

As you walk in

Welcome!

- 1) Help draw some aliens for our dataset today!
 - Grab a sharpie and some sticky notes
 - Just stick figures, nothing quite this fancy →

Ca



Freepik
Suesse Aliens Bilder - ...



123RF
91,690 Cartoon Alien...



iStock
47,434 Alien Cartoon...



Shutterstock
228,873 Alien Cartoon...



Shutterstock
2,607 Alien Feet Image...



Shutterstock
228,873 Alien Cartoon...

An abstract graphic on the left side of the slide, featuring a sphere-like shape composed of a dense grid of intersecting red, blue, and green lines. The lines are curved and follow the contour of the sphere, creating a complex, woven pattern. The sphere is set against a dark gray background.

10-315 Introduction to ML

Instructor: Pat Virtue

Today

Course team

Quick course info

What is AI and ML?

ML: Input/Output Tasks

Example Input/Output Tasks

- Autoencoder (Aliens)



DALL-E: “Logo of a Scotty dog with a red collar whose brain is made of circuits”

Course Team

Instructor



Pat Virtue
pvirtue

Best way to contact Pat:

- Post on Ed (private post as needed)
- Just grab an OH appointment slot

(Not email 😞)

Education Associate



Nichelle Phillips
nichellp

Email Nichelle, nichellp@andrew.cmu.edu:

- Exceptions, extensions, etc
 - (may replace with exceptions form)
- Any course logistics

Course Team

Teaching Assistants



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Course Team

Students!!



Course Information

Website: <https://www.cs.cmu.edu/~10315>

Communication:

<https://edstem.org/>



E-mail Nichelle if Ed doesn't work:
nichellp@andrew.cmu.edu

Important posts coming soon!

- Office Hours
- Jupyter notebooks
- Recitation (Fri)
- Pre-reading (due Tue)
- HW0
- HW1

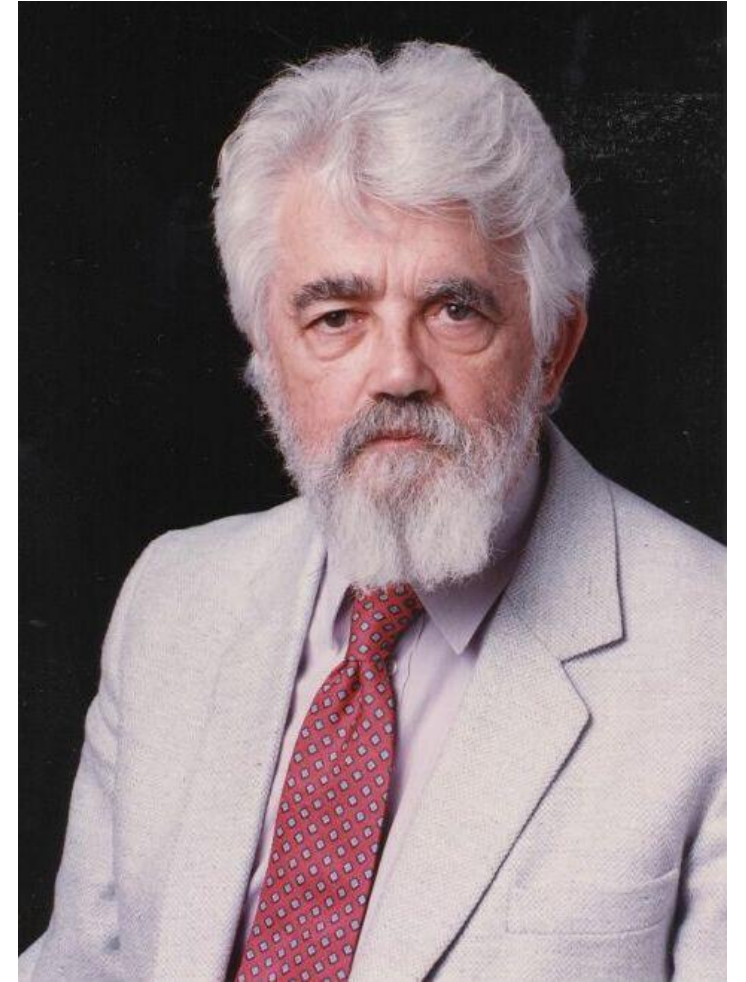
AI Definition by John McCarthy

What is artificial intelligence

- It is the science and engineering of making intelligent machines, especially intelligent computer programs

What is intelligence

- Intelligence is the computational part of the ability to achieve goals in the world



What is artificial Intelligence?

Why is folding clothes a research problem while robots are actively being used to assemble cars in factories?



AI Definition (Pat's Version)

What is intelligence

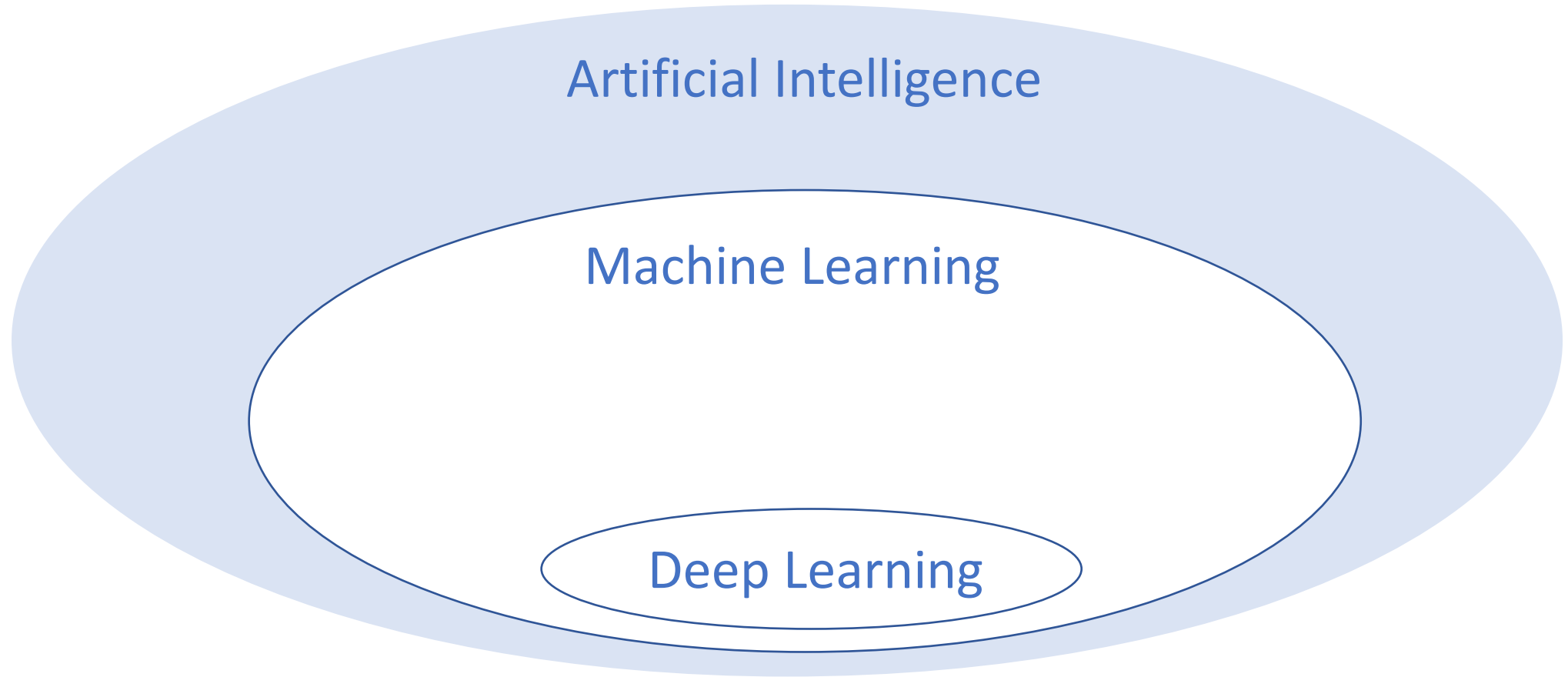
- Intelligence is the ability to perform well on a task that involves uncertainty

