Deep Learning Basics

Deep Learning in **One** Slide

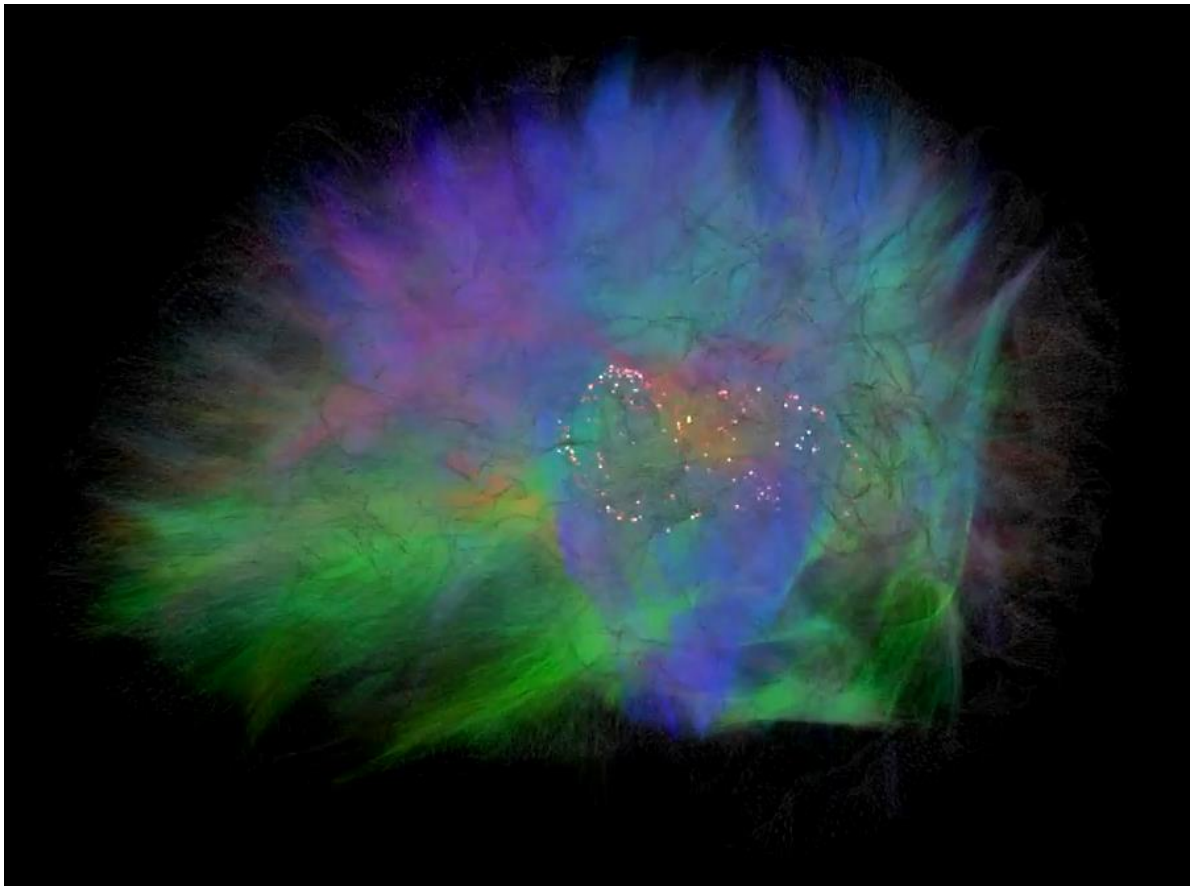
- **What is it:**
  Extract useful patterns from data.
- **How:**
  Neural network + optimization
- **How (Practical):**
  Python + TensorFlow & friends
- **Hard Part:**
  Good Questions + Good Data
- **Why now:**
  Data, hardware, community, tools, investment
- **Where do we stand?**
  Most big questions of intelligence have not been answered nor properly formulated

Exciting progress:

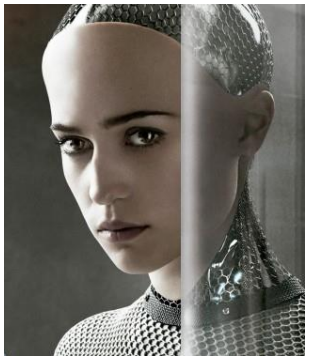
- Face recognition
- Image classification
- Speech recognition
- Text-to-speech generation
- Handwriting transcription
- Machine translation
- Medical diagnosis
- Cars: drivable area, lane keeping
- Digital assistants
- Ads, search, social recommendations
- Game playing with deep RL

“AI began with an ancient wish to forge the gods.”

- Pamela McCorduck, *Machines Who Think, 1979*



Frankenstein (1818)



Ex Machina (2015)

Visualized here are 3% of the neurons and 0.0001% of the synapses in the brain.

Thalamocortical system visualization via DigiCortex Engine.

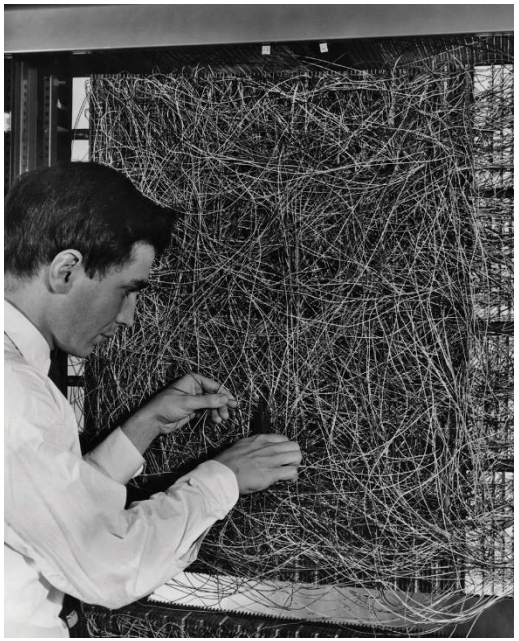
History of Deep Learning Ideas and Milestones*

Perspective:

- Universe created
  13.8 billion years ago
- Earth created
  4.54 billion years ago
- Modern humans
  300,000 years ago
- Civilization
  12,000 years ago
- Written record
  5,000 years ago

- 1943: Neural networks
- 1957: Perceptron
- 1974-86: Backpropagation, RBM, RNN
- 1989-98: CNN, MNIST, LSTM, Bidirectional RNN
- 2006: “Deep Learning”, DBN
- 2009: ImageNet
- 2012: AlexNet, Dropout
- 2014: GANs
- 2014: DeepFace
- 2016: AlphaGo
- 2017: AlphaZero, Capsule Networks
- 2018: BERT

* Dates are for perspective and not as definitive historical record of invention or credit



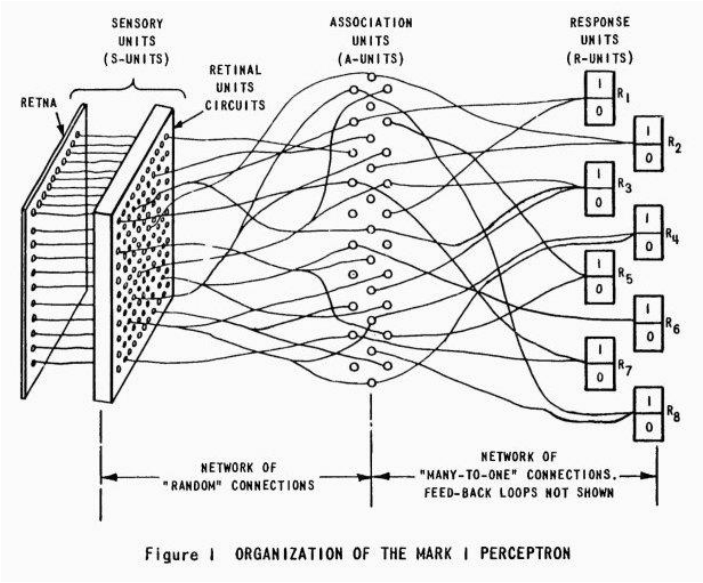


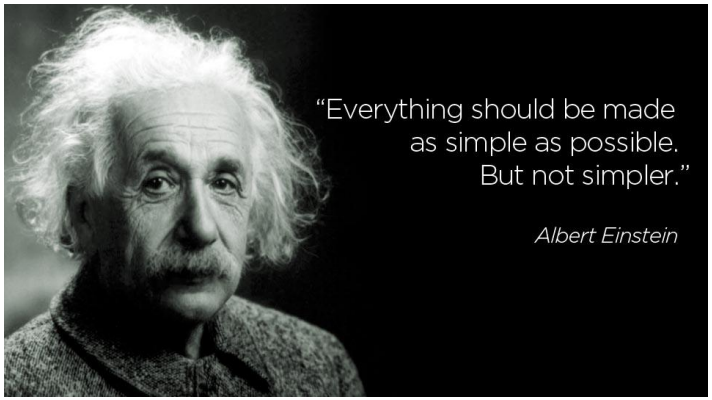
Figure 1 ORGANIZATION OF THE MARK 1 PERCEPTRON

History of DL Tools*

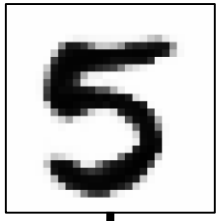
- Mark 1 Perceptron – 1960
- Torch – 2002
- CUDA – 2007
- Theano – 2008
- Caffe – 2014
- DistBelief – 2011
- TensorFlow 0.1 – 2015
- PyTorch 0.1 – 2017
- TensorFlow 1.0 – 2017
- PyTorch 1.0 – 2017
- TensorFlow 2.0 – 2019

* Truncated for clarity over completeness

First Steps: **Start Simple**



Input Image:



TensorFlow Model:

Neural Network

Output:

5

(with 87% confidence)

1
```
# import tensorflow and keras (tf.keras not "vanilla" Keras)
import tensorflow as tf
from tensorflow import keras
```

2
```
# get data
(train_images, train_labels), (test_images, test_labels) = \
keras.datasets.mnist.load_data()
```

