Spring 2023!

Introduction to Machine Learning

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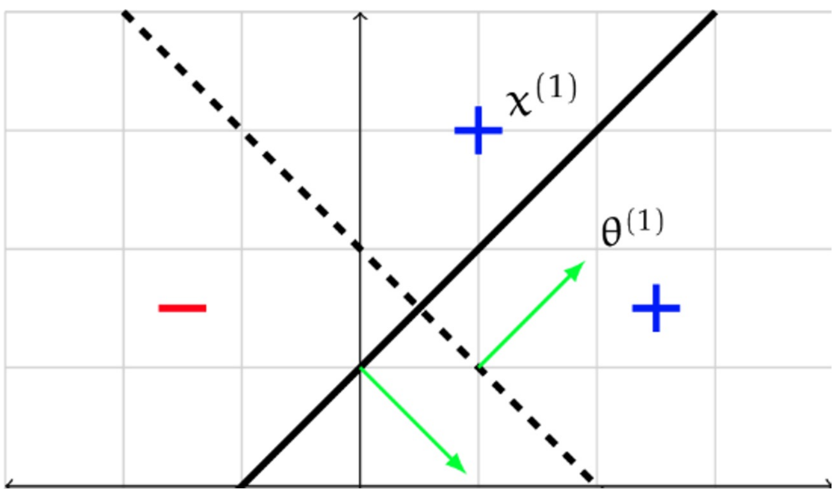

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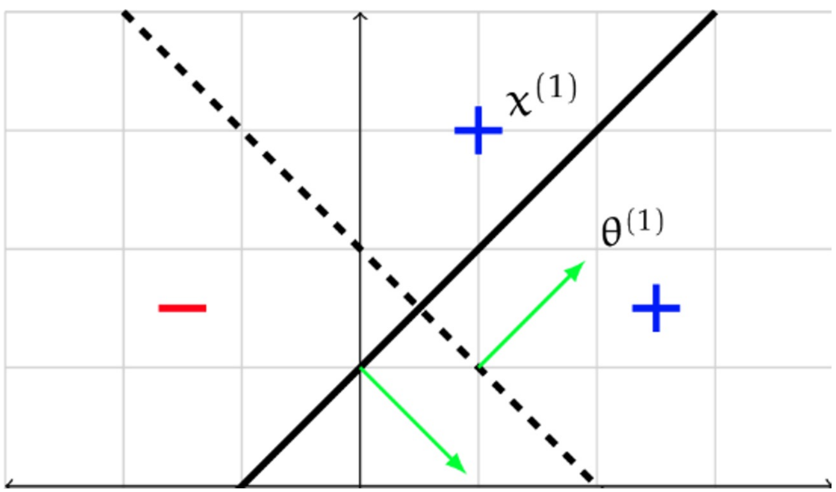

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6.390

Spring 2023!

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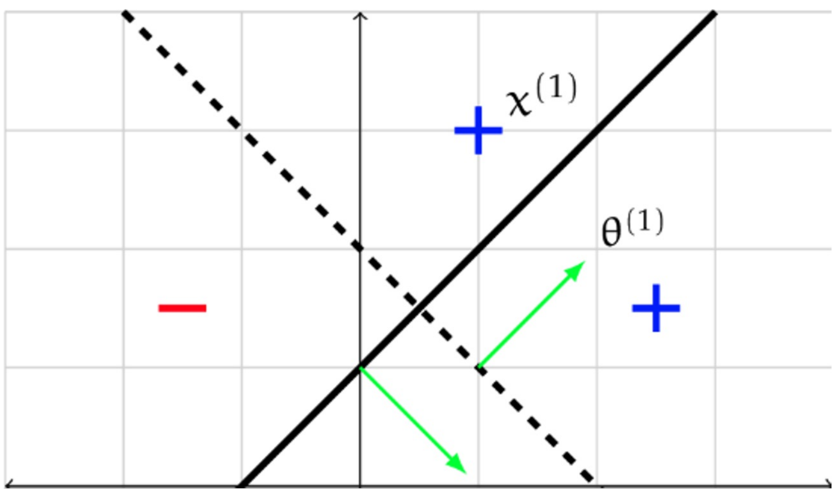

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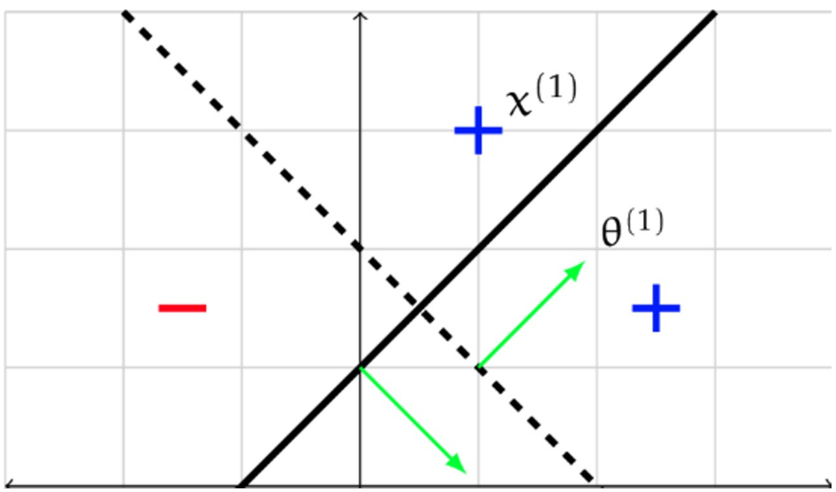

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Spring 2023!

