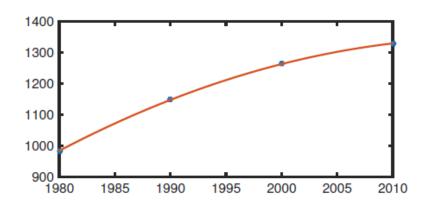
Chapter 2

Square linear systems: Ax = b



Square linear systems: objectives

- Where these systems may arise
- Efficient representation in MATLAB
- Learn increasingly sophisticated algorithms to solve these systems
- Learn tools to measure the performance of these algorithms
- Learn to recognize where difficulties may arise in solving linear systems
- Learn to recognize where structure of the problem can be exploited for fast and accurate solutions

2.1

Polynomial interpolation

- The idea of interpolation is determine a function that passes through, or recovers, given data
- Say we have (t_i, y_i) for i = 1, 2, ..., n.
- We assume that no two t_i are the same
- If we consider putting a polynomial through this data, we choose an n-1 degree polynomial because there are n constants to find, which matches the number of data points available:

$$f(t) = a_1 t^{n-1} + a_2 t^{n-2} + \dots + a_{n-1} t + a_n.$$

• To make this pass through the data, enforce $y_i = f(t_i)$ at each i

Polynomial interpolation

- Enforcing $y_i = f(t_i)$ at each i gives \rightarrow
- The unknowns are the coefficients a_i
- This is n equations and n unknowns, and the a_i appear linearly: linear system!

$$t_1^{n-1}a_1 + t_1^{n-2}a_2 + \dots + t_1a_{n-1} + a_n = y_1$$

$$t_2^{n-1}a_1 + t_2^{n-2}a_2 + \dots + t_2a_{n-1} + a_n = y_2$$

$$t_3^{n-1}a_1 + t_3^{n-2}a_2 + \dots + t_3a_{n-1} + a_n = y_3$$

$$t_n^{n-1}a_1 + t_n^{n-2}a_2 + \cdots + t_na_{n-1} + a_n = y_n.$$

Polynomial interpolation

- It is convenient to write the system in matrixvector form →
- The (known) matrix has a special name:
 Vandermonde matrix V
- The right hand side (rhs) vector y is known
- The unknown vector a must satisfy Va = y

```
\begin{bmatrix} t_1^{n-1} & t_1^{n-2} & \cdots & t_1 & 1 \\ t_2^{n-1} & t_2^{n-2} & \cdots & t_2 & 1 \\ t_3^{n-1} & t_3^{n-2} & \cdots & t_3 & 1 \\ \vdots & \vdots & & \vdots & \vdots \\ t_n^{n-1} & t_n^{n-2} & \cdots & t_n & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix}
```

An example: Fitting population data

- Census data is often measured in 10 year intervals.
- How to get population estimates in other years?
- May affect policy decisions ranging from social programs like health care to education, business planning, and many other things
- We can apply interpolation to available data to compute values in intervening years
- Our data is 4 populations for China at 10 year intervals
- The idea is to put a cubic polynomial through this data: we have to find the 4 coefficients such that this happens.

Population example

- Input years and population →
- The rhs vector y is now pop \rightarrow
- The Vandermonde matrix V has columns in decreasing powers of t
- The method works better for measuring t as years since 1980 →

```
vear = (1980:10:2010)'
pop = [
    984.736
    1148.364
                  [Example 2.1.1]
    1263.638
    1330.141
   pop;
V = zeros(4.4):
for i = 1:4
   V(i,:) = [t(i)^3 t(i)^2 t(i) 1];
end
V =
        1000
                    100
                    400
       8000
```

900

27000

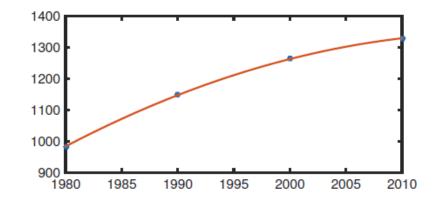
Population example

- Solve linear system for coefficients a using the backslash (\)
- Use the command polyval to calculate polynomial
- Plot the populations (dots) and cubic polynomial fit (red curve)
- Note how curve passes through the data

```
a = V \ y
```

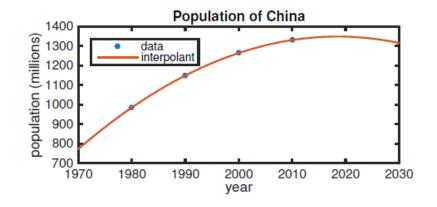
```
a =
-0.0001
-0.2397
18.7666
984.7360
```

```
tt = linspace(0,30,300)';
yy = polyval(a,tt);
plot(1980+tt,yy)
```



Population example

- A better plot with labels
- Using the cubic polynomial between the data points is interpolation: solid results
- Using the cubic outside the data interval is extrapolation: use with care!!