Intelligence is not binary

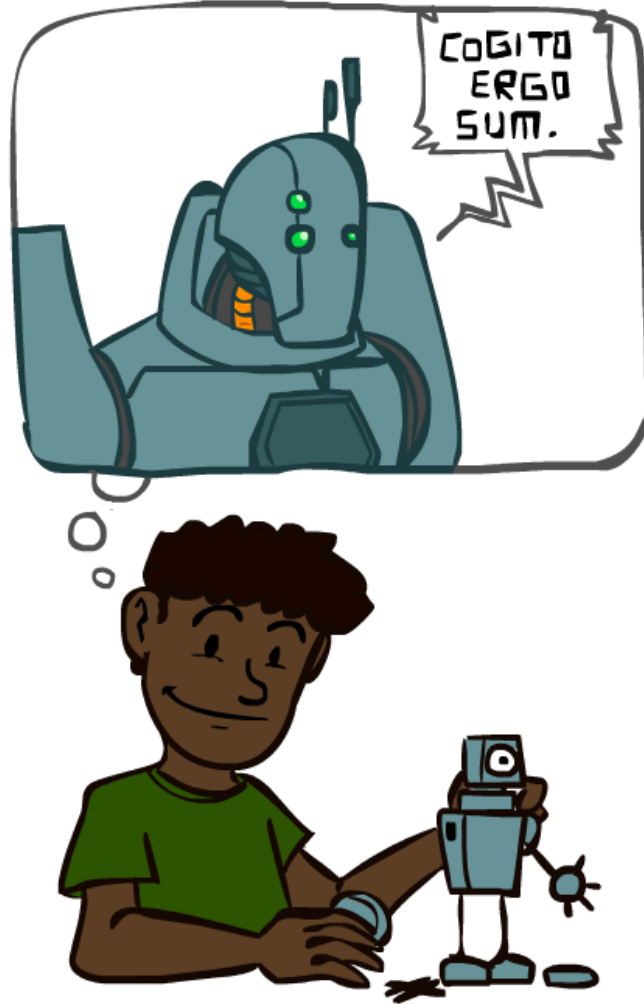
- How **well** an agent performs and how much **uncertainty** is involved will determine how intelligent we consider the agent to be



Artificial Intelligence vs Machine Learning?



A Brief History of AI



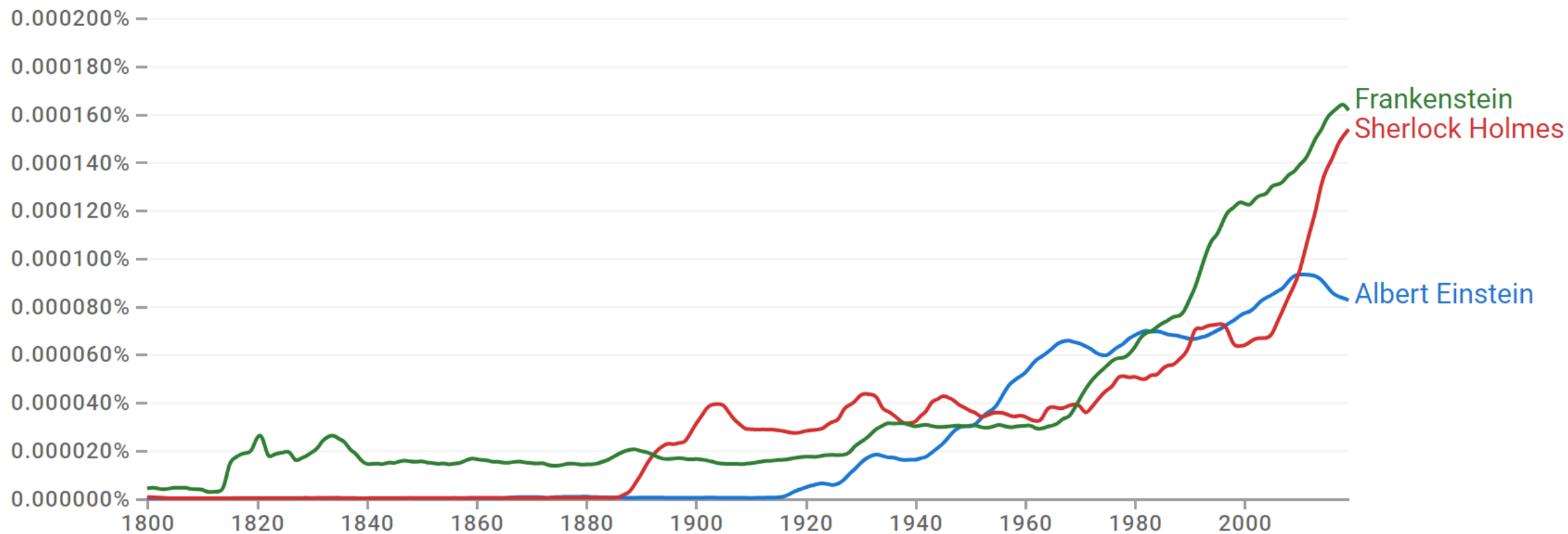
Albert Einstein, Sherlock Holmes, Frankenstein