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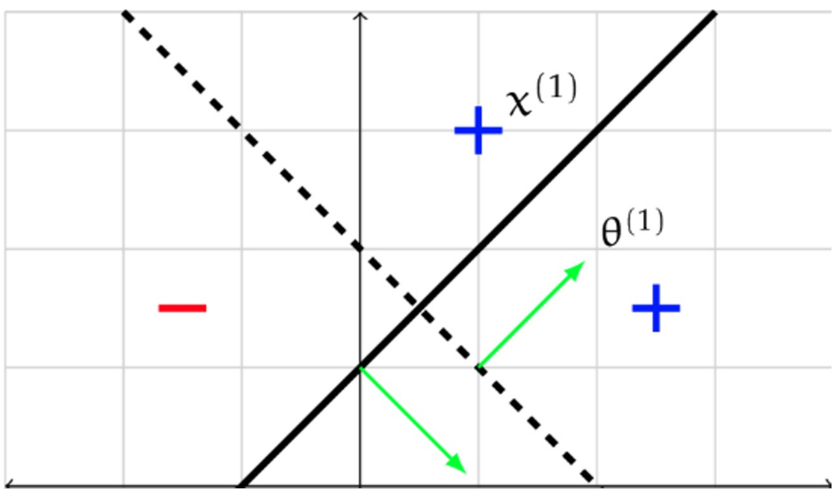

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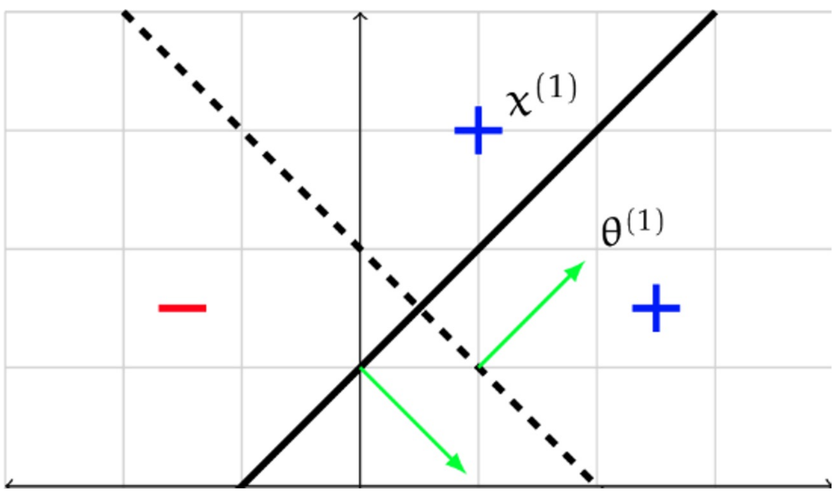

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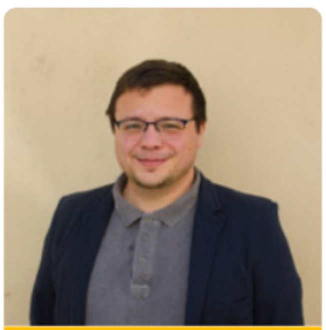
Full Staff

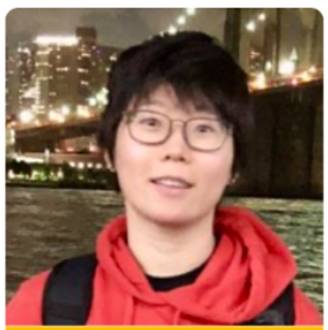
Instructors


Marzyeh Ghassemi


Tomas Lozano-Perez


Wojciech Matusik


Vince Monardo


Shen Shen


Ashia Wilson

Course Assistant

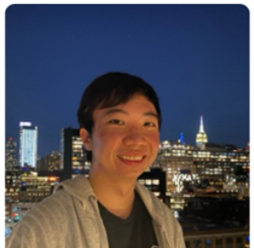

Taylor Braun

Logistical issues? Personal concerns? We'd love to help out at 6.390-personal@mit.edu

