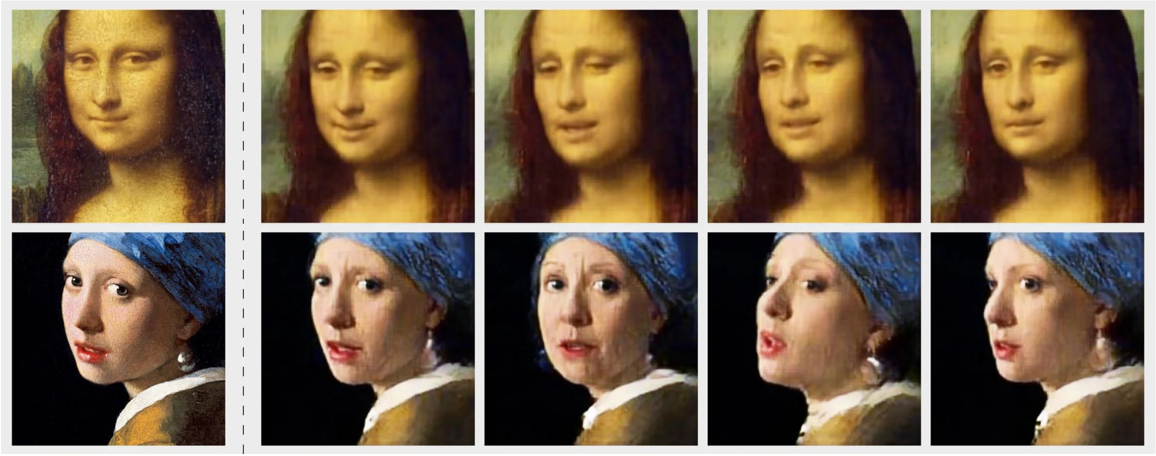
ICME Summer Workshops 2020

Introduction to Deep Learning

Session 1: 9:00–10:30 AM
Instructor: Sherrie Wang

icme-workshops.github.io/deep-learning



Zakharov *et al.* "Few-Shot Adversarial Learning of Realistic Neural Talking Head Models" (2019)

Workshop Schedule

Session 1 (9:00—10:30 AM)
- Introduction
- Current state-of-the-art in deep learning
- Math review
- Fully connected neural networks

Session 2 (10:45—12:00 PM)
- Loss functions
- Gradient descent
- Backpropagation
- Overfitting and underfitting

Lunch (12:00—2:00 PM)

Session 3 (2:00—3:15 PM)
- Convolutional neural networks
- Recurrent neural networks
- Other architectures
- Deep learning libraries
- Hands-on coding session in Tensorflow

Session 4 (3:30—4:45 PM)
- Hands-on coding session in Keras
- Hands-on coding session on transfer learning
- Failures of deep learning

Workshop Logistics

- Post questions to Piazza: https://piazza.com/icme/summer2020/icme
- I'll pause periodically to gather questions from the class
- Will be recorded and uploaded online -- will share information by end of month

About me

Hello
my name is

Sherrie Wang

@sherwang

- **PhD student** in ICME, Year 5
- **Research focus:** Machine learning methods for remote sensing and applications in sustainability
- **Relevant courses:**
    - CS 221 (Artificial Intelligence)
    - CS 229 (Machine Learning)
    - CS 228 (Probabilistic Graphical Models)
    - CS 230 (Deep Learning)
    - CS 231n (Convolutional Neural Networks)
    - CS 236 (Generative Adversarial Networks)
    - CS 330 (Deep Multi-Task and Meta Learning)
- **Relevant teaching:** CME 250 (Introduction to Machine Learning), Summer Workshop 2019

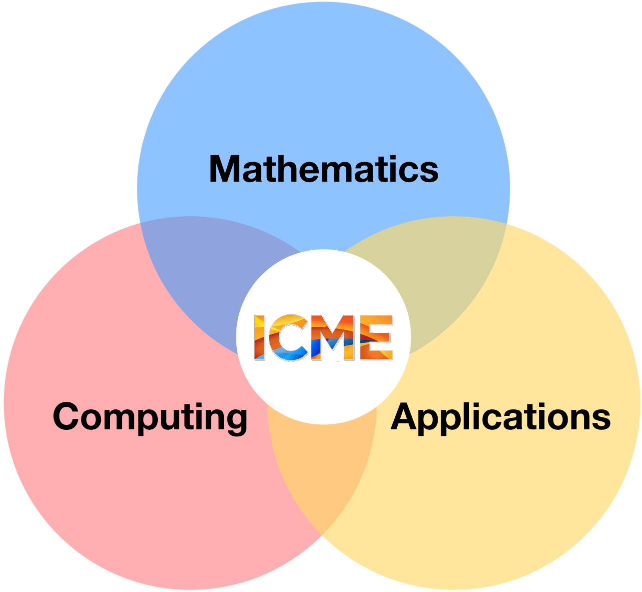
What is ICME?

Stanford Institute for Computational and Mathematical Engineering

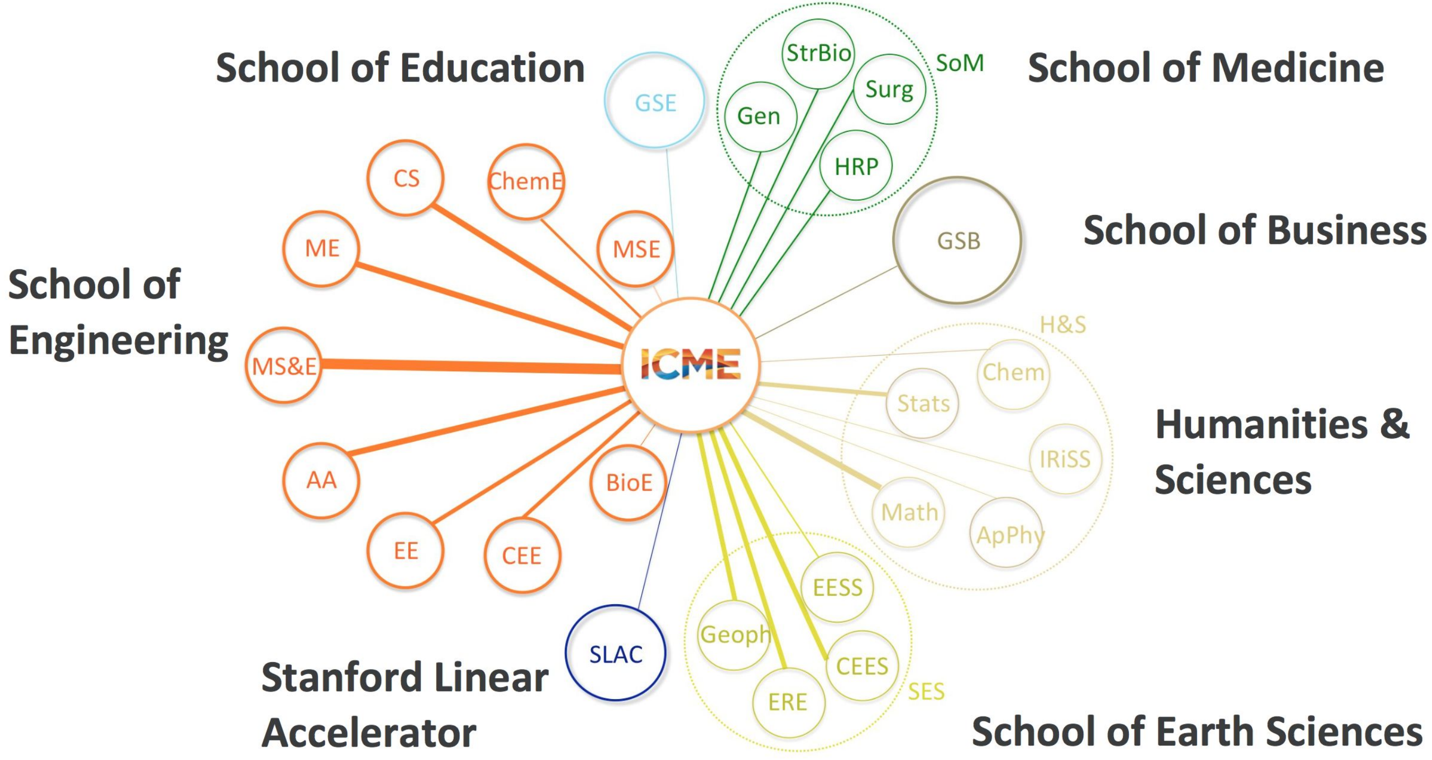
Hub at Stanford

Interdisciplinary field using advanced mathematics and computing to address complex problems

icme.stanford.edu



55+ affiliated faculty across Stanford



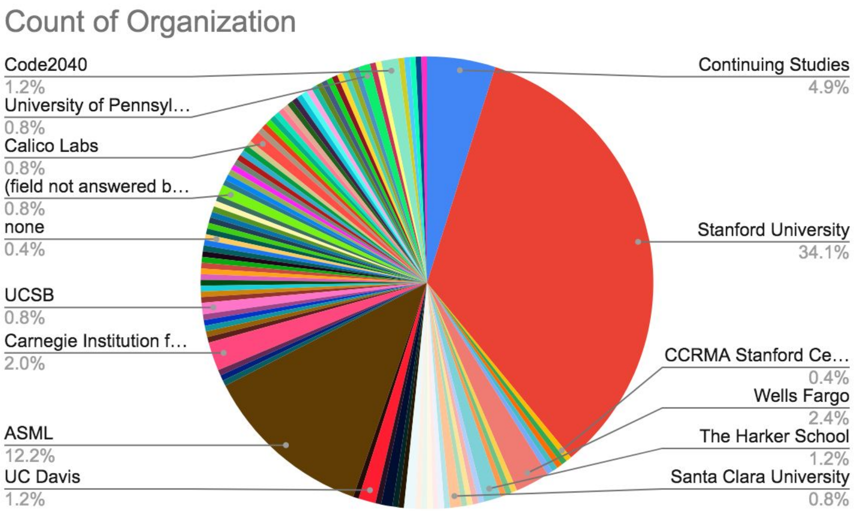
150+ MS and PhD students

ICME industry-academia ecosystem

Who's here today

Go to **PollEv.com/dlworkshop2020**

250+ registered participants



Job title:

- 34% student
- 17% in research
- 5% continuing studies
- 4% software engineer
- 4% professor

Academia / industry:

- 66% academia
- 34% industry

The Deep Learning Revolution

What is “deep learning”?

