# **Lecture 1:** Introduction

CIS 4190/5190

Spring 2025

# Agenda

- **Logistics**
  - Course description
  - Tentative Schedule
  - Grading
- **Introduction**
  - Motivation
  - Basic definitions
  - Examples

# Description

- **Key skills**
  - Understand the standard machine learning algorithms
  - Identify opportunities for applying machine learning (ML) algorithms
  - Diagnose and debug issues in ML models
- Lectures will focus on developing mathematical understanding
- Assignments will focus on applying this understanding to implementing ML solutions

# Prerequisites

- **Math:** University-level courses in probability, linear algebra, and multivariable calculus
  - Understand how to compute $\nabla_A(Ax)$ for a matrix $A$ and vector $x$
  - Understand matrix ranks, inverses, and eigenvalues
  - Understand prior and posterior probabilities, $\mathbb{E}[X] = \int p(x)dx$, etc.
  - Tested in HW 1 (more on this later)

- **Programming:** Previously coded up projects (preferably in Python) that were at least 100 lines of code long
  - We have made available a Python primer on the course website for students who know how to program but do not know Python

# Course Comparisons

- **CIS 4190/5190 (this course)**
  - Basic mathematical ideas behind ML
  - Apply existing ML algorithms to new problems as an engineer or researcher
- **CIS 5200**
  - Deeper, more mathematically demanding introduction to ML
  - Perhaps do fundamental ML research in the future

Also see: https://priml.upenn.edu/courses

# Course Comparisons

- **CIS 4190/5190 (this course)**
  - Basic mathematical ideas behind ML
  - Apply existing ML algorithms to new problems as an engineer or researcher
- **CIS 5220**
  - Deep learning techniques and applications in more detail

Also see: https://priml.upenn.edu/courses

# Course Comparisons

- **CIS 4190/5190 (this course)**
  - Basic mathematical ideas behind ML
  - Apply existing ML algorithms to new problems as an engineer or researcher
- **CIS 5450**
  - Data science workflow including data wrangling, ML modeling, and analytics
  - Scaling ML to big datasets and clusters

Also see: https://priml.upenn.edu/courses

# CIS 4190 vs. 5190

- 5190 will have extra, **mandatory** components in the HW, which are **optional** for 4190

- **Example**
  - HW may have 45 points for 4190, and 5 extra points for 5190 (total of 50)
  - Student taking 4190 will get 100% if they get at least 45 points (typically by skipping the 5190 problem, but not necessarily)
  - You cannot score more than 100%
  - The written and coding portion are counted separately; you cannot make up written points using coding points and vice versa

# Waitlist

- **Class is almost at capacity (222 students)**

- **We are prioritizing students that either:**
  - Can only take the class this fall
  - Need to take the course this semester for a graduation requirement

- We plan to make all waitlist decision by next class
  - Unfortunately, we won’t be able to respond to individual emails

# Schedule (Tentative)

| Week | Content | Homework |
|---|---|---|
| 1 | Introduction | |
| 2 | Linear Regression | |
| 3 | Linear Regression | HW 0 Due |
| 4 | Logistic Regression | |
| 5 | Neural Networks | HW 1 Due |
| 6 | KNNs + Decision Trees | |
| 7 | Unsupervised Learning | |
| 8 | Midterm 1 | HW 2 Due |
| 9 | Computer Vision | |
| 10 | Natural Language Processing | |
| 11 | Reinforcement Learning | HW 3 Due |
| 12 | Ensembles | |
| 13 | Recommender Systems + Robustness | |
| 14 | Generative AI + Ethics | HW 4 Due |
| 15 | Midterm 2 | |

# Grading Scheme (Tentative)

| | |
|---|---|
| • **Homeworks (5×):** | 30% |
| • **Project:** | 25% |
| • **Midterms exams:** | 40% |
| • **Good citizenship points:** | 5% |

# Grading Scheme (Tentative)

- **A+:** 95+
- **A:** 90-95
- **A-:** 85-90
- **B+:** 80-85
- **B:** 75-80
- **B-:** 70-75
- **Lower passing grades:** 50-70

- May be curved up

# Late Policy

- For each hour late, lose 0.5% on the points for that assignment
  - **Homeworks only**
  - Max 48 late hours per assignment
- **Example**
  - Submit HW 1 20 hours late
  - Lose $20 \times 0.5$ = 10% on HW 1 (0.5% of overall grade)
- If you have a medical reason, email us a copy of your medical visit report, and we will grant an extension (typically 2 days)
  - We will consider other reasons on a case-by-case basis

# Course Instructors

Osbert Bastani
Assistant Professor, CIS

Mingmin Zhao
Assistant Professor, CIS

# TA & Office Hours

- We have a team of 14 amazing TAs

- Each TA (and professor) will have 1-2 hours of office hours each week
  - Times still being decided

# Communication

- All materials will be posted on the course website:
  - [https://www.seas.upenn.edu/~cis5190/spring2025/](https://www.seas.upenn.edu/~cis5190/spring2025/)
- We plan to post lecture videos up to one week after the lecture
  - We make no guarantees about quality/availability, e.g., due to technical issues
- We will use **Ed Discussion** for questions and course discussions
  - Send a message to “instructors” to contact the TAs and me
  - You can contact me directly on Ed Discussion or by email (posted on course website)

# Homework Schedule

- **5 homeworks**
  - Released roughly every other Wednesday
  - Typically due Wednesday 2 weeks later (see schedule for actual deadline)

- **HW 0**
  - Designed to test mathematical background
  - **Expected time:** 3 hours
  - Opportunity to get used to the workflow

# Homework

- **Written problems:** GradeScope submission
  - LaTeX encouraged; handwritten + scanned at your own risk
  - Won’t be graded if you don’t annotate your answers correctly!
- **Coding problems:** AutoGrader + GradeScope submission of notebook
  - Colab/iPython notebook skeletons; AutoGrader as unit tests within skeleton
  - Only difference between AutoGrader and unit tests is different data
  - If code passes the unit tests and you didn’t “game” it, it should pass AutoGrader
- Discussion permitted for clarifications, but never share solutions/code; acknowledge all your discussions at the beginning of your report

# First Assignments

- **HW 0:** Released today, **due 1/29**
  - No office hours planned for HW 0
  - You can ask questions via Ed Discussion, but we will only answer clarifying questions
- More on the project later in the course

# Agenda

- **Logistics**
  - Course description
  - Tentative Schedule
  - Grading

- **Introduction**
  - Motivation
  - Basic definitions
  - Examples

# What is Machine Learning?

"Learning is any process by which a system improves performance from experience."

**Herbert Simon**

# What is Machine Learning?

"Machine learning … gives computers the ability to learn without being explicitly programmed."

**Arthur Samuel**

# What is Machine Learning?

- **Tom Mitchell:** Algorithms that
  - improve their **performance** $P$
  - at **task** $T$
  - with **experience** $E$

