Chapter 2, Linear Systems
Outline

1. Existence, Uniqueness, and Conditioning
2. Solving Linear Systems
3. Special Types of Linear Systems
4. Software for Linear Systems
The Geometry of Linear Equations\(^1\)

- Example, 2 × 2 system:

\[
\begin{align*}
2x - y &= 1 \\
x + y &= 5
\end{align*}
\]

- Can look at this system by *rows* or *columns*.

- We will do both.

\(^1\)Gilbert Strang: *Linear Algebra and Its Applications*
Row Form

- In the $2 \times 2$ system, each equation represents a line:

  \[
  2x - y = 1 \quad \text{line 1}
  \]

  \[
  x + y = 5 \quad \text{line 2}
  \]

- The intersection of the two lines gives the unique point $(x, y) = (2, 3)$, which is the solution.
Column Form

- The second (and more important) geometry is column based.
- Here, we view the system of equations as one vector equation:

\[
\begin{align*}
\text{Column form} \quad & x \begin{bmatrix} 2 \\ 1 \end{bmatrix} + y \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 5 \end{bmatrix}.
\end{align*}
\]

- The problem is to find coefficients, \(x\) and \(y\), such that the combination of vectors on the left equals the vector on the right.
Row Form: A Case with $n=3$.

$$2u + v + w = 5$$

Three planes

$$4u - 6v = -2$$

$$-2u + 7v + 2w = 9$$

- Each equation (row) defines a plane in $\mathbb{R}^3$.
- The first plane is $2u + v + w = 5$ and it contains points $(\frac{5}{2}, 0, 0)$ and $(0, 5, 0)$ and $(0, 0, 5)$.
- It is determined by three points, provided they do not lie on a line.
- Changing 5 to 10 would shift the plane to be parallel this one, with points $(5, 0, 0)$ and $(0, 10, 0)$ and $(0, 0, 10)$. 
Row Form: A Case with $n=3$, cont’d.

- The second plane is $4u - 6v = -2$.
- It is vertical because it can take on any $w$ value.
- The intersection of this plane with the first is a line.
- The third plane, $-2u + 7v + 2w = 9$ intersects this line at a point, $(u, v, w) = (1, 1, 2)$, which is the solution.
- In $n$ dimensions, the solution is the intersection point of $n$ hyperplanes, each of dimension $n - 1$. A bit confusing.

Note that $u=5$ is also a plane....
Row Form

The green & blue planes (rows 2 and 3) intersect in a line. Equation 1 (red) intersects this line.

\[2u + v + w = 5\]
\[4u - 6v = -2\]
\[-2u + 7v + 2w = 9\]
Column Vectors and Linear Combinations

• The preceding system is viewed as the vector equation

\[
\begin{bmatrix}
2 \\
4 \\
-2
\end{bmatrix}
+ \begin{bmatrix}
1 \\
-6 \\
7
\end{bmatrix}
+ \begin{bmatrix}
1 \\
0 \\
2
\end{bmatrix}
= \begin{bmatrix}
5 \\
-2 \\
9
\end{bmatrix}
= \mathbf{b}.
\]

• Our task is to find the multipliers, \(u\), \(v\), and \(w\).

• The vector \(\mathbf{b}\) is identified with the point \((5,-2,9)\).

• We can view \(\mathbf{b}\) as a list of numbers, a point, or an arrow.

• For \(n > 3\), it’s probably best to view it as a list of numbers.
Vector Addition Example

\[ \begin{bmatrix} 5 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} -2 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 9 \end{bmatrix} = \begin{bmatrix} -2 \\ 0 \\ 9 \end{bmatrix} \]
Linear Combination

\[
b = \begin{bmatrix} 5 \\ -2 \\ 9 \end{bmatrix} = 2 \begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix} + \begin{bmatrix} 2 \\ 4 \\ -2 \end{bmatrix} + 1 \begin{bmatrix} -1 \\ -6 \\ 7 \end{bmatrix} + 2 \begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix} = \begin{bmatrix} 5 \\ -2 \\ 9 \end{bmatrix}
\]
The Singular Case: Row Picture

\[ 4x - 2y = -2 \]
\[ 2x - y = 1 \]

\[ 2x - y = 1 \]
\[ 4x - 2y = -2 \]

- No solution.
The Singular Case: Row Picture

\[ 4x - 2y = 2 \]
\[ 2x - y = 1 \]

(0, -1)

- Infinite number of solutions.
The Singular Case: Column Picture

\[ b = \begin{pmatrix} 1 \\ 2 \end{pmatrix} \]

\[ x \begin{pmatrix} 2 \\ 4 \end{pmatrix} + y \begin{pmatrix} -1 \\ -2 \end{pmatrix} = \begin{pmatrix} 1 \\ -2 \end{pmatrix} \]

- No solution.
The Singular Case: Column Picture

\[ b = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \]

\[ x \begin{bmatrix} 2 \\ 4 \end{bmatrix} + y \begin{bmatrix} -1 \\ -2 \end{bmatrix} = \begin{bmatrix} 1 \\ -2 \end{bmatrix} \]

- Infinite number of solutions.
Singular Case: Row Picture with $n=3$

(a) two parallel planes
(b) no intersection
(c) line of intersection
(d) all planes parallel
Singular Case: Column Picture with $n=3$

- In this case, the three columns of the system matrix lie in the same plane.

Example:

$$u \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} + v \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix} + w \begin{bmatrix} 7 \\ 8 \\ 9 \end{bmatrix} = b.$$
Matrix Form and Matrix-Vector Products.

• We start with the familiar (row) form

\[
\begin{align*}
2u + v + w &= 5 \\
4u - 6v &= -2 \\
-2u + 7v + 2w &= 9
\end{align*}
\]

• In matrix form, this is

\[
\begin{bmatrix}
2 & 1 & 1 \\
4 & -6 & 0 \\
-2 & 7 & 2
\end{bmatrix}
\begin{bmatrix}
u \\
v \\
w
\end{bmatrix}
=
\begin{bmatrix}
5 \\
-2 \\
9
\end{bmatrix}, \text{ or } A\mathbf{u} = \mathbf{b}.
\]

• Of course, this must equal our column form,

\[
\begin{bmatrix}
2 \\
4 \\
-2
\end{bmatrix}
\begin{bmatrix}
u \\
v \\
w
\end{bmatrix}
+
\begin{bmatrix}
1 \\
-6 \\
7
\end{bmatrix}
\begin{bmatrix}
u \\
v \\
w
\end{bmatrix}
+
\begin{bmatrix}
1 \\
0 \\
2
\end{bmatrix}
\begin{bmatrix}
u \\
v \\
w
\end{bmatrix}
=
\begin{bmatrix}
5 \\
-2 \\
9
\end{bmatrix}
= \mathbf{b}.
\]
Matrix Form and Matrix-Vector Products, 2.

- So, if $A$ is the matrix with columns $\mathbf{a}_1$, $\mathbf{a}_2$, and $\mathbf{a}_3$,

$$A := \begin{bmatrix} 2 & 1 & 1 \\ 4 & -6 & 0 \\ -2 & 7 & 2 \end{bmatrix} =: \begin{bmatrix} \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 \end{bmatrix}, \quad \text{and} \quad \mathbf{u} := \begin{bmatrix} u \\ v \\ w \end{bmatrix}$$

- Then

$$A\mathbf{u} = u \mathbf{a}_1 + v \mathbf{a}_2 + w \mathbf{a}_3$$
Matrix Form and Matrix-Vector Products, 3.

- In general, if \( \mathbf{x} \) is the \( n \)-vector

\[
\mathbf{x} := \begin{bmatrix}
  x_1 \\
  x_2 \\
  \vdots \\
  x_n
\end{bmatrix},
\]

and \( A \) is an \( m \times n \) matrix, then

\[
A\mathbf{x} = x_1 \mathbf{a}_1 + x_2 \mathbf{a}_2 + \cdots + x_n \mathbf{a}_n
\]

= linear combination of the columns of \( A \).

- Always.
Matrix-Vector Products, Example.

If \( \hat{x} := V (V^T A V)^{-1} V^T b \)

\[ = Vy. \]

Then \( \hat{x} \) = linear combination of the columns of \( V \).

- \( \hat{x} \) lies in the column space of \( V \).
- \( \hat{x} \) lies in the range of \( V \).
- \( \hat{x} \in \text{span}(V) \)
Sigma Notation

• Let $A$ be an $m \times n$ matrix,

$$A = \begin{bmatrix} a_1 & \cdots & a_j & \cdots & a_n \\ a_1 & \cdots & a_j & \cdots & a_n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mj} & \cdots & a_{mn} \end{bmatrix}$$

• Then

$$w = Ax = \sum_{j=1}^{n} x_j a_j = \sum_{j=1}^{n} a_j x_j$$

$$w_i = (Ax)_i = \sum_{j=1}^{n} a_{ij} x_j$$
Matrix Multiplication

If \( B = \begin{bmatrix} b_1 & b_2 \end{bmatrix} \),

Then \( C = AB = \begin{bmatrix} Ab_1 & Ab_2 \end{bmatrix} \).

\[ c_{ij} = \sum_{k=1}^{n} a_{ik} b_{kj} \]

Q: (Important.) Suppose \( A \) and \( B \) are \( n \times n \) matrices.

- How many floating point operations (flops) are required to compute \( C = AB \)?
- What is the number of memory accesses?
Systems of Linear Equations

- Given $m \times n$ matrix $A$ and $m$-vector $b$, find unknown $n$-vector $x$ satisfying $Ax = b$

  - System of equations asks “Can $b$ be expressed as linear combination of columns of $A$?”

  - If so, coefficients of linear combination are given by components of solution vector $x$

  - Solution may or may not exist, and may or may not be unique

  - For now, we consider only square case, $m = n$
An $n \times n$ matrix $A$ is **nonsingular** if it has any of the following equivalent properties:

1. Inverse of $A$, denoted by $A^{-1}$, exists
2. $\det(A) \neq 0$
3. $\text{rank}(A) = n$
4. For any vector $z \neq 0$, $Az \neq 0$
Existence and uniqueness of solution to $Ax = b$ depend on whether $A$ is singular or nonsingular.

Can also depend on $b$, but only in singular case.

If $b \in \text{span}(A)$, system is *consistent*.

<table>
<thead>
<tr>
<th>$A$</th>
<th>$b$</th>
<th># solutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>nonsingular</td>
<td>arbitrary</td>
<td>one (unique)</td>
</tr>
<tr>
<td>singular</td>
<td>$b \in \text{span}(A)$</td>
<td>infinitely many</td>
</tr>
<tr>
<td>singular</td>
<td>$b \notin \text{span}(A)$</td>
<td>none</td>
</tr>
</tbody>
</table>
Geometric Interpretation

- In two dimensions, each equation determines straight line in plane
- Solution is intersection point of two lines
- If two straight lines are not parallel (nonsingular), then intersection point is unique
- If two straight lines are parallel (singular), then lines either do not intersect (no solution) or else coincide (any point along line is solution)
- In higher dimensions, each equation determines hyperplane; if matrix is nonsingular, intersection of hyperplanes is unique solution
Example: Nonsingularity

- 2 × 2 system

\[2x_1 + 3x_2 = b_1\]
\[5x_1 + 4x_2 = b_2\]

or in matrix-vector notation

\[Ax = \begin{bmatrix} 2 & 3 \\ 5 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = b\]

is nonsingular regardless of value of \(b\)

- For example, if \(b = \begin{bmatrix} 8 & 13 \end{bmatrix}^T\), then \(x = \begin{bmatrix} 1 & 2 \end{bmatrix}^T\) is unique solution
Example: Singularity

- $2 \times 2$ system

$$Ax = \begin{bmatrix} 2 & 3 \\ 4 & 6 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = b$$

is singular regardless of value of $b$

- With $b = \begin{bmatrix} 4 \\ 7 \end{bmatrix}^T$, there is no solution

- With $b = \begin{bmatrix} 4 \\ 8 \end{bmatrix}^T$, $x = \begin{bmatrix} \gamma \\ (4 - 2\gamma)/3 \end{bmatrix}^T$ is solution for any real number $\gamma$, so there are infinitely many solutions
Nearly Singular Matrices

- In two dimensions, uncertainty in intersection point of two lines depends on whether lines are nearly parallel.

Well-Conditioned  
Ill-Conditioned  
(nearly singular)

[ An interesting question: For the 2x2 case, can you relate the angle to the condition number?]
Conditioning of Linear Systems:  \[ Ax = b \]

- As before, we ask the question, "If we perturb \( b \), how much change do we see in \( x \)?"

\[
A(x + \Delta x) = (b + \Delta b)
\]

To pursue the answer to this question, we need a measure of the size of \( \Delta x \).

- We introduce **vector norms**, \( ||x|| \), which measure the magnitude of a vector \( x \).

- Vector norms are also useful in measuring closeness of approximate solutions.

- Their closely-associated **matrix norms** are valuable in predicting how easy it is to solve a system, either directly (via LU factorization) or iteratively.
Vector Norms

- Magnitude, modulus, or absolute value for scalars generalizes to \textit{norm} for vectors

- We will use only \( p \)-norms, defined by

\[
\| \mathbf{x} \|_p = \left( \sum_{i=1}^{n} |x_i|^p \right)^{1/p}
\]

for integer \( p > 0 \) and \( n \)-vector \( \mathbf{x} \)

- Important special cases
  - 1-norm: \( \| \mathbf{x} \|_1 = \sum_{i=1}^{n} |x_i| \)
  - 2-norm: \( \| \mathbf{x} \|_2 = \left( \sum_{i=1}^{n} |x_i|^2 \right)^{1/2} \)
  - \( \infty \)-norm: \( \| \mathbf{x} \|_\infty = \max_i |x_i| \)
Example: Vector Norms

- Drawing shows unit sphere in two dimensions for each norm

![Diagram of unit sphere in two dimensions with norms 1, 2, and infinity]

- Norms have following values for vector shown

\[
\| \mathbf{x} \|_1 = 2.8 \quad \| \mathbf{x} \|_2 = 2.0 \quad \| \mathbf{x} \|_\infty = 1.6
\]
In general, for any vector $x$ in $\mathbb{R}^n$, $\|x\|_1 \geq \|x\|_2 \geq \|x\|_\infty$.

However, we also have

$$\|x\|_1 \leq \sqrt{n} \|x\|_2, \quad \|x\|_2 \leq \sqrt{n} \|x\|_\infty, \quad \|x\|_1 \leq n \|x\|_\infty$$

Thus, for given $n$, norms differ by at most a constant, and hence are equivalent: if one is small, they must all be proportionally small.