1800 - 2019 ▾

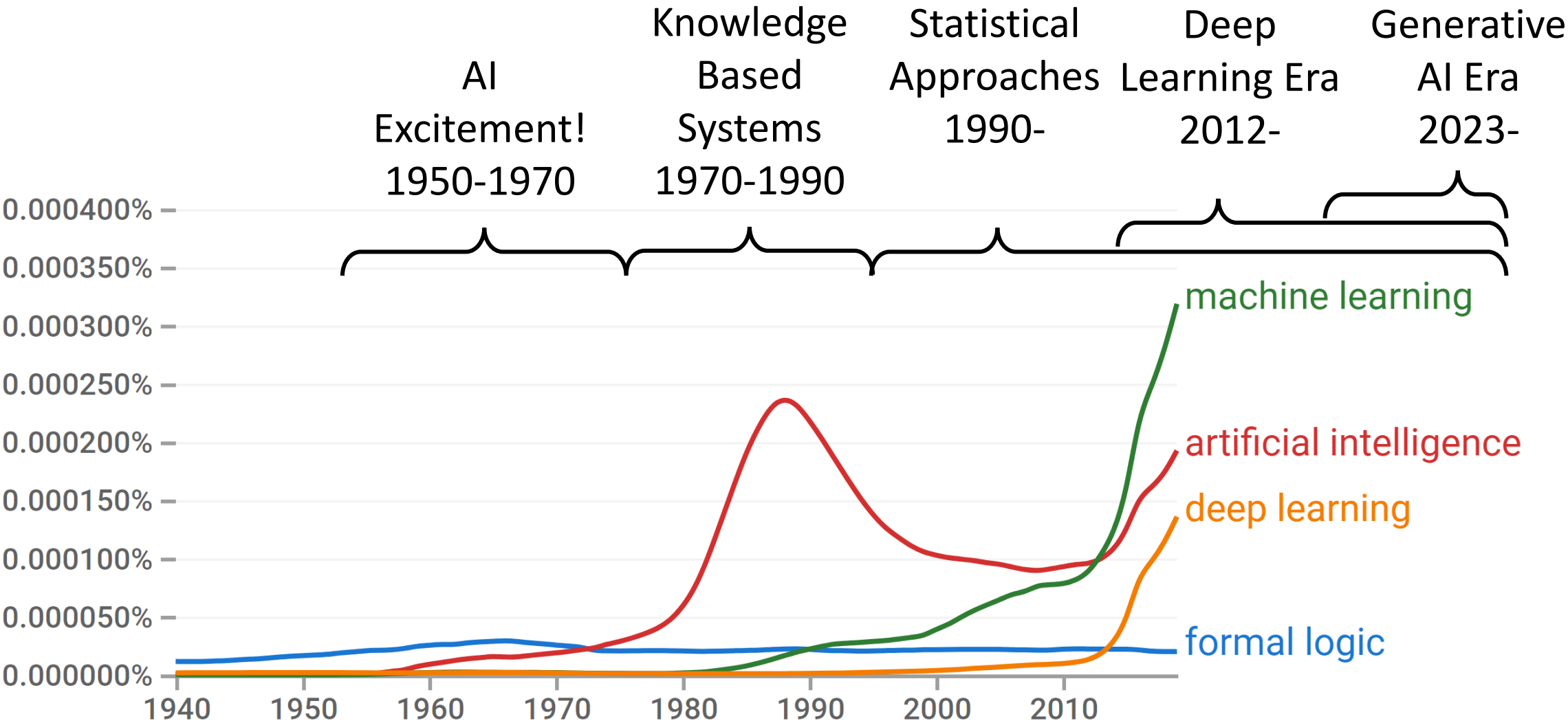
English (2019) ▾

Case-Insensitive

Smoothing ▾



A Brief History of AI



A Brief History of AI

1940-1950: Early days

- 1943: McCulloch & Pitts: Boolean circuit model of brain
- 1950: Turing's "Computing Machinery and Intelligence"

1950—70: Excitement: Look, Ma, no hands!

- 1950s: Early AI programs, including Samuel's checkers program, Newell & Simon's Logic Theorist, Gelernter's Geometry Engine
- 1956: Dartmouth meeting: "Artificial Intelligence" adopted

1970—90: Knowledge-based approaches

- 1969—79: Early development of knowledge-based systems
- 1980—88: Expert systems industry booms
- 1988—93: Expert systems industry busts: "AI Winter"

1990—: Statistical approaches

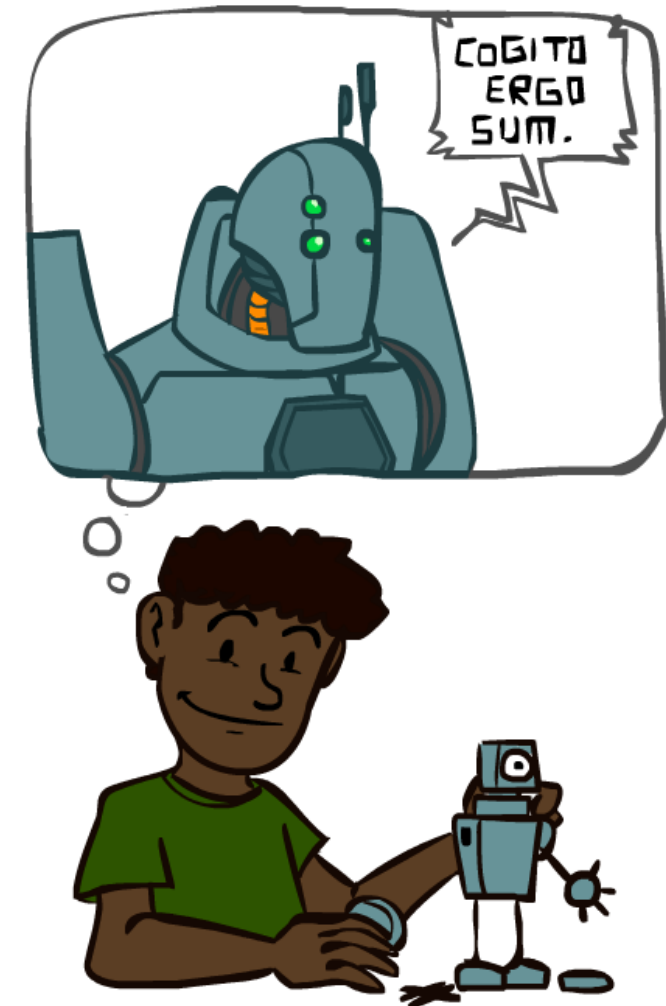
- Resurgence of probability, focus on uncertainty
- General increase in technical depth
- Agents and learning systems... "AI Spring"?

2012—: Deep learning

- 2012: ImageNet & AlexNet

2023—: Generative AI

- 2023: ChatGPT



ML Applications?

Speech Recognition

1. Learning to recognize spoken words


THEN	NOW
<p>"...the SPHINX system (e.g. Lee 1989) learns speaker-specific strategies for recognizing the primitive sounds (phonemes) and words from the observed speech signal...neural network methods...hidden Markov models..."</p> <p>(Mitchell, 1997)</p>	 <p>Google Now Siri Cortana</p>

Source: <https://www.stonetemple.com/great-knowledge-box-showdown/#VoiceStudyResults>

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Robotics

2. Learning to drive an autonomous vehicle

THEN	NOW
<p>"...the ALVINN system (Pomerleau 1989) has used its learned strategies to drive unassisted at 70 miles per hour for 90 miles on public highways among other cars..."</p> <p>(Mitchell, 1997)</p>	 <p>waymo.com</p>

waymo.com

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Games / Reasoning

3. Learning to beat the masters at board games

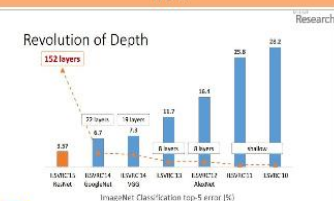

THEN	NOW
<p>"...the world's top computer program for backgammon, TD-GAMMON (Tesauro, 1992, 1995), learned its strategy by playing over one million practice games against itself..."</p> <p>(Mitchell, 1997)</p>	 <p>ALPHAGO 00:10:29 LEE SEDOL 00:01:00</p>

(Mitchell, 1997)

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Computer Vision

4. Learning to recognize images

THEN	NOW
<p>"...The recognizer is a convolution network that can be spatially replicated. From the network output, a hidden Markov model produces word scores. The entire system is globally trained to minimize word-level errors..."</p> <p>(LeCun et al., 1995)</p>	<p>Revolution of Depth</p>  <p>ImageNet Classification top-5 error (%)</p> 

Images from <https://blog.openai.com/generative-models/>

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Learning Theory

5. In what cases and how well can we learn?

Sample Complexity Results

Definition 6.1. The sample complexity of a learning algorithm is the number of examples required to achieve arbitrarily small error (with respect to the optimal hypothesis) with high probability (i.e. close to 1).

Four Cases we care about...