Artificial intelligence

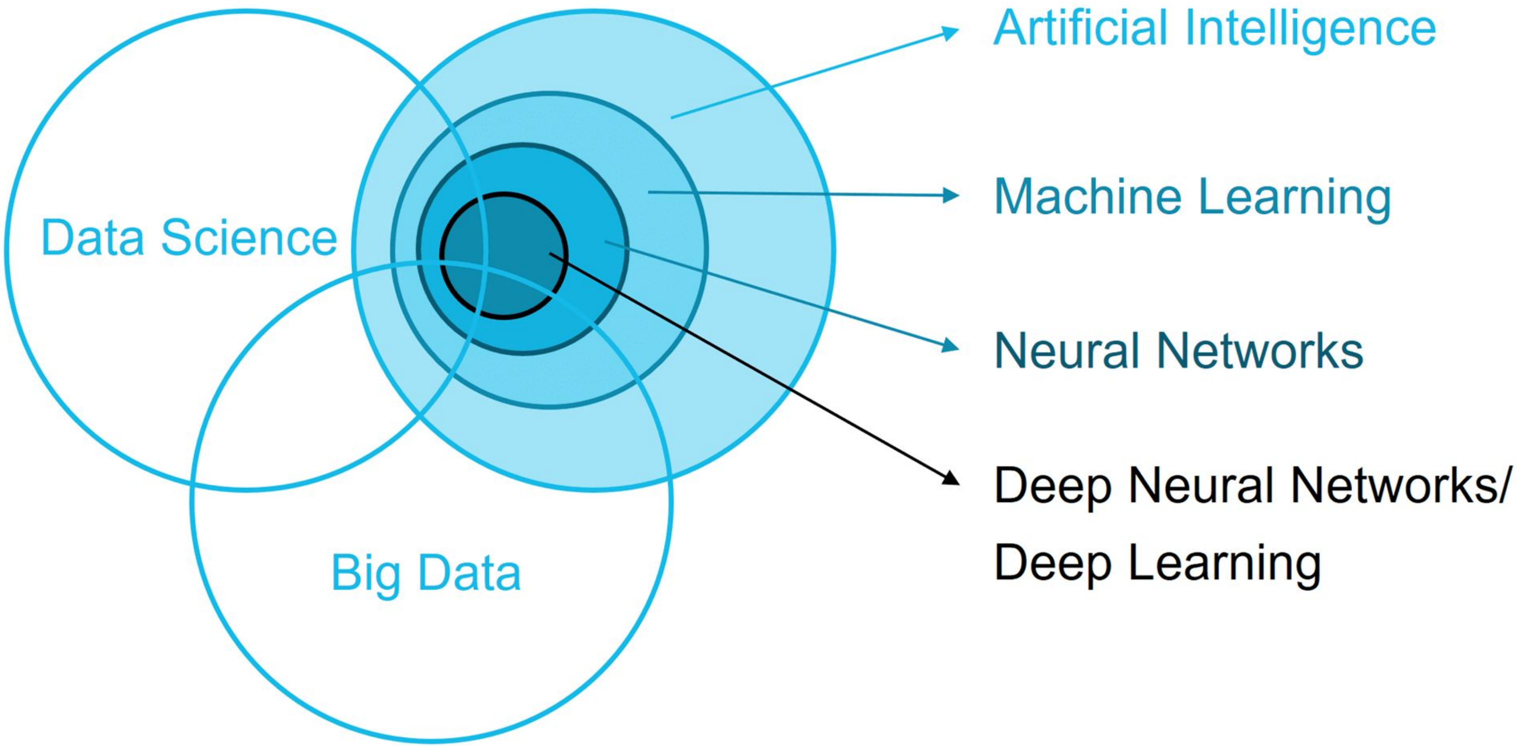
Big data

Machine learning

Deep learning

Data science

What is “deep learning”?



https://tamuk.quickstart.com/blog/artificial-intelligence-vs.-machine-learning-vs.-data-science/

Deep learning examples

1. Optical character recognition (OCR)
2. Image classification
3. Text translation
4. Image generation
5. Text generation
6. Audio generation
7. Reinforcement learning
8. Energy
9. Healthcare
10. Sustainable development
11. Investing
12. Surveillance

1. Optical character recognition

Computer vision is one of the first places where deep learning started to outshine other methods.

“The Street View House Numbers (SVHN) Dataset”: http://ufldl.stanford.edu/housenumbers/

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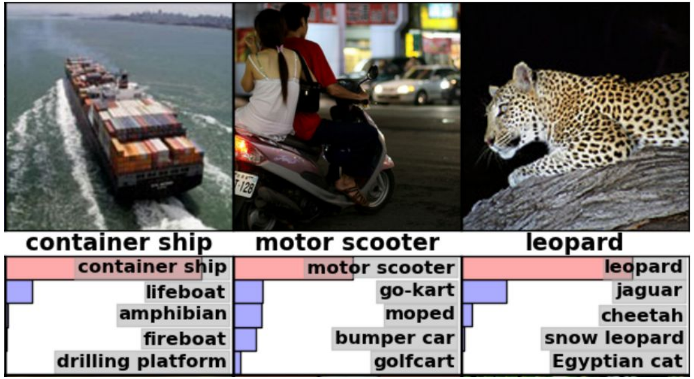
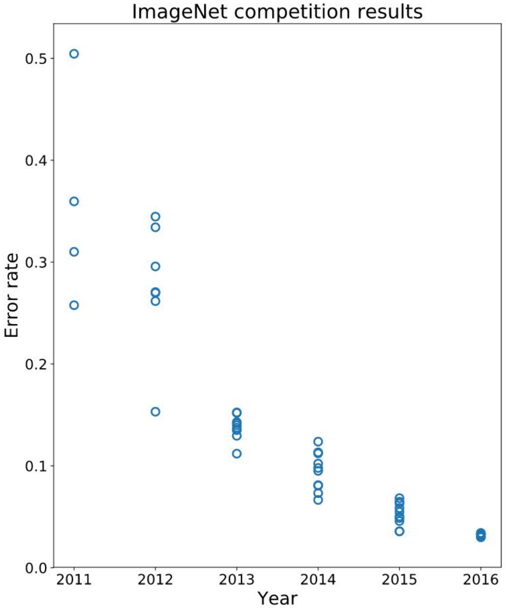
2. Image classification





Krizhevsky, Sutskever, and Hinton. "ImageNet Classification with Deep Convolutional Neural Networks" (2012)

Deep learning examples

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3. Text translation

Wu *et al.* “Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation” (2016)

Deep learning examples

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4. Image generation

Progression in the capabilities of GANs

Brundage *et al.* “The Malicious Use of Artificial Intelligence: Forecasting, Prevention, and Mitigation” (2018)

Brock *et al.* “Large Scale GAN Training for High Fidelity Natural Image Synthesis” (2018)

Deep learning examples

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4. Image generation

Image-to-image translation

Isola *et al.* “Image-to-Image Translation with Conditional Adversarial Networks” (2016)

Text-to-image translation

Reed *et al.* “Generative Adversarial Text to Image Synthesis” (2016)

Source: Instagram, FaceApp - AI Face Editor

Deep learning examples

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5. Text generation

GPT-3-aided poetry!

Human prompt (bolded):

Here's a poem by Dr. Seuss about Elon Musk launching rockets with SpaceX, building electric cars at Tesla, selling flame throwers, dating Grimes, fighting the SEC, crushing short sellers, building brain chips to fight AI, and colonizing mars, and tweeting at all hours of day and night. Musk wants to make humans interplanetary to prevent extinction. The poem rhymes every other line with an ABAB structure. The rhyme structure is typical of Dr. Seuss nursery rhymes.

GPT-3 output (with "several hours" of trial and error):

Elon Musk
By Dr. Seuss

Once there was a man
who really was a Musk.
He liked to build robots
and rocket ships and such.

He said, "I'm building a car
that's electric and cool.
I'll bet it outsells those
Gasoline-burning clunkers soon!"

They sell cool cars
that are electric and clean.
And then he wanted to go
even farther, you see.

The first Tesla, Roadster,
Was just the start of a bigger dream.
He said, "I'm building a plane
that's electric and green.

That's not all!
That man is also a Musk.
He likes electric cars,
flamethrowers, tunnels, and such.

But then he thought, "If we make
a very small, small chip,
We'll implant it in our heads,
And then connect our minds to the
Internet!"

...

Source: https://arr.am/2020/07/14/elon-musk-by-dr-seuss-gpt-3/ (2020)

Deep learning examples

5. Text generation

GPT-3-generated text:

Human prompt is bolded.

Movie plot summaries (from Wikipedia):

The Matrix (1999): "A computer hacker learns from mysterious rebels about the true nature of his reality and his role in the war against its controllers." (For the purposes of this post, we can set aside some of the specific details and just say that, basically, Neo learns that our world isn't real—that what we perceive isn't the real thing, but a simulation or "matrix" created to fool us.)

Inception (2010): "While competing with a rival thief to recover a potent artefact, Dom Cobb (Leonardo DiCaprio) falls into a dreamworld where he must 'extract' an idea from an influential businessman while being chased by the FBI."

Source: https://www.gwern.net/GPT-3 (2020)

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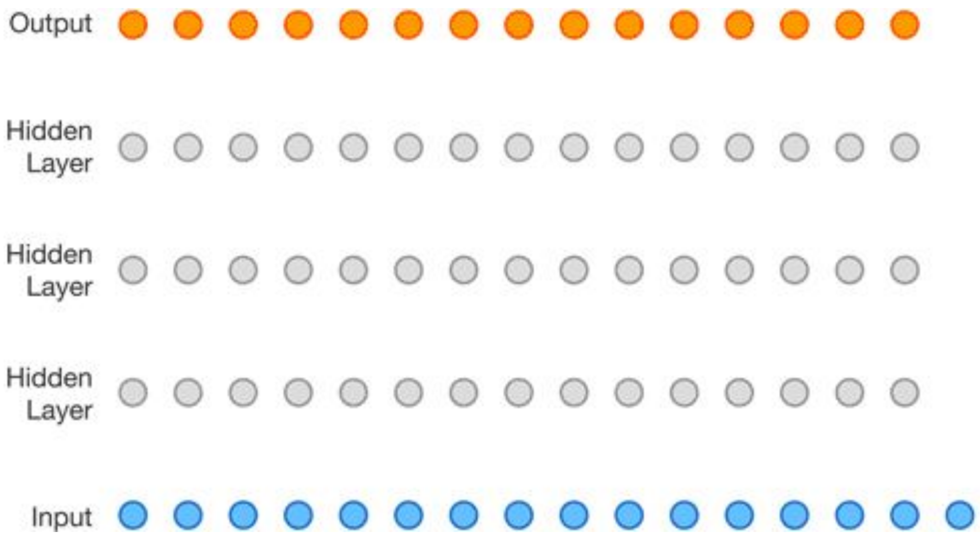
6. Audio generation

DeepMind's WaveNet



Source: https://deepmind.com/blog/article/wavenet-generative-model-raw-audio (2016)

Deep learning examples

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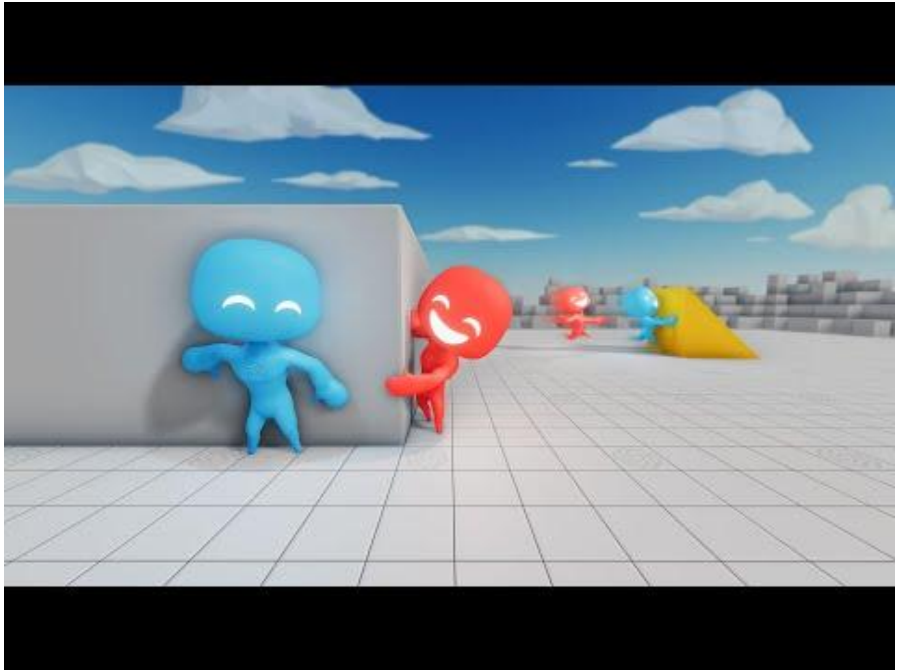
7. Reinforcement learning

OpenAI's "Hide and Seek" Game



Source: https://openai.com/blog/emergent-tool-use/ (2019)