TAs


Ben Dwyer

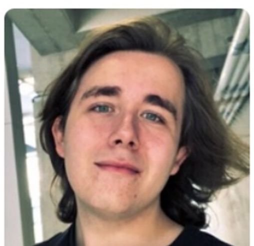

CJ Quines

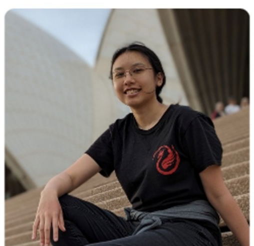

Dewei Feng

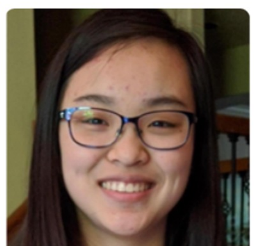

Emily Liu

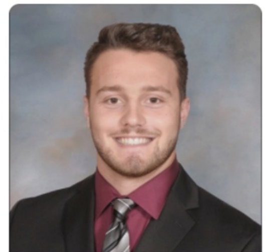

George Abu Daoud


George Bian


Kev Bunn


Lilian Luong

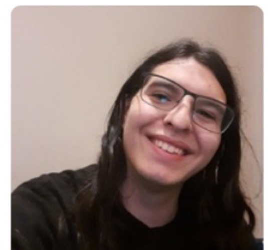

Melinda Sun


Michael Cantow


Prabhakar Kafle

Reggie Best


Sage Simhon

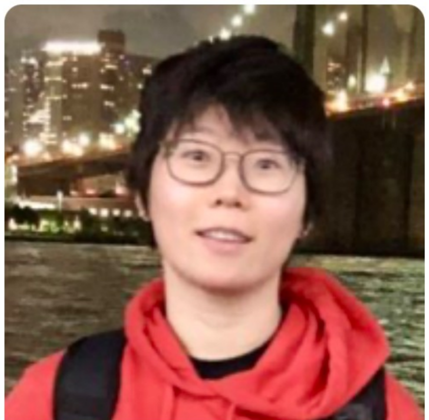

Shaunticlair Ruiz


Sophia Zhi


Warren Wang

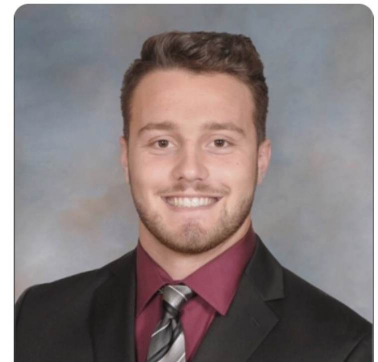
and ~40 awesome LAs

Section 1 staff


Shen Shen

Recitation + Lab


Lilian Luong


Michael Cantow

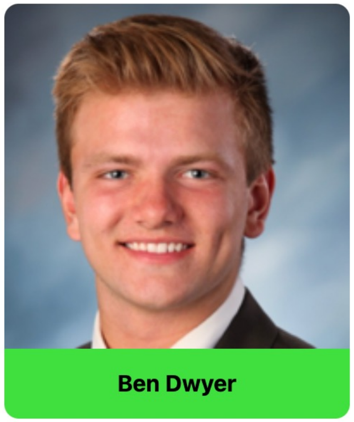
Lab

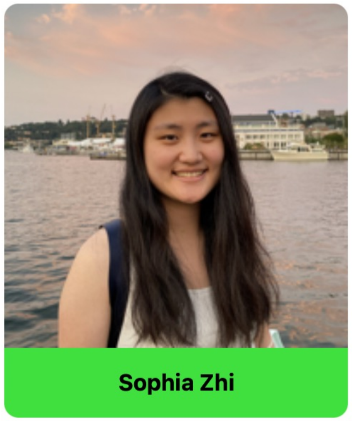

Emily Liu

plus ~7 awesome LAs

Section 2 staff

Recitation + Lab





Lab

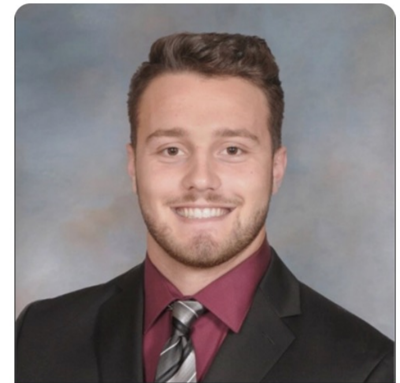
plus ~5 awesome LAs

Section 3 staff

Tomas Lozano-Perez

Recitation + Lab

Lilian Luong



Michael Cantow

Lab

Prabhakar Kafle

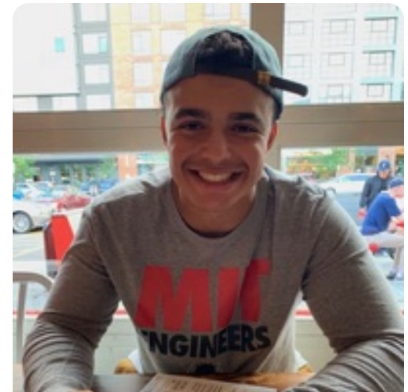
plus ~7 awesome LAs

Section 4 staff

Marzyeh Ghassemi

Recitation + Lab

Ben Dwyer



Reggie Best

Lab

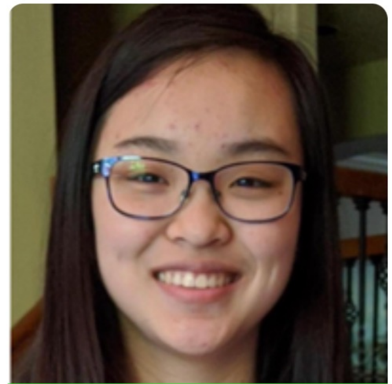
Dewei Feng

plus ~5 awesome LAs

Section 5 staff

Wojciech Matusik

Recitation + Lab



Melinda Sun

Sage Simhon

Lab

Warren Wang

CJ Quines

plus ~6 awesome LAs

Section 6 staff

Recitation + Lab

Ashia Wilson

Reggie Best

Sophia Zhi

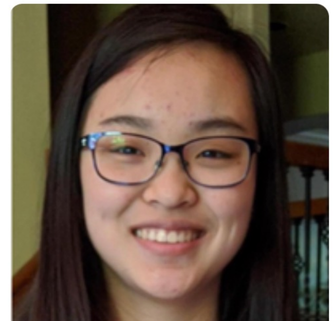
Lab

Kev Bunn

plus ~5 awesome LAs

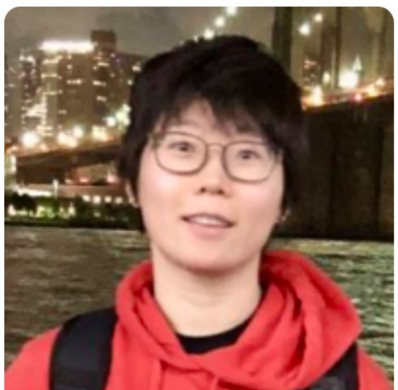
Section 7 staff

Recitation + Lab



Melinda Sun

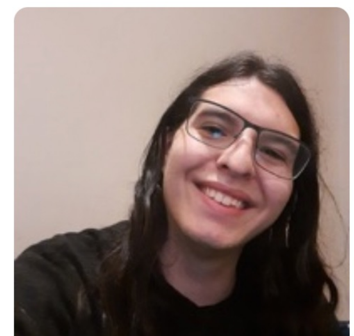
Sage Simhon



Shen Shen

Lab

Warren Wang



Shaunticlair Ruiz

plus ~6 awesome LAs

Course pedagogy:

A nominal week – mix of theory, concepts, and application to problems!

- **Exercises:** Releases on Wed 5pm, due the following Mon. 9am
  Easy questions based on that week's notes reading (and viewing optional recorded lecture)
- **Recitation**: Monday, with attendance check-in (not today)
  Assumes you have read and done exercises; start on homework
- **Homework:** Releases Monday 9am; due Wednesday (9 days later) at 11pm
  Harder questions: concepts, mechanics, implementations
- **Lab:** Wednesday, with attendance check-in (starting Feb 8)
  In-class empirical exploration of concepts
  Work with partner on lab assignment
  Check-off conversation with staff member, due the following Monday 11pm

Office hours: **lots!** posted on website. Also make use of Piazza and Psetpartners!

Exams:

- Midterm: *Thurs. March 23: 7:30-9:30 pm*
