

## Overview

Lu  
Eigenvalues

$$\begin{pmatrix} 0 & 1 \\ 1 & 2 \end{pmatrix}$$

A

$$PA = LU$$

$$\begin{pmatrix} 0.00001 & 1 \\ 2 & 3 \\ 3 & 4 \\ 4 & 5 \\ 5 & 1000,000 \end{pmatrix}$$

In partial piv swap  
the biggest entry to top

$$\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \xrightarrow{\quad} \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

## General LU Partial Pivoting

What does the overall process look like?

(and what pivot do we pick if all values in the column are nonzero)  $\rightarrow$  the largest in abs. val

$$P_1 A = \begin{pmatrix} 1 & 0 \\ l_{11} & L_{12} \end{pmatrix} \begin{pmatrix} u_{11} & u_{12} \\ 0 & u_{22} \end{pmatrix}$$

[Recurse to produce

$$\bar{P} A_{22} = \bar{L}_{22} \bar{U}_{22}$$

$$P = \left( \begin{array}{c|cc} 1 & -o & - \\ \hline 0 & \bar{P} & \end{array} \right) P_1$$

$$\rightarrow PA = LU$$

why  $LU$ ?

$$Ax = b$$

$$PA = LU$$

$$A = P^{-1}LU$$

$$= P^T LU$$

$$\underbrace{P^T L h}_{A} x = b$$

$$L h \approx P^\dagger b$$

$$x = \underbrace{U^{-1} L^{-1} P^\dagger b}_\text{}$$

How do I compute

$$L \vec{x} - \vec{y} \quad \leadsto L^{-1} \vec{y} = \vec{x} \quad (\text{w/ } \vec{y} = P^\dagger b)$$

/  
forward subst



$$\vec{x} = \vec{y}$$

$$\begin{pmatrix} 0 & 0 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix}$$

Apply  $P$  in just  $O(n)$

Given an LU factorization

$P_A = LU$ , can solve

$Ax = b$  in  $\Theta(n^2)$

## More cost concerns

What's the cost of solving  $Ax = b$ ?

(given  $(U)$ )

$$O(n^2)$$

→ What's the cost of solving  $Ax_1 = b_1, \dots, Ax_n = b_n$ ?

(given  $(U)$ )

$$O(n^3) = O(n^2) \cdot O(n)$$

What's the cost of finding  $A^{-1}$ ?

# RTIS

→ What's the cost of  $n$  solves? (not given  $(U)$ )

$$O(n^3) + O(n^3) = O(n^3)$$

$$A \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

$$A \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{pmatrix}$$

$$A \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} - I \rightsquigarrow X = A^{-1}$$

$\hookrightarrow O(n^3)$

$$\begin{aligned}\det(A) &= \det(P^T U) \\ &= \det(P) \cdot \det(L) \cdot \det(U) \\ &\quad \pm 1 \quad | \quad T_{ii} u_{ii}\end{aligned}$$

$$\det(AB) = \det(A) \det(B)$$

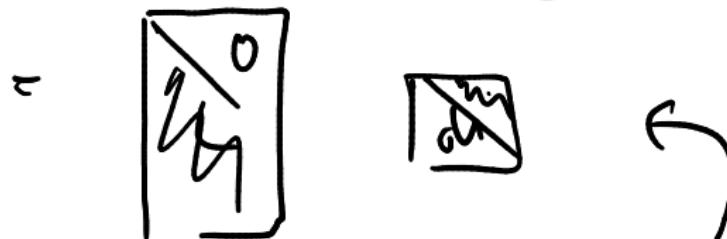
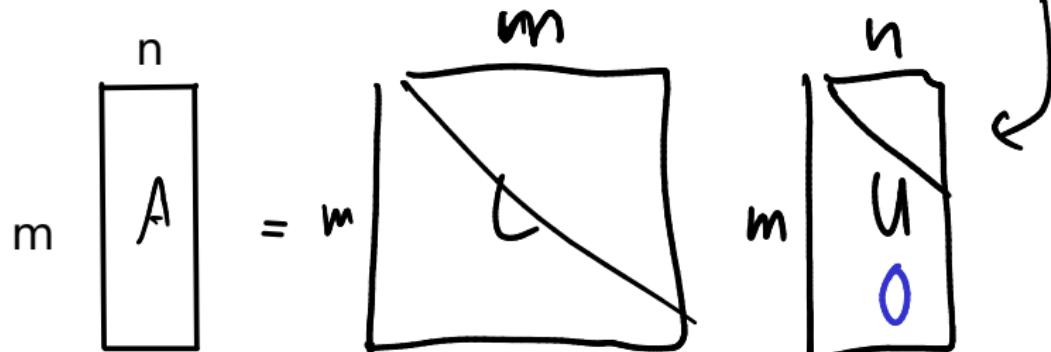
$$m \overset{n}{A} = L \cup$$

↑                      ↑

$$m \times ? \quad ? \times n$$

## LU: Rectangular Matrices

Can we compute LU of an  $m \times n$  rectangular matrix?