Deep learning examples

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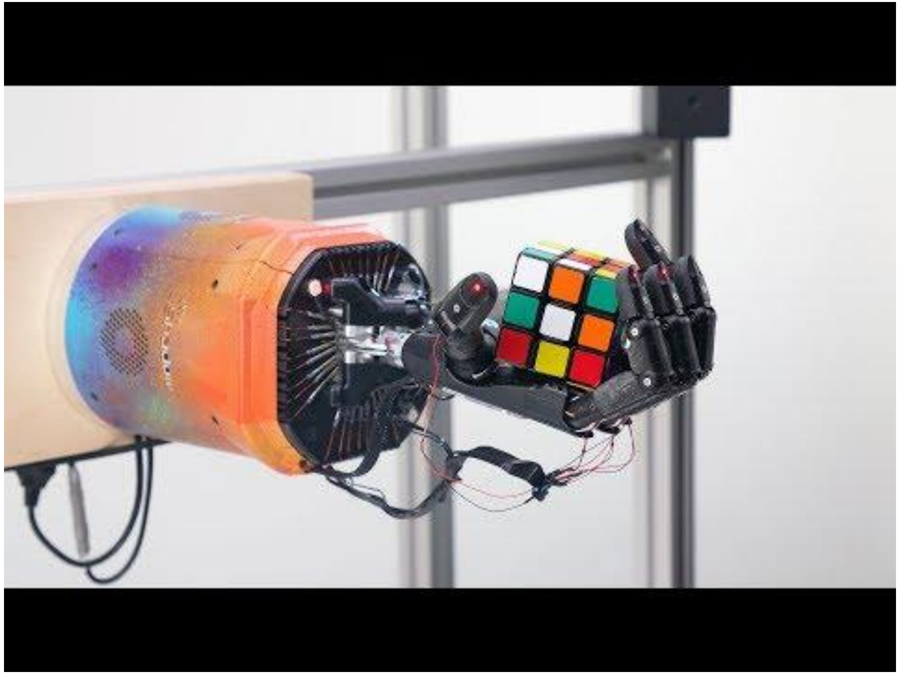
7. Reinforcement learning

Solving a Rubik's cube with a robot hand



Source: https://openai.com/blog/solving-rubiks-cube/ (2019)

Deep learning examples

7. Reinforcement learning

OpenAI vs. best human players in DOTA 2

Source: https://openai.com/projects/five/ (2019)

Deep learning examples

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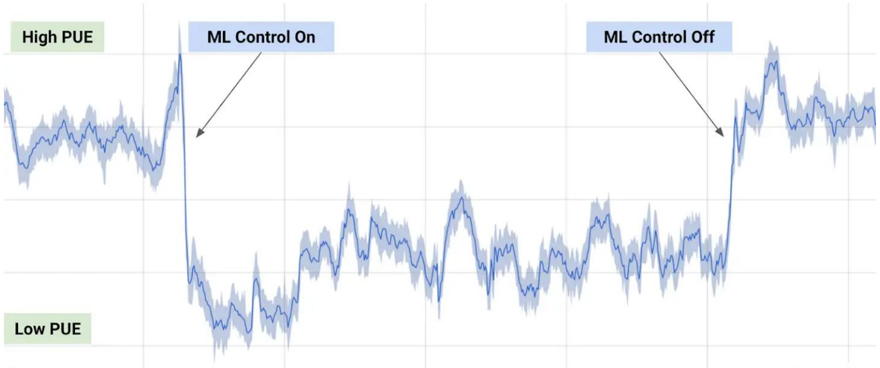
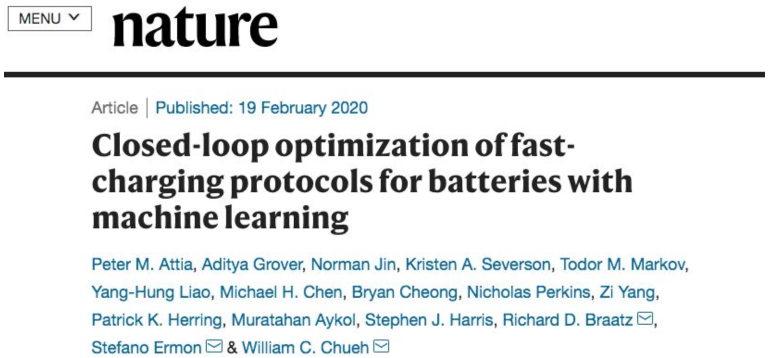
8. Energy

"DeepMind AI Reduces Google Data Centre Cooling Bill by 40%"





MENU

nature

Article | Published: 19 February 2020

Closed-loop optimization of fast-charging protocols for batteries with machine learning

Peter M. Attia, Aditya Grover, Norman Jin, Kristen A. Severson, Todor M. Markov, Yang-Hung Liao, Michael H. Chen, Bryan Cheong, Nicholas Perkins, Zi Yang, Patrick K. Herring, Muratahan Aykol, Stephen J. Harris, Richard D. Braatz, Stefano Ermon & William C. Chueh

Source: (top) https://deepmind.com/blog/article/deepmind-ai-reduces-google-data-centre-cooling-bill-40 (2016)

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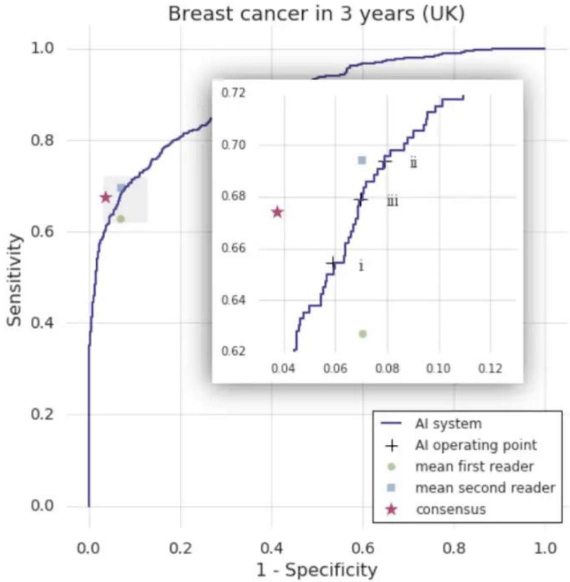
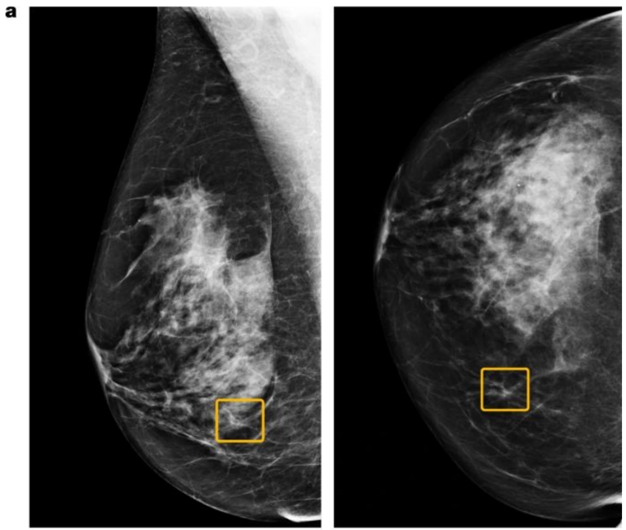
9. Healthcare

DeepMind's AI for breast cancer screening





Source: McKinney *et al.* "International evaluation of an AI system for breast cancer screening" (2020)

Deep learning examples

10. Sustainable development

Estimating poverty using transfer learning and night lights

Source: Jean *et al.* “Combining satellite imagery and machine learning to predict poverty” (2016)

Deep learning examples

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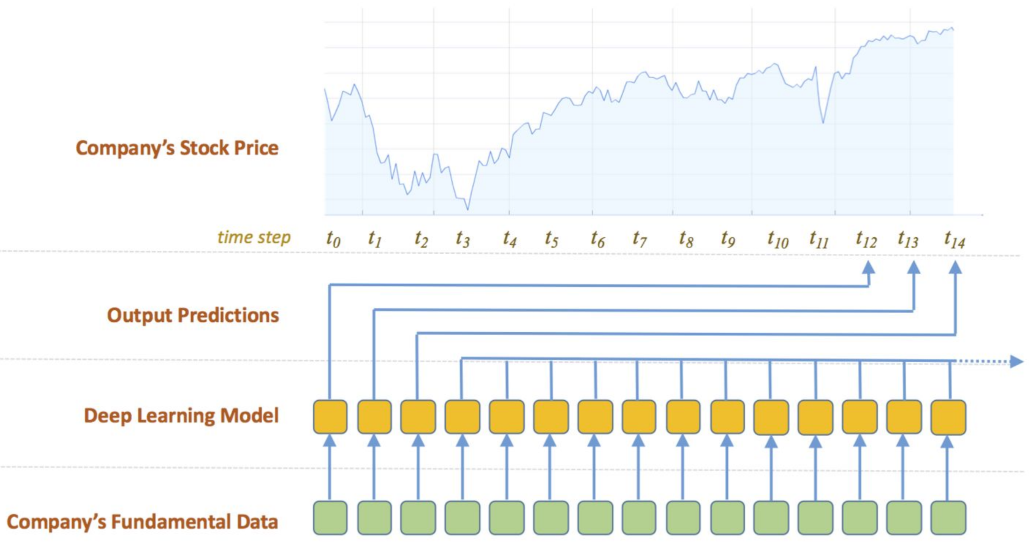
11. Investing

Predicting stock price from company fundamentals



Source: Alberg and Lipton. "Improving Factor-Based Quantitative Investing by Forecasting Company Fundamentals" (2017)

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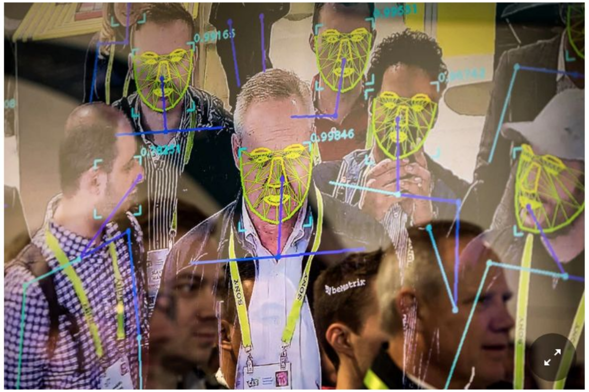
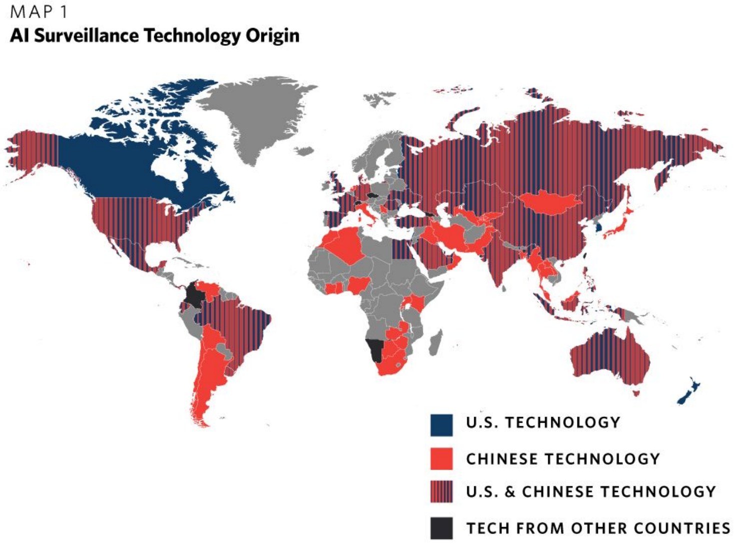
The New York Times

San Francisco Bans Facial Recognition Technology



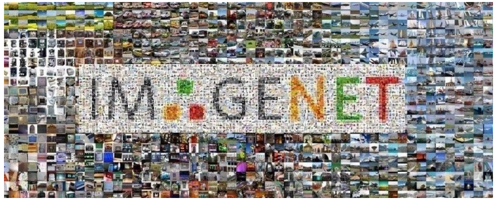
Attendees interacting with a facial recognition demonstration at this year's CES in Las Vegas. Joe Buglewicz for The New York Times



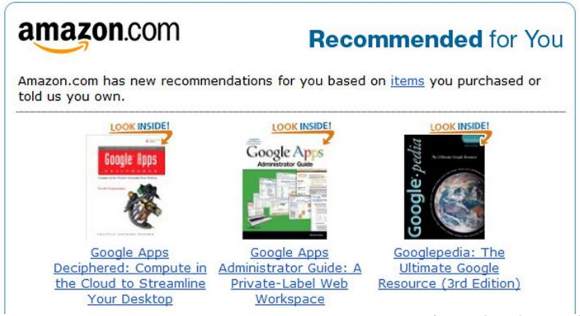
Sources: https://www.nytimes.com/2019/05/14/us/facial-recognition-ban-san-francisco.html (2019)
https://carnegieendowment.org/2019/09/17/global-expansion-of-ai-surveillance-pub-79847 (2019)

Why is deep learning at the forefront now?

