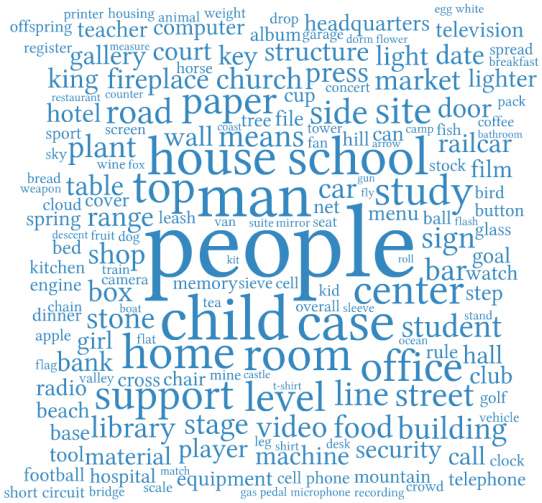
- **Inefficient Learners:**
  Every “concept” needs a lot of examples

- **Label Cost:**
  Supervised data is costly

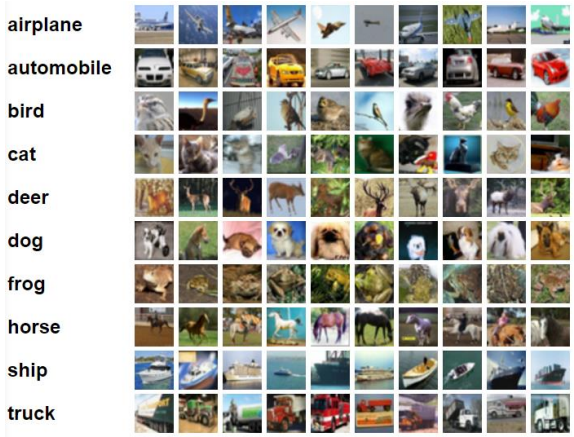
Supervised Data Example: Computer Vision Datasets



