## GAUSSIAN ELIMINATION - REVISITED

Consider solving the linear system

$$
\begin{gathered}
2 x_{1}+x_{2}-x_{3}+2 x_{4}=5 \\
4 x_{1}+5 x_{2}-3 x_{3}+6 x_{4}=9 \\
-2 x_{1}+5 x_{2}-2 x_{3}+6 x_{4}=4 \\
4 x_{1}+11 x_{2}-4 x_{3}+8 x_{4}=2
\end{gathered}
$$

by Gaussian elimination without pivoting. We denote this linear system by $A x=b$. The augmented matrix for this system is

$$
[A \mid b]=\left[\begin{array}{rrrr|r}
2 & 1 & -1 & 2 & 5 \\
4 & 5 & -3 & 6 & 9 \\
-2 & 5 & -2 & 6 & 4 \\
4 & 11 & -4 & 8 & 2
\end{array}\right]
$$

To eliminate $x_{1}$ from equations 2 , 3 , and 4 , use multipliers

$$
m_{2,1}=2, \quad m_{3,1}=-1, \quad m_{4,1}=2
$$

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$$
m_{2,1}=2, \quad m_{3,1}=-1, \quad m_{4,1}=2
$$

This will introduce zeros into the positions below the diagonal in column 1, yielding

$$
\left[\begin{array}{rrrr|r}
2 & 1 & -1 & 2 & 5 \\
0 & 3 & -1 & 2 & -1 \\
0 & 6 & -3 & 8 & 9 \\
0 & 9 & -2 & 4 & -8
\end{array}\right]
$$

To eliminate $x_{2}$ from equations 3 and 4 , use multipliers

$$
m_{3,2}=2, \quad m_{4,2}=3
$$

This reduces the augmented matrix to

$$
\left[\begin{array}{rrrr|r}
2 & 1 & -1 & 2 & 5 \\
0 & 3 & -1 & 2 & -1 \\
0 & 0 & -1 & 4 & 11 \\
0 & 0 & 1 & -2 & -5
\end{array}\right]
$$

To eliminate $x_{3}$ from equation 4, use the multiplier

$$
m_{4,3}=-1
$$

This reduces the augmented matrix to

$$
\left[\begin{array}{rrrr|r}
2 & 1 & -1 & 2 & 5 \\
0 & 3 & -1 & 2 & -1 \\
0 & 0 & -1 & 4 & 11 \\
0 & 0 & 0 & 2 & 6
\end{array}\right]
$$

Return this to the familiar linear system

$$
\begin{aligned}
2 x_{1}+x_{2}-x_{3}+2 x_{4} & =5 \\
3 x_{2}-x_{3}+2 x_{4} & =-1 \\
-x_{3}+4 x_{4} & =11 \\
2 x_{4} & =6
\end{aligned}
$$

Solving by back substitution, we obtain

$$
x_{4}=3, \quad x_{3}=1, \quad x_{2}=-2, \quad x_{1}=1
$$

There is a surprising result involving matrices associated with this elimination process. Introduce the upper triangular matrix

$$
U=\left[\begin{array}{rrrr}
2 & 1 & -1 & 2 \\
0 & 3 & -1 & 2 \\
0 & 0 & -1 & 4 \\
0 & 0 & 0 & 2
\end{array}\right]
$$

which resulted from the elimination process. Then introduce the lower triangular matrix

$$
L=\left[\begin{array}{cccc}
1 & 0 & 0 & 0 \\
m_{2,1} & 1 & 0 & 0 \\
m_{3,1} & m_{3,2} & 1 & 0 \\
m_{4,1} & m_{4,2} & m_{4,3} & 1
\end{array}\right]=\left[\begin{array}{rrrr}
1 & 0 & 0 & 0 \\
2 & 1 & 0 & 0 \\
-1 & 2 & 1 & 0 \\
2 & 3 & -1 & 1
\end{array}\right]
$$