Big data



YouTube



Compute

aws

Google Cloud

Microsoft Azure

Why is deep learning at the forefront now?

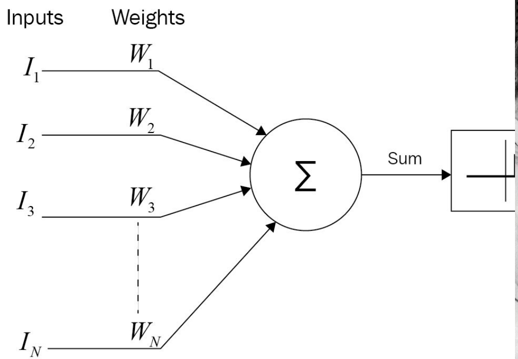
Algorithms

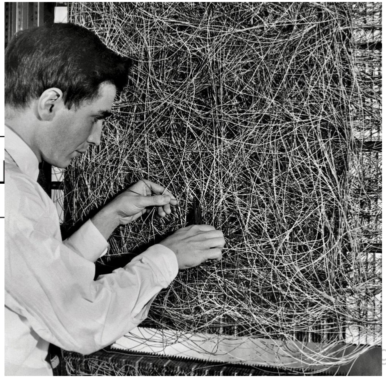
1943: McCulloch and Pitts develop a mathematical model of the neuron

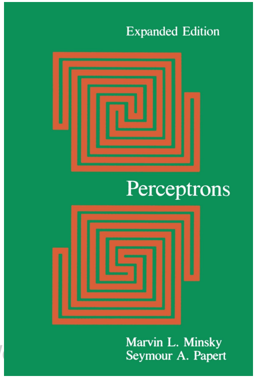
1957: Rosenblatt invents the perceptron algorithm and machine

1969: Minsky and Papert improve the perceptron and prove it cannot model nonlinearities like XOR

1974–1980: The First AI Winter







Why is deep learning at the forefront now?

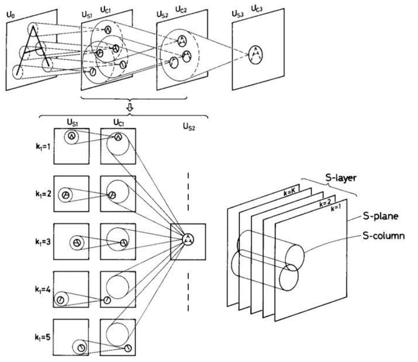
Algorithms

1980: Fukushima creates the “neocognitron”, introducing convolutional and downsampling layers

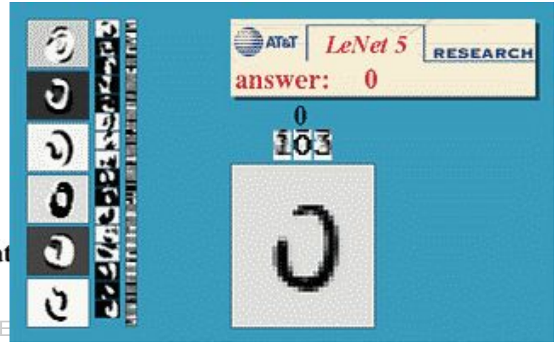
1986: Rumelhart, Hinton, and Williams apply backpropagation to train neural networks

1989: LeCun uses backprop to train convolutional neural networks to read digits

1987–1993: The Second AI Winter



D.E. Rumelhart, G.E. Hinton, R.J. Williams
Learning representation by back-propagat errors. *Nature*, 323 (1986), pp. 533–536



Why is deep learning at the forefront now?

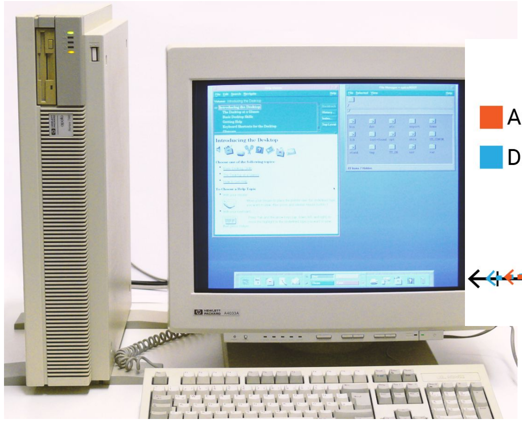
Algorithms

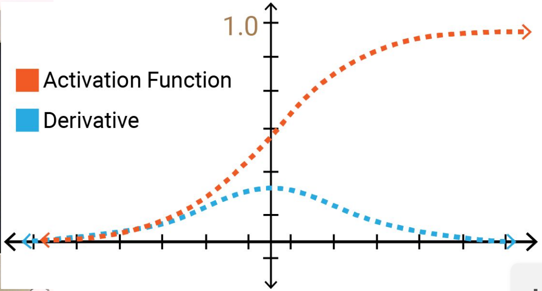
1990s: Computers become faster, GPUs developed

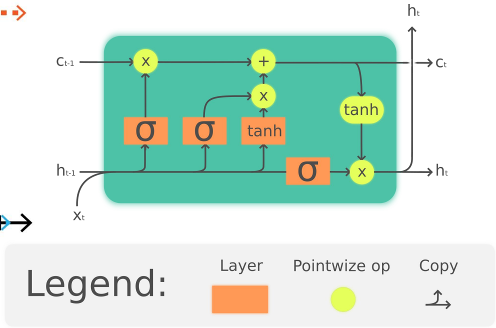
1991: The vanishing gradient problem is identified

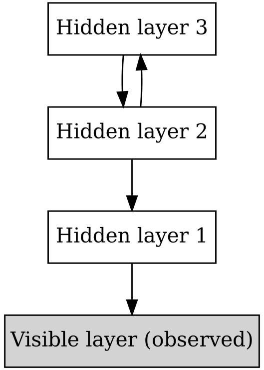
1997: Hochreiter and Schmidhuber develop long short-term memory

2006: Hinton and others show that deeper networks can be trained one layer at a time









Why is deep learning at the forefront now?

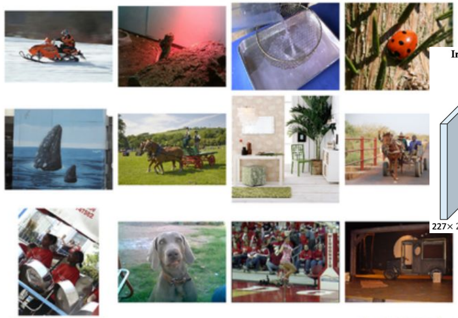
Algorithms

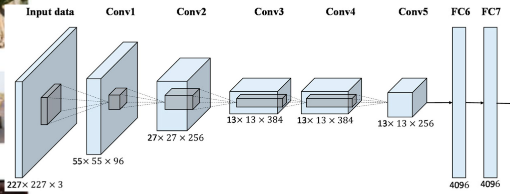
2009: Fei-fei Li releases ImageNet, a classification dataset of 14 million labeled images

2012: AlexNet, a CNN, wins the Large Scale Visual Recognition Challenge — by a lot

2014: Goodfellow designs generative adversarial networks for data generation

2015-2016: Deep learning frameworks like TensorFlow, Keras, and PyTorch are released





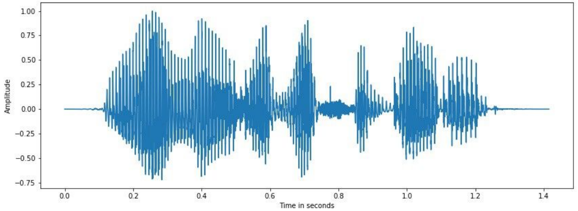
What’s so special about deep learning?

Deep learning has made significant improvements in performance on tasks involving unstructured data