MNIST: handwritten digits



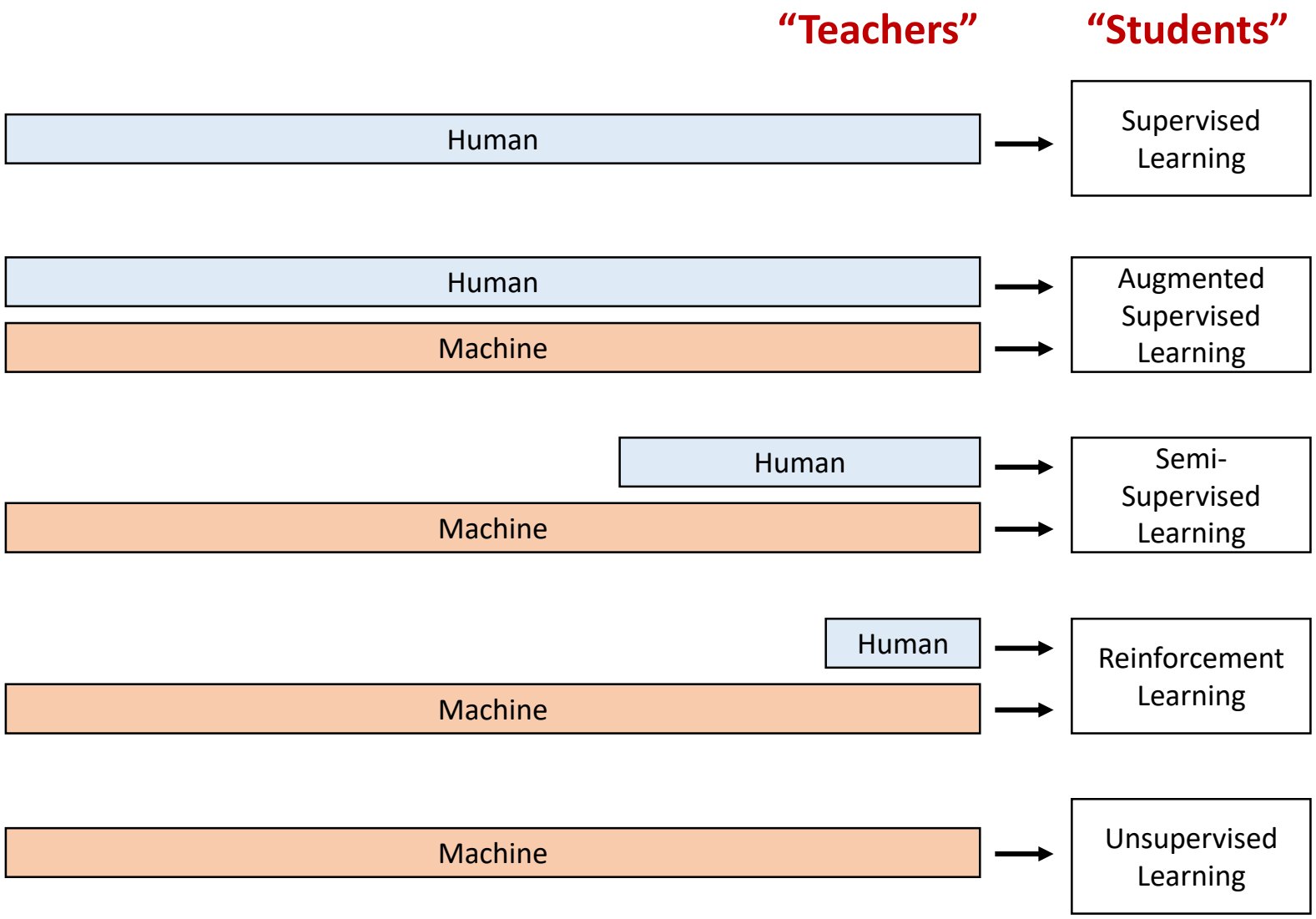
ImageNet: WordNet hierarchy



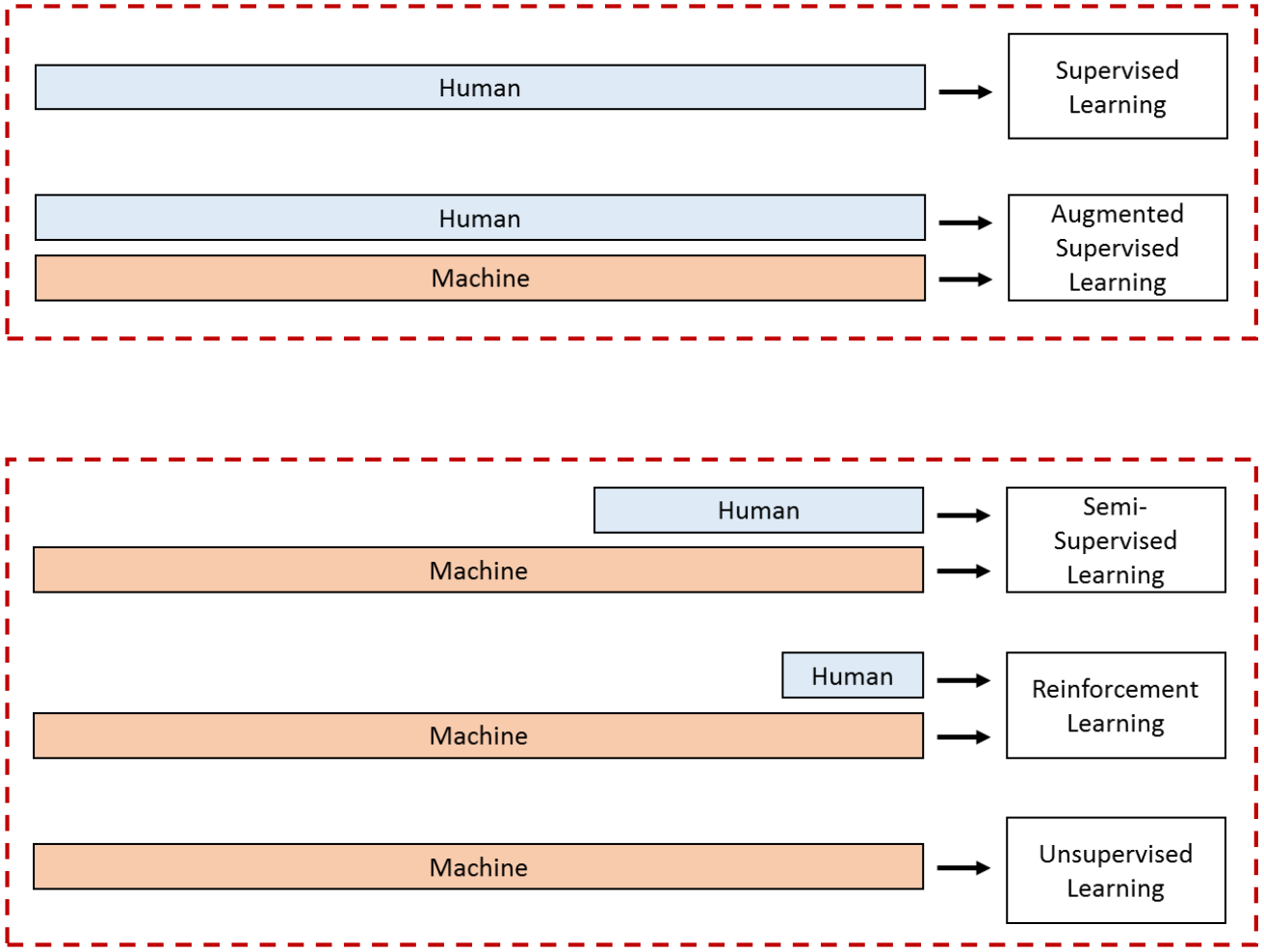
CIFAR-10(0): tiny images

Places: natural scenes

Machine Learning from Human and Machine



Machine Learning from Human and Machine



Memorization

Understanding

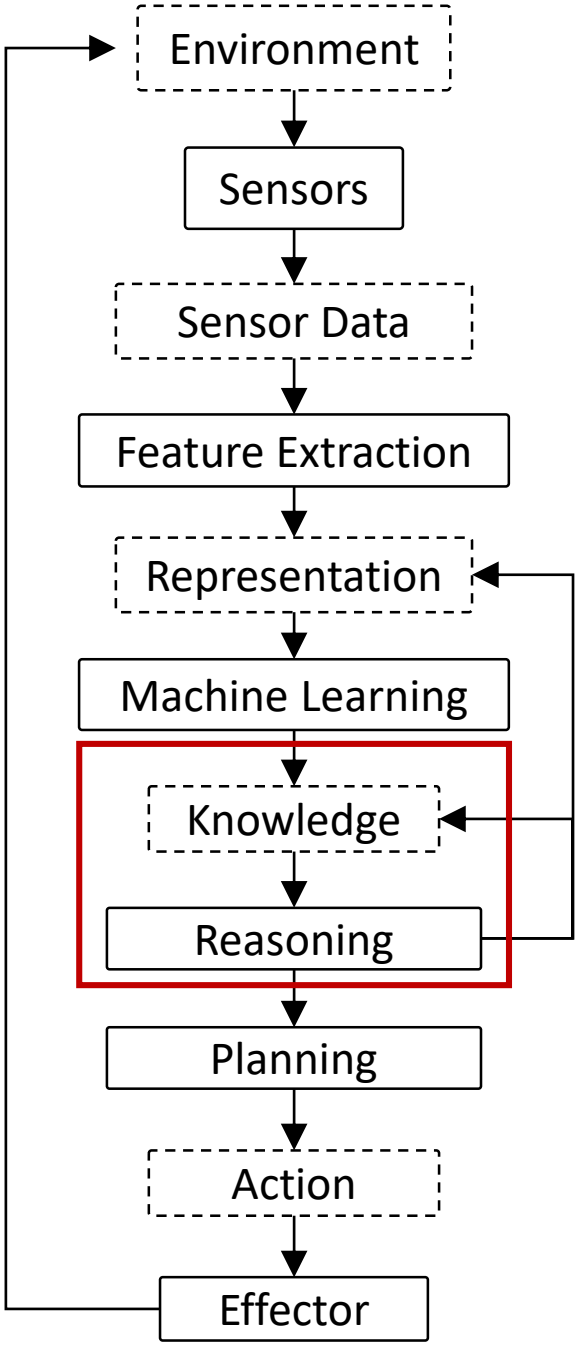