- A well-defined machine learning task is given by $(P, T, E)$

# **Example:** Prediction

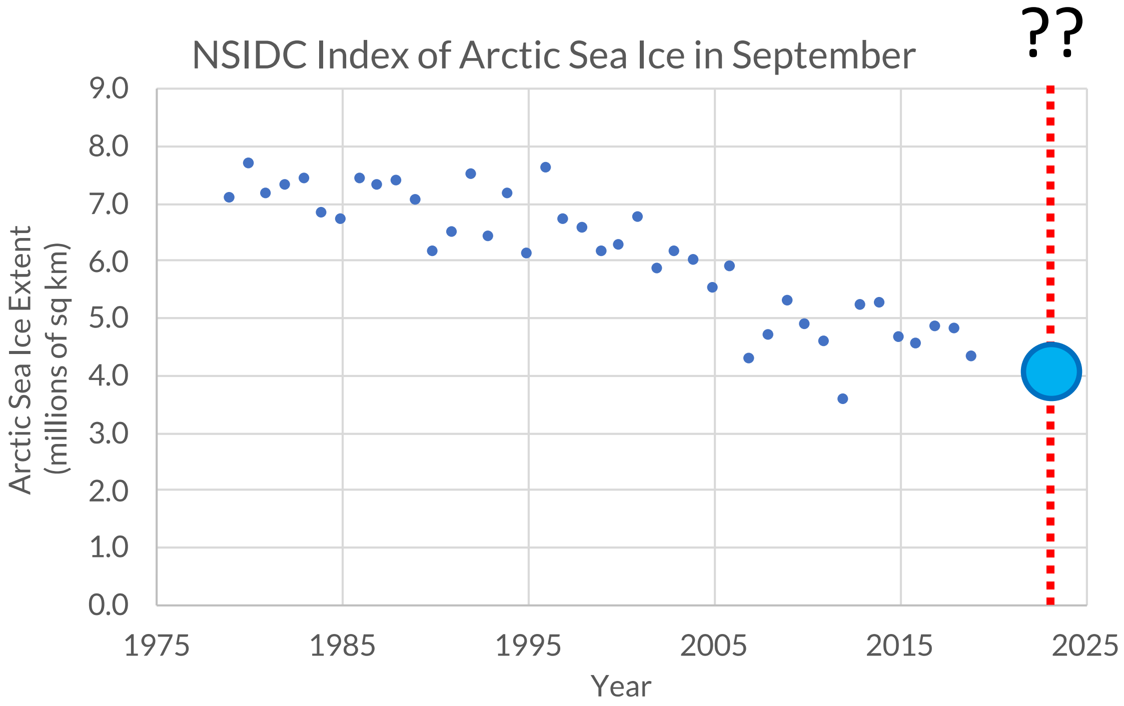



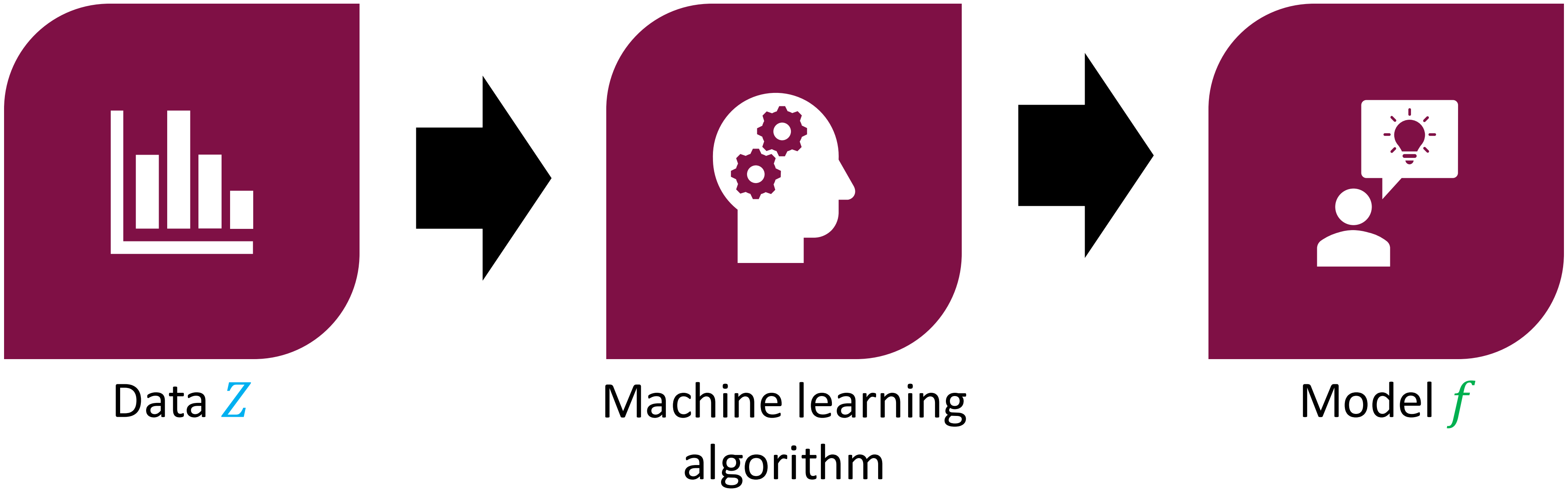

Image: https://www.flickr.com/photos/gsfc/5937599688/
Data from https://nsidc.org/arcticseaicenews/sea-ice-tools/

# Example: Prediction

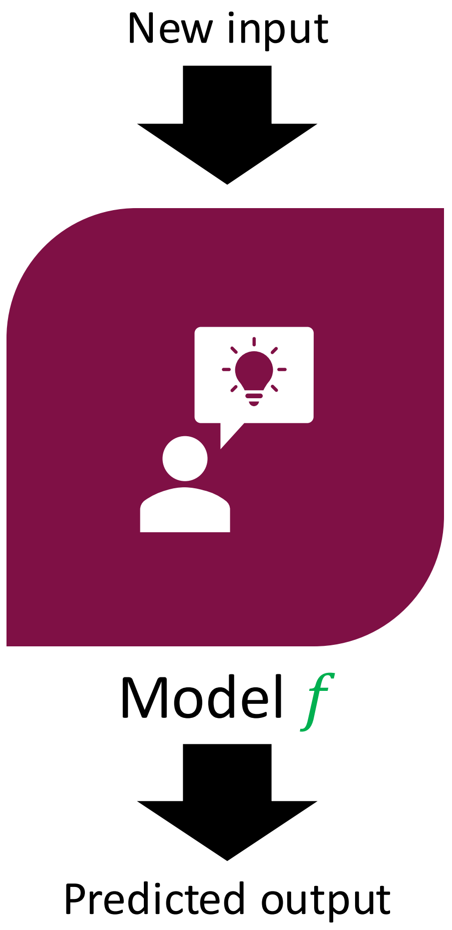
- **Tom Mitchell:** Algorithms that
  - improve their **performance** $P$
  - at some **task** $T$
  - with **experience** $E$

- $T =$ predict Arctic sea ice extent
- $P =$ prediction error (e.g., absolute difference)
- $E =$ historical data

# Machine Learning for Prediction



# Machine Learning for Prediction



# **Example:** Prediction

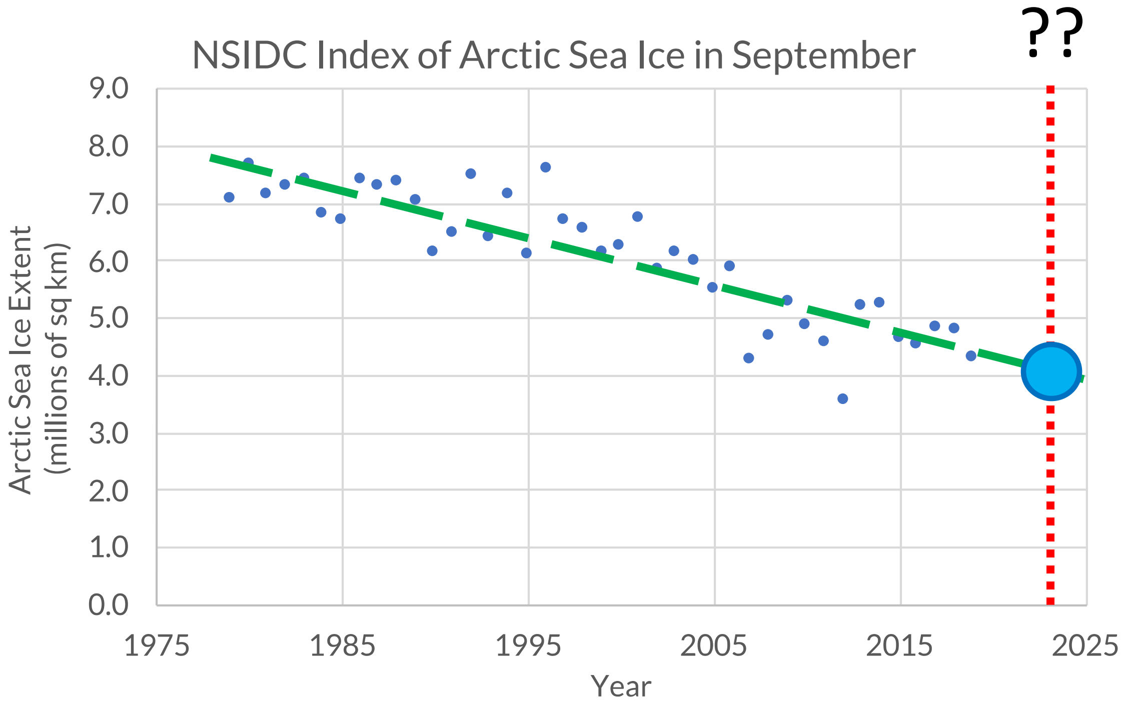




Image: https://www.flickr.com/photos/gsfc/5937599688/
Data from https://nsidc.org/arcticseaicenews/sea-ice-tools/

