# CME 302: NUMERICAL LINEAR ALGEBRA <br> FALL 2005/06 <br> LECTURE 9 

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## 1. Error Analysis of Gaussian Elimination

In this section, we will consider the case of Gaussian elimination and perform a detailed error analysis, illustrating the analysis originally carried out by J.H. Wilkinson. The process of solving $A \mathbf{x}=\mathbf{b}$ consists of three stages:
(1) Factoring $A=L U$, resulting in an approximate $L U$ decomposition $A+E=\bar{L} \bar{U}$. We assume that partial pivoting is used.
(2) Solving $L \mathbf{y}=\mathbf{b}$, or, numerically, computing $\mathbf{y}$ such that

$$
(\bar{L}+\delta \bar{L})(\mathbf{y}+\delta \mathbf{y})=\mathbf{b}
$$

(3) Solving $U \mathbf{x}=\mathbf{y}$, or, numerically, computing $\mathbf{x}$ such that

$$
(\bar{U}+\delta \bar{U})(\mathbf{x}+\delta \mathbf{x})=\mathbf{y}+\delta \mathbf{y}
$$

Combining these stages, we see that

$$
\begin{aligned}
\mathbf{b} & =(\bar{L}+\delta \bar{L})(\bar{U}+\delta \bar{U})(\mathbf{x}+\delta \mathbf{x}) \\
& =(\bar{L} \bar{U}+\delta \bar{L} \bar{U}+\bar{L} \delta \bar{U}+\delta \bar{L} \delta \bar{U})(\mathbf{x}+\delta \mathbf{x}) \\
& =(A+E+\delta \bar{L} \bar{U}+\bar{L} \delta \bar{U}+\delta \bar{L} \delta \bar{U})(\mathbf{x}+\delta \mathbf{x}) \\
& =(A+\Delta)(\mathbf{x}+\delta \mathbf{x})
\end{aligned}
$$

where $\Delta=E+\delta \bar{L} \bar{U}+\bar{L} \delta \bar{U}+\delta \bar{L} \delta \bar{U}$.
In this analysis, we will view the computed solution $\overline{\mathbf{x}}=\mathbf{x}+\delta \mathbf{x}$ as the exact solution to the perturbed problem $(A+\Delta) \mathbf{x}=\mathbf{b}$. This perspective is the idea behind backward error analysis, which we will use to determine the size of the perturbation $\Delta$, and, eventually, arrive at a bound for the error in the computed solution $\overline{\mathbf{x}}$.

Let $A^{(k)}$ denote the matrix $A$ after $k-1$ steps of Gaussian elimination have been performed in exact arithmetic, where a step denotes the process of making all elements below the diagonal within a particular column equal to zero. Then the elements of $A^{(k+1)}$ are given by

$$
\begin{equation*}
a_{i j}^{(k+1)}=a_{i j}^{(k)}-m_{i k} a_{k j}^{(k)}, \quad m_{i k}=\frac{a_{i k}^{(k)}}{a_{k k}^{(k)}} . \tag{1.1}
\end{equation*}
$$

Let $B^{(k)}$ denote the matrix $A$ after $k-1$ steps of Gaussian elimination have been performed in floating-point arithmetic. Then the elements of $B^{(k+1)}$ are given by

$$
\begin{equation*}
b_{i j}^{(k+1)}=a_{i j}^{(k)}-s_{i k} b_{k j}^{(k)}+\epsilon_{i j}^{(k+1)}, \quad s_{i k}=f l\left(\frac{b_{i k}^{(k)}}{b_{k k}^{(k)}}\right) \tag{1.2}
\end{equation*}
$$

Date: November 25, 2005, version 1.1.
Notes originally due to James Lambers. Edited by Lek-Heng Lim.