Image Recognition:
If it looks like a duck

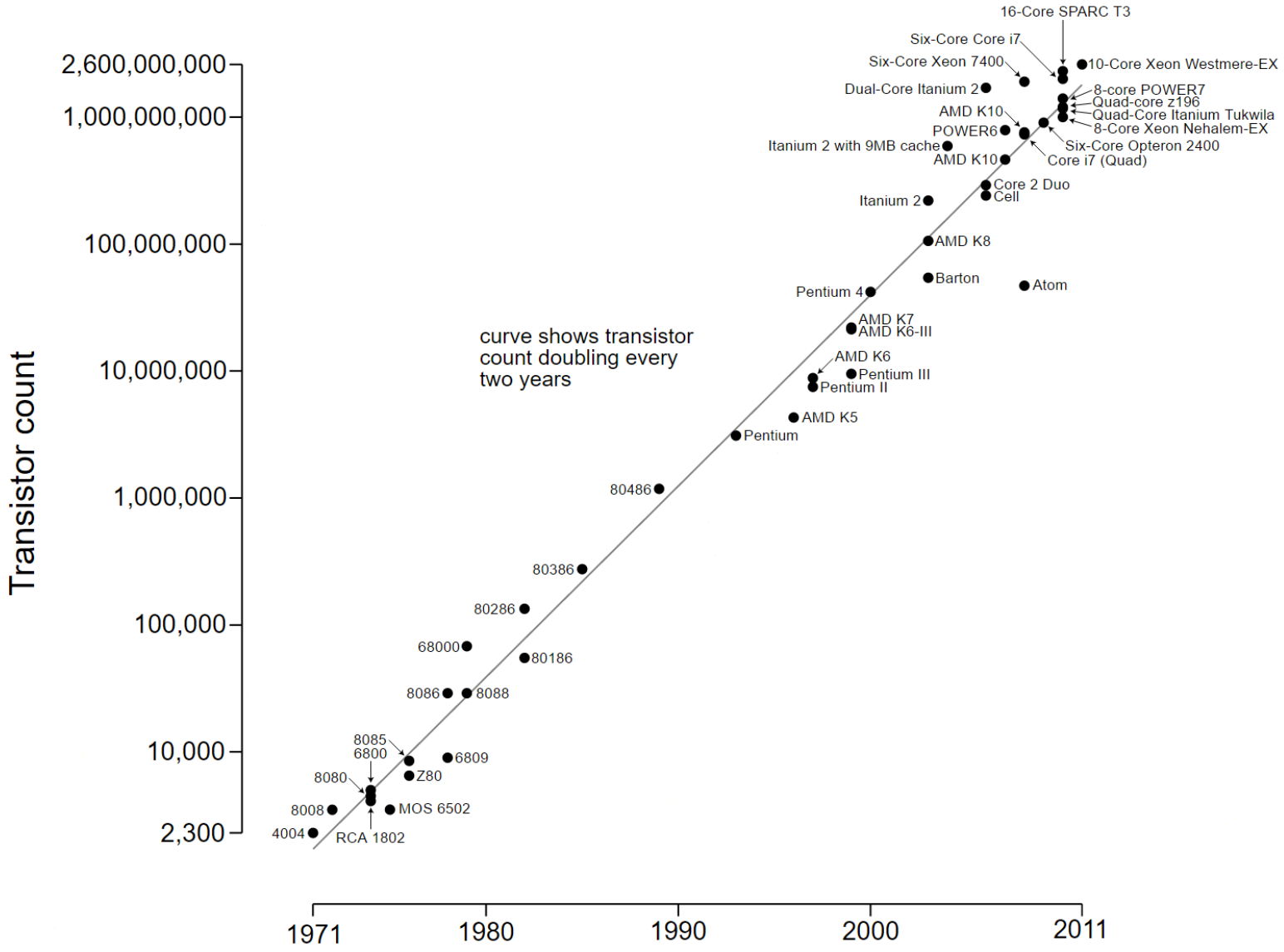
Audio Recognition:
Quacks like a duck

Activity Recognition:
Swims like a duck

Challenge and Opportunity:

Compute

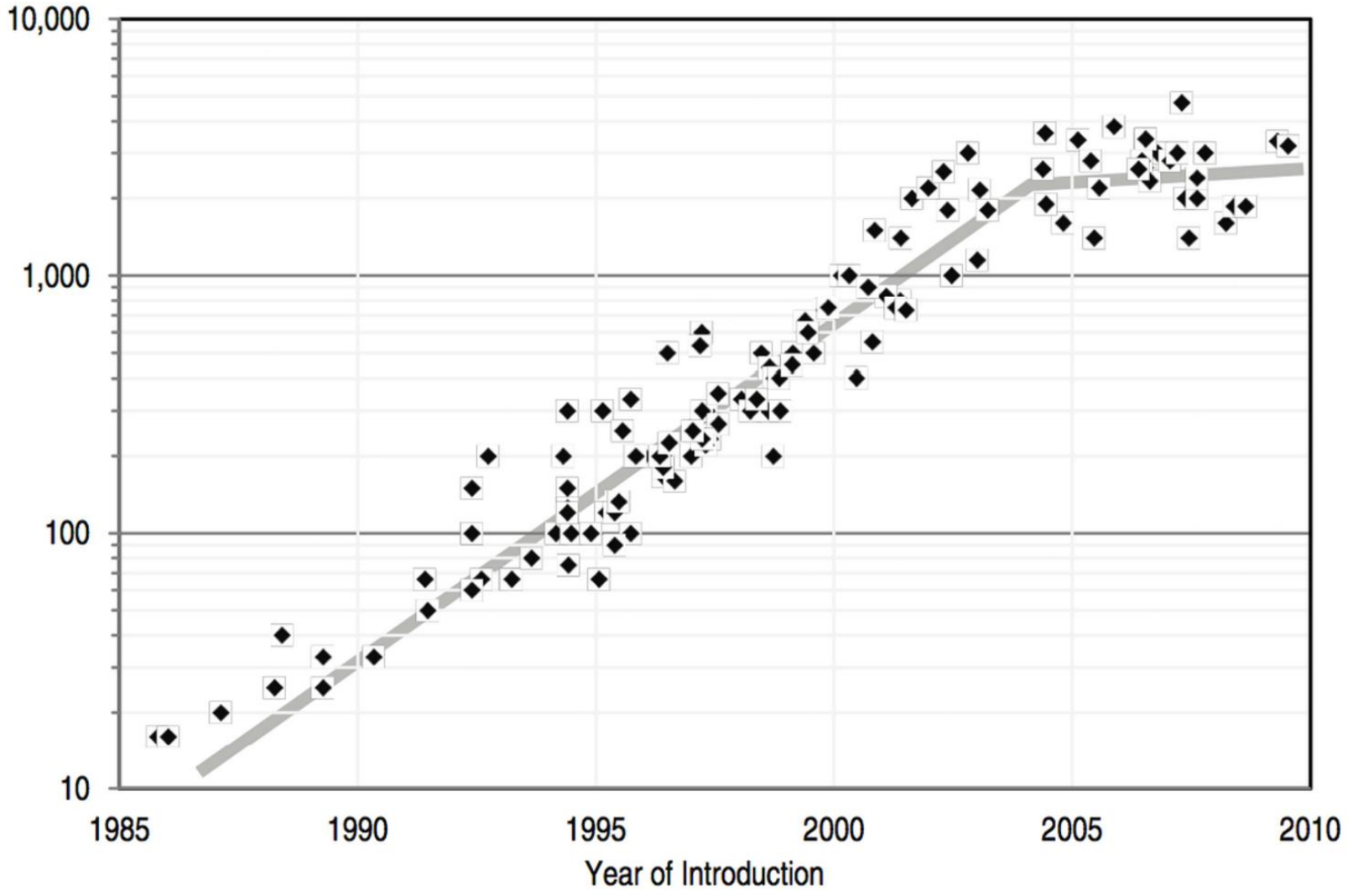
Microprocessor Transistor Counts 1971-2011 & Moore's Law



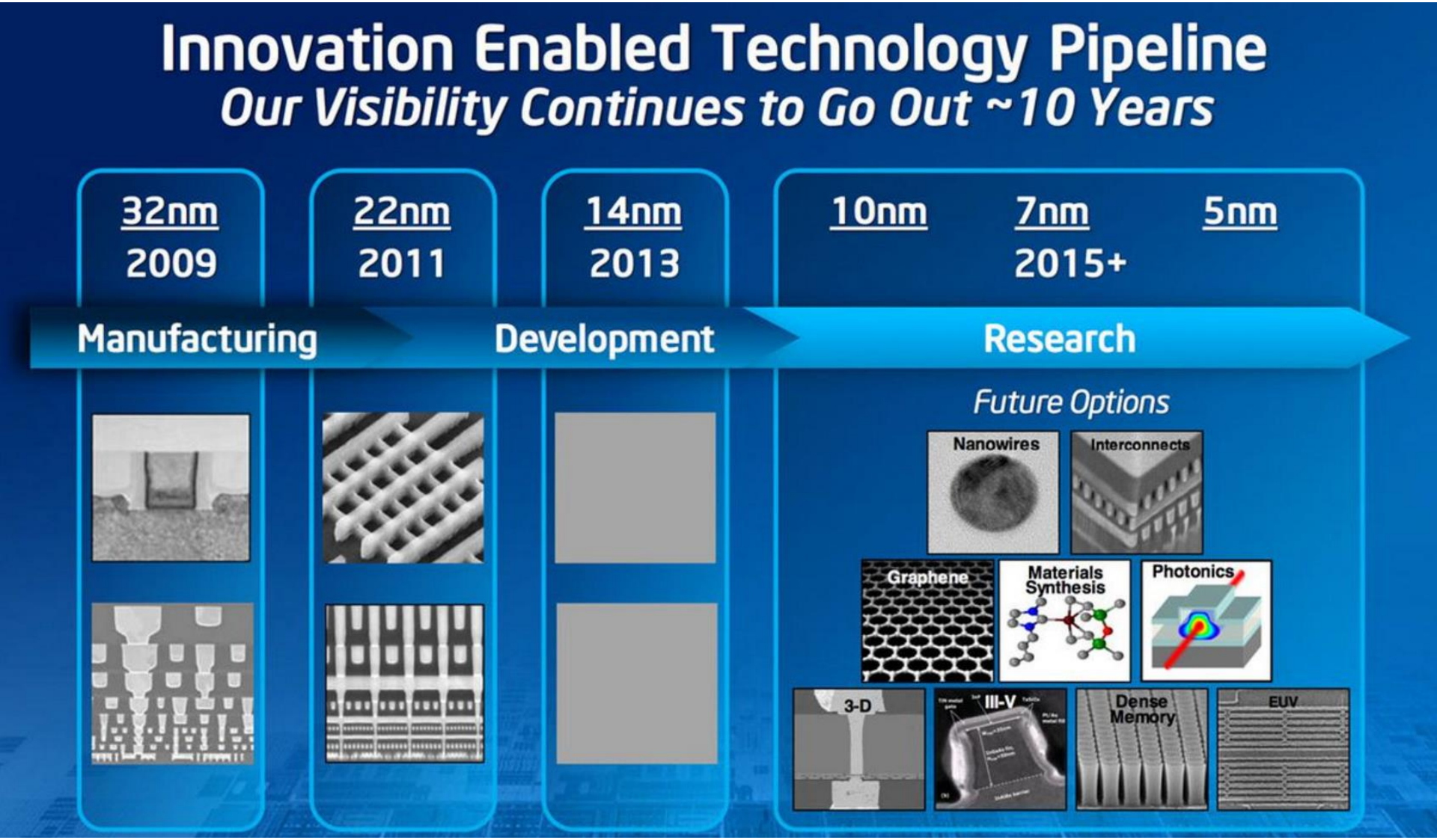
References: [137]