# **Example:** Game Playing

- **Tom Mitchell:** Algorithms that
  - improve their **performance** $P$
  - at some **task** $T$
  - with **experience** $E$

- $T$ = playing Chess
- $P$ = win rate against opponents
- $E$ = playing games against itself

# Machine Learning Workflow

- Framing an ML problem (Mitchell's P, T, E)
- Data curation (sourcing, scraping, collection, labeling)
- Data analysis / visualization
- ML Design (hypothesis class, loss function, optimizer, hyperparameters, features)
- Train model
- Validate / Evaluate
- Deploy (and generate new data)
- Monitor performance on new data

Our focus

# Types of Learning

- **Supervised learning**
  - **Input:** Examples of inputs and desired outputs
  - **Output:** Model that predicts output given a new input

- **Unsupervised learning**
  - **Input:** Examples of some data (no “outputs”)
  - **Output:** Representation of structure in the data

- **Reinforcement learning**
  - **Input:** Sequence of interactions with an environment
  - **Output:** Policy that performs a desired task

# Supervised Learning

- Given $(x_1, y_1), \dots, (x_n, y_n)$, learn a function that predicts $y$ given $x$

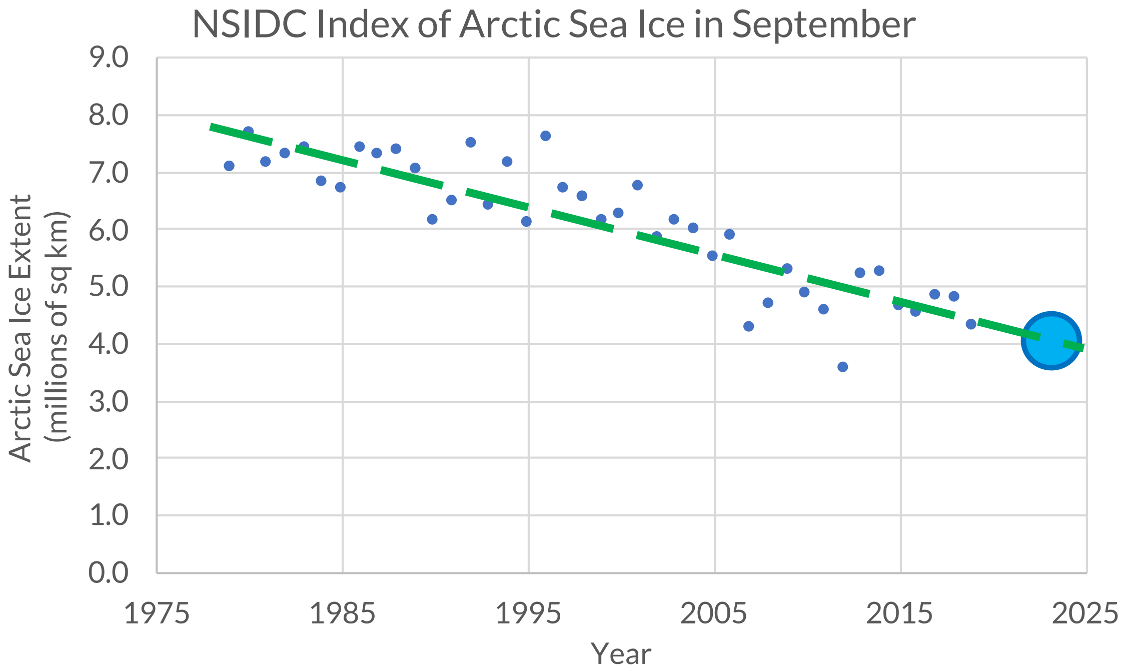




Image: https://www.flickr.com/photos/gsfc/5937599688/
Data from https://nsidc.org/arcticseaicenews/sea-ice-tools/

# Supervised Learning

- Given $(x_1, y_1), \ldots, (x_n, y_n)$, learn a function that predicts $y$ given $x$
- **Regression:** Labels $y$ are real-valued


Photo by NASA Goddard

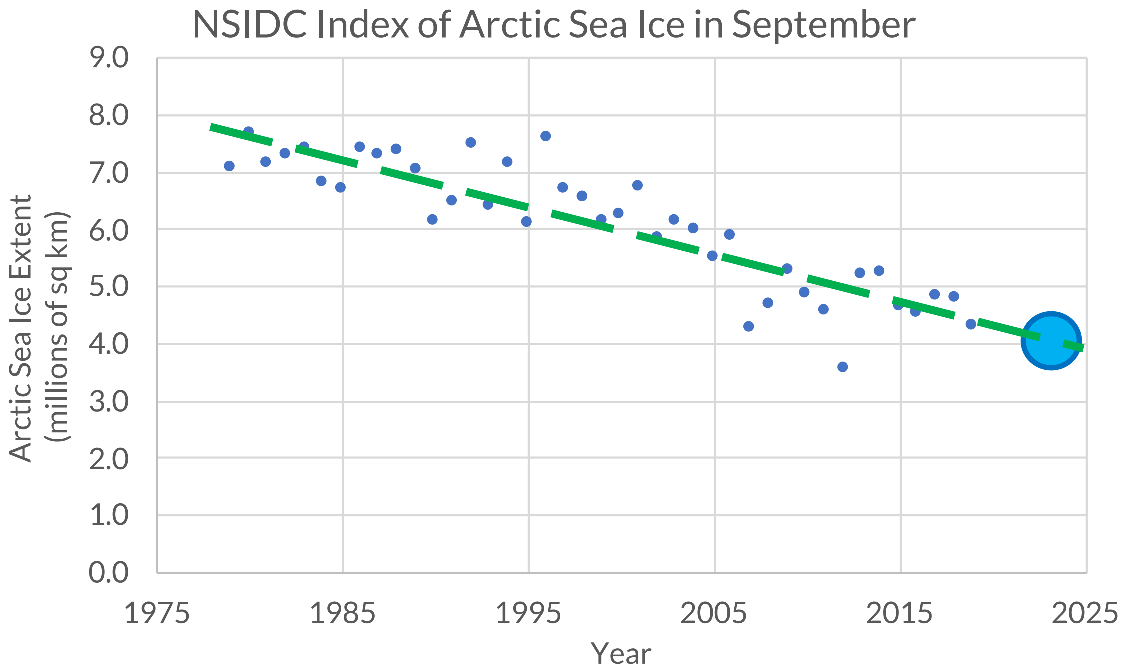


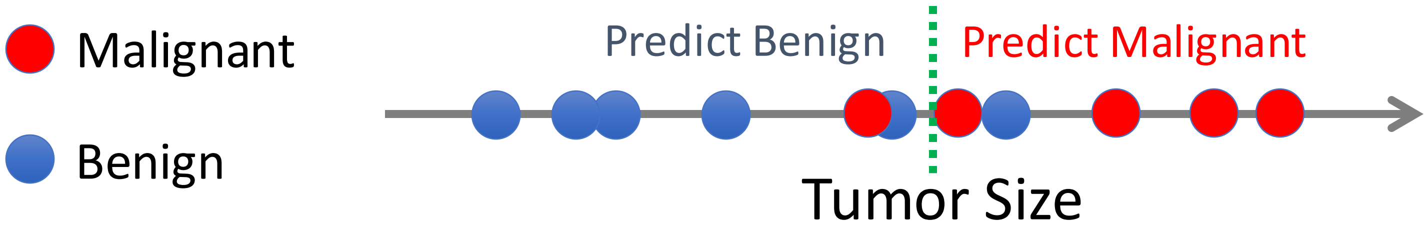

Image: https://www.flickr.com/photos/gsfc/5937599688/
Data from https://nsidc.org/arcticseaicenews/sea-ice-tools/

# Supervised Learning

- Given $(x_1, y_1), \dots, (x_n, y_n)$, learn a function that predicts $y$ given $x$
- **Classification:** Labels $y$ are categories

Ocular Tumor (Malignant / Benign)