3
```
# setup model
model = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation=tf.nn.relu),
    keras.layers.Dense(10, activation=tf.nn.softmax)
])

model.compile(optimizer=tf.train.AdamOptimizer(),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

4
```
# train model
model.fit(train_images, train_labels, epochs=5)
```

5
```
# evaluate
test_loss, test_acc = model.evaluate(test_images, test_labels)
print('test accuracy:', test_acc)
```

6
```
# make predictions
predictions = model.predict(test_images)
```

TensorFlow in **One Slide**

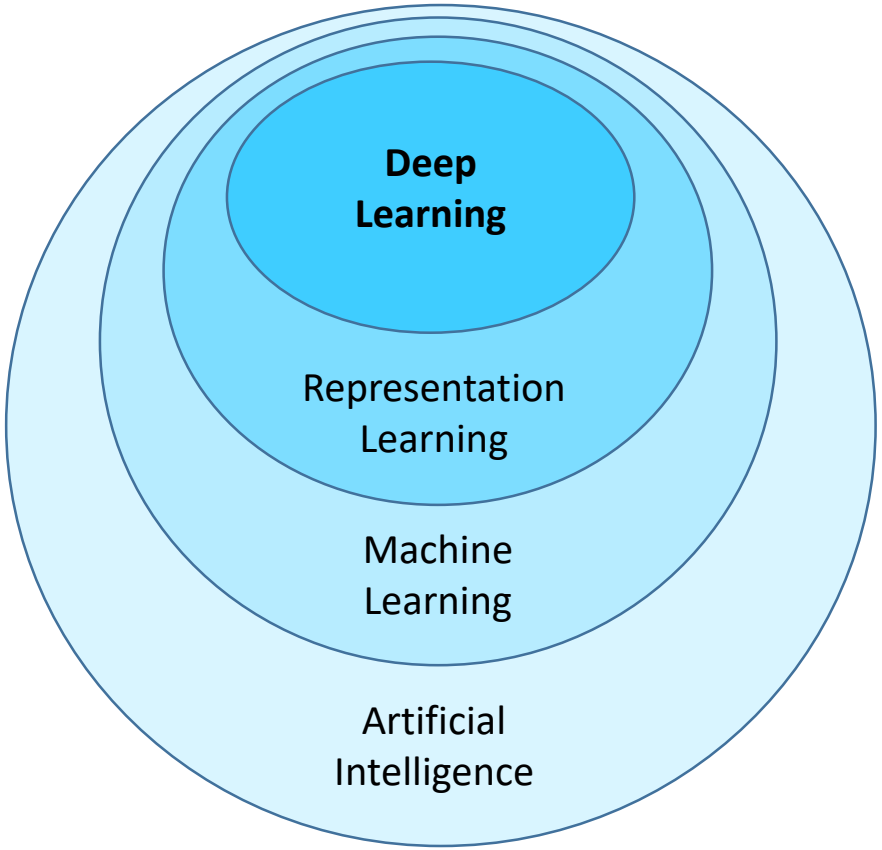
- **What is it:** Deep Learning Library *(and more)*
  - **Facts:** Open Source, Python, Google
- **Community:**
  - 117,000+ GitHub stars
  - TensorFlow.org: Blogs, Documentation, DevSummit, YouTube talks
- **Ecosystem:**
  - Keras: high-level API
  - TensorFlow.js: in the browser
  - TensorFlow Lite: on the phone
  - Colaboratory: in the cloud
  - TPU: optimized hardware
  - TensorBoard: visualization
  - TensorFlow Hub: graph modules
- **Alternatives**: PyTorch, MXNet, CNTK

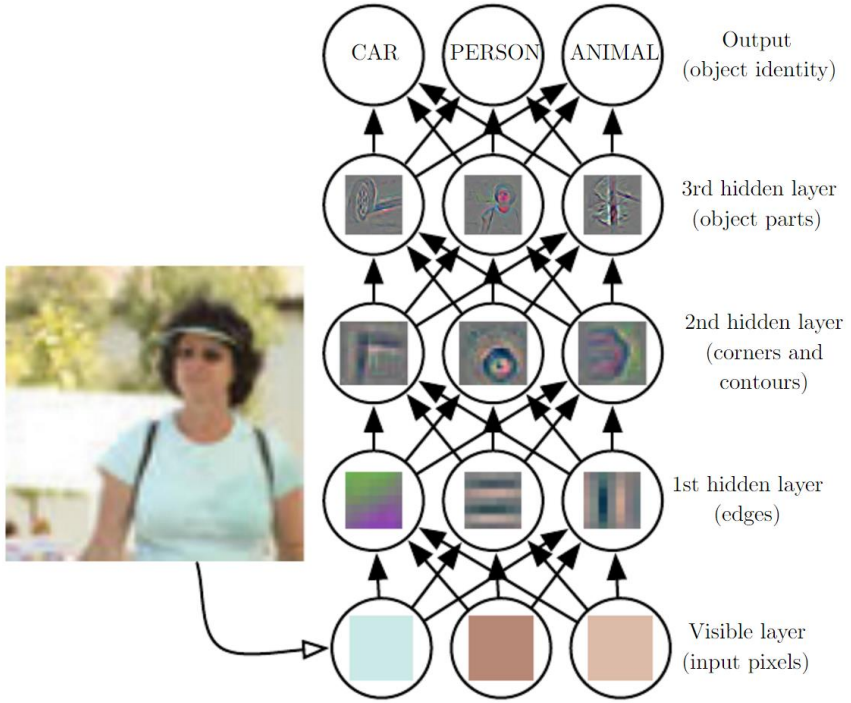
Extras:

- Swift for TensorFlow
- TensorFlow Serving
- TensorFlow Extended (TFX)
- TensorFlow Probability
- Tensor2Tensor

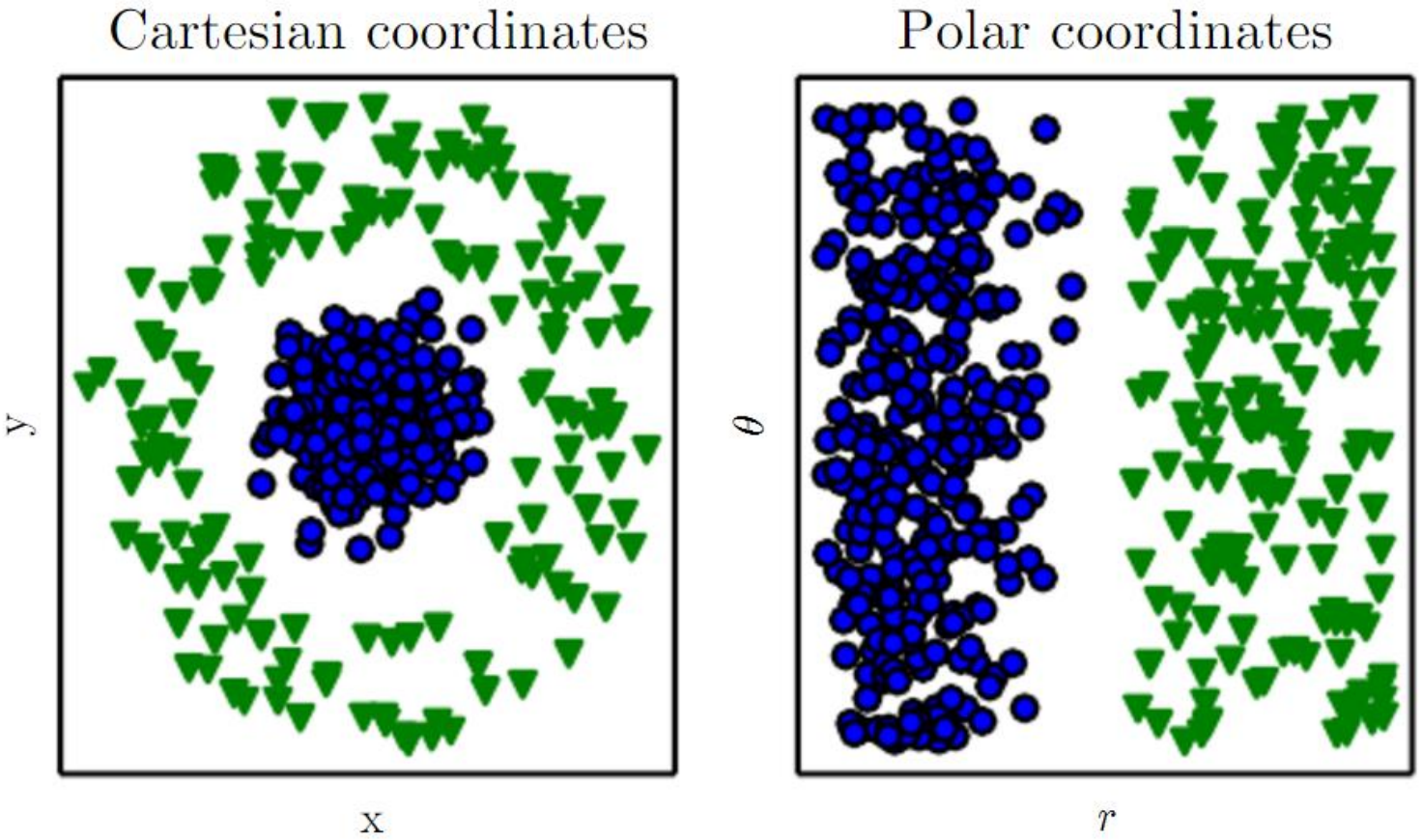
Deep Learning is **Representation Learning**

(aka Feature Learning)





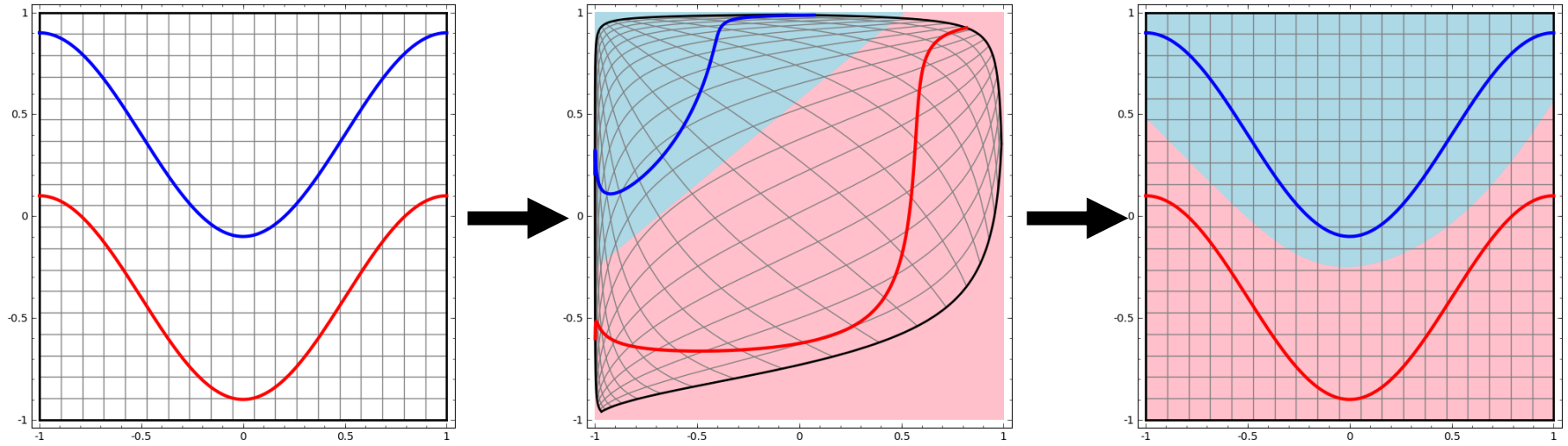
Representation Matters



Task: Draw a line to separate the **green triangles** and **blue circles**.

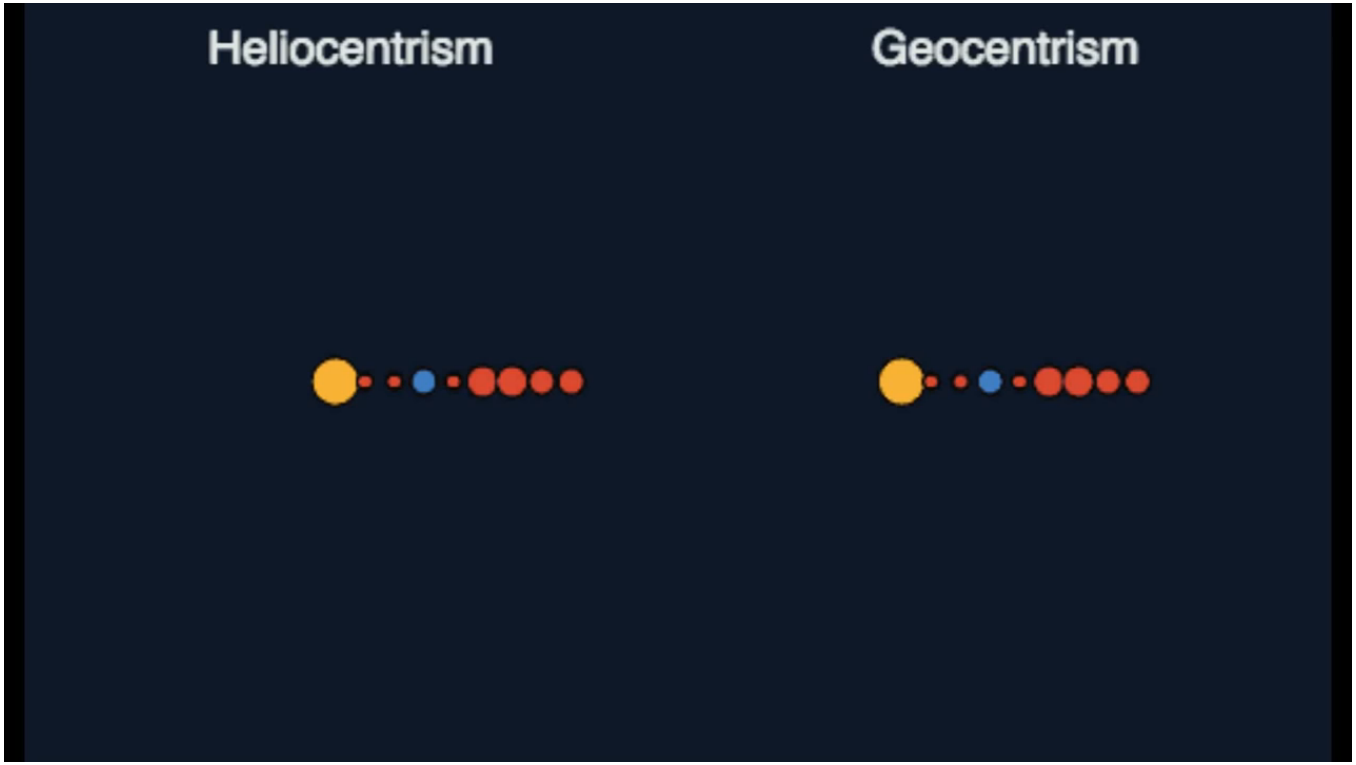
Deep Learning is **Representation Learning**

(aka Feature Learning)



Task: Draw a line to separate the **blue curve** and **red curve**

Representation Matters

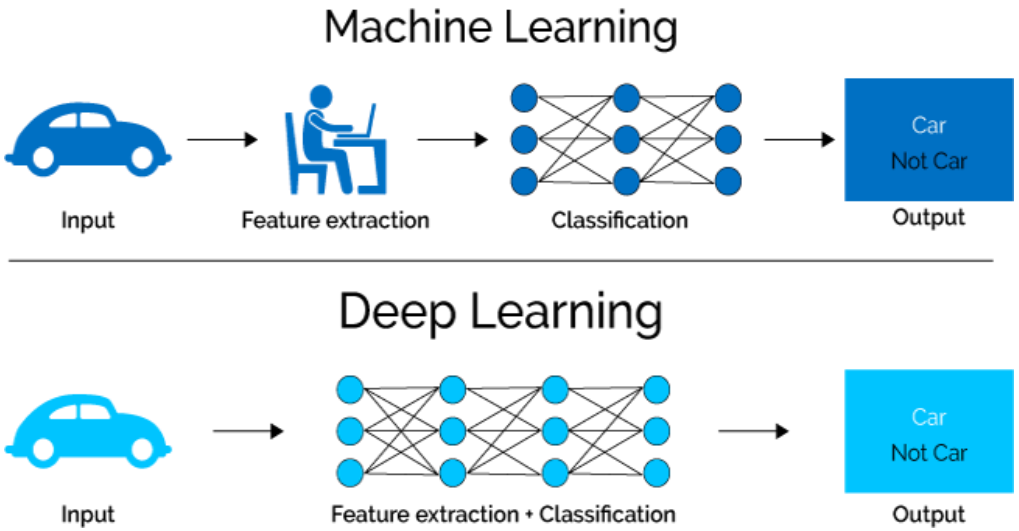


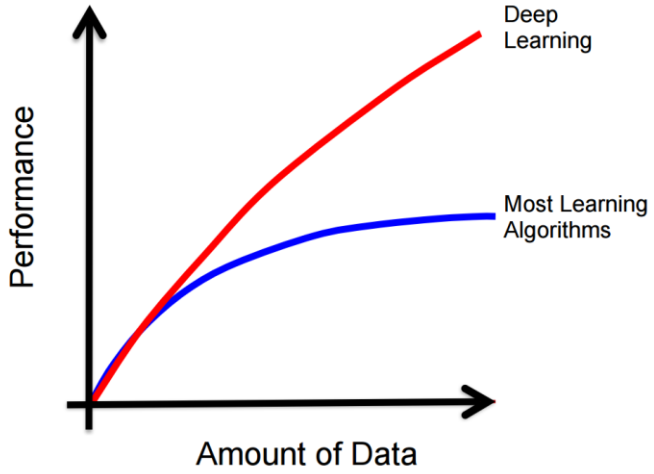
Sun-Centered Model
(Formalized by Copernicus in 16th century)

Earth-Centered Model

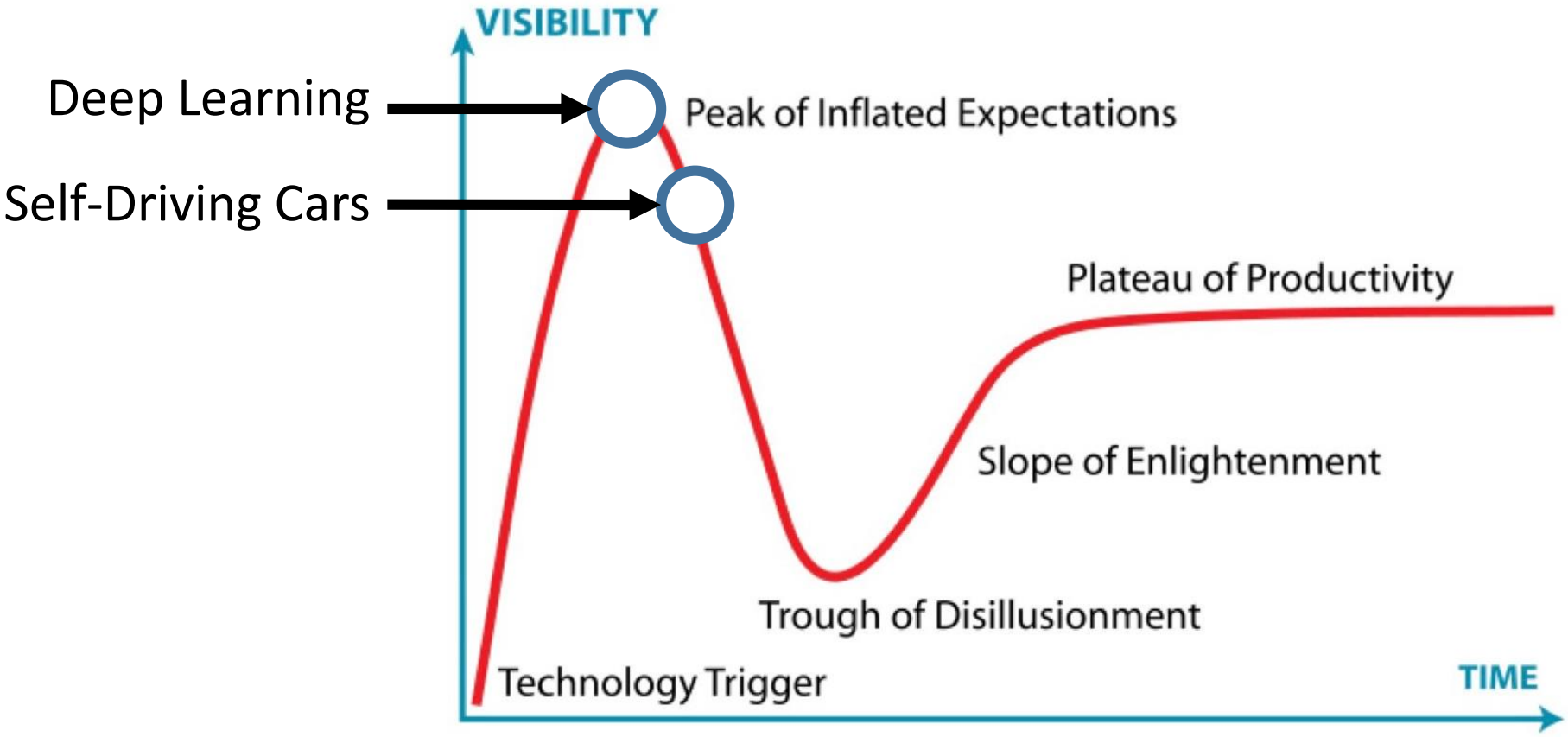
"History of science is the history of compression progress."
- Jürgen Schmidhuber

Why Deep Learning? **Scalable** Machine Learning

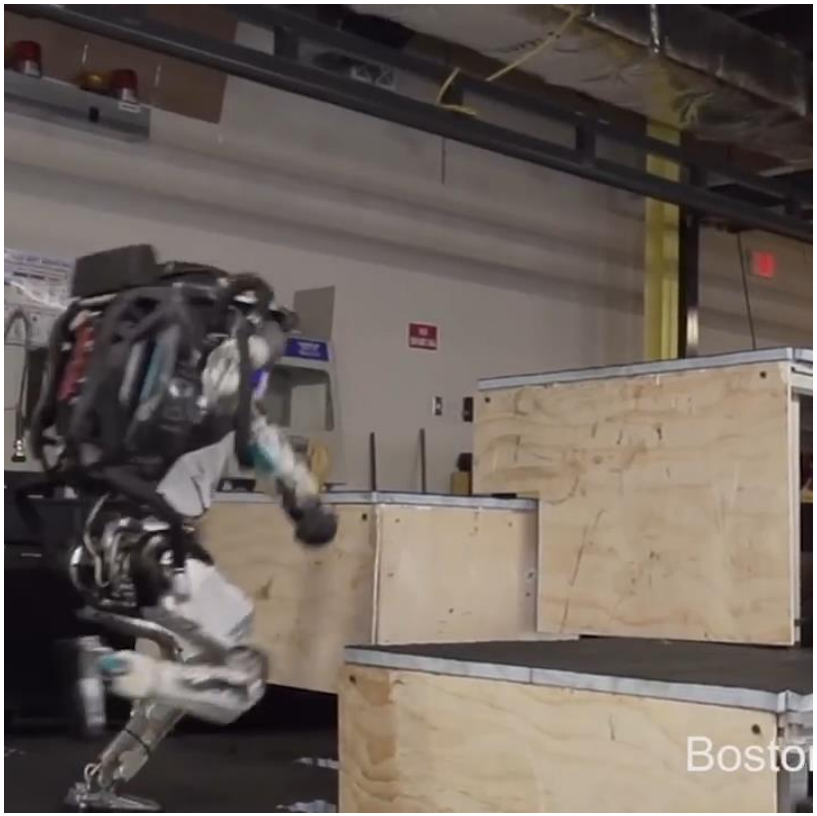


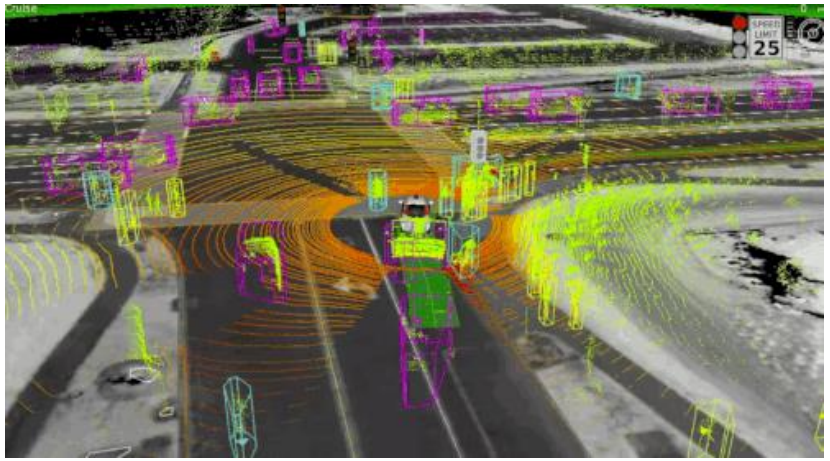


Gartner Hype Cycle



Why Not Deep Learning? Real World Applications





Why **Not** Deep Learning? Unintended Consequences

Human

AI (Deep RL Agent)

Player gets reward based on:

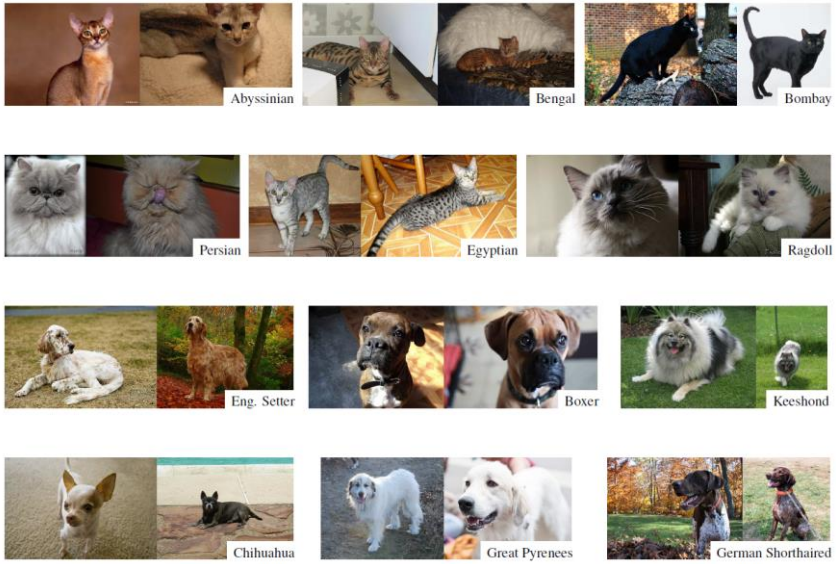
1. Finishing time
2. Finishing position
3. Picking up “turbos”

The Challenge of Deep Learning

- Ask the right question and know what the answer means:
  image classification ≠ scene understanding

- Select, collect, and organize the right data to train on:
  photos ≠ synthetic ≠ real-world video frames

Pure Perception is Hard



Visual Understanding is Harder

Examples of what we can't do well:

- Mirrors
- Sparse information
- 3D Structure
- Physics