This uses the multipliers introduced in the elimination process. Then

$$
\begin{gathered}
\\
A=L U \\
{\left[\begin{array}{rrrr}
2 & 1 & -1 & 2 \\
4 & 5 & -3 & 6 \\
-2 & 5 & -2 & 6 \\
4 & 11 & -4 & 8
\end{array}\right]=\left[\begin{array}{rrrr}
1 & 0 & 0 & 0 \\
2 & 1 & 0 & 0 \\
-1 & 2 & 1 & 0 \\
2 & 3 & -1 & 1
\end{array}\right]\left[\begin{array}{rrrr}
2 & 1 & -1 & 2 \\
0 & 3 & -1 & 2 \\
0 & 0 & -1 & 4 \\
0 & 0 & 0 & 2
\end{array}\right]}
\end{gathered}
$$

In general, when the process of Gaussian elimination without pivoting is applied to solving a linear system $A x=b$, we obtain $A=L U$ with $L$ and $U$ constructed as above.

For the case in which partial pivoting is used, we obtain the slightly modified result

$$
L U=P A
$$

where $L$ and $U$ are constructed as before and $P$ is a permutation matrix. For example, consider

$$
P=\left[\begin{array}{llll}
0 & 0 & 1 & 0 \\
1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0
\end{array}\right]
$$

Then

$$
P A=\left[\begin{array}{llll}
0 & 0 & 1 & 0 \\
1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0
\end{array}\right]\left[\begin{array}{llll}
a_{1,1} & a_{1,2} & a_{1,3} & a_{1,4} \\
a_{2,1} & a_{2,2} & a_{2,3} & a_{2,4} \\
a_{3,1} & a_{3,2} & a_{3,3} & a_{3,4} \\
a_{4,1} & a_{4,2} & a_{4,3} & a_{4,4}
\end{array}\right]=\left[\begin{array}{c}
A_{3, *} \\
A_{1, *} \\
A_{4, *} \\
A_{2, *}
\end{array}\right]
$$

$$
\begin{aligned}
P A & =\left[\begin{array}{llll}
0 & 0 & 1 & 0 \\
1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0
\end{array}\right]\left[\begin{array}{llll}
a_{1,1} & a_{1,2} & a_{1,3} & a_{1,4} \\
a_{2,1} & a_{2,2} & a_{2,3} & a_{2,4} \\
a_{3,1} & a_{3,2} & a_{3,3} & a_{3,4} \\
a_{4,1} & a_{4,2} & a_{4,3} & a_{4,4}
\end{array}\right] \\
& =\left[\begin{array}{l}
A_{3, *} \\
A_{1, *} \\
A_{4, *} \\
A_{2, *}
\end{array}\right]
\end{aligned}
$$

The matrix $P A$ is obtained from $A$ by switching around rows of $A$. The result $L U=P A$ means that the $L U$ factorization is valid for the matrix $A$ with its rows suitably permuted.

Consequences: If we have a factorization

$$
A=L U
$$

with $L$ lower triangular and $U$ upper triangular, then we can solve the linear system $A x=b$ in a relatively straightforward way.

The linear system can be written as

$$
L U x=b
$$

Write this as a two stage process:

$$
L g=b, \quad U x=g
$$

The system $L g=b$ is a lower triangular system

$$
\begin{array}{lll}
g_{1} & =b_{1} \\
\ell_{2,1} g_{1}+g_{2} & =b_{2} \\
\ell_{3,1} g_{1}+\ell_{3,2} g_{2}+g_{3} & =b_{3} \\
\ell_{n, 1} g_{1}+\cdots \ell_{n, n-1} g_{n-1}+g_{n} & =b_{n}
\end{array}
$$

We solve it by "forward substitution". Then we solve the upper triangular system $U x=g$ by back substitution.

## VARIANTS OF GAUSSIAN ELIMINATION

If no partial pivoting is needed, then we can look for a factorization

$$
A=L U
$$

without going thru the Gaussian elimination process.