$f(x)$



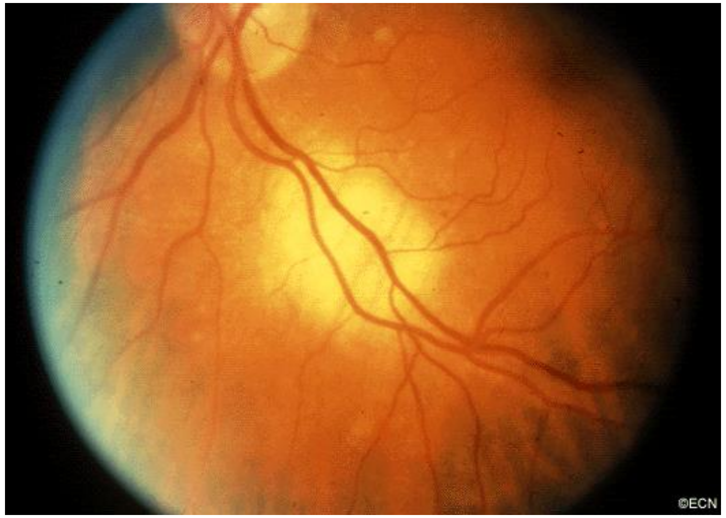
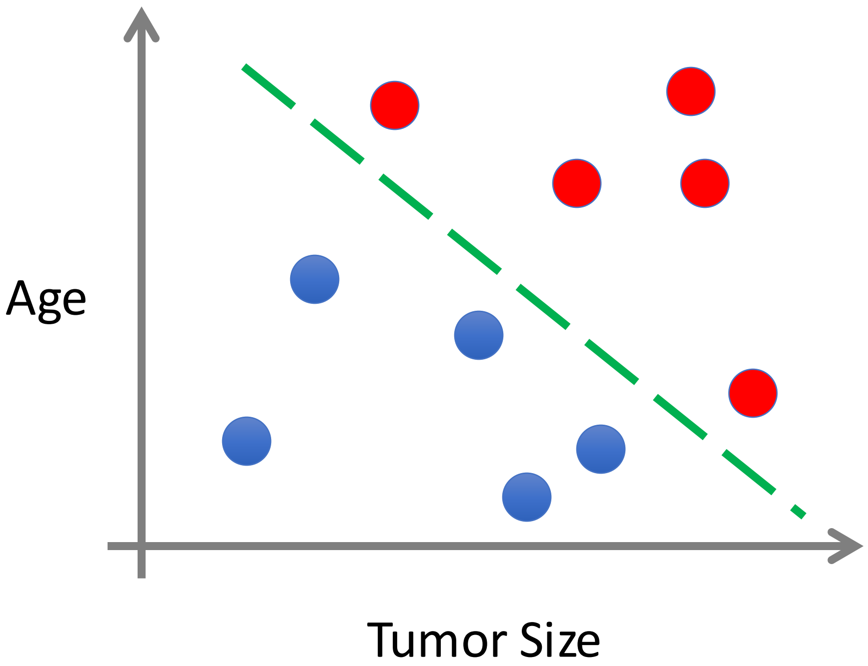




Image: https://eyecancer.com/uncategorized/choroidal-metastasis-test/

# Supervised Learning

- Given $(x_1, y_1), \ldots, (x_n, y_n)$, learn a function that predicts $y$ given $x$
- Inputs $x$ can be multi-dimensional




- Patient age
- Clump thickness
- Tumor Color
- Cell type
- …

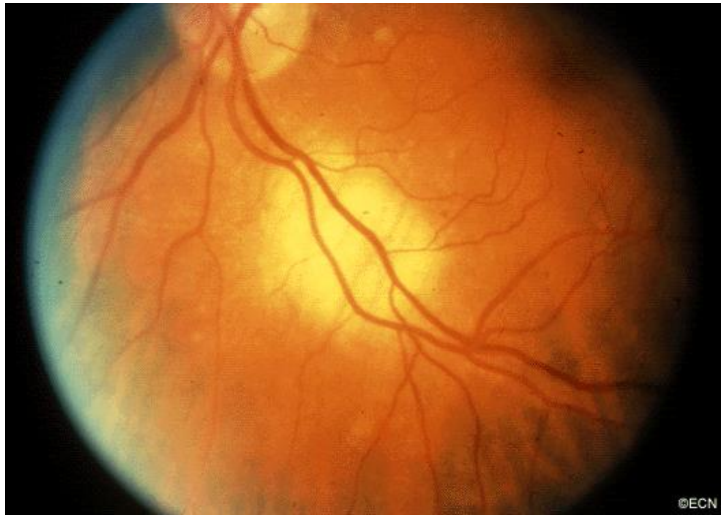
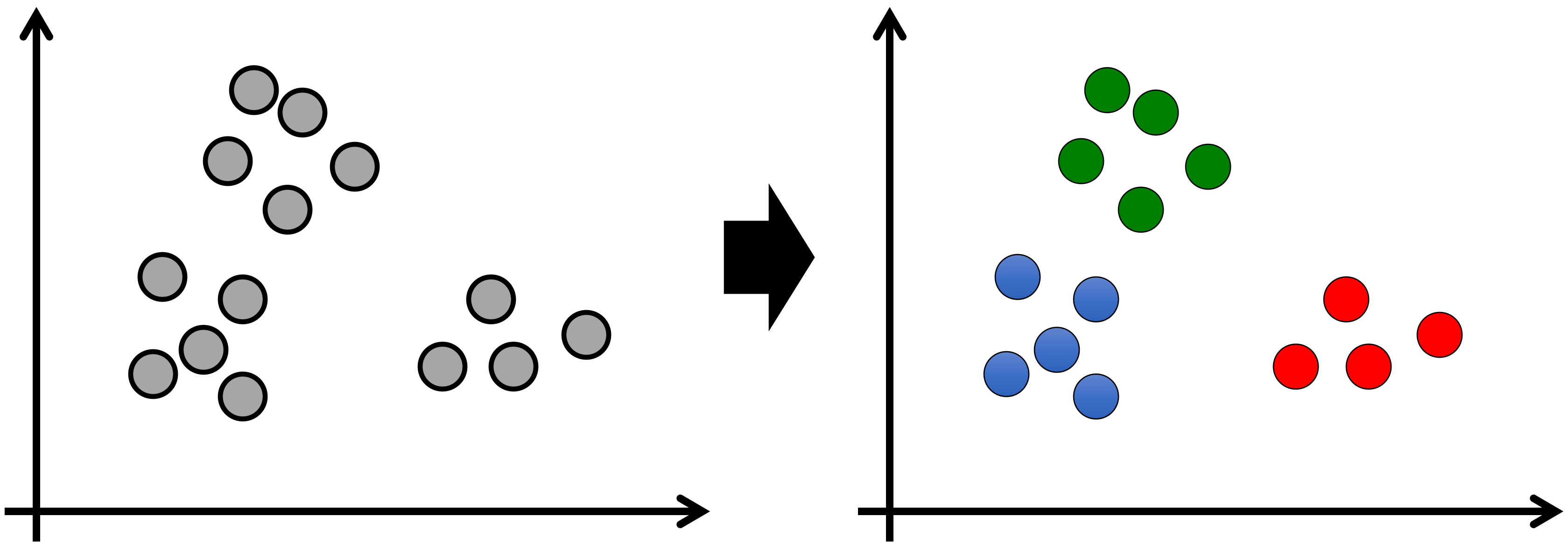



Image: https://eyecancer.com/uncategorized/choroidal-metastasis-test/

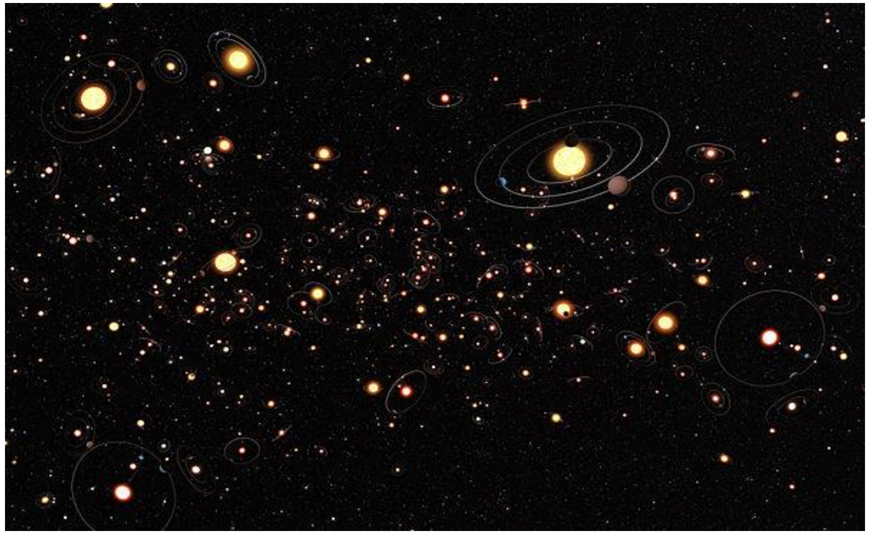
# Unsupervised Learning

- Given $x_1, \ldots, x_n$ (no labels), output hidden structure in $x$'s
  - E.g., clustering