Computing with matrices in MATLAB

- MATLAB originally stood for "Matrix Laboratory"
- It is particularly easy to use MATLAB for this kind of computing
- Section 2.2 contains a tutorial on creating and manipulating matrices
- Try it!

Needed operations for matrices

- Consider the j-th column of the identity matrix: $e_1 = [1\ 0\ 0\ ...\ 0]^\mathsf{T}, \, e_2 = [0\ 1\ 0\ ...\ 0]^\mathsf{T}, \, \text{etc, } I = [e_1\ e_2\ ...\ e_n] = \begin{bmatrix} 0\ 0\ 0\ ...\ 0 \end{bmatrix}^\mathsf{T}$ Then if $A = [a_1\ a_2\ ...\ a_n]$ shows the columns of A...
- Right-multiplying by e_i gives the j-th column of A: $Ae_i=a_i$
- Left multiplying by e_i^T gives the i-th row of A: $e_i^T A = [A_{i1} A_{i2} \dots A_{in}]$
- ullet Combining the two can pick out a single element: $e_i^T A e_j = A_{ij}$
- We will use these soon!

Linear Systems

- Consider the system
- The compact form is Ax = h
- The exact solution from theory is $x = A^{-1}b$ provided that A is nonsingular, i.e., A^{-1} exists
- This is great, but for computing, we almost never want to solve this way!!

- $a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1$ $a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2$
- $a_{n1}x_1 + a_{n2}x_2 + \cdots + a_{nn}x_n = b_n.$

Linear Systems

- A convenient and powerful capability for solving Ax = b in MATLAB is \
- An example is at left
- Is the answer good? Look at residual
- Small residual indicates a good answer here: how much we missed exactly satisfying the equation is close to eps

```
A = magic(3)
b = [1;2;3];
x = A\b
```

```
A =

    8    1    6
    3    5    7
    4    9    2

x =

0.0500
0.3000
0.0500
```

```
residual = b - A*x
```

```
residual =
1.0e-15 *
0
0
0.4441
```

2.3 Linear Systems

- Care and understanding is still needed though
- Note that even for singular A, one still gets an answer from \

```
A = [0 1; 0 0];
b = [1;2];
x = A\b

Warning: Matrix is singular to working precision.
x =
   -Inf
   Inf
```

- We will understand why later
- If you see a warning, investigate!!

- Let's begin with simple systems to understand algorithms for solving Ax = b
- Consider *lower triangular* systems where elements above a_{ii} are zero
- Said another way, $a_{ij}=0$, j>i
- Solve by starting with $x_1 = \frac{8}{4} = 2$
- Continue with $x_2 = \frac{5 (3)(2)}{-1} = 1$
- Then find x_3 , then x_4 , to get solution
- This is called forward substitution

$$\begin{bmatrix} 4 & 0 & 0 & 0 \\ 3 & -1 & 0 & 0 \\ -1 & 0 & 3 & 0 \\ 1 & -1 & -1 & 2 \end{bmatrix} x = \begin{bmatrix} 8 \\ 5 \\ 0 \\ 1 \end{bmatrix}$$

$$x = \begin{bmatrix} 2\\1\\2/3\\1/3 \end{bmatrix}$$

- For the more general system Lx = b where L is lower triangular, we can still do forward substitution
- L_{ij} are elements of \boldsymbol{L}
- No trouble here unless $L_{ii}=0$, then we can divide by it
- Theorem 2.1: If at least one of the $L_{ii}=0$, then \boldsymbol{L} is singular
- How to implement in MATLAB?