National Academy of Sciences:

Clock Speed (MHz) Scaling Hits a Wall

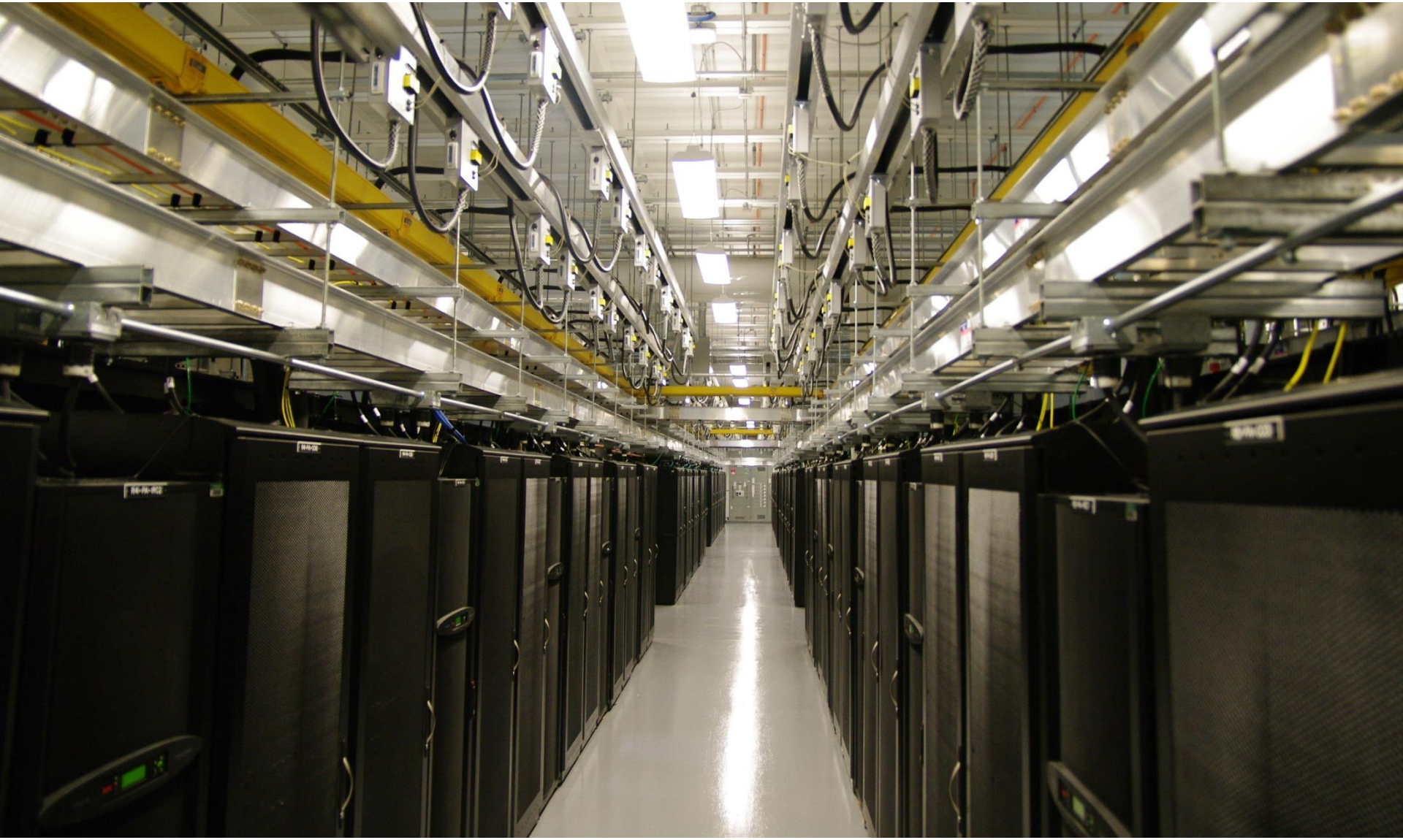


Intel: Innovation Continues
(Aggressively Solving Technical Challenges)