Images

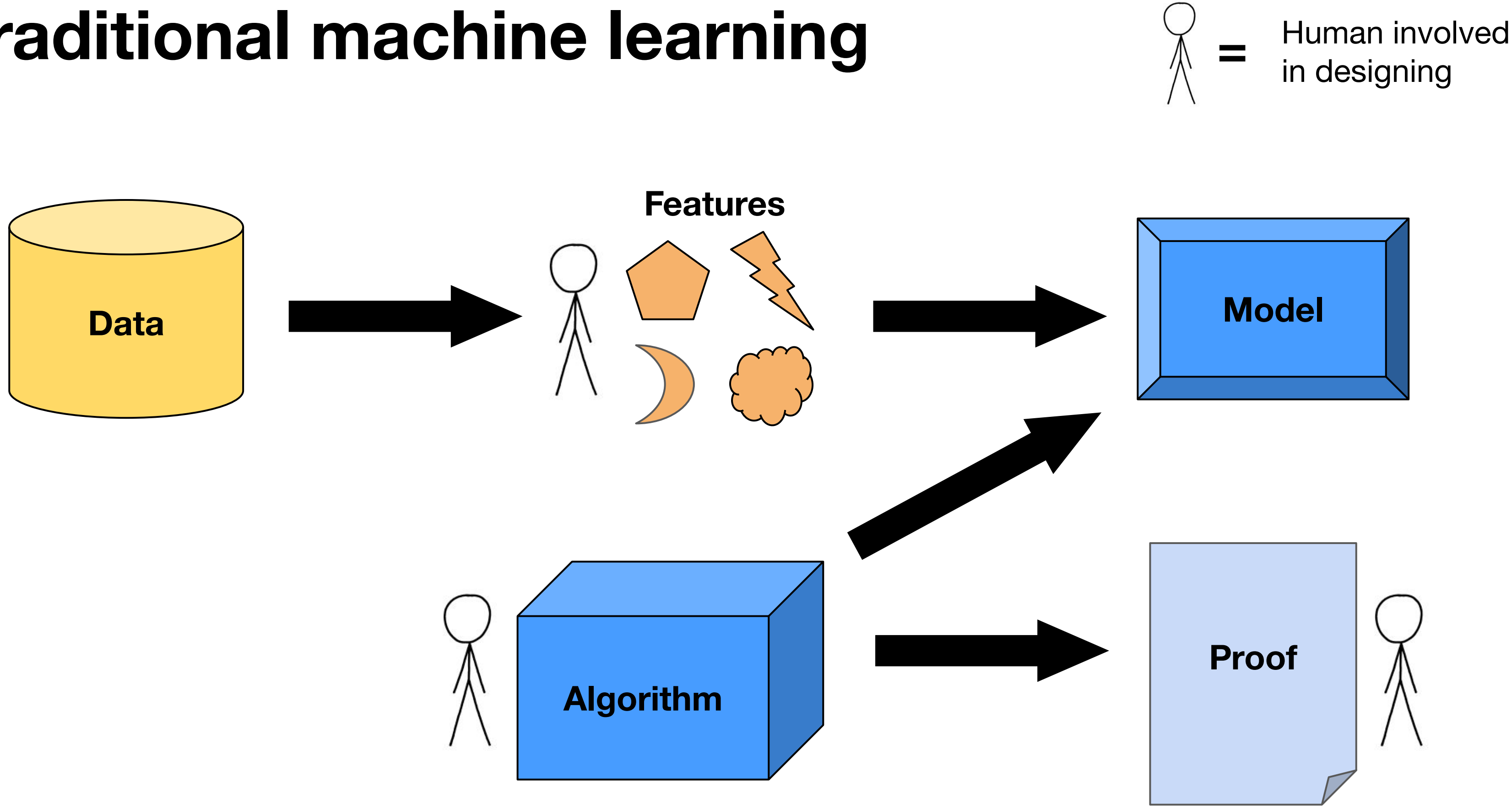
Speech

Text

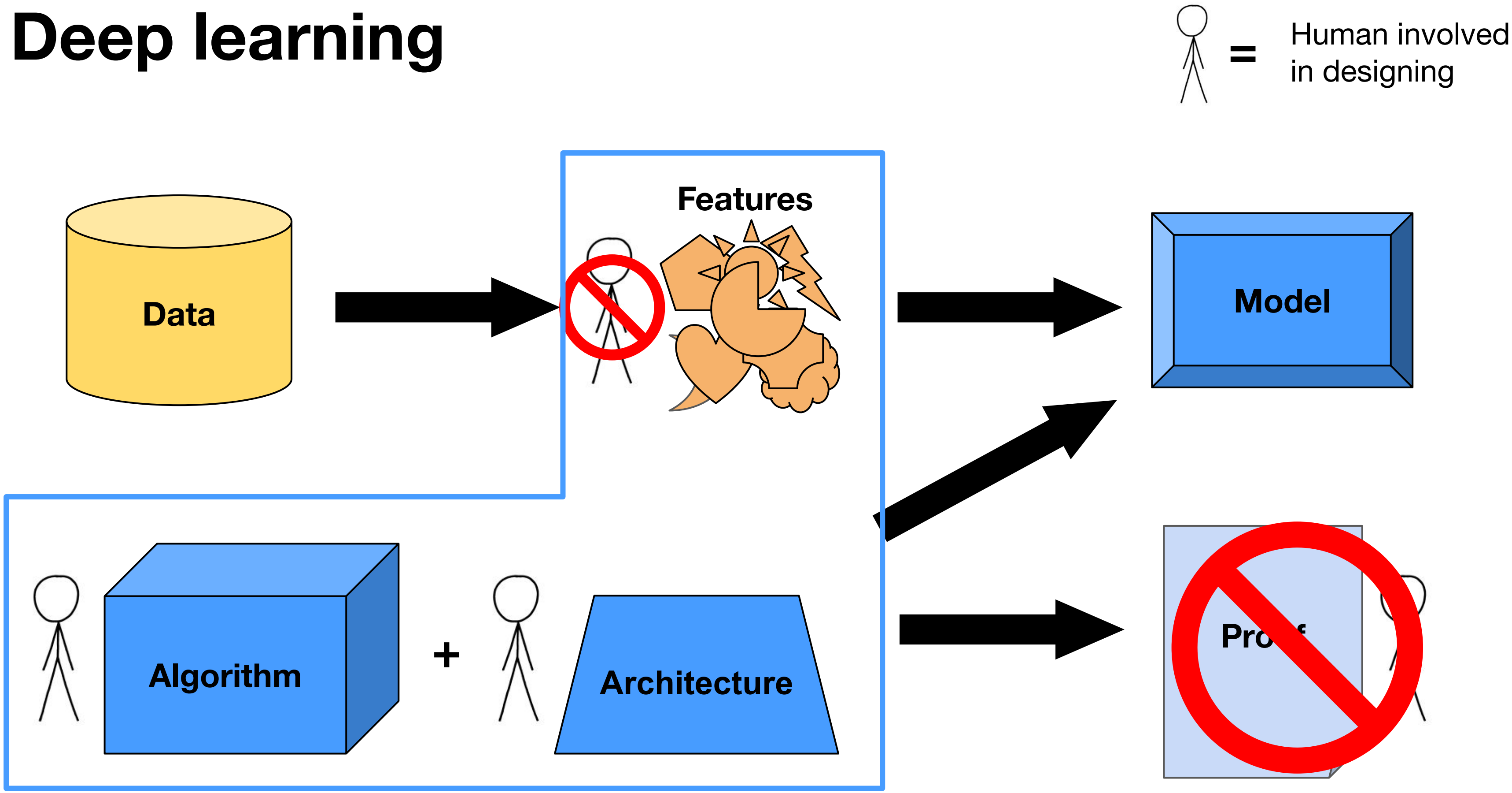


It is a truth universally acknowledged, that a single man in possession of a good fortune, must be in want of a wife. However little known the feelings or views of such a man may be on his first entering a neighbourhood, this truth is so well fixed in the minds of the surrounding families, that he is considered ...

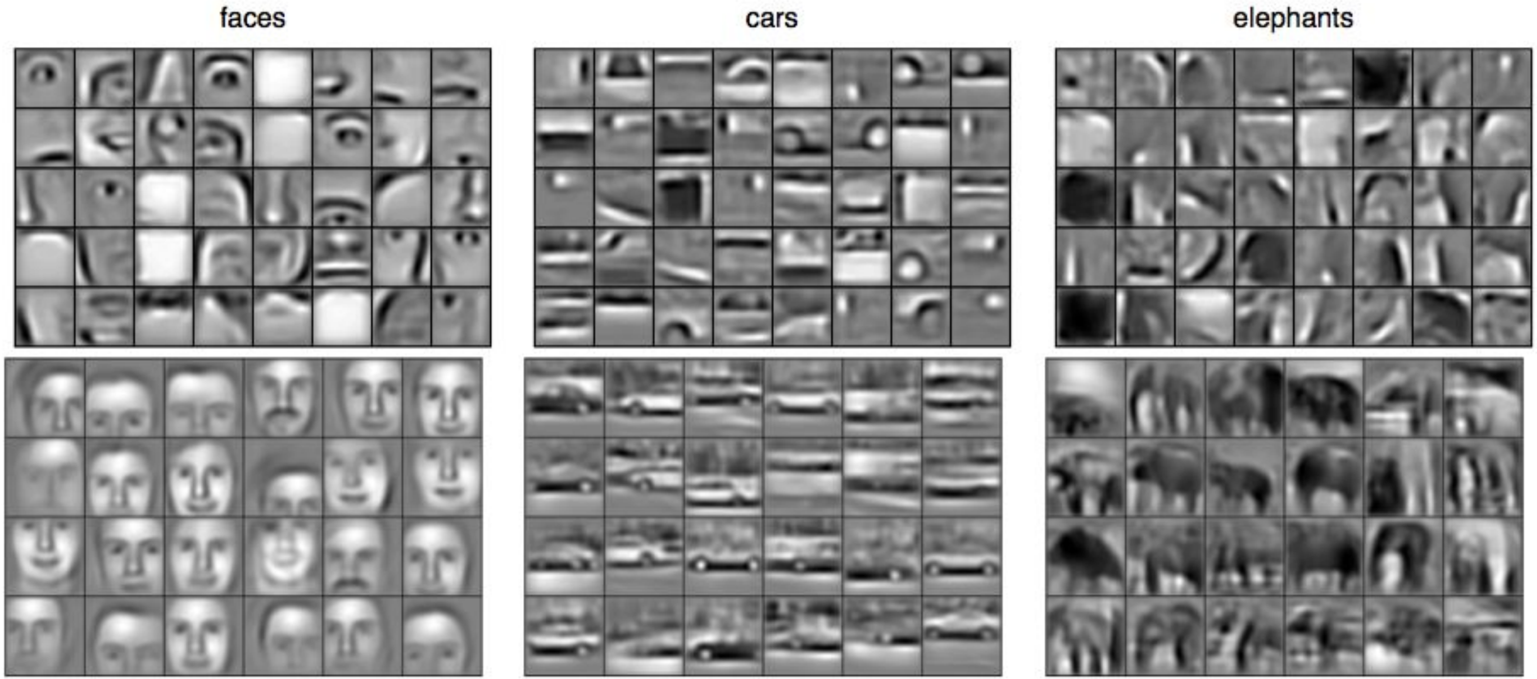
Traditional machine learning



Deep learning

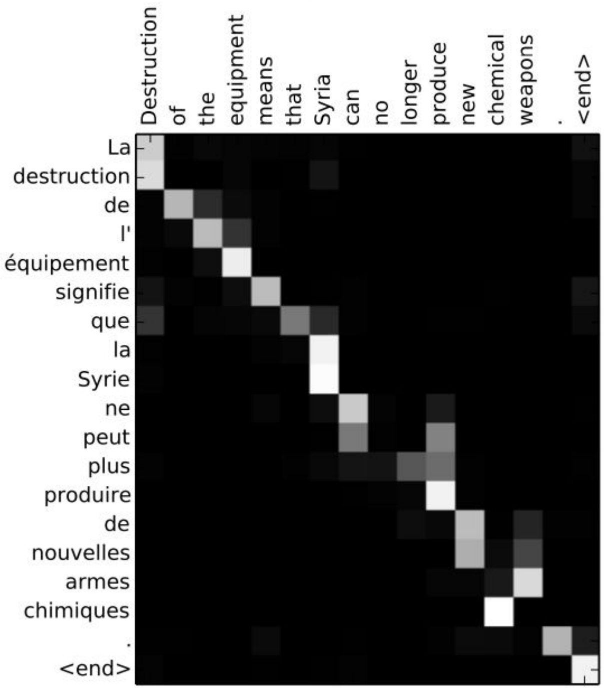


Deep learning-generated features



Lee *et al.* “Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations” (2009)

Deep learning-generated features



Bahdanau, Cho, and Bengio. "Neural Machine Translation by Jointly Learning to Align and Translate" (2015)

Math Review

Vectors, matrices, and tensors

What is a vector?

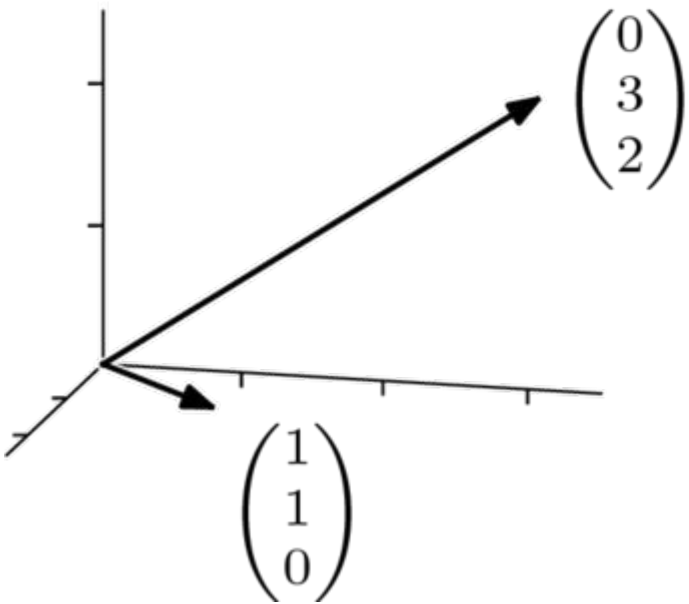
$$\begin{bmatrix} 2 \\ 7 \\ 3 \end{bmatrix}$$

An array (or list) of numbers

Dimension = 3

$\vec{v} \in \mathbb{R}^3$

What is a vector?