- What's on peoples' minds?
- What happens next?
- Humor

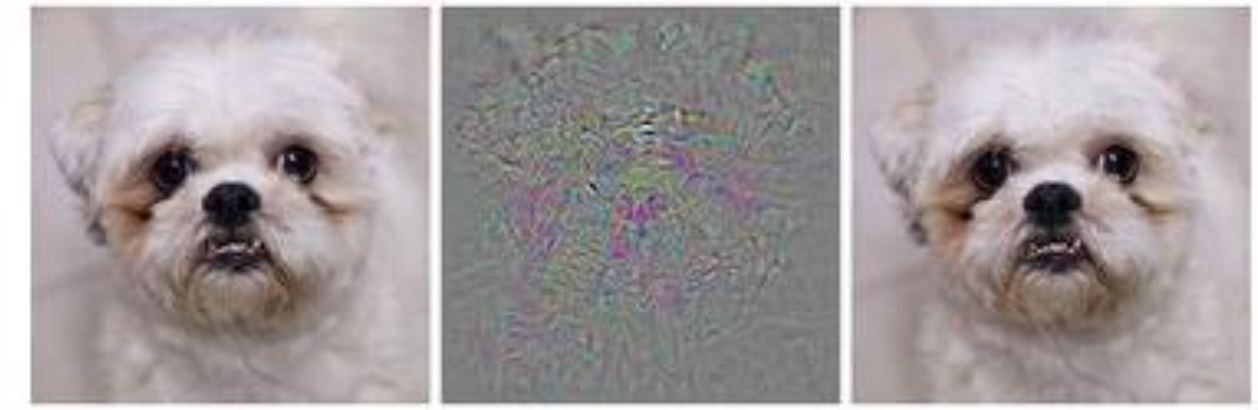
Deep Learning:

Our intuition about what's "hard" is flawed (in complicated ways)

Visual perception: 540,000,000 years of data

Bipedal movement: 230,000,000 years of data

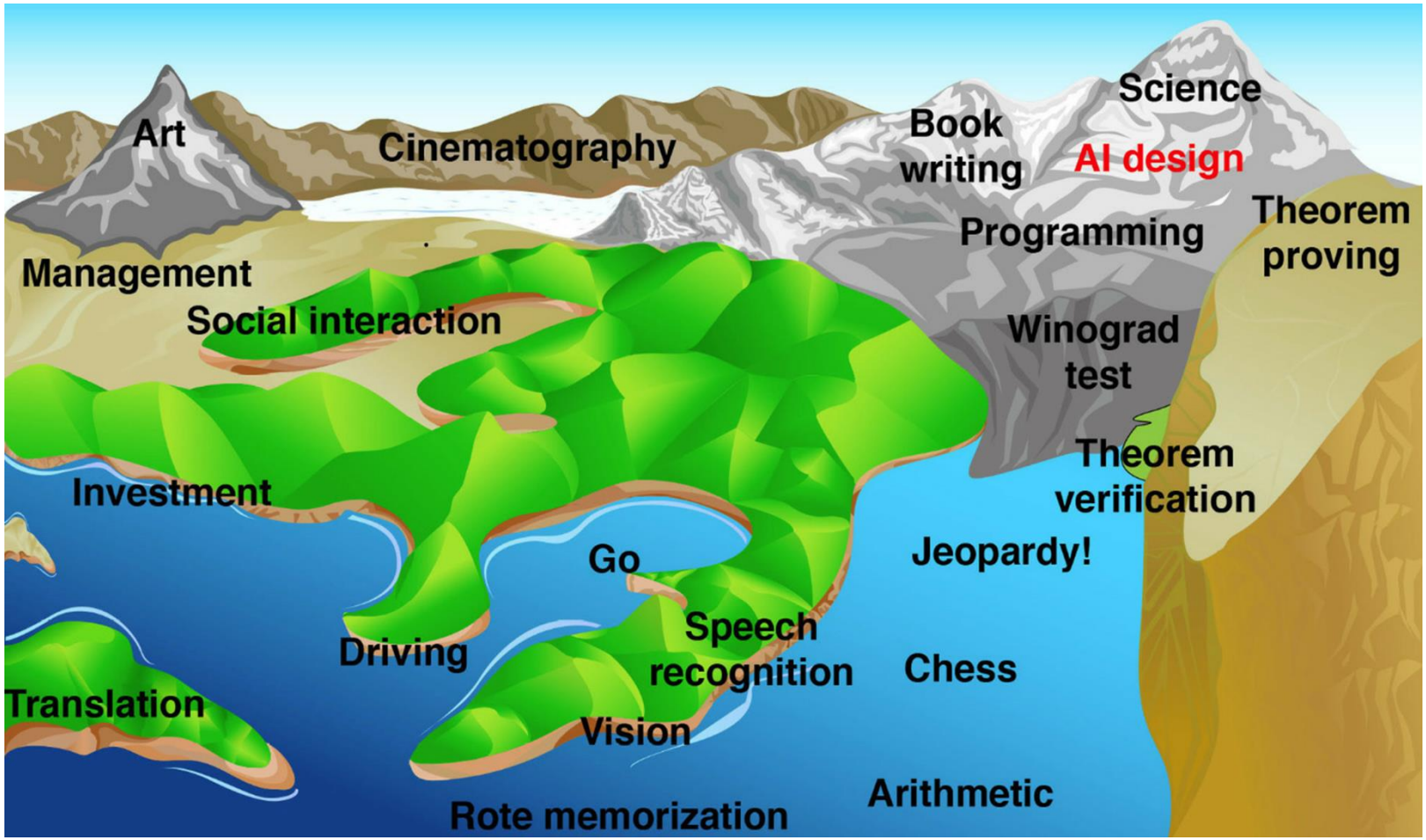
Abstract thought: 100,000 years of data



Prediction: **Dog** + Distortion Prediction: **Ostrich**

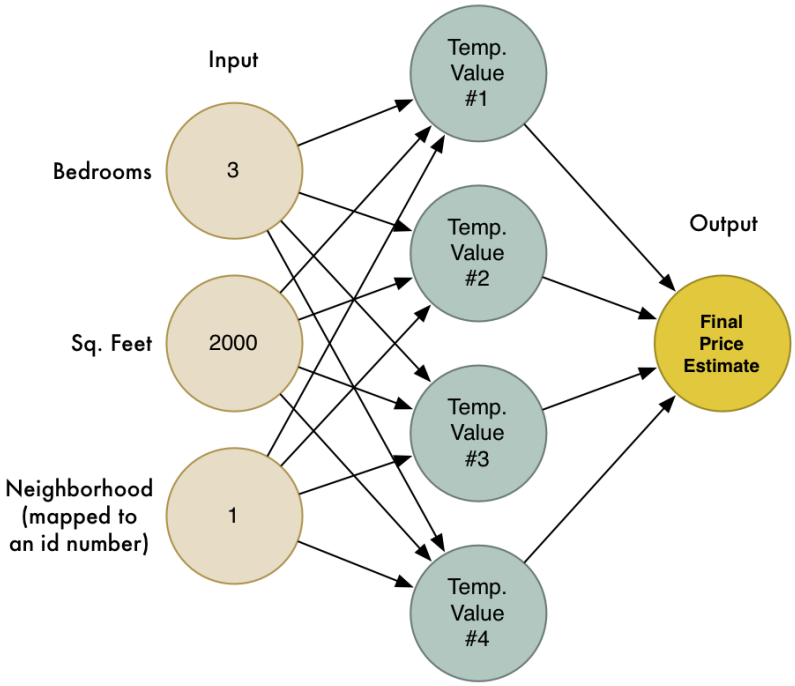
"Encoded in the large, highly evolve sensory and motor portions of the human brain is a **billion years of experience** about the nature of the world and how to survive in it.… Abstract thought, though, is a new trick, perhaps less than **100 thousand years** old. We have not yet mastered it. It is not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

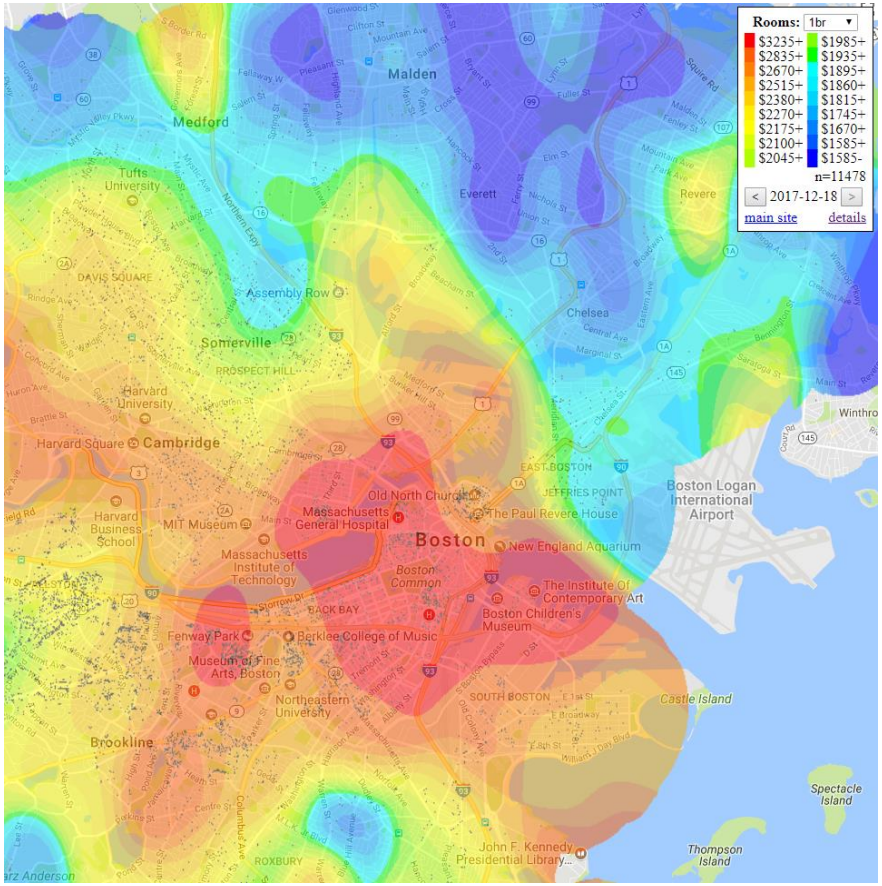
Measuring Progress: Einstein vs Savant



Max Tegmark's rising sea visualization of
Hans Moravec's landscape of human competence

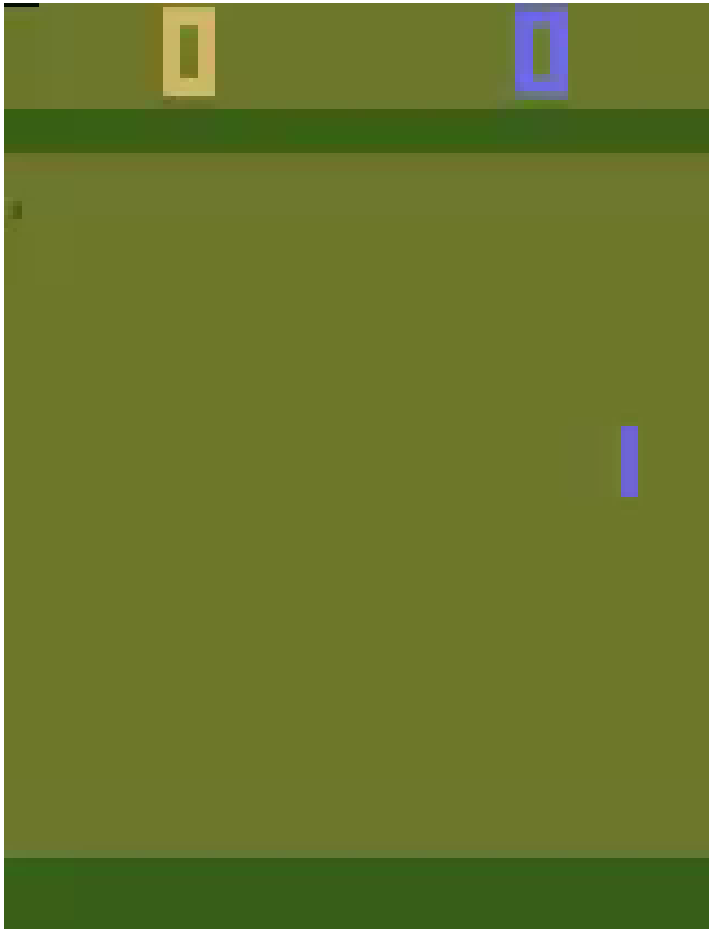
Special Purpose Intelligence:
Estimating Apartment Cost





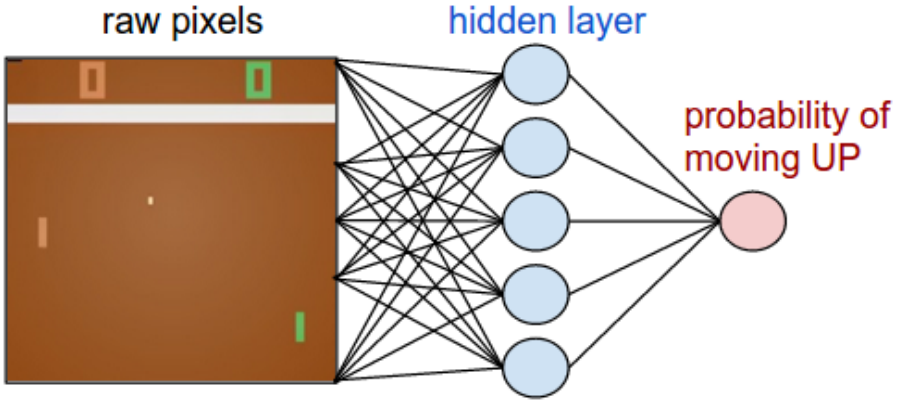
(Toward) General Purpose Intelligence:

Pong to Pixels



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

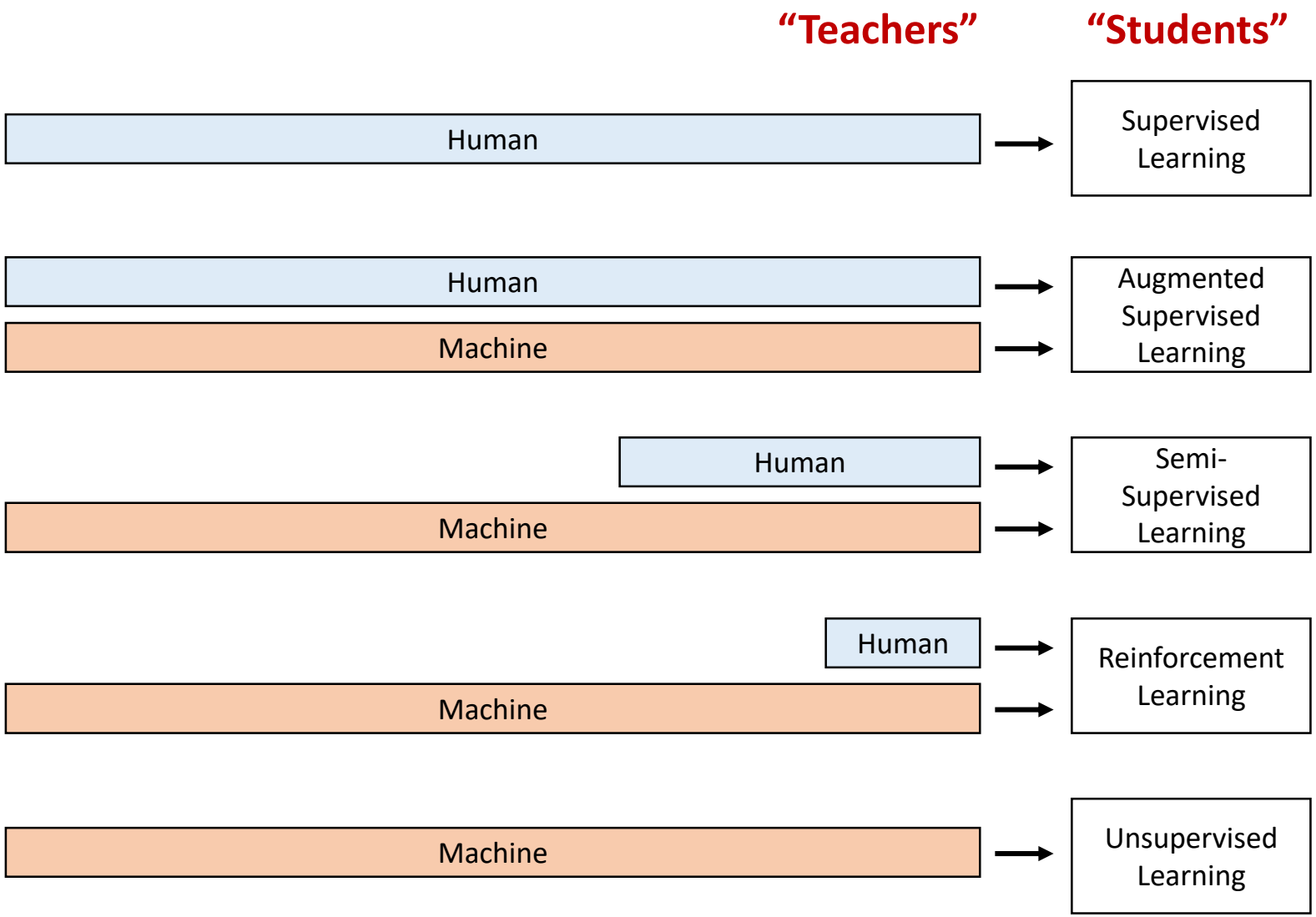
Policy Network:



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

This is a step towards general purpose artificial intelligence!

Deep Learning from Human and Machine



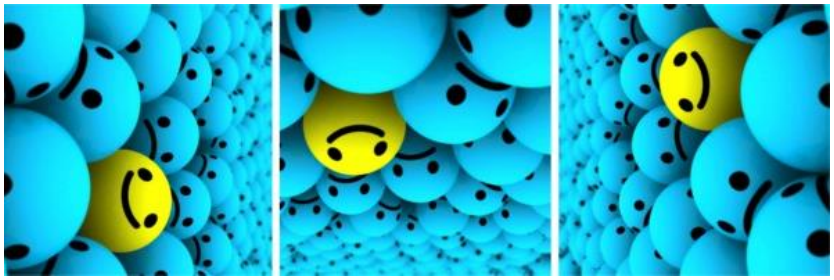
Data Augmentation

Crop:

Flip:

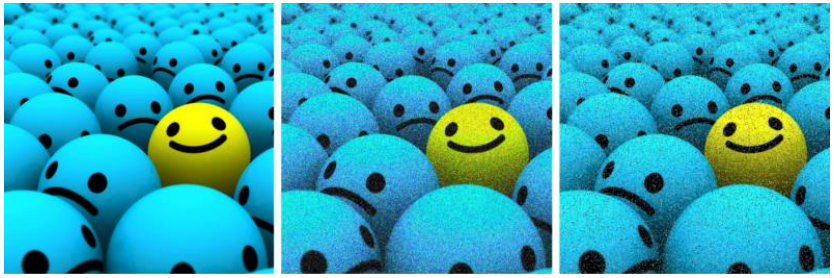
Scale:

Rotate:



Translation:

Noise:

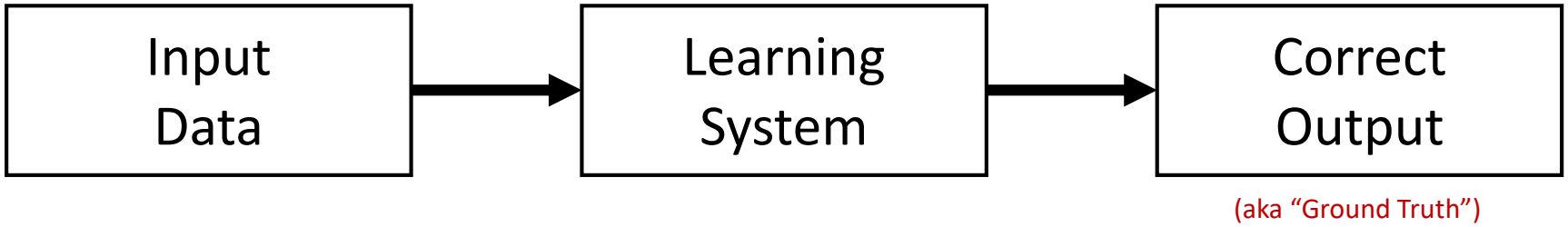


The Challenge of Deep Learning:
Efficient Teaching + Efficient Learning

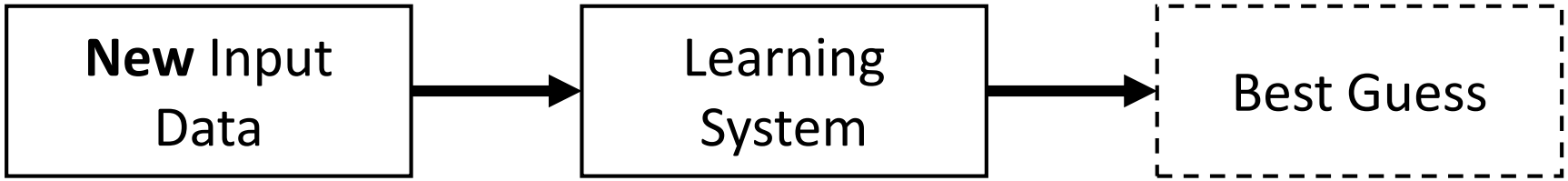
- Humans can learn from very few examples
- Machines (in most cases) need thousands/millions of examples

Deep Learning: Training and Testing

Training Stage:

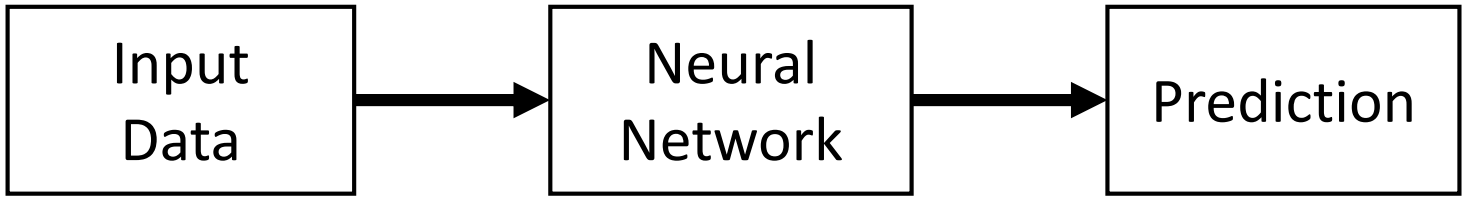


Testing Stage:

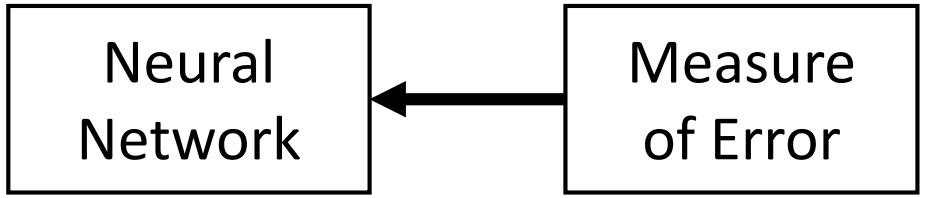


How Neural Networks Learn: Backpropagation

Forward Pass:



Backward Pass (aka Backpropagation):

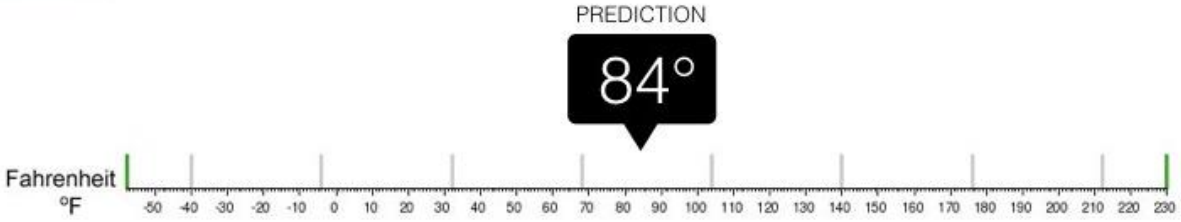


Adjust to Reduce Error

Regression vs Classification

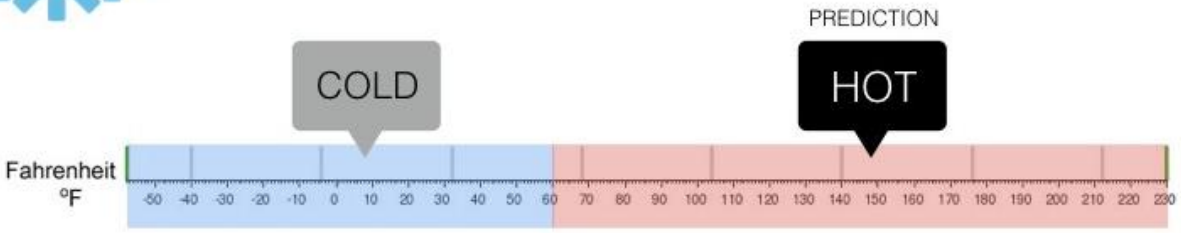
Regression

What is the temperature going to be tomorrow?

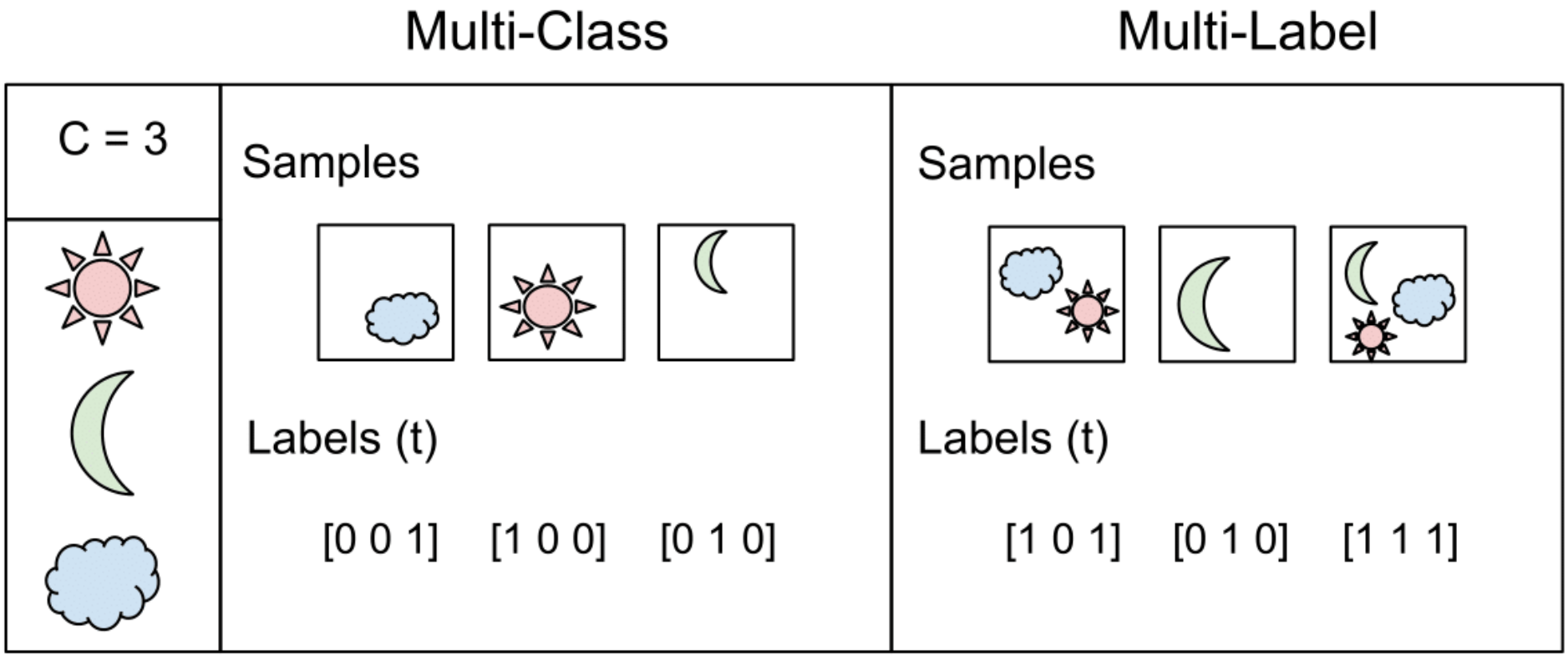


Classification

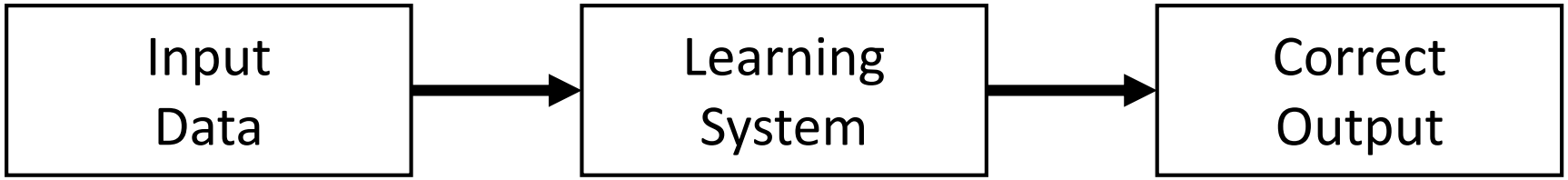
Will it be Cold or Hot tomorrow?



Multi-Class vs Multi-Label

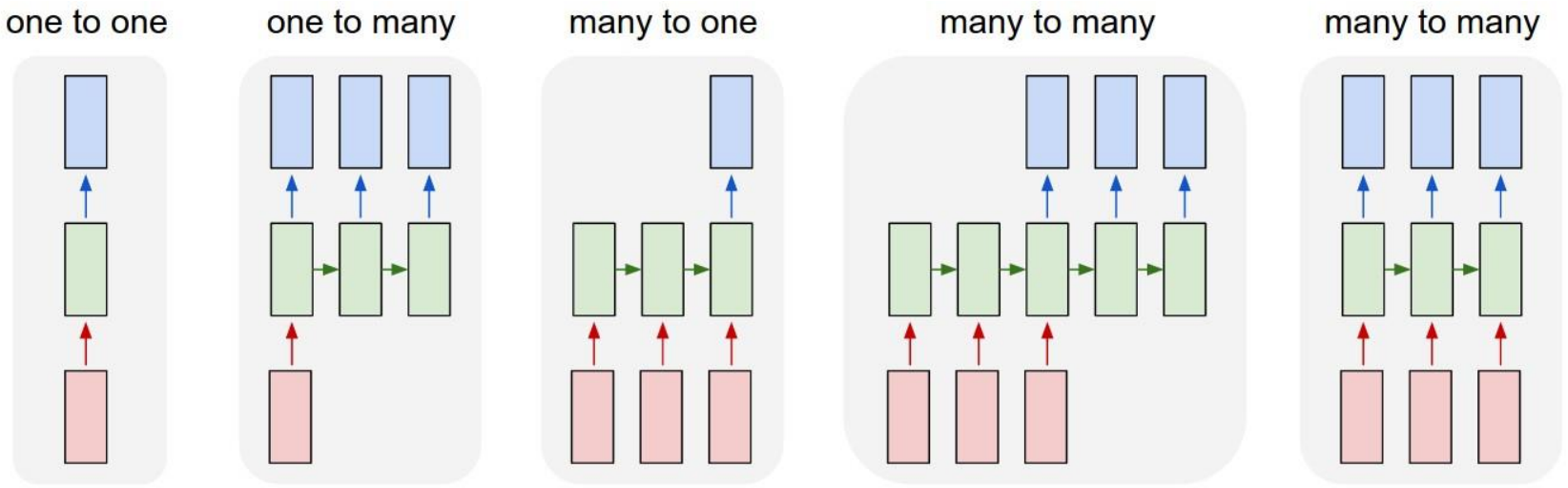


What can we do with Deep Learning?

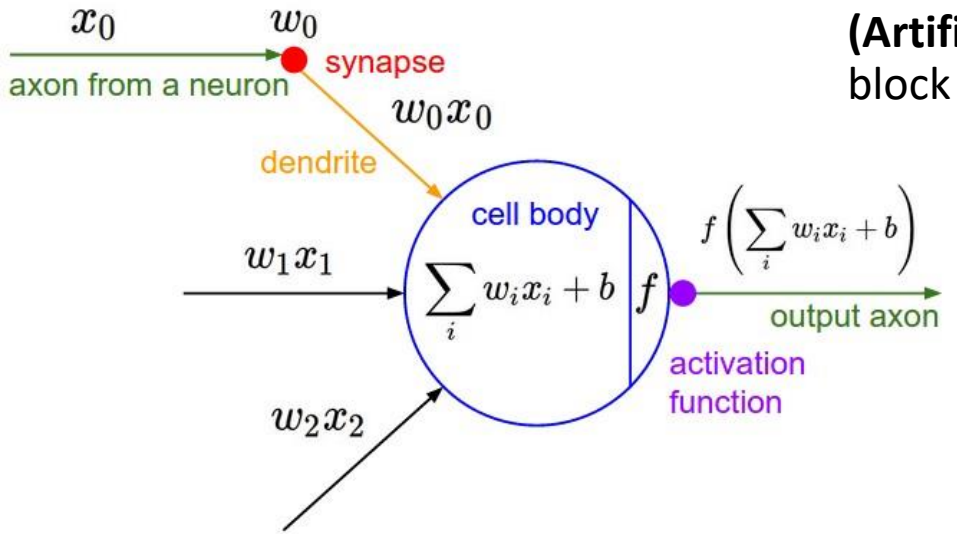


- Number
- Vector of numbers
- Sequence of numbers
- Sequence of vectors of numbers

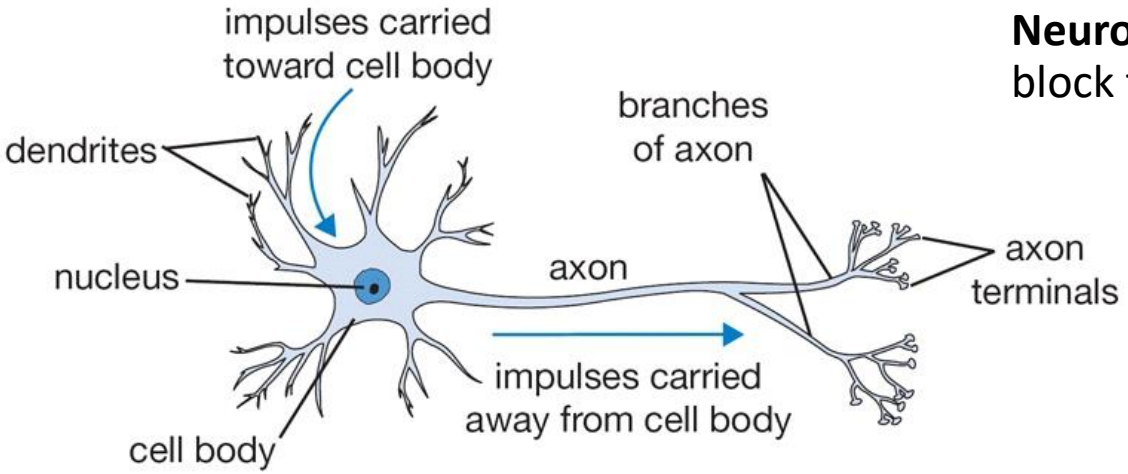
- Number
- Vector of numbers
- Sequence of numbers
- Sequence of vectors of numbers