- **Important Point**: **Equivalence of Norms** (for $n$ fixed):
  For all vector norms $\|x\|_m$ and $\|x\|_M$  \ exist constants $c$ and $C$ such that

  $$c \|x\|_m \leq \|x\|_M \leq C \|x\|_m$$

  Allows us to work with the norm that is most convenient.
For any vector norm

- $\|x\| > 0$ if $x \neq 0$
- $\|\gamma x\| = |\gamma| \cdot \|x\|$ for any scalar $\gamma$
- $\|x + y\| \leq \|x\| + \|y\|$ (triangle inequality)

In more general treatment, these properties taken as \textit{definition} of vector norm

Useful variation on triangle inequality

- $|\|x\| - \|y\|| \leq \|x - y\|
Matrix Norms

- **Matrix norm** corresponding to given vector norm is defined by

\[
\|A\| = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|}
\]

- Norm of matrix measures maximum stretching matrix does to any vector in given vector norm

*Example....*
Matrix Norms

For any vector norm $\|x\|_\ast$, define

$$
\|A\|_\ast = \max_{x \neq 0} \frac{\|Ax\|_\ast}{\|x\|_\ast} = \max_{\|x\|_\ast = 1} \|Ax\|_\ast
$$

- Often called the induced or subordinate matrix norm associated with the vector norm $\|x\|_\ast$. 
Matrix Norms

- Matrix norm corresponding to vector 1-norm is maximum absolute column sum

\[ \| A \|_1 = \max_j \sum_{i=1}^n |a_{ij}| \]

- Matrix norm corresponding to vector \( \infty \)-norm is maximum absolute row sum

\[ \| A \|_\infty = \max_i \sum_{j=1}^n |a_{ij}| \]

- Handy way to remember these is that matrix norms agree with corresponding vector norms for \( n \times 1 \) matrix
Matrix Norms: 2-norm

- The 2-norm of a symmetric matrix is \( \max_i |\lambda_i| \)

- Here, \( \lambda_i \) is the \( i \)th eigenvalue of \( A \)

- We say \( A \) is symmetric if \( a_{ij} = a_{ji} \) for \( i,j \in \{1,2,\ldots,n\}^2 \)

- That is, \( A = A^\top \) (\( A \) is equal to its transpose)
Symmetric Matrices

\[
A = \begin{bmatrix}
1 & 4 & -2 \\
4 & 2 & -5 \\
-2 & -5 & 3
\end{bmatrix} = A^T
\]

\[
B = \begin{bmatrix}
1 & 4 & -2 \\
4 & 2 & -5 \\
0 & -5 & 3
\end{bmatrix}
\]

\[
B^T = \begin{bmatrix}
1 & 4 & 0 \\
4 & 2 & -5 \\
-2 & -5 & 3
\end{bmatrix}
\]

- \(A\) is symmetric: \(a_{ij} = a_{ji}\) for all \(i, j\).
- \(B\) is nonsymmetric: \(b_{ij} \neq b_{ji}\) for all \(i, j\).
- Many (many) systems give rise to symmetric matrices.
Properties of Matrix Norms

- Any matrix norm satisfies
  - $\|A\| > 0$ if $A \neq 0$
  - $\|\gamma A\| = |\gamma| \cdot \|A\|$ for any scalar $\gamma$
  - $\|A + B\| \leq \|A\| + \|B\|$

- Matrix norms we have defined also satisfy
  - $\|AB\| \leq \|A\| \cdot \|B\|$
  - $\|Ax\| \leq \|A\| \cdot \|x\|$ for any vector $x$
Matrix Norm Example

- Matrix norms are particularly useful in analyzing *iterative solvers*.
- Consider the system $Ax = b$ to be solved with the following iterative scheme.
- Start with initial guess $x_0 = 0$ and, for $k=0, 1, \ldots$,

$$x_{k+1} = x_k + M (b - Ax_k).$$

(1)

- Let $G := I - MA$. We can use the matrix norm of $G$ to bound the error in the above iteration and determine its rate of convergence.
- Begin by defining the error to be $e_k := x - x_k$.
- Note that $b - Ax_k = Ax - Ax_k = A(x - x_k) = Ae_k$.
- Using the preceding result and subtracting (1) from the equation $x = x$ yields the error equation

$$e_{k+1} = e_k - MAe_k = [I - MA] e_k = GE_k.$$
Matrix Norm Example

• Error equation

\[ e_{k+1} = e_k - MAe_k = [I - MA] e_k = Ge_k. \]

• From the definition of the matrix norm, we have

\[ ||e_k|| \leq ||G|| ||e_{k-1}|| \leq ||G||^2 ||e_{k-2}|| \ldots \leq ||G||^k ||e_0|| \]

• With \( x_0 = 0 \), we have \( e_0 = x \) and thus the relative error

\[ \frac{||e_k||}{||x||} \leq ||G||^k \]

• If \( ||G|| < 1 \), the scheme (1) is convergent.

• By the equivalence of norms, if \( ||G|| < 1 \) for any matrix norm, it is convergent.

• Q: Suppose \( ||G|| \leq 0.25 \). What is the bound on the number of iterations required to converge to machine precision in IEEE 64-bit arithmetic? (Hint: Think carefully. What is the best base to use in considering this question?)
Matrix Norm Example

• Consider the following example:

\[ A = nI + 0.1R, \quad R = \text{rand}(n, n) \quad r_{ij} \in [0, 1] \]

\[ M = \text{diag}(1/a_{ii}) \]

• In this case,

\[ g_{ii} = 0 \]

\[ g_{ij} = 0.1 \frac{-r_{ij}}{n + 0.1r_{ii}} \]

• The $\infty$-norm for $G$ is given by

\[
\|G\|_\infty = \max_i \sum_{j=1}^{n} |g_{ij}| \leq \max_i \sum_{i \neq j} M^* = (n - 1)M^*,
\]

where

\[
M^* := \max_{i \neq j} |g_{ij}| < \frac{0.1}{n}.
\]

• In this case, we have a relative error bounded by $\|G\|^k_\infty \leq (0.1)^k$.

• Q: Estimate the number of iterations required to reduce the error to machine epsilon when using IEEE 64-bit floating point arithmetic.
Condition Number

- **Condition number** of square nonsingular matrix $A$ is defined by

$$
\text{cond}(A) = \|A\| \cdot \|A^{-1}\|
$$

- By convention, $\text{cond}(A) = \infty$ if $A$ is singular

- Since

$$
\|A\| \cdot \|A^{-1}\| = \left( \max_{x \neq 0} \frac{\|Ax\|}{\|x\|} \right) \cdot \left( \min_{x \neq 0} \frac{\|Ax\|}{\|x\|} \right)^{-1}
$$

  condition number measures ratio of maximum stretching to maximum shrinking matrix does to any nonzero vectors

- Large $\text{cond}(A)$ means $A$ is *nearly singular*
Condition Number Examples

\[ A_1 = \begin{bmatrix} 0.87 & 0.5 \\ -0.5 & 0.87 \end{bmatrix}, \quad \text{cond}_2(A_1) = 1 \]

\[ A_2 = \begin{bmatrix} 2 & 0 \\ 0 & 0.5 \end{bmatrix}, \quad \text{cond}_2(A_2) = 4 \]

\[ A_3 = \begin{bmatrix} 1.73 & 0.25 \\ -1 & 0.43 \end{bmatrix}, \quad \text{cond}_2(A_3) = 4 \]

\[ A_4 = \begin{bmatrix} 1.52 & 0.91 \\ 0.47 & 0.94 \end{bmatrix}, \quad \text{cond}_2(A_4) = 4 \]
For any matrix $A$, $\text{cond}(A) \geq 1$

For identity matrix, $\text{cond}(I) = 1$

For any matrix $A$ and scalar $\gamma$, $\text{cond}(\gamma A) = \text{cond}(A)$

For any diagonal matrix $D = \text{diag}(d_i)$, $\text{cond}(D) = \frac{\max |d_i|}{\min |d_i|}$
Computing Condition Number

- Definition of condition number involves matrix inverse, so it is nontrivial to compute.

- Computing condition number from definition would require much more work than computing solution whose accuracy is to be assessed.

- In practice, condition number is estimated inexpensively as byproduct of solution process.

- Matrix norm $\|A\|$ is easily computed as maximum absolute column sum (or row sum, depending on norm used).

- Estimating $\|A^{-1}\|$ at low cost is more challenging.
From properties of norms, if $Az = y$, then

$$\frac{\|z\|}{\|y\|} \leq \|A^{-1}\|$$

and bound is achieved for optimally chosen $y$

Efficient condition estimators heuristically pick $y$ with large ratio $\|z\|/\|y\|$, yielding good estimate for $\|A^{-1}\|$.

Good software packages for linear systems provide efficient and reliable condition estimator.
Error Bounds

- Condition number yields error bound for computed solution to linear system

- Let $x$ be solution to $Ax = b$, and let $\hat{x}$ be solution to $A\hat{x} = b + \Delta b$

- If $\Delta x = \hat{x} - x$, then

$$b + \Delta b = A(\hat{x}) = A(x + \Delta x) = Ax + A\Delta x$$

which leads to bound

$$\frac{\|\Delta x\|}{\|x\|} \leq \text{cond}(A) \frac{\|\Delta b\|}{\|b\|}$$

for possible relative change in solution $x$ due to relative change in right-hand side $b$
Condition Number and Relative Error: $Ax = b$.

- Want to solve $Ax = b$, but computed rhs is:
  
  $$b' = b + \Delta b,$$

  where we anticipate

  $$\frac{||\Delta b||}{||b||} \approx \leq \epsilon_M.$$

- Net result is we end up solving $Ax' = b'$ and want to know how large is the relative error, $x' = x + \Delta x$,

  $$\frac{||\Delta x||}{||x||}.$$

- Since $Ax' = b'$ and (by definition) $Ax = b$, we have:

  $$||\Delta x|| \leq ||A^{-1}|| ||\Delta b||$$

  $$||b|| \leq ||A|| ||x||$$

  $$\frac{1}{||x||} \leq ||A|| \frac{1}{||b||}$$

  $$\frac{\Delta x}{||x||} \leq ||A|| \frac{\Delta x}{||b||}$$

  $$\leq ||A|| ||A^{-1}|| \frac{\Delta b}{||b||}$$

  $$= \text{cond}(A) \frac{\Delta b}{||b||}.$$

- Key point: If cond$(A)=10^k$, then expected relative error is $\approx 10^k\epsilon_M$, meaning that you will lose $k$ digits (of 16, if $\epsilon_M \approx 10^{-16}$).
Here, we see that $\varepsilon_M \cdot \text{cond}(A)$ bounds the error in the solution to $Au=f$, as expected.
Error Bounds, continued

- Similar result holds for relative change in matrix: if $(A + E)\hat{x} = b$, then

\[
\frac{\|\Delta x\|}{\|\hat{x}\|} \leq \text{cond}(A) \frac{\|E\|}{\|A\|}
\]

- If input data are accurate to machine precision, then bound for relative error in solution $x$ becomes

\[
\frac{\|\hat{x} - x\|}{\|x\|} \leq \text{cond}(A) \epsilon_{\text{mach}}
\]

- Computed solution loses about $\log_{10}(\text{cond}(A))$ decimal digits of accuracy relative to accuracy of input data.
A Nearly Singular Example

\[ A = \begin{bmatrix} a_1 & a_2 \end{bmatrix} = \begin{bmatrix} 1 & c \\ 0 & s \end{bmatrix} \]

\[ c = \cos \theta, \quad s = \sin \theta. \]

- Clearly, as \( \theta \to 0 \) the matrix becomes singular.
- Can show that

\[ \text{cond} = \sqrt{\frac{1 + |c|}{1 - |c|}} \approx \frac{2}{\theta} \]

for small \( \theta \) (by Taylor series!)  

\textit{matlab demo.}
This example plots \( \text{cond}(A) \) as a function of \( \theta \), as well as the estimates from the preceding slide.

- The computed value of \( \text{cond}(A) \) given by Matlab exactly matches \( \left[ \frac{(1+|\cos \theta|)}{(1-|\cos \theta|)} \right]^{1/2} \)

- The more interesting result is \( \text{cond}(A) \sim \frac{2}{\theta} \), which is very accurate for small angles.

Matlab code:

```matlab
%% Note - eigenvalues of A'*A are evals of C=A'*A =
  
    1 0
    c 1

  \( (1-lam)*(1-lam) - c^2 \), which is \( z^2 - c^2 \) with roots

  \( z=c \) and \( z=-c \)

  \( 1-lam = c \rightarrow lam = 1 - c \)

  \( 1-lam = -c \rightarrow lam = 1+c \)

  \( K2 = 1+c / 1 - c \)

  \[ - 2 / (1/2 \theta^2) \text{ for small } \theta \sim 4 / \theta^2 \]

  Therefore: \( K(A) = sqrt(K2) - 2/\theta \)

format compact

jj=0; for j=.01:.01:(2*pi); cj=cos(j); sj=sin(j); jj=jj+1;
    R=[ cj -sj; sj cj ];
    a1 = [ 1 ; 0 ]; a2 = R*a1; A = [ a1 a2 ];

    C(jj) = cond(A);
    t(jj)=j; aj = abs(cj); z(jj)=sqrt( (1+aj)/(1-aj) );
end;

plot(t,C,'r--',t,z,'k-.',t,2./abs(t),'g-','LineWidth',3);
axis([0 2*pi 0 40]);text(pi,2,'2/\theta','FontSize',18) axis square;
xlabel('\theta','FontSize',18);ylabel('Cond(A)','FontSize',18);
title('Cond. Number: Nearly Parallel Unit Columns','FontSize',18)
```
In two dimensions, uncertainty in intersection point of two lines depends on whether lines are nearly parallel.

well-conditioned

ill-conditioned
Error Bounds – Caveats

- Normwise analysis bounds relative error in *largest* components of solution; relative error in smaller components can be much larger
  - Componentwise error bounds can be obtained, but somewhat more complicated

- Conditioning of system is affected by relative scaling of rows or columns
  - Ill-conditioning can result from poor scaling as well as near singularity
  - Rescaling can help the former, but not the latter
### Residual

**Residual vector** of approximate solution \( \hat{x} \) to linear system \( Ax = b \) is defined by

\[
\mathbf{r} = \mathbf{b} - A\hat{x}
\]

- In theory, if \( A \) is nonsingular, then \( \| \hat{x} - x \| = 0 \) if, and only if, \( \| \mathbf{r} \| = 0 \), but they are not necessarily small simultaneously.

