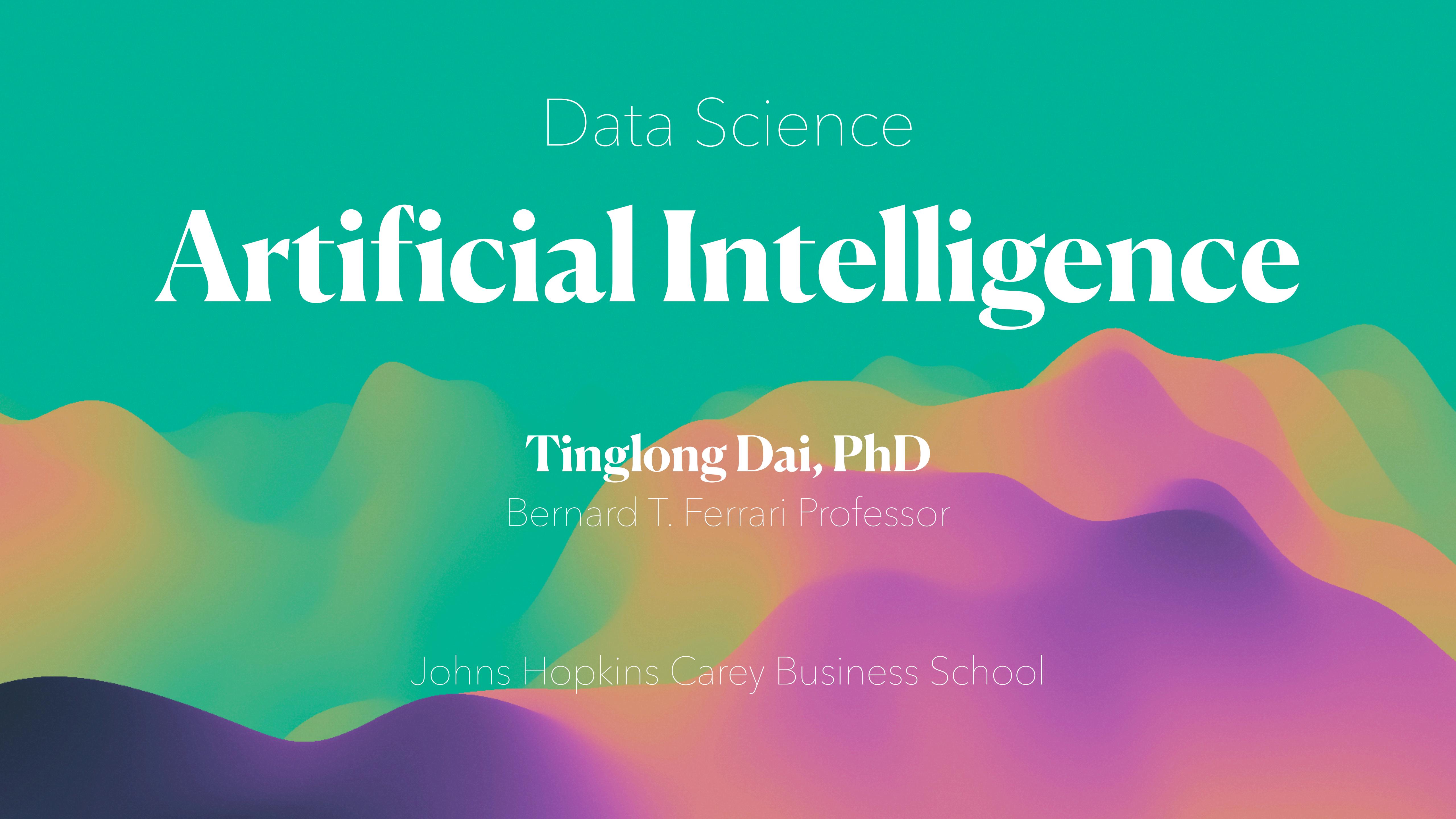


Data Science

Artificial Intelligence

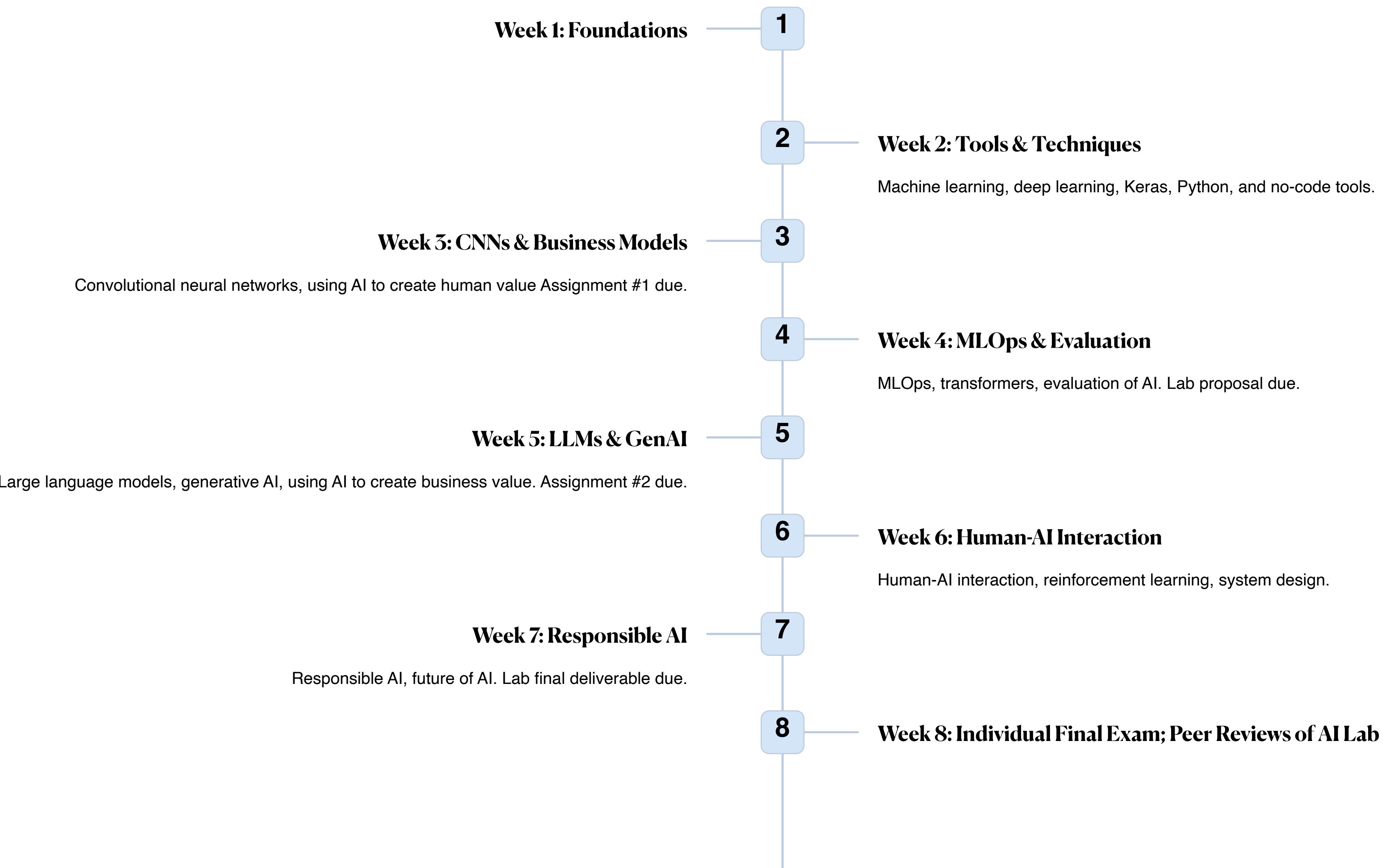


Tinglong Dai, PhD

Bernard T. Ferrari Professor

Johns Hopkins Carey Business School

Agenda



Python Basics: First TA Tutorial



Friday, 10/31, 12:00–1:00 PM



Join via Zoom: <https://bit.ly/jhuaita25>

Attendance is optional. Materials will be posted on Canvas

No-Code AI Development Tools

Sean Cusack, a beekeeper, was curious if anything other than bees was entering his hives. So he made a tiny photo booth that snapped pictures whenever something moved around it. However, sorting through thousands of insect portraits proved time-consuming... So he used Lobe to create an AI solution.

“It was just really simple,” Mr. Cusack said, adding that the underlying data science was “over my head..” The Lobe platform allowed him to drag and drop sample photos and click a few buttons to make a system that could recognize his beloved bees and spot unwelcome visitors.

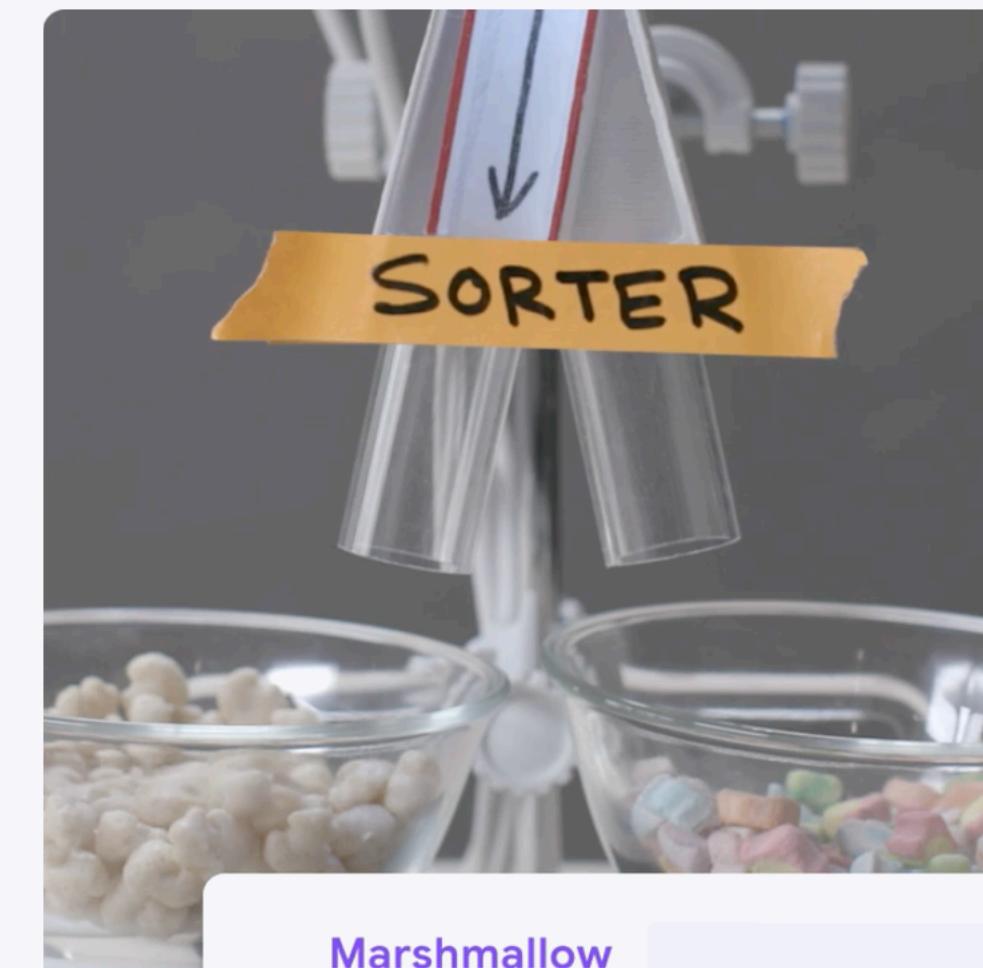
Smith, C. S. (2022) “‘No-code’ brings the power of A.I. to the masses,” *New York Times* (Mar. 15). <https://nyti.ms/3p78s2g>

Teachable Machine

Train a computer to recognize your own images, sounds, & poses.

A fast, easy way to create machine learning models for your sites, apps, and more – no expertise or coding required.

[Get Started](#)



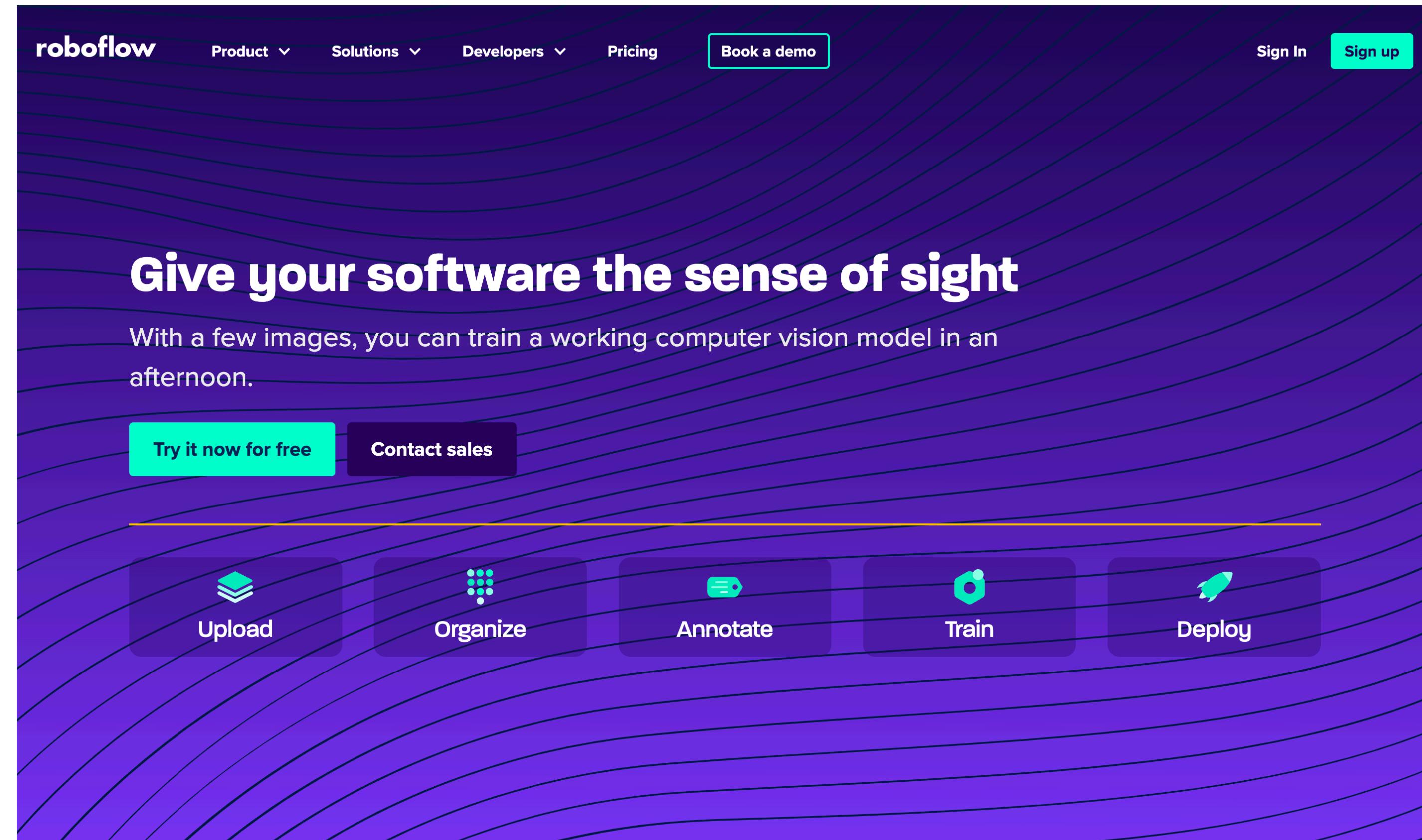
<https://teachablemachine.withgoogle.com>

How to Build AI That Actually Works for Your Business

Mims, C. (2022) *Wall Street Journal* (July 23)

- Stories from the article – Can anyone explain these stories?
 - **PreciTaste** by Ingo Stork: Using real-time sensor data and AI algorithms to predict how much food people will order at any given moment, and prepare just enough food
 - **Phuc Labs** by Phuc Vinh Truong: Using AI to make recycling electronic waste more efficient
 - **Gong** by Amit Bendov: Capturing and analyzing multi-channel communications used by a sales team. It then makes suggestions to help salespeople close more deals.

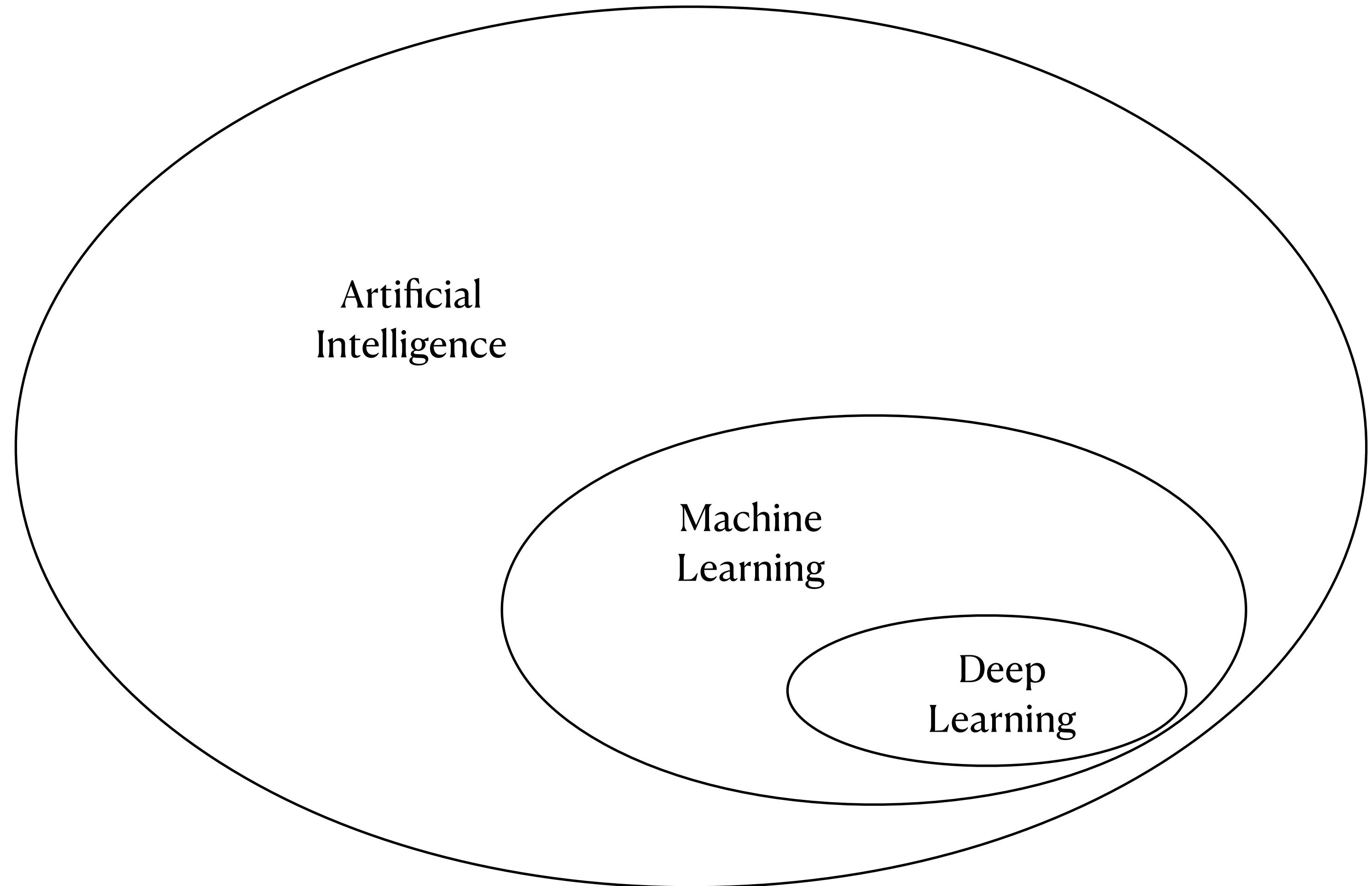
Roboflow: Commercial-Grade, No-Code AI Development