For $j \geq i$, we have

$$
\begin{aligned}
& b_{i j}^{(2)}=b_{i j}^{(1)}-s_{i 1} b_{1 j}^{(1)}+\epsilon_{i j}^{(2)} \\
& b_{i j}^{(3)}=b_{i j}^{(2)}-s_{i 2} b_{2 j}^{(2)}+\epsilon_{i j}^{(3)} \\
& \quad \vdots \\
& b_{i j}^{(i)}=b_{i j}^{(i-1)}-s_{i, i-1} b_{i-1, j}^{(i-1)}+\epsilon_{i j}^{(i)} .
\end{aligned}
$$

Combining these equations yields

$$
\sum_{k=2}^{i} b_{i j}^{(k)}=\sum_{k=1}^{i-1} b_{i j}^{(k)}-\sum_{k=1}^{i-1} s_{i k} b_{k j}^{(k)}+\sum_{k=2}^{i} \epsilon_{i j}^{(k)} .
$$

Cancelling terms, we obtain

$$
\begin{equation*}
b_{i j}^{(1)}=b_{i j}^{(i)}+\sum_{k=1}^{i-1} s_{i k} b_{k j}^{(k)}+e_{i j}, \quad j \geq i, \tag{1.3}
\end{equation*}
$$

where $e_{i j}:=-\sum_{k=2}^{i} \epsilon_{i j}^{(k)}$.
For $i>j$,

$$
\begin{aligned}
b_{i j}^{(2)} & =b_{i j}^{(1)}-s_{i 1} b_{1 j}^{(1)}+\epsilon_{i j}^{(2)} \\
& \vdots \\
b_{i j}^{(j)} & =b_{i j}^{(j-1)}-s_{i, j-1} b_{j-1, j}^{(j-1)}+\epsilon_{i j}^{(j)}
\end{aligned}
$$

where $s_{i j}=f l\left(b_{i j}^{(j)} / b_{j j}^{(j)}\right)=b_{i j}^{(j)} / b_{j j}^{(j)}+\eta_{i j}$, and therefore

$$
\begin{align*}
0 & =b_{i j}^{(j)}-s_{i j} b_{j j}^{(j)}+b_{j j}^{(j)} \eta_{i j} \\
& =b_{i j}^{(j)}-s_{i j} b_{j j}^{(j)}+\epsilon_{i j}^{(j+1)} \\
& =b_{i j}^{(1)}-\sum_{k=1}^{j} s_{i k} b_{k j}^{(k)}+e_{i j} \tag{1.4}
\end{align*}
$$

From (1.3) and (1.4), we obtain

$$
\bar{L} \bar{U}=\left[\begin{array}{cccc}
1 & & & \\
s_{21} & 1 & & \\
\vdots & & \ddots & \\
s_{n 1} & \cdots & \cdots & 1
\end{array}\right]\left[\begin{array}{cccc}
b_{11}^{(1)} & b_{12}^{(1)} & \cdots & b_{1 n}^{(1)} \\
& \ddots & & \vdots \\
& & \ddots & \vdots \\
& & & b_{n n}^{(n)}
\end{array}\right]=A+E .
$$

where

$$
s_{i k}=f l\left(\frac{b_{i k}^{(k)}}{b_{k k}^{(k)}}\right)=\frac{b_{i k}^{(k)}}{b_{k k}^{(k)}}\left(1+\eta_{i k}\right), \quad\left|\eta_{i k}\right| \leq \mathrm{u}
$$

Then,

$$
f l\left(s_{i k} b_{k j}^{(k)}\right)=s_{i k} b_{k j}^{(k)}\left(1+\theta_{i j}^{(k)}\right), \quad\left|\theta_{i j}^{(k)}\right| \leq \mathrm{u}
$$

and so,

$$
\begin{aligned}
b_{i j}^{(k+1)} & =f l\left(b_{i j}^{(k)}-s_{i k} b_{k j}^{(k)}\left(1+\theta_{i j}^{(k)}\right)\right) \\
& =\left(b_{i j}^{(k)}-s_{i k} b_{k j}^{(k)}\left(1+\theta_{i j}^{(k)}\right)\right)\left(1+\varphi_{i j}^{(k)}\right), \quad\left|\varphi_{i j}^{(k)}\right| \leq \mathrm{u} .
\end{aligned}
$$