- Since

\[
\frac{\| \Delta x \|}{\| \hat{x} \|} \leq \text{cond}(A) \frac{\| \mathbf{r} \|}{\| A \| \cdot \| \hat{x} \|}
\]

small relative residual implies small relative error in approximate solution *only if* \( A \) is well-conditioned.
If computed solution $\hat{x}$ exactly satisfies

$$ (A + E)\hat{x} = b $$

then

$$ \frac{\|r\|}{\|A\| \|\hat{x}\|} \leq \frac{\|E\|}{\|A\|} $$

so large relative residual implies large backward error in matrix, and algorithm used to compute solution is unstable.

- Stable algorithm yields small relative residual regardless of conditioning of nonsingular system.
- Small residual is easy to obtain, but does not necessarily imply computed solution is accurate.
To solve linear system, transform it into one whose solution is same but easier to compute.

What type of transformation of linear system leaves solution unchanged?

We can *premultiply* (from left) both sides of linear system $Ax = b$ by any *nonsingular* matrix $M$ without affecting solution.

Solution to $MAx = Mb$ is given by

$$x = (MA)^{-1}Mb = A^{-1}M^{-1}Mb = A^{-1}b$$
Example: Permutations

- **Permutation matrix** $P$ has one 1 in each row and column and zeros elsewhere, i.e., identity matrix with rows or columns permuted.

- Note that $P^{-1} = P^T$.  

- Premultiplying both sides of system by permutation matrix, $PAX = Pb$, reorders rows, but solution $x$ is unchanged.

- Postmultiplying $A$ by permutation matrix, $APx = b$, reorders columns, which permutes components of original solution.

\[
x = (AP)^{-1}b = P^{-1}A^{-1}b = P^T(A^{-1}b)
\]
Example: Diagonal Scaling

- **Row scaling**: premultiplying both sides of system by nonsingular diagonal matrix $D$, $DAx = Db$, multiplies each row of matrix and right-hand side by corresponding diagonal entry of $D$, but solution $x$ is unchanged.

- **Column scaling**: postmultiplying $A$ by $D$, $ADx = b$, multiplies each column of matrix by corresponding diagonal entry of $D$, which rescales original solution

$$x = (AD)^{-1}b = D^{-1}A^{-1}b$$
Premultiply by Diagonal Matrix: Row Scaling

\[
\begin{pmatrix}
d_1 a_{11} & d_1 a_{12} & d_1 a_{13} \\
d_2 a_{21} & d_2 a_{22} & d_2 a_{23} \\
d_3 a_{31} & d_3 a_{32} & d_3 a_{33}
\end{pmatrix}
= 
\begin{pmatrix}
d_1 \\
d_2 \\
d_3
\end{pmatrix}
\begin{pmatrix}
a_{11} & a_{12} & a_{13} \\
a_{21} & a_{22} & a_{23} \\
a_{31} & a_{32} & a_{33}
\end{pmatrix}
\]
Note on Row Scaling / Permutation

\[ Dv = \text{scale rows of } v \]

\[ Pv = \text{permute rows of } v \]

\[ DA = [Da_1 \, Da_2 \, \cdots \, Da_n] = \text{scale rows of } A \]

\[ PA = [Pa_1 \, Pa_2 \, \cdots \, Pa_n] = \text{permute rows of } A \]
What type of linear system is easy to solve?

If one equation in system involves only one component of solution (i.e., only one entry in that row of matrix is nonzero), then that component can be computed by division.

If another equation in system involves only one additional solution component, then by substituting one known component into it, we can solve for other component.

If this pattern continues, with only one new solution component per equation, then all components of solution can be computed in succession.

System with this property is called triangular.
Two specific triangular forms are of particular interest

- **lower triangular**: all entries above main diagonal are zero, \( a_{ij} = 0 \) for \( i < j \)
- **upper triangular**: all entries below main diagonal are zero, \( a_{ij} = 0 \) for \( i > j \)

Successive substitution process described earlier is especially easy to formulate for lower or upper triangular systems

Any triangular matrix can be permuted into upper or lower triangular form by suitable row and column permutation
Forward-Substitution

- **Forward-substitution** for lower triangular system $Lx = b$

$$x_1 = b_1 / l_{11}, \quad x_i = \left( b_i - \sum_{j=1}^{i-1} l_{ij} x_j \right) / l_{ii}, \quad i = 2, \ldots, n$$

for $j = 1$ to $n$  
  if $l_{jj} = 0$ then stop  
  $x_j = b_j / l_{jj}$  
  for $i = j + 1$ to $n$  
      $b_i = b_i - l_{ij} x_j$  
  end  
end

{ loop over columns }  
{ stop if matrix is singular }  
{ compute solution component }  
{ update right-hand side }
Back-Substitution

**Back-substitution** for upper triangular system $Ux = b$

$$x_n = b_n / u_{nn}, \quad x_i = \left( b_i - \sum_{j=i+1}^{n} u_{ij} x_j \right) / u_{ii}, \quad i = n - 1, \ldots, 1$$

for $j = n$ to 1
  if $u_{jj} = 0$ then stop
  $x_j = b_j / u_{jj}$
  for $i = 1$ to $j - 1$
    $b_i = b_i - u_{ij} x_j$
  end
end

{ loop backwards over columns }  
{ stop if matrix is singular }  
{ compute solution component }  
{ update right-hand side }
Solution of Lower Triangular Systems

\[
\begin{bmatrix}
    l_{11} \\
    l_{21} & l_{22} \\
    l_{31} & l_{32} & l_{33} \\
    \vdots & \ddots & \ddots \\
    \vdots & & \ddots \\
    l_{n1} & l_{n2} & l_{n3} & \cdots & \cdots & l_{nn}
\end{bmatrix}
\begin{bmatrix}
    x_1 \\
    x_2 \\
    x_3 \\
    \vdots \\
    \vdots \\
    x_n
\end{bmatrix}
= \begin{bmatrix}
    b_1 \\
    b_2 \\
    b_3 \\
    \vdots \\
    \vdots \\
    b_n
\end{bmatrix}
\]

for \( i = 1, 2, \ldots, n \) : 
\[
x_i = \frac{1}{l_{ii}} \left( b_i - \sum_{j=1}^{i-1} l_{ij} x_j \right).
\]

As written:

\[
\begin{array}{l}
\text{for } i = 1 : n \\
x_i = b_i \\
\text{for } j = 1 : i - 1 \\
x_i = x_i - l_{ij} x_j \\
\text{end}
\end{array}
\]
\[
x_i = x_i / l_{ii}
\]

Better memory access (faster):

\[
\begin{array}{l}
\text{for } j = 1 : n \\
\text{if } l_{jj} = 0, \text{ stop - matrix is singular.} \\
x_j = b_j / l_{jj} \\
\text{for } i = j + 1 : n \\
b_i = b_i - l_{ij} x_j \\
\text{end}
\end{array}
\]
\[
b_i = b_i / l_{ii}
\]

end
Solution of Upper Triangular Systems

\[
\begin{bmatrix}
  u_{11} & u_{12} & u_{13} & \cdots & u_{1n} \\
  u_{22} & u_{23} & \cdots & \cdots & u_{2n} \\
  u_{33} & \cdots & \cdots & \cdots & \cdots \\
  \vdots & \cdots & \ddots & \cdots & \cdots \\
  u_{nn} & \cdots & \cdots & \cdots & \cdots \\
\end{bmatrix}
\begin{bmatrix}
  x_1 \\
  x_2 \\
  x_3 \\
  \vdots \\
  x_n \\
\end{bmatrix}
=
\begin{bmatrix}
  b_1 \\
  b_2 \\
  b_3 \\
  \vdots \\
  b_n \\
\end{bmatrix}
\]

for \(i = n, n - 1, \ldots, 1\):

\[
x_i = \frac{1}{u_{ii}} \left( b_i - \sum_{j=i+1}^{n} u_{ij} x_j \right).
\]

As written:

for \(i = n : 1\)

\[
x_i = b_i
\]

for \(j = i + 1 : n\)

\[
x_i = x_i - u_{ij} x_j
\]

end

\[
x_i = x_i / u_{ii}
\]

end

Better memory access (faster):

for \(j = n : 1\)

if \(u_{jj} = 0\), stop - matrix is singular.

\[
x_j = b_j / u_{jj}
\]

for \(i = 1 : j - 1\)

\[
b_i = b_i - u_{ij} x_j
\]

end

end

What is the cost ??
Solution of Upper Banded Systems

Suppose $U$ is a banded matrix: $u_{ij} = 0$, $j > i + \beta$.

For example, $\beta = 2$:

$$
\begin{bmatrix}
  u_{11} & u_{12} & u_{13} \\
  u_{22} & u_{23} & u_{14} \\
  & u_{33} & \ddots \\
  & & \ddots & u_{n-2,n} \\
  & & & \ddots & u_{n-1,n} \\
  & & & & u_{nn}
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
\vdots \\
x_n
\end{bmatrix}
=
\begin{bmatrix}
b_1 \\
b_2 \\
b_3 \\
\vdots \\
b_n
\end{bmatrix}
$$

for $i = n, n-1, \ldots, 1$: $x_i = \frac{1}{u_{ii}} \left( b_i - \sum_{j=i+1}^{\min(i+\beta,n)} u_{ij} x_j \right)$.
Solution of Upper Banded Systems

for $i = n, n-1, \ldots, 1$:

$$x_i = \frac{1}{u_{ii}} \left( b_i - \sum_{j=i+1}^{\min(i+\beta,n)} u_{ij} x_j \right).$$

As written:

for $i = n : 1$

$$x_i = b_i, \quad j_{\text{max}} := \min(j + \beta, n)$$

for $j = i + 1 : j_{\text{max}}$

$$x_i = x_i - u_{ij} x_j$$

end

$$x_i = x_i / u_{ii}$$

end

Better memory access (faster):

for $j = n : 1$

if $u_{jj} = 0$, stop - matrix is singular.

$$x_j = b_j / u_{jj}, \quad i_{\text{min}} := \max(1, j - \beta)$$

for $i = i_{\text{min}} : j - 1$

$$b_i = b_i - u_{ij} x_j$$

end

end

- In this case, there are $\sim 2\beta n$ operations and $\sim \beta n$ memory references (one for each $u_{ij}$).

- Often $\beta \ll n$, which means that the upper-banded system is much faster to solve than the full upper triangular system.

- The same savings applies to the lower-banded case.
Generating Triangular Systems: LU Factorization

\[ A = LU \]
Generating Upper Triangular Systems: *LU* Factorization

- Example:

\[
\begin{bmatrix}
1 & 2 & 3 \\
4 & 4 & 6 & 1 \\
8 & 8 & 9 & 2 \\
6 & 1 & 3 & 3 \\
4 & 2 & 8 & 4 \\
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5 \\
\end{bmatrix}
= 
\begin{bmatrix}
0 \\
4 \\
4 \\
4 \\
4 \\
\end{bmatrix}
\]

- First column is already in upper triangular form.

- Eliminate second column:

\[
\begin{align*}
\text{row}_3 & \leftarrow \text{row}_3 - \frac{8}{4} \times \text{row}_2 \\
\text{row}_4 & \leftarrow \text{row}_4 - \frac{6}{4} \times \text{row}_2 \\
\text{row}_5 & \leftarrow \text{row}_5 - \frac{4}{4} \times \text{row}_2
\end{align*}
\]

\[
\begin{bmatrix}
1 & 2 & 3 \\
4 & 4 & 6 & 1 \\
0 & -3 & 0 \\
-5 & -6 & \frac{3}{2} \\
-2 & 2 & 3 \\
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5 \\
\end{bmatrix}
= 
\begin{bmatrix}
0 \\
4 \\
-4 \\
-2 \\
0 \\
\end{bmatrix}
\]

- \(a_{22} = 4\) is the pivot
- \(\text{row}_2\) is the pivot row
- \(l_{32} = \frac{8}{4}, \ l_{42} = \frac{6}{4}, \ l_{52} = \frac{4}{4}\) is the multiplier column.
Generating Upper Triangular Systems: \(LU\) Factorization

- Augmented form. Store \(b\) in \(A(:, n+1)\):

\[
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
8 & 8 & 9 & 2 & 4 \\
6 & 1 & 3 & 3 & 4 \\
4 & 2 & 8 & 4 & 4
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
0 & -3 & 0 & -4 \\
-5 & -6 & \frac{3}{2} & -2 \\
-2 & 2 & 3 & 0
\end{bmatrix}
\]

**This Case.**

pivot \( = 4 \)

pivot row \( = \begin{bmatrix} 4 & 6 & 1 & 4 \end{bmatrix} \)

multiplier column \( = \frac{1}{4} \begin{bmatrix} 8 \\ 6 \\ 4 \end{bmatrix} \)

\( = \begin{bmatrix} 2 \\ \frac{3}{2} \\ 1 \end{bmatrix} \)

**General Case.**

\( = a_{kk}\) when zeroing the \(k\)th column.

pivot row \( = r_k^T = a_{kj}, j = k+1, \ldots, n [+b_k] \)

multiplier column \( = c_k = \frac{a_{ik}}{a_{kk}}, i = k+1, \ldots, n \)
Generating Upper Triangular Systems: \textit{LU} Factorization

- Augmented form. Store $b$ in $A(:, n + 1)$:

\[
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
8 & 8 & 9 & 2 & 4 \\
6 & 1 & 3 & 3 & 4 \\
4 & 2 & 8 & 4 & 4
\end{bmatrix} \quad \rightarrow \quad
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
0 & -3 & 0 & -4 \\
-5 & -6 & \frac{3}{2} & -2 \\
-2 & 2 & 3 & 0
\end{bmatrix}
\]

\textit{This Case.}

pivot row = $\begin{bmatrix} 4 & 6 & 1 \end{bmatrix}$

pivot row = $\begin{bmatrix} 4 & 6 & 1 \end{bmatrix}$

multiplier column = $\begin{bmatrix} \frac{8}{4} & 6 & \frac{4}{4} \end{bmatrix}$

multiplier column = $\begin{bmatrix} \frac{8}{4} & 6 & \frac{4}{4} \end{bmatrix}$

\textit{General Case.}

pivot = 4

pivot = $a_{kk}$ when zeroing the $k$th column.