- Final: scheduled by Registrar (posted in 3rd week). **Alert – might be as late as May 24!**

Grading and collaboration (details on web)

Our **objective** (and we hope yours) is **for you to learn about machine learning**

- take responsibility for your understanding
- we will help!

Formula:

exercises 5% + attendance 5% + homework 15% + labs 15% + midterm 25% + final 35%

Lateness: 20% penalty per day, applied linearly (so 1 hour late is -0.83%)

Extensions:

- **20 one-day extensions** (move one assignment's deadline forward by one day) will be **applied automatically** at the end of the term in a way that is maximally helpful
- for medical or personal difficulties see S^3 & contact us at **`6.390-personal@mit.edu`**

Collaboration: don't cheat!

- Understand everything you turn in
- Coding and detailed derivations must be done by you
- See collaboration policy/examples on course web site

Expected prerequisite background

Things we expect you to know (we use these constantly, but don't teach them explicitly):

Programming (e.g. as in 6.009 or 6.006)

- Intermediate Python, including classes
- Exposure to algorithms – ability to understand & discuss pseudo-code, and implement in Python

Linear Algebra (e.g. as in 18.06, 18.C06, 18.03, or 18.700)

- Matrix manipulations: transpose, multiplication, inverse etc.
- Points and planes in high-dimensional space
- (Together with calculus): taking gradients, matrix calculus

Useful background

Things it helps to have prior exposure to, but we don’t expect (we use these in 6.390, but will discuss as we go):

- numpy (Python package for matrix/linear algebra)
- pytorch (python package for modern ml models like deep neural networks)
- Basic discrete probability: random variables, independence, conditioning

Heads-up for Wednesday

- Attend your assigned section only starting Wednesday Feb 8
- If you need to change your permanent section assignment, you will be able to self-switch, starting 5pm today; details on introml homepage

Rest of Today

- Start our ML journey with an overview
- Work through recitation handout with others at your table
- Ask questions by putting yourself in the help queue
- No worries if no introml access yet; great chance to know your neighbor (ask them to put you in the queue)

What we're teaching: Machine Learning!

Given:

- a **collection of examples** (gene sequences, documents, tree sections)
- an **encoding of those examples** in a computer (as vectors)

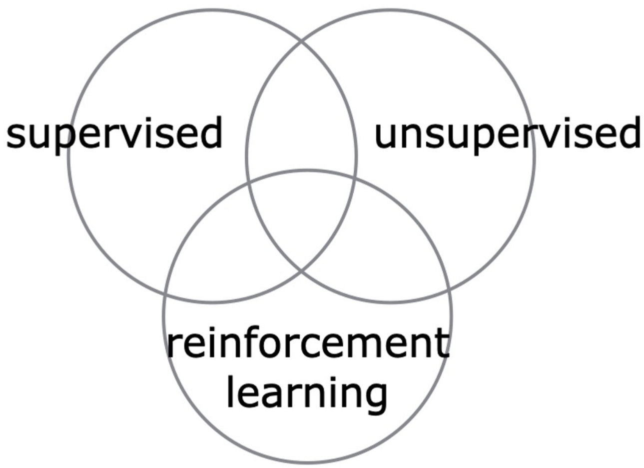
Derive:

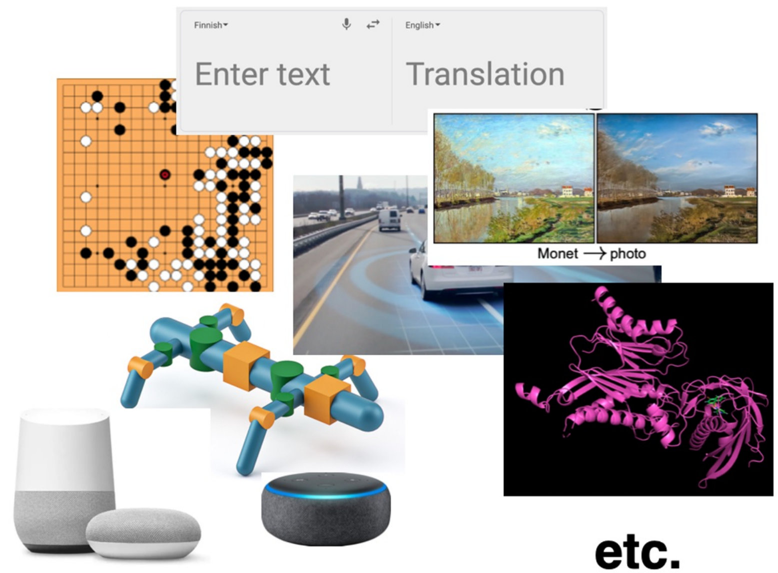
- a **computational model** (called a hypothesis) that describes relationships within and among the examples that is expected to characterize well new examples from that same population, to make good predictions or decisions

A model might:

- **classify images** of cells as to whether they're cancerous
- **specify groupings (clusters)** of documents that address similar topics
- **steer** a car appropriately given lidar images of the surroundings

Very roughly, ML can be categorized into



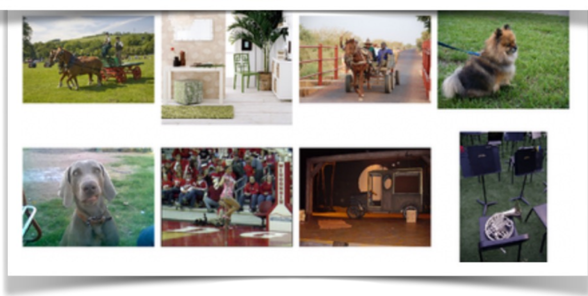


(the categorization can be refined, e.g. there are active learning, semi-supervised, selective, contrastive, few-shot, inverse reinforcement learning…)

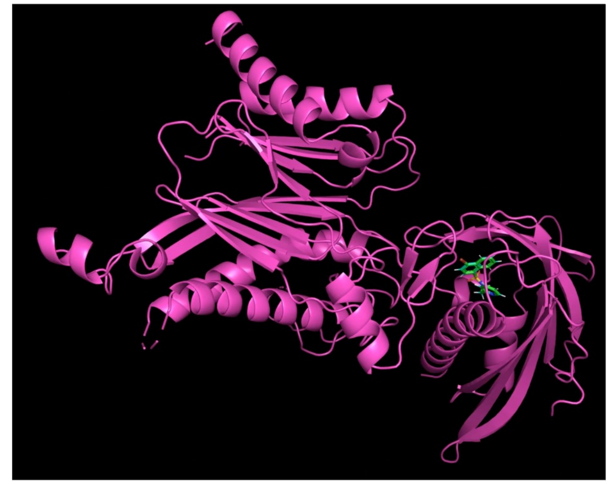
[Slides adapted from 6.790]

Supervised learning

Goal: correctly classify so far unseen test images



Goal: predict to what degree a drug candidate binds to the intended target protein (based on a dataset of already screened molecules against the target)



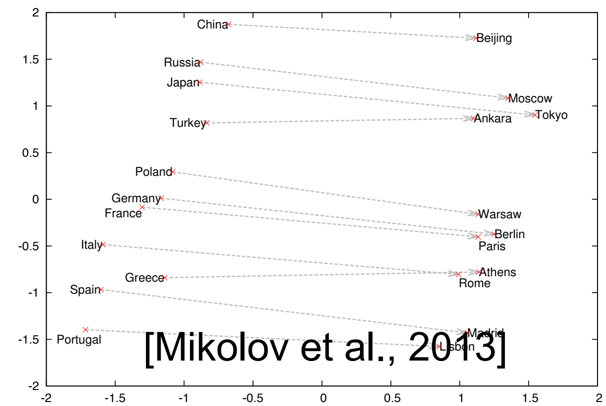
- Learning a machine translation system from pairs of sentences

Spanish (input)	**English (output)**
Aquí tienes un bolígrafo	Here's a pen
Las conferencias de ML son divertidas	ML conferences are fun
Todo el mundo debería estudiar AI	Everyone should study AI
...	...