<https://roboflow.com/>

<https://roboflow.com/>

Machine Learning Basics

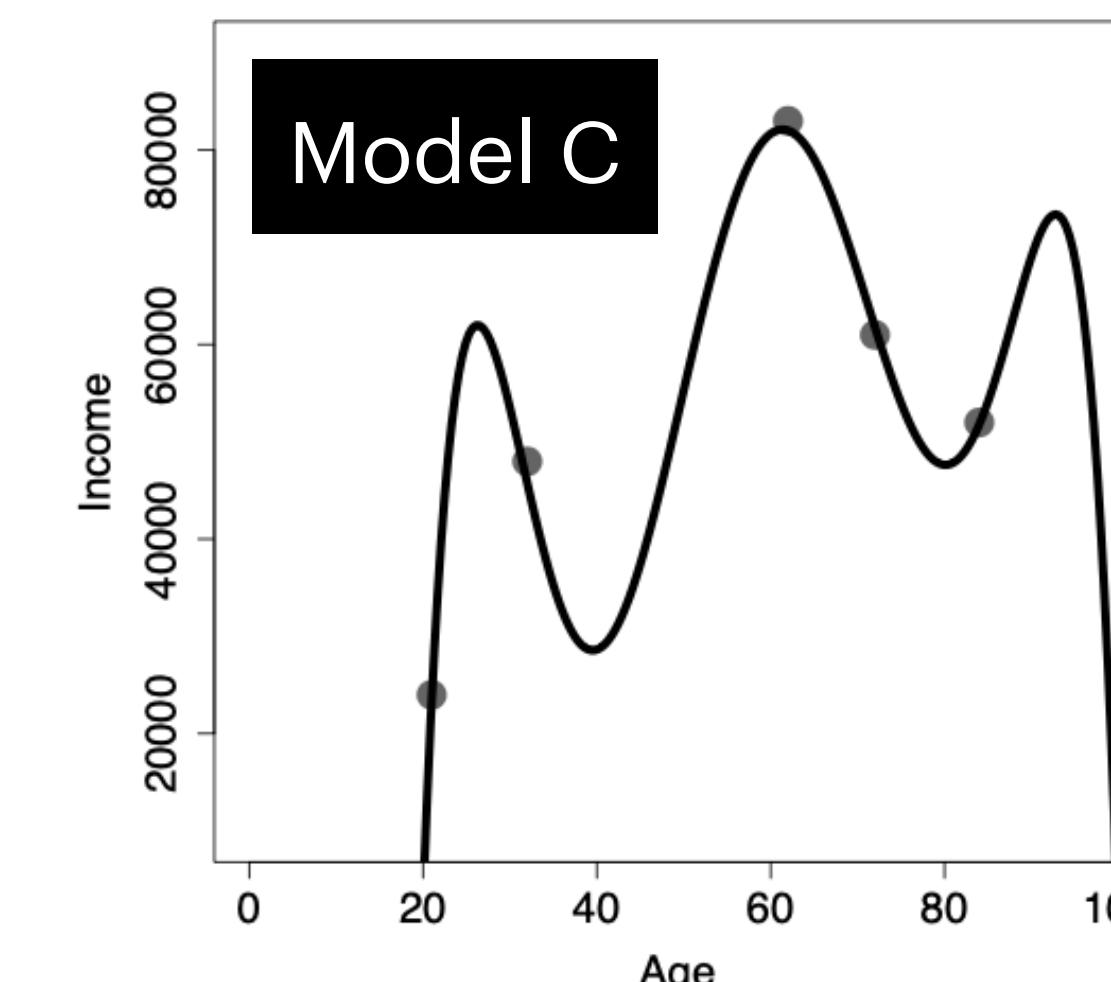
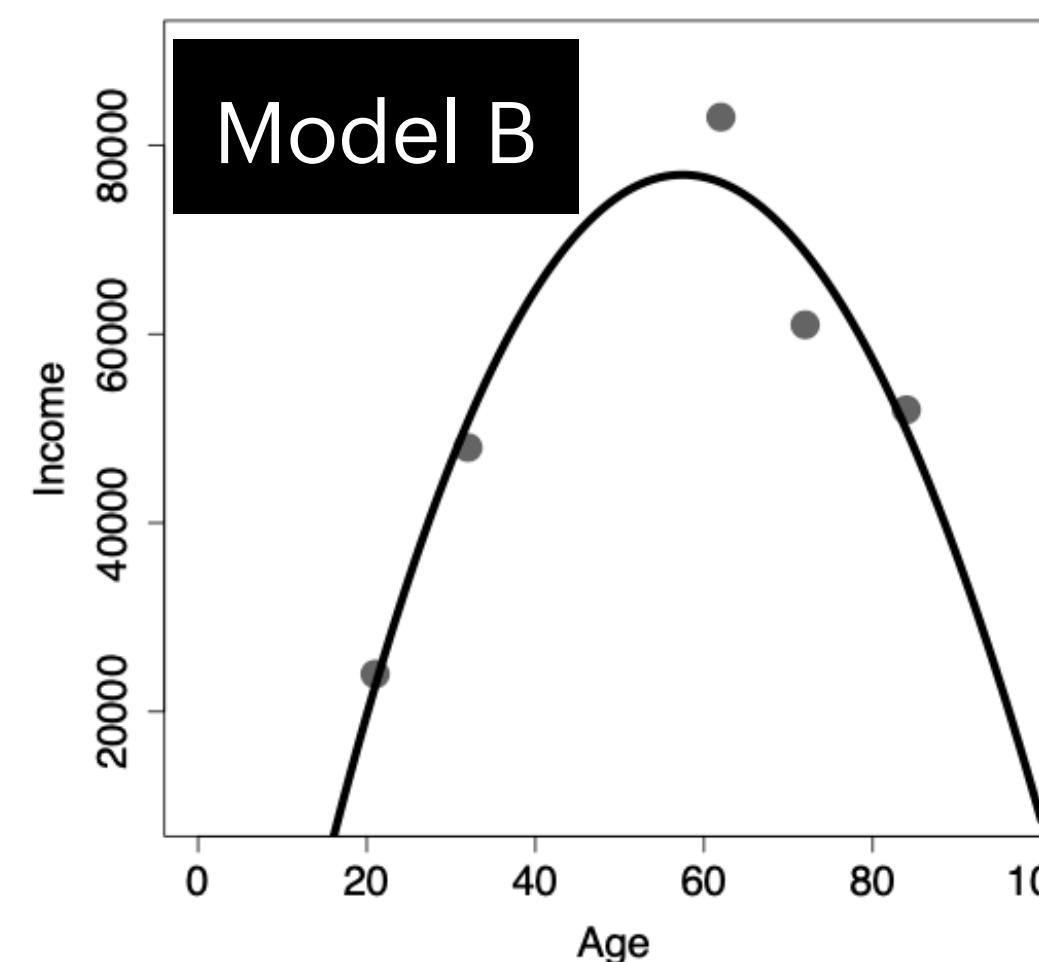
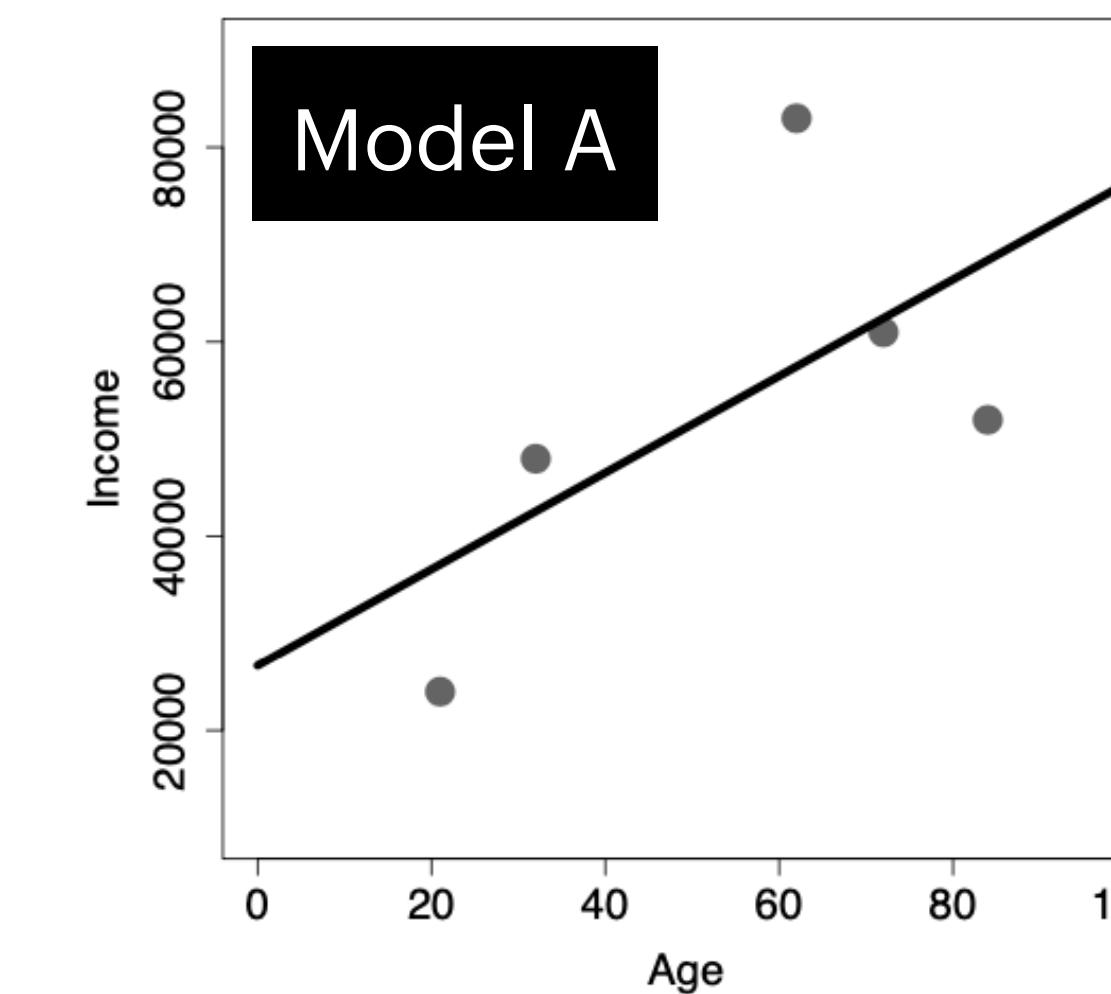
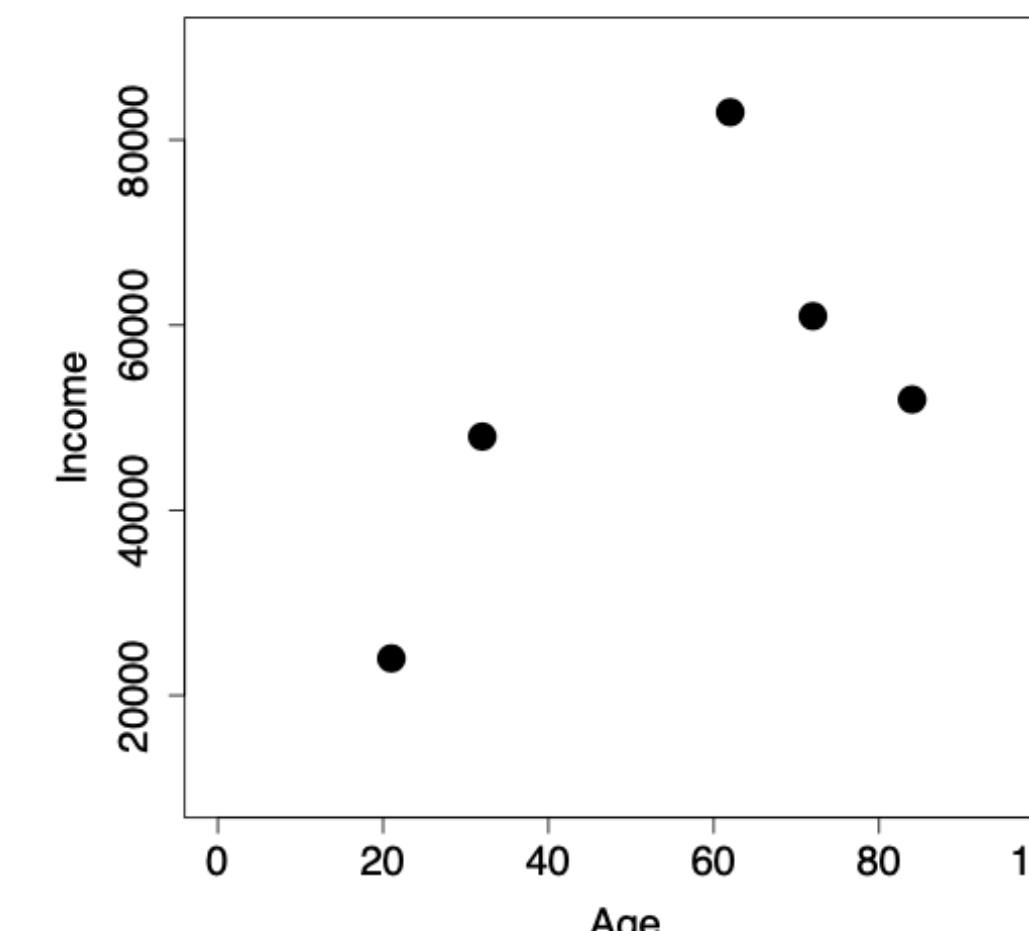


What's the difference between deep learning and “shallow learning”?

Deep vs. “Shallow” Learning

- Deep learning completely automates the most crucial step in machine learning: *feature engineering*
- Prior to deep learning, machine learning transforms the input data into one or two successive representative spaces, via, e.g.,
 - Linear regression
 - Support vector machine (SVM)
 - Decision trees
- But machine learning is known to be an “ill-posed problem” that requires significant human effort to make sense of

Machine Learning, “An Ill-Posed Problem”



Which model is the best?

A Fundamental Tension in ML: Overfitting vs. Underfitting

Optimization vs. Generalization

- Machine learning has two tasks:
 - Optimization: adjust the model to best fit the training data
 - Generalization: ensure the model performs well on data it has *never* seen before
- Example: What's the best way to prepare for the U.S. medical licensing exam?
 - Memorizing answers to the sample tests \neq doing well in the real test
- **Overfitting** occurs when the algorithm has learned too much from the training data
- **Underfitting** occurs when the algorithm hasn't modeled all relevant patterns in the training data

Overfitting?



Friends S3.E8 “The One with the Giant Poking Device”

The Washington Post

Is Taylor Swift's Eras Tour a curse on NBA teams?

A Redditor's theory says yes



By [María Luisa Paúl](#)

June 5, 2023 at 6:23 a.m. EDT

Weeks ago, 24-year-old Matt Moses noticed [a trend](#): Whenever Taylor Swift's Eras Tour came to an NBA team's city during the playoffs, that team was doomed to lose.

Those three Atlanta shows in late April? Boom, the [Hawks lost their series to the Celtics](#) just before Swift arrived. When Swift played in Philadelphia in May? [The 76ers lost the series](#), also to the Celtics, after a Game 7 defeat on Swift's final night at Lincoln Financial Field.

Example: Using Decision Trees to Predict Loan Outcome

ID	OCCUPATION	AGE	LOAN-SALARY	OUTCOME
			RATIO	
1	industrial	39	3.40	default
2	industrial	22	4.02	default
3	professional	30	2.70	repay
4	professional	27	3.32	default
5	professional	40	2.04	repay
6	professional	50	6.95	default
7	industrial	27	3.00	repay
8	industrial	33	2.60	repay
9	industrial	30	4.50	default
10	professional	45	2.78	repay

Model 1

```
if LOAN-SALARY RATIO > 3.00 then
    OUTCOME = default
else
    OUTCOME = repay
```

Model 2

```
if AGE= 50 then
    OUTCOME = default
else if AGE= 39 then
    OUTCOME = default
else if AGE= 30 and OCCUPATION = industrial then
    OUTCOME = default
else if AGE= 27 and OCCUPATION = professional then
    OUTCOME = default
else
    OUTCOME = repay
```

Which model is better?

Example: Predicting Loan Outcome

Which model is better?

Model 1

```
if LOAN-SALARY RATIO > 3.00 then
    OUTCOME = default
else
    OUTCOME = repay
```

Model 2

```
if AGE= 50 then
    OUTCOME = default
else if AGE= 39 then
    OUTCOME = default
else if AGE= 30 and OCCUPATION = industrial then
    OUTCOME = default
else if AGE= 27 and OCCUPATION = professional then
    OUTCOME = default
else
    OUTCOME = repay
```

- Model 2 is overfitting because each of the decision rules specified in Model 2 is specific to a single instance. It lacks generalizability
- Model 1 appears to generalize beyond the data

Feature Leakage

- **Feature leakage** occurs when some of the features specified in the machine learning model leaks information and allows the system to “cheat”
- Example: Cancer prediction (Kaufman et al. 2011)
 - Objective: Predicting the probability that a patient has cancer
 - Features: patient age, gender, medical history, hospital name, vital signs, tests
 - The machine learning model has excellent performance on test data
 - Yet real-world performance was surprisingly poor. What happened?

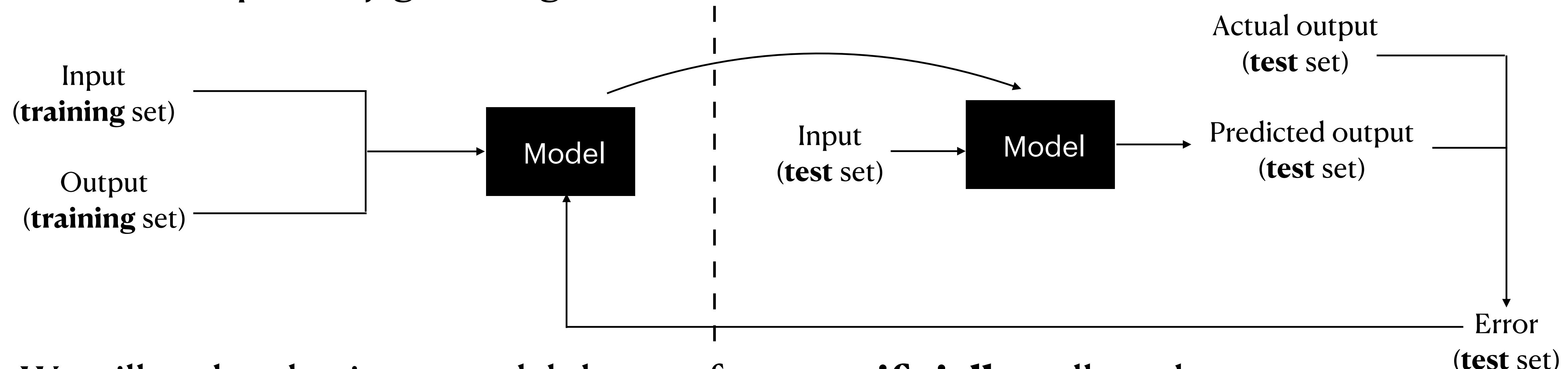
“Hospital name” leaks the information about cancer diagnosis. So the model doesn’t work for patients whose hospitals have yet to be assigned.

Training Leakage

- Imagine when you try to build a diagnosis model using 20,000 patient records
- Let's divide patient records into two parts:



- What could possibly go wrong?



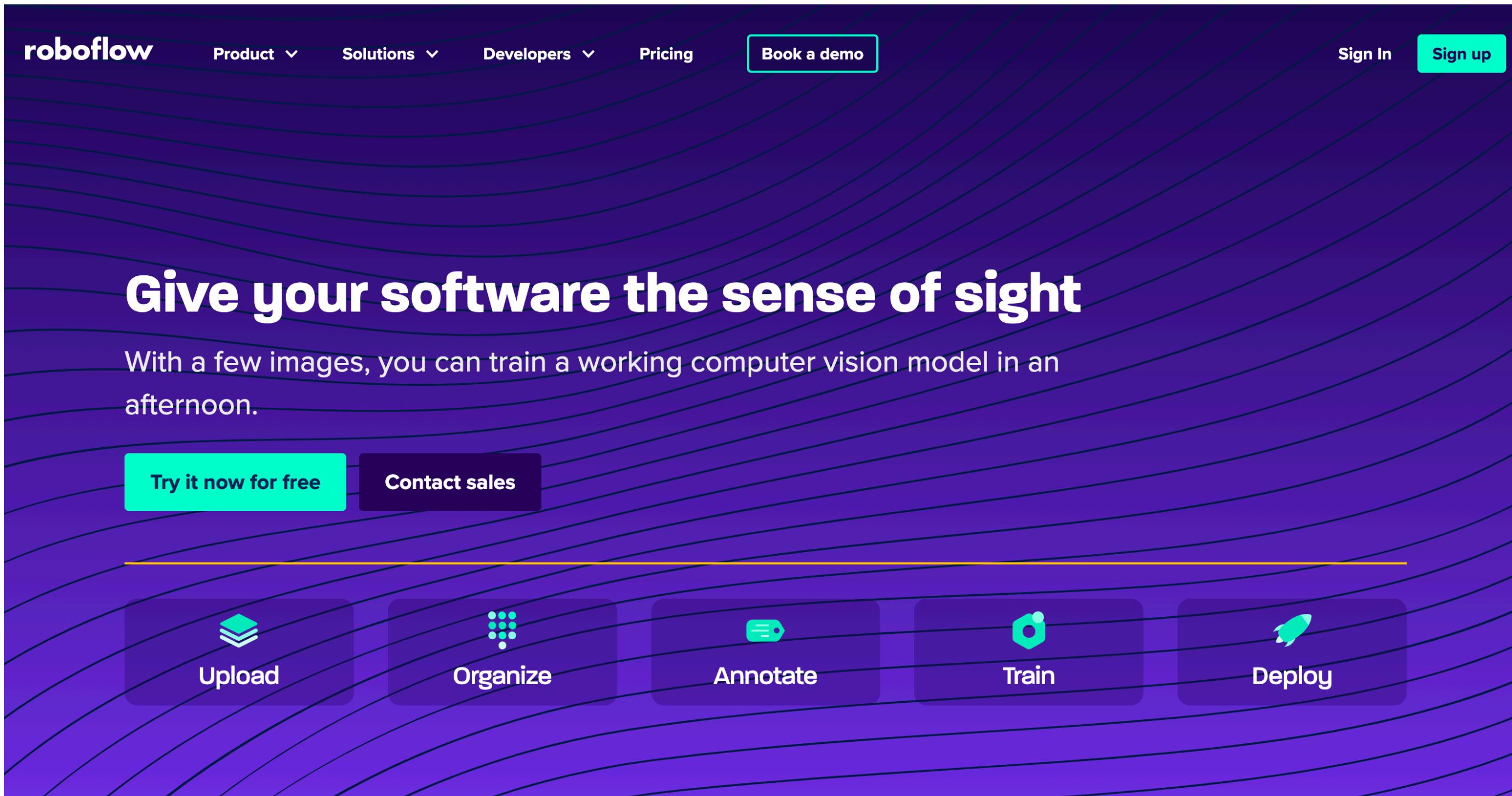
- We will end up having a model that performs **artificially** well on the test set

Solution to Training Leakage

- Principle: To avoid leakage, our model shouldn't have had access to *any* information about the test set, either directly or indirectly
- Solution: Split data into *three* parts: training, **validation**, and test sets
 - The test set is also known as “holdout set” and should never be used to train the model
- Common options: splitting datasets into 6/2/2, 7/2/1, or 8/1/1
- We will discuss more sophisticated strategies in MLOps (session 4)

No-code AI Example: Roboflow

Training, Validation, and Testing Sets



The image shows the homepage of the Roboflow website. The background features a dark purple gradient with white diagonal lines. At the top, there is a navigation bar with the Roboflow logo, dropdown menus for Product, Solutions, Developers, and Pricing, a "Book a demo" button, and links for Sign In and Sign up. The main headline reads "Give your software the sense of sight" followed by the subtext "With a few images, you can train a working computer vision model in an afternoon." Below this, there are two calls-to-action: "Try it now for free" and "Contact sales". A horizontal yellow line separates the main content from a row of five rounded rectangular buttons. Each button contains an icon and a label: "Upload" (stacked files), "Organize" (grid), "Annotate" (pencil), "Train" (neuron), and "Deploy" (rocket). At the bottom of the page, the text "TRUSTED BY COMPANIES BIG AND SMALL" is centered above a row of logos for Walmart, AMGEN, USG, getaround, OkCredit, and CardinalHealth.

roboflow

Product Solutions Developers Pricing Book a demo

Sign In Sign up

Give your software the sense of sight

With a few images, you can train a working computer vision model in an afternoon.

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TRUSTED BY COMPANIES BIG AND SMALL

Walmart AMGEN USG getaround OkCredit CardinalHealth

<https://roboflow.com/>



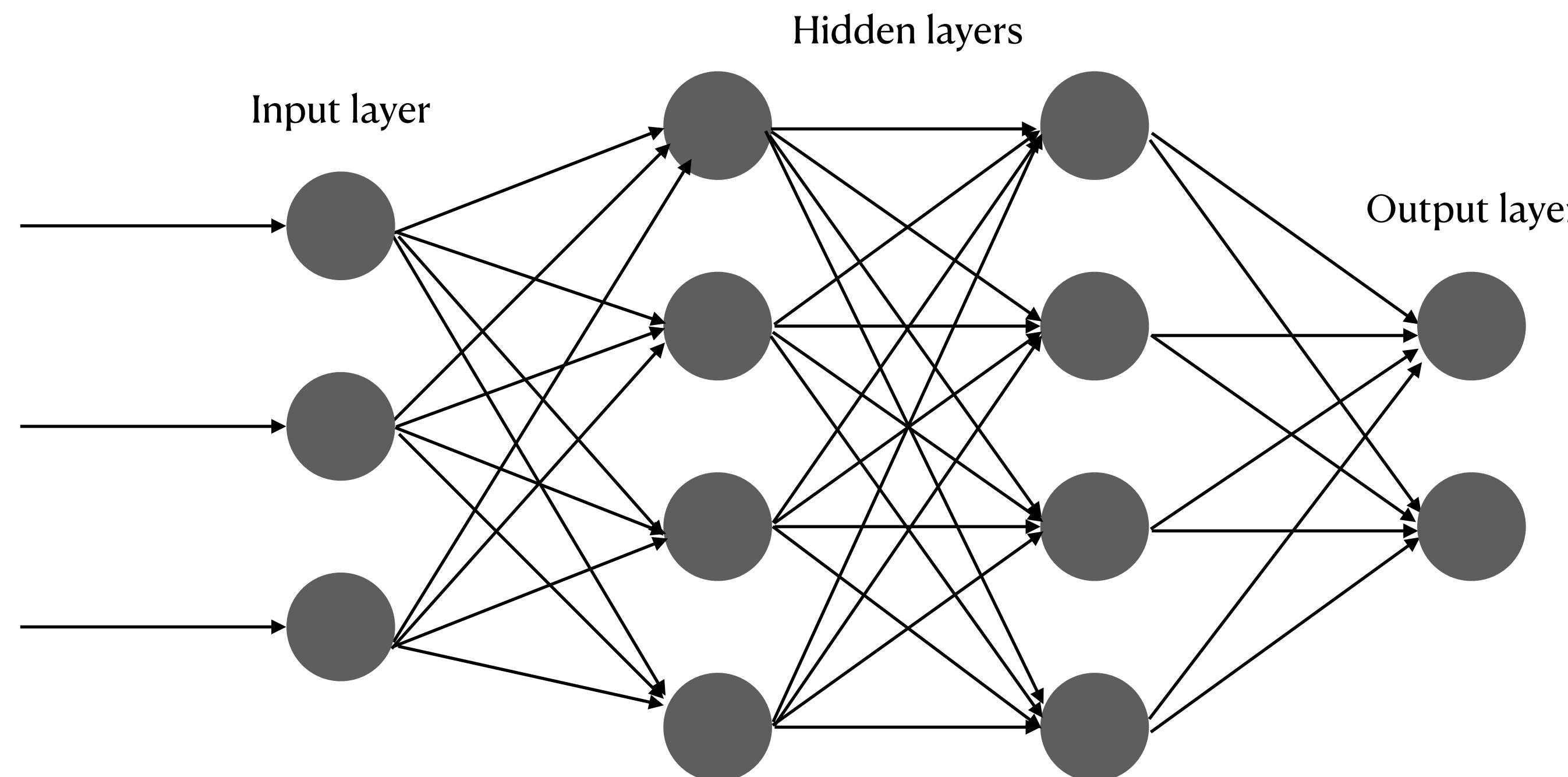
Deep Learning

Artificial Neural Networks &

Convolutional Neural Networks

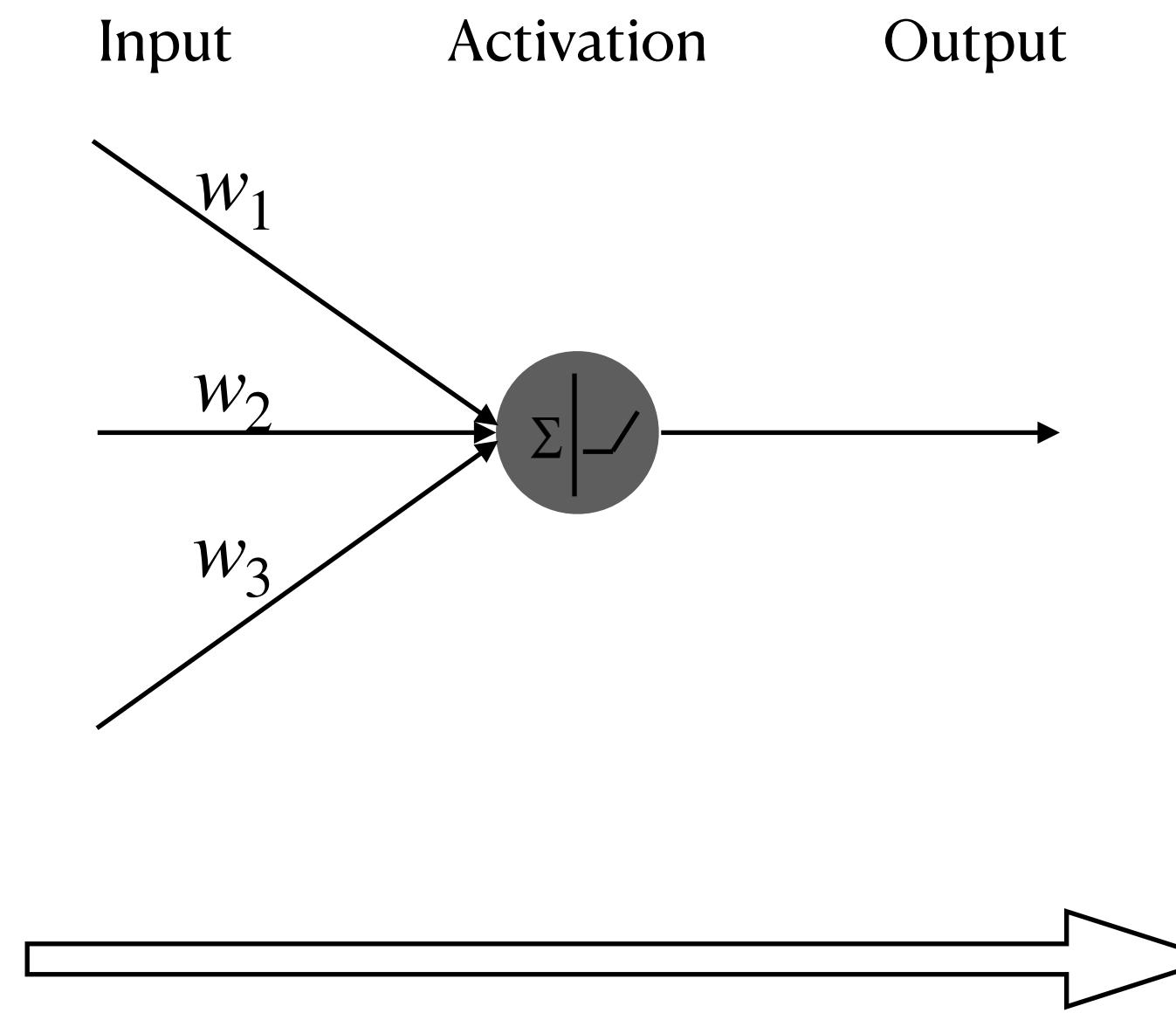
Deep Learning

- Deep learning is an incremental, layer-by-layer learning approach in which increasingly complex representations are developed to map the input to output