$\begin{bmatrix} 4 & 6 & 1 \end{bmatrix}$

$\begin{bmatrix} 4 & 6 & 1 \end{bmatrix}$

$\begin{bmatrix} \frac{8}{4} & 6 & \frac{4}{4} \end{bmatrix}$

$\begin{bmatrix} \frac{8}{4} & 6 & \frac{4}{4} \end{bmatrix}$

$\begin{bmatrix} \frac{2}{3} & \frac{3}{2} & 1 \end{bmatrix}$

$\begin{bmatrix} \frac{2}{3} & \frac{3}{2} & 1 \end{bmatrix}$

$\begin{bmatrix} \frac{2}{3} & \frac{3}{2} & 1 \end{bmatrix}$
Generating Upper Triangular Systems: \( LU \) Factorization

- Augmented form. Store \( \mathbf{b} \) in \( A(:, n+1) \):

\[
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
8 & 8 & 9 & 2 & 4 \\
6 & 1 & 3 & 3 & 4 \\
4 & 2 & 8 & 4 & 4 \\
\end{bmatrix} \quad \rightarrow \quad \begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
0 & -3 & 0 & -4 \\
-5 & -6 & 3 & -2 \\
-2 & 2 & 3 & 0 \\
\end{bmatrix}
\]

**This Case.**

pivot = 4

pivot row = \([ 4 \ 6 \ 1 | 4 ]\)

multiplier column = \( \frac{1}{4} \begin{bmatrix} 8 \\ 6 \\ 4 \end{bmatrix} \)

\[
= \begin{bmatrix} 2 \\ 3/2 \\ 1 \end{bmatrix}
\]

**General Case.**

\( a_{kk} \) when zeroing the \( k \)th column.

pivot row = \( \mathbf{r}_k^T = a_{kj}, j = k+1, \ldots, n \begin{bmatrix} +b_k \end{bmatrix} \)

multiplier column = \( c_k = \frac{a_{ik}}{a_{kk}}, i = k+1, \ldots, n \)

\( c_k \rightarrow 1_k, \) store as column \( k \) of \( L. \)
**kth Update Step**

- Look more closely at the $k$th update step for Gaussian elimination.
- Assume $A$ is $m \times n$, which covers the case where $A$ is augmented with the right-hand side vector.
- For each row $i$, with $i > k$, we want to generate a zero in place of $a_{ij}$.
- We do this by subtracting a multiple of row $k$ from row $i$.
- This operation can be expressed in several equivalent ways:

\[
\begin{align*}
\text{row}_i &= \text{row}_i - \frac{a_{ik}}{a_{kk}} \times \text{row}_k \\
 a_{ij} &= a_{ij} - a_{ik} a_{kk}^{-1} a_{kj} \quad j = k + 1, \ldots, n \\
 &= a_{ij} - (c_k)_i \left( r_k^T \right)_j \quad j = k + 1, \ldots, n \\
A^{(k+1)} &= A^{(k)} - c_k r_k^T,
\end{align*}
\]

- Here, $c_k$ is the column vector with entries $(c_k)_i = a_{ik}/a_{kk}$, and $r_k^T$ is the row vector with entries $(r_k^T)_j = a_{kj}$.
- Formally, we think of $(c_k)_i = 0, i \leq k$ and $(r_k^T)_j = 0, j \leq k$, though we would implement as an update only to the active submatrix.
- The $m \times n$ matrix $c_k r_k^T$ is of rank 1. All columns are multiples of the only linearly independent column, $c_k$.
- We typically save the entries of the multiplier column as the $k$th column of a lower triangular matrix: $l_{ik} := (c_k)_i$. 

Matlab: *lu_demo_1.m*
**kth Update Step**

- Look more closely at the $k$th update step for Gaussian elimination.
- Assume $A$ is $m \times n$, which covers the case where $A$ is augmented with the right-hand side vector.
- For each row $i$, with $i > k$, we want to generate a zero in place of $a_{ij}$.
- We do this by subtracting a multiple of row $k$ from row $i$.
- This operation can be expressed in several equivalent ways:

\[
\text{row}_i = \text{row}_i - \frac{a_{ik}}{a_{kk}} \times \text{row}_k
\]

\[
a_{ij} = a_{ij} - a_{ik} a_{kk}^{-1} a_{kj} \quad j = k + 1, \ldots, n
\]

\[
= a_{ij} - (c_k)_i (r_k^T)_j \quad j = k + 1, \ldots, n
\]

\[
A^{(k+1)} = A^{(k)} - c_k r_k^T,
\]

- Here, $c_k$ is the column vector with entries $(c_k)_i = a_{ik}/a_{kk}$, and $r_k^T$ is the row vector with entries $(r_k^T)_j = a_{kj}$.
- Formally, we think of $(c_k)_i = 0, i \leq k$ and $(r_k^T)_j = 0, j \leq k$, though we would implement as an update only to the active submatrix.
- The $m \times n$ matrix $c_k r_k^T$ is of rank 1. All columns are multiples of the only linearly independent column, $c_k$.
- We typically save the entries of the multiplier column as the $k$th column of a lower triangular matrix: $l_{ik} := (c_k)_i$. 
Multiplier Columns $= l_k$: $LU = A$

- $A^{(1)} := A$, $A^{(k+1)} = A^{(k)} - c_k r_k^T$.

$$LU = \begin{bmatrix} 1 & \frac{a_2^{(1)}}{a_{11}} & \frac{a_3^{(1)}}{a_{11}} & \frac{a_2^{(2)}}{a_{22}} & 1 \\ \frac{a_2^{(1)}}{a_{11}} & 1 & \frac{a_2^{(2)}}{a_{11}} & \frac{a_2^{(2)}}{a_{22}} & 1 \\ \frac{a_3^{(1)}}{a_{11}} & \frac{a_3^{(2)}}{a_{22}} & 1 & \frac{a_2^{(2)}}{a_{22}} & 1 \\ \end{bmatrix} \begin{bmatrix} a_{11}^{(1)} & a_{12}^{(1)} & a_{13}^{(1)} \\ a_{22}^{(2)} & a_{23}^{(2)} \\ a_{33}^{(3)} \\ \end{bmatrix} = \begin{bmatrix} a_{11}^{(1)} & a_{12}^{(1)} & a_{13}^{(1)} \\ a_{22}^{(2)} & a_{23}^{(2)} \\ a_{33}^{(3)} \\ \end{bmatrix}$$

- Recall, for example,

$$a_{22}^{(2)} = a_{22}^{(1)} - \frac{a_{21}^{(1)} a_{12}^{(1)}}{a_{11}^{(1)}}, \text{ or}$$

$$a_{ij}^{(k+1)} = a_{ij}^{(k)} - \frac{a_{ik}^{(k)} a_{kj}^{(k)}}{a_{kk}^{(k)}}, \text{ in general.}$$

- Thus, we see that the 2-2 entry of $LU$ is indeed $a_{22}^{(1)} = a_{22}$, etc.
Consider solution of $A\mathbf{x} = \mathbf{b}$ via Gaussian elimination.

Let $A^{(1)} := A$ and $b^{(1)} := \mathbf{b}$.

Take $n = 4$ for purposes of illustration.

Apply one-step of Gaussian elimination to the augmented system $[A^{(1)} | b^{(1)}]$.

After one round, we have:

$$[A^{(2)} | b^{(2)}] = M_1 [A^{(1)} | b^{(1)}]$$

That is, $M_1 [A^{(1)} | b^{(1)}] = [A^{(2)} | b^{(2)}]$, where $A^{(2)}$ is zero in column 1 for $i > 1$. 
• That is, $M_1 \begin{bmatrix} A^{(1)} | b^{(1)} \end{bmatrix} = \begin{bmatrix} A^{(2)} | b^{(2)} \end{bmatrix}$, where $A^{(2)}$ is zero in column 1 for $i > 1$.

• The matrix that zeros out these entries in column one is given by:

$$M_1 = I - m_1 e_1^T, \quad m_1 = \frac{1}{a_{11}^{(1)}} \begin{bmatrix} 0 & a_{21}^{(1)} & a_{31}^{(1)} & a_{41}^{(1)} \end{bmatrix}^T,$$

and $e_1 = $ the 1st column of the identity matrix.

• **Test:** Apply $M_1$ to each column of $\begin{bmatrix} A^{(1)} | b^{(1)} \end{bmatrix}$:

$$M_1 \cdot a_1^{(1)} = a_1^{(1)} - m_1 e_1^T a_1^{(1)}$$

$$\left[ M_1 a_1^{(1)} \right]_i = a_i^{(1)} - \left( \frac{a_{i1}^{(1)}}{a_{11}^{(1)}} \right) a_{i1}^{(1)} = 0, \quad i > 1.$$
• **Test:** Apply $M_1$ to each column of $[A^{(1)} | b^{(1)}]$:

$$M_1 \cdot a_i^{(1)} = a_1^{(1)} - m_1 e_1^T a_1^{(1)}$$

$$[M_1 a_i^{(1)}]_i = a_i^{(1)} - \left( \frac{a_{i1}^{(1)}}{a_{11}^{(1)}} \right) a_{11}^{(1)} = 0, \ i > 1.$$  

For any $z \in \mathbb{R}^n$,

$$[M_1 z]_i = z_i - \left( \frac{a_{i1}^{(1)}}{a_{11}^{(1)}} \right) z_1 \ i > 1.$$  

For any matrix $V \in \mathbb{R}^{n \times n'}$,

$$[M_1 V]_{ij} = V_{ij} - \left( \frac{a_{i1}^{(1)}}{a_{11}^{(1)}} \right) V_{1j} \ i > 1, \ j = 1, \ldots, n'.$$

\begin{align*}
\text{ith row} & \rightarrow \text{ith row} - 2^{nd} \text{ row} \times \left( \frac{a_{i1}^{(1)}}{a_{11}^{(1)}} \right).
\end{align*}

**Elimination Step!!**
Now, we take next step, \( [A^{(3)} | b^{(3)}] = M_2 [A^{(2)} | b^{(2)}] \):

\[
[A^{(3)} | b^{(3)}] = M_2
\begin{bmatrix}
   a^{(2)}_{11} & a^{(2)}_{12} & a^{(2)}_{14} & b^{(2)}_1 \\
   0 & a^{(2)}_{22} & a^{(2)}_{24} & b^{(2)}_2 \\
   0 & a^{(2)}_{32} & a^{(2)}_{34} & b^{(2)}_3 \\
   0 & a^{(2)}_{42} & a^{(2)}_{44} & b^{(2)}_4
\end{bmatrix}
\]

\[
= \begin{bmatrix}
   a^{(3)}_{11} & a^{(3)}_{12} & a^{(3)}_{14} & b^{(3)}_1 \\
   0 & a^{(3)}_{22} & a^{(3)}_{24} & b^{(3)}_2 \\
   0 & 0 & a^{(3)}_{34} & b^{(3)}_3 \\
   0 & 0 & a^{(3)}_{44} & b^{(3)}_4
\end{bmatrix},
\]

with

\[
M_2 = I - m_2 e^T_2, \quad m_2 = \frac{1}{a^{(2)}_{11}} \begin{bmatrix} 0 & 0 & a^{(2)}_{31} & a^{(2)}_{41} \end{bmatrix}^T,
\]

and \( e_2 \) = the 2nd column of the identity matrix.
• After $n - 1$ rounds, we have

$$
\begin{align*}
[A^{(n-1)} | b^{(n-1)}] &= M_{n-1} M_{n-2} \cdots M_2 M_1 [A | b],
\end{align*}
$$

with $U = A^{(n-1)}$ being upper triangular, and

$$
M_k = I - m_k e_k^T,
$$

the $k$th elementary elimination matrix.

• It’s easy to show that $M_k^{-1} = I + m_k e_k^T$. 
Gaussian Elimination and Elementary Elimination Matrices

\[
U = M_{n-1}M_{n-2}\cdots M_2M_1A \\
= L^{-1}A \quad \rightarrow \quad LU = A.
\]

\[
L^{-1} = M_{n-1}M_{n-2}\cdots M_2M_1 \\
L = M_{1}^{-1}M_{2}^{-1}\cdots M_{n-1}^{-1} \\
= L_1 L_2 \cdots L_{n-1},
\]

with

\[
L_k := M_k^{-1} = I + m_k e_k^T.
\]

• With more work, can show

\[
L = \begin{bmatrix}
1 \\
m_{21} & 1 \\
m_{31} & m_{32} & 1 \\
& \ddots & \ddots \\
& \vdots & \ddots \\
& \vdots \\
& \vdots \\
m_{n1} & m_{n2} & m_{n3} & \cdots & \cdots & 1
\end{bmatrix}
\]

That is, the entries of \( L \) are just the entries of the multiplier columns!
Update step viewed as matrix-matrix product.

Note that

\[ A_{k+1} = A_k - m_k e_k^T A_k = M_k A_k, \]

with

\[ M_k := I - m_k e_k^T, \]

as defined in the text.

Recall:

\[ MAx = Mb, \]

\[ M := M_{n-1} M_{n-2} \ldots M_1 =: L^{-1}. \]
Elementary Elimination Matrices

More generally, we can annihilate all entries below $k$th position in $n$-vector $\mathbf{a}$ by transformation

$$M_k \mathbf{a} = \begin{bmatrix}
1 & \cdots & 0 & 0 & \cdots & 0 \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & 1 & 0 & \cdots & 0 \\
0 & \cdots & -m_{k+1} & 1 & \cdots & 0 \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & -m_n & 0 & \cdots & 1
\end{bmatrix}
\begin{bmatrix}
a_1 \\
\vdots \\
a_k \\
a_{k+1} \\
\vdots \\
a_n
\end{bmatrix} = 
\begin{bmatrix}
a_1 \\
\vdots \\
a_k \\
0 \\
\vdots \\
0
\end{bmatrix},$$

where $m_i = a_i/a_k$, $i = k + 1, \ldots, n$

- Divisor $a_k$, called pivot, must be nonzero
Using \( LU \) Factorization in Practice

- Give \( LU = A \), we can solve \( Ax = b \) as follows:

  Given: \( Ax = LUx = b \)

  \[ L (Ux) = Ly = b \]

  Solve: \( Ly = b \)

  \[ Ux = y \]

- We have seen already that the total solve cost (for \( L \) and \( U \) solves) is \( 2 \times n^2 \).

- What about the factor cost, \( A \rightarrow LU \)?
**LU Factorization Costs (Important)**

- In general, the cost for $A \rightarrow LU$ is $O(n^3)$.
- It is large (i.e., it is not optimal, which would be $O(n)$), and therefore important.
- The dominant cost comes from the essential update step:

$$A^{(k+1)} = A^{(k)} - c_k r_k^T,$$

which is effected for $k = 1, \ldots, n - 1$ steps.

- If $A$ is square ($n \times n$), then $c_k r_k^T$ is a square matrix with $(n - k)^2$ nonzeros.
- Each entry requires one "*" and its subtraction from $A^{(k)}$ requires one "-".
- Total cost is $2 \times [(n - 1)^2 + (n - 2)^2 + \ldots (1)^2] \sim 2n^3/3$ operations.

**Example:** $n = 10^3 \rightarrow n^3 = 10^9$. Cost is about 0.6 billion operations. With a 3 GHz clock and 2 floating point ops / clock, expect about 0.1 seconds (very fast).