	Realizable	Agnostic
Finite [K]	$N \geq \frac{1}{\epsilon} \left(\frac{1}{\eta} \log \frac{1}{\delta} + \log \frac{1}{\eta} \right)$ <p>Related examples are sufficient as long as $\eta > 0$. If $\eta = 0$, we need more than $N(K) = \infty$.</p>	$N \geq \frac{1}{\epsilon} \left(\frac{1}{\eta} \log \frac{1}{\delta} + \log \frac{1}{\eta} \right)$ <p>Related examples are sufficient as long as $\eta > 0$. If $\eta = 0$, we need more than $N(K) = \infty$.</p>
Infinite [K]	$N \geq \frac{1}{\epsilon} \left(\frac{1}{\eta} \log \frac{1}{\delta} + \log \frac{1}{\eta} \right)$ <p>Related examples are sufficient as long as $\eta > 0$. If $\eta = 0$, we need more than $N(K) = \infty$.</p>	$N \geq \frac{1}{\epsilon} \left(\frac{1}{\eta} \log \frac{1}{\delta} + \log \frac{1}{\eta} \right)$ <p>Related examples are sufficient as long as $\eta > 0$. If $\eta = 0$, we need more than $N(K) = \infty$.</p>

PK Learning

Can we learn $R(x)$ in form of $\hat{R}(x)$?

A: Yes!

PK should be possible

Approximately correct

Correct

Def: PK Criterion

$E(R(x) - \hat{R}(x))^2 \leq \epsilon$

Two Types of Error
<p>① True Error (aka expected risk) (aka Generalization Error)</p> $R(x) = \mathbb{E}_{x \sim \mathcal{D}} \ell(x, h(x))$ <p>② Test Error (aka empirical risk)</p> $\hat{R}(x) = \frac{1}{N} \sum_{i=1}^N \ell(x_i, h(x_i))$ <p>③ Training Error (aka empirical risk)</p> $\hat{R}(x) = \frac{1}{N} \sum_{i=1}^N \ell(x_i, h(x_i))$

- How many examples do we need to learn?
- How do we quantify our ability to generalize to unseen data?
- Which algorithms are better suited to specific learning settings?

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Machine Learning and Statistics

Statistics is also about learning from data

Statistics has been around from much longer!

What's the difference?

Until the mid 1990s:

Statistics:

- A branch of mathematics
- Emphasized rigor, correctness, provable properties (“is it correct?”)
- Was not very concerned with scaling

Machine Learning:

- A branch of Computer Science / AI
- Focus on heuristics, making things work in practice (“does it work?”)
- Not much awareness of statistical theory

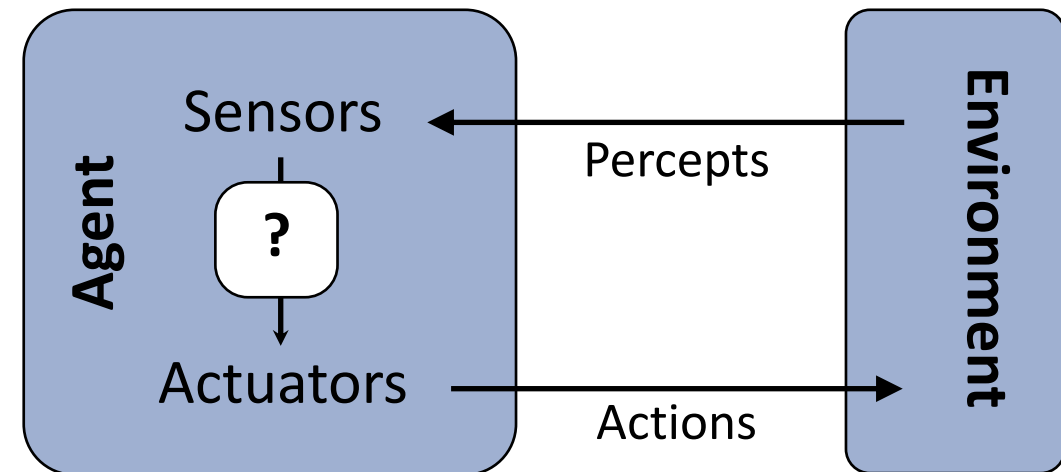
ML: Input/Output Tasks

Agents

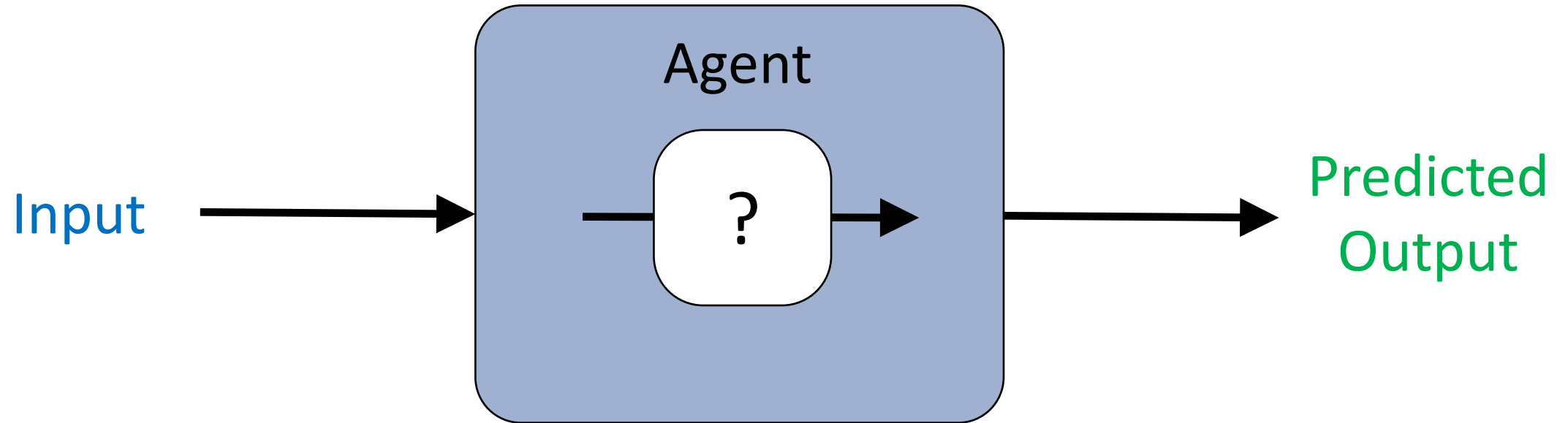
An **agent** is an entity that *perceives* and *acts*.

Actions can have an effect on the *environment*.

The specific *sensors* and *actuators* affect what the agent is capable of *perceiving* and what *actions* it is capable of taking



Agent: Simple Input/Output Task



Task: Image Classification

What is this?

Input:
Image (pixels)



Agent



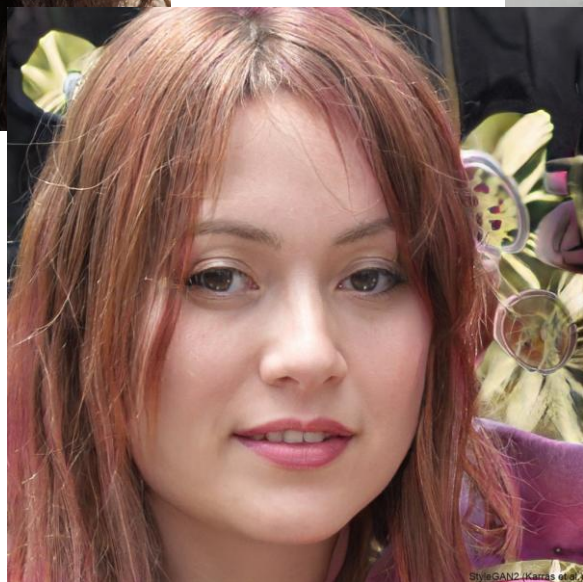
Predicted Output:
Category

Task Input and Output

Input	Task	Output
Petal measurements	Iris classification	Category
Time of day	Traffic prediction	Traffic Volume
Image	Image classification	Category
Image	Image denoising	Image
Text	Text to image generation	Image
???	Face generation	Image

Task: Face Generation

<https://thispersondoesnotexist.com/>



Task: Classification from Features

What is this?