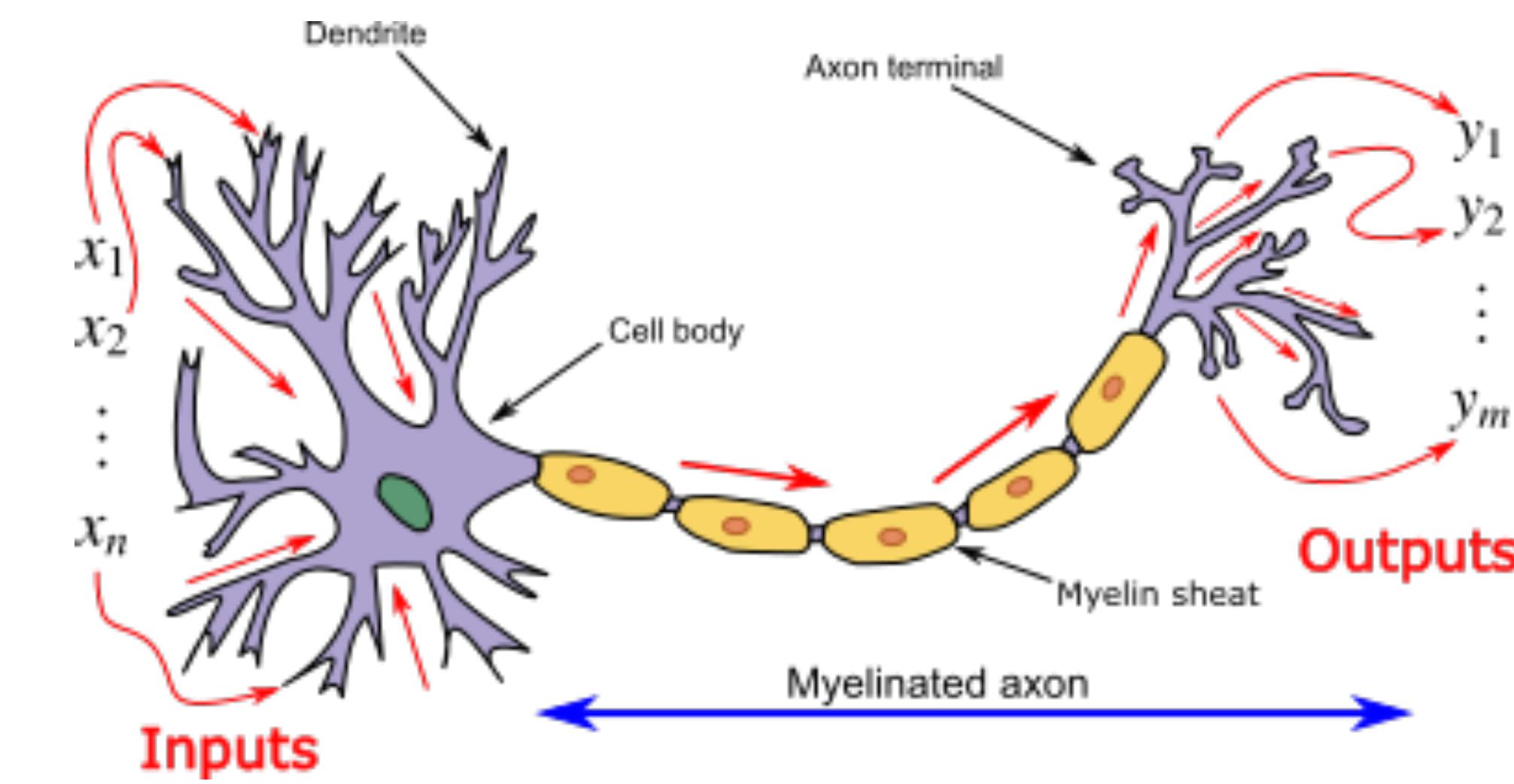


Artificial Neural Network

Artificial Neurons vs. Neurons



Artificial Neuron

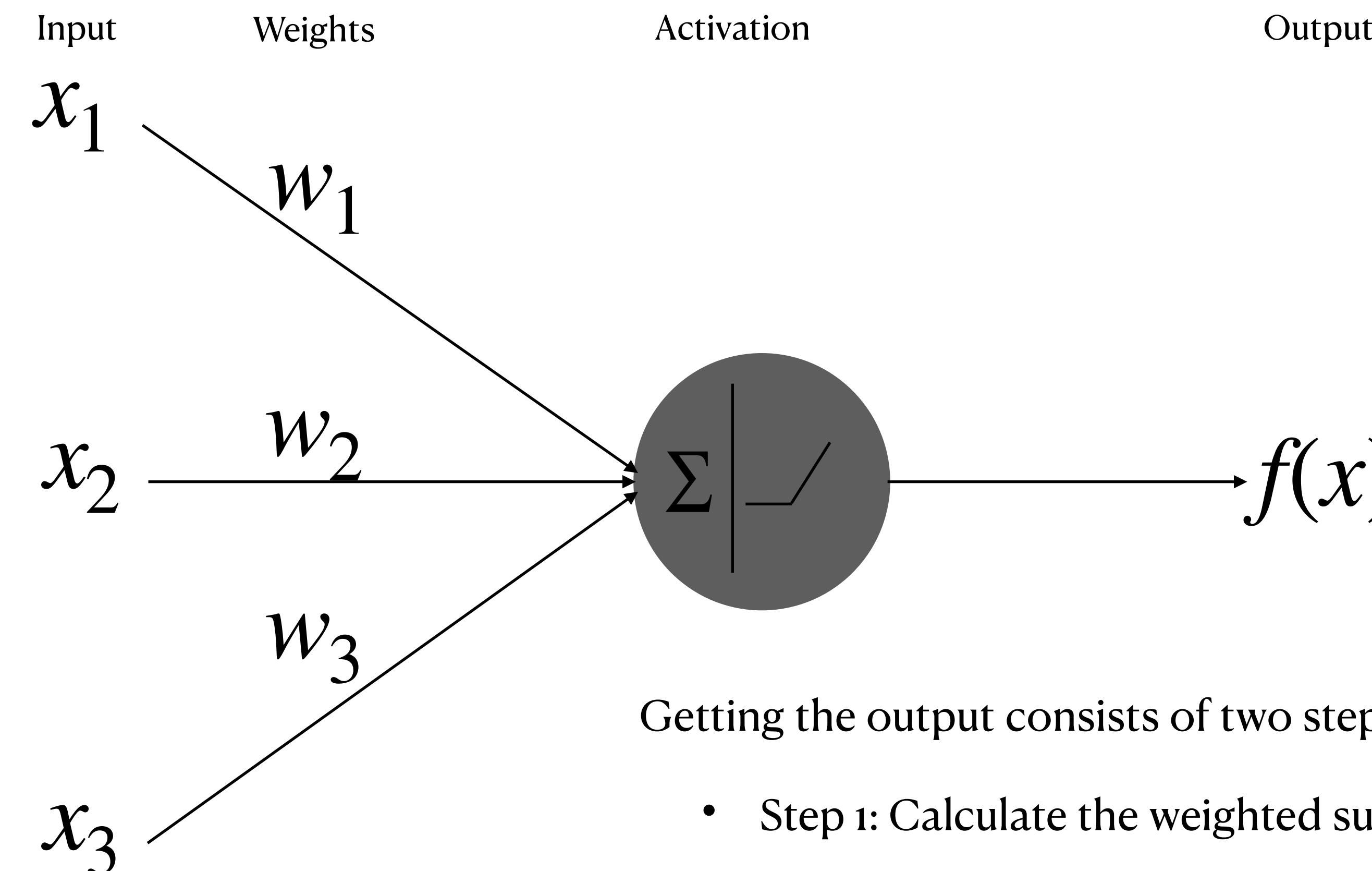


Neuron and Myelinated Axon
with signal flow from inputs at dendrites to outputs at axon terminals



Key insight: Part of what makes us intelligent is our capacity to filter information before processing it. Not everything will trigger the activation of neurons in our brains.

How Feedforward Neural Networks Work



Getting the output consists of two steps:

- Step 1: Calculate the weighted sum: $w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3$
- Step 2: Applying the activation function a :
$$f(x) = a(w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3)$$

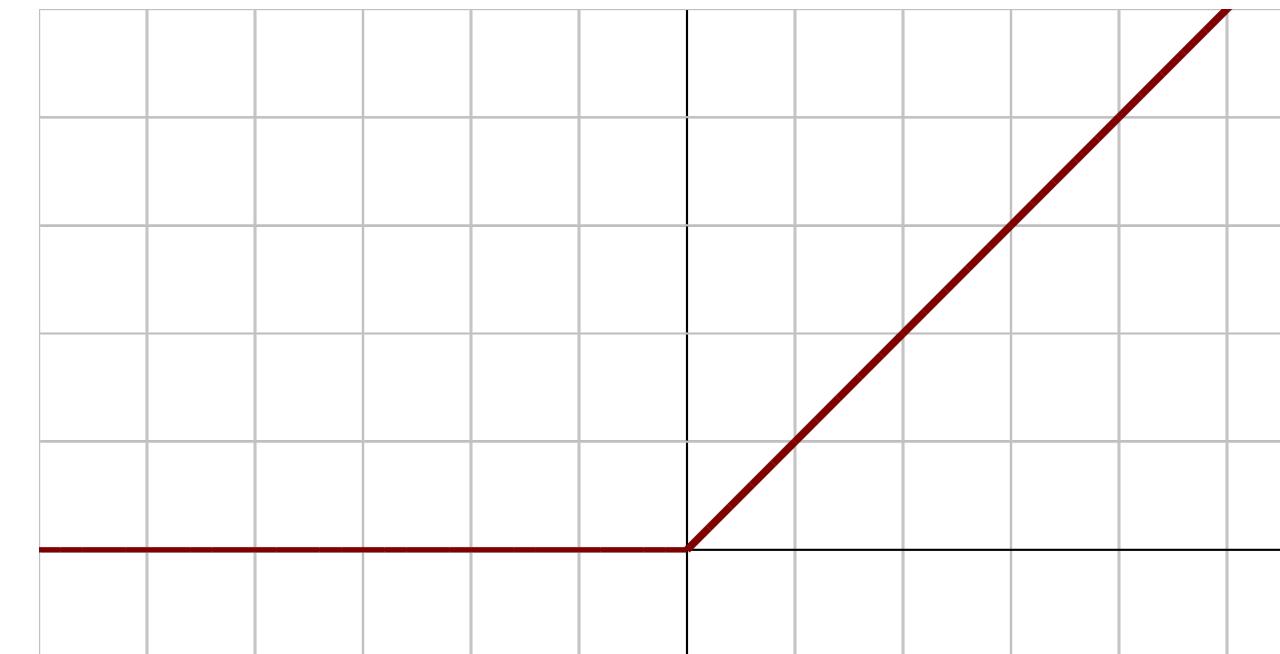
Activation Functions

ReLU

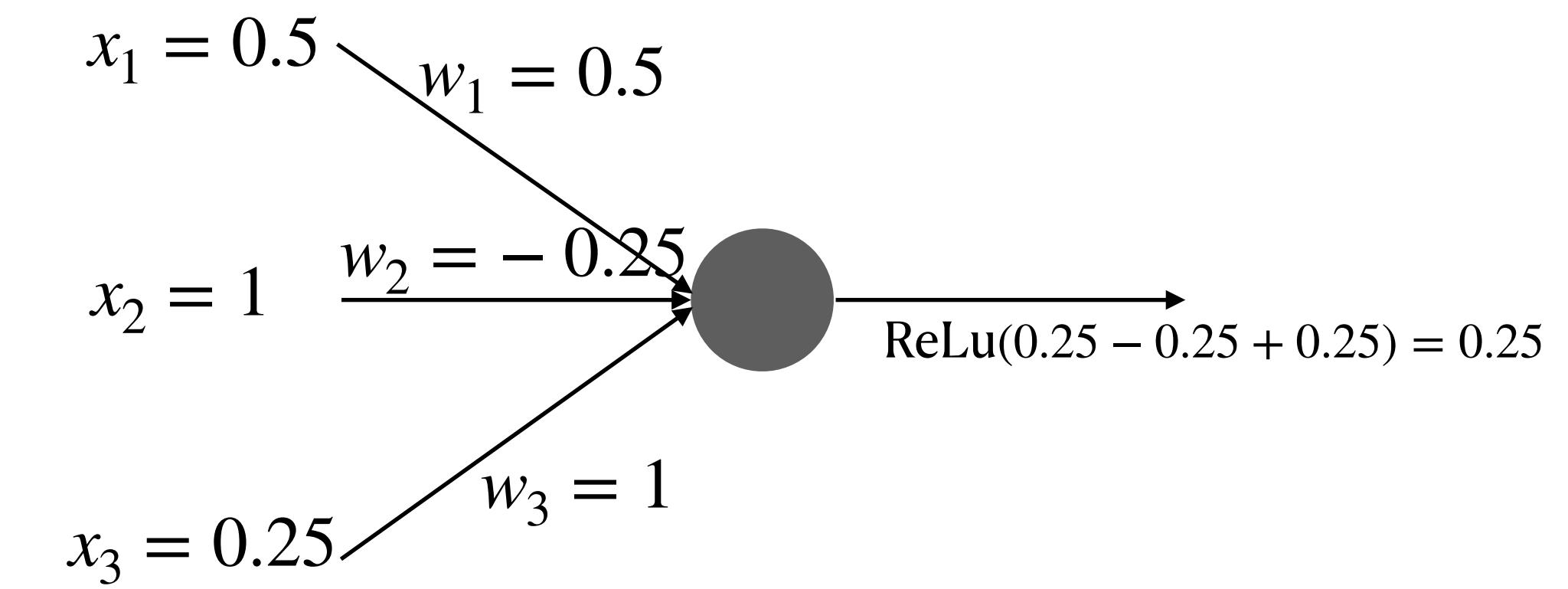
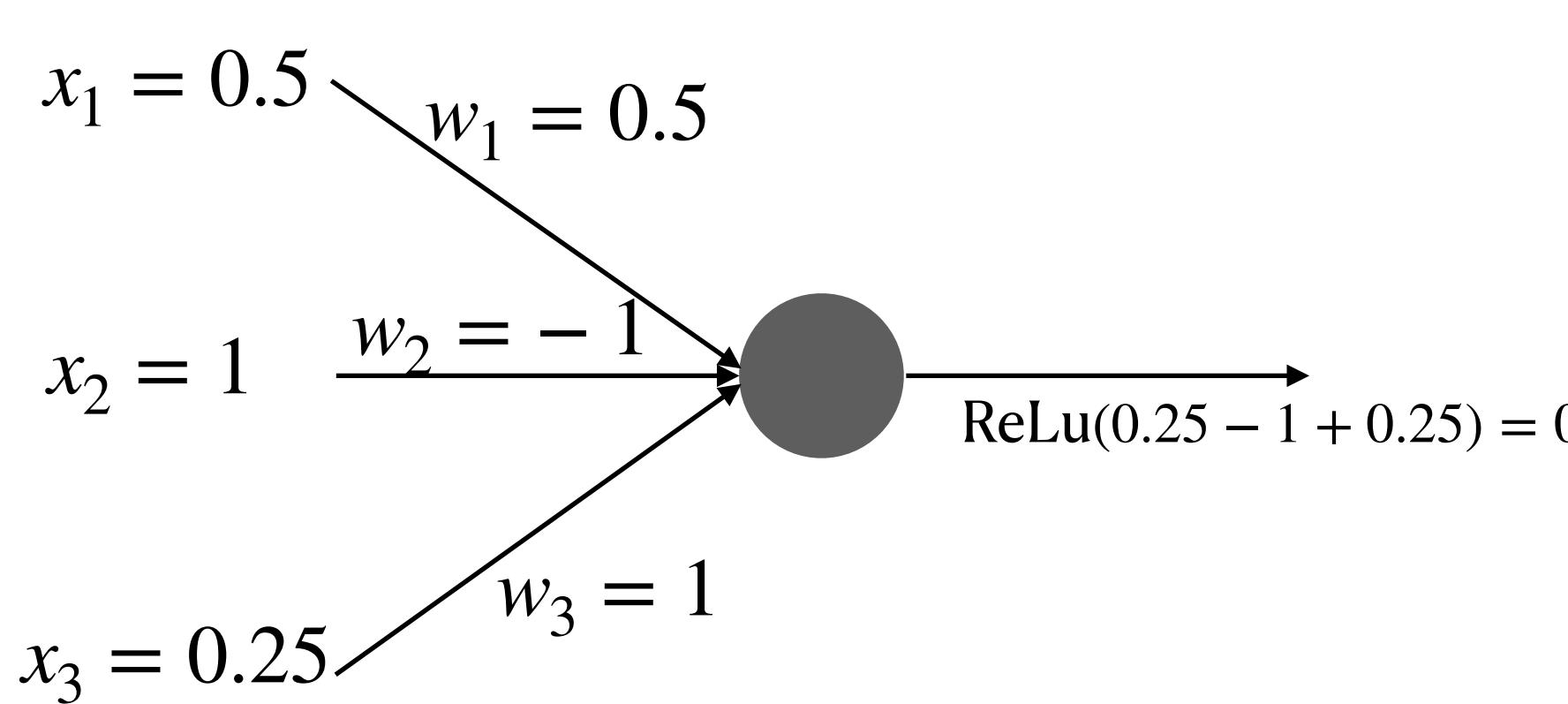
- The most widely used activation function is the **ReLU** (Rectified Linear Unit) function:

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

- Given an input x , the output is x if it is positive and zero otherwise.



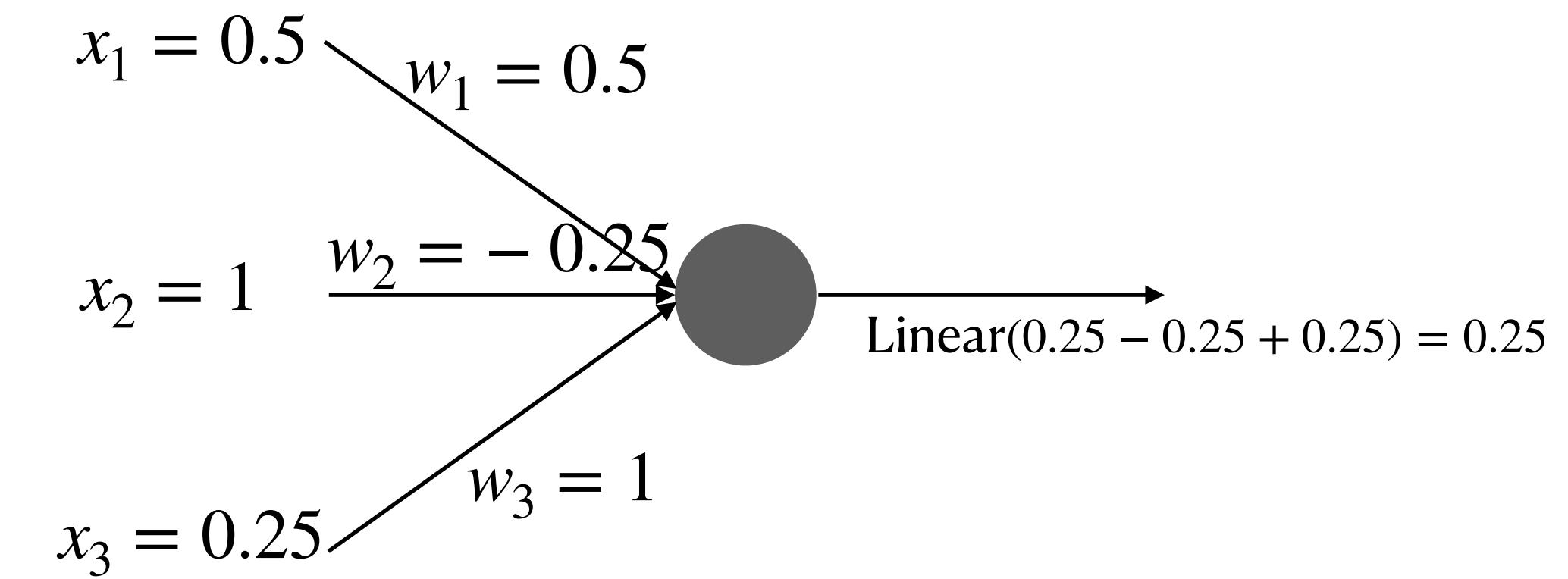
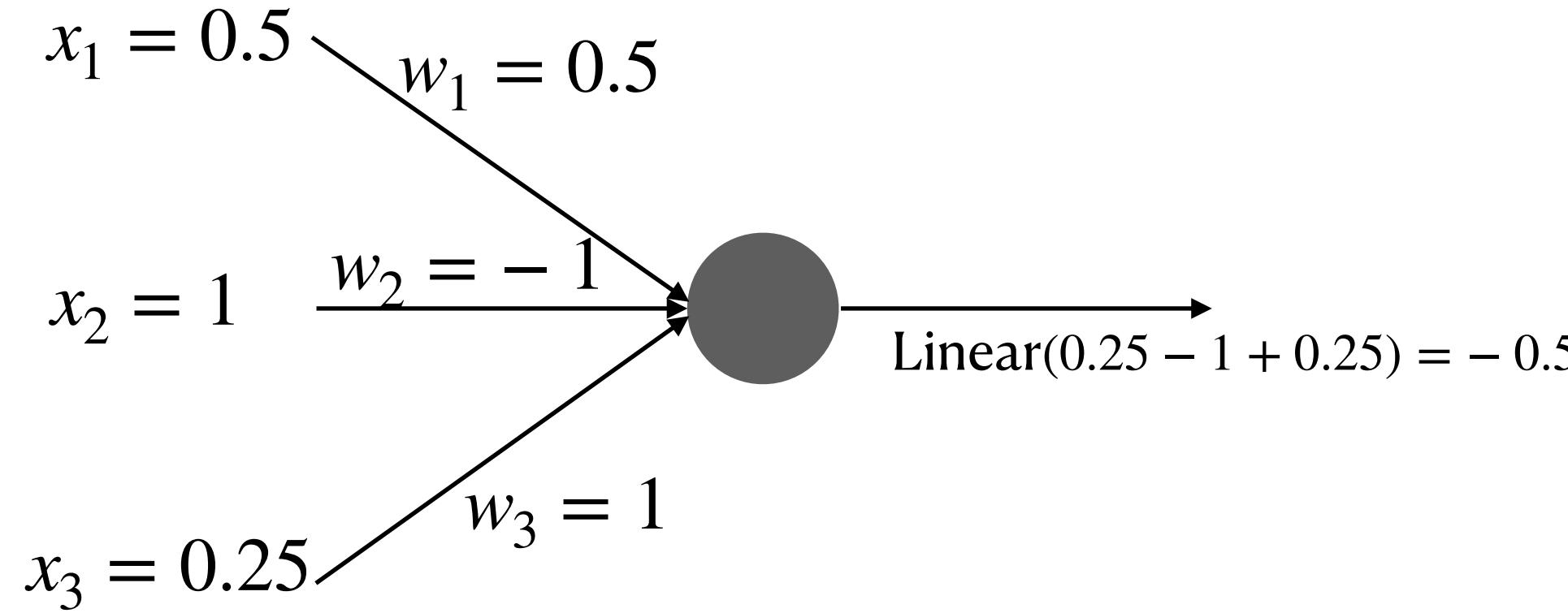
- Examples:



Activation Function

Linear Function

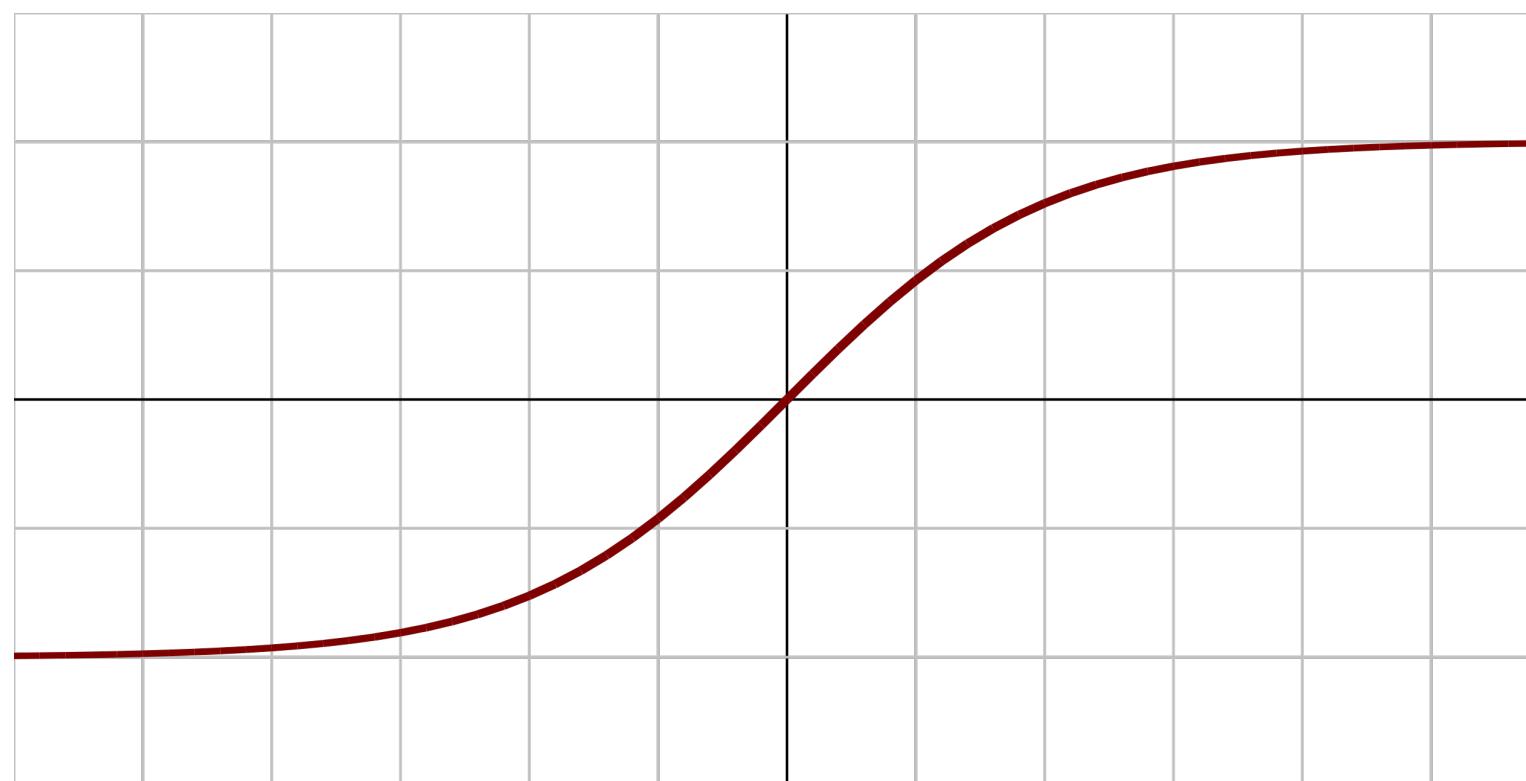
- Under a **linear** activation function ($y = x$):
 - Given an input x , the output is the same as x
- Examples:



A linear activation function means a linear model regardless of the number of hidden layers

Other Activation Functions

Tanh and Sigmoid – “S”-shaped functions



Tanh function

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

“Tanh” rhymes with “branch”



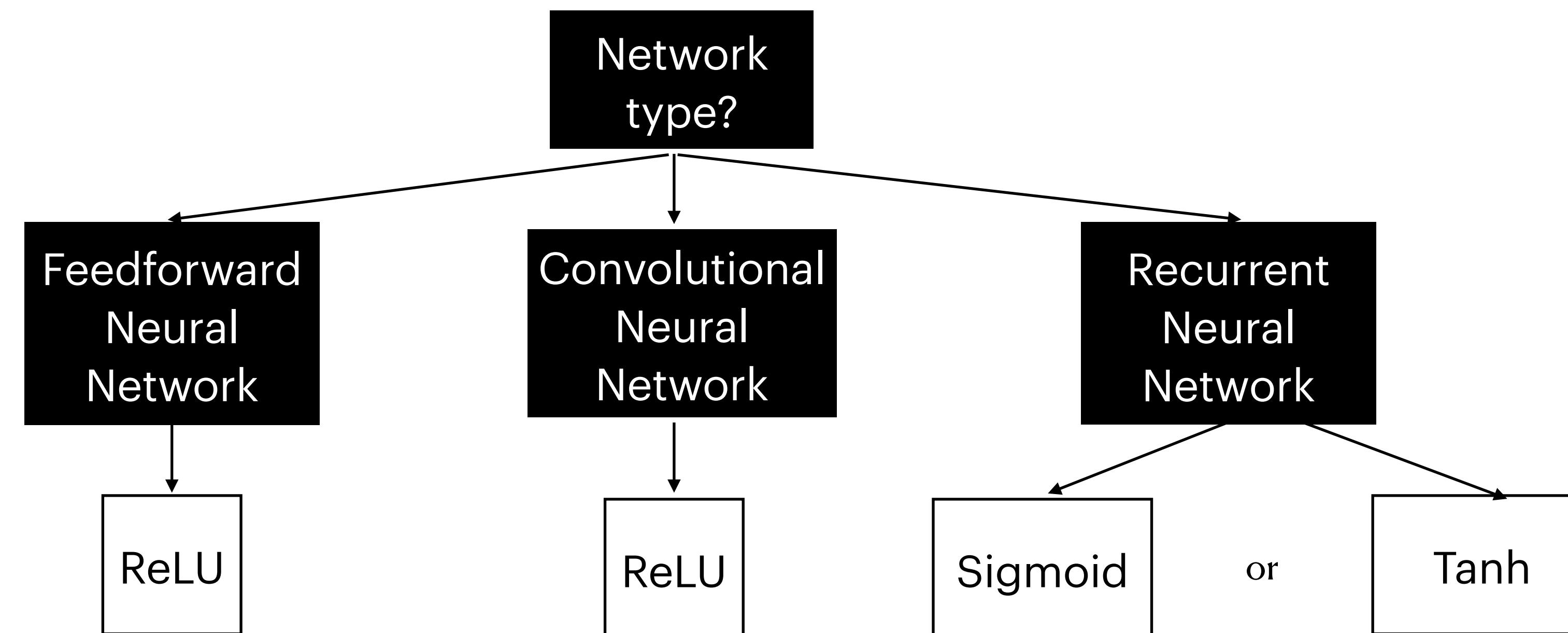
Sigmoid function

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

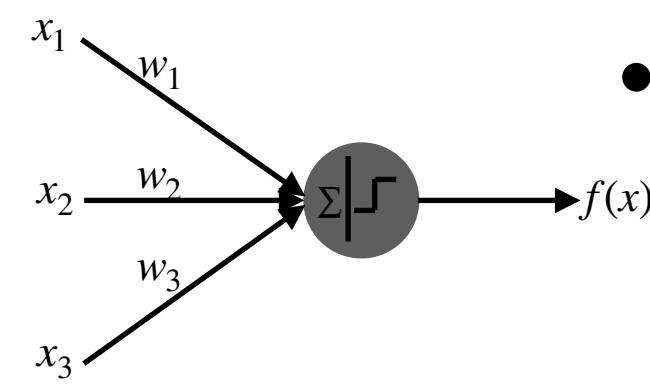
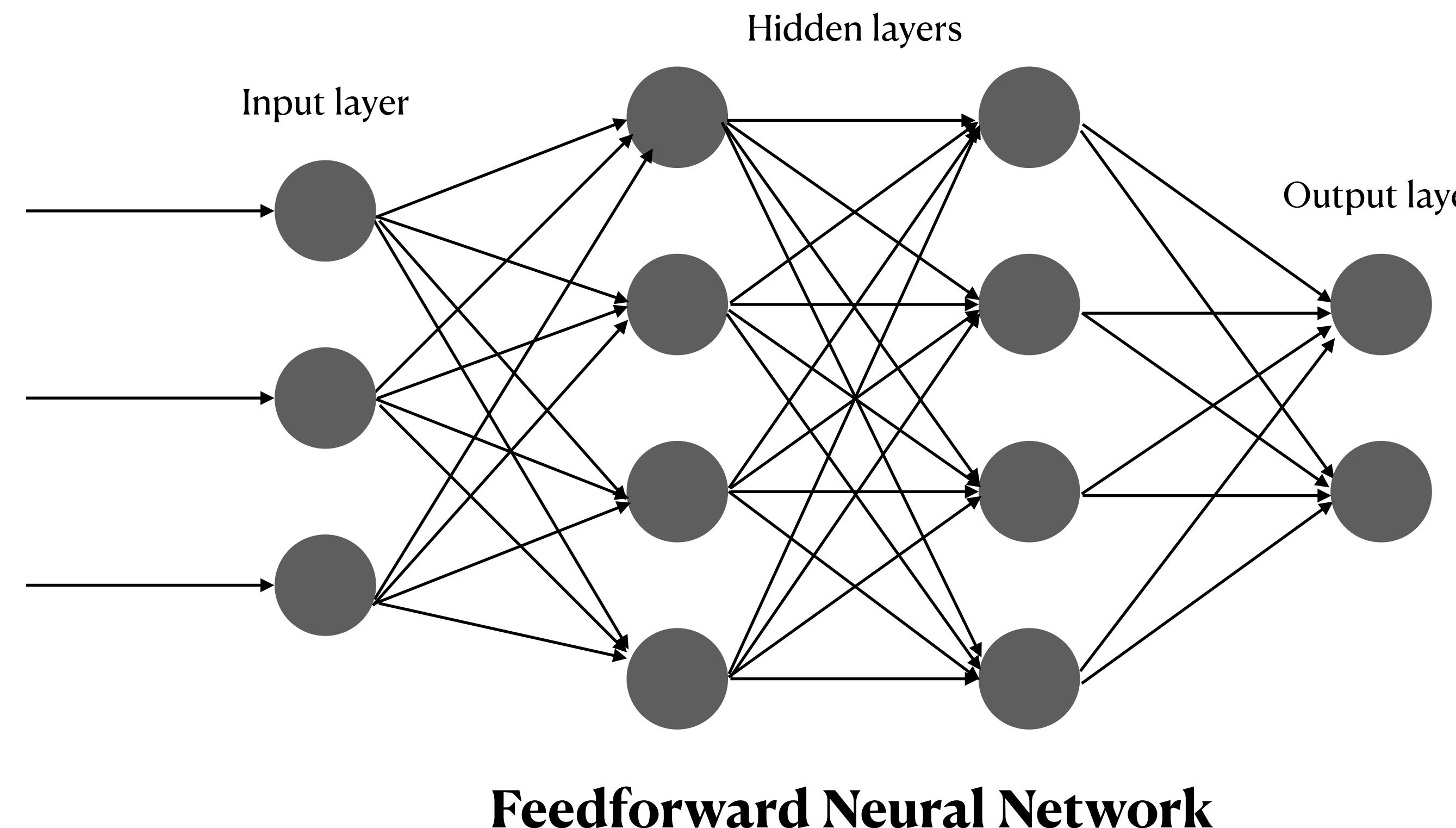
How to Choose Activation Function

A bit of a history lesson

- Until mid-1990s: Sigmoid was the default activation function for training neural networks
- Between mid-1990s to 2010s: Tanh became default activation function for hidden layers
- 2010s to now: the default recommendation is **ReLU** for most of the modern neural networks



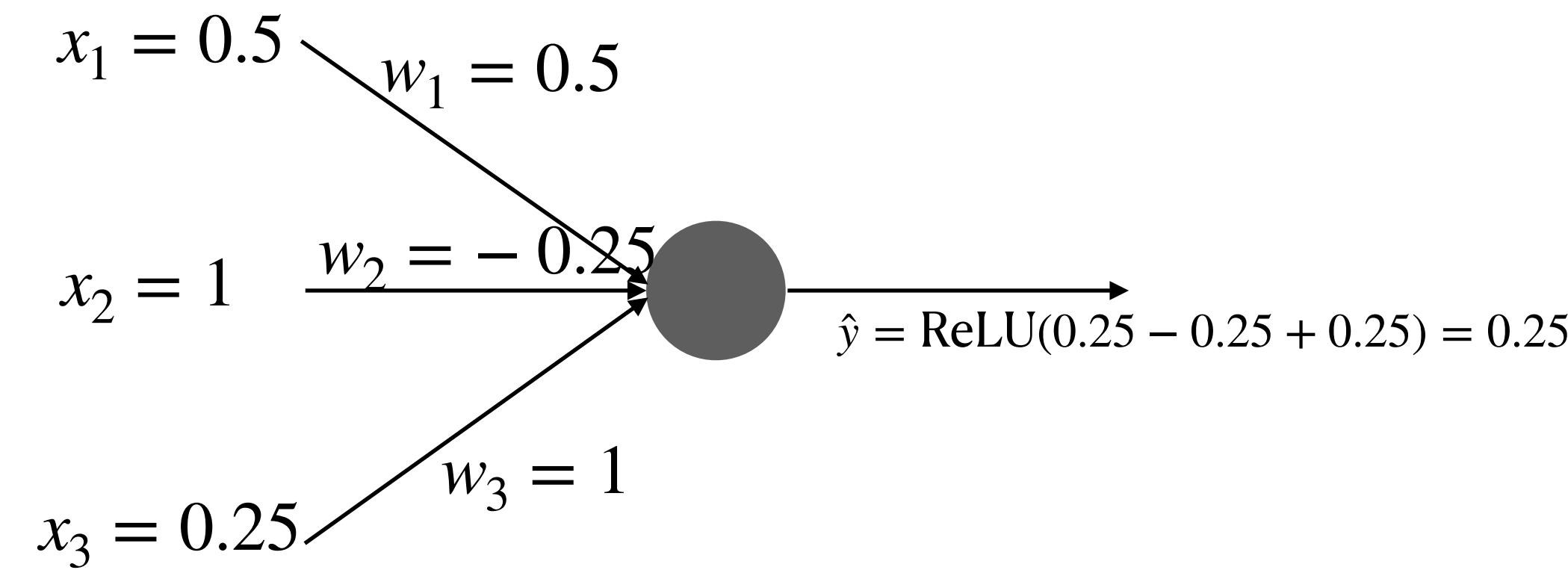
Why Feedforward Neural Network Works



- Universal Approximation Theorem: A feedforward network with at least one hidden layer with any “squashing” activation function (e.g., ReLU, Sigmoid, and Tanh) can learn any continuous input-output function

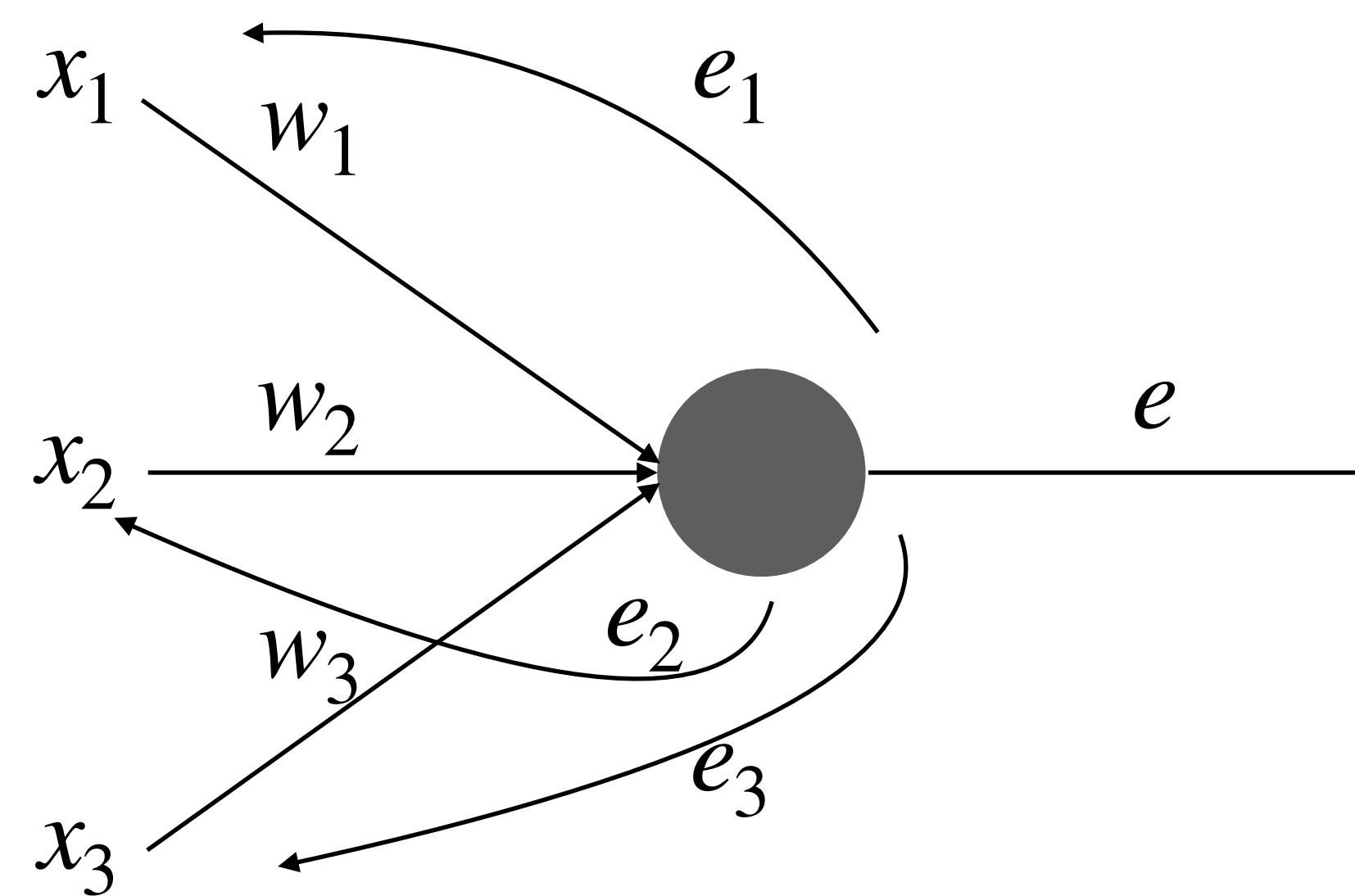
How Feedforward Neural Networks Learn

It's Essentially About Learning the Weights!



- We start with randomly assigned weights.
- In the above example, the predicted output $\hat{y} = 0.25$
- If the actual output is 0.5, then the MSE (mean squared error) is $e = (y - \hat{y})^2 = 0.0625$
- Now what? How can we use the *feedback* to adjust the weights?

Error Backpropagation



$$e_1 = \left(\frac{w_1}{w_1 + w_2 + w_3} \right) \times e$$

$$e_2 = \left(\frac{w_2}{w_1 + w_2 + w_3} \right) \times e$$

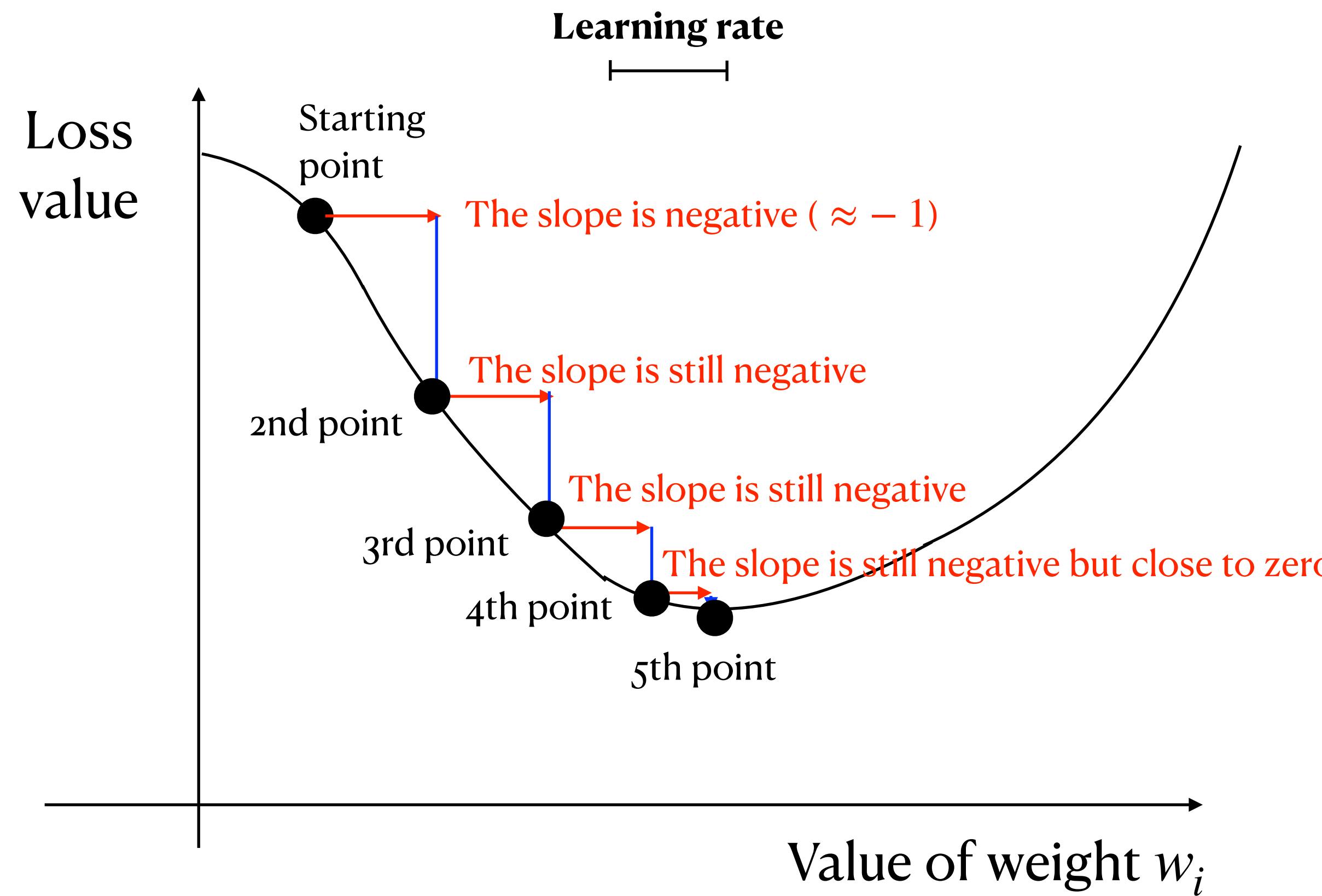
$$e_3 = \left(\frac{w_3}{w_1 + w_2 + w_3} \right) \times e$$

- We can next apply the gradient descent algorithm calculate the **slope** (i.e., gradient) of each weight —how increasing each weight will contribute to the error
- Once we know the slope, we can update the weight:

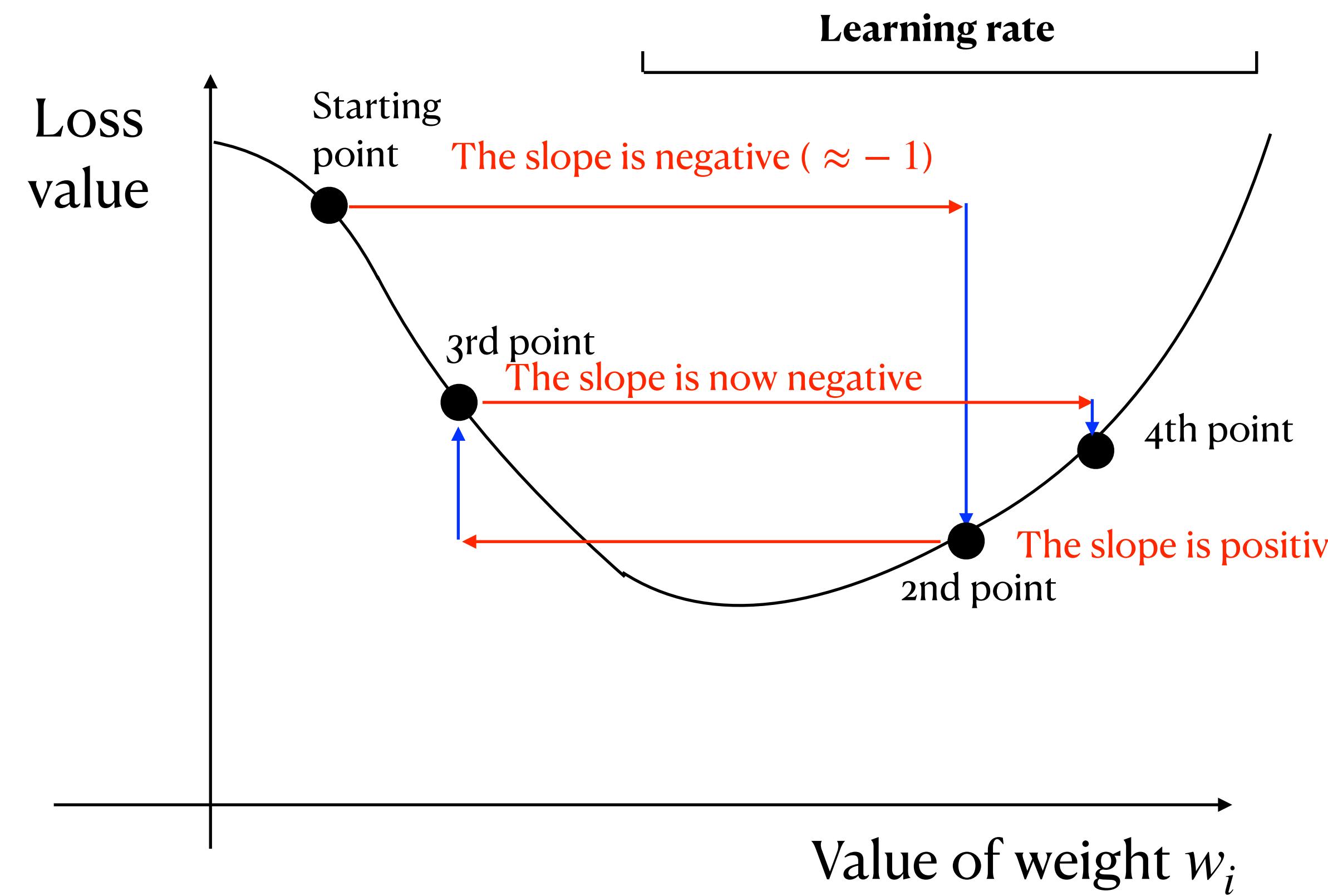
new $w_i = \text{old } w_i - \text{learning rate} \cdot \text{slope}$