Neuron: Biological Inspiration for Computation

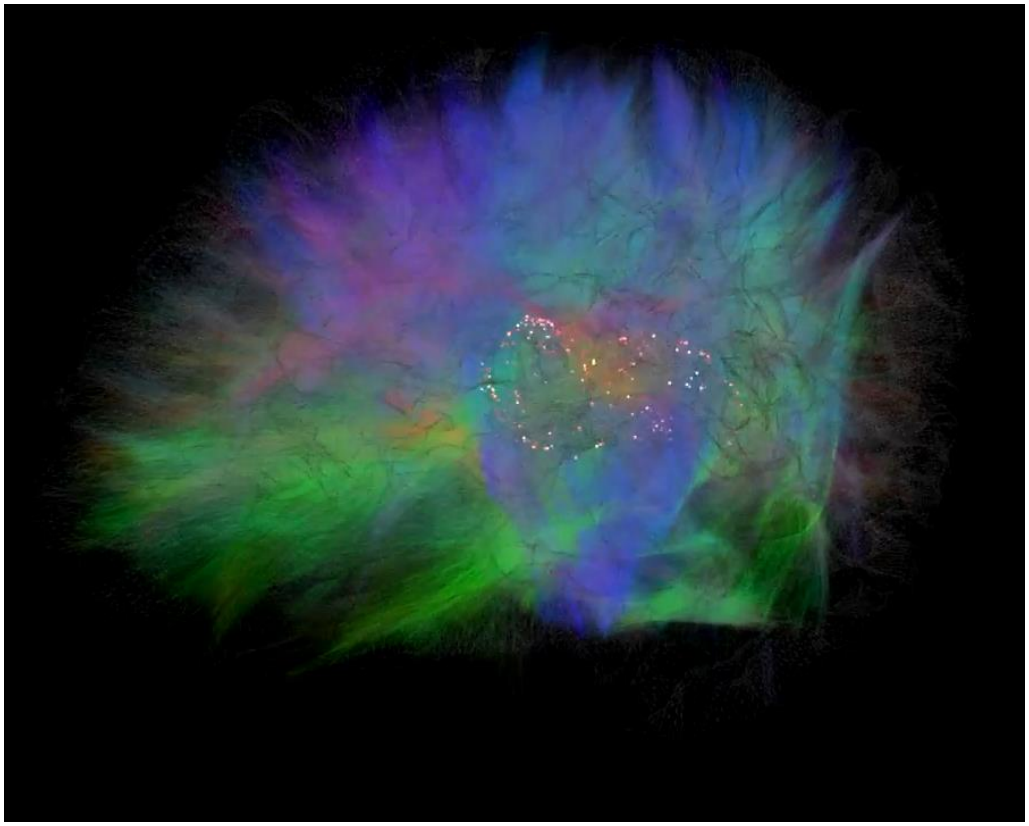


(Artificial) Neuron: computational building block for the "neural network"



Neuron: computational building block for the brain

Biological and Artificial Neural Networks



Human Brain

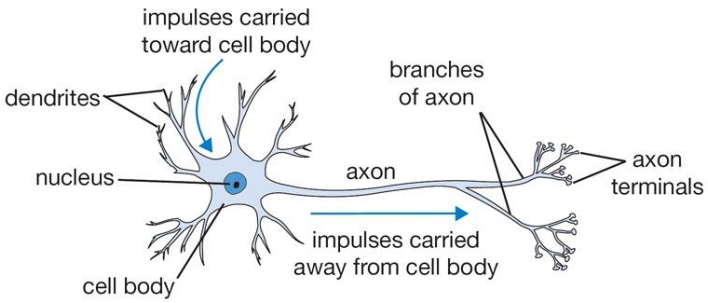
- Thalamocortical system:
  3 million neurons
  476 million synapses
- Full brain:
  100 billion neurons
  1,000 trillion synapses

Artificial Neural Network

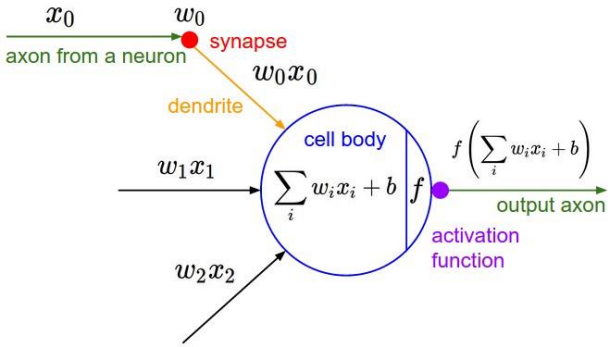
- ResNet-152:
  60 million synapses

Human brains have ~10,000,000 times synapses
than artificial neural networks.

Neuron: Biological Inspiration for Computation



- **Neuron:** computational building block for the brain

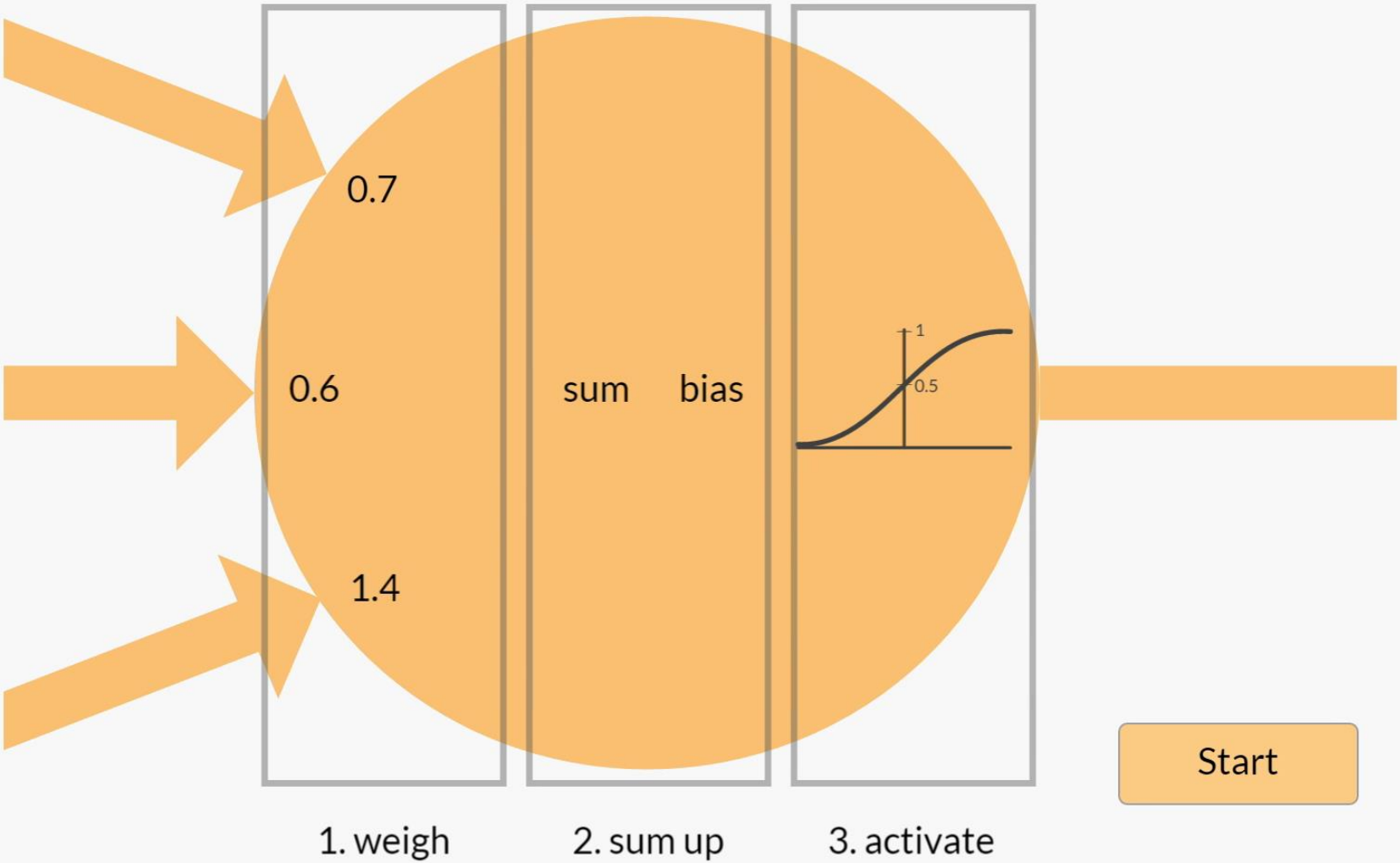


- **(Artificial) Neuron:** computational building block for the "neural network"

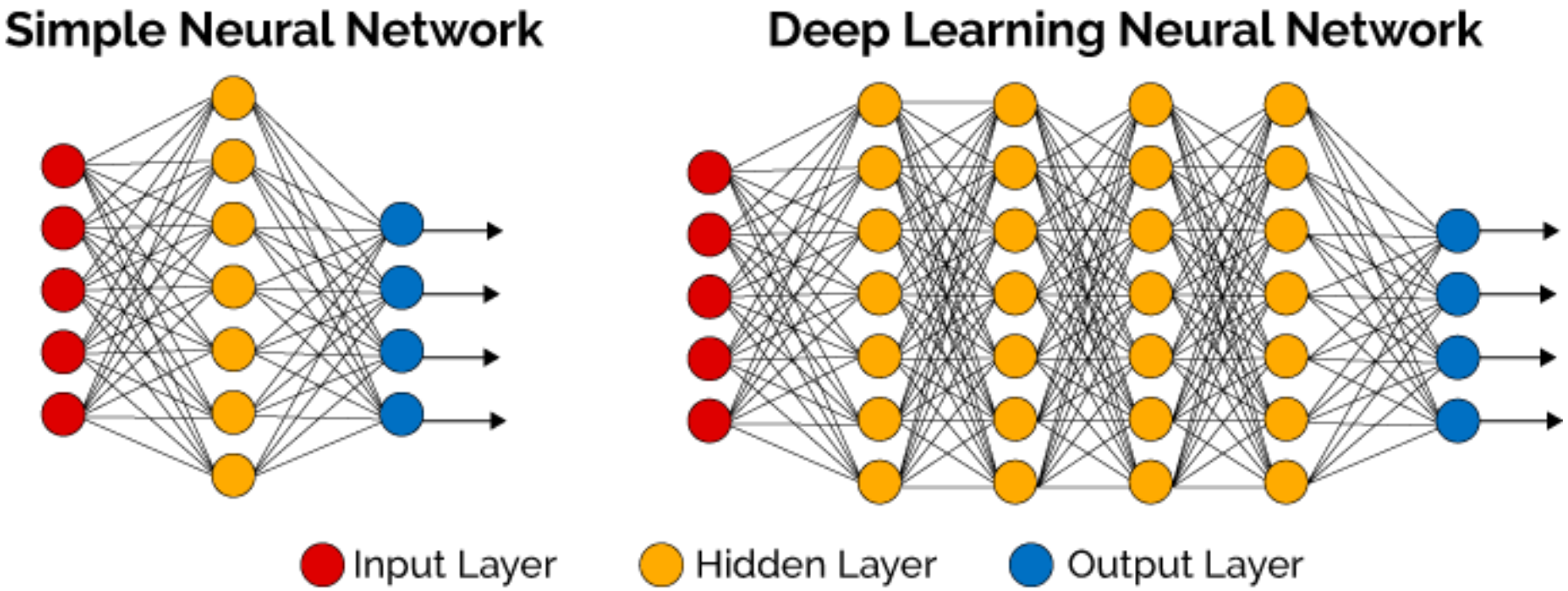
Key Difference:

- **Parameters:** Human brains have ~10,000,000 times synapses than artificial neural networks.
- **Topology:** Human brains have no "layers". **Async:** The human brain works asynchronously, ANNs work synchronously.
- **Learning algorithm**: ANNs use gradient descent for learning. We don't know what human brains use
- **Power consumption:** Biological neural networks use very little power compared to artificial networks
- **Stages:** Biological networks usually never stop learning. ANNs first train then test.

Neuron: Forward Pass



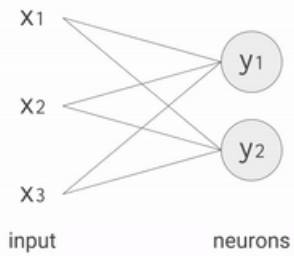
Combing Neurons in Hidden Layers:
The "Emergent" Power to Approximate



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

Neural Networks are Parallelizable

Step 1



Step 2

Step 3

$$y_1 = w_{11}x_1 + w_{12}x_2 + w_{13}x_3$$

Step 4

$$y_1 = f(w_{11}x_1 + w_{12}x_2 + w_{13}x_3)$$

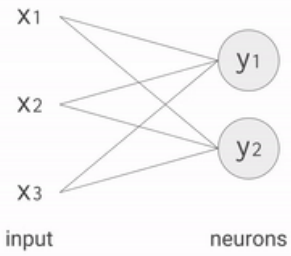
activation function

Step 5

$$y_1 = f(w_{11}x_1 + w_{12}x_2 + w_{13}x_3)$$

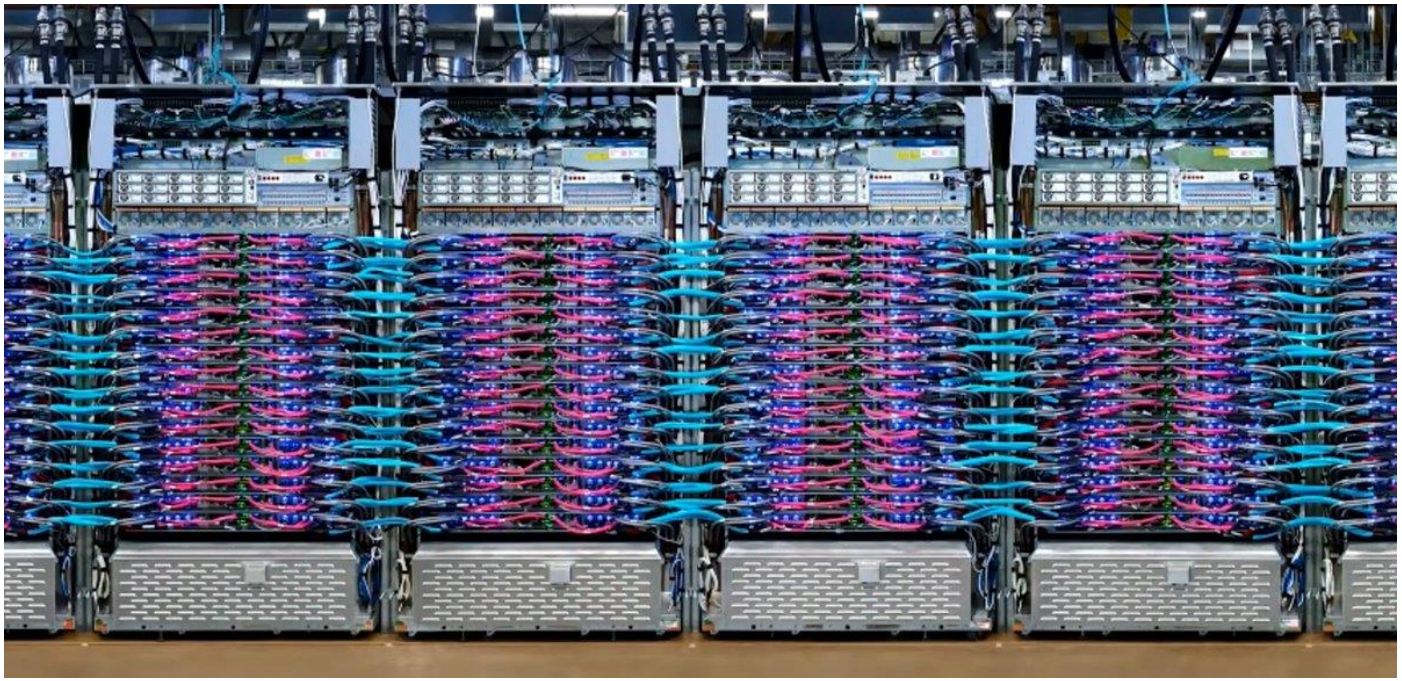
$$y_2 = f(w_{21}x_1 + w_{22}x_2 + w_{23}x_3)$$

Animated



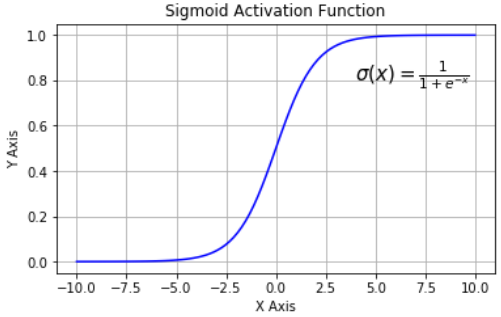
Compute Hardware

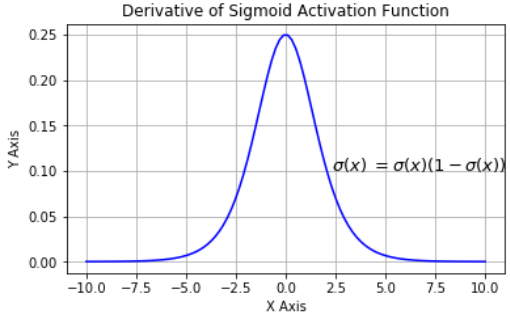
- **CPU** – serial, general purpose, everyone has one
- **GPU** – parallelizable, still general purpose
- **TPU** – custom ASIC (Application-Specific Integrated Circuit) by Google, specialized for machine learning, low precision



Key Concepts:

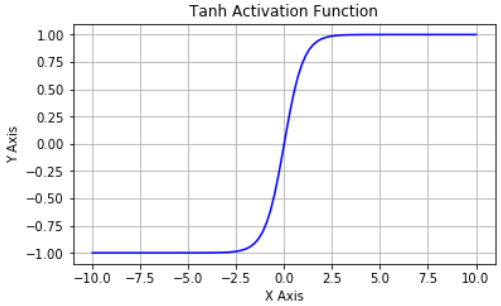
Activation Functions

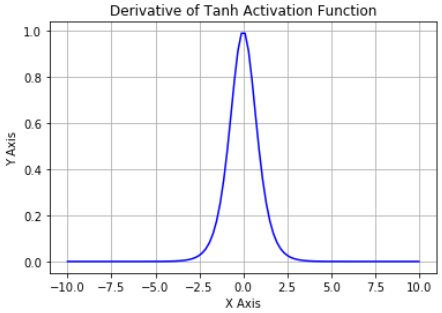




Sigmoid

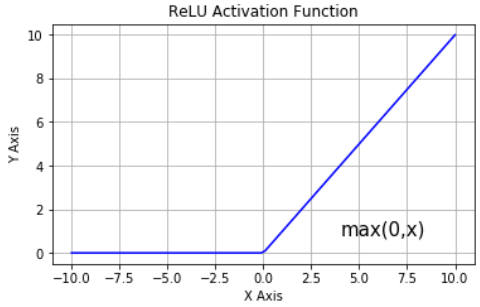
- Vanishing gradients
- Not zero centered

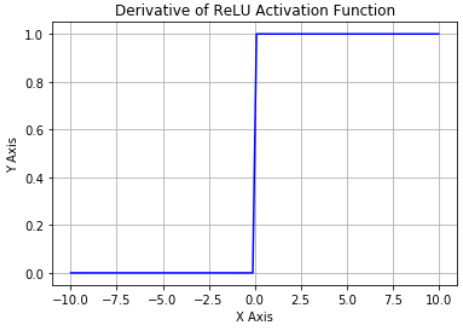




Tanh

- Vanishing gradients

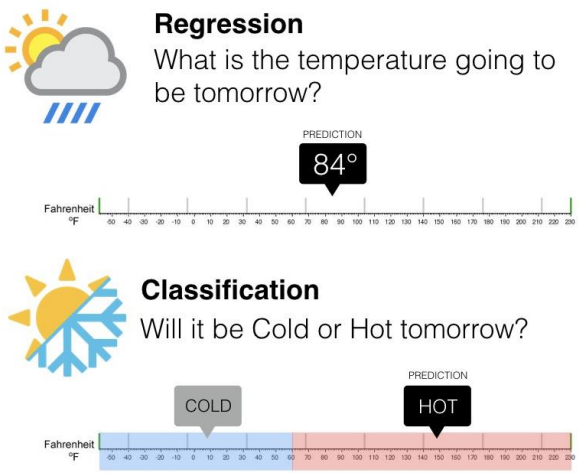




ReLU

- Not zero centered

Loss Functions



- Loss function quantifies gap between prediction and ground truth
- For regression:
  - Mean Squared Error (MSE)
- For classification:
  - Cross Entropy Loss

Mean Squared Error

$$MSE = \frac{1}{N}\sum(t_i - s_i)^2$$

Prediction

Ground Truth

Cross Entropy Loss

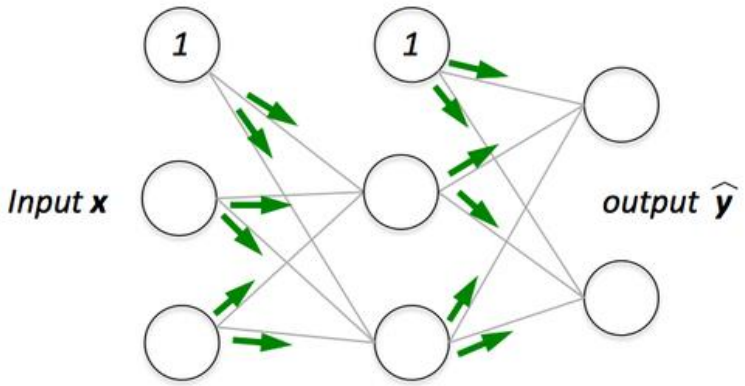
$$CE = -\sum_{i}^{C} t_i log(s_i)$$

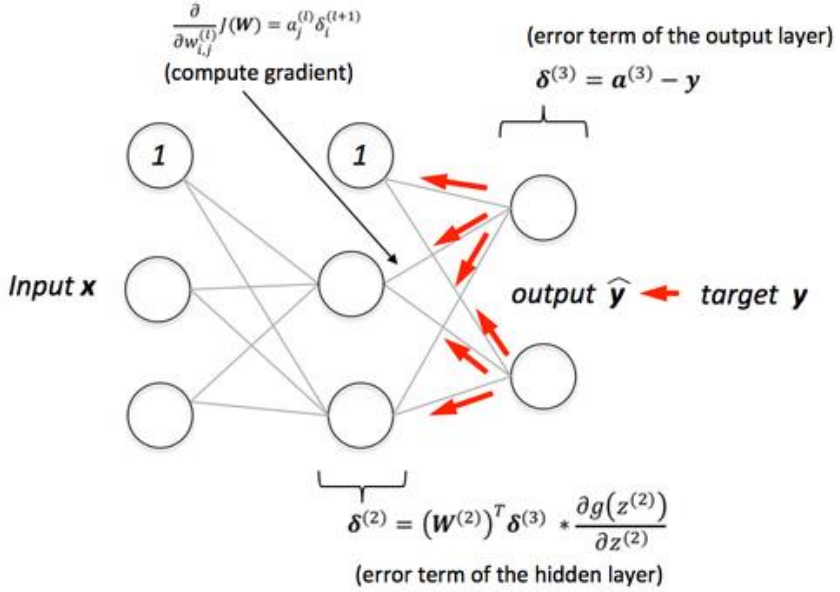
Classes

Prediction

Ground Truth {0,1}

Backpropagation





Task: Update the **weights** and **biases** to decrease **loss function**

Subtasks:

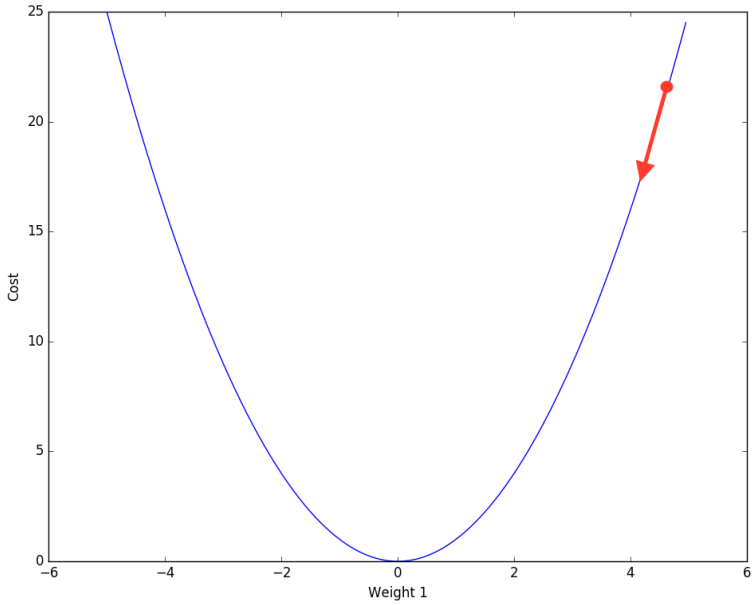
1. Forward pass to compute network output and "error"
2. Backward pass to compute gradients
3. A fraction of the weight's gradient is subtracted from the weight.

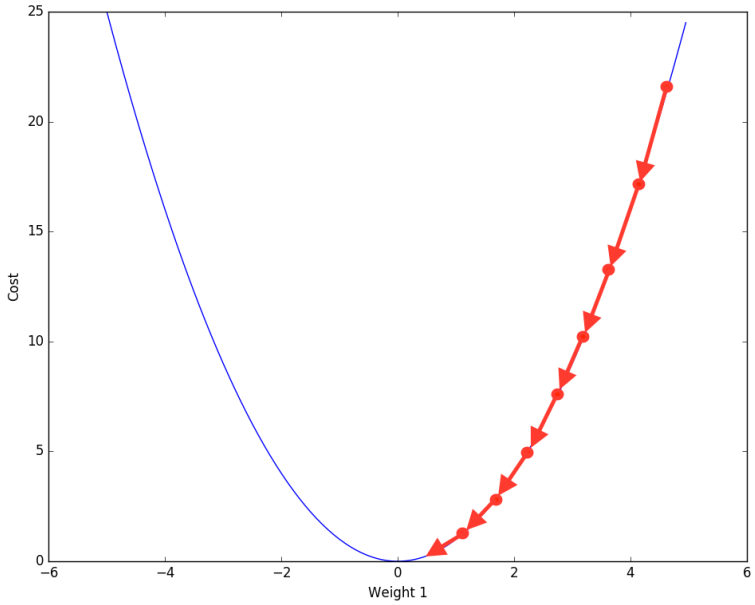
Learning Rate

Numerical Method: Automatic Differentiation

Learning is an Optimization Problem

Task: Update the **weights** and **biases** to decrease **loss function**

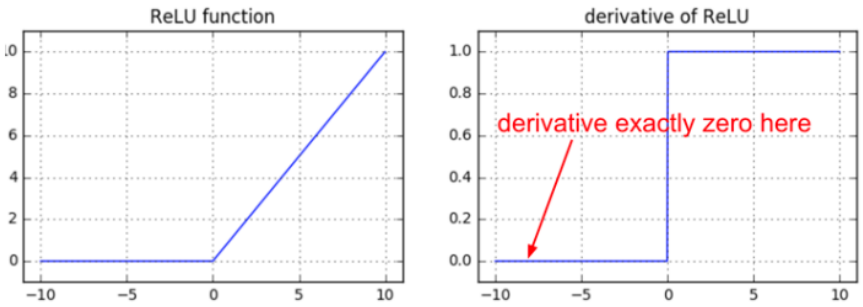




SGD: Stochastic Gradient Descent

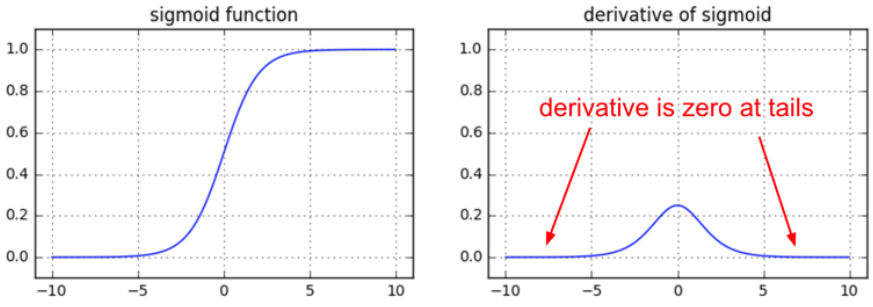
References: [103]

Dying ReLUs



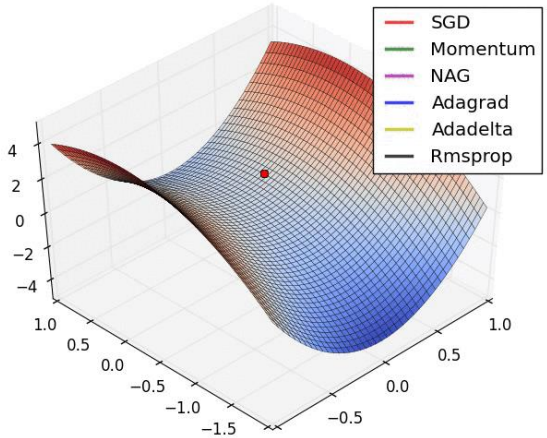
- If a neuron is initialized poorly, it might not fire for entire training dataset.
- Large parts of your network could be dead ReLUs!

Vanishing Gradients:

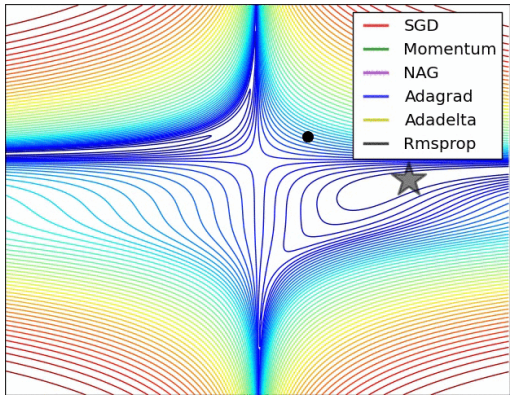


$$\frac{d\sigma(x)}{dx} = (1 - \sigma(x))\,\sigma(x)$$

Partial derivatives are small = Learning is slow



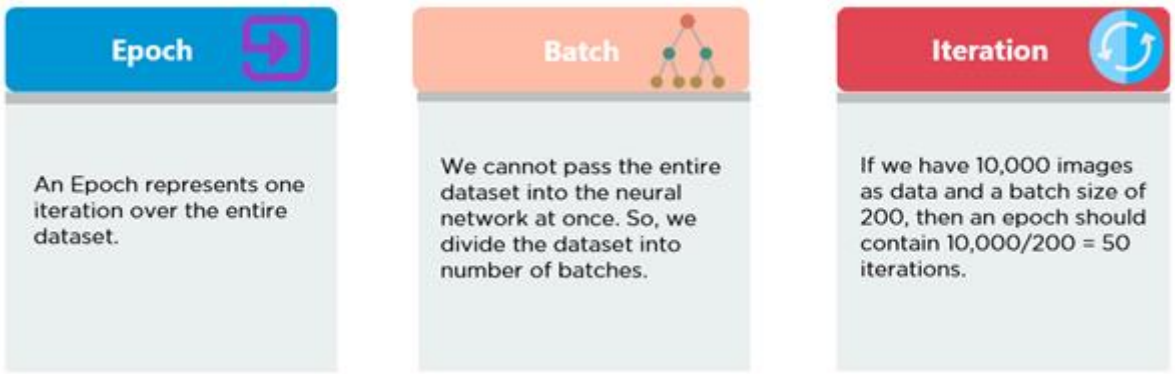
Hard to break symmetry



Vanilla SGD gets your there, but can be slow

References: [102, 104]

Mini-Batch Size



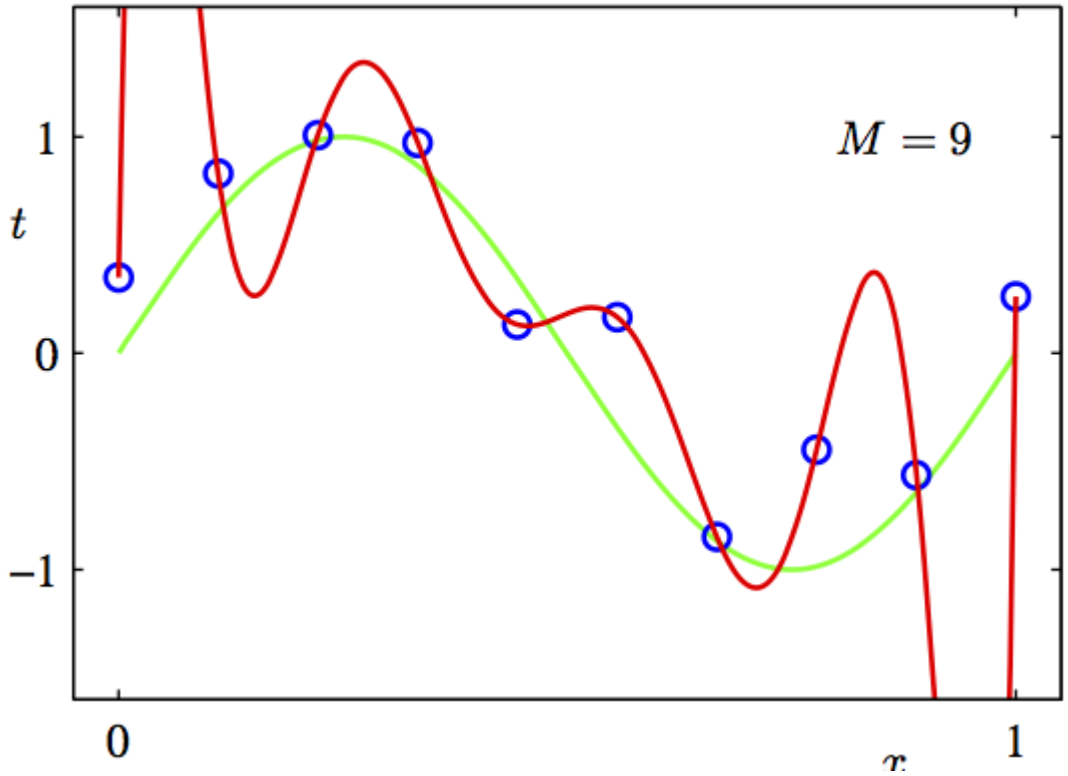
Mini-Batch size: Number of training instances the network evaluates per weight update step.

- Larger batch size = more computational speed
- Smaller batch size = (empirically) better generalization

"Training with large minibatches is bad for your health. More importantly, it's bad for your test error. Friends don't let friends use minibatches larger than 32."
- Yann LeCun
Revisiting Small Batch Training for Deep Neural Networks (2018)

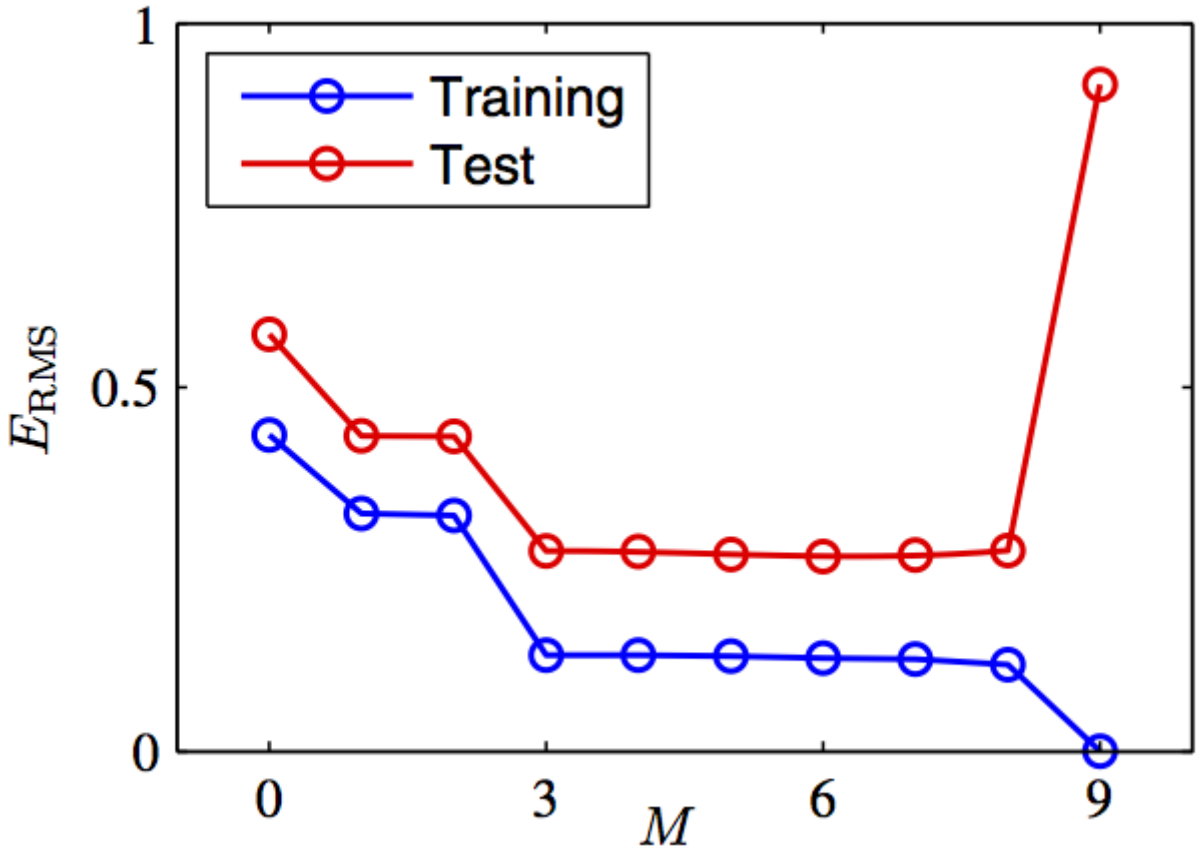
Overfitting and Regularization

- Help the network **generalize** to data it hasn't seen.
- Big problem for **small datasets**.
- Overfitting example (a sine curve vs 9-degree polynomial):

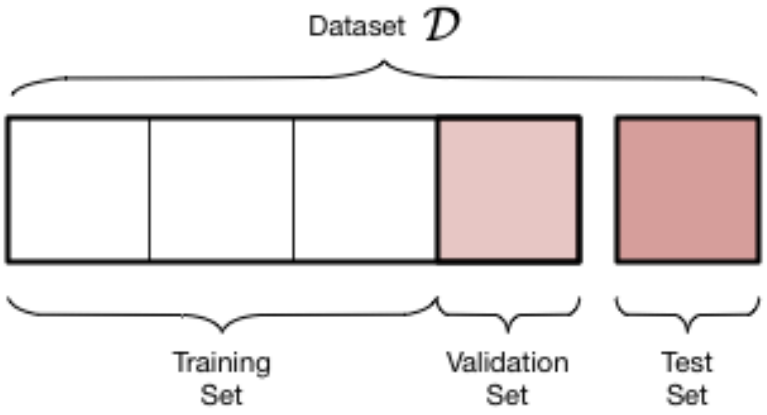


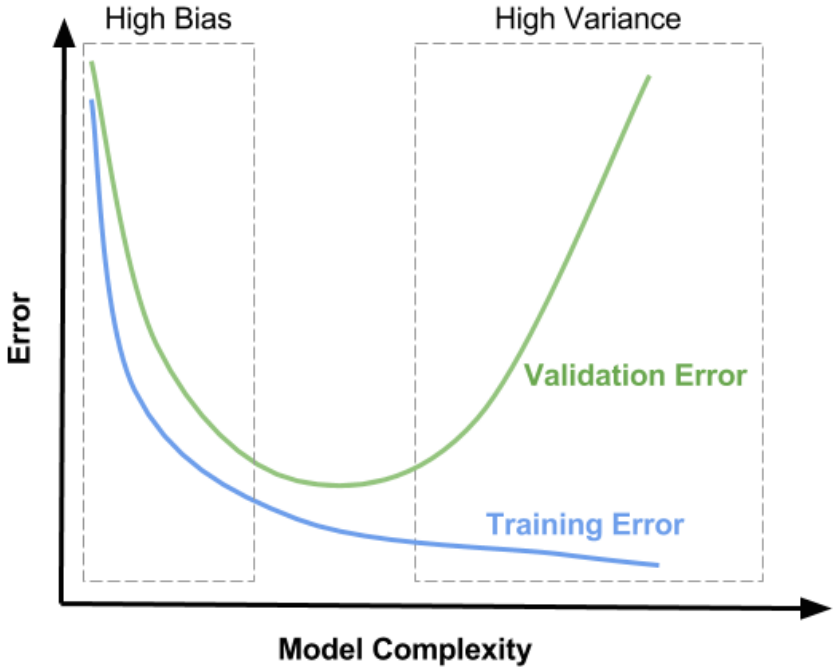
Overfitting and Regularization

- Overfitting: The error decreases in the training set but increases in the test set.



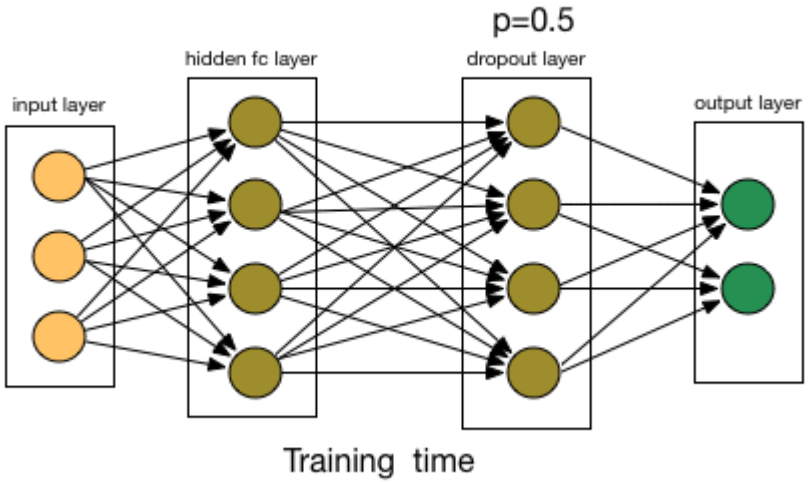
Regularization: Early Stoppage





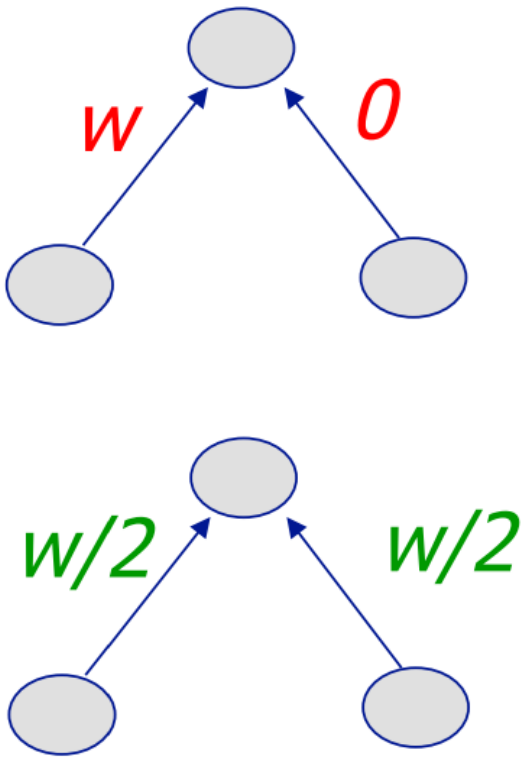
- Create "validation" set (subset of the training set).
  - Validation set is assumed to be a representative of the testing set.
- **Early stoppage:** Stop training (or at least save a checkpoint) when performance on the validation set decreases