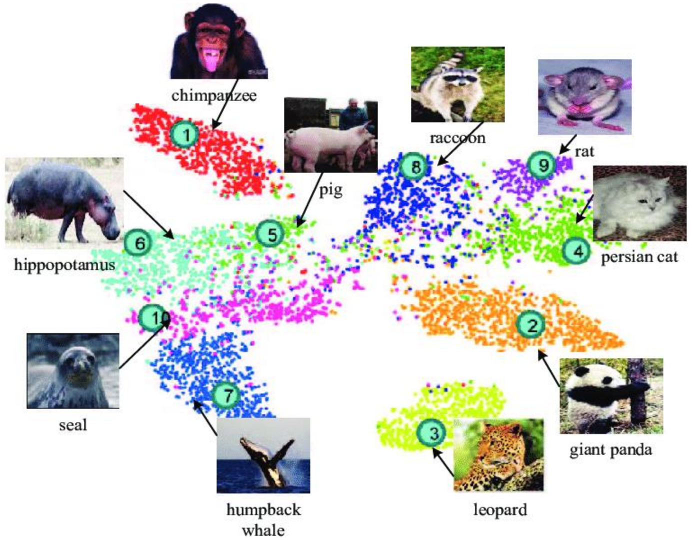


# Unsupervised Learning


Find Subgroups in Social Networks



Identify Types of Exoplanets



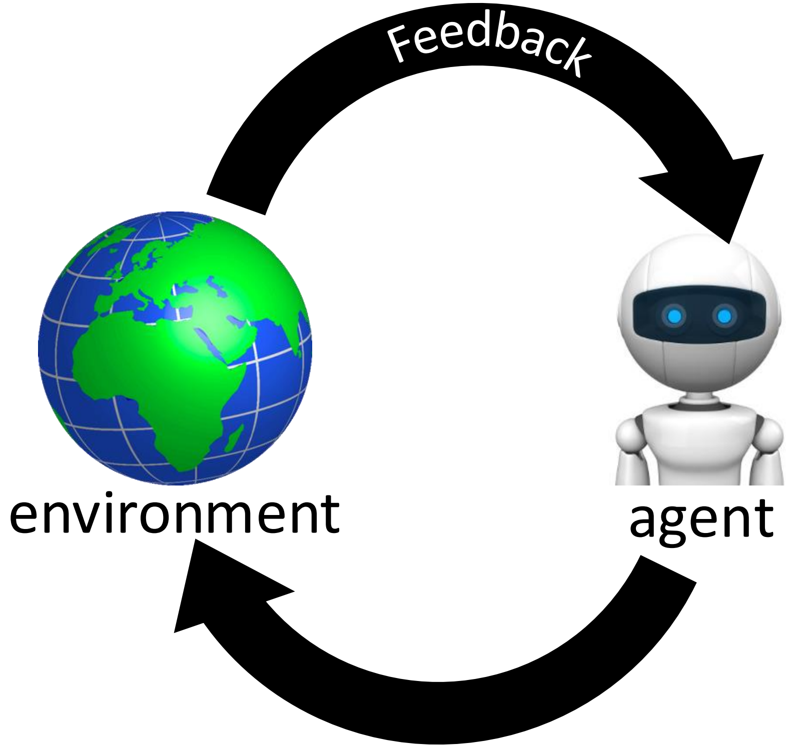

Visualize Data

Image Credits:
https://medium.com/graph-commons/finding-organic-clusters-in-your-complex-data-networks-5c27e1d4645d
https://arxiv.org/pdf/1703.08893.pdf
https://en.wikipedia.org/wiki/Exoplanet

# Reinforcement Learning

- Learn how to perform a task from interactions with the **environment**

- **Examples:**
  - Playing chess (interact with the game)
  - Robot grasping an object (interact with the object/real world)
  - Optimize inventory allocations (interact with the inventory system)