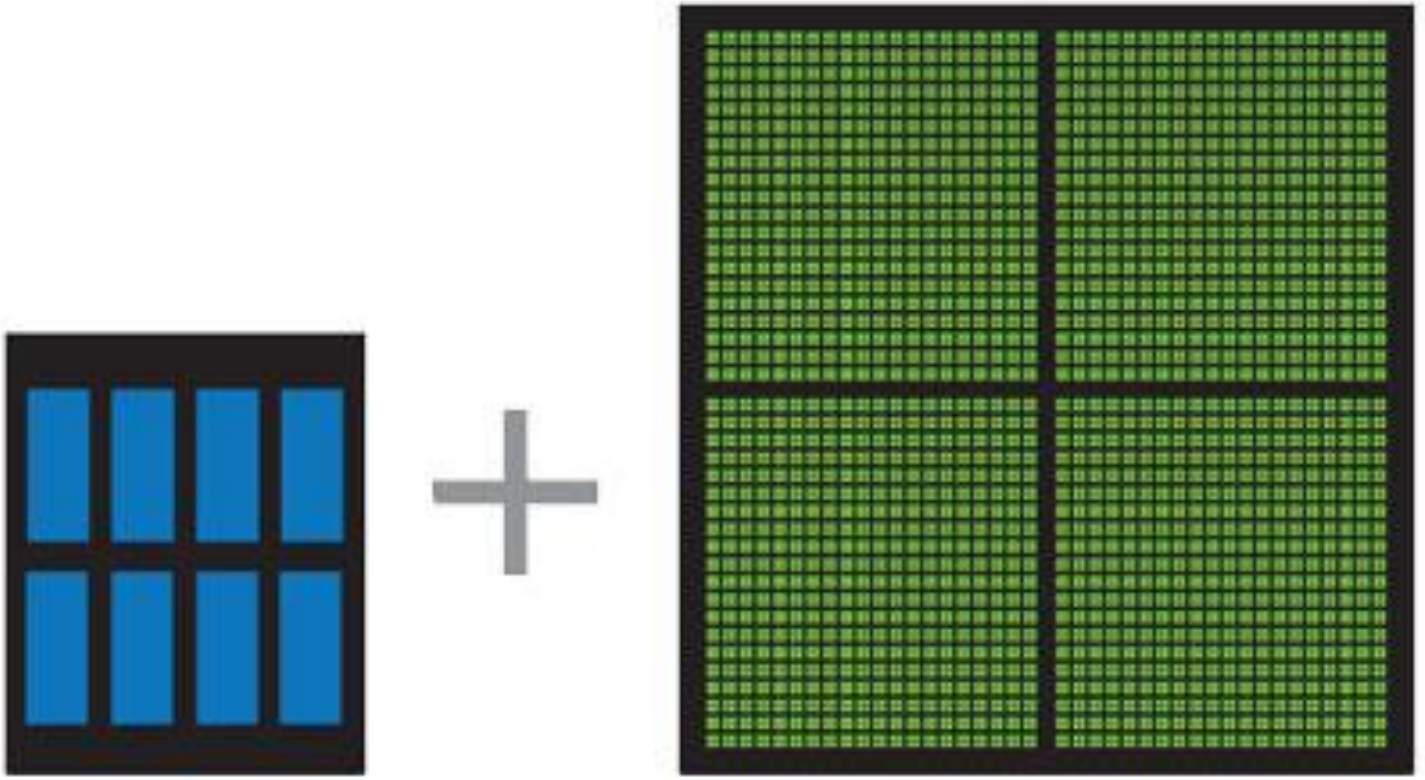
Beyond Moore's Law: Machine Learning

Massive Parallelism & Distributed Compute



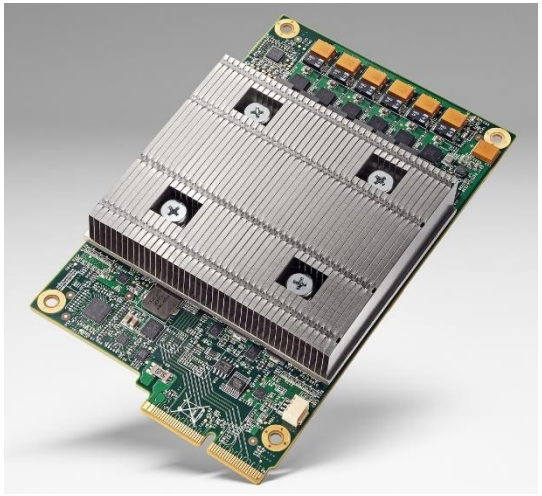
Beyond Moore's Law: Machine Learning

Graphics Processing Unit (GPU) Parallelism



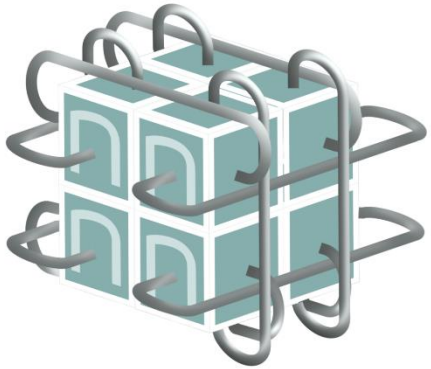
Beyond Moore's Law: Machine Learning

Custom Deep Neural Network Chips



Google Tensor Processing Unit

IBM True North (Brain-Inspired Chip)