**Example:** $n = 10^4 \rightarrow n^3 = 10^{12}$. Cost is about 600 billion operations. With a 3 GHz clock and 2 floating point ops / clock, expect about 10.0 seconds.
First Step: Define sub-block
Single Gaussian Elimination Step

\[ U^k \]

\[ A^k \]

\[ M_k \]

\[ U^{k+1} \]

\[ A^{k+1} \]
Second Step: Annihilate $c_k$

- Update step is:

$$A^{k+1} = \tilde{A}^{k+1} - c_k\tilde{a}_{kk}^{-1}r^T_k$$

which is a rank one update to $A_k$:

$$A_{k+1} = A_k - m_ke^T_kA_k$$
Can also be Implemented in **Block Form**

- Advantage is that, if $A_{kk}$ is a $b \times b$ block, you revisit the $A_k$ sub-block only $n/b$ times, and thus need fewer memory accesses.

**An order-of-magnitude faster.** (LAPACK vs. LINPACK)
Matlab demo, gauss2.m

- Blue curve is rank-1 update
- Red curve is rank-4 update
- Black curve is `matlab lu()` function
  - It uses a 4 CPUs on the Mac and achieves an impressive 50 Gflops, which is very near peak
- Note that the black curve represents a **10-20x** speed up over a naïve rank-1 update approach.
Next Topics

- Pivoting / zeros & stability
  - Approach
  - Permutation Matrices
  - Stability
  - Cost

- Sherman Morrison

- Computing matrix 2-norm

- SPD / Cholesky Factorization

- Banded Factorization
  - Approach
  - Cost
Recall our earlier example:

\[
\begin{bmatrix}
1 & 2 & 3 \\
4 & 4 & 6 & \end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5 \\
\end{bmatrix}
= 
\begin{bmatrix}
0 \\
4 \\
4 \\
4 \\
4 \\
\end{bmatrix}
\]

• First column is already in upper triangular form.

• Eliminate second column:

\[
\begin{align*}
row_3 & \leftarrow row_3 - \frac{8}{4} \times row_2 \\
row_4 & \leftarrow row_4 - \frac{6}{4} \times row_2 \\
row_5 & \leftarrow row_5 - \frac{4}{4} \times row_2
\end{align*}
\]

\[
\begin{bmatrix}
1 & 2 & 3 \\
4 & 4 & 6 & 1 \\
0 & -3 & 0 \\
-5 & -6 & \frac{3}{2} \\
-2 & 2 & 3 \\
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5 \\
\end{bmatrix}
= 
\begin{bmatrix}
0 \\
4 \\
-4 \\
-2 \\
0 \\
\end{bmatrix}
\]

• \(a_{22} = 4\) is the pivot

• row2 is the pivot row

• \(l_{32} = \frac{8}{4},\ l_{42} = \frac{6}{4},\ l_{52} = \frac{4}{4}\), is the multiplier column.
Generating Upper Triangular Systems: \textit{LU} Factorization

- Augmented form. Store $b$ in $A(:,n+1)$:

\[
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & | & 4 \\
8 & 8 & 9 & 2 & | & 4 \\
6 & 1 & 3 & 3 & | & 4 \\
4 & 2 & 8 & 4 & | & 4
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & | & 4 \\
0 & -3 & 0 & -4 \\
-5 & -6 & \frac{3}{2} & -2 \\
-2 & 2 & 3 & 0
\end{bmatrix}
\]

\textbf{This Case.}

pivot \quad = \quad 4

pivot row \quad = \quad \begin{bmatrix} 4 & 6 & 1 & | & 4 \end{bmatrix}

multiplier column \quad = \quad \frac{1}{4} \begin{bmatrix} 8 \\ 6 \\ 4 \end{bmatrix}

\textbf{General Case.}

pivot \quad = \quad a_{kk} \quad \text{when zeroing the } k\text{th column.}

pivot row \quad = \quad r_k^T = a_{kj}, \quad j = k+1, \ldots, n [ + b_k ]

multiplier column \quad = \quad c_k = \frac{a_{ik}}{a_{kk}}, \quad i = k+1, \ldots, n
Generating Upper Triangular Systems: \textit{LU} Factorization

- Augmented form. Store $b$ in $A(:, n+1)$:

\[
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
8 & 8 & 9 & 2 & 4 \\
6 & 1 & 3 & 3 & 4 \\
4 & 2 & 8 & 4 & 4
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
0 & -3 & 0 & -4 \\
-5 & -6 & 3/2 & -2 \\
-2 & 2 & 3 & 0
\end{bmatrix}
\]

\textbf{This Case.}

pivot = 4
pivot row = $\begin{bmatrix} 4 & 6 & 1 & | & 4 \end{bmatrix}$
multiplier column = $\begin{bmatrix} 1/4 & 6/4 \end{bmatrix}$

\textbf{General Case.}

$a_{kk}$ when zeroing the $k$th column.
$r_k^T = a_{kj}, j = k+1, \ldots, n \ [ + b_k ]$
$c_k = \frac{a_{ik}}{a_{kk}}, i = k+1, \ldots, n$
Generating Upper Triangular Systems: $LU$ Factorization

- Augmented form. Store $b$ in $A(:, n + 1)$:

$$
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
8 & 8 & 9 & 2 & 4 \\
6 & 1 & 3 & 3 & 4 \\
4 & 2 & 8 & 4 & 4
\end{bmatrix} \quad \rightarrow \quad
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
0 & -3 & 0 & -4 \\
-5 & -6 & \frac{3}{2} & -2 \\
-2 & 2 & 3 & 0
\end{bmatrix}
$$

**This Case.**

- pivot $= 4$

- pivot row $= \begin{bmatrix} 4 & 6 & 1 \end{bmatrix}^T$

- multiplier column $= \frac{1}{4} \begin{bmatrix} 8 \\
6 \\
4 \end{bmatrix}$

- $L\begin{bmatrix} y \\ x \end{bmatrix} = b$

**General Case.**

- $a_{kk}$ when zeroing the $k$th column.

- $r_k^T = a_{kj}$, $j = k + 1, \ldots, n [+ b_k]$

- $c_k = \frac{a_{ik}}{a_{kk}}$, $i = k + 1, \ldots, n$

\[ c_k \rightarrow 1_k, \text{ store as column } k \text{ of } L. \]
Pivoting

• We return to our original $5 \times 5$ example. The next step would be:

\[
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
0 & -3 & 0 & | & -4 \\
-5 & -6 & \frac{3}{2} & | & -2 \\
-2 & 2 & 3 & | & 0
\end{bmatrix}
\]

• Here, we have difficulty because the nominal pivot, $a_{33}$ is zero.

• The remedy is to exchange rows with one of the remaining two, since the order of the equations is immaterial.

• For numerical stability, we choose the row that maximizes $|a_{ik}|$.

• This choice ensures that all entries in the multiplier column are less than one in modulus.
Next Step: \( k = k + 1 \)

- After switching rows, we have

\[
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
-5 & -6 & \frac{3}{2} & | & -2 \\
0 & -3 & 0 & -4 \\
-2 & 2 & 3 & | & 0
\end{bmatrix}
\rightarrow
\begin{bmatrix}
1 & 2 & 3 & | & 0 \\
4 & 4 & 6 & 1 & 4 \\
-5 & -6 & \frac{3}{2} & | & -2 \\
0 & -3 & 0 & -4 \\
0 & 4\frac{2}{5} & 2\frac{2}{5} & | & \frac{4}{5}
\end{bmatrix}
\]

pivot = \(-5\)

pivot row = \[
\begin{bmatrix}
-6 & \frac{3}{2} & | & -2
\end{bmatrix}
\]

multiplier column = \[
\frac{1}{-5}
\begin{bmatrix}
0 \\
-2
\end{bmatrix}
\]
Row Interchanges

- Gaussian elimination breaks down if leading diagonal entry of remaining unreduced matrix is zero at any stage.
- Easy fix: if diagonal entry in column $k$ is zero, then interchange row $k$ with some subsequent row having nonzero entry in column $k$ and then proceed as usual.
- If there is no nonzero on or below diagonal in column $k$, then there is nothing to do at this stage, so skip to next column.
- Zero on diagonal causes resulting upper triangular matrix $U$ to be singular, but LU factorization can still be completed.
- Subsequent back-substitution will fail, however, as it should for singular matrix.
In principle, any nonzero value will do as pivot, but in practice pivot should be chosen to minimize error propagation.

To avoid amplifying previous rounding errors when multiplying remaining portion of matrix by elementary elimination matrix, multipliers should not exceed 1 in magnitude.

This can be accomplished by choosing entry of largest magnitude on or below diagonal as pivot at each stage.

Such *partial pivoting* is essential in practice for numerically stable implementation of Gaussian elimination for general linear systems.
LU Factorization with Partial Pivoting

- With partial pivoting, each \( M_k \) is preceded by permutation \( P_k \) to interchange rows to bring entry of largest magnitude into diagonal pivot position
- Still obtain \( MA = U \), with \( U \) upper triangular, but now
  \[
  M = M_{n-1} P_{n-1} \cdots M_1 P_1
  \]
- \( L = M^{-1} \) is still triangular in general sense, but not necessarily lower triangular
- Alternatively, we can write
  \[
  PA = LU
  \]
  where \( P = P_{n-1} \cdots P_1 \) permutes rows of \( A \) into order determined by partial pivoting, and now \( L \) is lower triangular
Complete Pivoting

- **Complete pivoting** is more exhaustive strategy in which largest entry in entire remaining unreduced submatrix is permuted into diagonal pivot position.
- Requires interchanging columns as well as rows, leading to factorization

\[ PAQ = LU \]

with \( L \) unit lower triangular, \( U \) upper triangular, and \( P \) and \( Q \) permutations.
- Numerical stability of complete pivoting is theoretically superior, but pivot search is more expensive than for partial pivoting.
- Numerical stability of partial pivoting is more than adequate in practice, so it is almost always used in solving linear systems by Gaussian elimination.
Example: Permutations

- **Permutation matrix** $P$ has one 1 in each row and column and zeros elsewhere, i.e., identity matrix with rows or columns permuted.

- Note that $P^{-1} = P^T$.

- Premultiplying both sides of system by permutation matrix, $PAx = Pb$, reorders rows, but solution $x$ is unchanged.

- Postmultiplying $A$ by permutation matrix, $APx = b$, reorders columns, which permutes components of original solution.

$$x = (AP)^{-1}b = P^{-1}A^{-1}b = P^T(A^{-1}b)$$
Comments About Permutation Matrices

- As with $A^{-1}$, we never actually form them – we simply use pointers to swap rows (or columns).

- However, they are notationally convenient, and can be constructed from elementary permutation matrices that swap just two rows, e.g. If $P_{ij}$ is the identity matrix with rows $i$ and $j$ swapped, then we have:

\[ P_{ij}^{-1} = P_{ij}^T = P_{ij} \]

So applying $P_{ij}$ twice brings two rows back to their original position.

- We can construct a compound permutation matrix as the product of these swaps, e.g., $P = P_{21}P_{43}$

- The compound permutation matrix is not symmetric, but we still have

\[ P^{-1} = P^T = P_{43}^T P_{21}^T = P_{43} P_{21} \]
%% perm.m - permutation demo

A = [ 1 2 3 4 ;
     2 3 4 5 ;
     3 4 5 6 ;
     4 5 6 7 ];

p = [ 4 ;
     1 ;
     2 ;
     3 ];

I=eye(4); P = I(p,:);
A, P

display('Row permutation: P*A'), PA=P*A
display('Col permutation: A*P'), AP=A*P

display('Permutation of vector:')
c = [ b P*b ];
b1 = b(p); b2(p,1) = b;
[c b1 b2]
Example: Pivoting

- Need for pivoting has nothing to do with whether matrix is singular or nearly singular
- For example,

\[ A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \]

is nonsingular yet has no LU factorization unless rows are interchanged, whereas

\[ A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \]

is singular yet has LU factorization
Example: Small Pivots

To illustrate effect of small pivots, consider

\[
A = \begin{bmatrix}
\epsilon & 1 \\
1 & 1
\end{bmatrix}
\]

where \( \epsilon \) is positive number smaller than \( \epsilon_{\text{mach}} \).

- If rows are not interchanged, then pivot is \( \epsilon \) and multiplier is \(-1/\epsilon\), so

\[
M = \begin{bmatrix}
1 & 0 \\
-1/\epsilon & 1
\end{bmatrix}, \quad L = \begin{bmatrix}
1 & 0 \\
1/\epsilon & 1
\end{bmatrix},
\]

\[
U = \begin{bmatrix}
\epsilon & 1 \\
0 & 1 - 1/\epsilon
\end{bmatrix} = \begin{bmatrix}
\epsilon & 1 \\
0 & -1/\epsilon
\end{bmatrix}
\]

in floating-point arithmetic, but then

\[
LU = \begin{bmatrix}
1 & 0 \\
1/\epsilon & 1
\end{bmatrix} \begin{bmatrix}
\epsilon & 1 \\
0 & -1/\epsilon
\end{bmatrix} = \begin{bmatrix}
\epsilon & 1 \\
1 & 0
\end{bmatrix} \neq A
\]
Example, continued

- Using small pivot, and correspondingly large multiplier, has caused loss of information in transformed matrix.
- If rows interchanged, then pivot is 1 and multiplier is $-\epsilon$, so

$$M = \begin{bmatrix} 1 & 0 \\ -\epsilon & 1 \end{bmatrix}, \quad L = \begin{bmatrix} 1 & 0 \\ \epsilon & 1 \end{bmatrix},$$

$$U = \begin{bmatrix} 1 & 1 \\ 0 & 1 - \epsilon \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$

in floating-point arithmetic.

- Thus,

$$LU = \begin{bmatrix} 1 & 0 \\ \epsilon & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ \epsilon & 1 \end{bmatrix}$$

which is correct after permutation.
Pivoting:

- Moving small pivots down moves us closer to upper triangular form, with **no round-off**.

\[
PA = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} \epsilon & 1 \\ 1 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ \epsilon & 1 \end{pmatrix}
\]

- A general principle in numerical computing regarding round-off: **Small corrections are preferred to large ones**.