# Outline

Python, Numpy, and Matplotlib  
Making Models with Polynomials  
Making Models with Monte Carlo  
Error, Accuracy and Convergence  
Floating Point  
Modeling the World with Arrays  
    The World in a Vector  
    What can Matrices Do?  
    Graphs  
    Sparsity  
Norms and Errors  
The 'Undo' Button for Linear Operations: LU  
**Repeating Linear Operations:**  
Eigenvalues and Steady States  
Eigenvalues: Applications

Approximate Undo: SVD and Least Squares  
SVD: Applications  
    Solving Funny-Shaped Linear Systems  
    Data Fitting  
    Norms and Condition Numbers  
    Low-Rank Approximation  
Interpolation  
Iteration and Convergence  
Solving One Equation  
Solving Many Equations  
Finding the Best: Optimization in 1D  
Optimization in  $n$  Dimensions

## Eigenvalue Problems: Setup/Math Recap

$A$  is an  $n \times n$  matrix.

- ▶  $x \neq 0$  is called an **eigenvector** of  $A$  if there exists a  $\lambda$  so that

$$Ax = \lambda x.$$

- ▶ In that case,  $\lambda$  is called an **eigenvalue**.
- ▶ By this definition if  $x$  is an eigenvector then so is  $\alpha x$ , therefore we will usually seek normalized eigenvectors, so  $\|x\|_2 = 1$ .

$$\lambda \vec{x} = \vec{y}$$

$$Ay = \lambda A\vec{x} = \lambda \lambda \vec{x} = \lambda \vec{y}$$

## Finding Eigenvalues

How do you find eigenvalues?

$$\det(A - \lambda I)$$

= characteristic polynomial( $\lambda$ )

→ solve  $(Pf\lambda) = 0$   
for eigenvalues  $\lambda$ .

Polynomials of degree 5 or higher

may not have a closed-form solution.

→ comp. consequence:  
no algorithm with finite

# of steps.

## Distinguishing eigenvectors

$$A \vec{x}_1 = \lambda_1 \vec{x}_1$$

Assume we have normalized eigenvectors  $x_1, \dots, x_n$  with eigenvalues  $|\lambda_1| > |\lambda_2| > \dots > |\lambda_n|$ . Show that the eigenvectors are linearly-independent.

$$\vec{0} = \underbrace{\alpha_1 \vec{x}_1 + \alpha_2 \vec{x}_2 + \dots + \alpha_n \vec{x}_n}_{\text{sum of scaled eigenvectors}} \rightarrow \vec{x}$$

▷ To show:  $\alpha_1 = \dots = \alpha_n = 0$ .

$$A \vec{x} = \alpha_1 A \vec{x}_1 + \dots + \alpha_n A \vec{x}_n$$

$$= \underbrace{\alpha_1 \lambda_1 \vec{x}_1}_{\alpha_1 \lambda_1} + \underbrace{\alpha_2 \lambda_2 \vec{x}_2}_{\alpha_2 \lambda_2} + \dots + \underbrace{\alpha_n \lambda_n \vec{x}_n}_{\alpha_n \lambda_n}$$

$$\frac{\vec{Ax}}{\lambda_1} = \alpha_1 \vec{x} + \underbrace{\alpha_2 \frac{\lambda_2}{\lambda_1} \vec{x}_2 + \dots + \frac{\lambda_n}{\lambda_1} \vec{x}_n}_{< 1}$$

$$\frac{\vec{A}^{10,000} \vec{x}}{\lambda_1^{10,000}} = \vec{\alpha}_1 \vec{x} + \alpha_2 \left( \frac{\lambda_2}{\lambda_1} \right)^{10,000} \vec{x}_2 + \dots$$

$$\lim_{l \rightarrow \infty} 0 = \frac{\vec{A}^l \vec{x}}{\lambda_1^l} = \left( \alpha_1, \vec{x}_1 \right) \Rightarrow \alpha_1 = 0$$

Incl.  $\alpha_2 = \dots = \alpha_n = 0$

## Diagonalizability

If we have  $n$  eigenvectors with different eigenvalues, the matrix is diagonalizable.

## Are all Matrices Diagonalizable?

Give characteristic polynomial, eigenvalues, eigenvectors of

$$\begin{pmatrix} 1 & 1 \\ & 1 \end{pmatrix}.$$

## Power Iteration

We can use linear-independence to find the eigenvector with the largest eigenvalue. Consider the eigenvalues of  $A^{1000}$ .

## Power Iteration: Issues?

What could go wrong with Power Iteration?

## What about Eigenvalues?

Power Iteration generates eigenvectors. What if we would like to know eigenvalues?

$$Ax = \lambda x$$

$$\frac{Ax}{x} = \frac{\lambda x}{x} = \lambda$$

The diagram shows the fraction  $\frac{Ax}{x}$  with yellow arrows indicating cancellation of the vector  $x$  from both the numerator and the denominator. The fraction is then simplified to  $\frac{\lambda x}{x} = \lambda$ .

## Convergence of Power Iteration

What can you say about the convergence of the power method?  
Say  $\mathbf{v}_1^{(k)}$  is the  $k$ th estimate of the eigenvector  $\mathbf{x}_1$ , and

$$e_k = \|\mathbf{x}_1 - \mathbf{v}_1^{(k)}\|.$$