For example, suppose $A$ is $4 \times 4$. We write

$$
\begin{aligned}
& {\left[\begin{array}{cccc}
a_{1,1} & a_{1,2} & a_{1,3} & a_{1,4} \\
a_{2,1} & a_{2,2} & a_{2,3} & a_{2,4} \\
a_{3,1} & a_{3,2} & a_{3,3} & a_{3,4} \\
a_{4,1} & a_{4,2} & a_{4,3} & a_{4,4}
\end{array}\right]} \\
& =\left[\begin{array}{cccc}
1 & 0 & 0 & 0 \\
\ell_{2,1} & 1 & 0 & 0 \\
\ell_{3,1} & \ell_{3,2} & 1 & 0 \\
\ell_{4,1} & \ell_{4,2} & \ell_{4,3} & 1
\end{array}\right]\left[\begin{array}{cccc}
u_{1,1} & u_{1,2} & u_{1,3} & u_{1,4} \\
0 & u_{2,2} & u_{2,3} & u_{2,4} \\
0 & 0 & u_{3,3} & u_{3,4} \\
0 & 0 & 0 & u_{4,4}
\end{array}\right]
\end{aligned}
$$

To find the elements $\left\{\ell_{i, j}\right\}$ and $\left\{u_{i, j}\right\}$, we multiply the right side matrices $L$ and $U$ and match the results with the corresponding elements in $A$.

Multiplying the first row of $L$ times all of the columns of $U$ leads to

$$
u_{1, j}=a_{1, j}, \quad j=1,2,3,4
$$

Then multiplying rows $2,3,4$ times the first column of $U$ yields

$$
\ell_{i, 1} u_{1,1}=a_{i, 1}, \quad i=2,3,4
$$

and we can solve for $\left\{\ell_{2,1}, \ell_{3,1}, \ell_{4,1}\right\}$. We can continue this process, finding the second row of $U$ and then the second column of $L$, and so on. For example, to solve for $\ell_{4,3}$, we need to solve for it in

$$
\ell_{4,1} u_{1,3}+\ell_{4,2} u_{2,3}+\ell_{4,3} u_{3,3}=a_{4,3}
$$

Why do this? A hint of an answer is given by this last equation. If we had an $n \times n$ matrix $A$, then we would find $\ell_{n, n-1}$ by solving for it in the equation

$$
\begin{aligned}
& \ell_{n, 1} u_{1, n-1}+\ell_{n, 2} u_{2, n-1}+\cdots+\ell_{n, n-1} u_{n-1, n-1}=a_{n, n-1} \\
& \ell_{n, n-1}=\frac{a_{n, n-1}-\left[\ell_{n, 1} u_{1, n-1}+\cdots+\ell_{n, n-2} u_{n-2, n-1}\right]}{u_{n-1, n-1}}
\end{aligned}
$$

Embedded in this formula we have a dot product. This is in fact typical of this process, with the length of the inner products varying from one position to another.

Recalling $\S 2.4$ and the discussion of dot products, we can evaluate this last formula by using a higher precision arithmetic and thus avoid many rounding errors. This leads to a variant of Gaussian elimination in which there are far fewer rounding errors.

With ordinary Gaussian elimination, the number of rounding errors is proportional to $n^{3}$. This reduces the number of rounding errors, with the number now being proportional to only $n^{2}$. This can lead to major increases in accuracy, especially for matrices $A$ which are very sensitive to small changes.

## TRIDIAGONAL MATRICES

$$
A=\left[\begin{array}{cccccc}
b_{1} & c_{1} & 0 & 0 & \cdots & 0 \\
a_{2} & b_{2} & c_{2} & 0 & & \\
0 & a_{3} & b_{3} & c_{3} & & \vdots \\
& & & \ddots & & \\
\vdots & & & a_{n-1} & b_{n-1} & c_{n-1} \\
0 & & \cdots & & a_{n} & b_{n}
\end{array}\right]
$$

These occur very commonly in the numerical solution of partial differential equations, as well as in other applications (e.g. computing interpolating cubic spline functions).

We factor $A=L U$, as before. But now $L$ and $U$ take very simple forms. Before proceeding, we note with an example that the same may not be true of the matrix inverse.

## EXAMPLE

Define an $n \times n$ tridiagonal matrix

$$
A=\left[\begin{array}{rrrccc}
-1 & 1 & 0 & 0 & \cdots & 0 \\
1 & -2 & 1 & 0 & & \\
0 & 1 & -2 & 1 & & \vdots \\
& & & \ddots & & \\
\vdots & & & 1 & -2 & 1 \\
0 & & \cdots & & 1 & -\frac{n-1}{n}
\end{array}\right]
$$

Then $A^{-1}$ is given by

$$
\left(A^{-1}\right)_{i, j}=\max \{i, j\}
$$

Thus the sparse matrix $A$ can (and usually does) have a dense inverse.