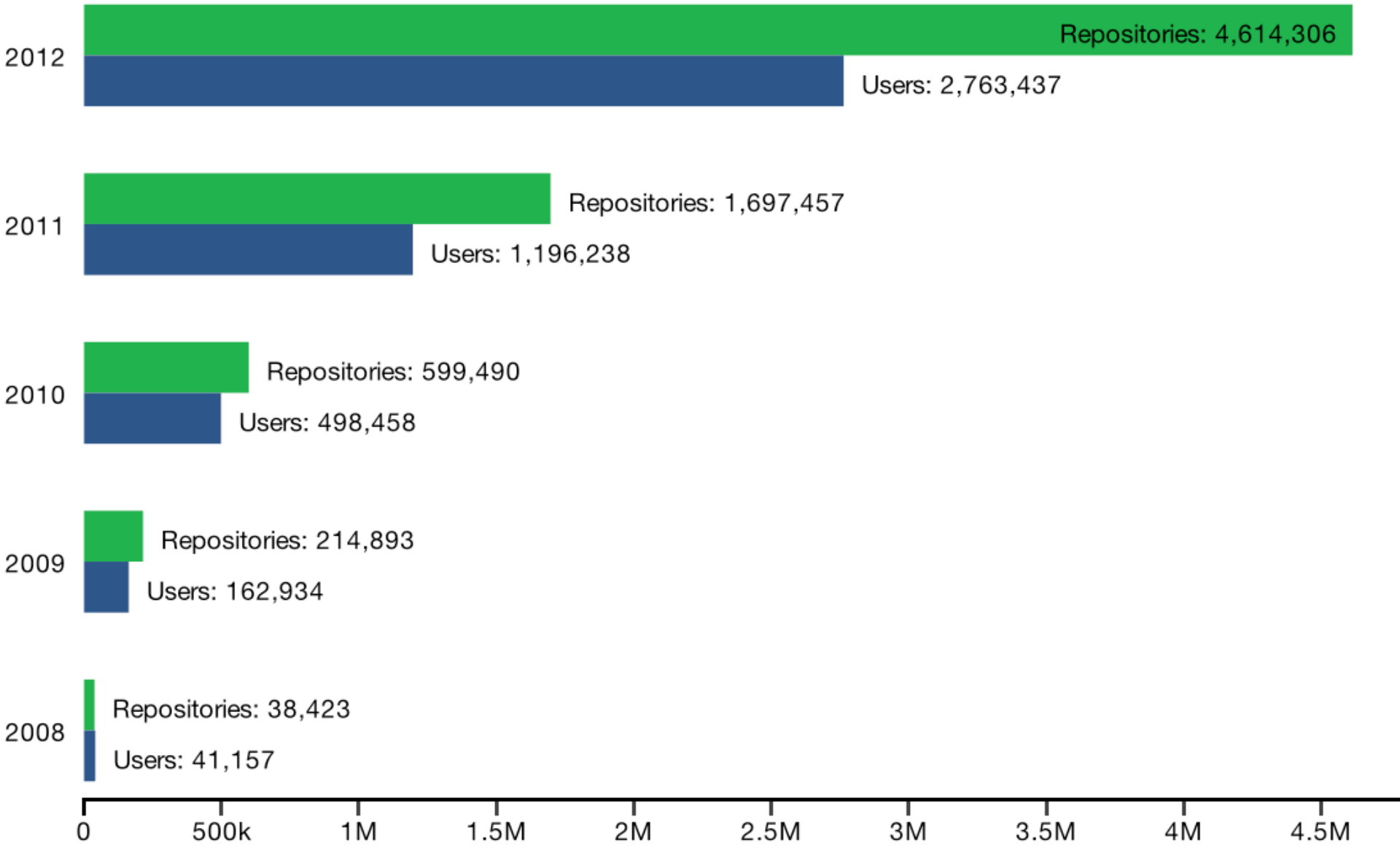


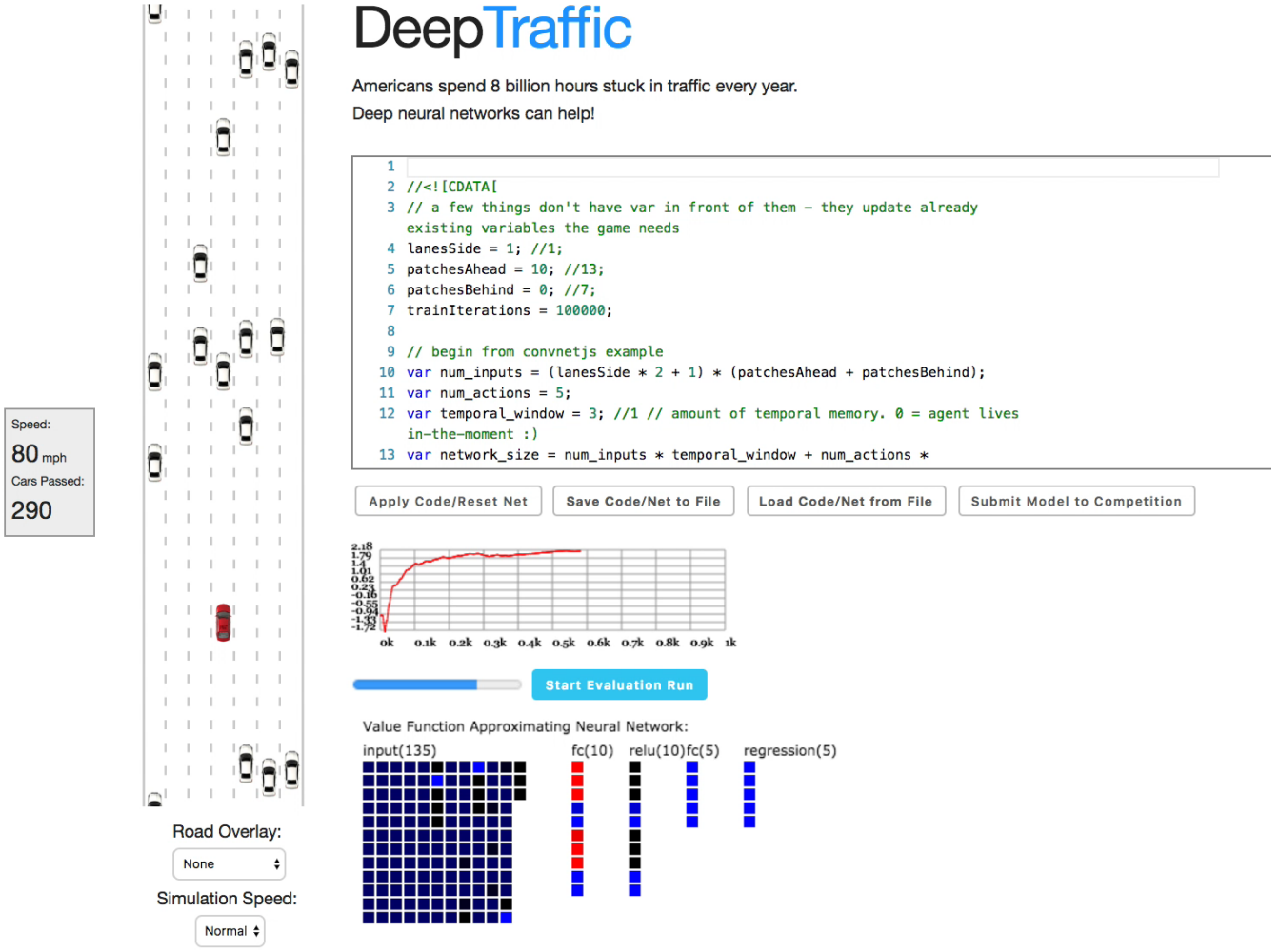
Intel Deep Learning Chip (Nervana Acquisition)

Challenge and Opportunity:

Community

GitHub Growth





http://cars.mit.edu

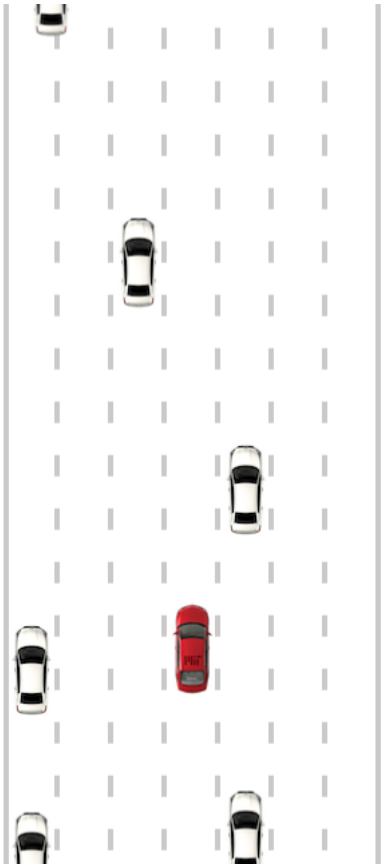
The Road, The Car, The Speed

Speed:

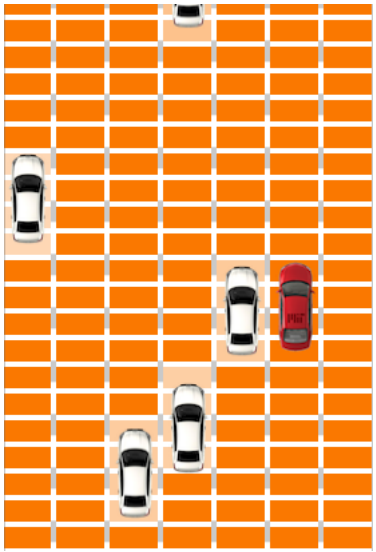
47 mph

Cars Passed:

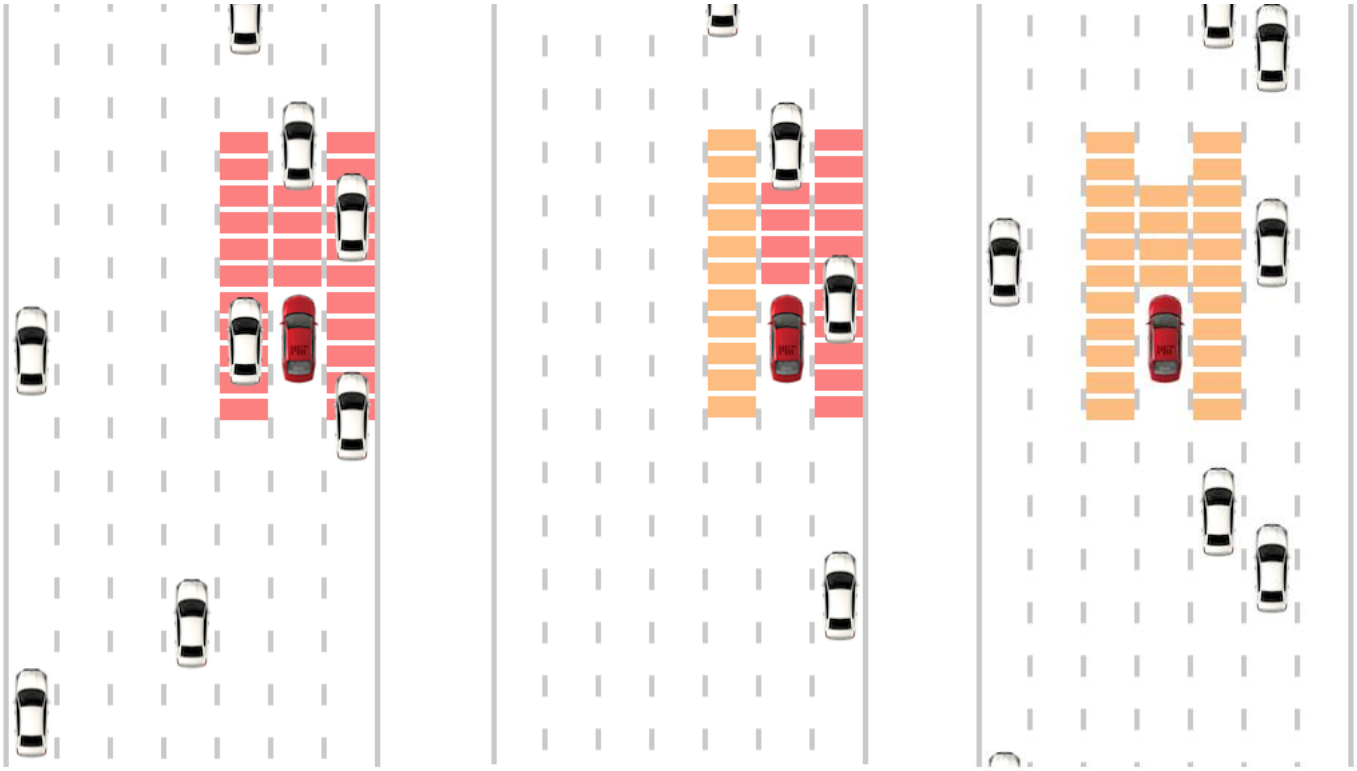
5



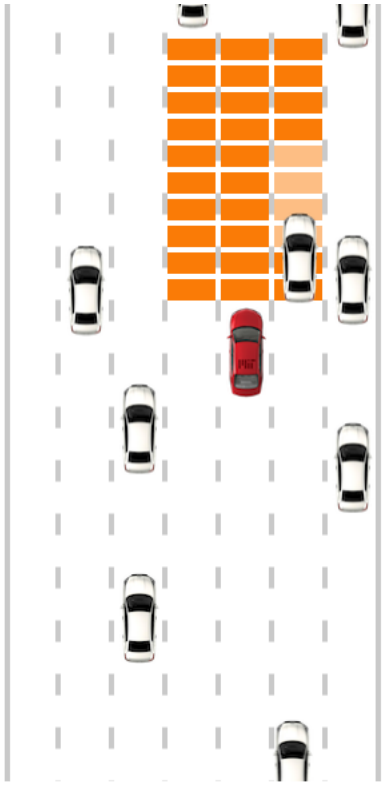
State Representation:



“Safety System”



Learning Input

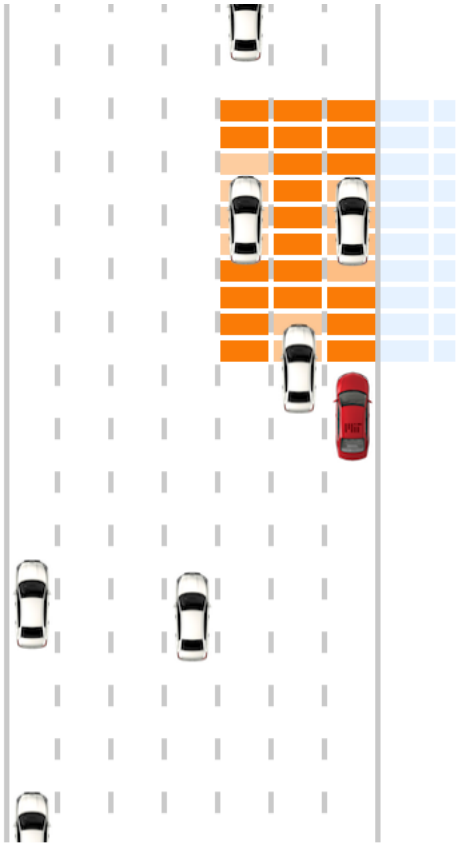


Road Overlay:

Learning Input

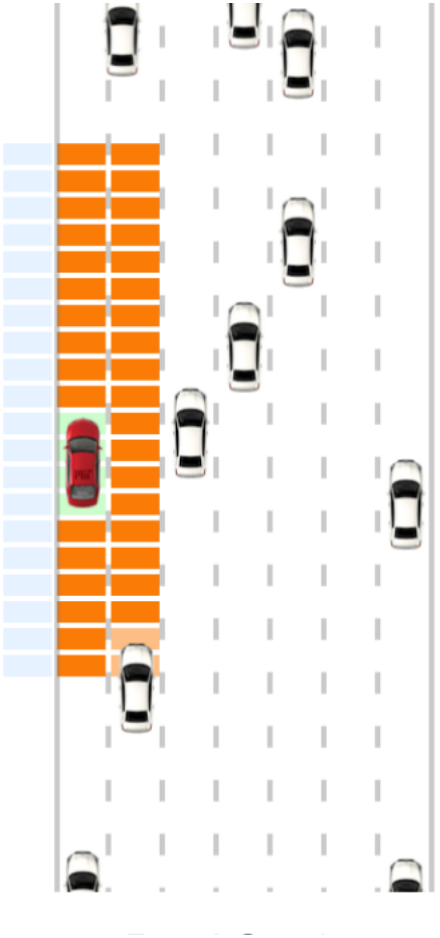
```
lanesSide = 1;
patchesAhead = 10;
patchesBehind = 0;
```

Learning Input



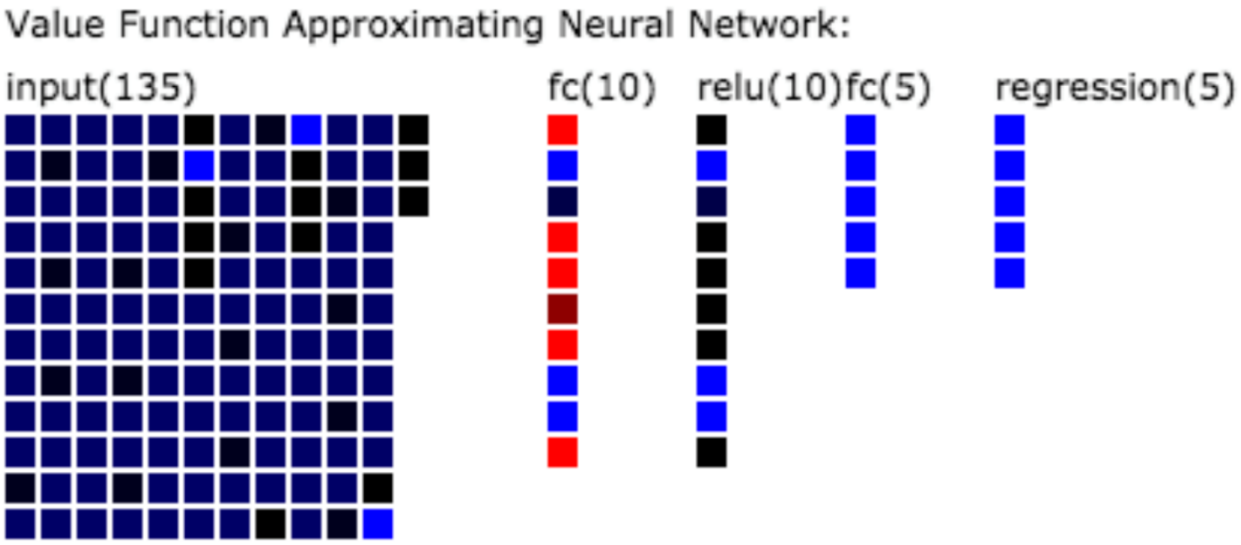
```
lanesSide = 2;
patchesAhead = 10;
patchesBehind = 0;
```