In addition to linear algebra, you may have learned about vectors in physics courses as entities with direction and magnitude

Here are two more vectors of dimension 3, visualized in Euclidean space

Vector operations

1. Scalar multiplication

$$4 * \begin{bmatrix} 2 \\ 7 \\ 3 \end{bmatrix} = \begin{pmatrix} 8 \\ 28 \\ 12 \end{pmatrix}$$

Vector operations

2. Addition

$$\begin{pmatrix} 2 \\ 7 \\ 3 \end{pmatrix} + \begin{pmatrix} 1 \\ 3 \\ 6 \end{pmatrix} = \begin{pmatrix} 3 \\ 10 \\ 9 \end{pmatrix}$$

Vector operations

3. Transpose

$$\begin{bmatrix} 2 \\ 7 \\ 3 \end{bmatrix}^T = \begin{bmatrix} 2 & 7 & 3 \end{bmatrix}$$

Row vector

Column vector

Vector operations

4. Inner product

$$\boxed{\vec{u}^\top \vec{v} = w}$$

$$\begin{pmatrix} 2 & 7 & 3 \end{pmatrix} \begin{pmatrix} 1 \\ 3 \\ 6 \end{pmatrix} = 2*1+7*3+3*6$$

$$= 41$$

What is a matrix?

$$\begin{pmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{pmatrix}$$

3 rows

3 columns

A rectangular array (or table) of numbers

What is a matrix?

$$
\begin{array}{c c}
 & \begin{array}{cccc} 1 & 2 & \dots & n \end{array} \\
\begin{array}{c} 1 \\ 2 \\ 3 \\ \vdots \\ m \end{array} & \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ a_{31} & a_{32} & \dots & a_{3n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}
\end{array}
$$

$$\mathbf{A} \in \mathbb{R}^{m \times n}$$

What is a matrix?

$$\begin{pmatrix} \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} & \begin{bmatrix} 4 \\ 3 \\ 7 \end{bmatrix} & \begin{bmatrix} 2 \\ 7 \\ 3 \end{bmatrix} \end{pmatrix}$$

You can think of a matrix as a row vector of column vectors

What is a matrix?

$$\begin{pmatrix} \begin{bmatrix} 2 & 4 & 2 \end{bmatrix} \\ \begin{bmatrix} 1 & 3 & 7 \end{bmatrix} \\ \begin{bmatrix} 0 & 7 & 3 \end{bmatrix} \end{pmatrix}$$

… or as a column vector of row vectors

Matrix operations

1. Scalar multiplication
2. Addition

$$2*\begin{pmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{pmatrix} = \begin{pmatrix} 4 & 8 & 4 \\ 2 & 6 & 14 \\ 0 & 14 & 6 \end{pmatrix}$$

Matrix operations

3. Transpose

$$A \quad \begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix}$$

Source: https://en.wikipedia.org/wiki/Transpose

Matrix operations

3. Transpose

$$\begin{pmatrix} \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} & \begin{bmatrix} 4 \\ 3 \\ 7 \end{bmatrix} & \begin{bmatrix} 2 \\ 7 \\ 3 \end{bmatrix} \end{pmatrix}^{T} = \begin{pmatrix} \begin{bmatrix} 2 & 1 & 0 \end{bmatrix} \\ \begin{bmatrix} 4 & 3 & 7 \end{bmatrix} \\ \begin{bmatrix} 2 & 7 & 3 \end{bmatrix} \end{pmatrix}$$

Matrix operations

3. Transpose

$$\begin{pmatrix} \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} & \begin{bmatrix} 4 \\ 3 \\ 7 \end{bmatrix} & \begin{bmatrix} 2 \\ 7 \\ 3 \end{bmatrix} \end{pmatrix}^T = \begin{pmatrix} \begin{bmatrix} 2 & 1 & 0 \end{bmatrix} \\ \begin{bmatrix} 4 & 3 & 7 \end{bmatrix} \\ \begin{bmatrix} 2 & 7 & 3 \end{bmatrix} \end{pmatrix}$$

Matrix operations

4. Multiplication with a vector

$$\begin{pmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{pmatrix} \begin{pmatrix} 1 \\ 3 \\ 2 \end{pmatrix} = \begin{pmatrix} 18 \\ 24 \\ 27 \end{pmatrix}$$

Matrix operations

4. Multiplication with a vector

$$\left(\begin{bmatrix}2\\1\\0\end{bmatrix}\begin{bmatrix}4\\3\\7\end{bmatrix}\begin{bmatrix}2\\7\\3\end{bmatrix}\right)\begin{bmatrix}1\\3\\2\end{bmatrix}=\begin{bmatrix}18\\24\\27\end{bmatrix}$$

Matrix operations

4. Multiplication with a vector

$$1\begin{bmatrix}2\\1\\0\end{bmatrix}+3\begin{bmatrix}4\\3\\7\end{bmatrix}+2\begin{bmatrix}2\\7\\3\end{bmatrix}=\begin{bmatrix}18\\24\\27\end{bmatrix}$$

Matrix operations

4. Multiplication with a vector

$$\begin{pmatrix} [2 & 4 & 2] \\ [1 & 3 & 7] \\ [0 & 7 & 3] \end{pmatrix} \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} = \begin{bmatrix} 18 \\ 24 \\ 27 \end{bmatrix}$$

Matrix operations

4. Multiplication with a vector

$$\begin{pmatrix} \begin{bmatrix} 2 & 4 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} \\ \\ \begin{bmatrix} 1 & 3 & 7 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} \\ \vdots \end{pmatrix} = \begin{bmatrix} 18 \\ 24 \\ 27 \end{bmatrix}$$

Matrix operations

4. Multiplication with a vector

$$\begin{pmatrix} \vec{a}_1^\top \\ \vec{a}_2^\top \\ \vec{a}_3^\top \end{pmatrix} \vec{b} = \begin{pmatrix} 18 \\ 24 \\ 27 \end{pmatrix}$$

Matrix operations

4. Multiplication with a vector

$$\begin{pmatrix} \vec{a}_1^\top \vec{b} \\ \vec{a}_2^\top \vec{b} \\ \vec{a}_3^\top \vec{b} \end{pmatrix} = \begin{pmatrix} 18 \\ 24 \\ 27 \end{pmatrix}$$

Matrix operations

4. Multiplication with another matrix

$$\begin{pmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{pmatrix} \begin{pmatrix} 1 & 9 \\ 3 & 0 \\ 2 & 4 \end{pmatrix} = \begin{pmatrix} 18 & 26 \\ 24 & 37 \\ 27 & 12 \end{pmatrix}$$

3 rows **3 rows**

3 columns **2 columns**

Matrix operations

4. Multiplication with another matrix

$$\begin{pmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{pmatrix} \left(\begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} \begin{bmatrix} 9 \\ 0 \\ 4 \end{bmatrix} \right) = \begin{pmatrix} 18 & 26 \\ 24 & 37 \\ 27 & 12 \end{pmatrix}$$

Matrix operations

4. Multiplication with another matrix

$$\mathbf{A}\left(\begin{bmatrix}1\\3\\2\end{bmatrix}\begin{bmatrix}9\\0\\4\end{bmatrix}\right) = \left(\mathbf{A}\begin{bmatrix}1\\3\\2\end{bmatrix} \quad \mathbf{A}\begin{bmatrix}9\\0\\4\end{bmatrix}\right)$$

Matrix operations

4. Multiplication with another matrix

$$\begin{array}{cccccc}
 & & & \begin{array}{cc}\vec{b_1} & \vec{b_2}\\ \downarrow & \downarrow\end{array} & & \\
\begin{array}{c}\vec{a_1}\rightarrow\\ \vec{a_2}\rightarrow\end{array} & \begin{bmatrix}1&7\\2&4\end{bmatrix} & \cdot & \begin{bmatrix}3&3\\5&2\end{bmatrix} & = & \begin{bmatrix}\vec{a_1}\cdot\vec{b_1} & \vec{a_1}\cdot\vec{b_2}\\ \vec{a_2}\cdot\vec{b_1} & \vec{a_2}\cdot\vec{b_2}\end{bmatrix}\\
 & A & & B & & C
\end{array}$$

Source: https://ml-cheatsheet.readthedocs.io/en/latest/linear_algebra.html#matrix-multiplication

Poll: Matrix multiplication

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What are the dimensions of the matrix resulting from:

$$\begin{pmatrix} 2 & 4 & 2 & 8 & 4 & 1 & 5 & 0 \\ 1 & 3 & 7 & 9 & 3 & 2 & 6 & 8 \\ 0 & 7 & 3 & 1 & 0 & 4 & 9 & 3 \end{pmatrix} \begin{pmatrix} 3 & 4 \\ 2 & 9 \\ 0 & 1 \\ 5 & 5 \\ 3 & 7 \\ 6 & 4 \\ 2 & 1 \\ 4 & 0 \end{pmatrix}$$

A. 8 x 8

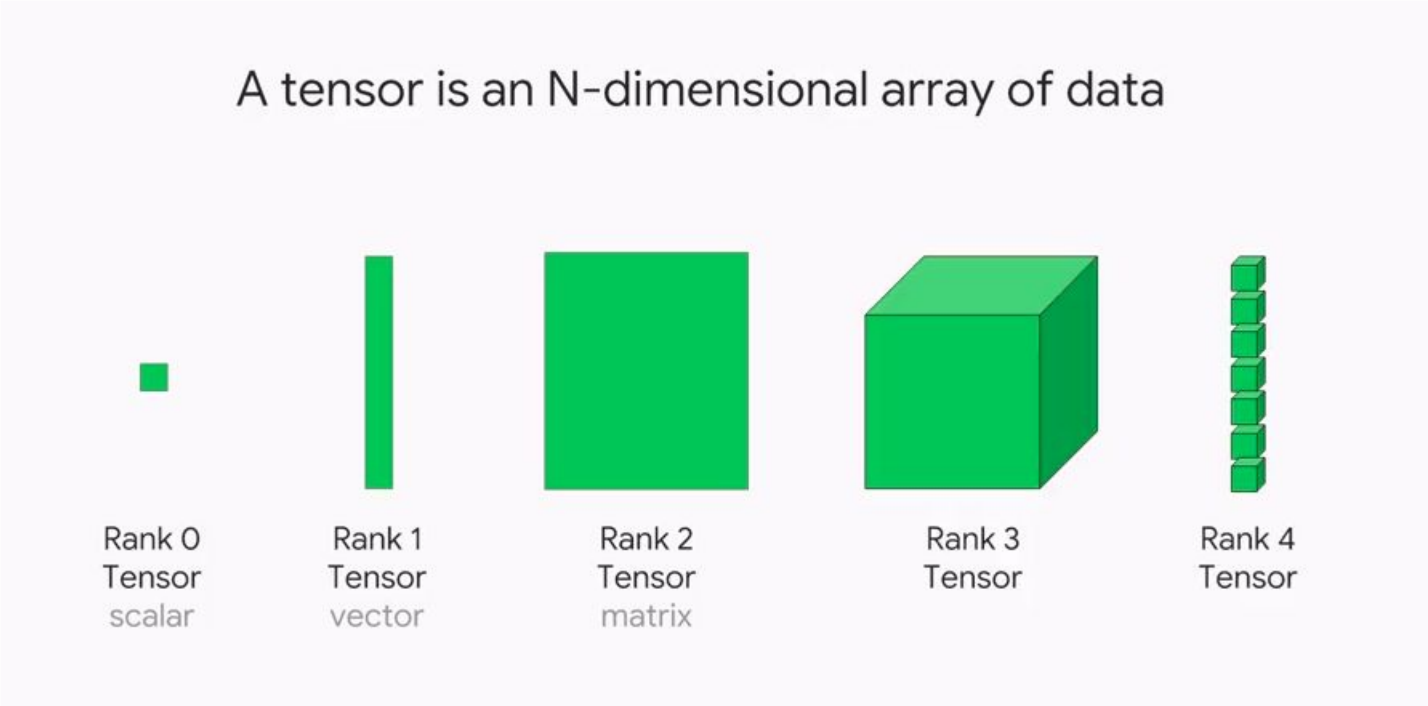
B. 8 x 2

C. 3 x 2

D. Not valid

Source: https://ml-cheatsheet.readthedocs.io/en/latest/linear_algebra.html#matrix-multiplication

What is a tensor?



Source: https://medium.com/mlait/tensors-representation-of-data-in-neural-networks-bbe8a711b93b

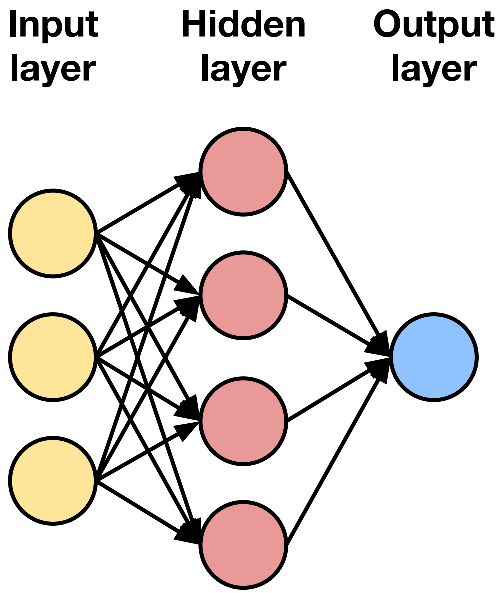
Neural Networks

Neural networks

We'll start with a *fully connected* neural network.