We factor $A=L U$, with

$$
\begin{aligned}
L & =\left[\begin{array}{cccccc}
1 & 0 & 0 & 0 & \cdots & 0 \\
\alpha_{2} & 1 & 0 & 0 & & \\
0 & \alpha_{3} & 1 & 0 & & \vdots \\
& & & \ddots & & \\
\vdots & & & \alpha_{n-1} & 1 & 0 \\
0 & & \cdots & & \alpha_{n} & 1
\end{array}\right] \\
U & =\left[\begin{array}{cccccc}
\beta_{1} & c_{1} & 0 & 0 & \cdots & 0 \\
0 & \beta_{2} & c_{2} & 0 & & \\
0 & 0 & \beta_{3} & c_{3} & & \vdots \\
\vdots & & & 0 & \beta_{n-1} & c_{n-1} \\
0 & & \cdots & & 0 & \beta_{n}
\end{array}\right]
\end{aligned}
$$

Multiply these and match coefficients with $A$ to find $\left\{\alpha_{i}, \gamma_{i}\right\}$.

By doing a few multiplications of rows of $L$ times columns of $U$, we obtain the general pattern as follows.

$$
\begin{array}{cl}
\beta_{1}=b_{1} & \text { : row } 1 \text { of } L U \\
\alpha_{2} \beta_{1}=a_{2}, \quad \alpha_{2} c_{1}+\beta_{2}=b_{2} & \text { : row } 2 \text { of } L U \\
\vdots & \\
\alpha_{n} \beta_{n-1}=a_{n}, \quad \alpha_{n} c_{n-1}+\beta_{n}=b_{n} & \text { : row } n \text { of } L U
\end{array}
$$

These are straightforward to solve.

$$
\begin{gathered}
\beta_{1}=b_{1} \\
\alpha_{j}=\frac{a_{j}}{\beta_{j-1}}, \quad \beta_{j}=b_{j}-\alpha_{j} c_{j-1}, \quad j=2, \ldots, n
\end{gathered}
$$

To solve the linear system

$$
A x=f
$$

or

$$
L U x=f
$$

instead solve the two triangular systems

$$
L g=f, \quad U x=g
$$

Solving $L g=f$ :

$$
\begin{aligned}
& g_{1}=f_{1} \\
& g_{j}=f_{j}-\alpha_{j} g_{j-1}, \quad j=2, \ldots, n
\end{aligned}
$$

Solving $U x=g$ :

$$
\begin{aligned}
x_{n} & =\frac{g_{n}}{\beta_{n}} \\
x_{j} & =\frac{g_{j}-c_{j} x_{j+1}}{\beta_{j}}, \quad j=n-1, \ldots, 1
\end{aligned}
$$

See the numerical example on page 278.

## OPERATIONS COUNT

Factoring $A=L U$.
Additions: $\quad n-1$
Multiplications: $n-1$
Divisions: $\quad n-1$
Solving $L z=f$ and $U x=z$ :
Additions:
$2 n-2$
Multiplications: $2 n-2$
Divisions: $n$

Thus the total number of arithmetic operations is approximately $3 n$ to factor $A$; and it takes about $5 n$ to solve the linear system using the factorization of $A$.

If we had $A^{-1}$ at no cost, what would it cost to compute $x=A^{-1} f$ ?

$$
x_{i}=\sum_{j=1}^{n}\left(A^{-1}\right)_{i, j} f_{j}, \quad i=1, \ldots, n
$$

## MATLAB MATRIX OPERATIONS

To obtain the $L U$-factorization of a matrix, including the use of partial pivoting, use the Matlab command lu. In particular,

$$
[L, U, P]=l u(X)
$$

returns the lower triangular matrix $L$, upper triangular matrix $U$, and permutation matrix $P$ so that

$$
P X=L U
$$