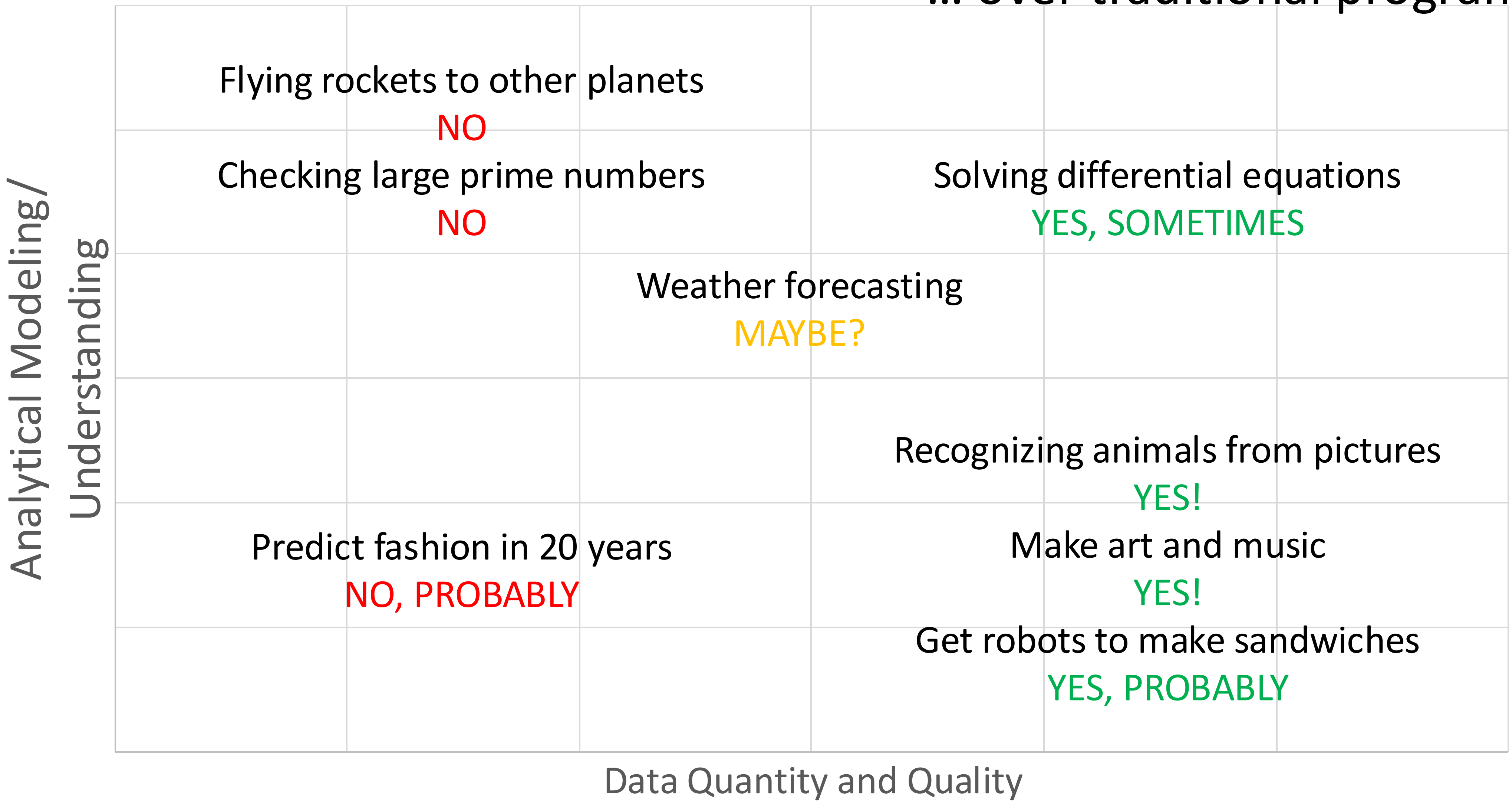


# Reinforcement Learning

https://www.youtube.com/watch?v=iaF43Ze1oeI

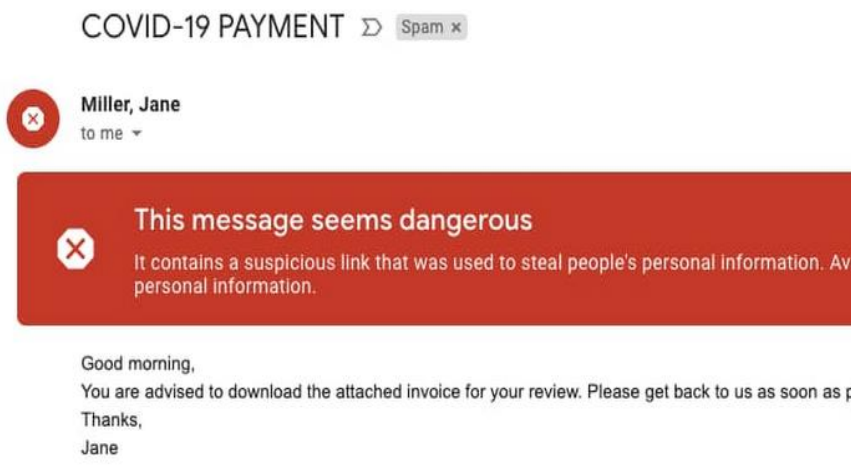
# When should we use machine learning …?

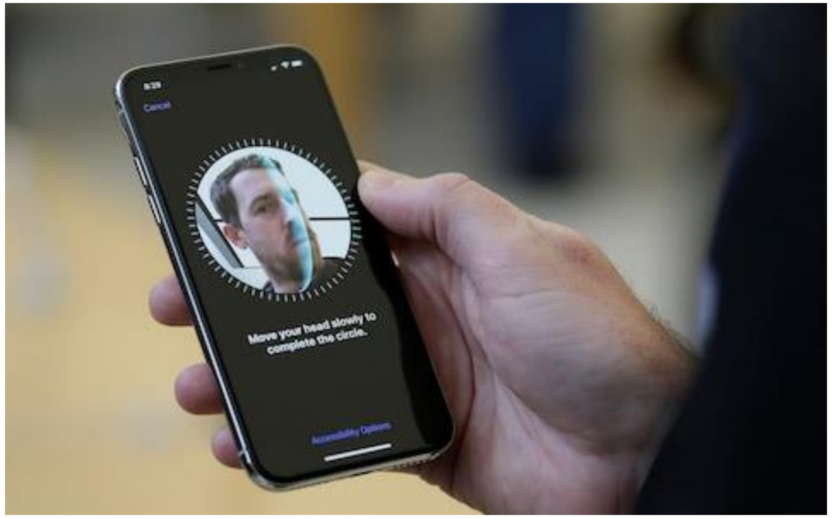
… over traditional programming?