1. Single layer
2. Single neuron
3. Multiple layers
4. Input and output

Later, we'll cover other types of layers (convolution, max-pool, …)



What does a single layer in a neural network do?

First, it involves some matrix operations...

$$\begin{pmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{pmatrix} \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} + \begin{bmatrix} -3 \\ 0 \\ 2 \end{bmatrix} = \begin{bmatrix} 15 \\ 24 \\ 29 \end{bmatrix}$$

What does a single layer in a neural network do?

Then, the intermediate values are passed through a nonlinear function...

$$g\left(\begin{bmatrix} 15 \\ 24 \\ 29 \end{bmatrix}\right) = \begin{pmatrix} g(15) \\ g(24) \\ g(29) \end{pmatrix}$$

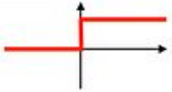
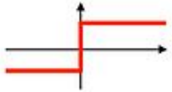
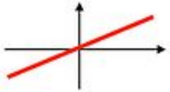
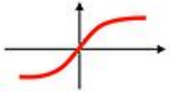
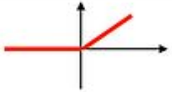
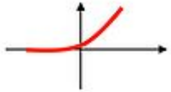
Activation function

Activation functions

There exist a number of activation functions, some of which were designed with neurons in mind

What's the purpose?

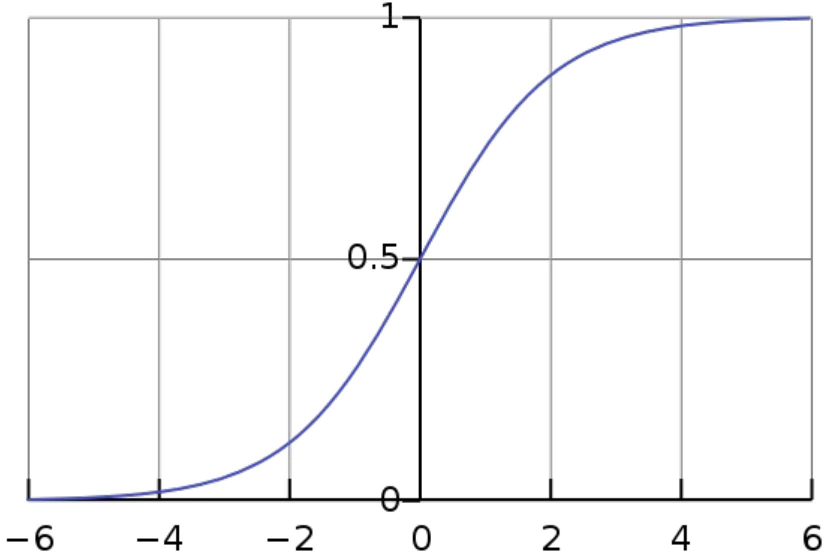
- Most phenomena are not linear, so we introduce some nonlinearities to the network

Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multi-layer Neural Networks	
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = max(0, z)$	Multi-layer Neural Networks	
Rectifier, softplus	$\phi(z) = \ln(1 + e^z)$	Multi-layer Neural Networks	

"A visual proof that neural nets can compute any function": http://neuralnetworksanddeeplearning.com/chap4.html

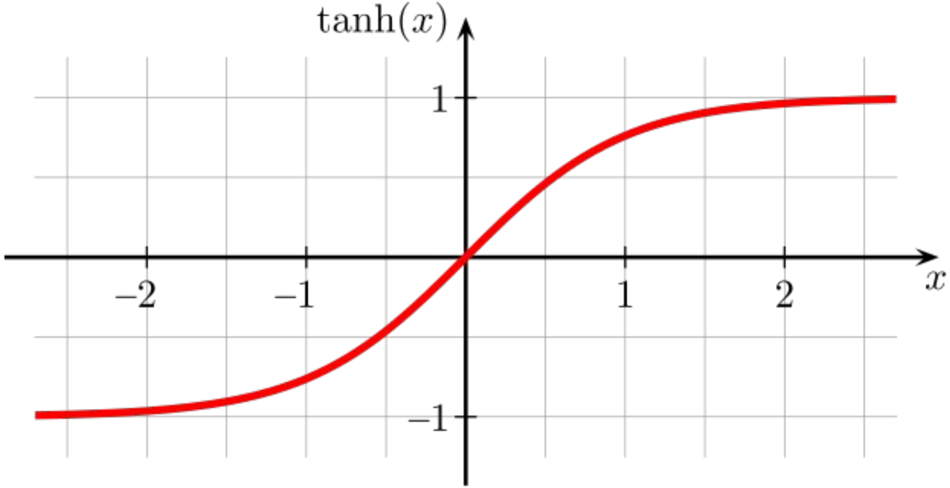
Sigmoid (logistic) activation function

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}}$$



Hyperbolic tangent activation function

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$



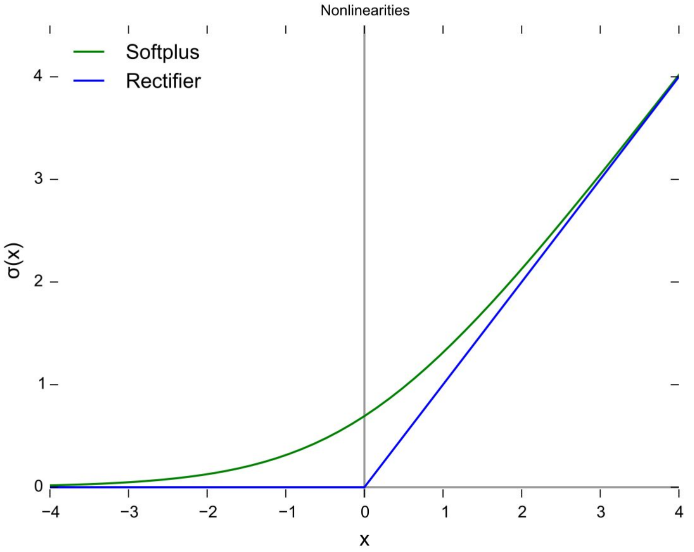
ReLU activation function

Stands for **Re**ctified **L**inear **U**nit

$$\mathrm{ReLU}(x) = \max(0, x)$$

A smooth version of ReLU is softplus

$$\mathrm{softplus}(x) = \ln(1 + e^x)$$



Poll: Activation functions

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As its input goes to infinity, the output of the logistic function goes to...

$$\lim_{x \to \infty} \frac{1}{1 + e^{-x}} =$$

A. 0

B. 0.5

C. 1

D. Infinity

Activation functions FAQ

1. Why these activation functions? Why not x^2 or other nonlinear functions?
    a. History of the field
    b. Normalizing layer outputs, concerns with backpropagation (to be discussed)
2. How does one choose among the various options for activation functions?
    a. You don’t have to choose -- architectures have already been designed
    b. Sigmoid, tanh, and ReLU are popular choices, with ReLU being the most common. ReLU has fewer vanishing gradient problems than the other 2 (see Session 3). If you’re developing your own architecture, you should use your validation set to experiment with choice of activation function.

What are the matrix and vectors?

Putting the linear operations and nonlinearity together, we get:

$$g\left(\begin{bmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{bmatrix}\begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} + \begin{bmatrix} -3 \\ 0 \\ 2 \end{bmatrix}\right)$$

Weight matrix **Input vector** **Bias vector**

What are the matrix and vectors?

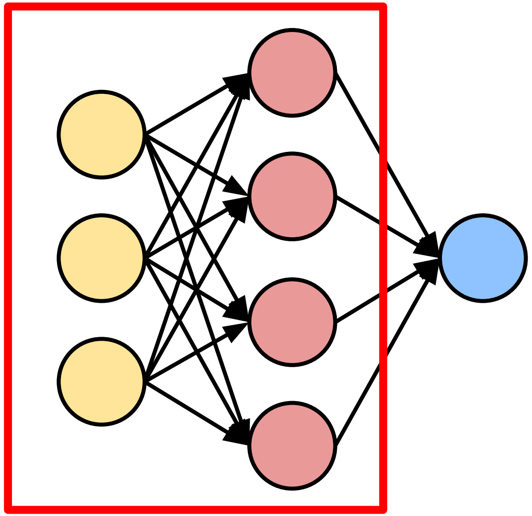
Putting the linear operations and nonlinearity together, we get:

$$g\left(\begin{pmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{pmatrix}\begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} + \begin{bmatrix} -3 \\ 0 \\ 2 \end{bmatrix}\right)$$

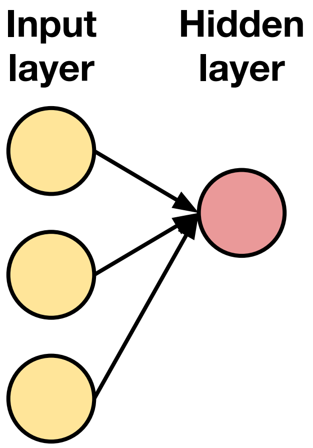
Trainable parameters

A more compact notation

$$g(\mathbf{W}\vec{x} + \vec{b})$$



What does a single neuron do?



Each circle is one element of an input or hidden layer

Each edge is a weight

$$g(\vec{w}_1^\top \vec{x} + b_1)$$

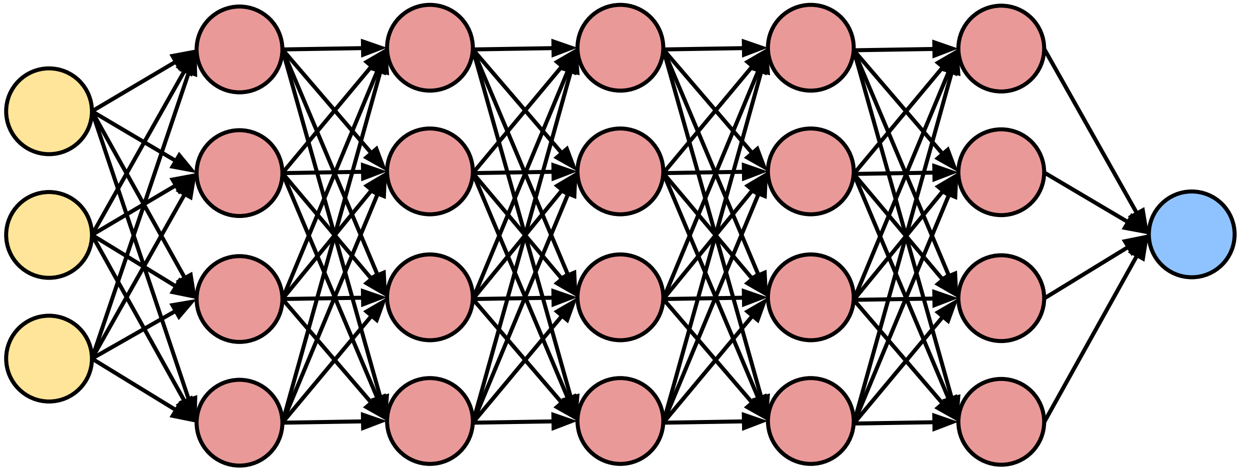
Weights for each neuron

$$\mathbf{W} = \begin{pmatrix} 2 & 4 & 2 \\ 1 & 3 & 7 \\ 0 & 7 & 3 \end{pmatrix} = \begin{bmatrix} w_1^\top \\ w_2^\top \\ w_3^\top \end{bmatrix}$$

