Plan for today

- ML examples.
- ML math/coding background.
- ML setting and meta-algorithms.
- First technique: linear regression.
What is machine learning?

**Machine learning**: improving computational mechanisms by fitting them to data.
Application 1: image classification

- Birdwatcher takes photos of birds, organizes by species.
- **Goal**: automatically recognize bird species in new photos.

![Indigo bunting](image)

- **Why ML**: variation in lighting, occlusions, morphology.
Application 2: recommender system

- Netflix users watch movies and provide ratings.
- **Goal**: predict user’s rating of unwatched movie.
- (Real goal: keep users paying customers.)
- (Real effect: reinforce stereotypes found in the data?)

![Graph showing user and item preferences](Image credit: Koren, Bell, and Volinsky, 2009.)

- **Why ML**: easily adapt to and leverage movie attributes, viewer attributes, viewer relationships, etc.
Application 3: machine translation

- Linguists provide translations of all English language books into French, sentence-by-sentence.
- **Goal:** translate any English sentence into French.

![Translation Interface]

**Note:** the text-to-speech is via ML (recurrent network transformer).

- **Why ML?** Not only avoid hard-coding many rules, but also capture idiom and other nuances.
Application 4: chess

- Chess enthusiasts construct a large corpus of chess games. (Or: start with nothing, play random games!)
- **Goal:** Win chess games.

- **Why ML?** Avoid hard-coding evaluation; magically interpolate between observed positions, as humans do.
Math/coding background

- Linear algebra (e.g., null spaces; eigendecomposition; SVD)
- Basic probability and statistics (e.g., variance of a random variable)
- Multivariable calculus (e.g., gradient of $\|Aw - b\|_2$ with respect to $w$)
- Basic proof writing (e.g., prove $A^TA$ is positive semi-definite)

Coding
- Python 3. It's slow, but often computation will be inside fast libraries.
- Numpy, an easy-to-use numeric library.
- Pytorch, a numeric library with gpu support, auto-differentiation, and deep learning helpers.

My opinion. Pytorch is one of the nicest libraries I've ever used, for anything. I use it for much more than deep learning.
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>>> import numpy
>>> import torch

>>> 3 / 2
1.5
>>> 3 // 2
1

>>> A = torch.randn(5,5)
>>> b = torch.randn(5,1)
>>> x = torch.gels(b, A)[0]
>>> (A @ x - b).norm()
tensor(3.7985e-06)

>>> x = numpy.linalg.lstsq(A, b)[0]
>>> (A @ torch.tensor(x) - b).norm()
tensor(1.1999e-06)
pytorch on gpu is easy

```python
>>> import torch

>>> A = torch.randn(5, 5)
>>> b = torch.randn(5)
>>> (A @ b).norm()
tensor(4.7746)

>>> device = torch.device("cuda:0")
>>> (A.to(device) @ b.to(device)).norm()
tensor(4.7746, device='cuda:0')

>>> (A.to(device) @ b).norm()
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
RuntimeError: Expected object of type torch.cuda.FloatTensor but found type torch.FloatTensor for argument #2 'vec'
```

**Note.** Homeworks will be graded in a gpu-free container!
Homework 0

- Homework 0 is posted on the class webpage.
- It is a sanity check of basic (math and coding) background.
- It is due Tuesday, February 2.
- It has two gradescope components: hw0 is multiple choice, hw0code is coding.
Main setting: supervised learning

Training data: labeled examples \((x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\) where

- each input \(x_i\) is a machine-readable description of an instance (e.g., image, sentence), and
- each corresponding label \(y_i\) is an annotation relevant to the task—typically not easy to automatically obtain.

Goal: learn a predictor (a function) \(\hat{f}\) from labeled examples, that accurately "predicts" the labels of new (previously unseen) inputs.
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**Goal:** learn a **predictor (a function)** \(\hat{f}\) from labeled examples, that accurately "predicts" the labels of **new (previously unseen) inputs.**
Unsupervised learning: find structure in some examples \((x_i)_{i=1}^n\) (there are no labels!).