After some manipulations, we obtain

$$
\epsilon_{i j}^{(k+1)}=b_{i j}^{(k+1)}\left(\frac{\varphi_{i j}^{(k)}}{1+\varphi_{i j}^{(k)}}\right)-s_{i k} b_{k j}^{(k)} \theta_{i j}^{(k)} .
$$

With partial pivoting, $\left|s_{i k}\right| \leq 1$, provided that $|f l(a / b)| \leq 1$ whenever $|a| \leq|b|$. In most modern implementations of floating-point arithmetic, this is in fact the case. It follows that

$$
\left|\epsilon_{i j}^{(k+1)}\right| \leq\left|b_{i j}^{(k+1)}\right| \frac{\mathrm{u}}{1-\mathrm{u}}+1 \cdot\left|b_{i j}^{(k)}\right| \mathrm{u} .
$$

How large can the elements of $B^{(k)}$ be? Returning to exact arithmetic, we assume that $\left|a_{i j}\right| \leq a$ and from (1.1), we obtain

$$
\begin{aligned}
\left|a_{i j}^{(2)}\right| & \leq\left|a_{i j}^{(1)}\right|+\left|a_{k j}^{(1)}\right| \leq 2 a \\
\left|a_{i j}^{(3)}\right| & \leq 4 a \\
\quad & \\
\left|a_{i j}^{(n)}\right| & =\left|a_{n n}^{(n)}\right| \leq 2^{n-1} a .
\end{aligned}
$$

We can show that a similar result holds in floating-point arithmetic:

$$
\left|b_{i j}^{(k)}\right| \leq 2^{k-1} a+O(\mathbf{u})
$$

This upper bound is achievable (by Hadamard matrices), but in practice it rarely occurs.

## 2. Error in the $L U$ Factorization

Recall from last time that we were analyzing the error in solving $A \mathbf{x}=\mathbf{b}$ using backward error analysis, in which we assume that our computed solution $\overline{\mathbf{x}}=\mathbf{x}+\delta \mathbf{x}$ is the exact solution to the perturbed problem

$$
(A+\delta A) \overline{\mathbf{x}}=\mathbf{b}
$$

where $\delta A$ is a perturbation that has the form

$$
\delta A=E+\bar{L} \delta \bar{U}+\delta \bar{L} \bar{U}+\delta \bar{L} \delta \bar{U}
$$

and the following relationships hold:
(1) $A+E=\bar{L} \bar{U}$
(2) $(\bar{L}+\delta \bar{L})(\mathbf{y}+\delta \mathbf{y})=\mathbf{b}$
(3) $(\bar{U}+\delta \bar{U})(\mathbf{x}+\delta \mathbf{x})=\mathbf{y}+\delta \mathbf{y}$

We concluded that when partial pivoting is used, the entries of $\bar{U}$ were bounded:

$$
\left|b_{i j}^{(k)}\right| \leq 2^{k-1} a+O(\mathrm{u})
$$

where $k$ is the number of steps of Gaussian elimination that effect the $i j$ element and $a$ is an upper bound on the elements of $A$.

For complete pivoting, Wilkinson gave a bound, denoted $G$, or growth factor. Until 1990, it was conjectured that $G \leq k$. It was shown to be true for $n \leq 5$, but there have been examples constructed for $n>5$ where $G \geq n$. In any event, we have the following bound for the entries of E:

$$
|E| \leq 2 \mathrm{u} G a\left[\begin{array}{cccccc}
0 & \cdots & \cdots & \cdots & \cdots & 0 \\
1 & \cdots & \cdots & \cdots & \cdots & 1 \\
1 & 2 & \cdots & \cdots & \cdots & 2 \\
\vdots & \vdots & 3 & \cdots & \cdots & 3 \\
\vdots & \vdots & \vdots & \ddots & \cdots & \vdots \\
1 & 2 & 3 & \cdots & n-1 & n-1
\end{array}\right]+O\left(\mathrm{u}^{2}\right)
$$