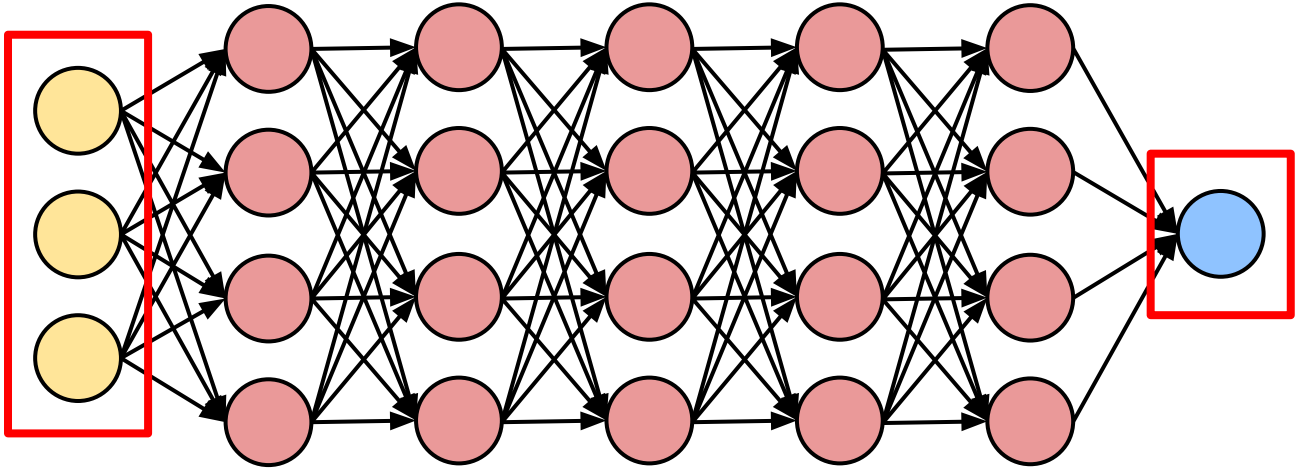
A fully connected layer with weight matrix $\mathbf{W} \in \mathbb{R}^{m \times n}$
is a function from $\mathbb{R}^n$ to $\mathbb{R}^m$

Stacking multiple layers

It becomes a *deep* neural network when you use many layers



What are the inputs and outputs?



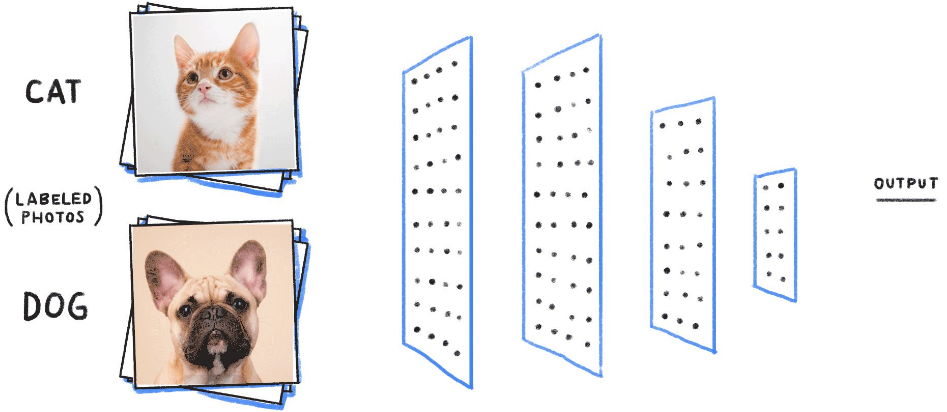
Defining the problem

- You want to predict some output **y** given input **x**
- If **y** is a discrete output (e.g. image classes), then it's a *classification problem*
- If **y** is a continuous variable (e.g. price), then it's a *regression problem*

$$y = \mathrm{DNN}(\vec{x})$$

Defining the problem

- If **y** is a discrete output, you can use one-hot encoding
- If **y** is a continuous variable, it can be output by the network directly



Classes = {cat, dog}

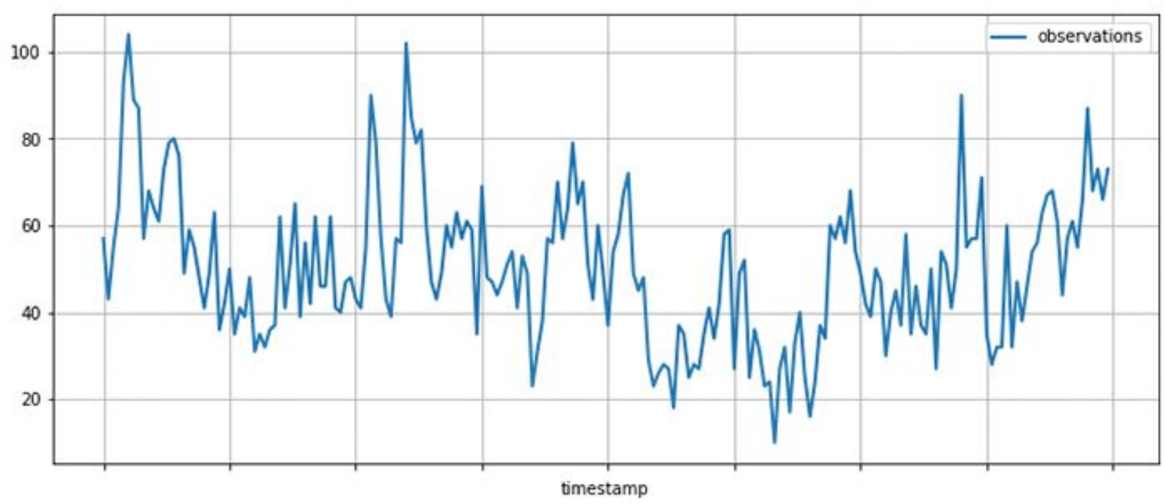
$$y = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \qquad y = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

"cat" "dog"

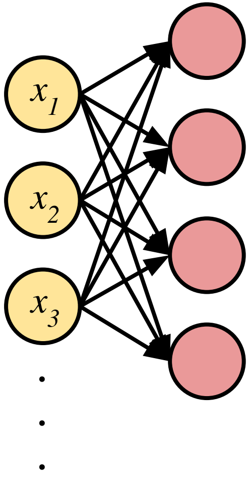
https://becominghuman.ai/building-an-image-classifier-using-deep-learning-in-python-totally-from-a-beginners-perspective-be8dbaf22dd8

Defining the problem

- If **x** is a discrete output, you can use one-hot encoding
- If **x** is a continuous variable, it can be input to the network directly



$$x = \begin{bmatrix} 59 \\ 42 \\ 63 \\ 93 \\ 102 \\ 88 \\ 86 \\ 58 \\ \dots \end{bmatrix}$$

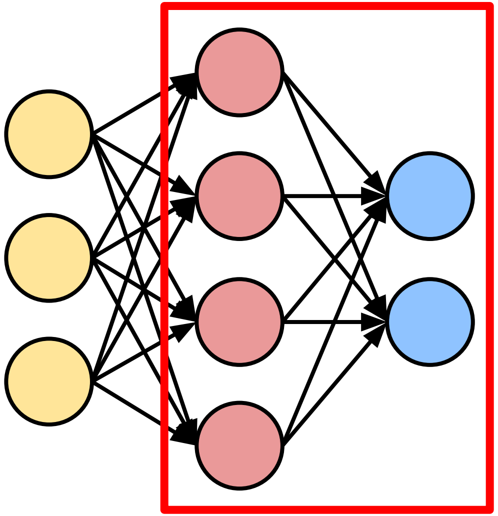


Last layer activation function

For classification, each neuron in the output represents one output class

You want the output to represent the probability that the input belongs to each class

What constraints must the output satisfy?



$\mathbf{P}(y = \text{“cat”})$

$\mathbf{P}(y = \text{“dog”})$

Last layer activation function

What constraints must the output satisfy?

- Probabilities are positive
- Probabilities sum to 1

$$\mathbf{P}(y = \text{``cat''}) \geq 0$$
$$\mathbf{P}(y = \text{``dog''}) \geq 0$$

$$\mathbf{P}(y = \text{``cat''}) + \mathbf{P}(y = \text{``dog''}) = 1$$

Softmax activation function

$$\text{softmax}(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Ensures positivity

Normalizes sum to 1

$$\mathbf{z} = \begin{pmatrix} 1.1 \\ 0.4 \\ -8.2 \\ -0.9 \\ 3.7 \end{pmatrix} \qquad e^{\mathbf{z}} = \begin{pmatrix} e^{1.1} \\ e^{0.4} \\ e^{-8.2} \\ e^{-0.9} \\ e^{3.7} \end{pmatrix} \qquad \frac{e^{\mathbf{z}}}{\sum_{j=1}^{n} e^{z_j}} = \begin{pmatrix} e^{1.1}/\sum_j e^{\mathbf{z}_j} \\ e^{0.4}/\sum_j e^{\mathbf{z}_j} \\ e^{-8.2}/\sum_j e^{\mathbf{z}_j} \\ e^{-0.9}/\sum_j e^{\mathbf{z}_j} \\ e^{3.7}/\sum_j e^{\mathbf{z}_j} \end{pmatrix} = \begin{pmatrix} 0.07 \\ 0.03 \\ 0.00 \\ 0.01 \\ 0.89 \end{pmatrix}$$

Poll: Weight matrix

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Suppose we have a neural network with 1 fully connected hidden layer. The input is a 32-dimensional vector. The output is a probability distribution across 8 classes. The weight matrix of the hidden layer should have dimension...

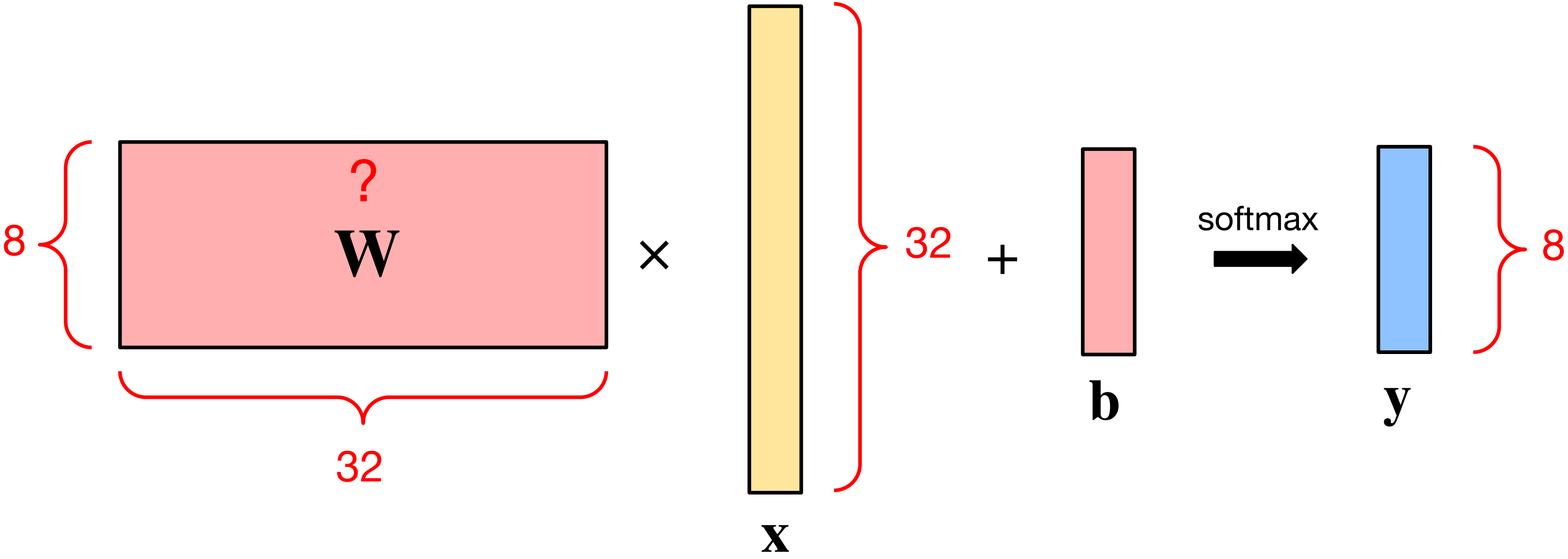
A. 32x1

B. 8x32

C. 32x8

D. 32x32

Poll: Weight matrix



Up Next:

Training Neural Networks