Input:
Image



Predicted Output:
Category

As you walk in

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- See table up front
- Just stick figures, nothing quite this fancy →

Cartoon alien hi-res...



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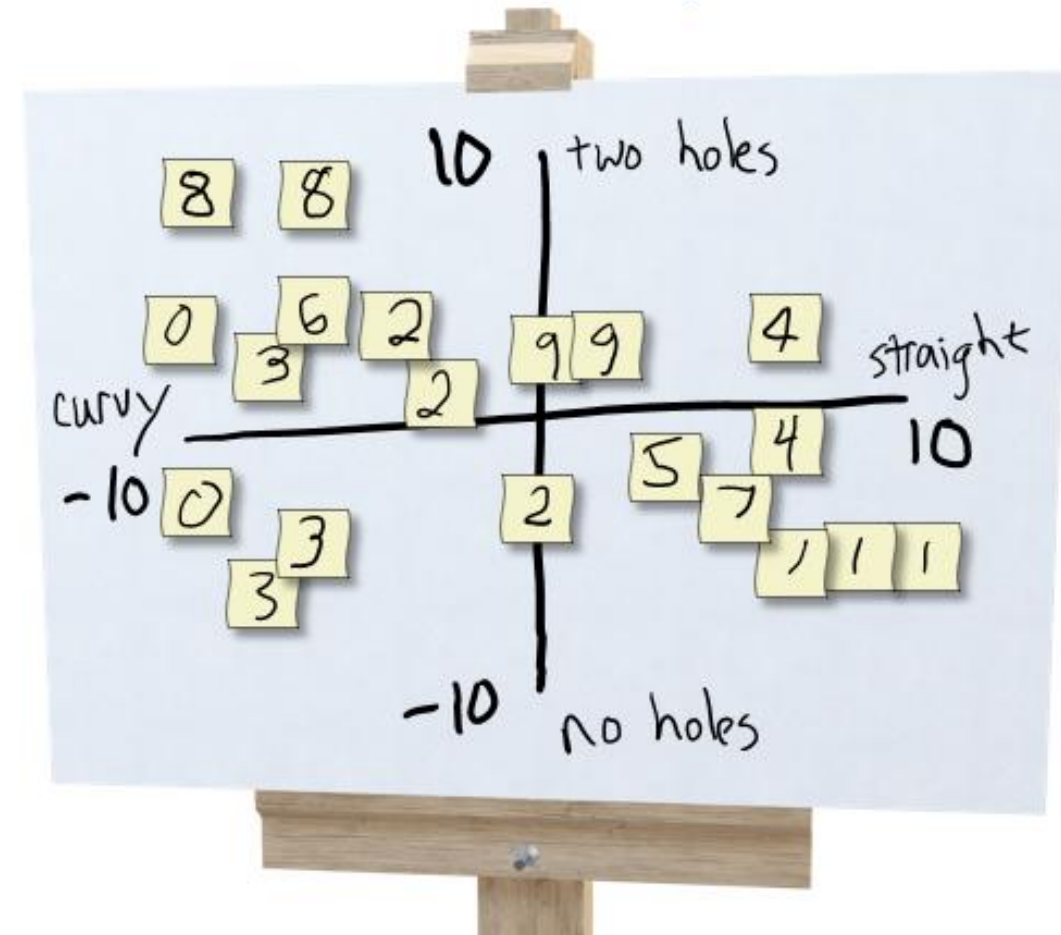
Exercise: Human-defined Feature Space

Try to organize data on a 2-D coordinate plot

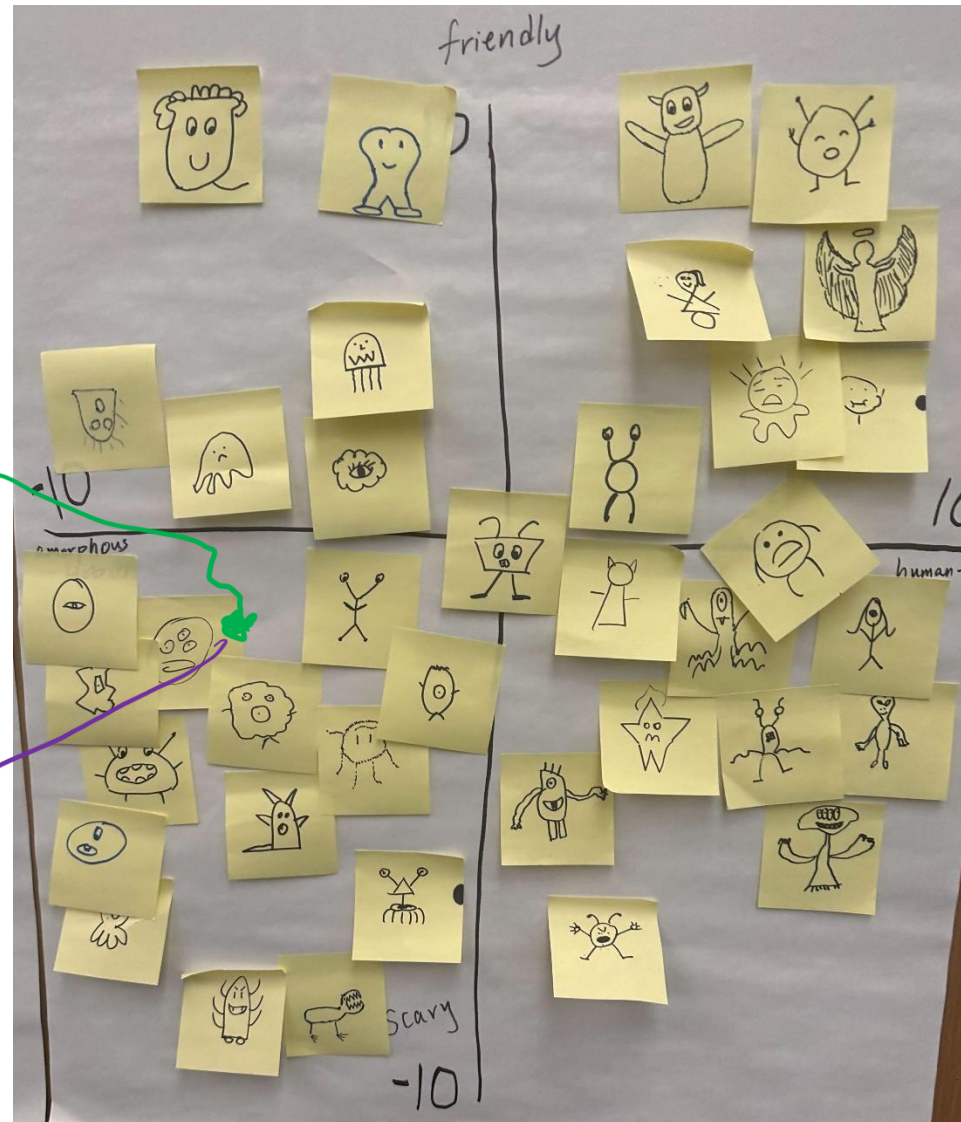
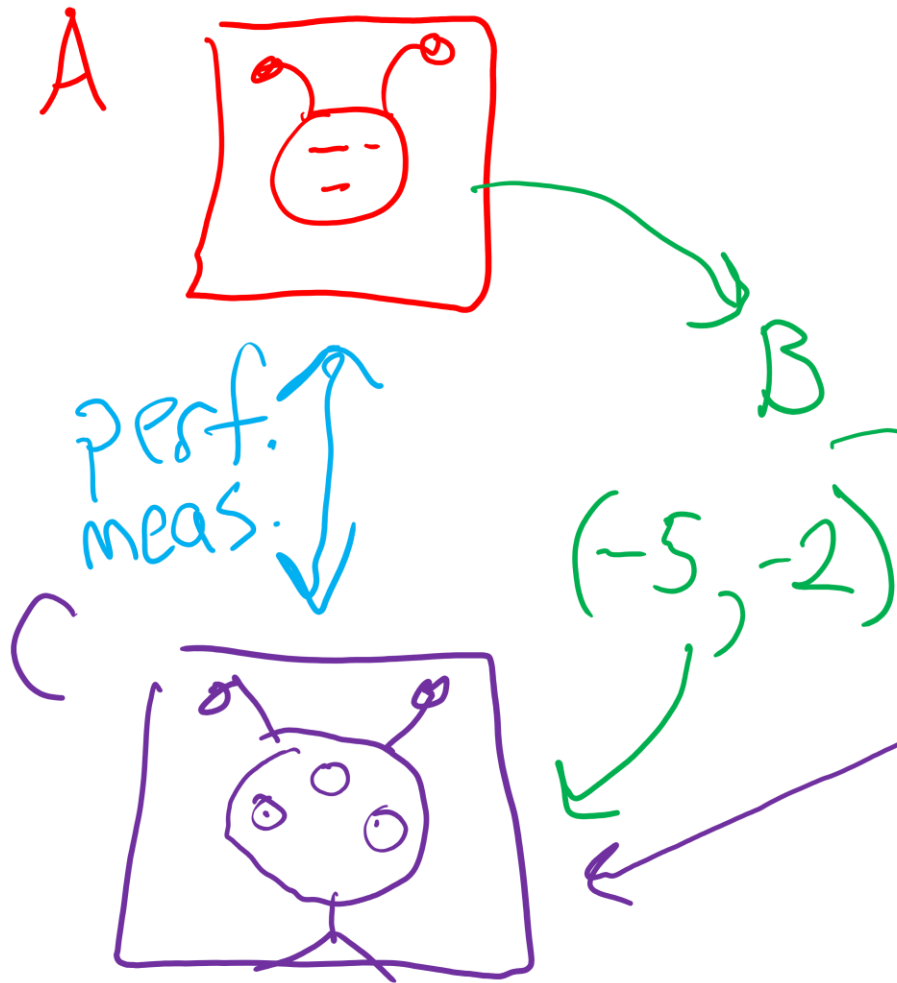
to win the following game:

Select three students: A, B, C

1. Student A draws a new alien and hands it to student B
2. Student B thinks about where to plot it and comes up with a 2-D coordinate, (x, y)
3. Student C looks at the coordinate and the plot (but not the drawing from A) and **draws a new alien**



Exercise: Human-defined Feature Space



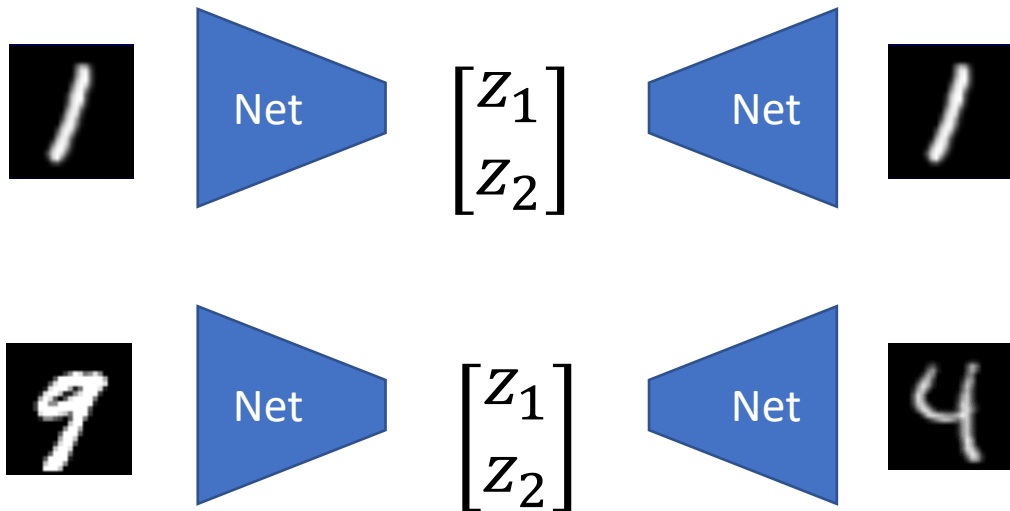
Poll 1

What features did you use?

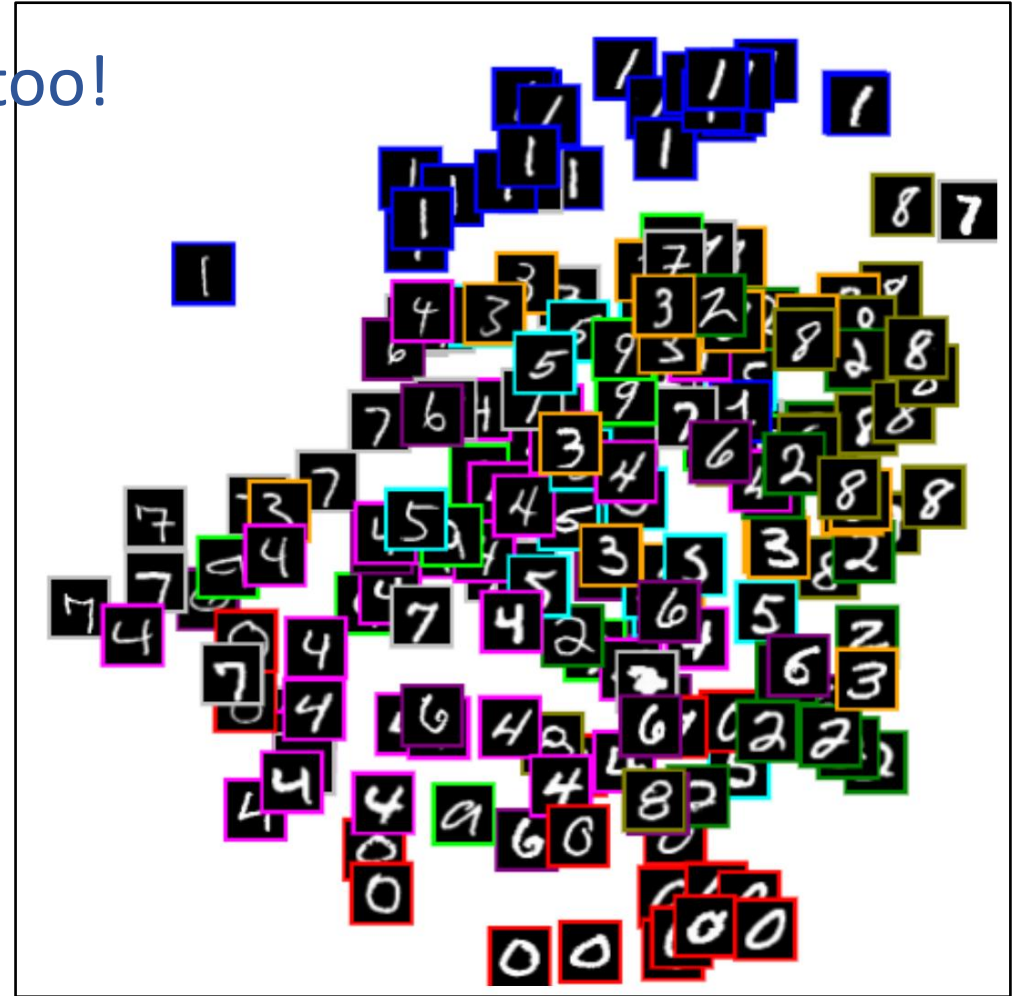
Learning to Organize Data

Neural networks can learn to organization too!