## 3. Error Analysis of Forward Substitution

We now study the process of forward substitution, to solve

$$
\left[\begin{array}{ccc}
t_{11} & & 0 \\
\vdots & \ddots & \\
t_{n 1} & & t_{n n}
\end{array}\right]\left[\begin{array}{c}
u_{1} \\
\vdots \\
u_{n}
\end{array}\right]=\left[\begin{array}{c}
h_{1} \\
\vdots \\
h_{n}
\end{array}\right] .
$$

Using forward substitution, we obtain

$$
\begin{aligned}
u_{1} & =\frac{h_{1}}{t_{11}} \\
& \vdots \\
u_{k} & =\frac{h_{k}-t_{k 1} u_{1}-\cdots-t_{k, k-1} u_{k-1}}{t_{k k}}
\end{aligned}
$$

which yields

$$
\begin{aligned}
f l\left(u_{k}\right) & =\frac{h_{k}\left(1+\epsilon_{k}\right)\left(1+\eta_{k}\right)-\sum_{i=1}^{k-1} t_{k i} u_{i}\left(1+\xi_{k i}\right)\left(1+\epsilon_{k}\right)\left(1+\eta_{k}\right)}{t_{k k}} \\
& =\frac{h_{k}-\sum_{i=1}^{k-1} t_{k i} u_{i}\left(1+\xi_{k i}\right)}{t_{k k}}
\end{aligned}
$$

or

$$
\sum_{i=1}^{k} u_{i} t_{k i}\left(1+\lambda_{k i}\right)=h_{k}
$$

which can be rewritten in matrix notation as

$$
T \mathbf{u}+\left[\begin{array}{ccc}
\lambda_{11} t_{11} & & \\
\lambda_{12} t_{12} & \lambda_{22} t_{22} & \\
\vdots & \vdots & \ddots
\end{array}\right] \mathbf{u}=\mathbf{h}
$$

In other words, the computed solution $\mathbf{u}$ is the exact solution to the perturbed problem $(T+\delta T) \mathbf{u}=$ h, where

$$
|\delta T| \leq \mathrm{u}\left[\begin{array}{cccc}
\left|t_{11}\right| & & & \\
\left|t_{21}\right| & 2\left|t_{22}\right| & & \\
\vdots & & \ddots & \\
(n-1)\left|t_{n 1}\right| & \cdots & \cdots & 2\left|t_{n n}\right|
\end{array}\right]+O\left(\mathrm{u}^{2}\right)
$$

Note that the perturbation $\delta T$ actually depends on $\mathbf{h}$.

## 4. Bounding the perturbation in $A$

Recall that our computed solution $\mathbf{x}+\delta \mathbf{x}$ solves

$$
(A+\delta A) \overline{\mathbf{x}}=\mathbf{b}
$$

where $\delta A$ is a perturbation that has the form

$$
\delta A=E+\bar{L} \delta \bar{U}+\delta \bar{L} \bar{U}+\delta \bar{L} \delta \bar{U} .
$$

For partial pivoting, $\left|\bar{l}_{i j}\right| \leq 1$, and we have the bounds

$$
\begin{aligned}
& \max _{i, j}\left|\delta \bar{L}_{i j}\right| \leq n \mathbf{u}+O\left(\mathbf{u}^{2}\right) \\
& \max _{i, j}\left|\delta \bar{U}_{i j}\right| \leq n \mathbf{u} G a+O\left(\mathbf{u}^{2}\right)
\end{aligned}
$$

were $a=\max _{i, j}\left|a_{i j}\right|$ and $G$ is the growth factor for partial pivoting. Putting our bounds together, we have

$$
\begin{aligned}
\max _{i, j}\left|\delta A_{i j}\right| & \leq \max _{i, j}\left|e_{i j}\right|+\max _{i, j}\left|\bar{L} \delta \bar{U}_{i j}\right|+\max _{i, j}\left|\bar{U} \delta \bar{L}_{i j}\right|+\max _{i, j}\left|\delta \bar{L} \delta \bar{U}_{i j}\right| \\
& \leq 2 \mathrm{u} G a n+n^{2} G a \mathbf{u}+n^{2} G a \mathbf{u}+O\left(\mathrm{u}^{2}\right)
\end{aligned}
$$

from which it follows that

$$
\|\delta A\|_{\infty} \leq 2 n^{2}(n+1) \mathrm{u} G a+O\left(\mathrm{u}^{2}\right)
$$

We conclude that Gaussian elimination is backward stable.