$$x_{1} = \frac{b_{1}}{L_{11}}$$

$$x_{2} = \frac{b_{2} - L_{21}x_{1}}{L_{22}}$$

$$x_{3} = \frac{b_{3} - L_{31}x_{1} - L_{32}x_{2}}{L_{33}}$$

$$x_{4} = \frac{b_{4} - L_{41}x_{1} - L_{42}x_{2} - L_{43}x_{3}}{L_{44}}$$

Lis nonsingular (=> Lii +0, Vi

- At right is an implementation using two nested for loops
- For the *i* loop, we work with x(i)
- For the j loop, we step through the columns j = 1, ..., i
- For i = 1, there is only one term (b(1)); for larger i, previous x's are used
- As a user, you can remove the semicolons and see how the loops progress
- We can be a little more elegant however

```
for i = 1:4

x(i) = b(i);

for j = 1:i-1

x(i) = x(i) - L(i,j)*x(j);

end

x(i) = x(i)/L(i,i);

end
```

- At right is two nested for loops, consider i = 4
- Considering the last unknown, we end up with

$$b_4 - (L_{41}x_1 + L_{42}x_2 + L_{43}x_3) = b_4 - \begin{bmatrix} L_{41} & L_{42} & L_{43} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

 The last vector product is a dot product, and we can eliminate the inner loop:

```
for i = 1:n
 x(i) = (b(i) - L(i,1:i-1)*x(1:i-1)) / L(i,i);
• Function next....
```

for i = 1:4

end

end

x(i) = b(i);for j = 1:i-1

x(i) = x(i)/L(i,i);

x(i) = x(i) - L(i,j)*x(j);

Lower Triangular Systems

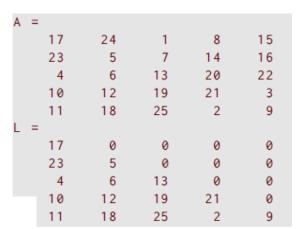
- Pass in L and b; return solution x
- Note comments;
 they appear in
 help
 forwardsub
- Detect system sizen automatically
- Single loop implementation
- No test for singularL

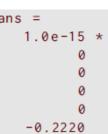
```
1 function x = forwardsub(L,b)
 % FORWARDSUB Forward substitution for lower-tri;
3 % Input:
            lower triangular square matrix (n by n)
            right-hand side vector (n by 1)
6 % Output:
7 % x solution of Lx=b (n by 1 vector)
   n = length(L);
10 x = zeros(n,1);
   for i = 1:n
   x(i) = (b(i) - L(i,1:i-1)*x(1:i-1)) / L(i,i);
   end
```

Lower Triangular Example

- Easy to make a lower triangular matrix
- Make up rhs
- Solve system by calling function forwardsub
- Compute the residual to check the solution; it is the size of ϵ_M

```
A = magic(5)
L = tril(A)
```





ones (5.1):

0.0588

-0.0706

0.0914

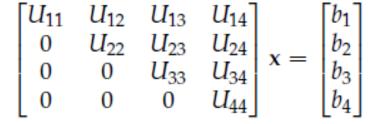
-0.0228

-0.0684

x = forwardsub(L,b)

Upper Triangular Systems

- For the upper triangular system Ux = b where U has $U_{ij} = 0, j < i$
- That is elements below the main diagonal are zero this time
- Solve for last variable first this time and work backward
- No trouble here unless $U_{ii}=0$, then we cannot divide by it
- Theorem 2.1: If at least one of the $U_{ii} = 0$, then U is singular
- Implementation similar



$$x_4 = \frac{U_{44}}{U_{44}}$$

$$x_3 = \frac{b_3 - U_{34}x_4}{U_{33}}$$

$$x_2 = \frac{b_2 - U_{23}x_3 - U_{24}x_4}{U_{22}}$$

$$x_1 = \frac{b_1 - U_{12}x_2 - U_{13}x_3 - U_{14}x_4}{U_{11}}$$

Upper Triangular Systems

- Pass in **U** and **b**;
 return solution **x**
- Note comments;
 they appear in
 help backsub
- Detect system sizen automatically
- Single loop counts down now
- No test for singularU

```
function x = backsub(U,b)
   % BACKSUB Backward substitution for upper-triang
3 % Input:
4 % U upper triangular square matrix (n by n)
5 % b right-hand side vector (n by 1)
  % Output:
   % x solution of Ux=b (n by 1 vector)
   n = length(U);
   x = zeros(n,1);
11 for i = n:-1:1
     x(i) = (b(i) - U(i, i+1:n) * x(i+1:n)) / U(i,i);
   end
```