Intuition Behind “new $w_i = \text{old } w_i - \text{learning rate} \cdot \text{slope}$ ”

Adjusting the Weight to Minimize the Loss



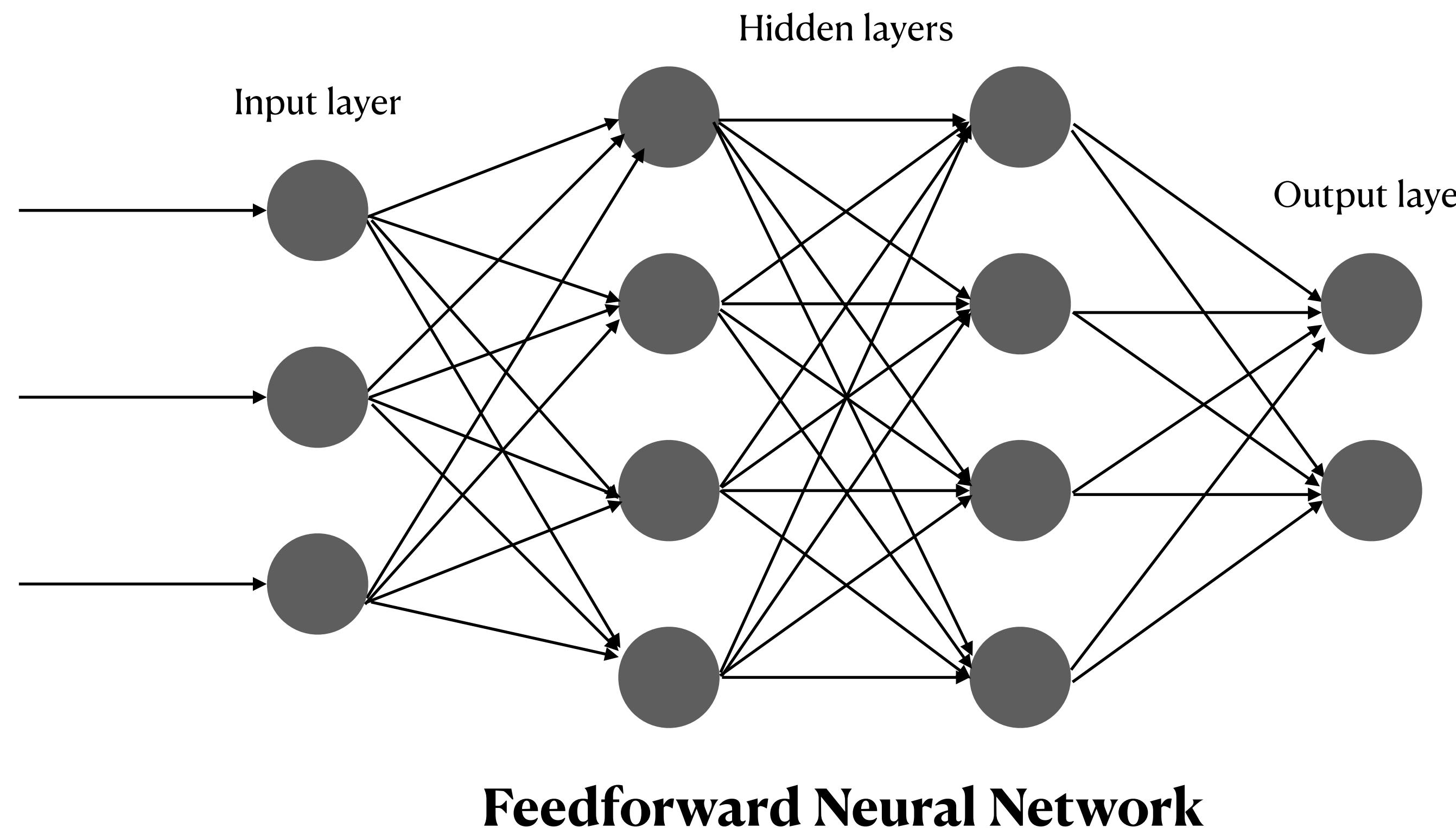
Avoid Excessively High Learning Rates



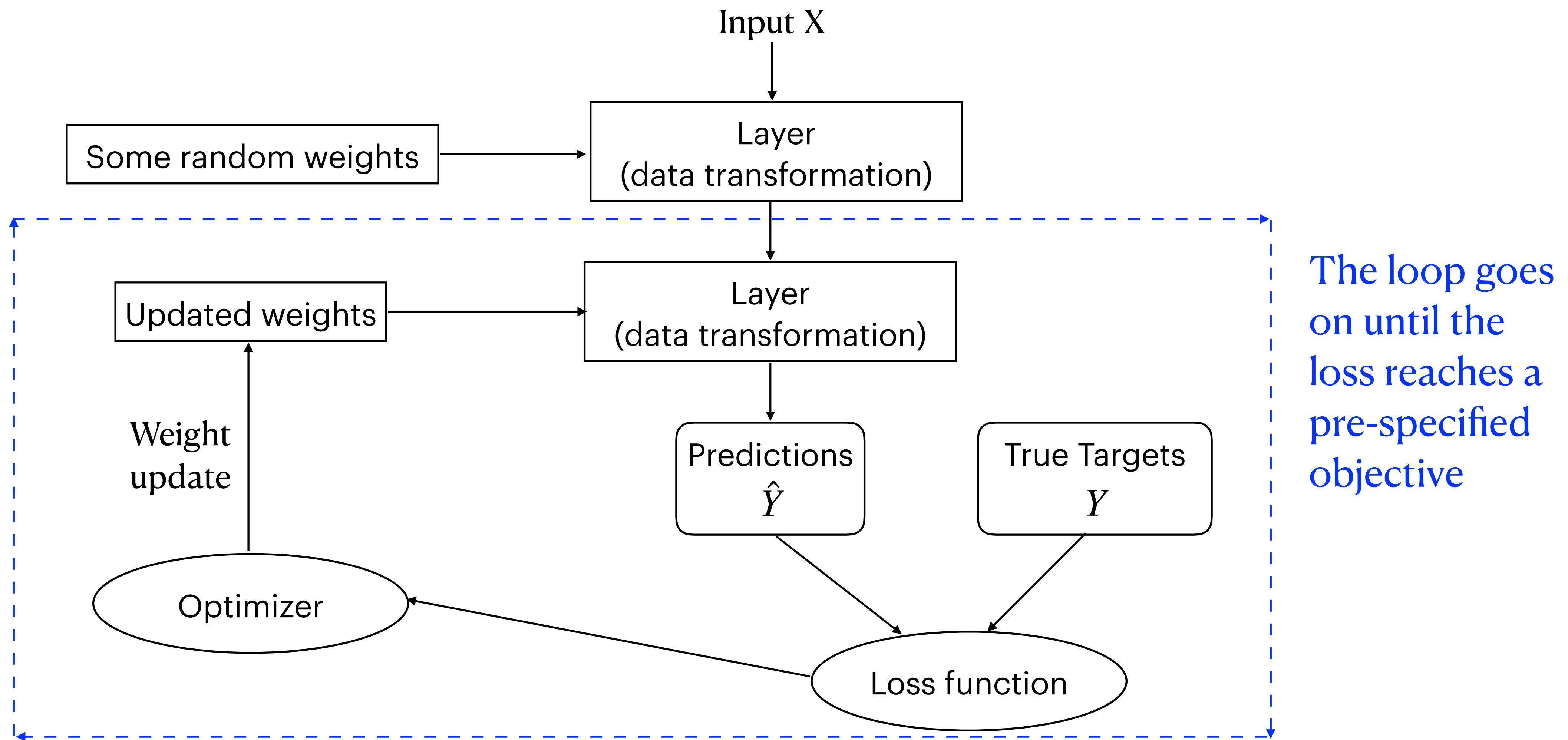
Excessively large learning rates may lead to a behavior like a quantum mechanics experiment gone horribly wrong

Deep Learning

- Deep learning is an incremental, layer-by-layer learning approach in which increasingly complex representations are developed to map the input to output



Summary: Feedforward Neural Networks

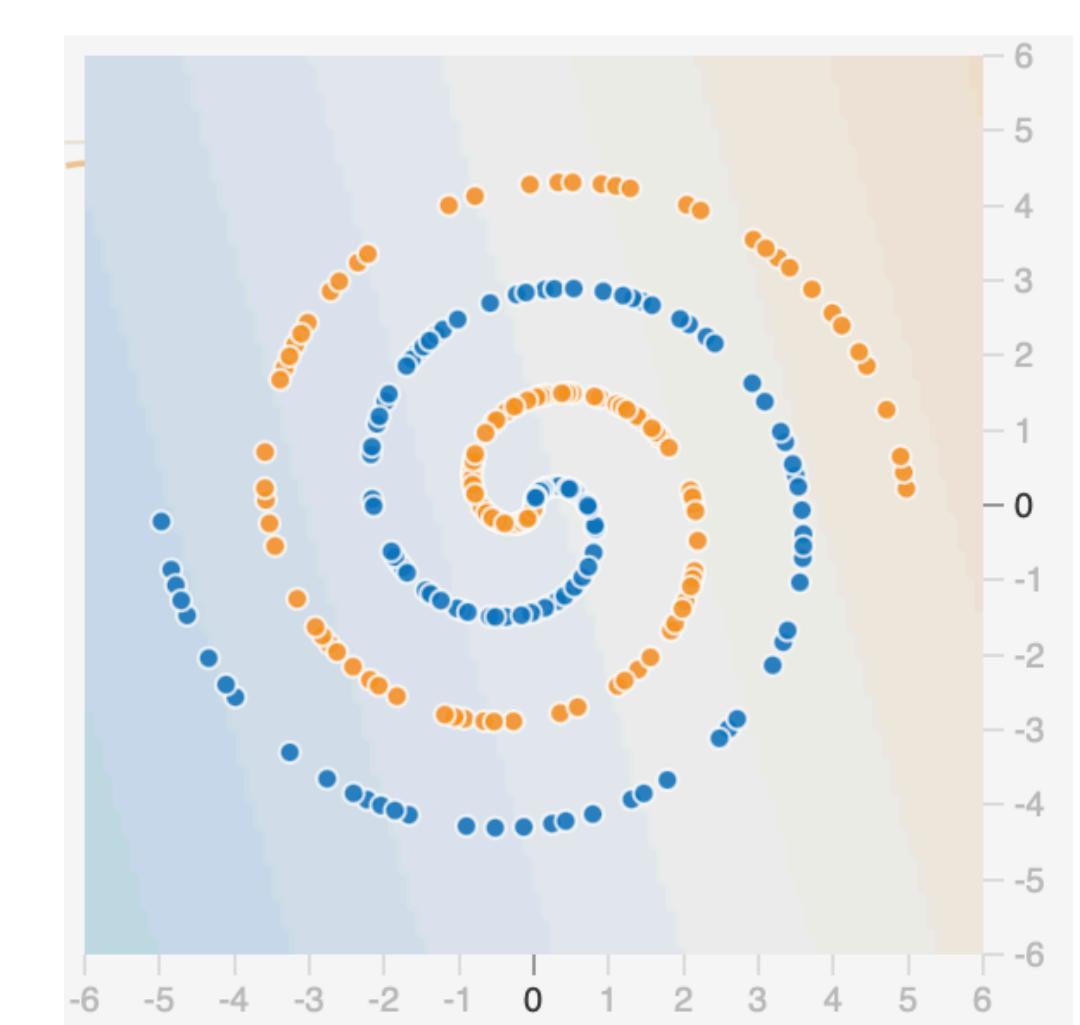
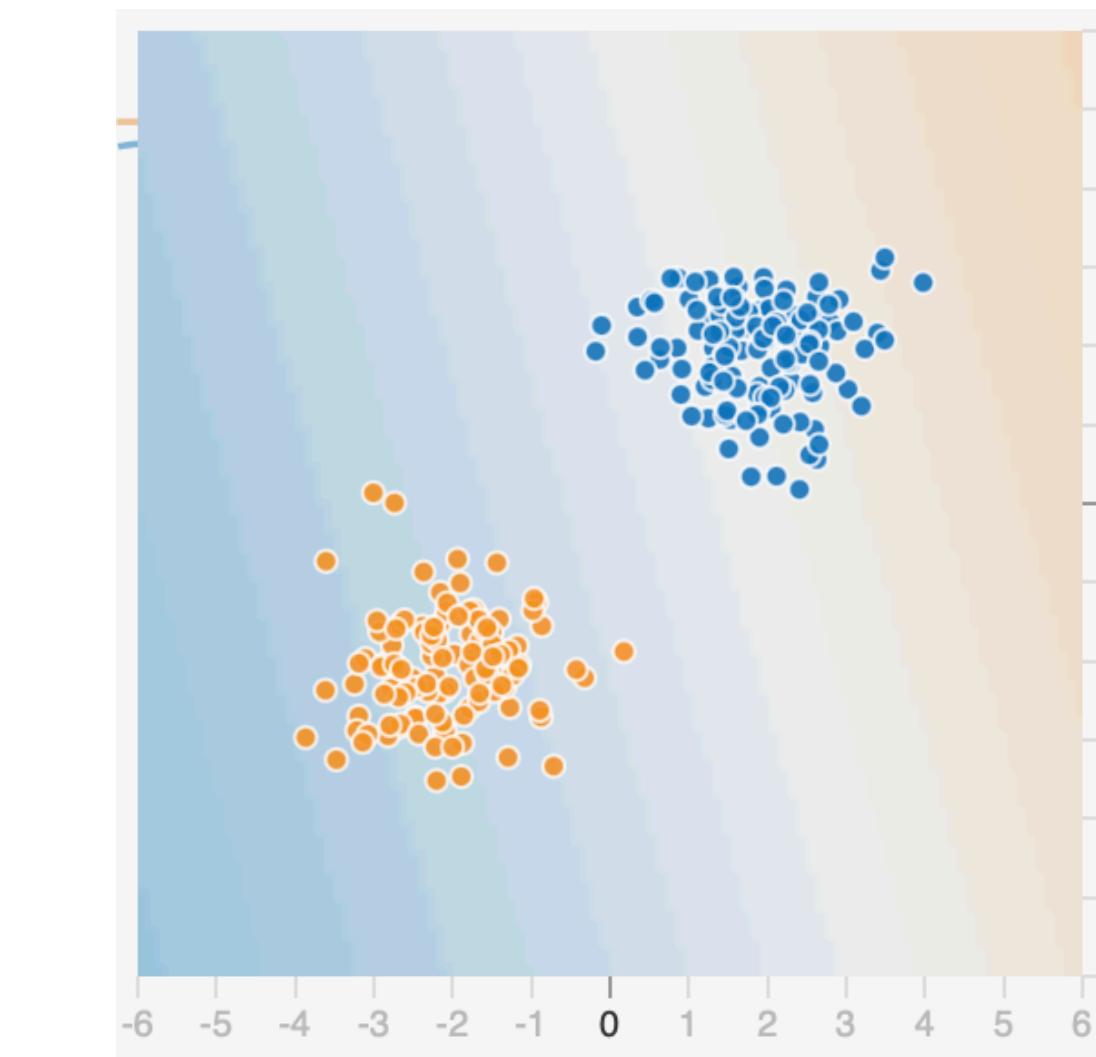
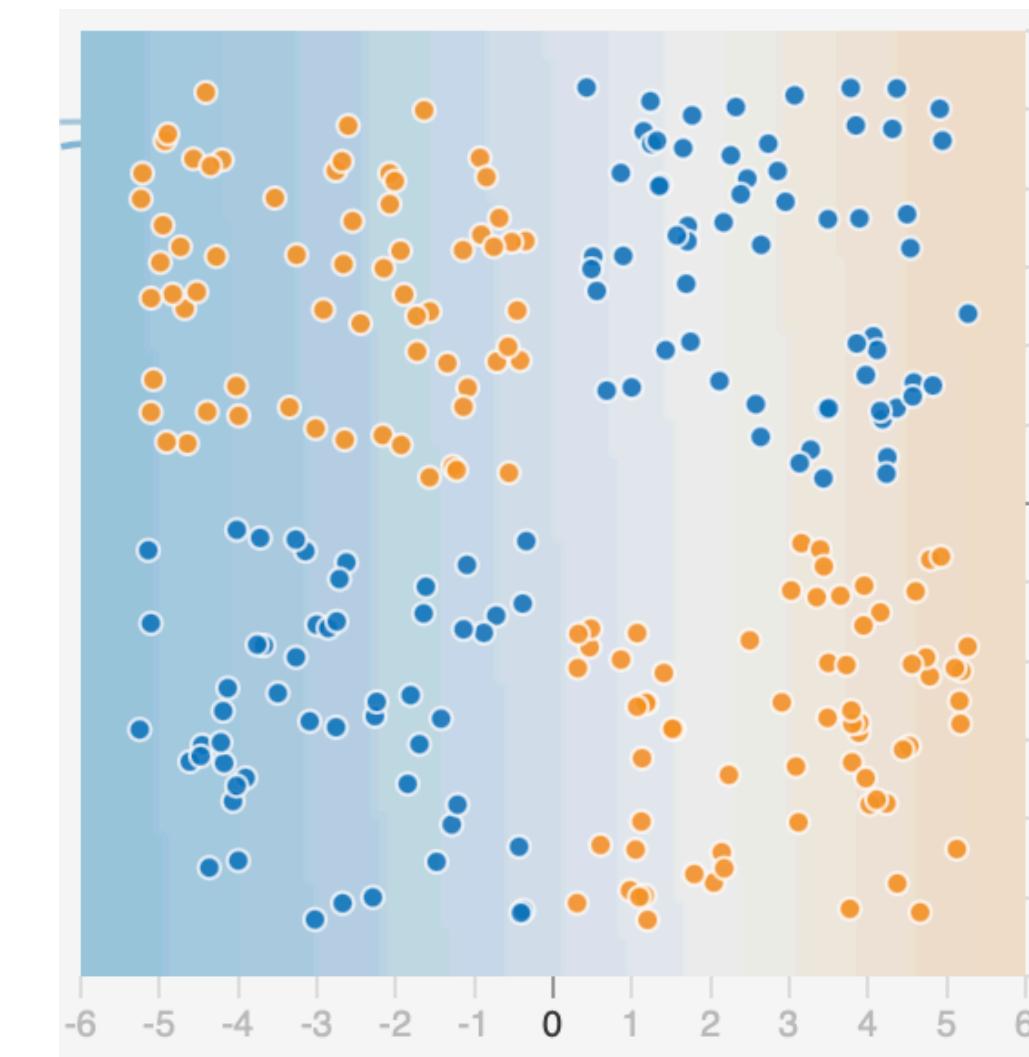
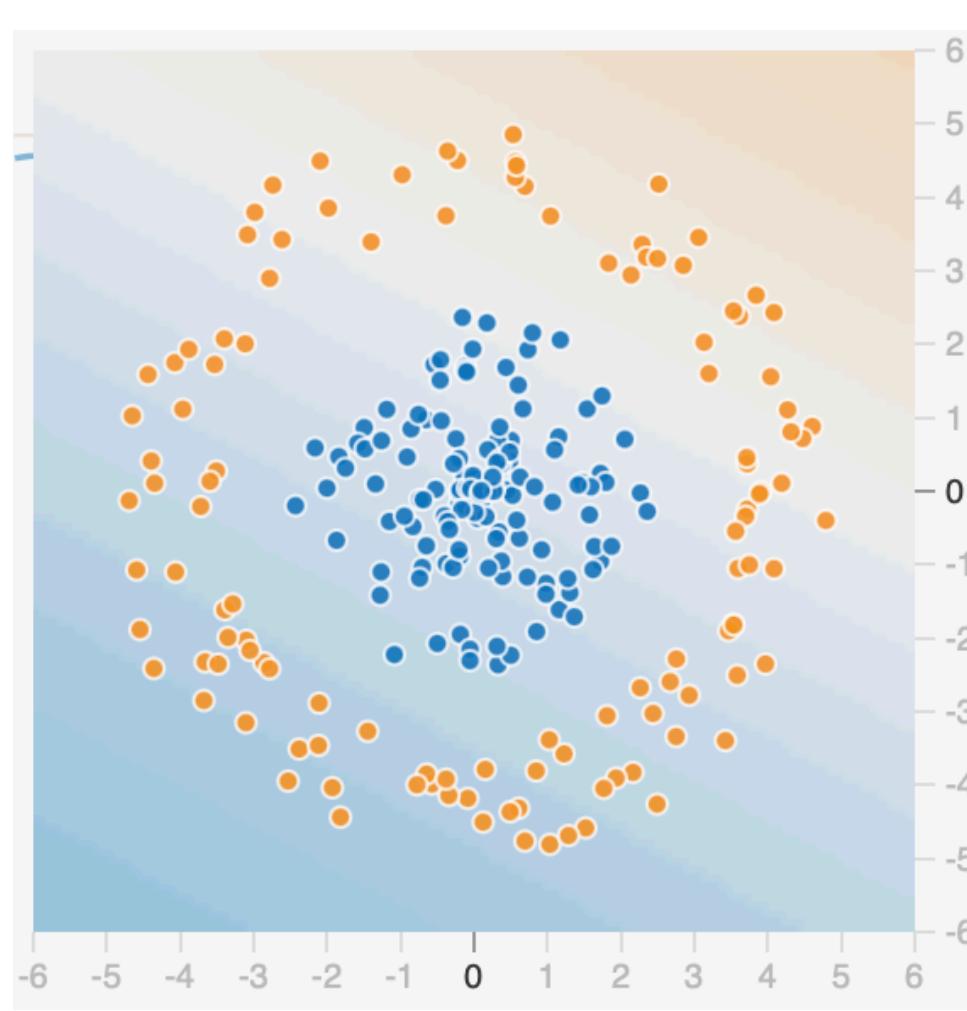


Time to Play!

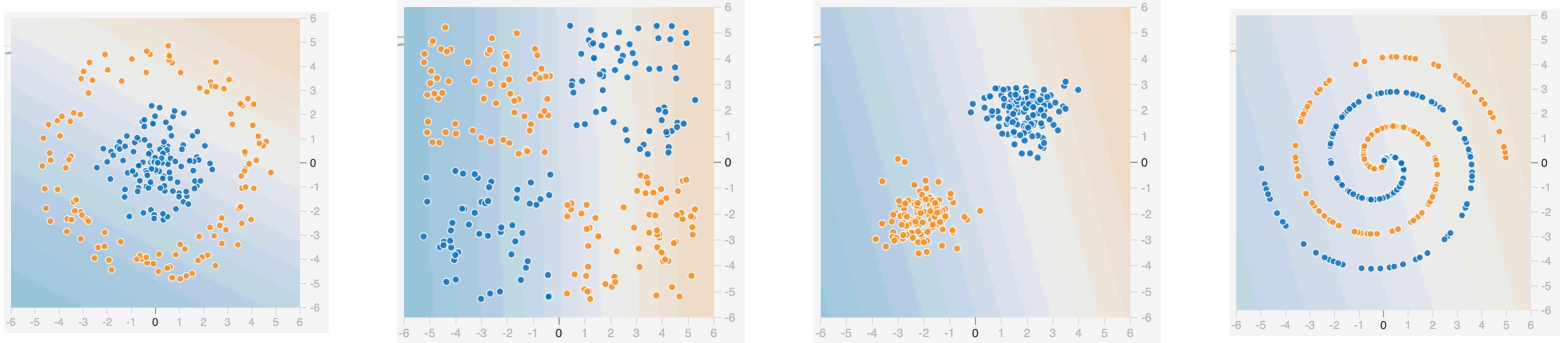
Let's go to the playground:
<https://bit.ly/anntest>

Let's Start with the Four Problems

Solving Classification Problems Using Artificial Neural Networks



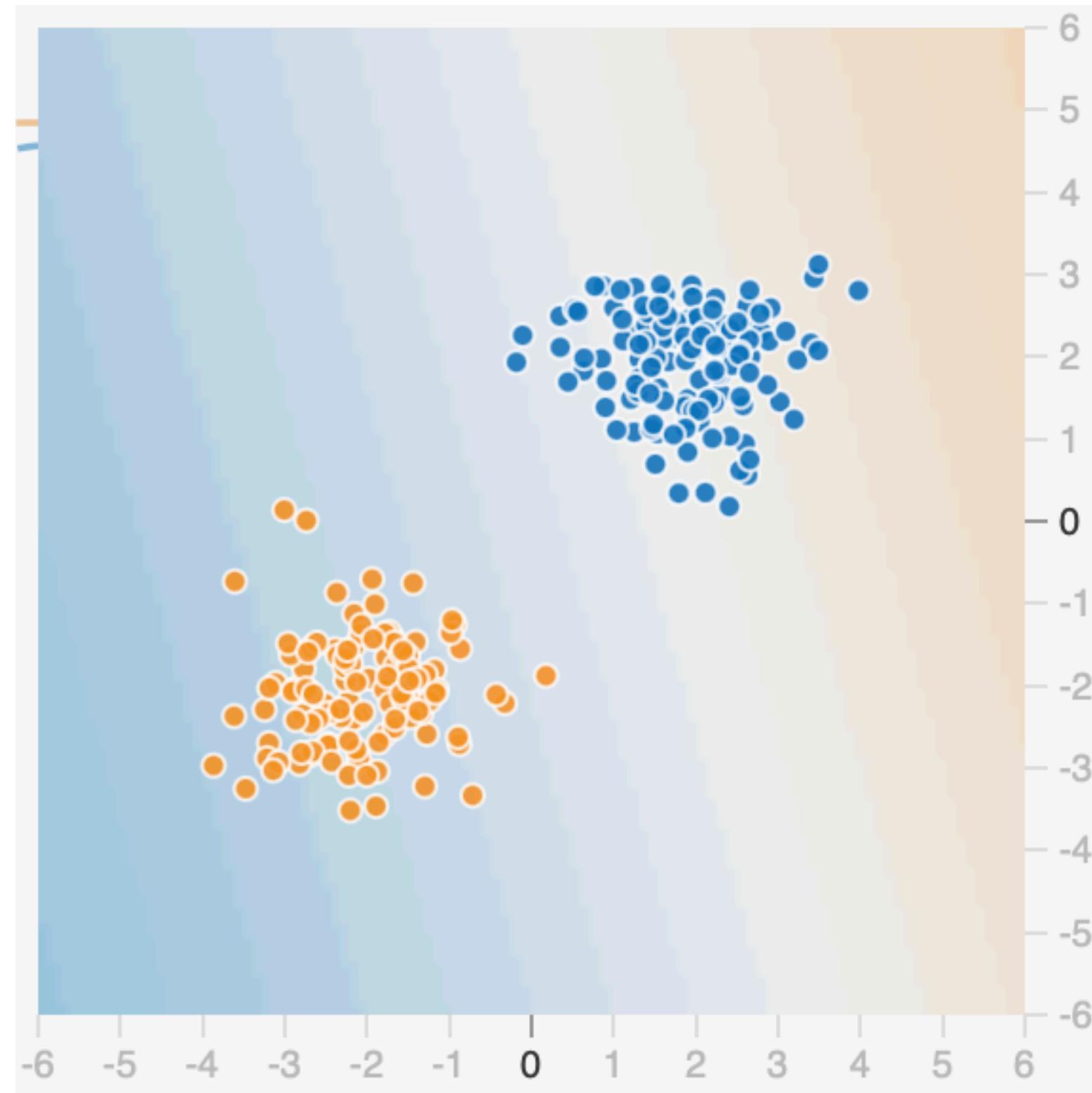
Are They Linearly Classifiable?