Regularization: Dropout



- **Dropout:** Randomly remove some nodes in the network (along with incoming and outgoing edges)
- Notes:
  - Usually *p >= 0.5* (*p* is probability of keeping node)
  - Input layers *p* should be much higher (and use noise instead of dropout)
  - Most deep learning frameworks come with a dropout layer

Regularization: Weight Penalty *(aka Weight Decay)*



- **L2 Penalty:** Penalize squared weights. Result:
  - Keeps weight small unless error derivative is very large.
  - Prevent from fitting sampling error.
  - Smoother model (output changes slower as the input change).
  - If network has two similar inputs, it prefers to put half the weight on each rather than all the weight on one.
- **L1 Penalty:** Penalize absolute weights. Result:
  - Allow for a few weights to remain large.

Normalization

- Network Input Normalization
  - *Example:* Pixel to [0, 1] or [-1, 1] or according to mean and std.

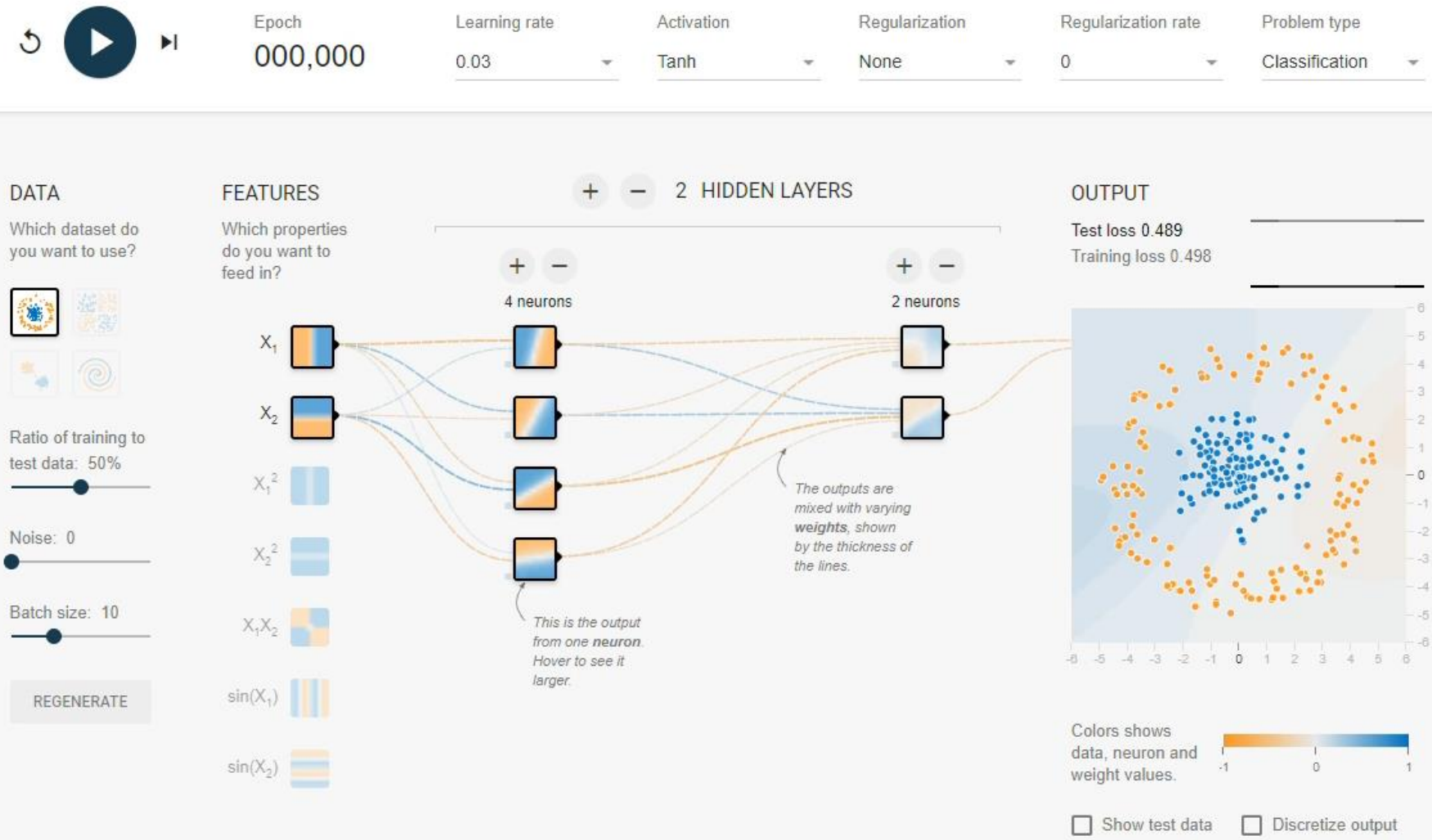
- Batch Normalization (BatchNorm, BN)
  - Normalize hidden layer inputs to mini-batch mean & variance
  - Reduces impact of earlier layers on later layers

- Batch Renormalization (BatchRenorm, BR)
  - Fixes difference b/w training and inference by keeping a moving average asymptotically approaching a global normalization.

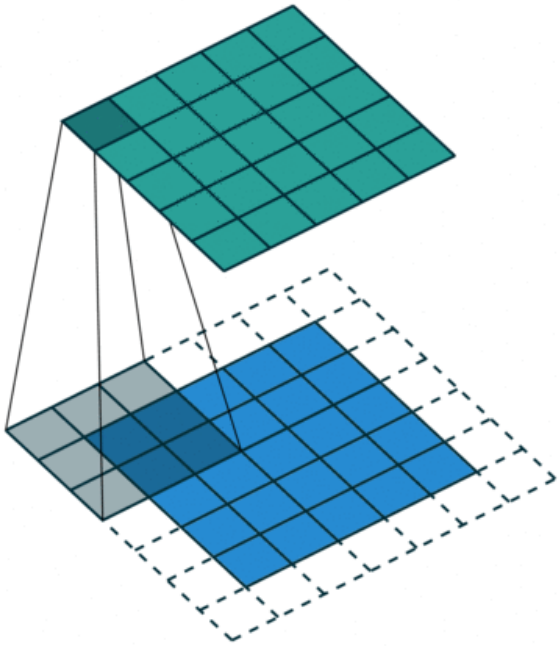
- Other options:
  - Layer normalization (LN) – conceived for RNNs
  - Instance normalization (IN) – conceived for Style Transfer
  - Group normalization (GN) – conceived for CNNs

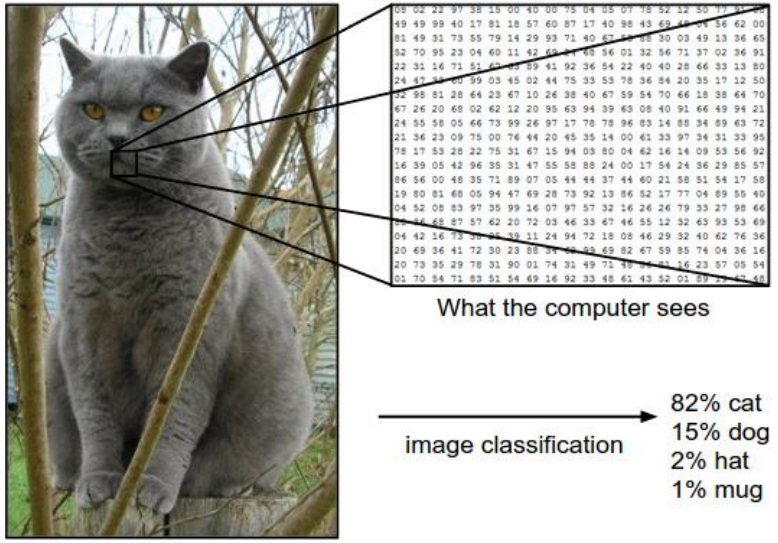
Neural Network Playground

http://playground.tensorflow.org

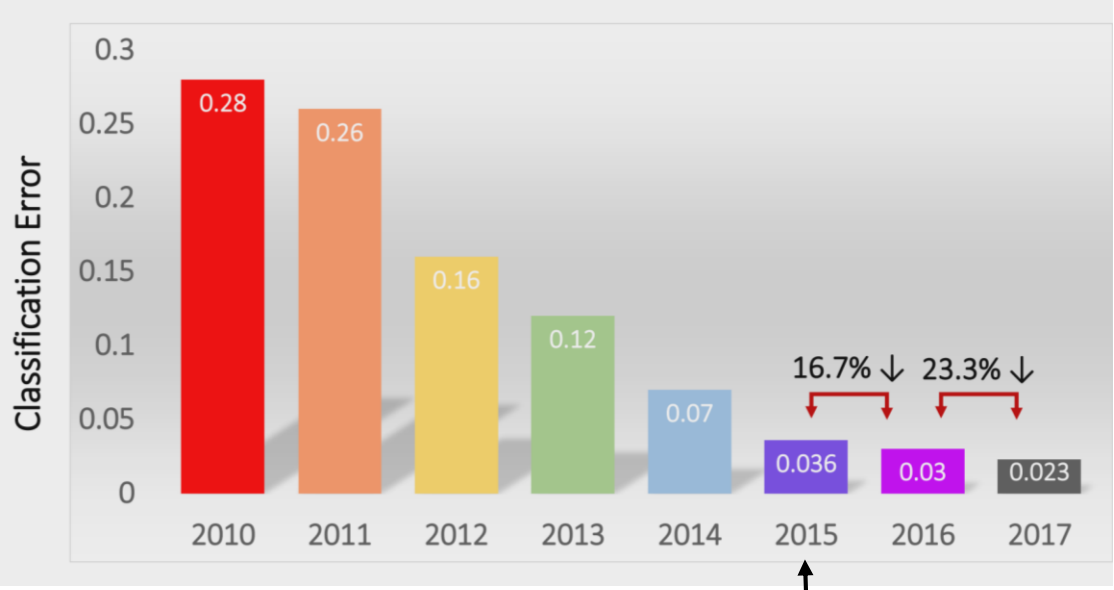


Convolutional Neural Networks: Image Classification





- Convolutional filters: take advantage of spatial invariance



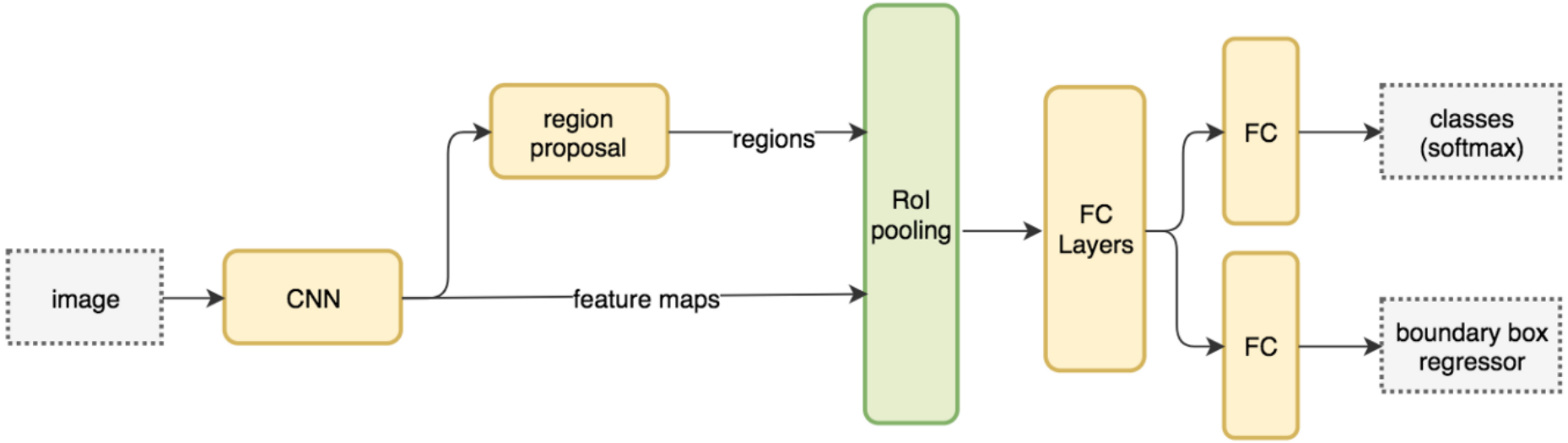
Human error (5.1%) surpassed in 2015

- **AlexNet (2012): First CNN (15.4%)**
  - 8 layers
  - 61 million parameters
- **ZFNet (2013): 15.4% to 11.2%**
  - 8 layers
  - More filters. Denser stride.
- **VGGNet (2014): 11.2% to 7.3%**
  - Beautifully uniform:
    3x3 conv, stride 1, pad 1, 2x2 max pool
  - 16 layers
  - 138 million parameters
- **GoogLeNet (2014): 11.2% to 6.7%**
  - Inception modules
  - 22 layers
  - 5 million parameters
    (throw away fully connected layers)
- **ResNet (2015): 6.7% to 3.57%**
  - More layers = better performance
  - 152 layers
- **CUImage (2016): 3.57% to 2.99%**
  - Ensemble of 6 models
- **SENet (2017): 2.99% to 2.251%**
  - Squeeze and excitation block: network is allowed to adaptively adjust the weighting of each feature map in the convolutional block.

References: [90]

Object Detection / Localization

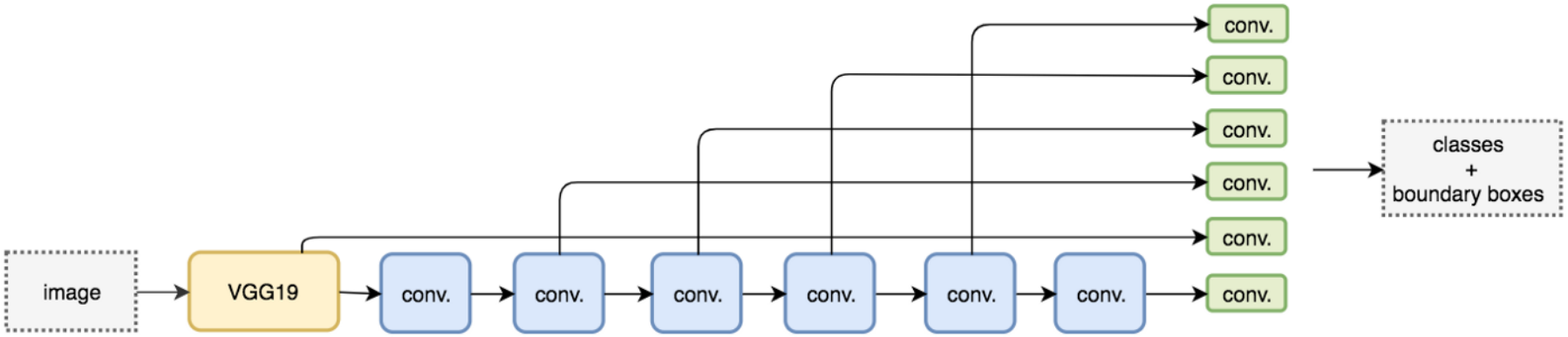
Region-Based Methods | Shown: Faster R-CNN

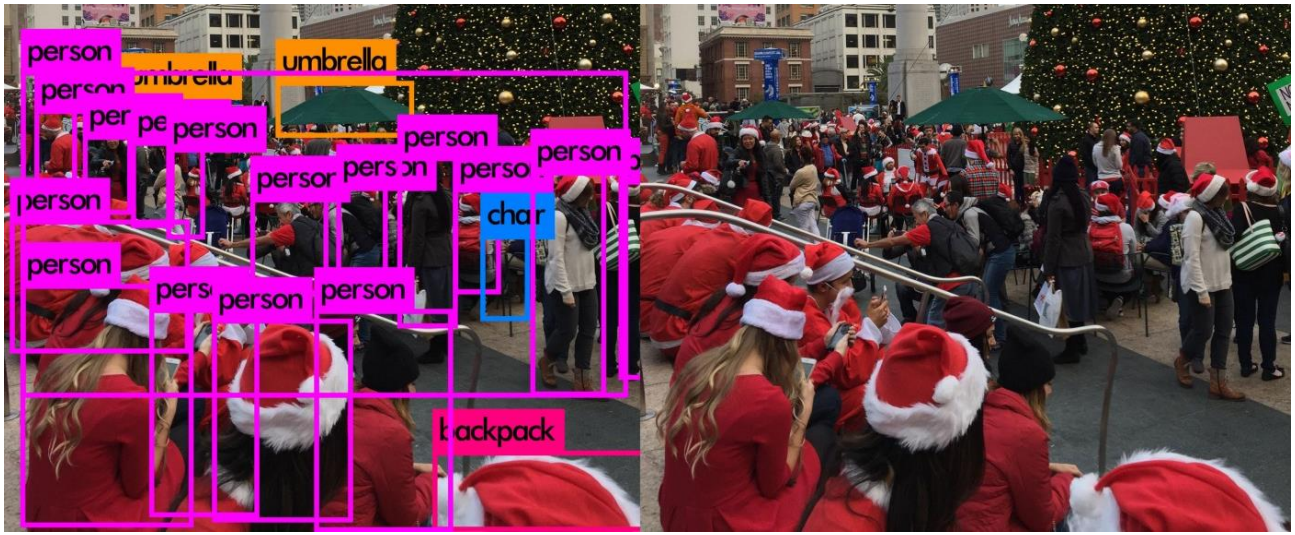