- Let's look at a made-up system where we know exact answer
- For $\beta=2.2$ and $\alpha=0.3$, there is no problem and the residual is the size of machine epsilon, eps
- However, we can create difficult systems with $\beta \gg \alpha$ with terrible residual!
- We'll improve this later

```
\begin{bmatrix} 1 & -1 & 0 & \alpha - \beta & \beta \\ 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}
```

```
alpha = 0.3;

beta = 1e12;

U = eye(5) + diag([-1 -1 -1 -1],1);

U(1,[4 5]) = [ alpha-beta, beta ];

b = [alpha;0;0;0;1];
```

```
err = x - x_exact
err =
```

= backsub(U,b);

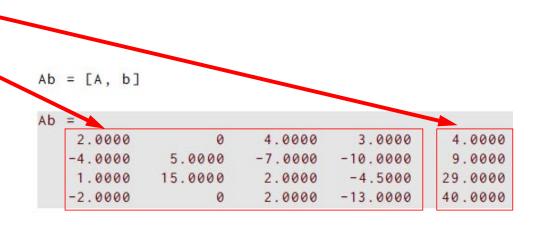
```
1.0e-04 *
-0.4883
0
0
```

[Example 2.3.3]

Gaussian elimination and LU factorization

- A general purpose algorithm for solving linear systems is Gaussian elimination (GE)
- We will use this algorithm to adapt it so that it yields an *LU* facutorization; this is just our first example of factorization
- We will further adapt the method to improve its stability and robustness a bit later
- You should have seen the basic GE method prior to this class
- We incorporate MATLAB in discussing the method here

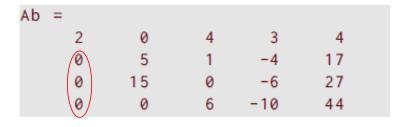
- First, create a 4x4 linear system
- Then, we append the right hand side to the coefficient matrix to obtain
 the augmented matrix
- GE is then performed on this augmented matrix



- We now want to make Ab(2:4,1)=0
- That is, elements below row 1 (R1) become zero in first column
- Compute multiplier mult, then do R2 <- R2- mult*R1
- Repeat this process for R3 and R4, recomputing mult for each row

```
mult = Ab(2,1)/Ab(1,1);
Ab(2,:) = Ab(2,:) - mult*Ab(1,:)
Ab =
    2.0000
                         4.0000
                                   3.0000
                                              4.0000
                        1.0000
                                  -4.0000
                                             17.0000
              5.0000
    1.0000
            15.0000
                        2.0000
                                  -4.5000
                                            29.0000
   -2.0000
                         2.0000
                                 -13.0000
                                             40.0000
```

```
mult = Ab(3,1)/Ab(1,1);
Ab(3,:) = Ab(3,:) - mult*Ab(1,:);
mult = Ab(4,1)/Ab(1,1);
Ab(4,:) = Ab(4,:) - mult*Ab(1,:);
Ab
```



- We now want to make Ab(3:4,2)=0
- That is, elements below R2 become zero in 2nd column
- Compute multipliers mult, for R3 and R4, recomputing mult for each row, in a loop

```
for i = 3:4
    mult = Ab(i,2)/Ab(2,2);
    Ab(i,:) = Ab(i,:) - mult*Ab(2,:);
end
Ab
```

- We now want to make Ab(4:4,3)=0
- That is, repeat the process for column 3, below R3
- This time loop only runs once, but can still be loop structure
- The first four columns are a 4x4 upper triangular matrix U, and the last column is a rhs z so that Ux=z
- Now use back substitution!

```
for i = 4
    mult = Ab(i,3)/Ab(3,3);
    Ab(i,:) = Ab(i,:) - mult*Ab(3,:);
end
Ab
```

```
U = Ab(:,1:4)
z = Ab(:,5)
```

- Solve for x with back substitution
- Error is quite small!

- This is a general strategy to solve systems
- How can we use this to get a factorization? And why?

```
x = backsub(U,z)
```

```
ans =
0
0
0
0
```

[Example 2.4.1]

GE or algebra rules

- There are three rules for manipulating systems (augmented matrix) and not changing the answer. We can:
 - 1. Switch two rows: $Ri \leftrightarrow Rj$
 - 2. Multiply a row by a scalar: c Ri \rightarrow Ri



- 3. Form a linear combination of two rows and replace one of them with the linear combo: a Ri + b Rj \rightarrow Rj
- We use these for GE, particularly the last, but we can write them as matrix vector operations
- This is a different take than linear algebra class; revisit our example