Image $\rightarrow \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \rightarrow$ Image



z_2

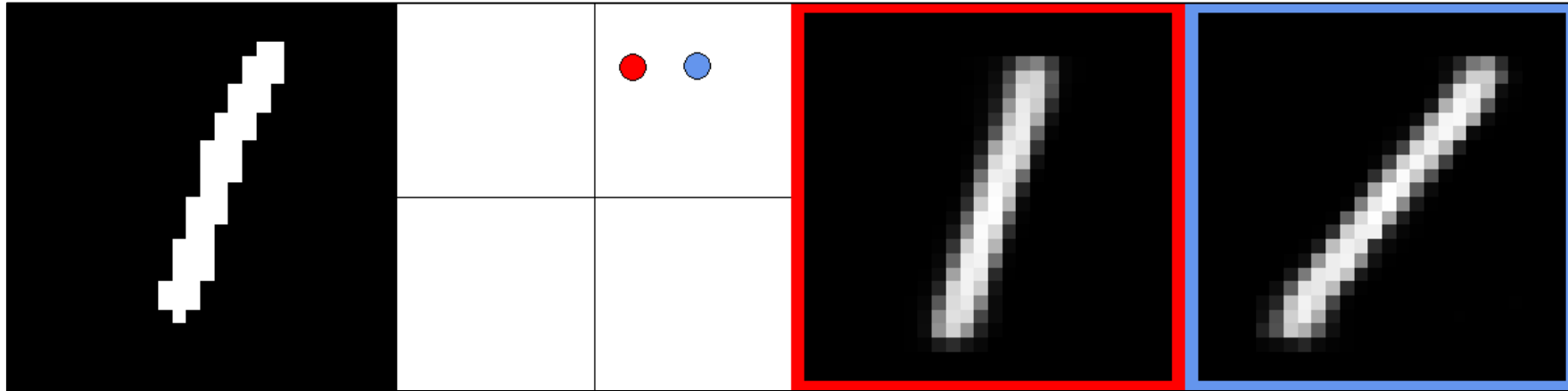


z_1

<https://cs.stanford.edu/people/karpathy/convnetjs/demo/autoencoder.html>

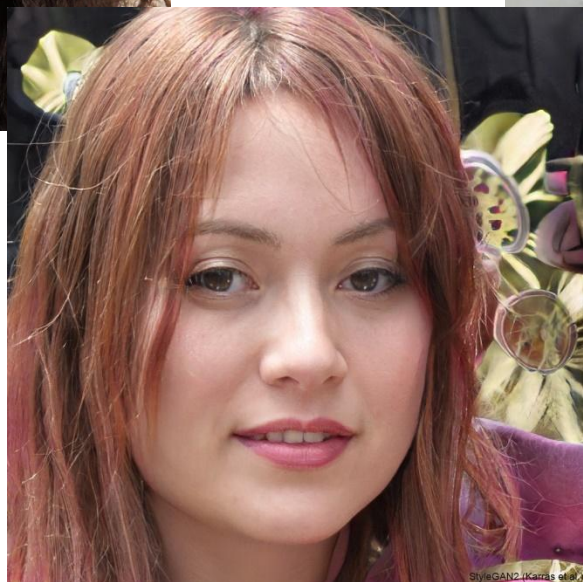
Digit Autoencoder

Demo: Using a learned feature space



Task: Face Generation

<https://thispersondoesnotexist.com/>

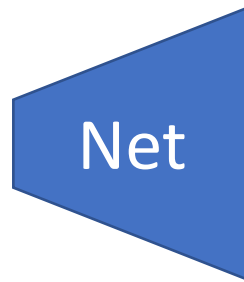


Task: Face Generation

<https://thispersondoesnotexist.com/>

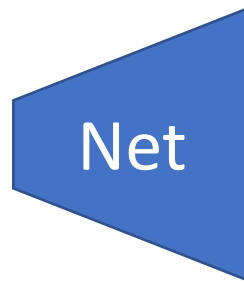
Random

$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$



Random

$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$



Face GAN Slider Demo

<https://github.com/genforce/interfacegan>

<https://colab.research.google.com/github/genforce/interfacegan/blob/master/docs/InterFaceGAN.ipynb>

age:


eyeglasses:

gender:

pose:

smile:

[Show code](#)



Face GAN Slider Demo

<https://github.com/genforce/interfacegan>

<https://colab.research.google.com/github/genforce/interfacegan/blob/master/docs/InterFaceGAN.ipynb>

age: -3


eyeglasses: 2.1

gender: 0

pose: 0

smile: 0

[Show code](#)

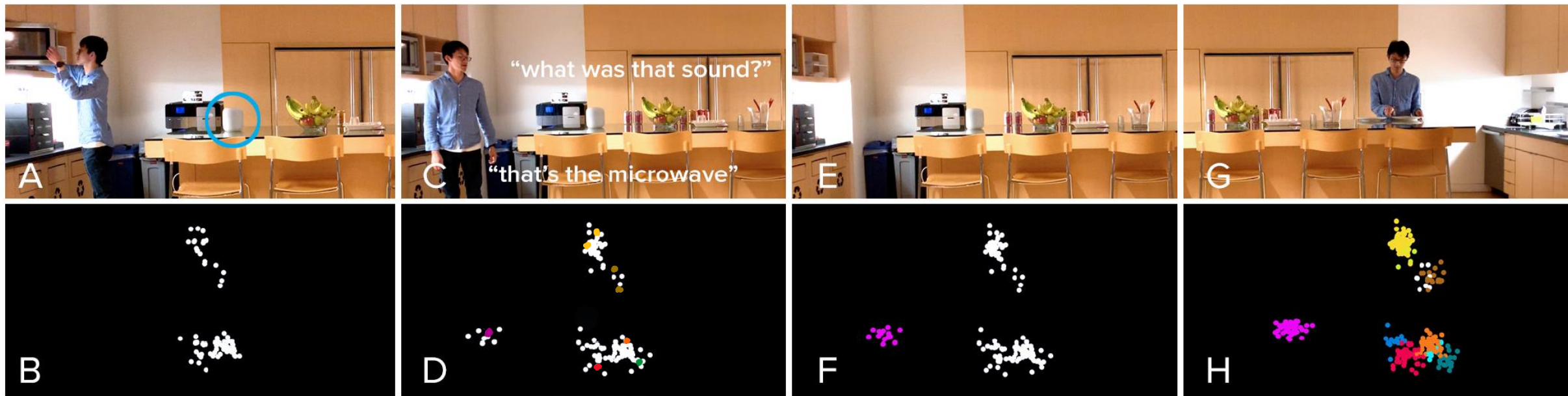


The image displays a user interface for a Face GAN slider demo. It features five horizontal sliders for adjusting face attributes: age, eyeglasses, gender, pose, and smile. Each slider has a blue dot indicating the current value, and a numerical value is shown to the right of each slider. Below the sliders is a 'Show code' link. At the bottom, there are four generated face images corresponding to the current slider settings: a man with glasses, a woman with pink hair, a girl with dark hair, and a boy with dark hair.