```
ROIs = region_proposal(image)
for ROI in ROIs
    patch = get_patch(image, ROI)
    results = detector(patch)
```

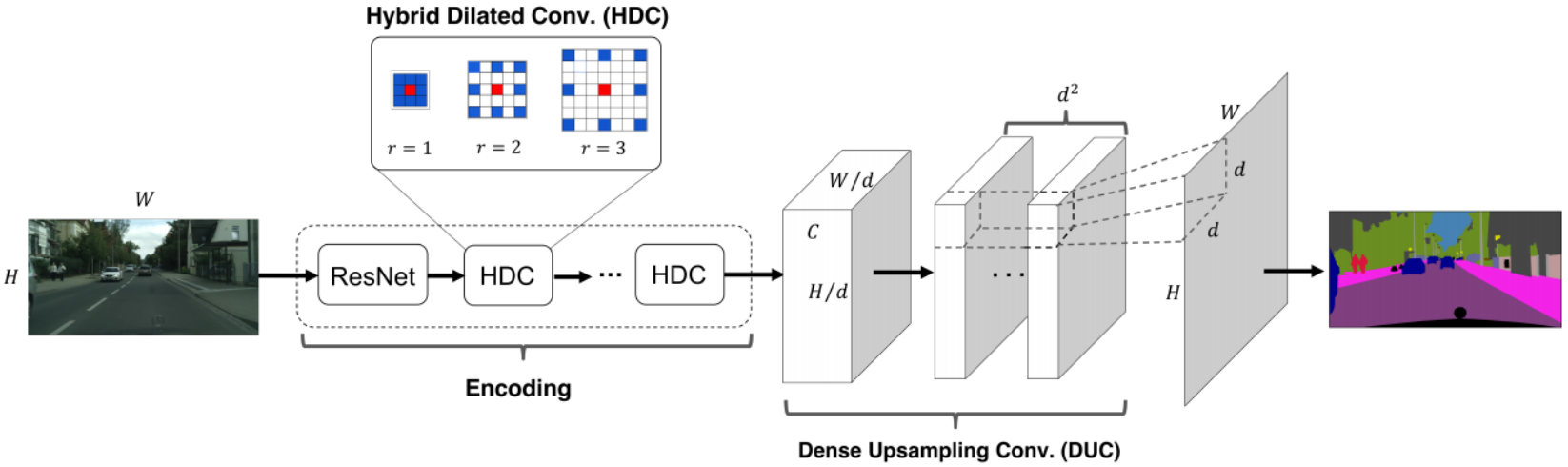
Object Detection / Localization

Single-Shot Methods | Shown: SSD

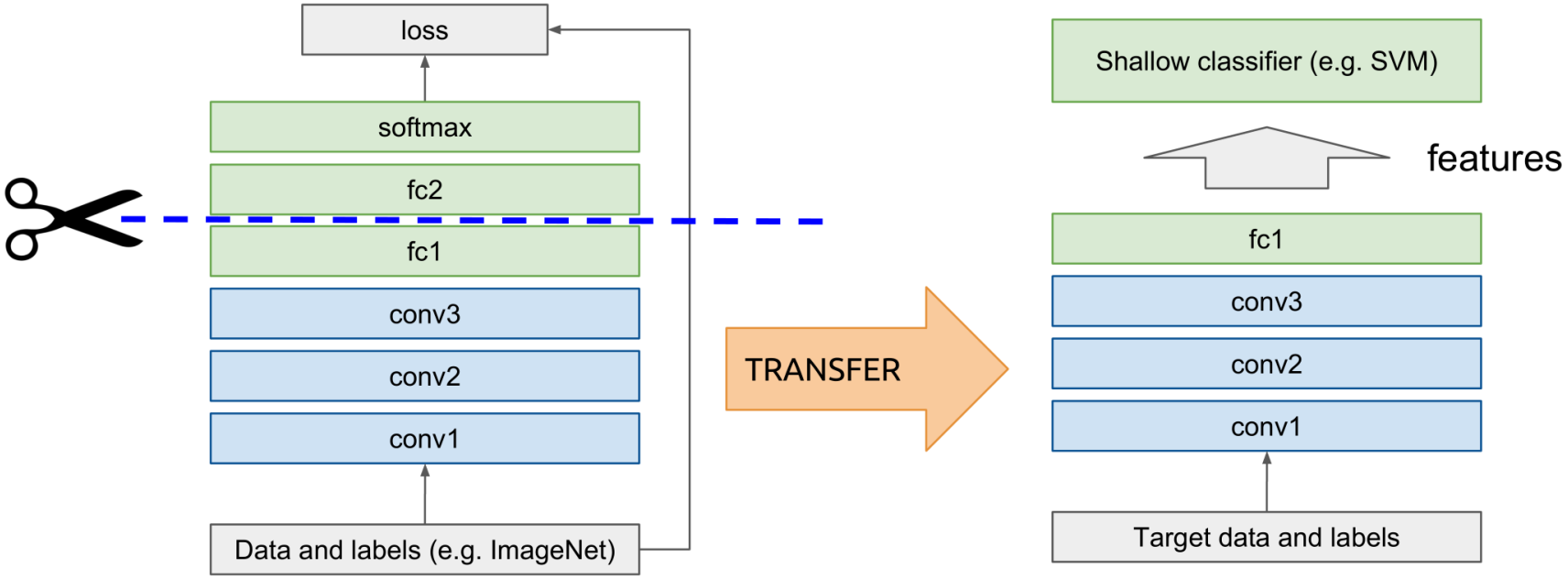




Semantic Segmentation

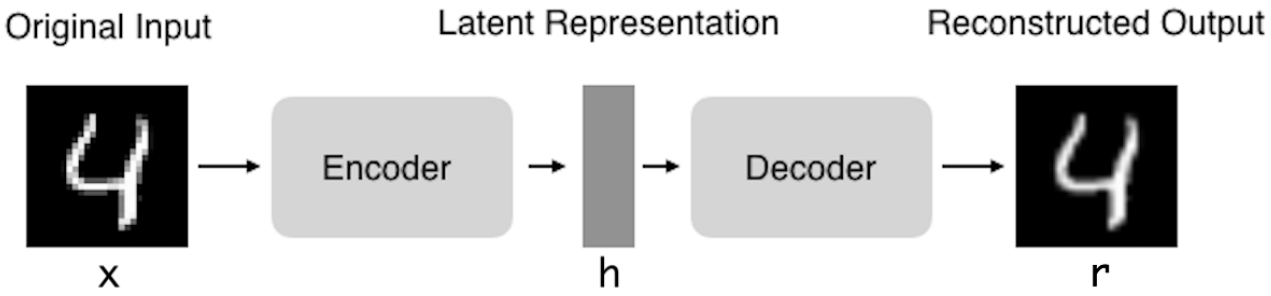


Transfer Learning

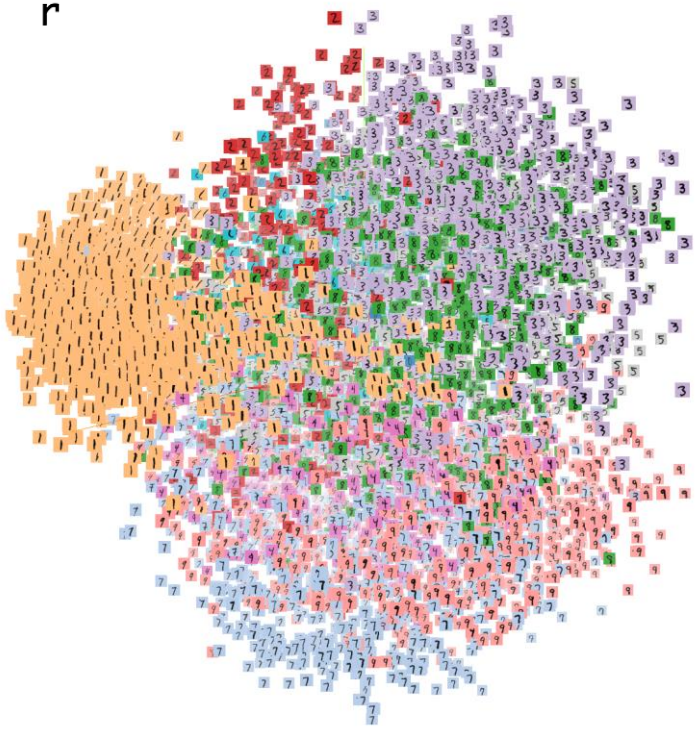


- Fine-tune a pre-trained model
- Effective in many applications: computer vision, audio, speech, natural language processing

Autoencoders



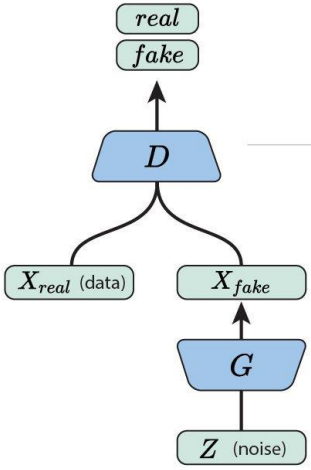
- Unsupervised learning
- Gives embedding
  - Typically better embeddings come from discriminative task



http://projector.tensorflow.org/

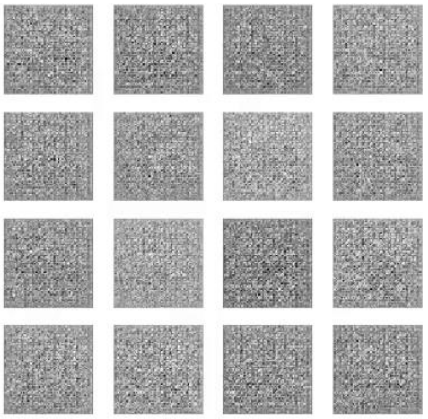
Generative Adversarial Network (GANs)

Generative Adversarial Networks (GANs) are a way to make a generative model by having two neural networks compete with each other.



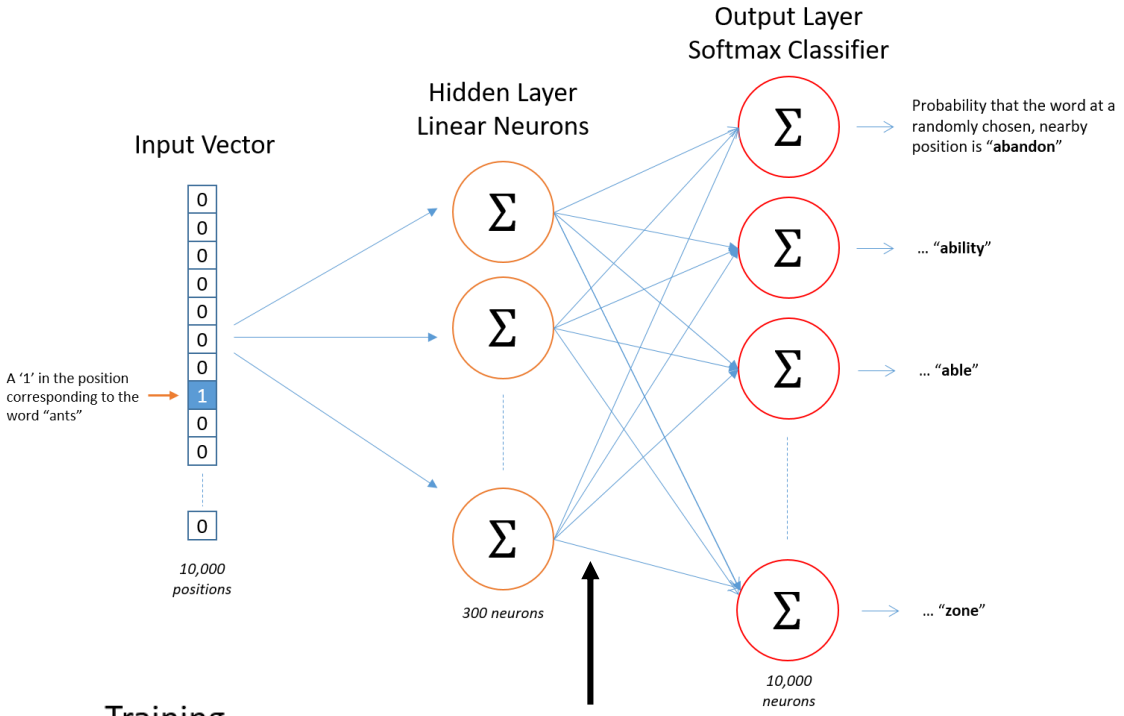
The **discriminator** tries to distinguish genuine data from forgeries created by the generator.

The **generator** turns random noise into immitations of the data, in an attempt to fool the discriminator.



Progressive GAN
10/2017
1024 x 1024

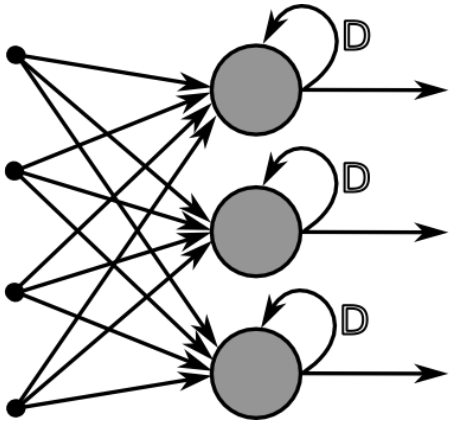
Word Embeddings (Word2Vec)



Skip Gram Model:

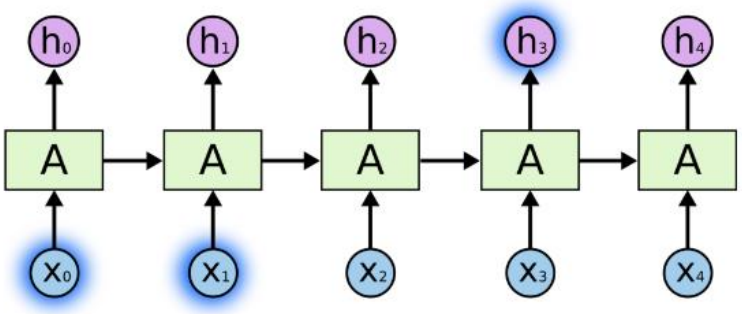
Source Text	Training Samples
The quick brown fox jumps over the lazy dog. ⟹	(the, quick) (the, brown)
The **quick** brown fox jumps over the lazy dog. ⟹	(quick, the) (quick, brown) (quick, fox)
The quick **brown** fox jumps over the lazy dog. ⟹	(brown, the) (brown, quick) (brown, fox) (brown, jumps)
The quick brown **fox** jumps over the lazy dog. ⟹	(fox, quick) (fox, brown) (fox, jumps) (fox, over)

Recurrent Neural Networks



- Applications
  - Sequence Data
  - Text
  - Speech
  - Audio
  - Video
  - Generation