GE matrix ops

- We now want to make Ab(2:4,1)=0
- We needed mult = -2, then do R2 <- R2- mult*R1
- Let e_j be jth column of thet identity matrix (col vector)
- Multiplication on the left with e_i^T gives jth row of A
- We can write $e_2^T (-2)e_1^T$ to subtract (-2)*R1 from R2 and obtain a zero element in A_{21}
- Matrix form!

```
mult = Ab(2,1)/Ab(1,1);

Ab(2,:) = Ab(2,:) - mult*Ab(1,:)
```

$$\begin{bmatrix} \mathbf{e}_{1}^{T} \\ \mathbf{e}_{2}^{T} - 2\mathbf{e}_{1}^{T} \\ \mathbf{e}_{3}^{T} \\ \mathbf{e}_{4}^{T} \end{bmatrix} \mathbf{A} = \begin{pmatrix} \mathbf{I} - \begin{bmatrix} 0\mathbf{e}_{1}^{T} \\ -2\mathbf{e}_{1}^{T} \\ 0\mathbf{e}_{1}^{T} \\ 0\mathbf{e}_{1}^{T} \end{bmatrix} \mathbf{A} = \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1}^{T} \mathbf{A} + \begin{pmatrix} \mathbf{I} + 2 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \mathbf{e}_{1$$

$$L_{1}^{-1} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$$

GE matrix ops

- Use matrix ops to make Ab(2:4,1)=0
- Elements below row 1 (R1) become zero in first column again
- Compute multiplier mult,
 then do R2 <- R2- mult*R1
- Repeat this process for R3 and R4, recomputing mult for each row

```
A = [2 \ 0 \ 4 \ 3 \ ; \ -4 \ 5 \ -7 \ -10 \ ; \ 1 \ 15 \ 2 \ -4.5 \ ; \ -2 \ 0 \ 2 \ -13];
I = eye(4);
mult = A(2,1)/A(1,1);
 L1 = I - mult*I(:,2)*I(:,1)';
A = L1*A
A =
     2.0000
                            4.0000
                                        3.0000
                5.0000
                            1.0000
                                       -4.0000
     1.0000
               15.0000
                            2.0000
                                       -4.5000
    -2.0000
                            2.0000
                                      -13.0000
mult = A(3,1)/A(1,1);
L2 = I - mult*I(:,3)*I(:,1)';
A = L2*A:
mult = A(4,1)/A(1,1);
L3 = I - mult*I(:,4)*I(:,1)';
A = L3*A
                                 -6
                                -10
```

Elementary Matrices for GE

- To change the A_{21} element, we used $I + 2e_2e_1^T$
- Call that matrix L_{21}
- To change A_{31} , use $L_{31} = I 0.5e_1^T e_3$
- To change A_{41} , use $L_{41} = I (-1)e_1^T e_4$
- So, to change the first column under A_{11} , we can write steps in the matrix form: $A_1=L_{41}L_{31}L_{21}A$
- We can also write $L_{j1} = I m_{j1}e_je_1^T$ and we had three different multipliers

Elementary Matrices, toward LU

- To change the second column, we use $L_{42}L_{32}$, with the right one done first, and multipliers m_{42} and m_{32}
- The cumulative operations are then $A_1 = L_{42}L_{32}L_{41}L_{31}L_{21}A$
- To change A_{43} , use $L_{43} = I m_{43}e_4e_3^T$
- So, combining all of these gives us the upper triangular form we sought: $U = L_{43}L_{42}L_{32}L_{41}L_{31}L_{21}A$
- Note that applying these to the right side b will give z for Ux = z
- We get something useful for recovering A...

Elementary Matrices, toward LU

- ullet These elementary matrices L_{ij} and their inverses have remarkably useful properties
- Multiply two that differ only in sign together:

$$(\mathbf{I} + \alpha \mathbf{e}_i \mathbf{e}_j^T) (\mathbf{I} - \alpha \mathbf{e}_i \mathbf{e}_j^T) = \mathbf{I} + \alpha \mathbf{e}_i \mathbf{e}_j^T - \alpha \mathbf{e}_i \mathbf{e}_j^T - \alpha^2 \mathbf{e}_i \mathbf{e}_j^T \mathbf{e}_i \mathbf{e}_j^T$$
$$= \mathbf{I} - \alpha^2 \mathbf{e}_i (\mathbf{e}_i^T \mathbf{e}_i) \mathbf{e}_i^T = \mathbf{I},$$

• This says that the two matrices on the left are inverses! So,

$$\left(\mathbf{I} + \alpha \mathbf{e}_i \mathbf{e}_j^T\right)^{-1} = \mathbf{I} - \alpha \mathbf{e}_i \mathbf{e}_j^T,$$

and think of α as a multiplier m_{ij}

• We then have $L_{ij}^{-1} = I + m_{ij}e_ie_j^T$, and we know all those inverses!