- Failure to exchange a small pivot on the diagonal can result in all subsequent rows looking like multiples of the current pivot row → **singular submatrix**.
Failure to pivot can result in all subsequent rows looking like multiples of the kth row:

- Consider

\[ A = \begin{pmatrix} \epsilon & r_1^T \\ a_{21} & r_2^T \\ a_{31} & r_3^T \\ \vdots & \vdots \end{pmatrix} \]

Gaussian elimination leads to

\[ r_i \leftarrow r_i - \frac{a_{i1}}{\epsilon} r_1 \approx -\frac{a_{i1}}{\epsilon} r_1. \]

- Matlab example “pivot.m”
<table>
<thead>
<tr>
<th></th>
<th>1.0e-18</th>
<th>1.0000</th>
<th>2.0000</th>
<th>3.0000</th>
<th>4.0000</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0000</td>
<td>4.0000</td>
<td>4.0000</td>
<td>6.0000</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>2.0000</td>
<td>8.0000</td>
<td>7.0000</td>
<td>9.0000</td>
<td>2.0000</td>
<td></td>
</tr>
<tr>
<td>3.0000</td>
<td>6.0000</td>
<td>1.0000</td>
<td>3.0000</td>
<td>3.0000</td>
<td></td>
</tr>
<tr>
<td>4.0000</td>
<td>4.0000</td>
<td>2.0000</td>
<td>8.0000</td>
<td>4.0000</td>
<td></td>
</tr>
</tbody>
</table>
Failure to Pivot, Noncatastrophic Case

- In cases where the nominal pivot is small but \( \epsilon_M > 2 \), we are effectively reducing the number of significant digits that represent the remainder of the matrix A.

- In essence, we are driving the rows (or columns) to be similar, which is equivalent to saying that we have nearly parallel columns.

- We saw already a 2 x 2 example where the condition number of the matrix with 2 unit-norm vectors scales like \( 2 / \theta \), where \( \theta \) is the (small) angle between the column vectors.
Partial Pivoting: Costs

Procedure:
- For each $k$, pick $k'$ such that $|a_{k'k}| \geq |a_{ik}|$, $i \geq k$.
- Swap rows $k$ and $k'$.
- Proceed with central update step: $A^{(k+1)} = A^{(k)} - c_k r_k^T$

Costs:
- For each step, search is $O(n - k)$, total cost is $\approx n^2/2$.
- For each step, row swap is $O(n - k)$, total cost is $\approx n^2/2$.
- Total cost for partial pivoting is $O(n^2) \lambda 2n^3/3$.
- If we use full pivoting, total search cost such that $|a_{k'k''}| \geq |a_{ij}|$, $i, j \geq k$, is $O(n^3)$.
- Row and column exchange costs still total only $O(n^2)$.

Notes:
- Partial (row) pivoting ensures that multiplier column entries have modulus $\leq 1$. (Good.)
- Full pivoting also destroys band structure, whereas partial pivoting leaves some band structure intact.
Partial Pivoting: LU=PA

- Note: If we swap rows of $A$, we are swapping equations.
- We must swap rows of $\mathbf{b}$.
- $LU$ routines normally return the pivot index vector to effect this exchange.
- Nominally, it looks like a permutation matrix $P$, which is simply the identity matrix with rows interchanged.
- If we swap equations, we must also swap rows of $L$
- If we are consistent, we can swap rows at any time (i.e., $A$, or $L$) and get the same final factorization: $LU = PA$.
- Most codes swap $A^{(k+1)}$, but not the factors in $L$ that have already been stored.
- Swapping rows of $A^{(k+1)}$ helps with speed (vectorization) of $A^{(k+1)} = A^{(k)} - c_k \mathbf{r}_k^T$.
- In parallel computing, one would not swap the pivot row. Just pass the pointer to the processor holding the new pivot row, where the swap would take place locally.
Although pivoting is generally required for stability of Gaussian elimination, pivoting is *not* required for some important classes of matrices

- **Diagonally dominant**

  $\sum_{i=1, i\neq j}^{n} |a_{i,j}| < |a_{j,j}|, \quad j = 1, \ldots, n$

- **Symmetric positive definite**

  $A = A^T \quad \text{and} \quad x^T A x > 0 \quad \text{for all} \quad x \neq 0$
Despite variations in computing it, LU factorization is unique up to diagonal scaling of factors.

Provided row pivot sequence is same, if we have two LU factorizations $PA = LU = \hat{L}\hat{U}$, then $\hat{L}^{-1}L = \hat{U}U^{-1} = D$ is both lower and upper triangular, hence diagonal.

If both $L$ and $\hat{L}$ are unit lower triangular, then $D$ must be identity matrix, so $L = \hat{L}$ and $U = \hat{U}$.

Uniqueness is made explicit in LDU factorization $PA = LDU$, with $L$ unit lower triangular, $U$ unit upper triangular, and $D$ diagonal.
Elementary elimination matrices $M_k$, their inverses $L_k$, and permutation matrices $P_k$ used in formal description of LU factorization process are not formed explicitly in actual implementation.

$U$ overwrites upper triangle of $A$, multipliers in $L$ overwrite strict lower triangle of $A$, and unit diagonal of $L$ need not be stored.

Row interchanges usually are not done explicitly; auxiliary integer vector keeps track of row order in original locations.
Inversion vs. Factorization

- Even with many right-hand sides $b$, inversion never overcomes higher initial cost, since each matrix-vector multiplication $A^{-1}b$ requires $n^2$ operations, similar to cost of forward- and back-substitution.

- Inversion gives less accurate answer; for example, solving $3x = 18$ by division gives $x = 18/3 = 6$, but inversion gives $x = 3^{-1} \times 18 = 0.333 \times 18 = 5.99$ using 3-digit arithmetic.

- Matrix inverses often occur as convenient notation in formulas, but explicit inverse is rarely required to implement such formulas.

- For example, product $A^{-1}B$ should be computed by LU factorization of $A$, followed by forward- and back-substitutions using each column of $B$. 
In principle, solution to linear system is unaffected by diagonal scaling of matrix and right-hand-side vector.

In practice, scaling affects both conditioning of matrix and selection of pivots in Gaussian elimination, which in turn affect numerical accuracy in finite-precision arithmetic.

It is usually best if all entries (or uncertainties in entries) of matrix have about same size.

Sometimes it may be obvious how to accomplish this by choice of measurement units for variables, but there is no foolproof method for doing so in general.

Scaling can introduce rounding errors if not done carefully.
Example: Scaling

- Linear system

\[
\begin{bmatrix}
1 & 0 \\
0 & \epsilon
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2
\end{bmatrix} =
\begin{bmatrix}
1 \\
\epsilon
\end{bmatrix}
\]

has condition number $1/\epsilon$, so is ill-conditioned if $\epsilon$ is small.

- If second row is multiplied by $1/\epsilon$, then system becomes perfectly well-conditioned.

- Apparent ill-conditioning was due purely to poor scaling.

- In general, it is usually much less obvious how to correct poor scaling.
Sherman Morrison Formula
If right-hand side of linear system changes but matrix does not, then LU factorization need not be repeated to solve new system.

Only forward- and back-substitution need be repeated for new right-hand side.

This is substantial savings in work, since additional triangular solutions cost only $O(n^2)$ work, in contrast to $O(n^3)$ cost of factorization.
Sherman-Morrison Formula

- Sometimes refactorization can be avoided even when matrix does change

- **Sherman-Morrison formula** gives inverse of matrix resulting from rank-one change to matrix whose inverse is already known

\[
(A - uv^T)^{-1} = A^{-1} + A^{-1}u(1 - v^TA^{-1}u)^{-1}v^TA^{-1}
\]

where \(u\) and \(v\) are \(n\)-vectors

- Evaluation of formula requires \(O(n^2)\) work (for matrix-vector multiplications) rather than \(O(n^3)\) work required for inversion
To solve linear system \((A - uv^T)x = b\) with new matrix, use Sherman-Morrison formula to obtain

\[
x = (A - uv^T)^{-1}b
= A^{-1}b + A^{-1}u(1 - v^T A^{-1}u)^{-1}v^T A^{-1}b
\]

which can be implemented by following steps

- Solve \(Az = u\) for \(z\), so \(z = A^{-1}u\)
- Solve \(Ay = b\) for \(y\), so \(y = A^{-1}b\)
- Compute \(x = y + ((v^T y)/(1 - v^T z))z\)

If \(A\) is already factored, procedure requires only triangular solutions and inner products, so only \(O(n^2)\) work and no explicit inverses
Example: Rank-One Updating of Solution

Consider rank-one modification

\[
\begin{bmatrix}
2 & 4 & -2 \\
4 & 9 & -3 \\
-2 & -1 & 7
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3
\end{bmatrix}
=
\begin{bmatrix}
2 \\
8 \\
10
\end{bmatrix}
\]

(with 3, 2 entry changed) of system whose LU factorization was computed in earlier example.

One way to choose update vectors is

\[
u = \begin{bmatrix}
0 \\
0 \\
-2
\end{bmatrix}
\quad\text{and}\quad
v = \begin{bmatrix}
0 \\
1 \\
0
\end{bmatrix}
\]

so matrix of modified system is \(A - uv^T\).
Example, continued

- Using LU factorization of $A$ to solve $Az = u$ and $Ay = b$,

$$
\begin{align*}
\mathbf{z} &= \begin{bmatrix}
\frac{-3}{2} \\
\frac{1}{2} \\
\frac{-1}{2}
\end{bmatrix}
\quad \text{and} \quad
\mathbf{y} = \begin{bmatrix}
-1 \\
2 \\
2
\end{bmatrix}
\end{align*}
$$

- Final step computes updated solution

$$
\mathbf{x} = \mathbf{y} + \frac{\mathbf{v}^T \mathbf{y}}{1 - \mathbf{v}^T \mathbf{z}} \mathbf{z} = \begin{bmatrix}
-1 \\
2 \\
2
\end{bmatrix} + \frac{2}{1 - \frac{1}{2}} \begin{bmatrix}
\frac{-3}{2} \\
\frac{1}{2} \\
\frac{-1}{2}
\end{bmatrix} = \begin{bmatrix}
-7 \\
4 \\
0
\end{bmatrix}
$$

- We have thus computed solution to modified system without factoring modified matrix

Q: Under what circumstances could the denominator be zero?
Sherman Morrison

[1] Solve $A\tilde{x} = \tilde{b}$:

$A \rightarrow LU$ ( $O(n^3)$ work )

Solve $L\tilde{y} = \tilde{b}$,

Solve $U\tilde{x} = \tilde{y}$ ( $O(n^2)$ work ).

[2] New problem:

$(A - uv^T)x = b$. (different $x$ and $b$)

Key Idea:

- $(A - uv^T)x$ differs from $Ax$ by only a small amount of information.

- Rewrite as: $Ax + u\gamma = b$

  $\gamma := -v^Tx \iff v^Tx + \gamma = 0$
Extended system:

\[ Ax + \gamma u = b \]
\[ v^T x + \gamma = 0 \]
Extended system:

\[ A\mathbf{x} + \gamma \mathbf{u} = \mathbf{b} \]
\[ \mathbf{v}^T \mathbf{x} + \gamma = 0 \]

In matrix form:

\[
\begin{bmatrix}
A & \mathbf{u} \\
\mathbf{v}^T & 1
\end{bmatrix}
\begin{bmatrix}
\mathbf{x} \\
\gamma
\end{bmatrix}
= 
\begin{bmatrix}
\mathbf{b} \\
0
\end{bmatrix}
\]
Sherman Morrison

Extended system:

\[ A\mathbf{x} + \gamma \mathbf{u} = \mathbf{b} \]
\[ \mathbf{v}^T \mathbf{x} + \gamma = 0 \]

In matrix form:

\[
\begin{bmatrix}
A & \mathbf{u} \\
\mathbf{v}^T & 1
\end{bmatrix}
\begin{bmatrix}
\mathbf{x} \\
\gamma
\end{bmatrix}
= 
\begin{bmatrix}
\mathbf{b} \\
0
\end{bmatrix}
\]

Eliminate for \( \gamma \):

\[
\begin{bmatrix}
A & \mathbf{u} \\
0 & 1 - \mathbf{v}^T \mathbf{A}^{-1} \mathbf{u}
\end{bmatrix}
\begin{bmatrix}
\mathbf{x} \\
\gamma
\end{bmatrix}
= 
\begin{bmatrix}
\mathbf{b} \\
-\mathbf{v}^T \mathbf{A}^{-1} \mathbf{b}
\end{bmatrix}
\]
Sherman Morrison

Extended system:  
\[
\begin{align*}
Ax + \gamma u &= b \\
v^T x + \gamma &= 0
\end{align*}
\]

In matrix form:  
\[
\begin{bmatrix}
A & u \\
v^T & 1
\end{bmatrix}
\begin{pmatrix}
x \\
\gamma
\end{pmatrix}
= 
\begin{pmatrix}
b \\
0
\end{pmatrix}
\]

Eliminate for $\gamma$:  
\[
\begin{bmatrix}
A & u \\
0 & 1 - v^T A^{-1} u
\end{bmatrix}
\begin{pmatrix}
x \\
\gamma
\end{pmatrix}
= 
\begin{pmatrix}
b \\
-v^T A^{-1} b
\end{pmatrix}
\]

\[
\gamma = - (1 - v^T A^{-1} u)^{-1} v^T A^{-1} b
\]
Sherman Morrison

Extended system:

\[ A\mathbf{x} + \gamma \mathbf{u} = \mathbf{b} \]
\[ \mathbf{v}^T \mathbf{x} + \gamma = 0 \]

In matrix form:

\[
\begin{bmatrix}
A & \mathbf{u} \\
\mathbf{v}^T & 1
\end{bmatrix}
\begin{pmatrix}
\mathbf{x} \\
\gamma
\end{pmatrix}
=
\begin{pmatrix}
\mathbf{b} \\
0
\end{pmatrix}
\]

Eliminate for \( \gamma \):

\[
\begin{bmatrix}
A & \mathbf{u} \\
0 & 1 - \mathbf{v}^T A^{-1} \mathbf{u}
\end{bmatrix}
\begin{pmatrix}
\mathbf{x} \\
\gamma
\end{pmatrix}
=
\begin{pmatrix}
\mathbf{b} \\
-\mathbf{v}^T A^{-1} \mathbf{b}
\end{pmatrix}
\]

\[
\gamma = - \left(1 - \mathbf{v}^T A^{-1} \mathbf{u}\right)^{-1} \mathbf{v}^T A^{-1} \mathbf{b}
\]

\[
\mathbf{x} = A^{-1} \left(\mathbf{b} - \mathbf{u} \gamma\right) = A^{-1} \left[\mathbf{b} + \mathbf{u} \left(1 - \mathbf{v}^T A^{-1} \mathbf{u}\right)^{-1} \mathbf{v}^T A^{-1} \mathbf{b}\right]
\]
Extended system:

\[ A \mathbf{x} + \gamma \mathbf{u} = \mathbf{b} \]
\[ \mathbf{v}^T \mathbf{x} + \gamma = 0 \]

In matrix form:

\[
\begin{bmatrix}
A \\
\mathbf{v}^T
\end{bmatrix}
\begin{bmatrix}
\mathbf{u} \\
1
\end{bmatrix}
\begin{bmatrix}
\mathbf{x} \\
\gamma
\end{bmatrix}
=
\begin{bmatrix}
\mathbf{b} \\
0
\end{bmatrix}
\]