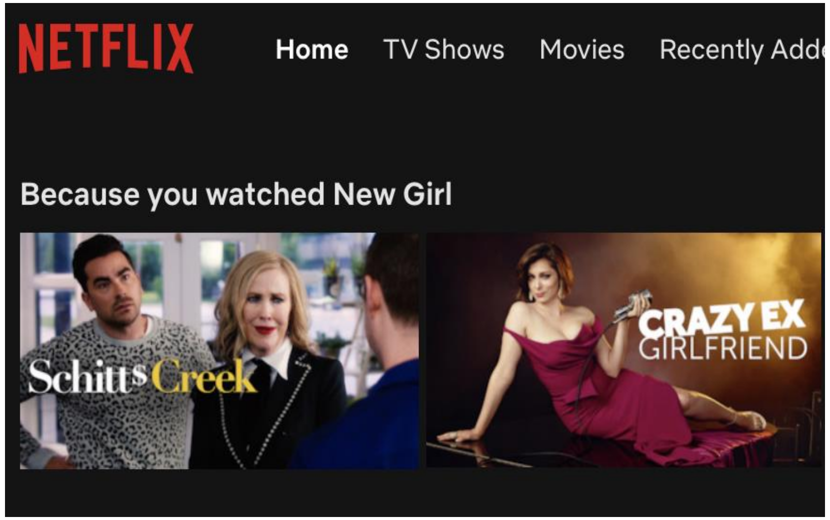
# Applications of Machine Learning

# Everyday Applications

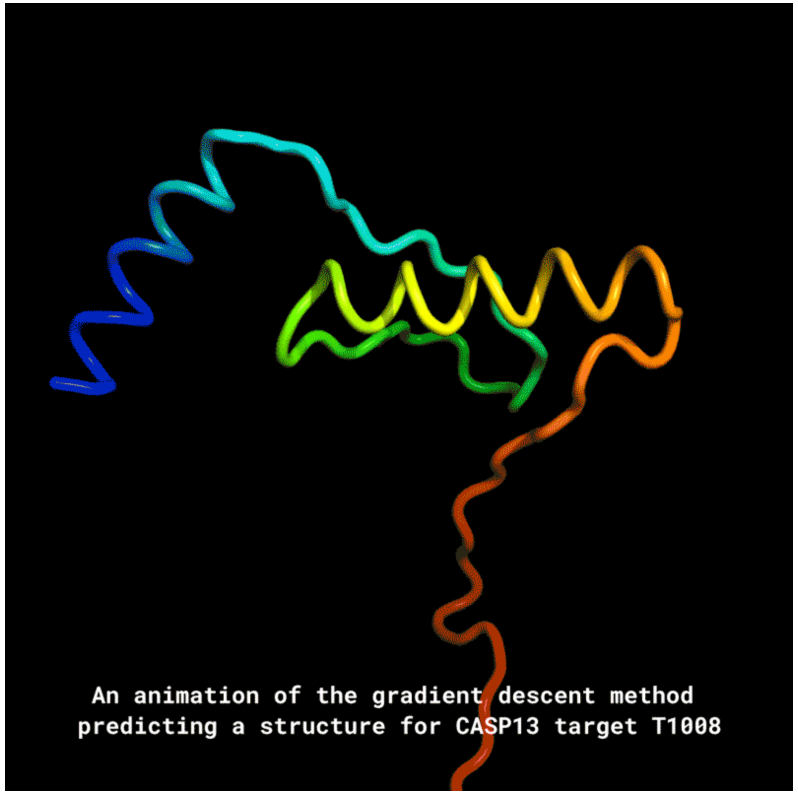


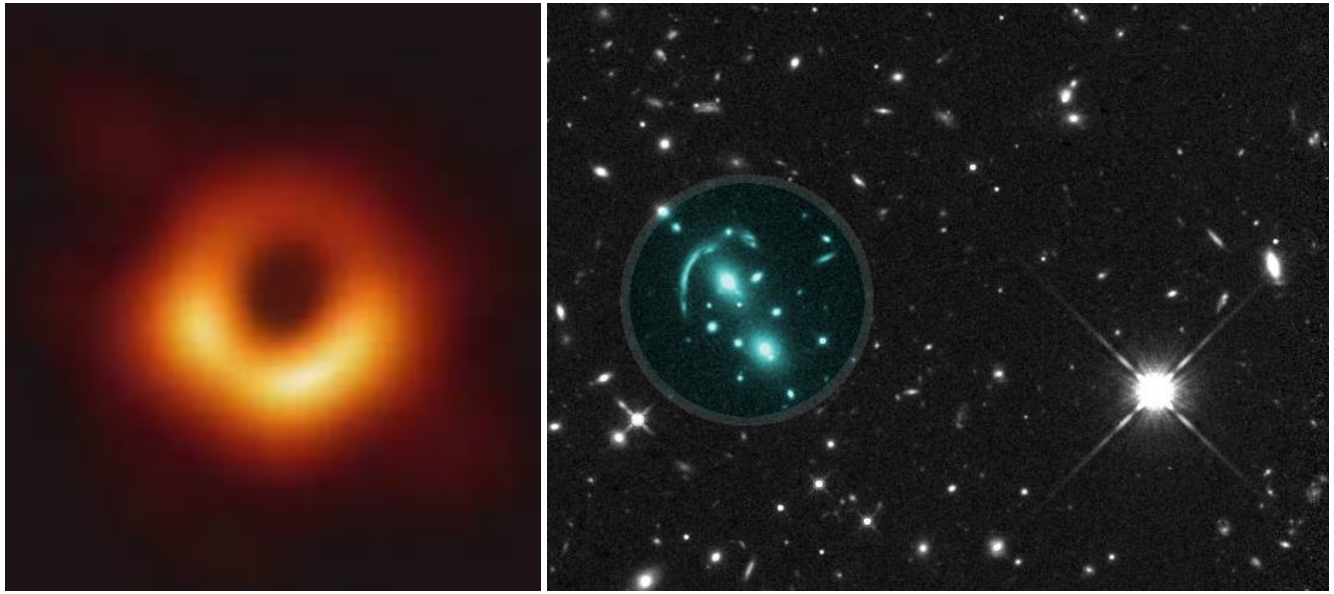


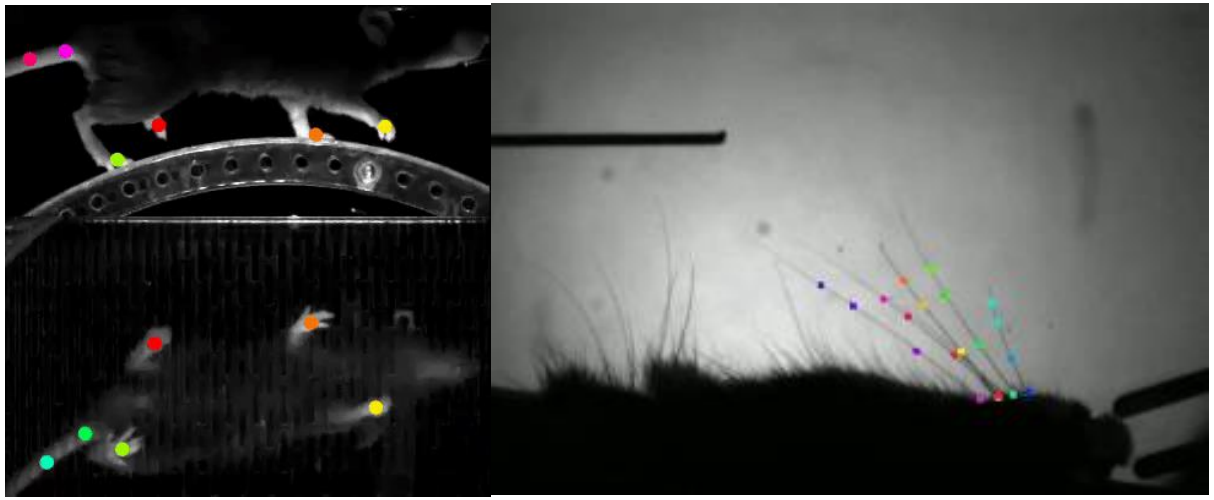

# Scientific Discovery




https://deepmind.com/blog/article/AlphaFold-Using-AI-for-scientific-discovery



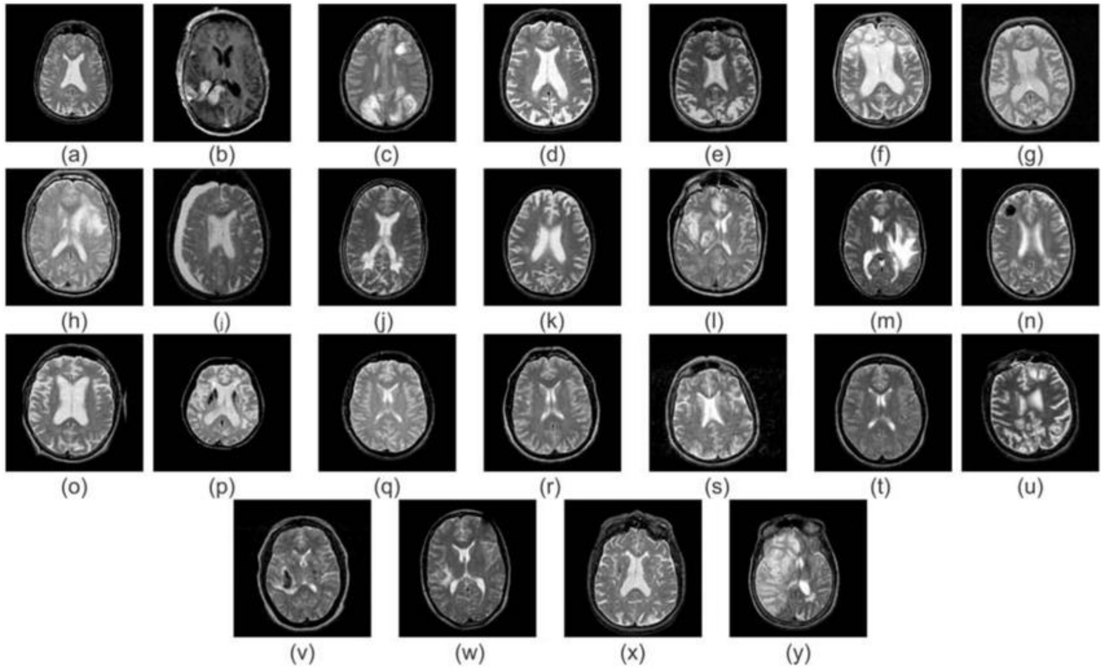
https://www.jpl.nasa.gov/edu/news/2019/4/19/how-scientists-captured-the-first-image-of-a-black-hole/



http://www.mousemotorlab.org/deeplabcut

# Radiology and Medicine

**Input:** Brain scans




**Output:** Neurological disease labels

**Machine learning studies on major brain diseases: 5-year trends of 2014–2018**

Koji Sakai[1] · Kei Yamada[1]

**Applications of machine learning in drug discovery and development**

https://www.nature.com/articles/s41573-019-0024-5

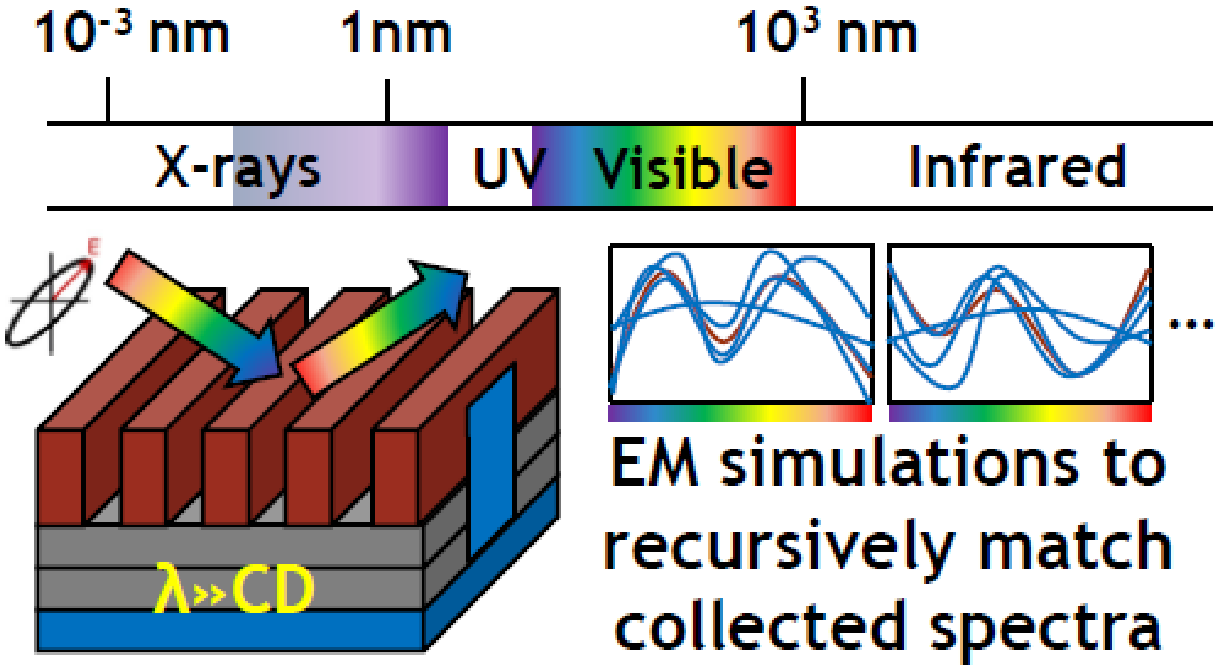
**Deep learning-enabled medical computer vision**