[Slides adapted from 6.790]

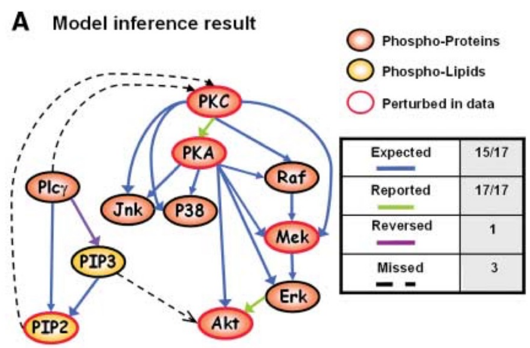
Unsupervised learning

dimensionality reduction, embedding

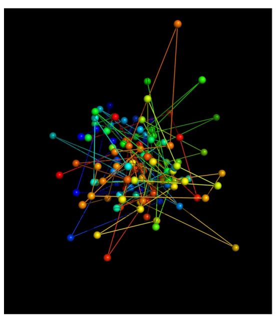


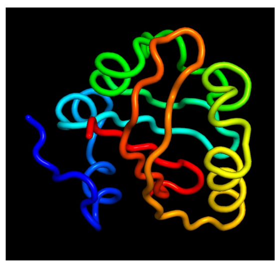
[Mikolov et al., 2013]

dependency /causal structure



[Sachs et al 05]

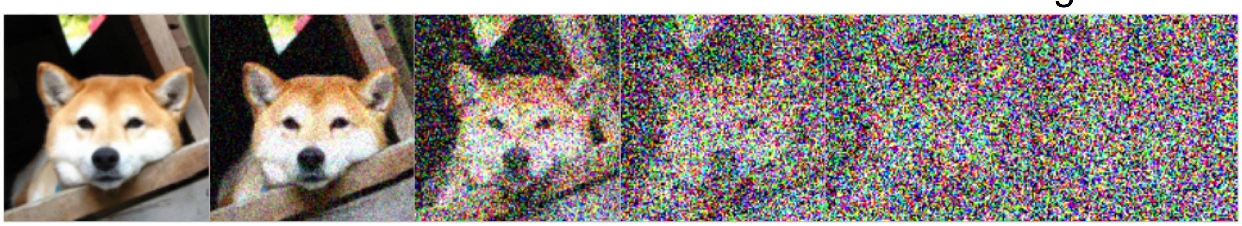




[courtesy of Jason Yim]

Over 3D protein structures, etc.

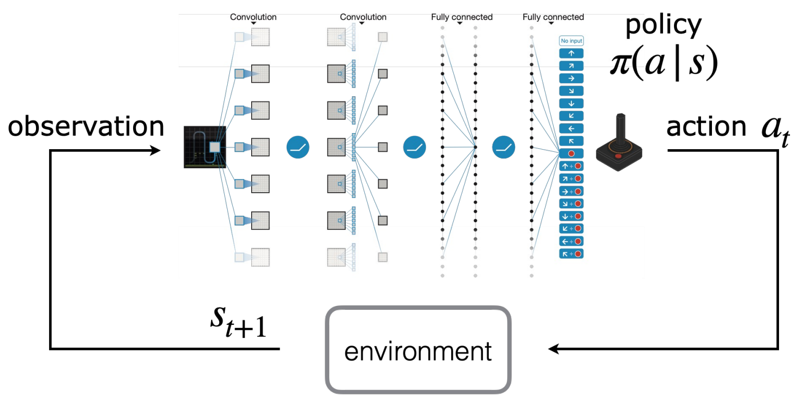
de-noising diffusion models over images

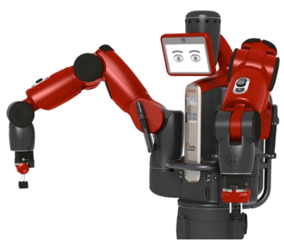


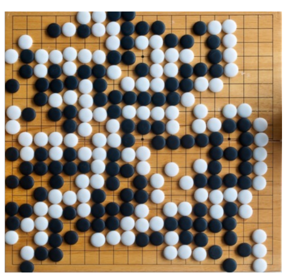
[image from Rissanen et al 2022]

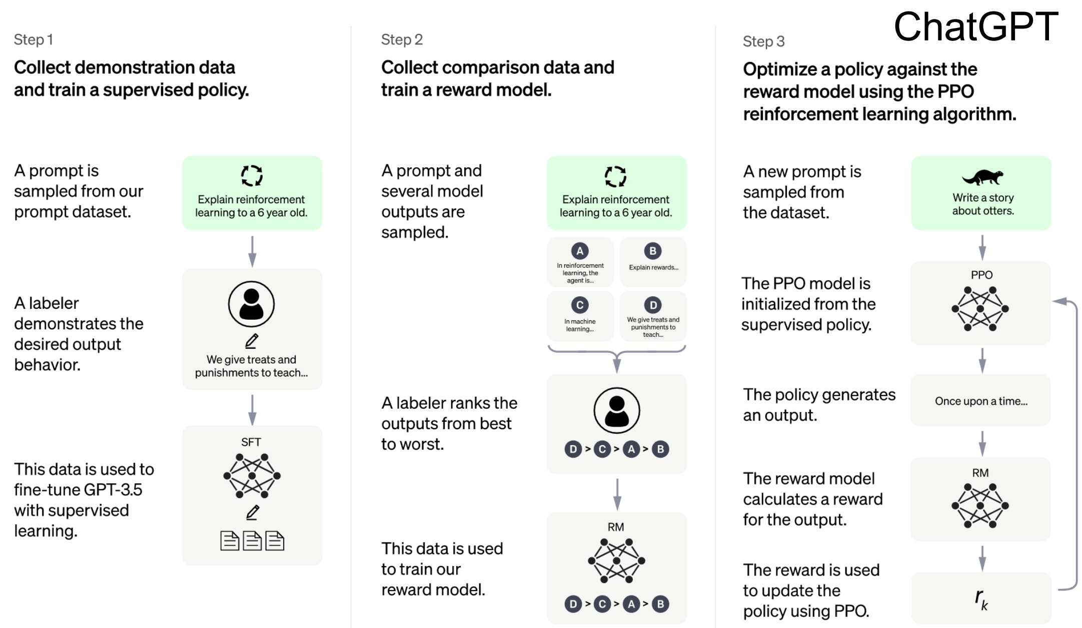
[Slides adapted from 6.790]