Definition: A pattern is **linearly classifiable** if there exists one line in the plane such that (1) all the blue dots are on one side of the line and (2) all the yellow dots are on the other side.

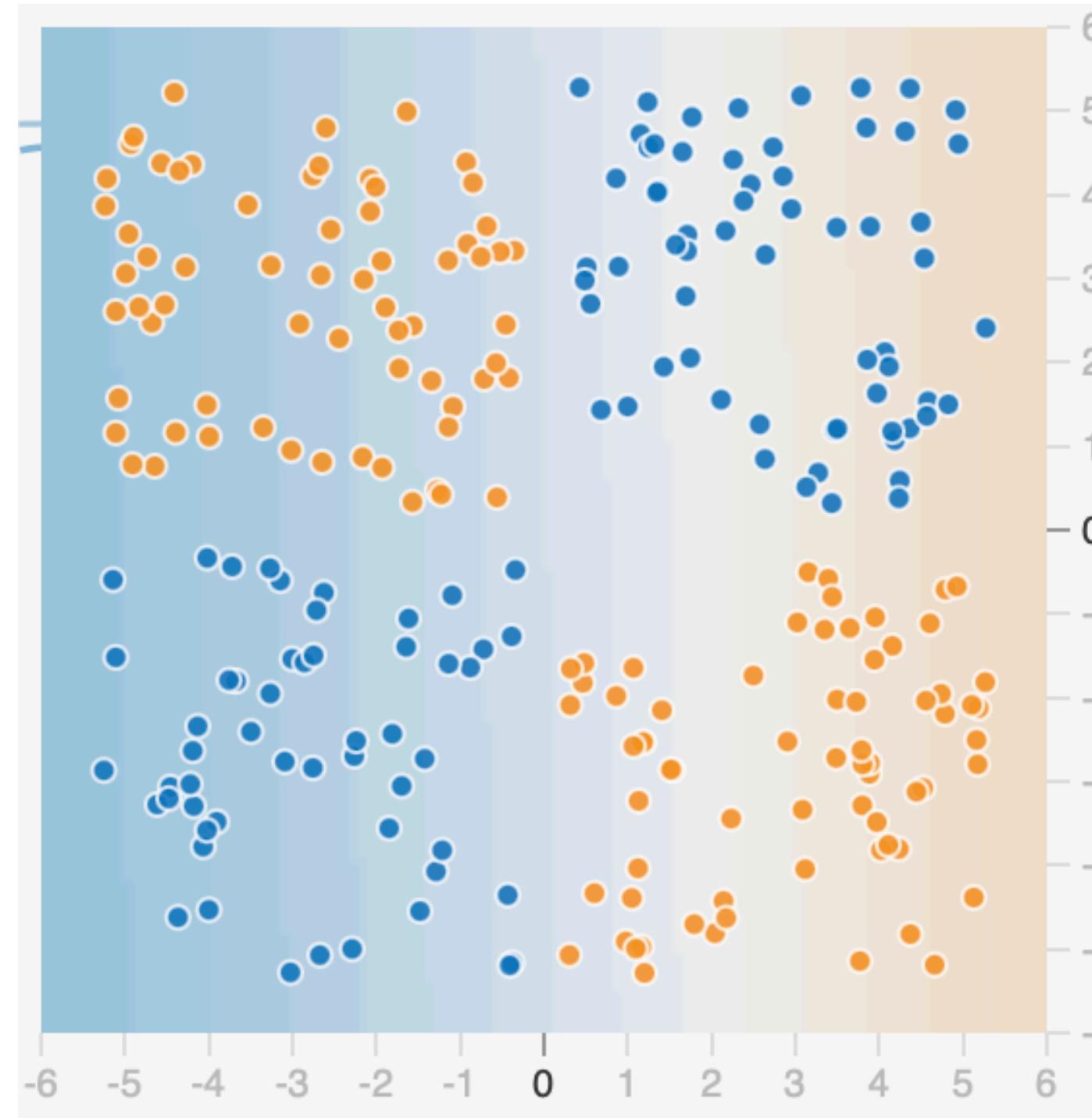
Which of these patterns are **linearly classifiable**?

Task 1: Learning a Linearly Classifiable Pattern



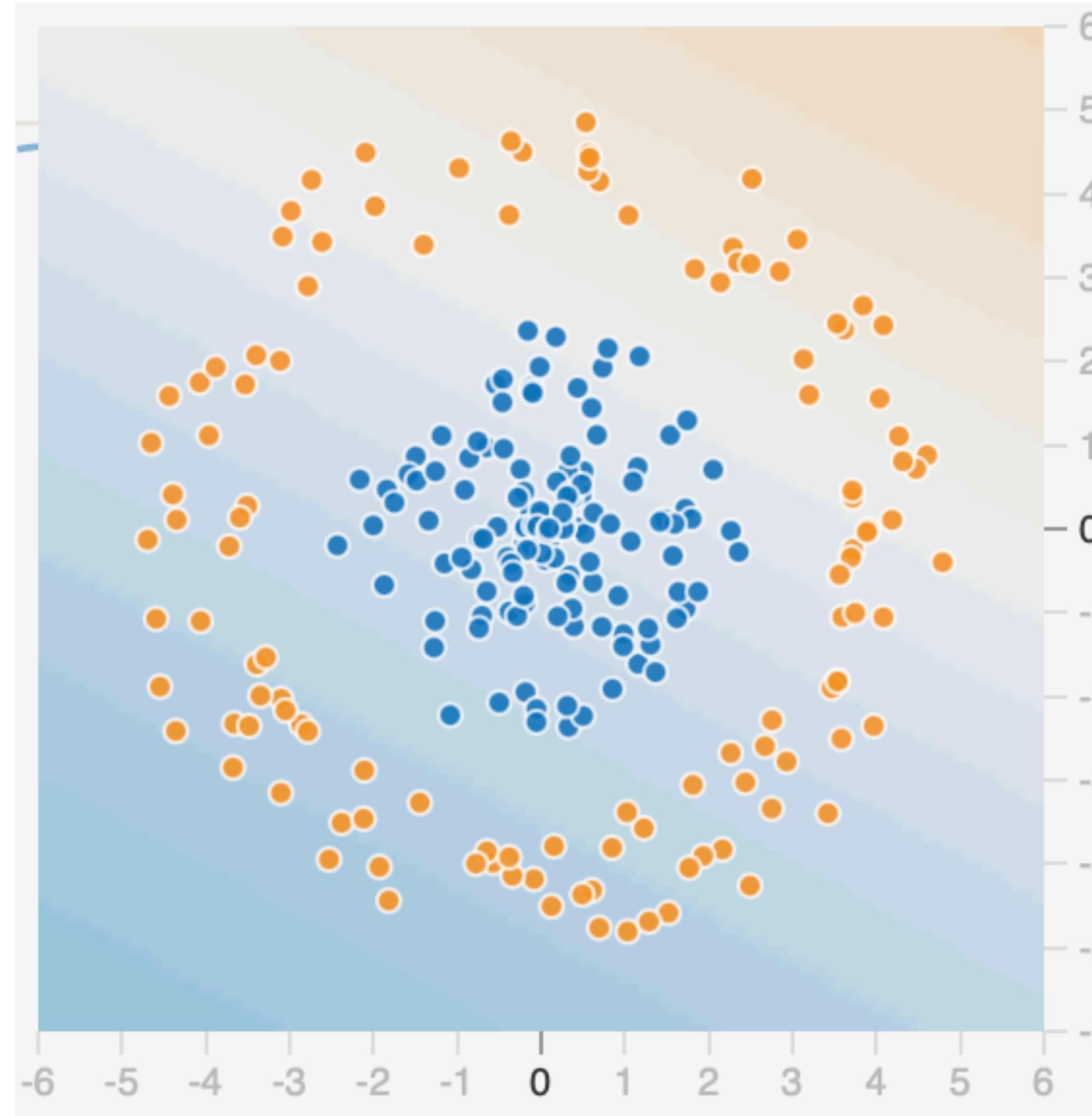
- Try different activation functions
 - ReLU
 - Tanh
 - Sigmoid
 - Linear
- Does it matter which activation function we use?

Task 2: Learning a Non-Linearly-Classifiable Pattern



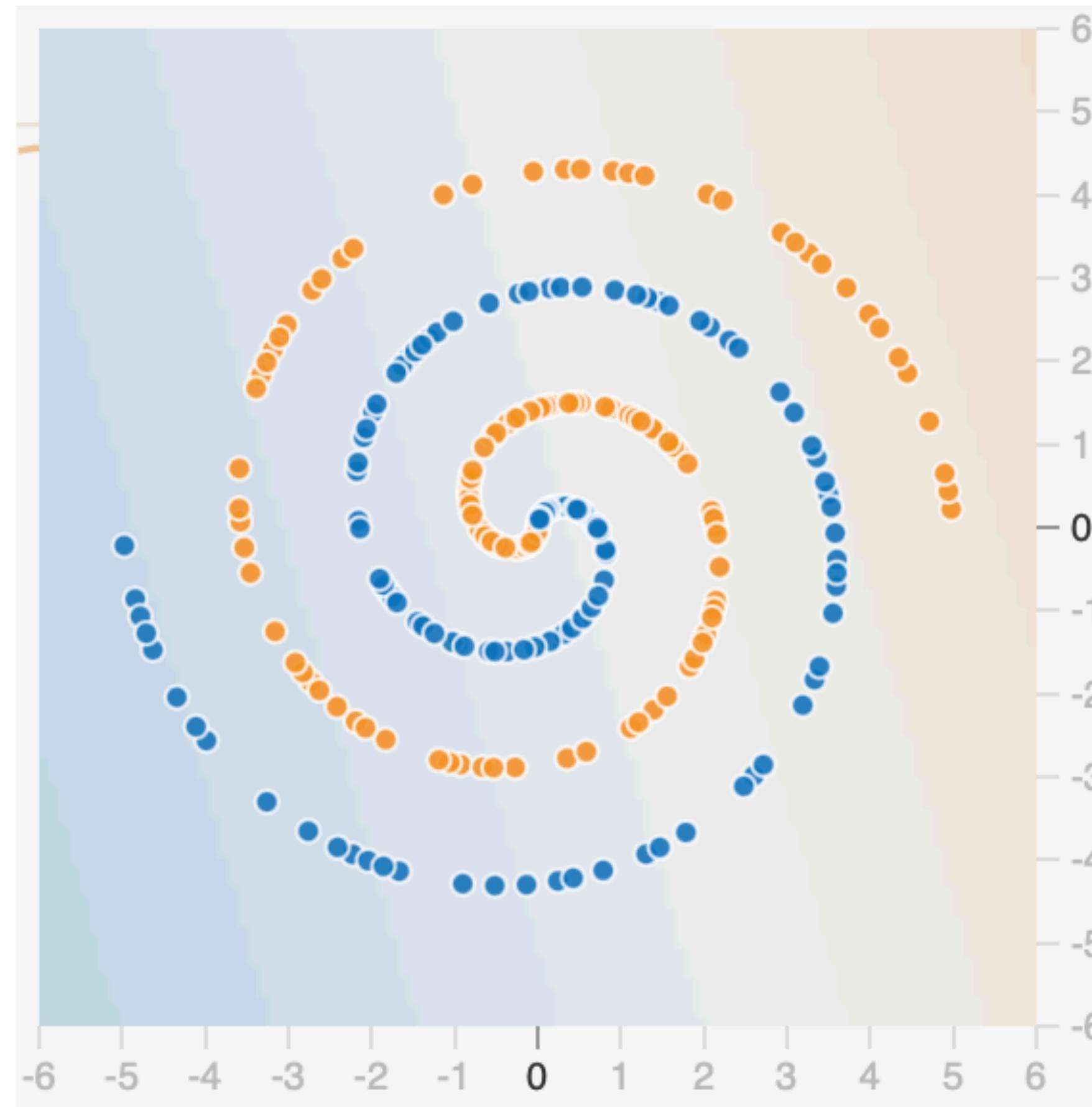
- Before each trial, hit the Reset the network button to get a new random initialization
- Start with a Linear activation function. Does it work? Why?
- Try other activation functions
 - ReLU
 - Tanh
 - Sigmoid
- Try different learning rates (0.00001, 0.003, 1, 10)

Task 3: Try a More Challenging Classification Problem



- Start with a Linear activation function. Does it work? Why?
- Try other activation functions
 - ReLU
 - Tanh
 - Sigmoid
- Try different learning rates (0.00001, 0.003, 1, 10)

Task 4: Learning A Spiral Pattern



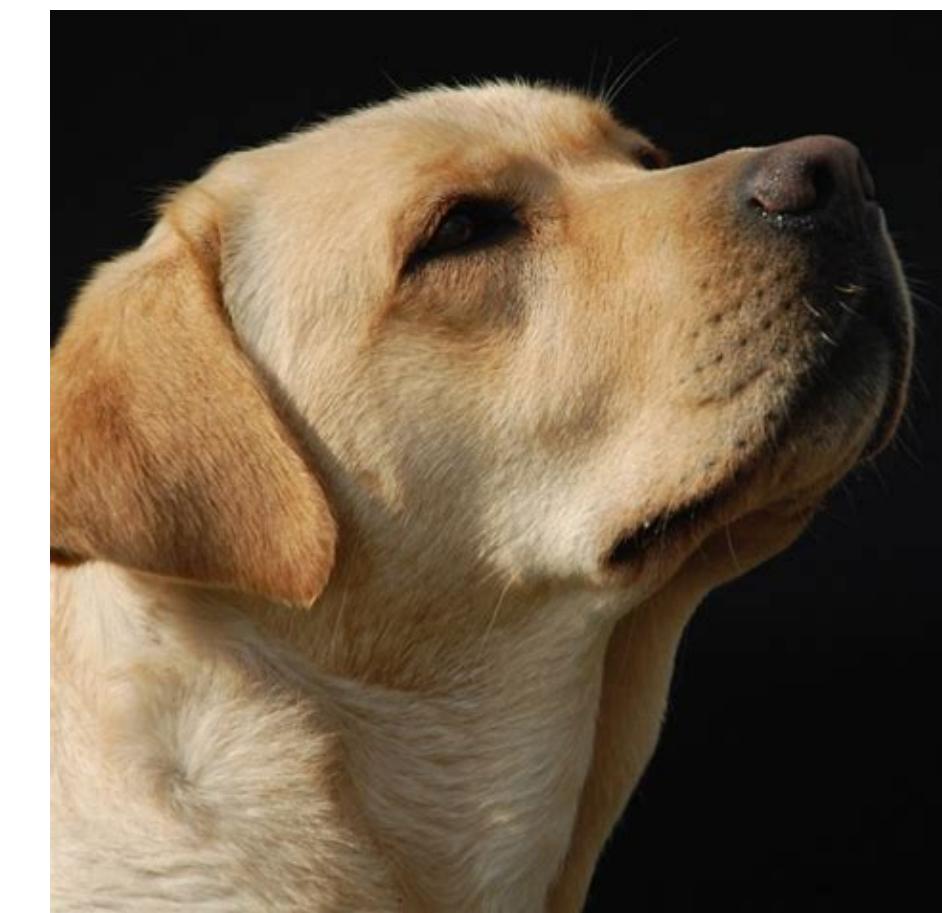
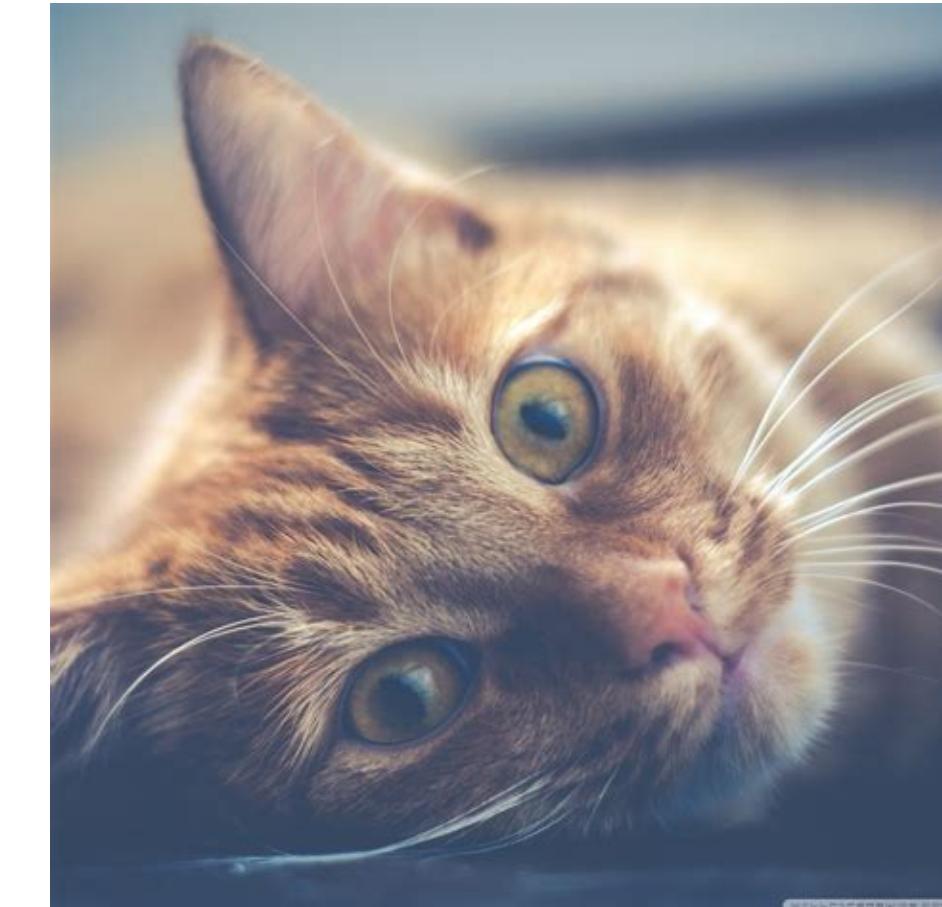
- Try other activation functions
 - ReLU
 - Tanh
 - Sigmoid
- Try different learning rates (0.00001, 0.003, 1, 10)
- Can you generate observations about when the model overfits or underfits?

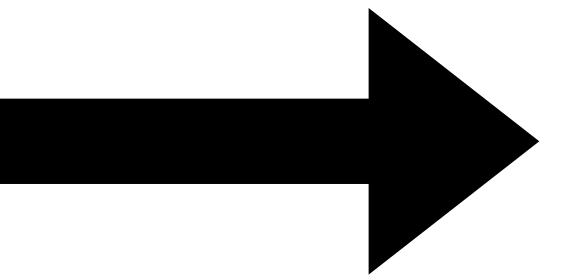
Let's now work *individually* to work on these tasks:

<https://bit.ly/anntest>

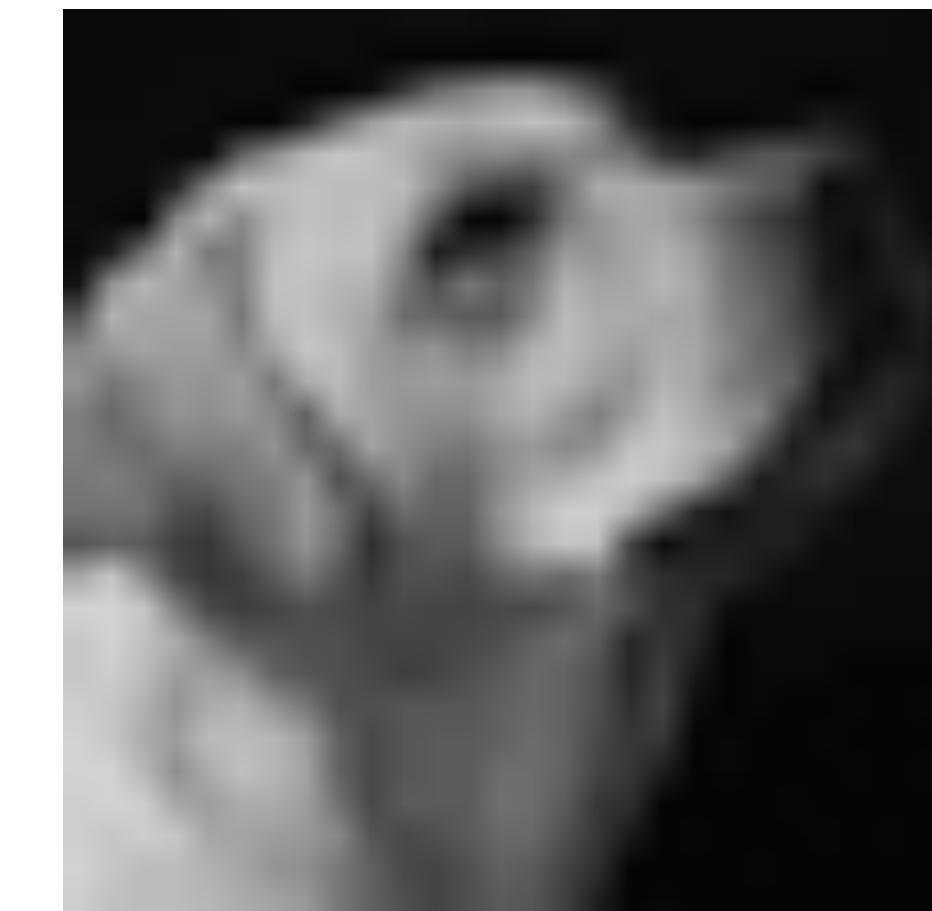
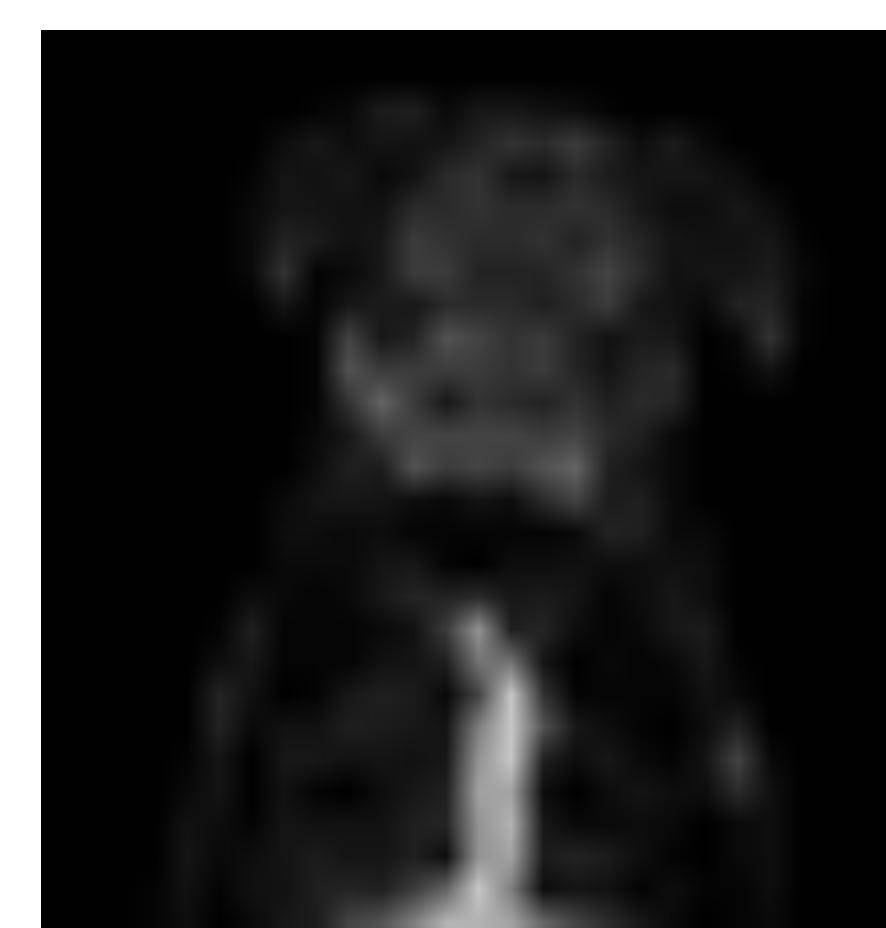
Time: 7 minutes

Can Feedforward Neural Network Recognize Cats or Dogs?