Andre Esteva, Katherine Chou, Serena Yeung, Nikhil Naik, Ali Madani, Ali Mottaghi, Yun Liu, Eric Topol, Jeff Dean & Richard Socher

https://www.nature.com/articles/s41746-020-00376-2

# Semiconductor Manufacturing

**Input:** light spectra after bouncing off silicon wafer

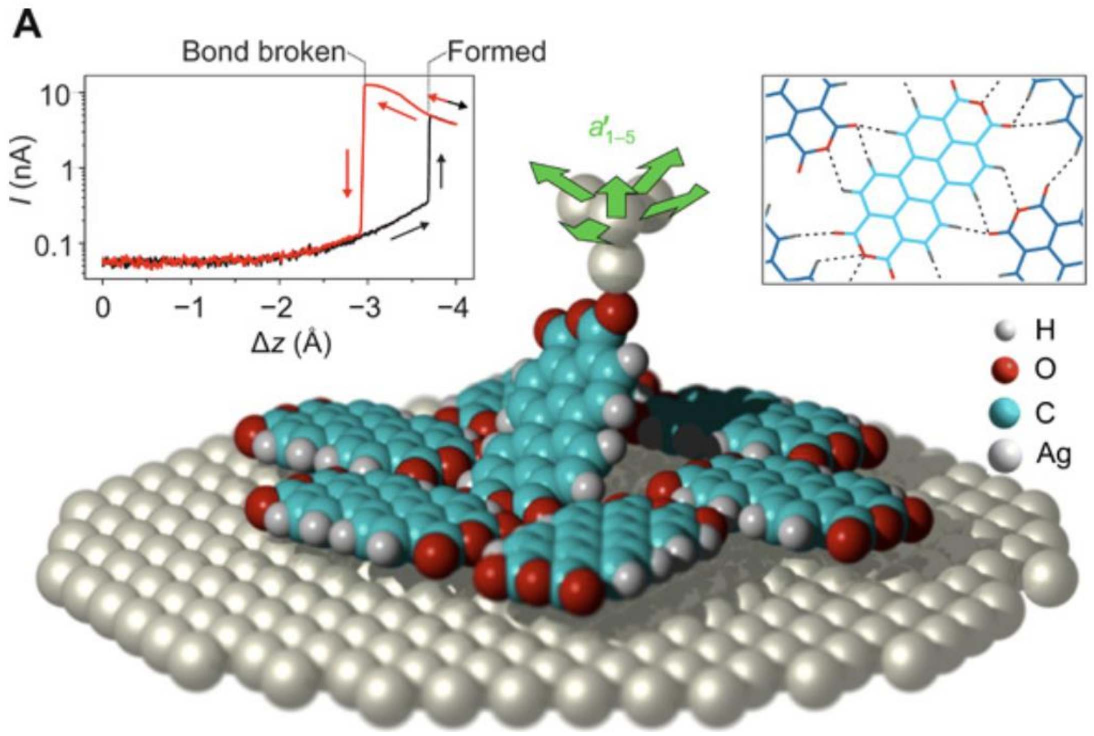



huge gains in manufacturing throughput
→ cheaper phones and computers!

**Output:** defective / perfect

https://semiwiki.com/semiconductor-manufacturers/287593-a-compelling-application-for-ai-in-semiconductor-manufacturing/

# Nanofabrication




Autonomous robotic nanofabrication with reinforcement learning

https://advances.sciencemag.org/content/6/36/eabb6987

Removing individual molecules autonomously with a scanning probe microscope to manufacture new material

**RL agent does better than humans!**

# Creating Music, Art, and Photos

https://thispersondoesnotexist.com/

https://openai.com/blog/jukebox/

# Text Generation

SYSTEM PROMPT (HUMAN-WRITTEN)

*Recycling is good for the world.*

*NO! YOU COULD NOT BE MORE WRONG!!*

MODEL COMPLETION (MACHINE-WRITTEN, 25 TRIES)

Recycling is NOT good for the world. It is bad for the environment, it is bad for our health, and it is bad for our economy. I'm not kidding. Recycling is not good for the environment. It is destructive to the earth and it is a major contributor to global warming. Recycling is not good for our health. It contributes to obesity and diseases like heart disease and cancer. Recycling is bad for our economy. It increases the cost of a product, and in turn, the price of everything that is made with that product. Recycling is not good for our nation. We pay a

https://transformer.huggingface.co/doc/gpt2-large

# Ethical Considerations

"The Pennsylvania Board of Probation and Parole has begun using machine learning forecasts to help inform parole release decisions. In this paper, we evaluate the impact of the forecasts on those decisions and subsequent recidivism."

An impact assessment of machine learning risk forecasts on parole board decisions and recidivism

Richard Berk

"In 2013, the University of Texas at Austin's computer science department began using a machine-learning system called GRADE to help make decisions about who gets into its Ph.D. program"

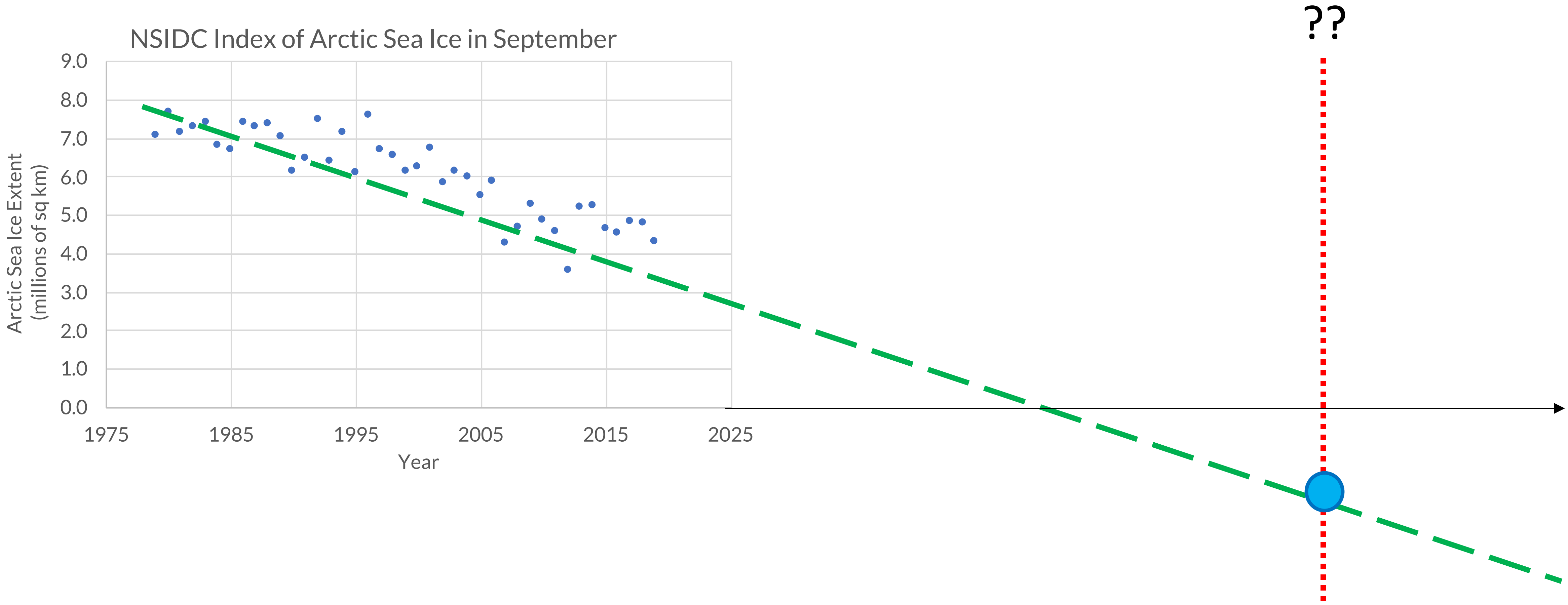
The Death and Life of an Admissions Algorithm

"Videos about vegetarianism led to videos about veganism. Videos about jogging led to videos about running ultramarathons. It seems as if you are never 'hard core' enough for YouTube's recommendation algorithm. It promotes, recommends and disseminates videos in a manner that appears to constantly up the stakes. Given its billion or so users, YouTube may be one of the most powerful radicalizing instruments of the 21st century."

YouTube, the great radicalizer

THE NEW YORK TIMES / ZEYNEP TUFEKCI / MAR 12

# Danger of Out-of-Domain Machine Learning




Any time you are evaluating on data “far” from your training data, beware!