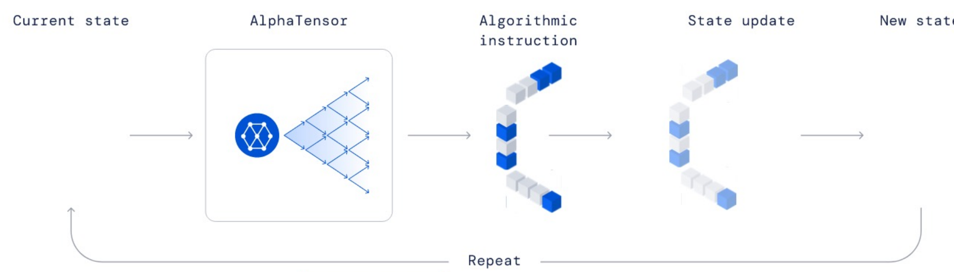
Reinforcement learning











Single-player game played by AlphaTensor, where the goal is to find a correct matrix multiplication algorithm. The state of the game is a cubic array of numbers (shown as grey for 0, blue for 1, and green for -1), representing the remaining work to be done.

[Slides adapted from 6.790]

Machine learning (ML): why & what

- **What is ML?** Roughly, a set of methods for making predictions and decisions from data.
- **Why study ML?** To apply; to understand; to evaluate; to create!
- **Notes:** ML is a tool with pros & cons

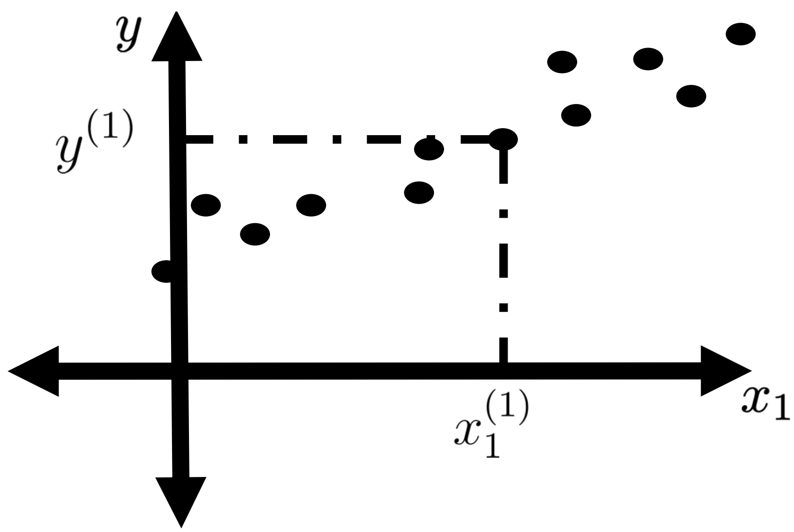
- **What do we have?** Data! And computation!
- **What do we want?** To make predictions on new data!
- **How do we learn to make those decisions?**
  - The topic of this course!

What do we have?

- There are many different problem classes in ML
  - We will first focus on an instance of supervised learning known as **regression**.

(Training) data

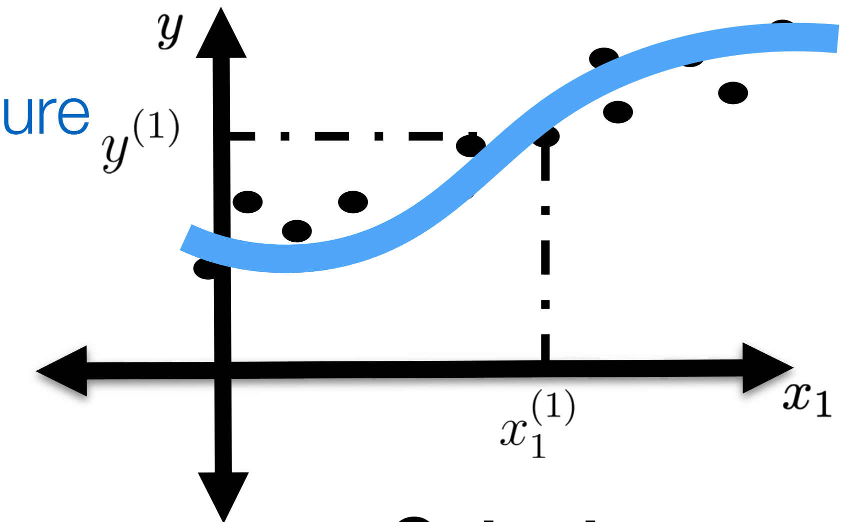
- n training data points
- For data point $i \in \{1, \ldots, n\}$
  - Feature vector $x^{(i)} = (x_1^{(i)}, \ldots, x_d^{(i)})^\top \in \mathbb{R}^d$
  - Label $y^{(i)} \in \mathbb{R}$
- Training data $\mathcal{D}_n = \{(x^{(1)}, y^{(1)}), \ldots, (x^{(n)}, y^{(n)})\}$



What do we want?