Elementary Matrices, toward LU

- We also need to know about the produce of all of them
- Multiply two general elementary matrices together:

$$(\mathbf{I} + \alpha \mathbf{e}_2 \mathbf{e}_1^T)(\mathbf{I} + \beta \mathbf{e}_3 \mathbf{e}_1^T) = \mathbf{I} + \alpha \mathbf{e}_2 \mathbf{e}_1^T + \beta \mathbf{e}_3 \mathbf{e}_1^T + \alpha \beta \mathbf{e}_2 \mathbf{e}_1^T \mathbf{e}_3 \mathbf{e}_1^T.$$

- Second term puts α in (2,1) location and β in (3,2) location
- Last term?

LU factorization

• The product of the inverses is then of the form

$$L = L_{21}^{-1} L_{31}^{-1} L_{32}^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ m_{21} & 1 & 0 \\ m_{31} & m_{32} & 1 \end{bmatrix}$$

- Those multipliers that we used to create zero in the columns can go right into the lower triangular matrix L!
- And, finally, we have

$$LU = A$$

- \bullet This shows that A can factored or factorized into a lower triangular L and upper triangular U
- Just our first instance of factorization...

Using LU factorization

- We can rewrite the system Ax = b as L(Ux) = b
- Substitute to get L(Ux) = b;
- then let Ux = z;
- Then Lz = b

- = b as L(Ux) = b
 - Ux=2

 $A x_1 = b_1$ $A x_2 = b_2$

- This suggests how to use LU:
- 1. Compute the factorization LU = A using Gaussian elimination
- 2. Solve Lz = b using forward substitution
- 3. Solve Ux = z using backward substitution
- 4. For same A, repeat 2 and 3 for different b without step 1

Function for LU

```
function [L,U] = lufact(A)
2 % LUFACT LU factorization (demo only--not stable!)
3 % Input:
4 % A square matrix
5 % Output:
  % L,U unit lower triangular and upper triangular such that LU=A
8 n = length(A);
   L = eye(n); % ones on diagonal
10
11 % Gaussian elimination
12 for j = 1:n-1
13 for i = j+1:n
14
   L(i,j) = A(i,j) / A(j,j); % row multiplier
15
  A(i,j:n) = A(i,j:n) - L(i,j)*A(j,j:n);
16
   end
17
   end
18
19
   U = triu(A):
```

LU example: compute factors

```
Example 2.8. A = [2 \ 0 \ 4 \ 3; \ -4 \ 5 \ -7 \ -10; \ 1 \ 15 \ 2 \ -4.5; \ -2 \ 0 \ 2 \ -13];
[L,U] = lufact(A)

    Lufact computes

                                                                       Land U
    1.0000

    Checking the

   -2.0000
           1.0000
                                                                       product: looks
    0.5000
           3.0000
                      1.0000
   -1.0000
                      -2.0000
                                 1.0000
                                                                       like A

    Error shows that

                      -4
                                                                       it works
LtimesU = L*U
                                                         LtimesU
LtimesU =
                                                     ans =
    2.0000
                           4.0000
                                      3.0000
                                                                 0
   -4.0000
             5.0000
                        -7.0000
                                   -10.0000
    1.0000
              15.0000 2.0000
                                   -4.5000
   -2.0000
                           2.0000
                                    -13.0000
```

LU example: solve a system

```
Example 2.8. A = [2 \ 0 \ 4 \ 3; \ -4 \ 5 \ -7 \ -10; \ 1 \ 15 \ 2 \ -4.5; \ -2 \ 0 \ 2 \ -13]; [L,U] = lufact(A)
```

```
b = [4;9;29;40];
z = forwardsub(L,b);
x = backsub(U,z)
```

```
x =

-3

1

4
-2
```

- Lufact computes L and U
- Forward solve to get z
- Backward solve for x

[Example 2.4.3]

b - A*x

```
ans =
0
0
0
0
0
```

Performance of Linear System Solutions

Sections 2.5 and later are in Part 2