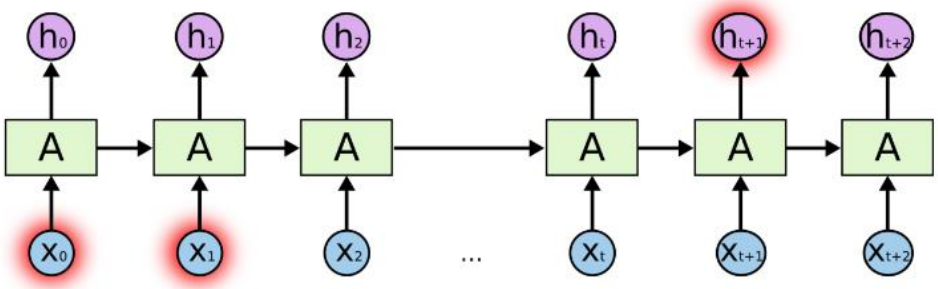
Long-Term Dependency



- Short-term dependence:
  Bob is eating an **apple.**

Context →

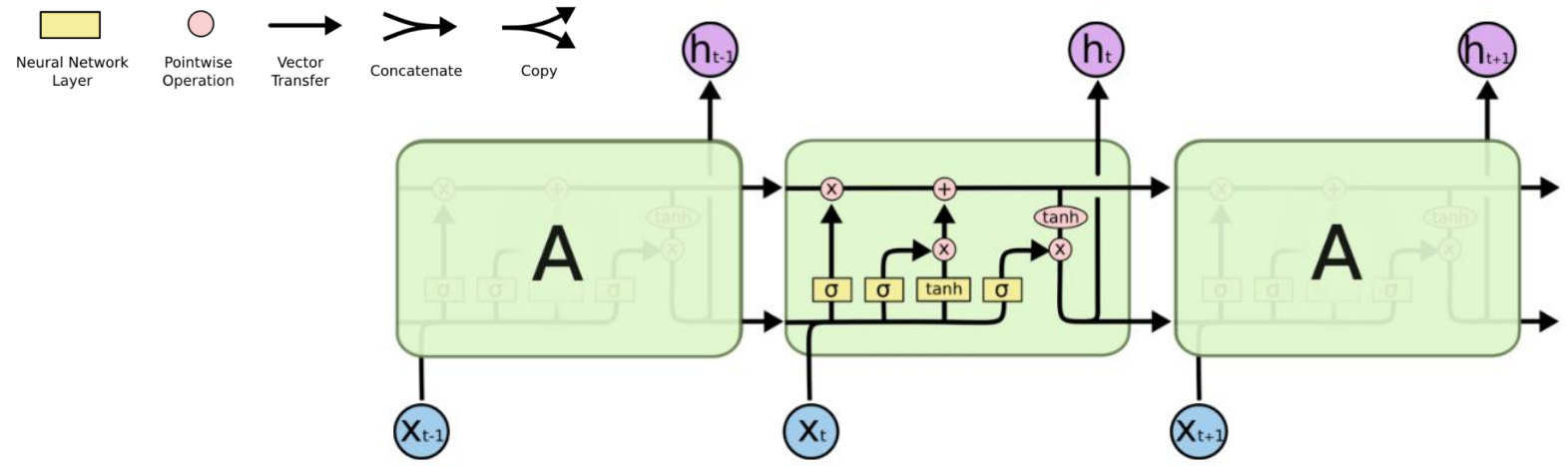
- Long-term dependence:
  Bob likes **apples**. He is hungry and decided to have a snack. So now he is eating an **apple.**



In theory, vanilla RNNs can handle arbitrarily long-term dependence.

In practice, it's difficult.

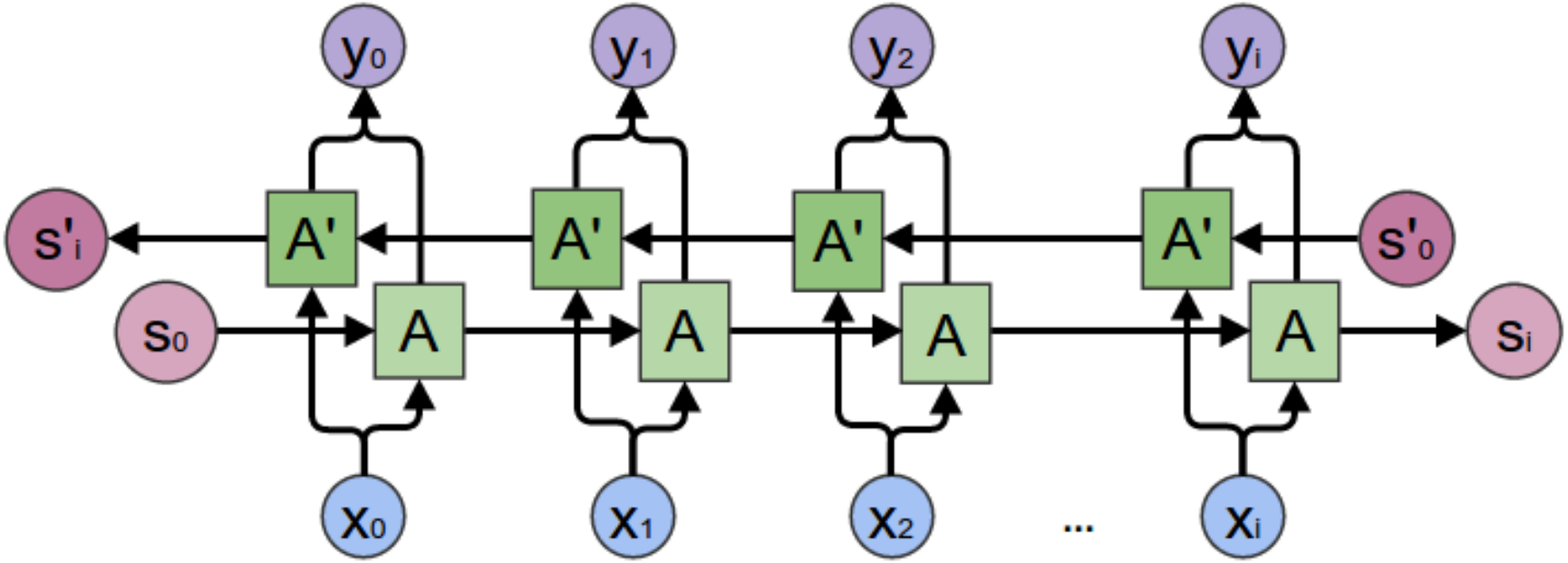
Long Short-Term Memory (LSTM) Networks:
Pick What to Forget and What To Remember



Conveyer belt for **previous state** and **new data**:

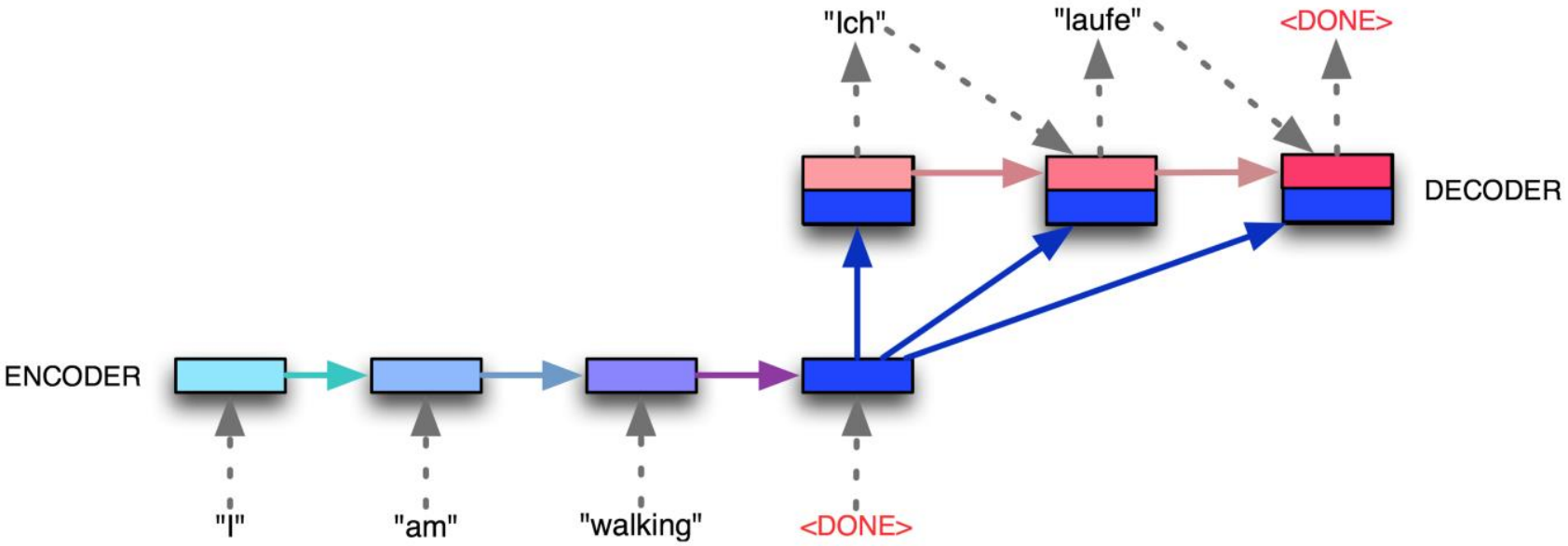
1. Decide what to forget (state)
2. Decide what to remember (state)
3. Decide what to output (if anything)

Bidirectional RNN



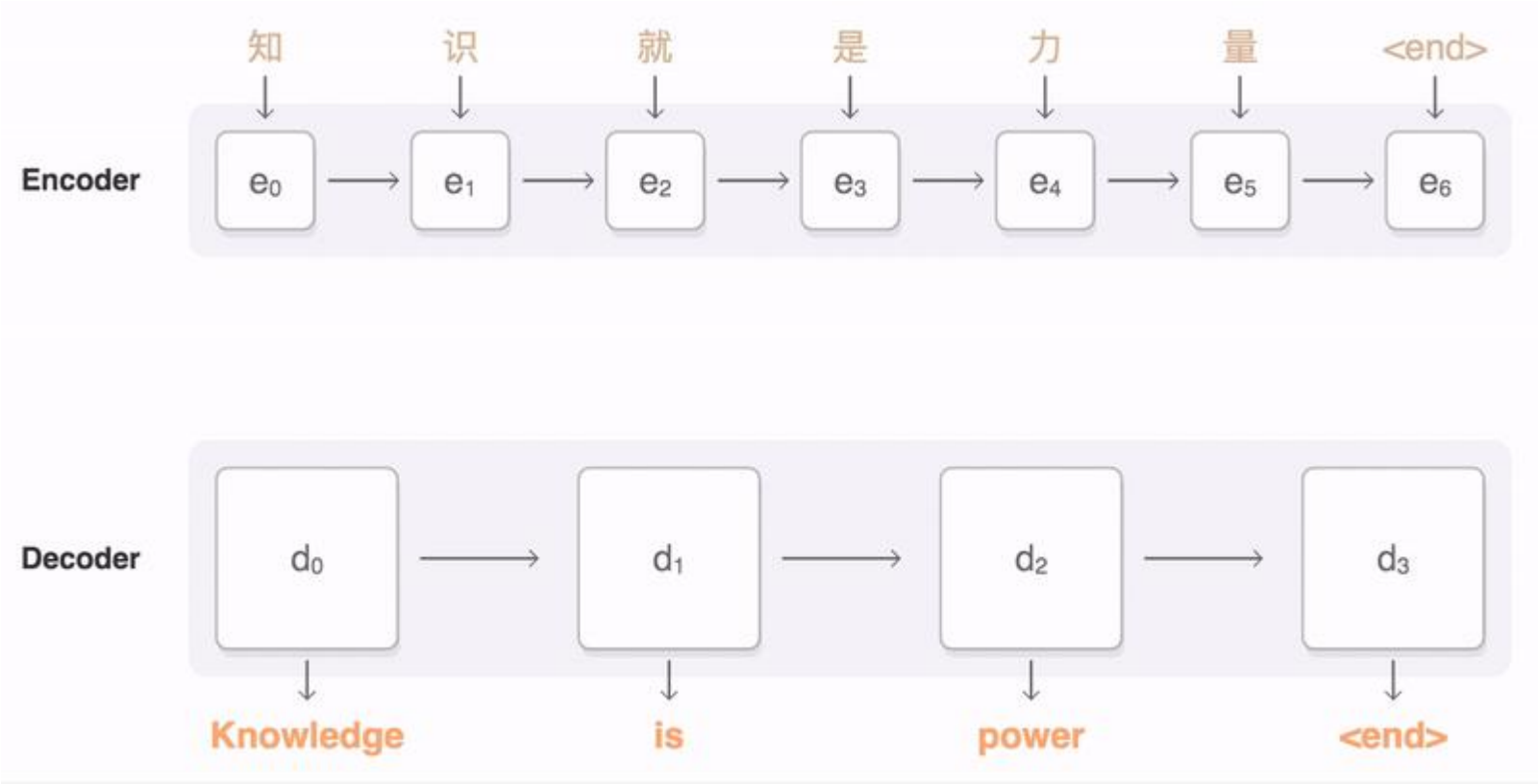
- Learn representations from both previous time steps and future time steps

Encoder-Decoder Architecture



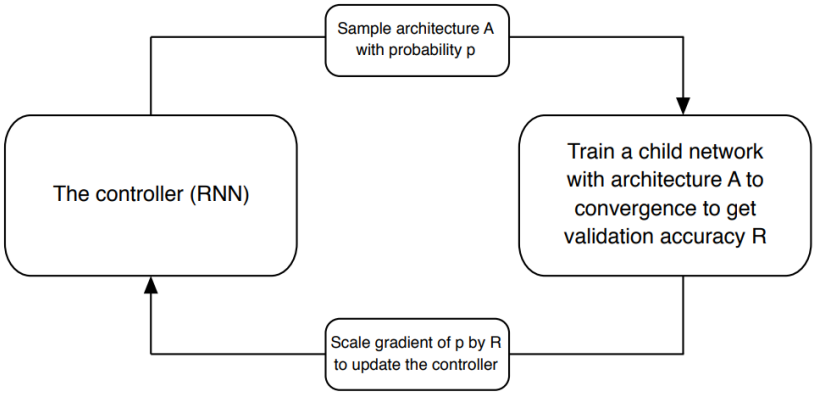
Encoder RNN encodes input sequence into a fixed size vector, and then is passed repeatedly to decoder RNN.

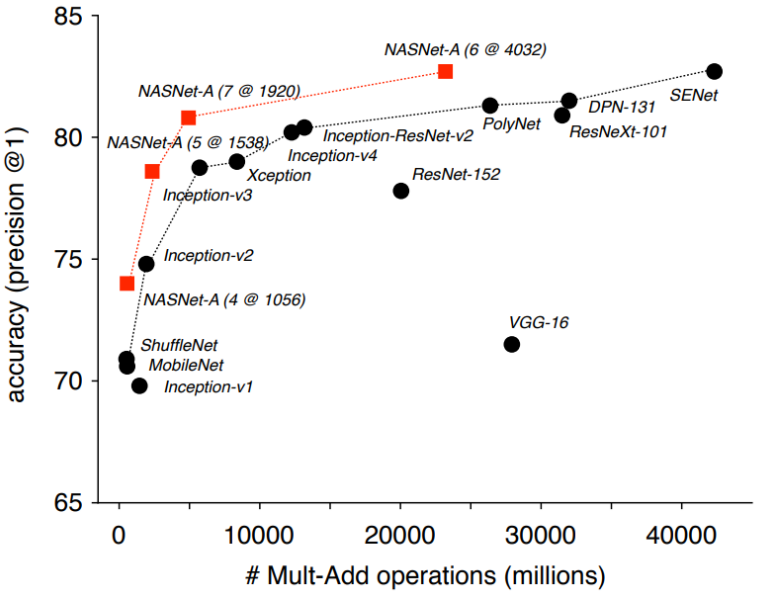
Attention

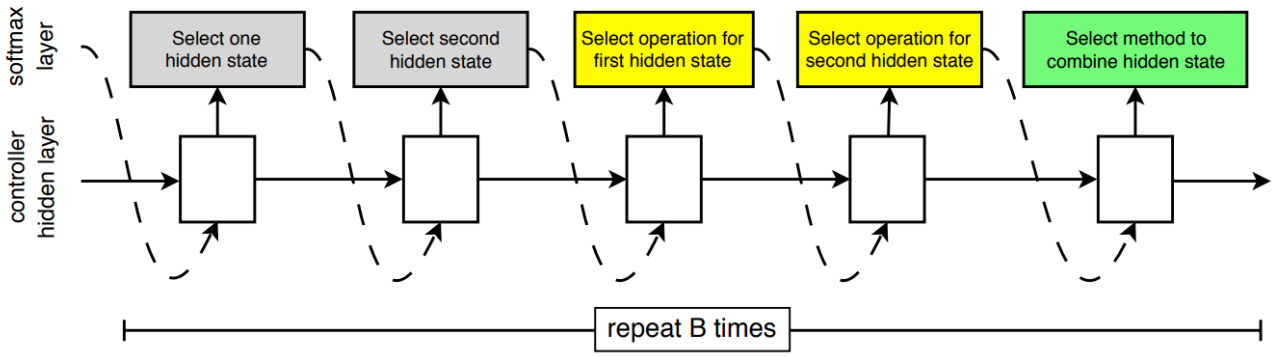


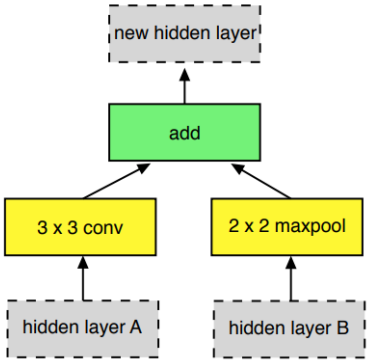
Attention mechanism allows the network to refer back to the input sequence, instead of forcing it to encode all information into one fixed-length vector.

AutoML and Neural Architecture Search (NASNet)

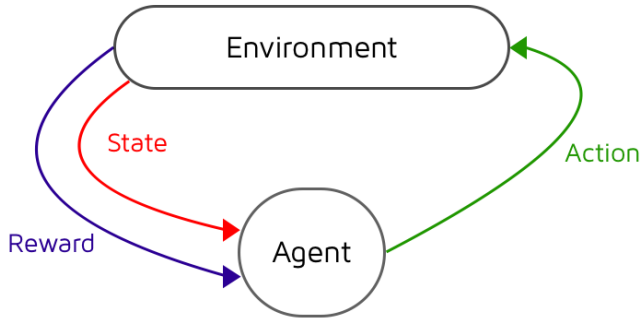


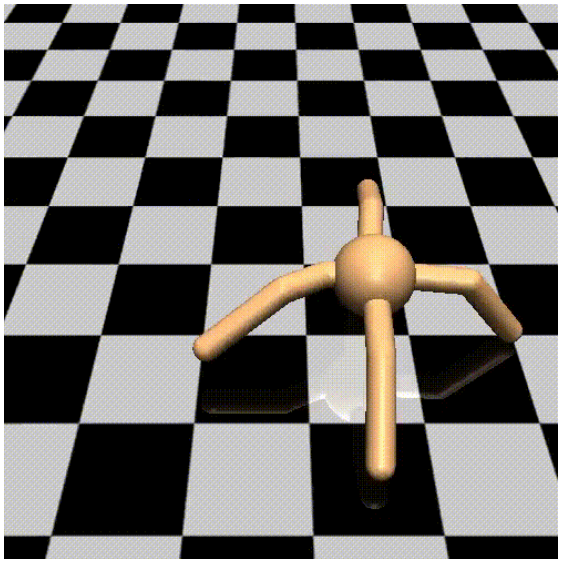


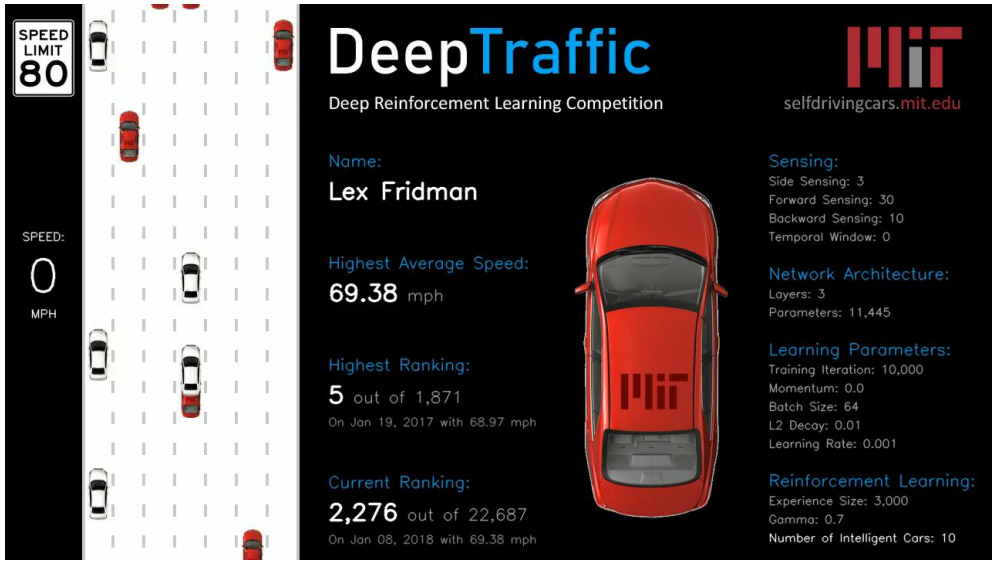




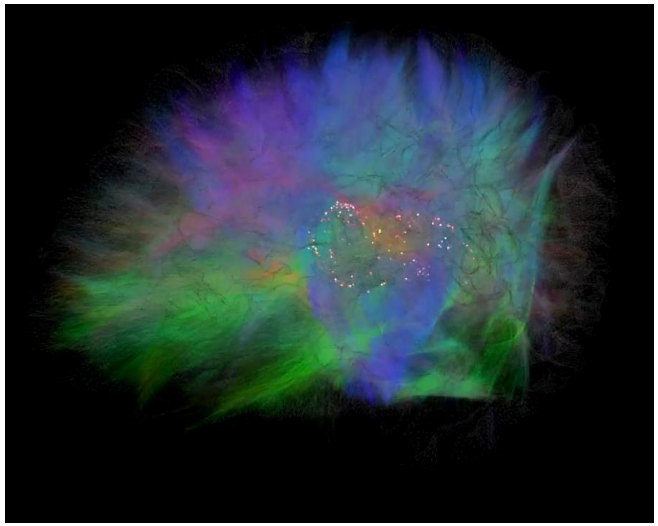
Deep Reinforcement Learning



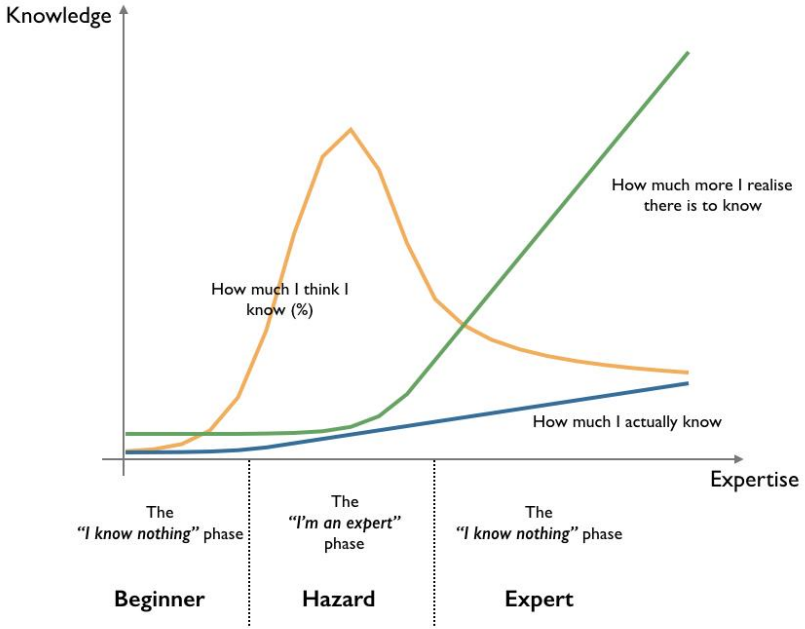




Toward Artificial General Intelligence



- Transfer Learning
- Hyperparameter Optimization
- Architecture Search
- Meta Learning



Thank You

Website:

deeplearning.mit.edu

- Videos and slides will be posted online
- Code will be posted on GitHub