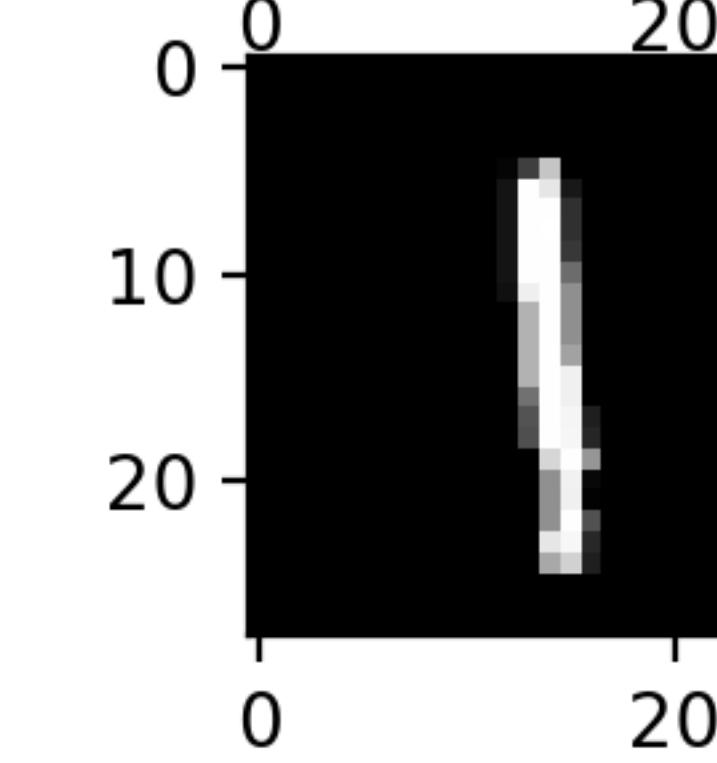
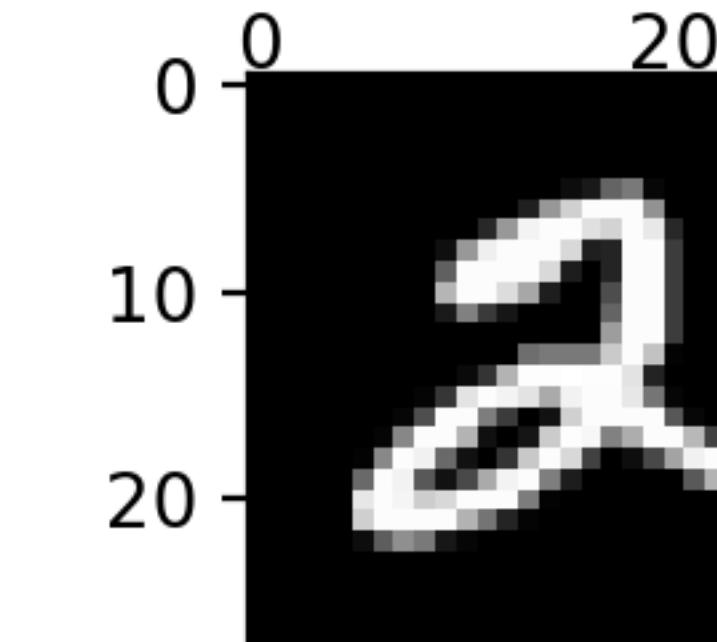
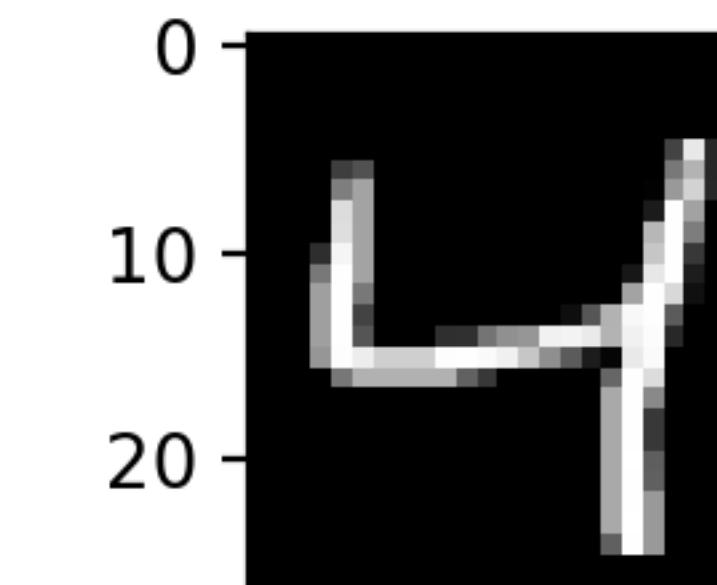
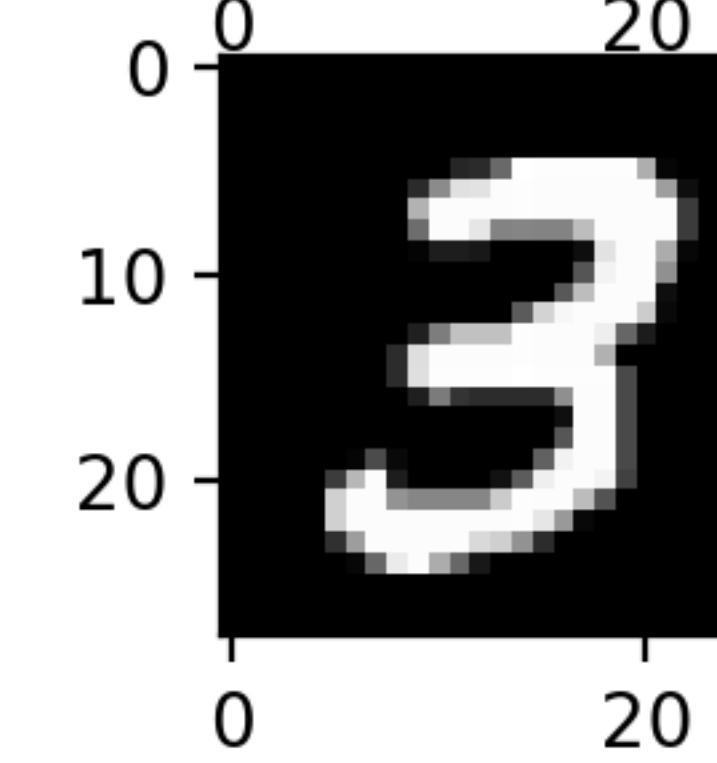
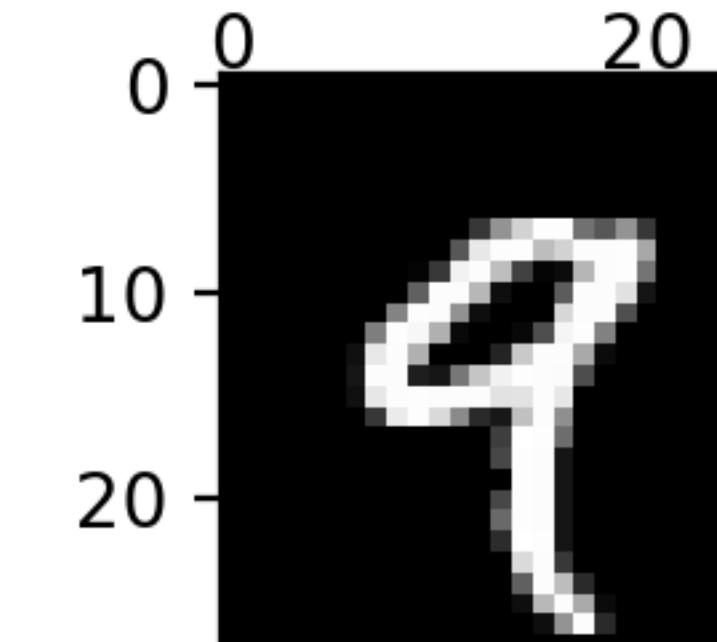
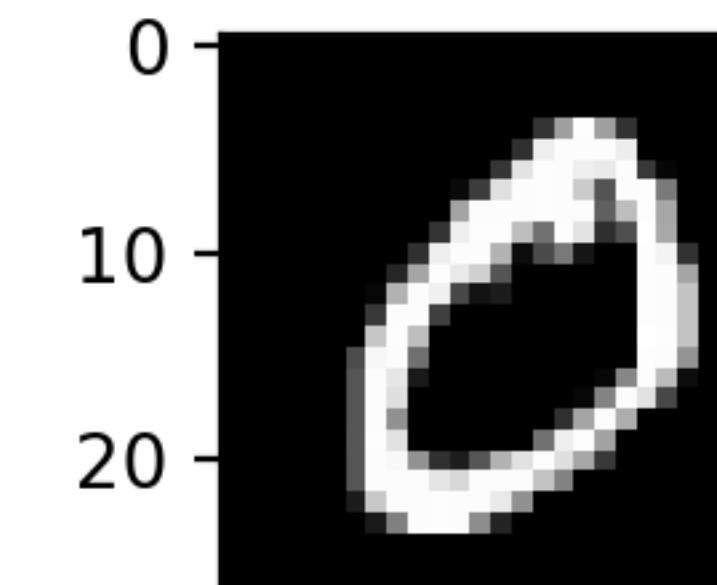
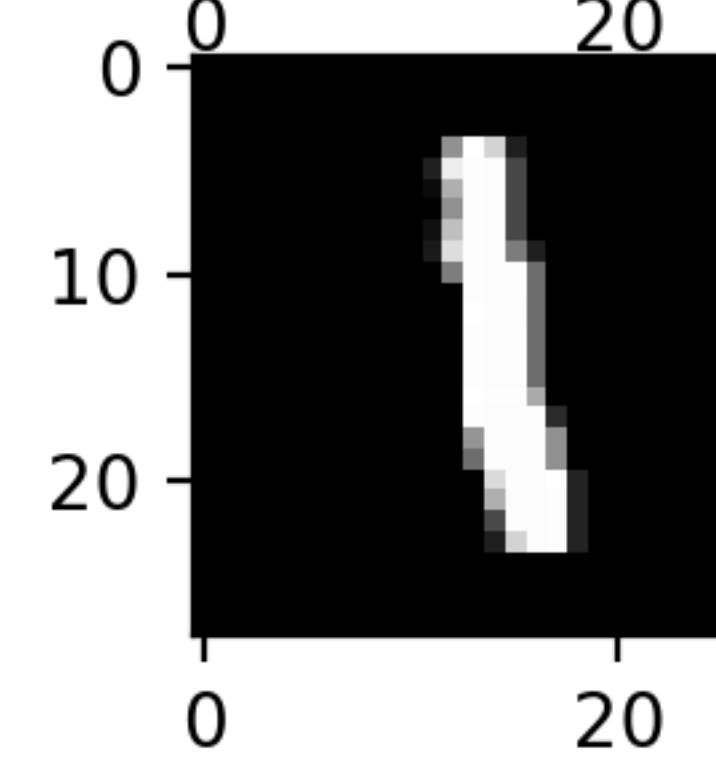
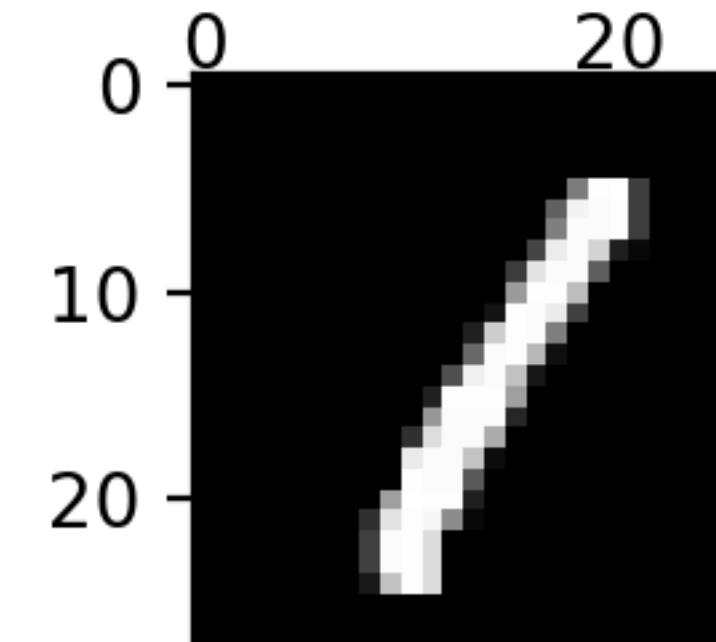
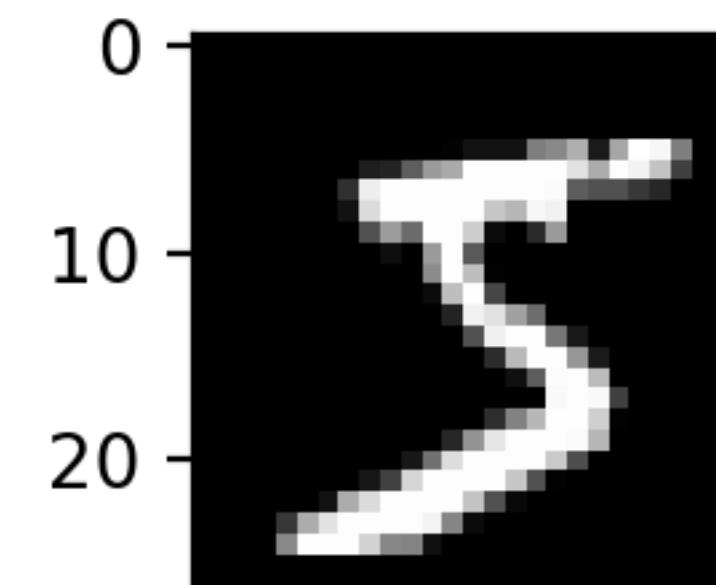




Can Feedforward Neural Network Recognize Cats or Dogs?

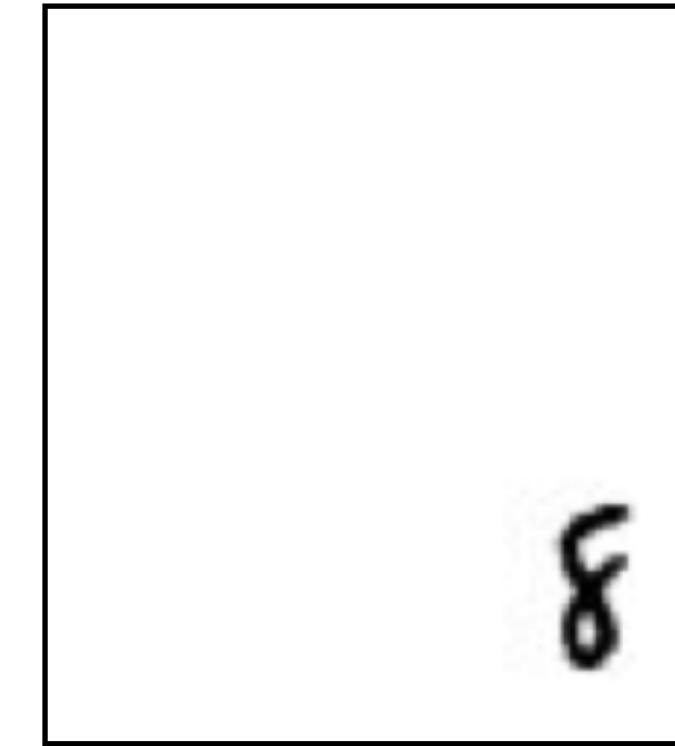
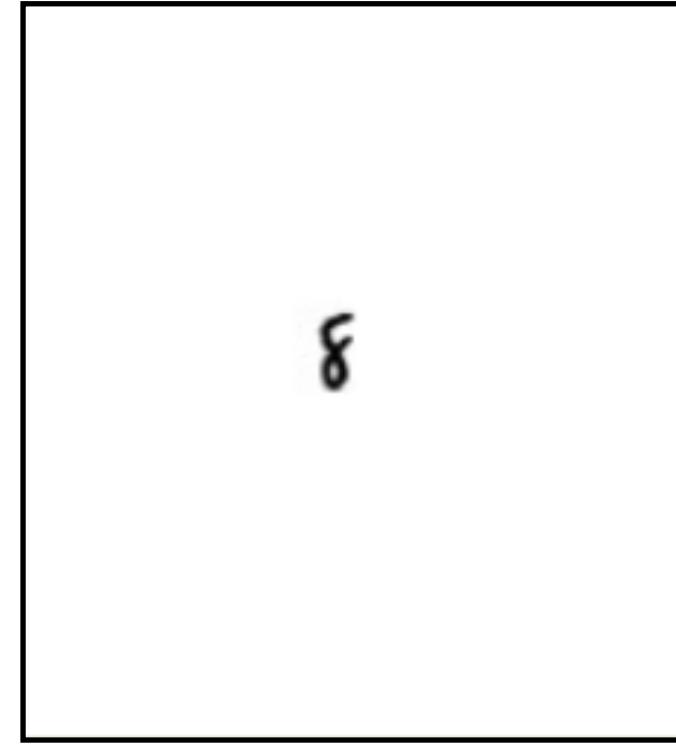
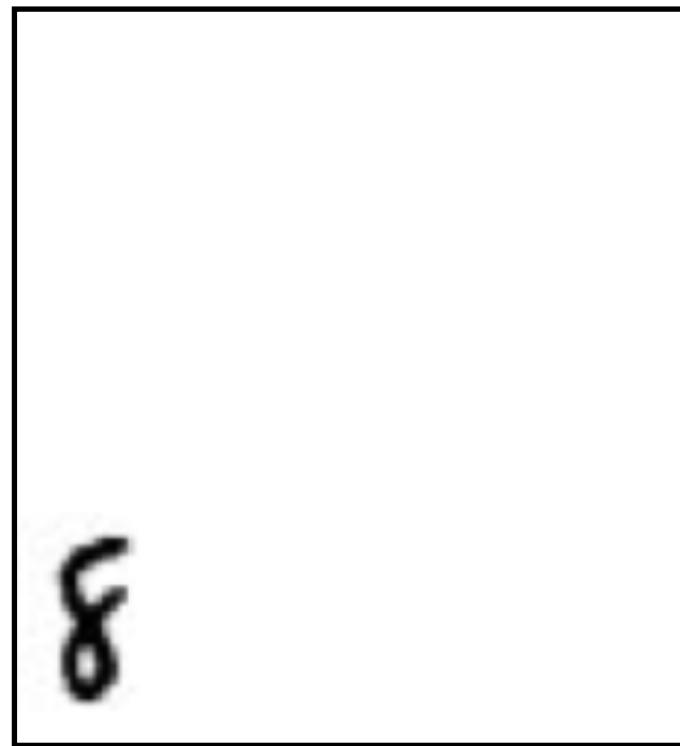
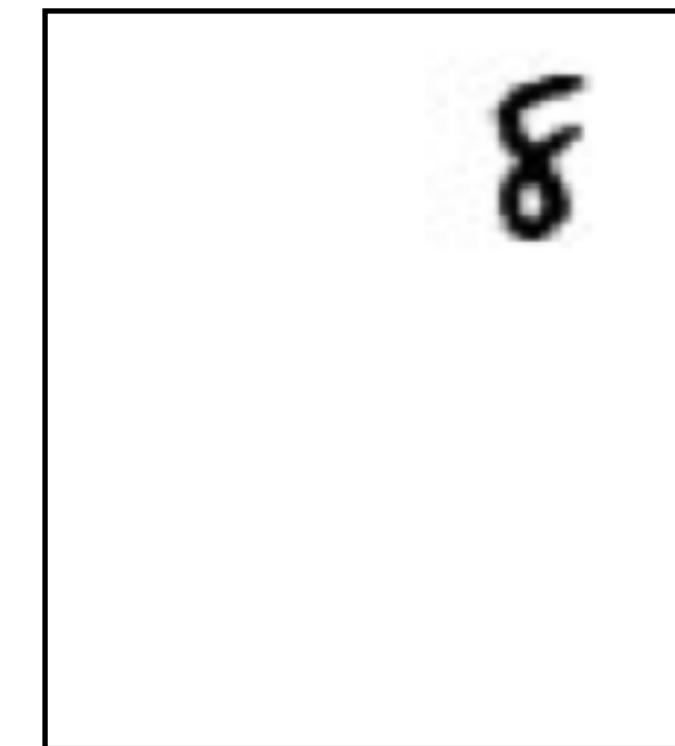
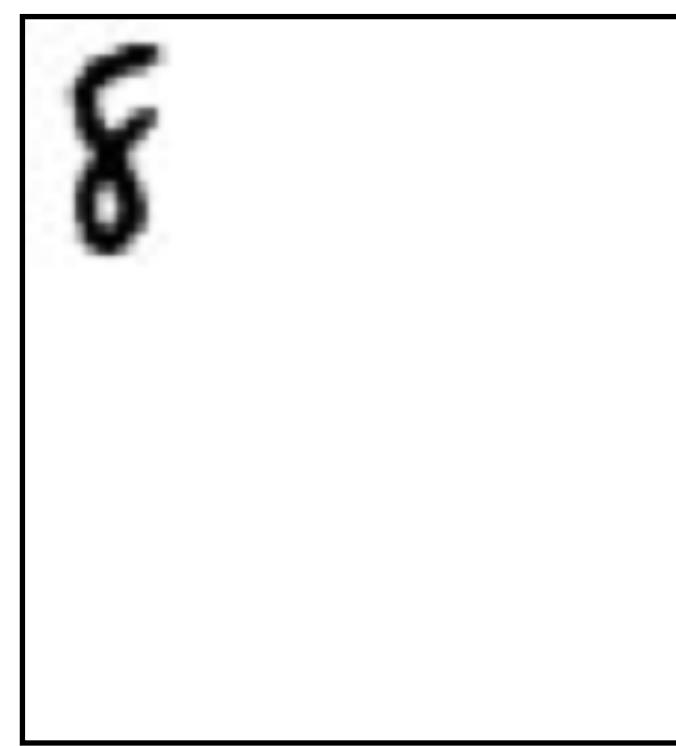
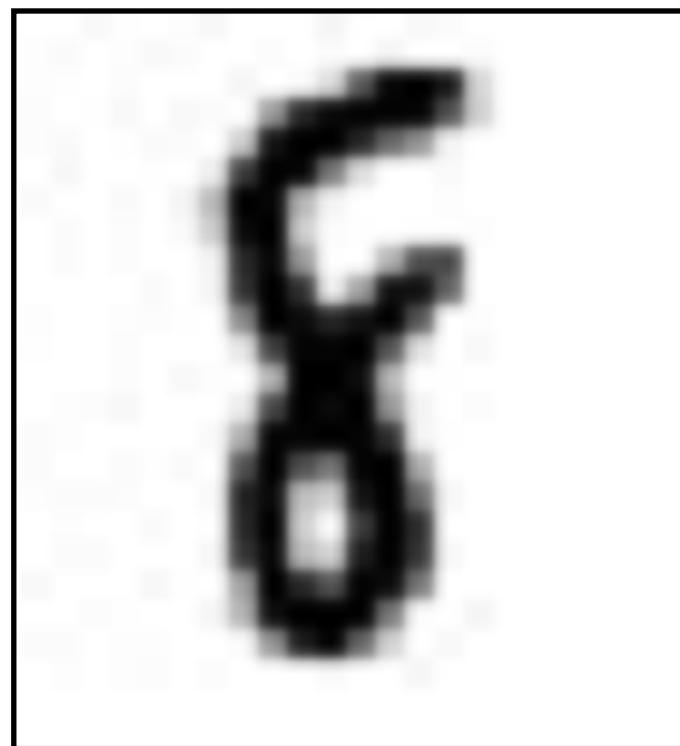
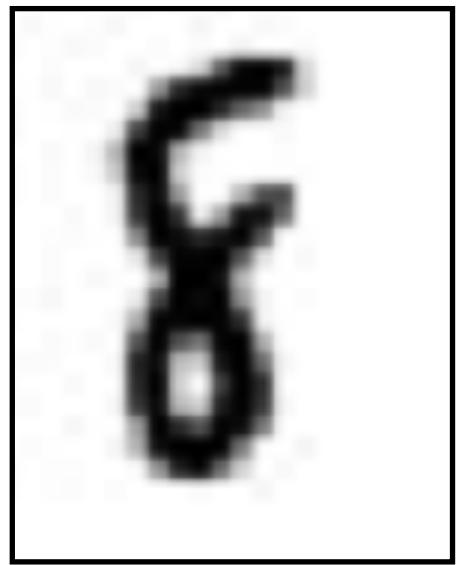


What about the MNIST Dataset?