Learning Input

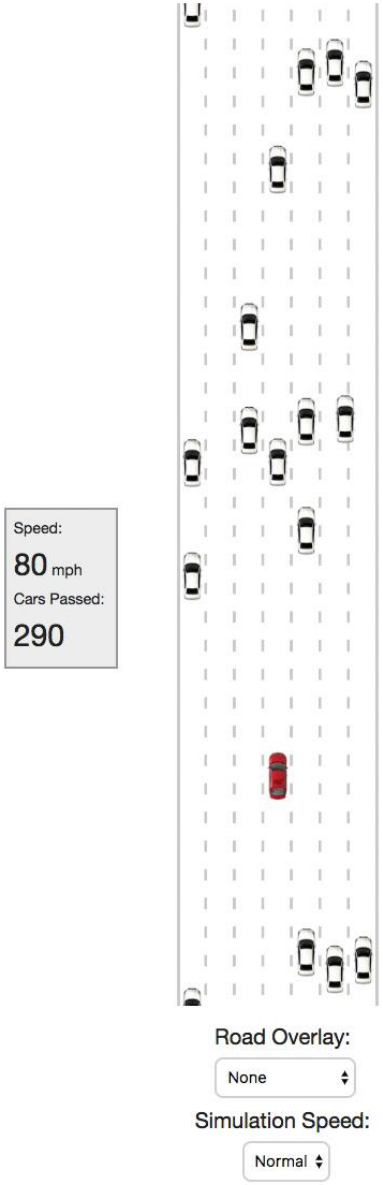


```
lanesSide = 1;
patchesAhead = 10;
patchesBehind = 10;
```

Deep RL: Q-Function Learning Parameters




```
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 (Goodfel

Comment: "I used a single hidden layer. window as 0). Spent some time on hyper times, because the test scores have a big

Michael Gump (74.04 mph)

Winnings: Udacity Self-Driving Car Engin

Comment: "I mainly played around with would get stuck in suboptimal strategies

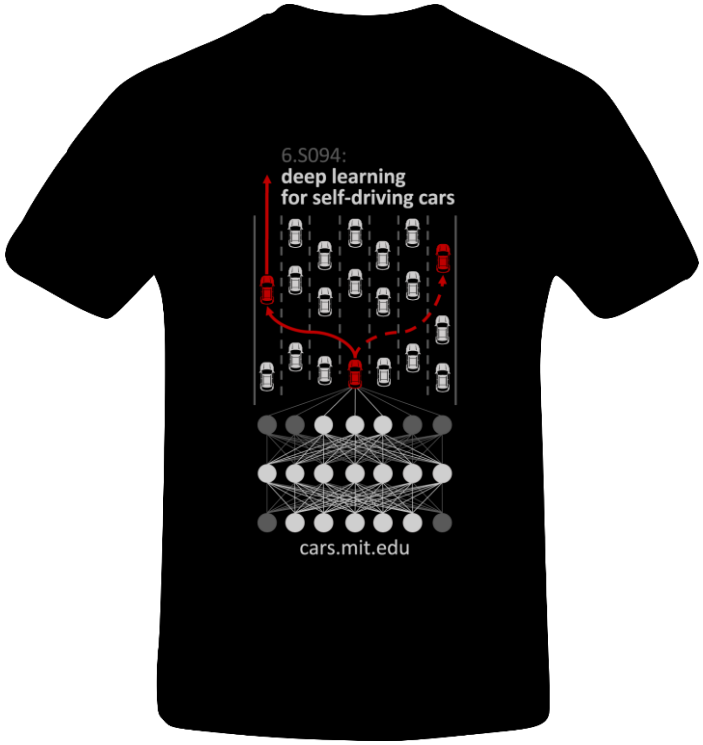
Jeffrey Hu (73.59 mph)

Winnings: Udacity Self-Driving Car Engin

Comment: "I preprocessed to reduce the layer fully connected network. Then I trie 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

http://cars.mit.edu

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

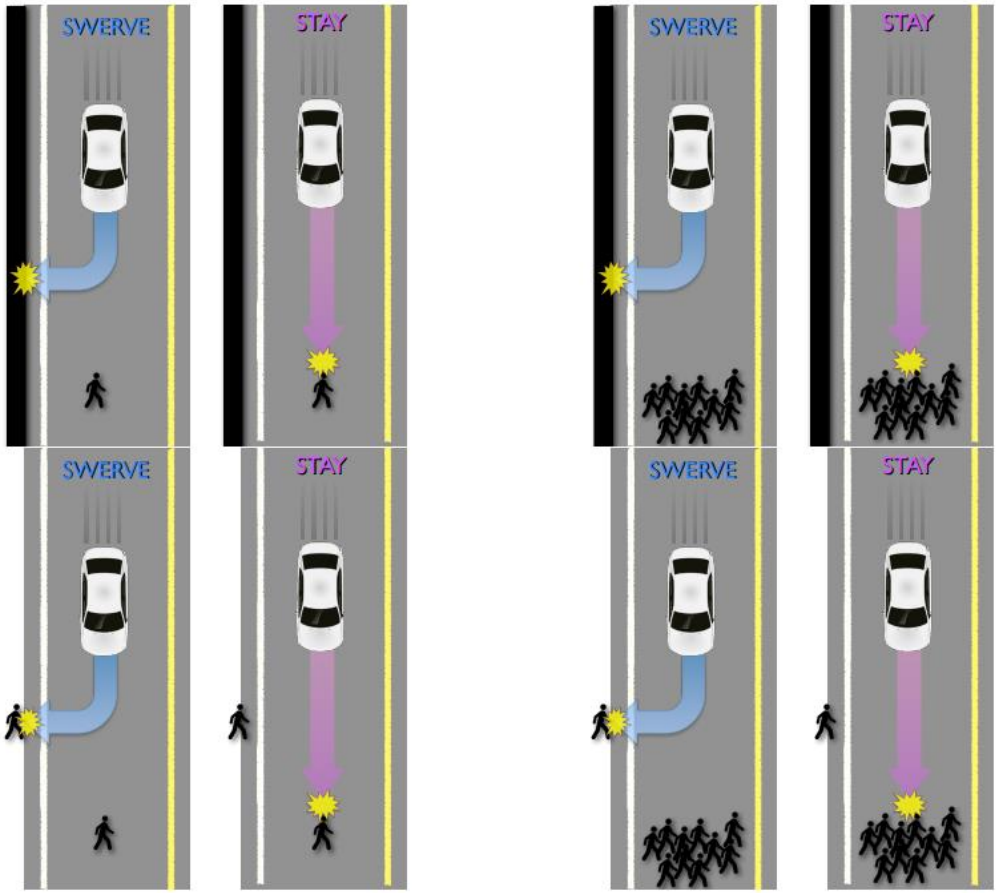
Challenge and Opportunity:

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?