We want a "good" way to label new feature vectors

- How to label? Learn a hypothesis
- We typically consider a class of possible hypotheses



Input:
Feature vector

$$x \rightarrow \boxed{h} \rightarrow y$$

Output:
Label

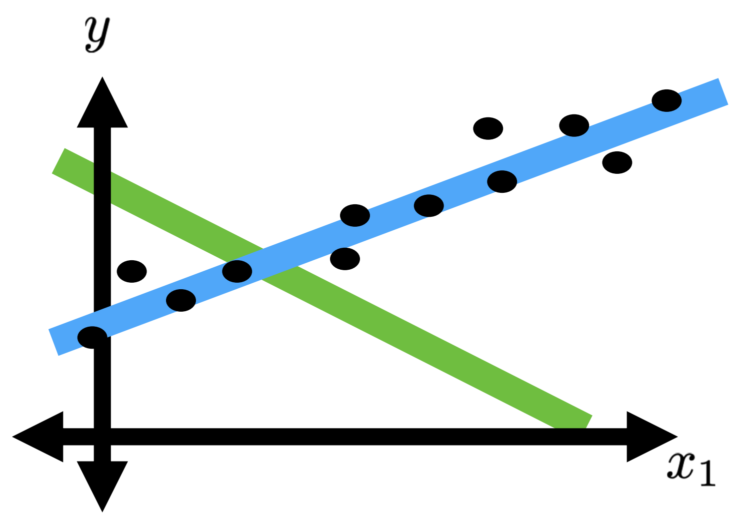
how well our hypothesis labels new feature vectors depends largely on how expressive the hypothesis class is

What do we want?

We may consider the class of linear regressors:

- Hypotheses take the form:

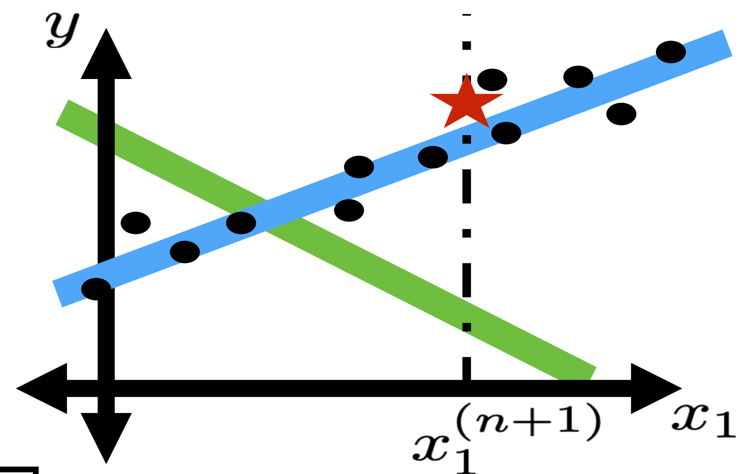
$$\underbrace{h(x;\theta,\theta_0)}_{\text{parameters to learn }\Theta} = \theta^\top x + \theta_0$$



- What we really want is to generalize to **future data**!
- What we don't want:
  - Model does not capture the input-output relationship (e.g., not enough data) —> Underfitting
  - Model too specific to training data —> Overfitting

How good is a hypothesis?

Hopefully predict well on future data



- How good is a regressor at one point?
  - Quantify the error using a loss function, $\mathcal{L}(g, a)$
  - Common choice: squared loss:

$$\mathcal{L}(g, a) = (g - a)^2$$

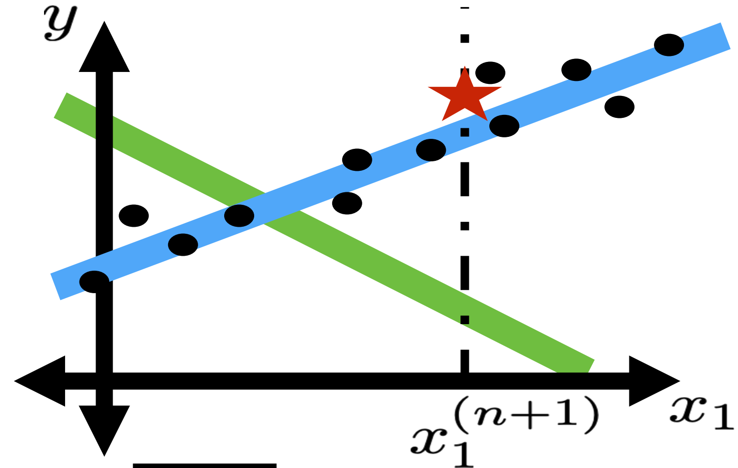
g: guess,
a: actual

- Training error: $$\mathcal{E}_n(h; \Theta) = \frac{1}{n} \sum_{i=1}^{n} \mathcal{L}\left(h(x^{(i)}; \Theta), y^{(i)}\right)$$

- Validation or Test error (*n'* new points): $$\mathcal{E}(h) = \frac{1}{n'} \sum_{i=n+1}^{n+n'} \mathcal{L}\left(h(x^{(i)}), y^{(i)}\right)$$

How do we learn?

- Have data; have hypothesis class
- Want to choose (learn) a good hypothesis (a set of parameters)



What we want:

$$x \rightarrow \boxed{h} \rightarrow y$$

How to get it:
(Next time!)

$$\mathcal{D}_n \rightarrow \boxed{\text{learning algorithm}} \rightarrow h$$