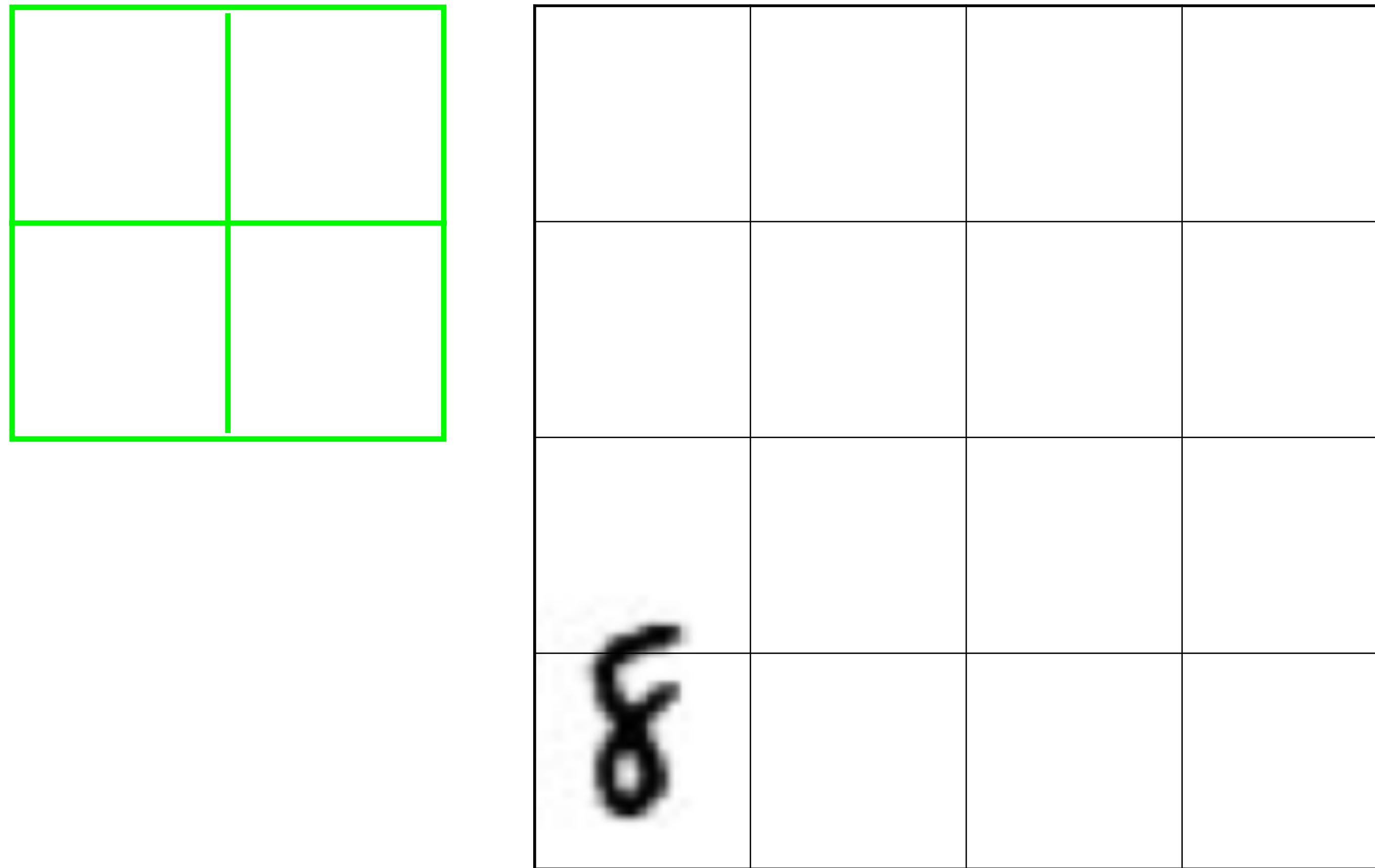
Practical Training Images

Original Training Image



How to “catch” the crucial information from ALL of these practical images?

Core Idea: Search with a “Sliding Window”



Convolutional Neural Networks (CNN)

- The “convolutional” part does the job of the sliding window
- The convolution step:

Convoltional filter

1	1
0	1

Input Feature Map

\mathbf{x}_0	\mathbf{x}_1	1	1
\mathbf{x}_0	\mathbf{x}_0	0	1
0	0	1	0
0	0	0	0

Output Feature Map

1	2	3
0	1	1
0	1	1

Exercise: Construct the Output Feature Map

What is the shape of the output feature map?

Convolutional filter

1	0	1
0	1	0
1	0	1

Input Feature Map

0	1	1	1
0	0	0	1
0	0	1	0
0	0	0	0

Output Feature Map

2	2
0	2

Are These Two Letters Identical?

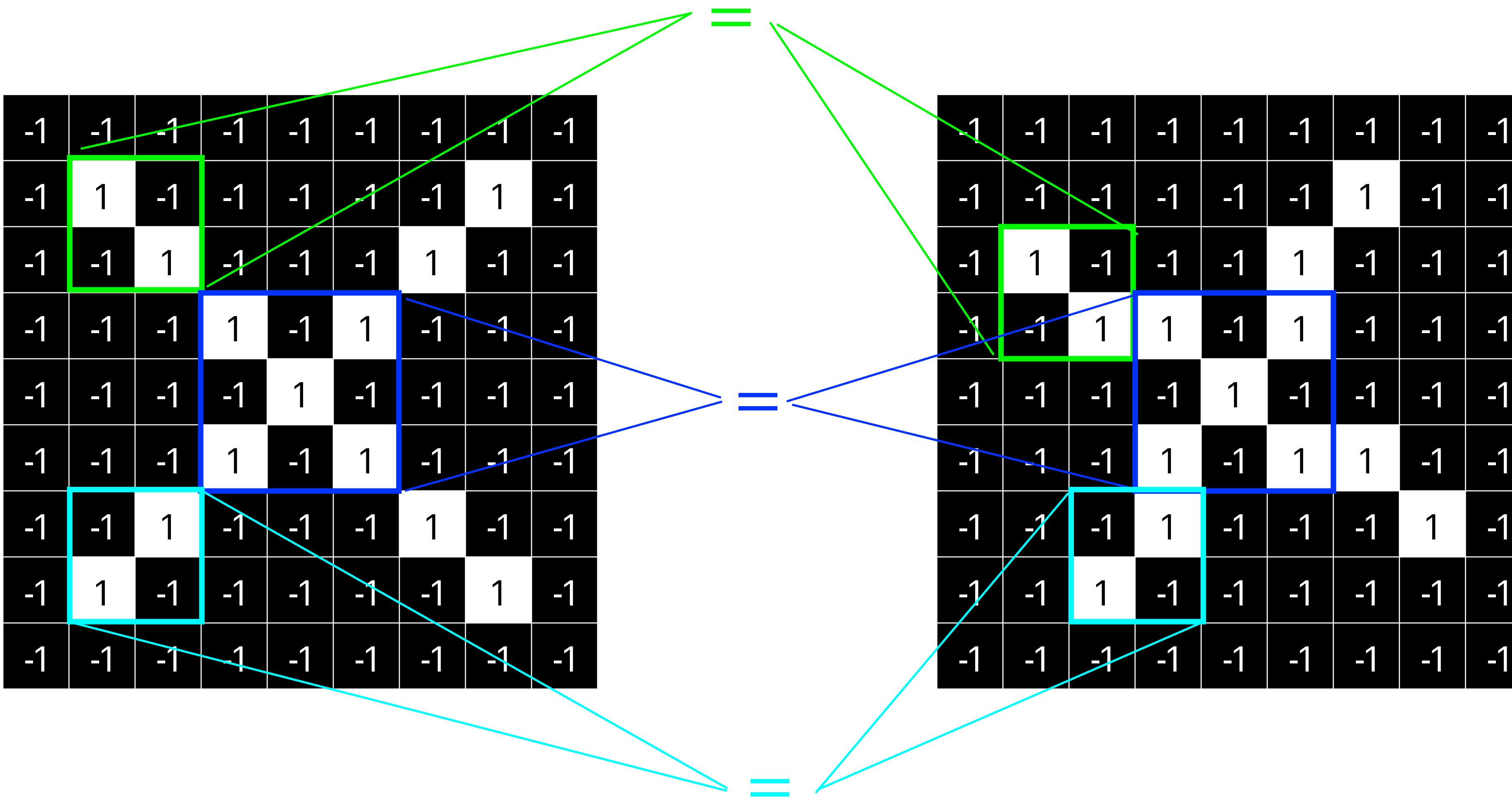
-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	1	-1
-1	1	-1	-1	-1	-1	1	-1	-1
-1	-1	1	1	-1	-1	1	-1	-1
-1	-1	-1	1	1	-1	1	-1	-1
-1	-1	-1	-1	-1	1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	1	-1	-1	1	1	-1
-1	-1	-1	1	1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Unfortunately, for a computer, the above two images can represent two very different patterns

We need to figure out a way for the computer to recognize shifted, shrunk, rotated, or deformed images.

Fundamental Features of Letter X



We Can Detect These Features Using Filters

Convolutional filter

1	-1	-1
-1	1	-1
-1	-1	1

Input Feature Map

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Apply the convolution operation:

$$= 9$$

We Will Dive Deeper Into
Convolutional Neural Networks (CNN)
Next Class

Why Python?

- Python is likely the easiest programming language to learn and it's completely free
- Python is expressive and powerful
- Python is **the language for artificial intelligence**
- Python is the most demanded programming language on the job market



An open-source software library for machine learning (esp. deep learning) and artificial intelligence. It's developed by Google in 2015

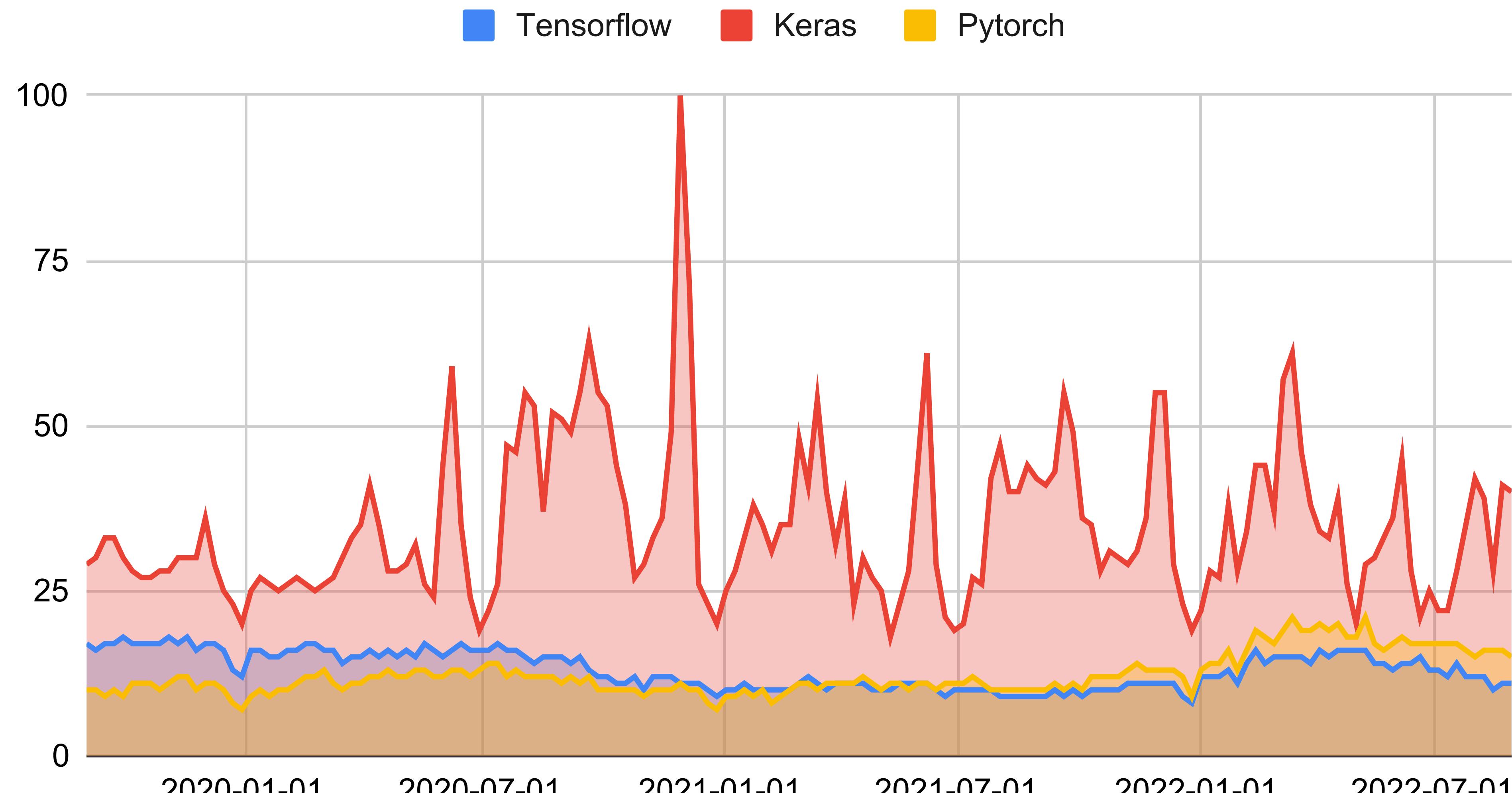


An open-source software library that provides Python interfaces to TensorFlow. It's developed in 2015 by **François Chollet**, a Google engineer and suitable for fast experimentation with deep neural networks

PyTorch



An open-source software library for machine learning (esp. deep learning). It's developed by Facebook in 2016 and provides a Python interface to Torch.



Worldwide Popularity of TensorFlow vs. Keras vs. PyTorch (2019–2022)

Source: Google Trends

Feedforward Neuron Network in Keras

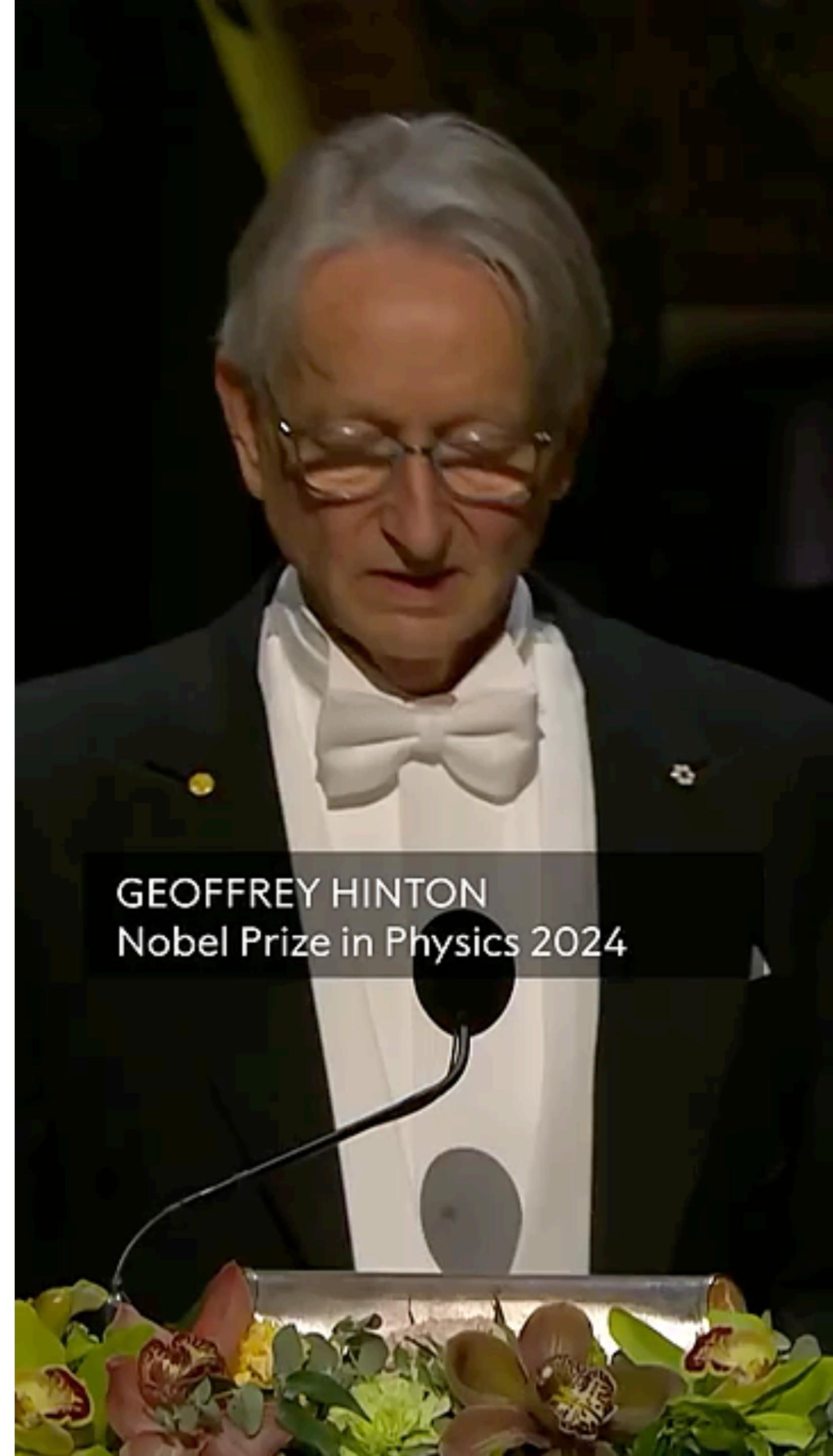
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

model=keras.Sequential([
    layers.Dense(512, activation = "relu"),
    layers.Dense(10, activation = "softmax")
])
```

An Initial Taste of Deep Learning Using Python:

<https://bit.ly/aisession3>

We are Doomed...



GEOFFREY HINTON
Nobel Prize in Physics 2024

NEW YORK TIMES BESTSELLER

“*Sapiens* tackles the biggest questions of history and of the modern world, and it is written in unforgettably vivid language.”

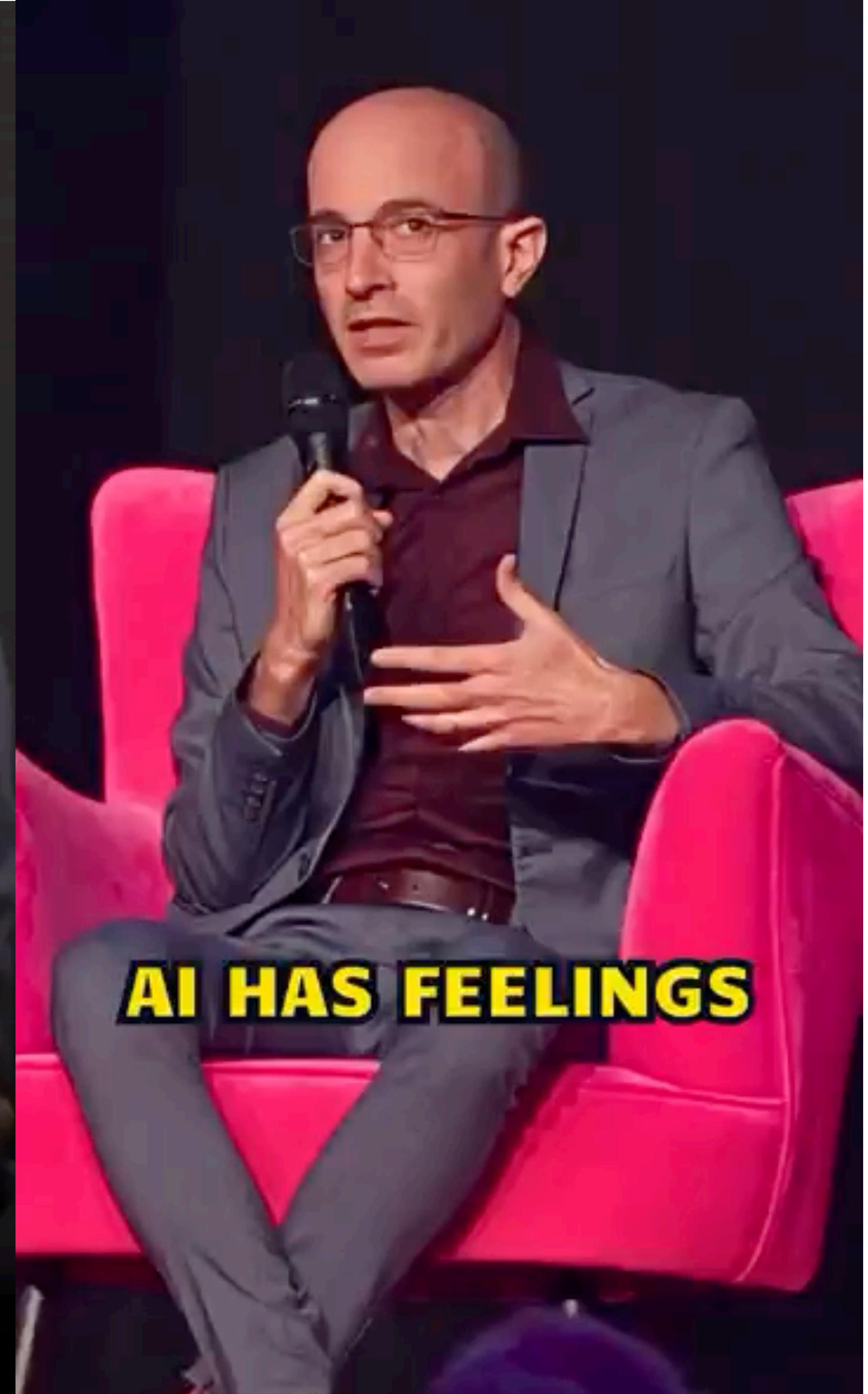
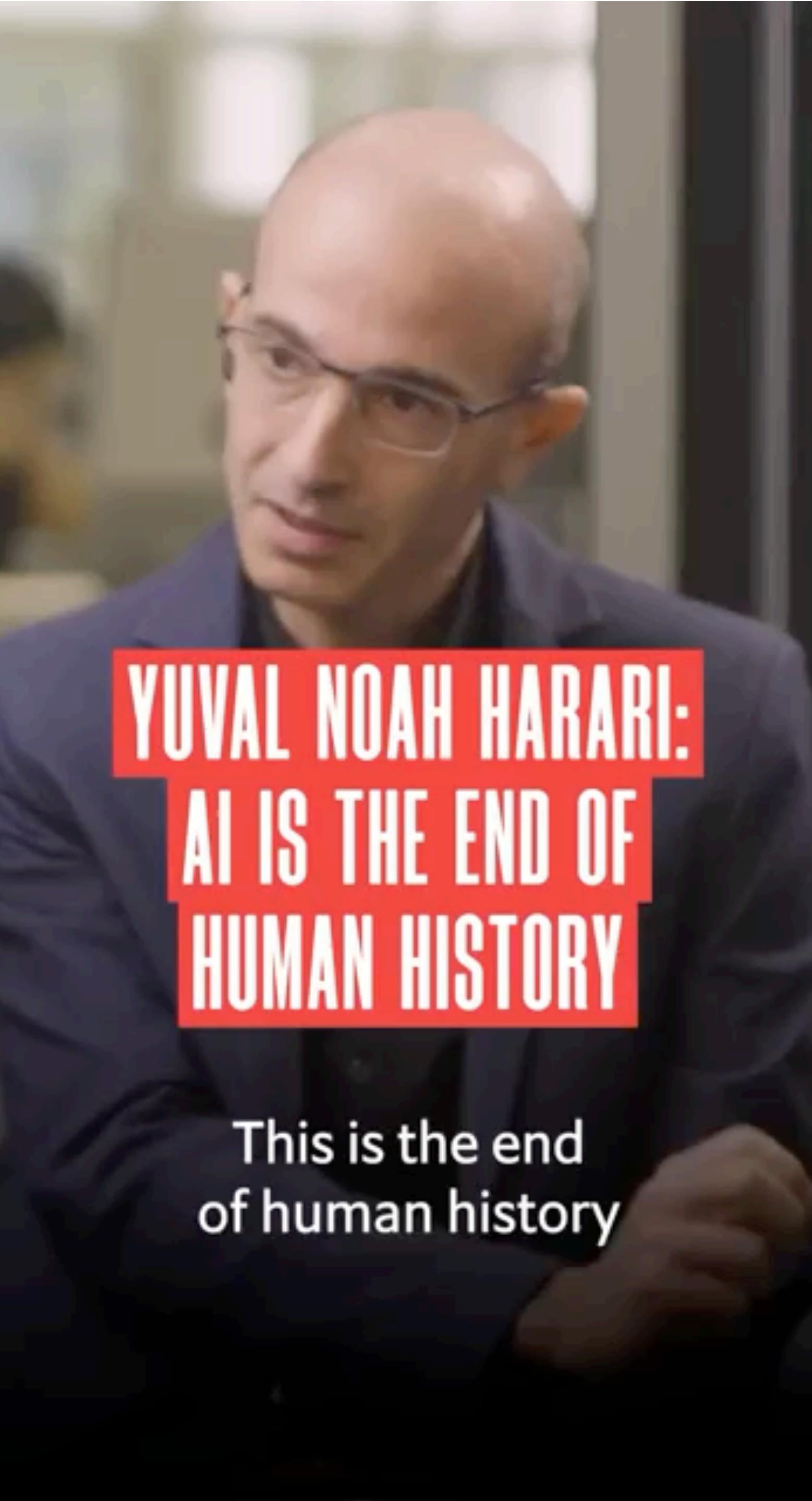
—JARED DIAMOND, Pulitzer Prize-winning
author of *Guns, Germs, and Steel*

Yuval Noah Harari



Sapiens

A Brief
History of
Humankind



Until Next Class

- **Group Assignment #1** due one hour before Session 3
- TA Tutorial on **Python Basics**
 -  Friday, 10/31, 12:00–1:00 PM
 -  Join via Zoom: <https://bit.ly/jhuaita25>
 - Attendance is optional. Materials will be posted on Canvas
- Refer to Syllabus for **Session 3 Readings**



Thank You!