Attribute	Value
age	-3
eyeglasses	2.1
gender	0
pose	0
smile	0

Listen Learner

Chris Harrison, CMU



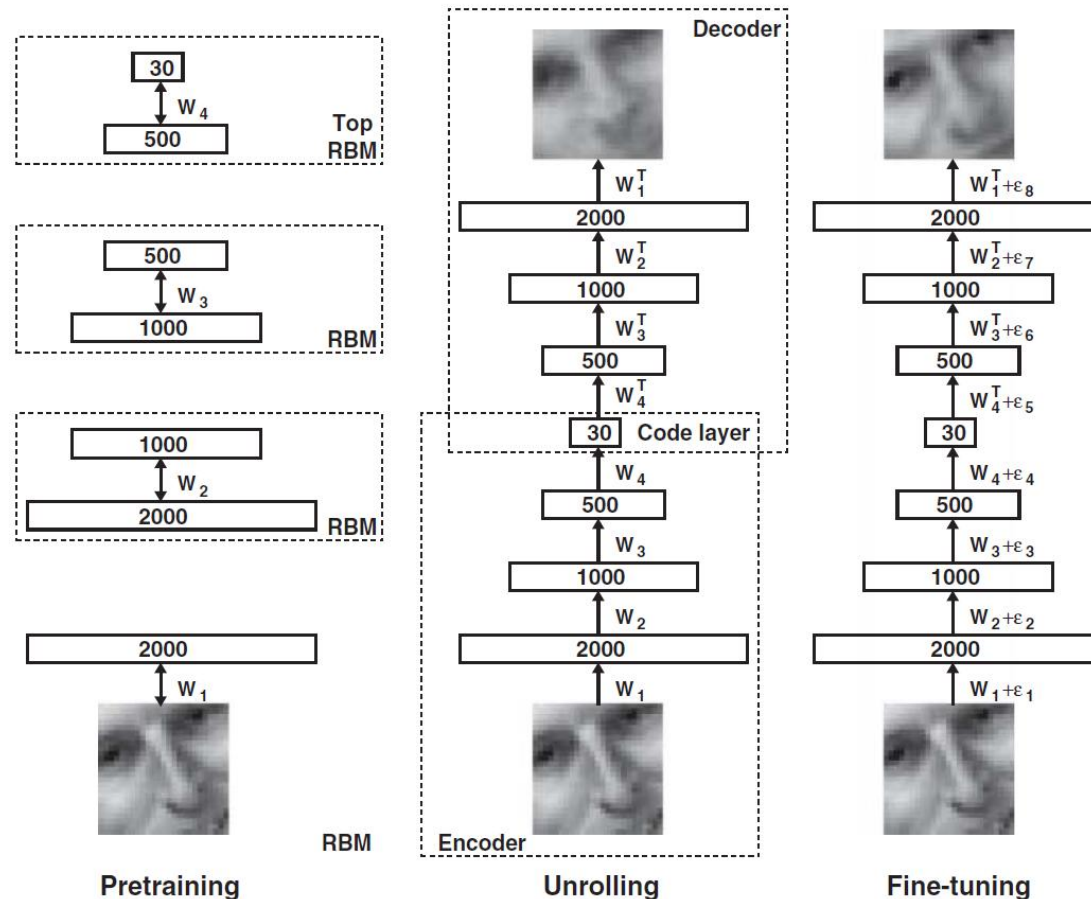
<https://chrisharrison.net/index.php/Research/ListenLearner>

Dimensionality Reduction with Deep Learning

Hinton, Geoffrey E., and Ruslan R. Salakhutdinov.

"Reducing the dimensionality of data with neural networks."

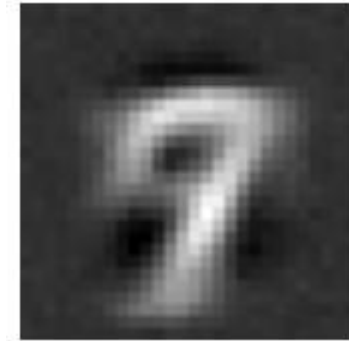
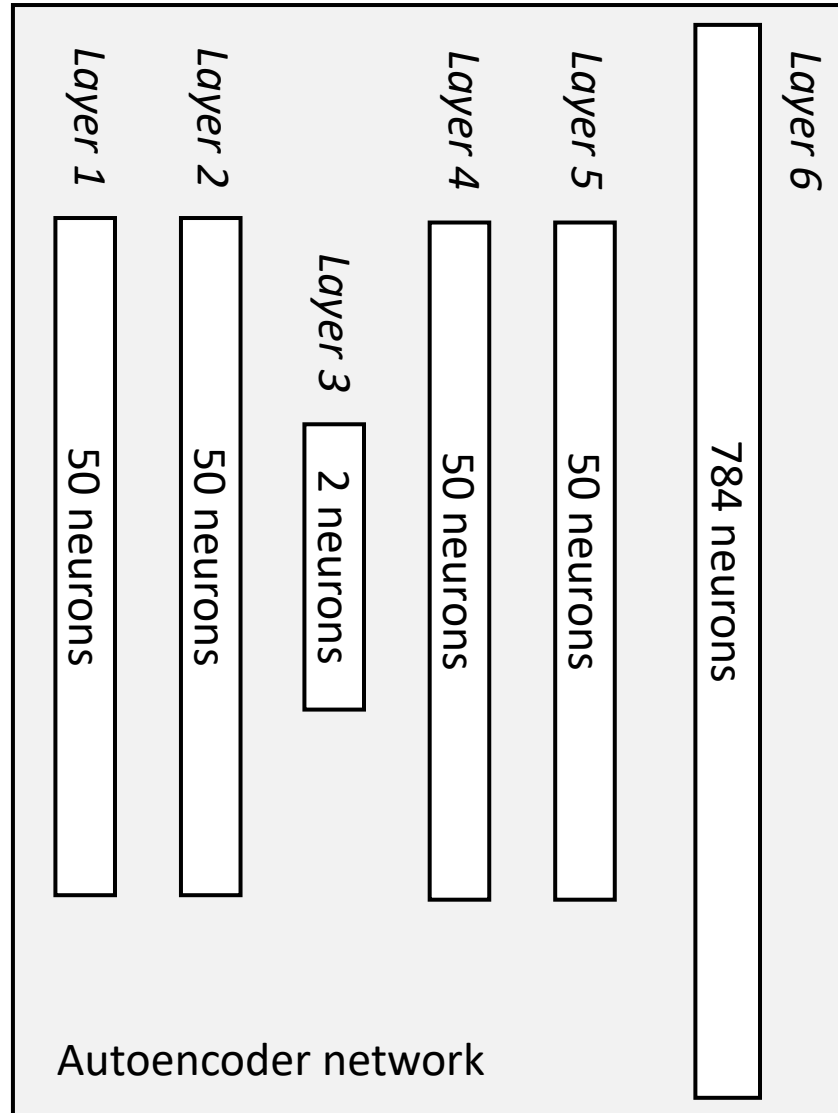
Science 313.5786 (2006): 504-507.



Digit Autoencoder

<https://cs.stanford.edu/people/karpathy/convnetjs/demo/autoencoder.html>

Input
28x28 = 784 pixels



Digit Autoencoder

Math for autoencoder model

Linear layer

ReLU layer

Tanh layer