Eliminate for \( \gamma \):

\[
\begin{bmatrix}
A \\
0
\end{bmatrix}
\begin{bmatrix}
\mathbf{u} \\
1 - \mathbf{v}^T A^{-1} \mathbf{u}
\end{bmatrix}
\begin{bmatrix}
\mathbf{x} \\
\gamma
\end{bmatrix}
=
\begin{bmatrix}
\mathbf{b} \\
-\mathbf{v}^T A^{-1} \mathbf{b}
\end{bmatrix}
\]

\[
\gamma = - \left( 1 - \mathbf{v}^T A^{-1} \mathbf{u} \right)^{-1} \mathbf{v}^T A^{-1} \mathbf{b}
\]

\[
\mathbf{x} = A^{-1} (\mathbf{b} - \mathbf{u} \gamma) = A^{-1} \left[ \mathbf{b} + \mathbf{u} \left( 1 - \mathbf{v}^T A^{-1} \mathbf{u} \right)^{-1} \mathbf{v}^T A^{-1} \mathbf{b} \right]
\]

\[
(A - \mathbf{u} \mathbf{v}^T)^{-1} = A^{-1} + A^{-1} \mathbf{u} \left( 1 - \mathbf{v}^T A^{-1} \mathbf{u} \right)^{-1} \mathbf{v}^T A^{-1}.
\]
Sherman Morrison: Potential Singularity

- Consider the modified system: \((A - uv^T) x = b\).
- The solution is

\[
x = (A - uv^T)^{-1} b
= \left[I + A^{-1}u (1 - v^T A^{-1}u)^{-1} v^T A^{-1}\right] A^{-1} b.
\]
- If \(1 - v^T A^{-1}u = 0\), failure.
- Why?
Sherman Morrison: Potential Singularity

- Let $\tilde{A} := (A - uv^T)$ and consider,

\[
\tilde{A} A^{-1} = (A - uv^T) A^{-1} = (I - uv^T A^{-1}).
\]

- Look at the product $\tilde{A} A^{-1} u$,

\[
\tilde{A} A^{-1} u = (I - uv^T A^{-1}) u = u - uv^T A^{-1} u.
\]

- If $v^T A^{-1} u = 1$, then

\[
\tilde{A} A^{-1} u = u - u = 0,
\]

which means that $\tilde{A}$ is singular since we assume that $A^{-1}$ exists.

- Thus, an unfortunate choice of $u$ and $v$ can lead to a singular modified matrix and this singularity is indicated by $v^T A^{-1} u = 1$. 
Computing $\|A\|_2$ and $\text{cond}_2(A)$.

- Recall: $\text{cond}(A) := \| A^{-1} \| \cdot \| A \|,$

$$\| A \| := \max_{x \neq 0} \frac{\| Ax \|}{\| x \|},$$

$$\| x \|_2 = \left( \sum_{i=1}^{n} x_i^2 \right)^{\frac{1}{2}} = \sqrt{x^T x},$$

$$\| x \|_2^2 = x^T x.$$

- From now on, drop the subscript “$_2$”.

$$\| x \|^2 = x^T x$$

$$\| Ax \|^2 = (Ax)^T(Ax) = x^T A^T A x.$$
• Matrix norm:

\[ \| A \| ^2 = \max_{x \neq 0} \frac{\| A x \|^2}{\| x \|^2} , \]

\[ = \max_{x \neq 0} \frac{x^T A^T A x}{x^T x} \]

\[ = \lambda_{\text{max}}(A^T A) =: \text{spectral radius of } (A^T A) . \]

• The symmetric positive definite matrix \( B := A^T A \) has positive eigenvalues.

• All symmetric matrices \( B \) have a complete set of orthonormal eigenvectors satisfying

\[ B z_j = \lambda_j z_j, \quad z_i^T z_j = \delta_{ij} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} . \]

• **Note:** If \( \lambda_i = \lambda_j, \ i \neq j \), then can have \( z_i^T z_j \neq 0 \), but we can orthogonalize \( z_i \) and \( z_j \) so that \( \tilde{z}_i^T \tilde{z}_j = 0 \) and

\[ B \tilde{z}_i = \lambda_i \tilde{z}_i \quad \lambda_i = \lambda_j \]

\[ B \tilde{z}_j = \lambda_j \tilde{z}_j . \]
• Assume eigenvalues are sorted with $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$.

• For any $\mathbf{x}$ we have: $\mathbf{x} = c_1 \mathbf{z}_1 + c_2 \mathbf{z}_2 + \cdots + c_n \mathbf{z}_n$.

• Let $||\mathbf{x}|| = 1$.

• Want to find $\max_{||\mathbf{x}||=1} \frac{\mathbf{x}^T \mathbf{B} \mathbf{x}}{\mathbf{x}^T \mathbf{x}} = \max_{||\mathbf{x}||=1} \mathbf{x}^T \mathbf{B} \mathbf{x}$.

• Note: $\mathbf{x}^T \mathbf{x} = \left( \sum_{i=1}^{n} c_i \mathbf{z}_i \right)^T \left( \sum_{j=1}^{n} c_j \mathbf{z}_j \right)$

  $= \sum_{i=1}^{n} \sum_{j=1}^{n} c_i c_j \mathbf{z}_i^T \mathbf{z}_j$

  $= \sum_{i=1}^{n} \sum_{j=1}^{n} c_i c_j \delta_{ij}$

  $= \sum_{i=1}^{n} c_i^2 = 1$.

  \[ \Rightarrow c_1^2 = 1 - \sum_{i=2}^{n} c_i^2. \]
\[ \mathbf{x}^T \mathbf{B} \mathbf{x} = \left( \sum_{i=1}^{n} c_i \mathbf{z}_i \right)^T \left( \sum_{j=1}^{n} c_j \mathbf{z}_j \right) \]

\[ = \left( \sum_{i=1}^{n} c_i \mathbf{z}_i \right)^T \left( \sum_{j=1}^{n} c_j \lambda_j \mathbf{z}_j \right) \]

\[ = \sum_{i=1}^{n} \sum_{j=1}^{n} c_i \lambda_j c_j \mathbf{z}_i^T \mathbf{z}_j \]

\[ = \sum_{i=1}^{n} \sum_{j=1}^{n} c_i \lambda_j c_j \delta_{ij} \]

\[ = \sum_{i=1}^{n} c_i^2 \lambda_i = c_1^2 \lambda_1 + c_2^2 \lambda_2 + \cdots + c_n^2 \lambda_n \]

\[ = \lambda_1 \left[ c_1^2 + c_2^2 \beta_2 + \cdots + c_n^2 \beta_n \right], \quad 0 < \beta_i := \frac{\lambda_i}{\lambda_1} \leq 1, \]

\[ = \lambda_1 \left[ (1 - c_2^2 - \cdots - c_n^2) + c_2^2 \beta_2 + \cdots + c_n^2 \beta_n \right] \]

\[ = \lambda_1 \left[ 1 - (1 - \beta_2)c_2^2 + (1 - \beta_3)c_3^2 + \cdots + (1 - \beta_n)c_n^2 \right] \]

\[ = \lambda_1 \left[ 1 - \text{some positive (or zero) numbers} \right]. \]

- Expression is maximized when \( c_2 = c_3 = \cdots = c_n = 0, \implies c_1 = 1. \)
- Maximum value \( \mathbf{x}^T \mathbf{B} \mathbf{x} = \lambda_{\text{max}}(B) = \lambda_1. \)
- Similarly, can show \( \min \mathbf{x}^T \mathbf{B} \mathbf{x} = \lambda_{\text{min}}(B) = \lambda_n. \)
• So, \( \|A\|^2 = \max_\lambda \lambda(A^T A) = \) spectral radius of \( A^T A \).

• Now,

\[
\|A^{-1}\|^2 = \max_{x \neq 0} \frac{\|A^{-1}x\|^2}{\|x\|^2}.
\]

• Let \( x = Ay \):

\[
\|A^{-1}\|^2 = \max_{y \neq 0} \frac{\|A^{-1}Ay\|^2}{\|Ay\|^2} = \max_{y \neq 0} \frac{\|y\|^2}{\|Ay\|^2} = \left( \min_{y \neq 0} \frac{\|Ay\|^2}{\|y\|^2} \right)^{-1} = \frac{1}{\lambda_{\min}(A^T A)}.
\]

• So, \( \text{cond}_2(A) = \|A^{-1}\| \cdot \|A\|, \)

\[
\text{cond}_2(A) = \sqrt{\frac{\lambda_{\max}(A^T A)}{\lambda_{\min}(A^T A)}}.
\]
Special Types of Linear Systems

- Work and storage can often be saved in solving linear system if matrix has special properties

- Examples include
  - **Symmetric**: $A = A^T$, $a_{ij} = a_{ji}$ for all $i, j$
  - **Positive definite**: $\mathbf{x}^T A \mathbf{x} > 0$ for all $\mathbf{x} \neq 0$
  - **Band**: $a_{ij} = 0$ for all $|i - j| > \beta$, where $\beta$ is bandwidth of $A$
  - **Sparse**: most entries of $A$ are zero
Symmetric Positive Definite (SPD) Matrices

- Very common in optimization and physical processes

- Easiest example:
  - If $B$ is invertible, then $A := B^T B$ is SPD.

- SPD systems of the form $A \mathbf{x} = \mathbf{b}$ can be solved using
  - (stable) Cholesky factorization $A = LL^T$, or
  - iteratively with the most robust iterative solver, conjugate gradient iteration (generally with preconditioning, known as preconditioned conjugate gradients, PCG).
If $A$ is symmetric and positive definite, then LU factorization can be arranged so that $U = L^T$, which gives Cholesky factorization

$$A = LL^T$$

where $L$ is lower triangular with positive diagonal entries.

Algorithm for computing it can be derived by equating corresponding entries of $A$ and $LL^T$.

In $2 \times 2$ case, for example,

$$\begin{bmatrix} a_{11} & a_{21} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} l_{11} & 0 \\ l_{21} & l_{22} \end{bmatrix} \begin{bmatrix} l_{11} & l_{21} \\ 0 & l_{22} \end{bmatrix}$$

implies

$$l_{11} = \sqrt{a_{11}}, \quad l_{21} = a_{21}/l_{11}, \quad l_{22} = \sqrt{a_{22} - l_{21}^2}$$
Cholesky Factorization (Text)

Algorithm 2.7 Cholesky Factorization

\[
\text{for } k = 1 \text{ to } n \\
a_{kk} = \sqrt{a_{kk}} \\
\text{for } i = k + 1 \text{ to } n \\
a_{ik} = a_{ik}/a_{kk} \\
\text{end} \\
\text{for } j = k + 1 \text{ to } n \\
\text{for } i = j \text{ to } n \\
a_{ij} = a_{ij} - a_{ik} \cdot a_{jk} \\
\text{end} \\
\text{end} \\
\text{end}
\]

{ loop over columns }
{ scale current column }
{ from each remaining column, subtract multiple of current column }

After a row scaling, this is just standard LU decomposition, exploiting symmetry in the LU factors and A. ( \( U=L^T \) )
One way to write resulting general algorithm, in which Cholesky factor $L$ overwrites original matrix $A$, is

\[
\begin{align*}
\text{for } j &= 1 \text{ to } n \\
&\quad \text{for } k = 1 \text{ to } j - 1 \\
&\quad \quad \text{for } i = j \text{ to } n \\
&\quad \quad \quad a_{ij} = a_{ij} - a_{ik} \cdot a_{jk} \\
&\quad \quad \text{end} \\
&\quad \text{end} \\
a_{jj} &= \sqrt{a_{jj}} \\
&\quad \text{for } k = j + 1 \text{ to } n \\
&\quad \quad a_{kj} = a_{kj} / a_{jj} \\
&\quad \text{end} \\
&\text{end}
\end{align*}
\]
Features of Cholesky algorithm for symmetric positive definite matrices

- All $n$ square roots are of positive numbers, so algorithm is well defined
- No pivoting is required to maintain numerical stability
- Only lower triangle of $A$ is accessed, and hence upper triangular portion need not be stored
- Only $n^3/6$ multiplications and similar number of additions are required

Thus, Cholesky factorization requires only about half work and half storage compared with LU factorization of general matrix by Gaussian elimination, and also avoids need for pivoting
Band Matrices

- Gaussian elimination for band matrices differs little from general case — only ranges of loops change
- Typically matrix is stored in array by diagonals to avoid storing zero entries
- If pivoting is required for numerical stability, bandwidth can grow (but no more than double)
- General purpose solver for arbitrary bandwidth is similar to code for Gaussian elimination for general matrices
- For fixed small bandwidth, band solver can be extremely simple, especially if pivoting is not required for stability
Consider tridiagonal matrix

\[
A = \begin{bmatrix}
  b_1 & c_1 & 0 & \cdots & 0 \\
  a_2 & b_2 & c_2 & \ddots & \vdots \\
  0 & \ddots & \ddots & \ddots & 0 \\
  \vdots & \ddots & a_{n-1} & b_{n-1} & c_{n-1} \\
  0 & \cdots & 0 & a_n & b_n
\end{bmatrix}
\]

Gaussian elimination without pivoting reduces to

\[
d_1 = b_1 \\
\text{for } i = 2 \text{ to } n \\
  m_i = a_i / d_{i-1} \\
  d_i = b_i - m_i c_{i-1}
\]

Cost is \(O(n)\)!
LU factorization of $A$ is then given by

$$L = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ m_2 & 1 & \cdots & \cdots & \vdots \\ 0 & \cdots & \cdots & \cdots & \vdots \\ \vdots & \cdots & m_{n-1} & 1 & 0 \\ 0 & \cdots & 0 & m_n & 1 \end{bmatrix}, \quad U = \begin{bmatrix} d_1 & c_1 & 0 & \cdots & 0 \\ 0 & d_2 & c_2 & \cdots & \vdots \\ \vdots & \cdots & \cdots & \cdots & \vdots \\ \vdots & \cdots & d_{n-1} & c_{n-1} & \vdots \\ 0 & \cdots & \cdots & 0 & d_n \end{bmatrix}$$
Example of Banded Systems

- Graphs (i.e., matrices) arising from differential equations in 1D, 2D, 3D (and higher…) are generally banded and sparse.