Time series modeling: the label of \(x_i\) also depends on \((x_{i-1}, x_{i-2}, \ldots)\).

Reinforcement learning: the machine learning method makes decisions, not just predictions: the outputs affect future inputs. (E.g., driving a car).
Consider easy setting: learn $\hat{f} : X \rightarrow Y$ from examples $((x_i, y_i))_{i=1}^n$.

Not easy.
What are the difficulties?

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- How to clean/improve/augment data?
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Not easy.

- How to clean/improve/augment data?
- How to choose structure/model for $\hat{f}$?
- How to algorithmically fit $\hat{f}$ to data?
- How to ensure $\hat{f}$ does not overfit, meaning it fits $((x_i, y_i))_{i=1}^{n}$ well, but is useless on future data?
1. Clean/augment data (lecture 10?).
2. Pick model/architecture (anything from lectures 2-13).
3. Pick a loss function measuring model fit to data.
4. Run a gradient descent variant to fit model to data.
5. Tweak 1-4 until training error is small.
6. Tweak 1-5, possibly reducing model complexity, until testing error is small.
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Is that all of ML?
No, but these days it’s much of it!
Model choice?

Should we use 1-nearest-neighbor or a 2-layer ReLU network?
Model/algorithm choice?

- Linear or Logistic Regression: 83.7%
- Decision Trees or Random Forests: 78.1%
- Gradient Boosting Machines (xgboost, lightgbm, etc.): 61.4%
- Convolutional Neural Networks: 43.2%
- Bayesian Approaches: 31.4%
- Recurrent Neural Networks: 30.2%
- Neural Networks (MLPs, etc.): 28.2%
- Transformer Networks (BERT, gpt-3, etc.): 14.8%
- Generative Adversial Networks: 7.3%
- Evolutionary Approaches: 6.5%
- Other: 4.5%
- None: 1.7%

(From kaggle 2020 survey.)
1. Start from **training data** $((x_i, y_i))_{i=1}^n$, with $x_i \in \mathbb{R}^d$ and $y_i \in \mathbb{R}$.

2. **Model** is a **linear predictor**: pick $w \in \mathbb{R}^d$ with

$$x_i \mapsto w^T x_i \approx y_i.$$ 

3. **Loss function** is squared loss (standard regression loss):

$$\ell(w^T x_i, y_i) = \frac{1}{2} (w^T x_i - y_i)^2.$$ 

We will minimize the **empirical risk** (average loss over training examples):

$$\hat{R}(w) = \frac{1}{n} \sum_{i=1}^n \ell(w^T x_i, y_i) = \frac{1}{2n} \sum_{i=1}^n (w^T x_i - y_i)^2.$$ 

Convenient form using matrices:

$$\hat{R}(w) = \frac{1}{2n} \|Xw - y\|^2 \quad \text{where} \quad X := \begin{bmatrix} x_1^T & \cdots & x_n^T \end{bmatrix}^T \in \mathbb{R}^{n \times d}.$$
3. Minimize the empirical risk

\[ \hat{R}(w) = \frac{1}{2n} \| Xw - y \|^2 \]

where \( X := \begin{bmatrix} \leftarrow x^T_1 \rightarrow \\ \vdots \\ \leftarrow x^T_n \rightarrow \end{bmatrix} \in \mathbb{R}^{n \times d}. \)

4. Basic method: gradient descent. Set \( w_0 = 0 \), and thereafter

\[ w_{i+1} := w_i - \eta \nabla \hat{R}(w_i) = w_i - \frac{\eta}{n} X^\top (Xw_i - y), \]

where \( \eta \) is a learning rate (step size).

```python
w = torch.zeros(d)
for _ in range(niters):
    w = X.T @ (X @ w - y) / 100 / n
```
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(Appendix.)
Supplemental reading

- Murphy: chapter 1.