- Example:

\[
\frac{d^2 u}{dx^2} = f(x) \quad \rightarrow \quad -\frac{u_{i-1} - 2u_i + u_{i+1}}{h^2} \approx f_i
\]
In Matrix Form

\[-\frac{d^2 u}{dx^2} = f(x) \quad \Rightarrow \quad -\frac{u_{i-1} - 2u_i + u_{i+1}}{h^2} \approx f_i\]

\[A_{1D} = \frac{1}{h^2} \begin{pmatrix}
2 & -1 \\
-1 & 2 & -1 \\
& -1 & \ddots & \ddots \\
& & \ddots & -1 \\
& & & -1 & 2
\end{pmatrix} \begin{pmatrix}
u_1 \\
u_2 \\
\vdots \\
u_m \\
\end{pmatrix} = \begin{pmatrix}f_1 \\
f_2 \\
\vdots \\
f_m \end{pmatrix}\]

Banded, tridiagonal matrix ("1D Poisson Operator")
In general, band system of bandwidth $\beta$ requires $O(\beta n)$ storage, and its factorization requires $O(\beta^2 n)$ work.

Compared with full system, savings is substantial if $\beta \ll n$. 
Banded Systems

- Significant savings in storage and work if A is banded $\rightarrow a_{ij} = 0$ if $|i-j| > \beta$

- The LU factors preserve the nonzero structure of A (unless there is pivoting, in which case, the bandwidth of L can grow by at most 2x).

- Storage / solve costs for LU is $\sim 2n \beta$

- Factor cost is $\sim n \beta^2 << n^3$
Definitely Do Not Invert A or L or U for Banded Systems
Solver Times, Banded, Cholesky (SPD), Full

LU time for full, banded, and SPD matrices

Factorization Time (seconds)

System Size, $n$
Solver Times, Banded, Cholesky (SPD), Full

% Demo of banded-matrix costs

clear all;

for pass=1:2;
    beta=10;

    for k=4:13; n = 2^k;
        R=9*eye(n)+rand(n,n); S=R'*R; A=spalloc(n,n,1+2*beta);
        for i=1:n; j0=max(1,i-beta); j1=min(n,i+beta);
            A(i,j0:j1)=R(i,j0:j1);
        end;

        tstart=tic; [L,U]=lu(A); tsparse(k) = toc(tstart);
        tstart=tic; [L,U]=lu(R); tfull(k) = toc(tstart);
        tstart=tic; [C]= chol(S); tchol(k) = toc(tstart);
        nk(k)=n;
        sk(k) = (2*(n^3)/3)/(1.e9*tfull(k)); % GFLOPS
        ck(k) = (2*(n^3)/3)/(1.e9*tchol(k)); % GFLOPS

        [n tsparse(k) tfull(k) tchol(k)]
    end;

loglog(nk,tsparse,'r.-',nk,tfull,'b.-',nk,tchol,'k.-')
axis square; title('LU time for full, banded, and SPD matrices')
LINPACK and LAPACK

- **LINPACK** is a software package for solving a wide variety of systems of linear equations, both general dense systems and special systems, such as symmetric or banded.

- Solving linear systems of such fundamental importance in scientific computing that **LINPACK** has become a standard benchmark for comparing the performance of computers.

- **LAPACK** is a more recent replacement for **LINPACK**, featuring higher performance on modern computer architectures, including some parallel computers.

- Both **LINPACK** and **LAPACK** are available from Netlib.
Basic Linear Algebra Subprograms

- High-level routines in LINPACK and LAPACK are based on lower-level Basic Linear Algebra Subprograms (BLAS).
- BLAS encapsulate basic operations on vectors and matrices so they can be optimized for given computer architecture while high-level routines that call them remain portable.
- Higher-level BLAS encapsulate matrix-vector and matrix-matrix operations for better utilization of memory hierarchies such as cache and virtual memory with paging.
- Generic Fortran versions of BLAS are available from Netlib, and many computer vendors provide custom versions optimized for their particular systems.


### Examples of BLAS

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<td></td>
<td></td>
<td>snrm2</td>
<td>Euclidean vector norm</td>
</tr>
<tr>
<td>2</td>
<td>$O(n^2)$</td>
<td>sgemv</td>
<td>Matrix-vector product</td>
</tr>
<tr>
<td></td>
<td></td>
<td>strsv</td>
<td>Triangular solution</td>
</tr>
<tr>
<td></td>
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<td>sger</td>
<td>Rank-one update</td>
</tr>
<tr>
<td>3</td>
<td>$O(n^3)$</td>
<td>sgemm</td>
<td>Matrix-matrix product</td>
</tr>
<tr>
<td></td>
<td></td>
<td>strsm</td>
<td>Multiple triang. solutions</td>
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<tr>
<td></td>
<td></td>
<td>ssyrk</td>
<td>Rank-$k$ update</td>
</tr>
</tbody>
</table>

- Level-3 **BLAS** have more opportunity for data reuse, and hence higher performance, because they perform more operations per data item than lower-level **BLAS**
Linear Algebra Very Short Summary

Main points:

- Conditioning of matrix $\text{cond}(A)$ bounds our expected accuracy.
  - e.g., if $\text{cond}(A) \sim 10^5$ we expect at most 11 significant digits in $x$.
  - Why?
  - We start with IEEE double precision – 16 digits. We lose 5 because condition $(A) \sim 10^5$, so we have $11 = 16-5$.

- Stable algorithm (i.e., pivoting) important to realizing this bound.
  - Some systems don’t need pivoting (e.g., SPD, diagonally dominant)
  - Unstable algorithms can sometimes be rescued with iterative refinement.

- Costs:
  - Full matrix $\rightarrow O(n^2)$ storage, $O(n^3)$ work (wall-clock time)
  - Sparse or banded matrix, substantially less.
The following slides present the book’s derivation of the LU factorization process.

I’ll highlight a few of them that show the equivalence between the outer product approach and the elementary elimination matrix approach.
Example: Triangular Linear System

\[
\begin{bmatrix}
2 & 4 & -2 \\
0 & 1 & 1 \\
0 & 0 & 4 \\
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
\end{bmatrix}
= 
\begin{bmatrix}
2 \\
4 \\
8 \\
\end{bmatrix}
\]

- Using back-substitution for this upper triangular system, last equation, \(4x_3 = 8\), is solved directly to obtain \(x_3 = 2\).
- Next, \(x_3\) is substituted into second equation to obtain \(x_2 = 2\).
- Finally, both \(x_3\) and \(x_2\) are substituted into first equation to obtain \(x_1 = -1\).
To transform general linear system into triangular form, we need to replace selected nonzero entries of matrix by zeros.

This can be accomplished by taking linear combinations of rows.

Consider 2-vector \( \mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \).

If \( a_1 \neq 0 \), then

\[
\begin{bmatrix}
1 & 0 \\
-a_2/a_1 & 1
\end{bmatrix}
\begin{bmatrix}
a_1 \\
a_2
\end{bmatrix}
= \begin{bmatrix}
a_1 \\
0
\end{bmatrix}
\]
More generally, we can annihilate all entries below the $k$th position in $n$-vector $a$ by transformation

\[
M_k a = \begin{bmatrix}
1 & \cdots & 0 & 0 & \cdots & 0 \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & 1 & 0 & \cdots & 0 \\
0 & \cdots & -m_{k+1} & 1 & \cdots & 0 \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & -m_n & 0 & \cdots & 1 \\
\end{bmatrix}
\begin{bmatrix}
a_1 \\
\vdots \\
a_k \\
a_{k+1} \\
\vdots \\
a_n \\
\end{bmatrix} = \begin{bmatrix}
a_1 \\
\vdots \\
a_k \\
0 \\
\vdots \\
0 \\
\end{bmatrix}
\]

where $m_i = a_i / a_k$, $i = k + 1, \ldots, n$

Divisor $a_k$, called pivot, must be nonzero
Matrix $M_k$, called *elementary elimination matrix*, adds multiple of row $k$ to each subsequent row, with *multipliers* $m_i$ chosen so that result is zero.

$M_k$ is unit lower triangular and nonsingular.

$M_k = I - m_k e_k^T$, where $m_k = [0, \ldots, 0, m_{k+1}, \ldots, m_n]^T$ and $e_k$ is $k$th column of identity matrix.

$M_k^{-1} = I + m_k e_k^T$, which means $M_k^{-1} =: L_k$ is same as $M_k$ except signs of multipliers are reversed.
If $M_j$, $j > k$, is another elementary elimination matrix, with vector of multipliers $m_j$, then

\[
M_k M_j = I - m_k e_k^T - m_j e_j^T + m_k e_k^T m_j e_j^T
\]

\[
= I - m_k e_k^T - m_j e_j^T
\]

which means product is essentially “union,” and similarly for product of inverses, $L_k L_j$.
Comment on update step and $m_k e^T_k$

- Recall, $v = Cw \in \text{span}\{C\}$.
- \[
    V = (v_1 \ v_2 \ldots v_n) = C (w_1 \ w_2 \ldots w_n) \in \text{span}\{C\}.
    \]

- If $C = c$, i.e., $C$ is a column vector and therefore of rank 1, then $V$ is in $\text{span}\{C\}$ and is of rank 1.

- All columns of $V$ are multiples of $c$.

- Thus, $W = c \ r^T$ is an $n \times n$ matrix of rank 1.
    - All columns are multiples of the first column and
    - All rows are multiples of the first row.
Matrix $M_k$, called **elementary elimination matrix**, adds multiple of row $k$ to each subsequent row, with **multipliers** $m_i$ chosen so that result is zero.

- $M_k$ is unit lower triangular and nonsingular.

- $M_k = I - m_k e_k^T$, where $m_k = [0, \ldots, 0, m_{k+1}, \ldots, m_n]^T$ and $e_k$ is $k$th column of identity matrix.

- $M_k^{-1} = I + m_k e_k^T$, which means $M_k^{-1}=: L_k$ is same as $M_k$ except signs of multipliers are reversed.
Example: Elementary Elimination Matrices

For \( \mathbf{a} = \begin{bmatrix} 2 \\ 4 \\ -2 \end{bmatrix} \),

\[
\mathbf{M}_1 \mathbf{a} = \begin{bmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \\ -2 \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}
\]

and

\[
\mathbf{M}_2 \mathbf{a} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1/2 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \\ -2 \end{bmatrix} = \begin{bmatrix} 2 \\ 4 \\ 0 \end{bmatrix}
\]
Example, continued

Note that

$$L_1 = M_1^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ -1 & 0 & 1 \end{bmatrix}, \quad L_2 = M_2^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -1/2 & 1 \end{bmatrix}$$

and

$$M_1 M_2 = \begin{bmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 1 & 1/2 & 1 \end{bmatrix}, \quad L_1 L_2 = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ -1 & -1/2 & 1 \end{bmatrix}$$
Gaussian Elimination

- To reduce general linear system $Ax = b$ to upper triangular form, first choose $M_1$, with $a_{11}$ as pivot, to annihilate first column of $A$ below first row
  - System becomes $M_1Ax = M_1b$, but solution is unchanged

- Next choose $M_2$, using $a_{22}$ as pivot, to annihilate second column of $M_1A$ below second row
  - System becomes $M_2M_1Ax = M_2M_1b$, but solution is still unchanged

- Process continues for each successive column until all subdiagonal entries have been zeroed
To reduce general linear system $Ax = b$ to upper triangular form, first choose $M_1$, with $a_{11}$ as pivot, to annihilate first column of $A$ below first row

- System becomes $M_1 Ax = M_1 b$, but solution is unchanged

Next choose $M_2$, using $a_{22}$ as pivot, to annihilate second column of $M_1 A$ below second row

- System becomes $M_2 M_1 Ax = M_2 M_1 b$, but solution is still unchanged

Technically, this should be $a'_{22}$, the 2-2 entry in $A' := M_1 A$. Thus, we don’t know all the pivots in advance.
Gaussian Elimination, continued

- Resulting upper triangular linear system

\[
M_{n-1} \cdots M_1 Ax = M_{n-1} \cdots M_1 b \\
MAx = Mb
\]

can be solved by back-substitution to obtain solution to original linear system \(Ax = b\)

- Process just described is called *Gaussian elimination*
LU Factorization

- Product $L_k L_j$ is unit lower triangular if $k < j$, so

$$L = M^{-1} = M_1^{-1} \cdots M_{n-1}^{-1} = L_1 \cdots L_{n-1}$$

is unit lower triangular

- By design, $U = MA$ is upper triangular

- So we have

$$A = LU$$

with $L$ unit lower triangular and $U$ upper triangular

- Thus, Gaussian elimination produces *LU factorization* of matrix into triangular factors
Having obtained LU factorization, $Ax = b$ becomes $LUx = b$, and can be solved by forward-substitution in lower triangular system $Ly = b$, followed by back-substitution in upper triangular system $Ux = y$.

Note that $y = Mb$ is same as transformed right-hand side in Gaussian elimination.

Gaussian elimination and LU factorization are two ways of expressing same solution process.
Example: Gaussian Elimination

- Use Gaussian elimination to solve linear system

\[ A x = \begin{bmatrix} 2 & 4 & -2 \\ 4 & 9 & -3 \\ -2 & -3 & 7 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 2 \\ 8 \\ 10 \end{bmatrix} = b \]

- To annihilate subdiagonal entries of first column of \( A \),

\[ M_1 A = \begin{bmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & 4 & -2 \\ 4 & 9 & -3 \\ -2 & -3 & 7 \end{bmatrix} = \begin{bmatrix} 2 & 4 & -2 \\ 0 & 1 & 1 \\ 0 & 1 & 5 \end{bmatrix} , \]

\[ M_1 b = \begin{bmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 8 \\ 10 \end{bmatrix} = \begin{bmatrix} 2 \\ 4 \\ 12 \end{bmatrix} \]
To annihilate subdiagonal entry of second column of $M_1A$,

$$M_2M_1A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 4 & -2 \\ 0 & 1 & 1 \\ 0 & 1 & 5 \end{bmatrix} = \begin{bmatrix} 2 & 4 & -2 \\ 0 & 1 & 1 \\ 0 & 0 & 4 \end{bmatrix} = U,$$

$$M_2M_1b = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \\ 12 \end{bmatrix} = \begin{bmatrix} 2 \\ 4 \\ 8 \end{bmatrix} = Mb$$
Example, continued

- We have reduced original system to equivalent upper triangular system

\[
U \mathbf{x} = \begin{bmatrix}
2 & 4 & -2 \\
0 & 1 & 1 \\
0 & 0 & 4
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3
\end{bmatrix}
= \begin{bmatrix}
2 \\
4 \\
8
\end{bmatrix}
= M \mathbf{b}
\]

which can now be solved by back-substitution to obtain

\[
\mathbf{x} = \begin{bmatrix}
-1 \\
2 \\
2
\end{bmatrix}
\]
Example, continued

To write out LU factorization explicitly,

\[
L_1 L_2 = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ -1 & 1 & 1 \end{bmatrix} = L
\]

so that

\[
A = \begin{bmatrix} 2 & 4 & -2 \\ 4 & 9 & -3 \\ -2 & -3 & 7 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ -1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 4 & -2 \\ 0 & 1 & 1 \\ 0 & 0 & 4 \end{bmatrix} = LU
\]