## 5. Bounding the error in the solution

Let $\overline{\mathbf{x}}=\mathbf{x}+\delta \mathbf{x}$ be the computed solution. Then, from $(A+\delta A) \overline{\mathbf{x}}=\mathbf{b}$ we obtain

$$
\delta A \overline{\mathbf{x}}=\mathbf{b}-A \overline{\mathbf{x}}=\mathbf{r}
$$

where $\mathbf{r}$ is called the residual vector. From our previous analysis,

$$
\frac{\|\mathbf{r}\|_{\infty}}{\|\overline{\mathbf{x}}\|_{\infty}} \leq\|\delta A\|_{\infty} \leq 2 n^{2}(n+1) G a \mathbf{u} .
$$

Also, recall

$$
\frac{\|\delta \mathbf{x}\|}{\|\mathbf{x}\|} \leq \frac{\kappa(A)}{1-\kappa(A) \frac{\|\delta A\|}{\|A\|}} \frac{\|\delta A\|}{\|A\|} .
$$

We know that $\|A\|_{\infty} \leq n a$, so

$$
\frac{\|\delta A\|_{\infty}}{\|A\|_{\infty}} \leq 2 n(n+1) G \mathrm{u}
$$

Note that if $\kappa(A)$ is large and $G$ is large, our solution can be very inaccurate. The important factors in the accuracy of the computed solution are:

- The growth factor $G$
- The condition number $\kappa$
- The accuracy u

In particular, $\kappa$ must be large with respect to the accuracy in order to be troublesome. For example, consider the scenario where $\kappa=10^{2}$ and $u=10^{-3}$, as opposed to the case where $\kappa=10^{2}$ and $\mathbf{u}=10^{-50}$.

## 6. Iterative Refinement

The process of iterative refinement proceeds as follows to find a solution to $A \mathbf{x}=\mathbf{b}$ :

$$
\begin{aligned}
\mathbf{x}^{(0)} & =\mathbf{0} \\
\mathbf{r}^{(i)} & =\mathbf{b}-A \mathbf{x}^{(i)} \\
A \boldsymbol{\delta}^{(i)} & =\mathbf{r}^{(i)} \\
\mathbf{x}^{(i+1)} & =\mathbf{x}^{(i)}+\boldsymbol{\delta}^{(i)}
\end{aligned}
$$

Numerically, this translates to

$$
\begin{aligned}
\left(A+\delta A^{(i)}\right) \boldsymbol{\delta}^{(i)} & =\left(I+E^{(i)}\right) \mathbf{r}^{(i)} \\
\mathbf{x}^{(i+1)} & =\left(I+F^{(i)}\right)\left(\mathbf{x}^{(i)}+\boldsymbol{\delta}^{(i)}\right)
\end{aligned}
$$

where the matrices $E^{(i)}$ and $F^{(i)}$ denote roundoff error. Let $\mathbf{z}^{(i)}=\mathbf{x}-\mathbf{x}^{(i)}$. Then

$$
\begin{aligned}
& \mathbf{x}^{(i+1)}-\mathbf{x}=\left(I+F^{(i)}\right)\left(\mathbf{x}^{(i)}+\boldsymbol{\delta}^{(i)}\right)-\mathbf{x} \\
&=\left(I+F^{(i)}\right)\left(\mathbf{x}^{(i)}-\mathbf{x}\right)+F^{(i)} \mathbf{x}+\left(I+F^{(i)}\right) \boldsymbol{\delta}^{(i)} \\
&=\left(I+F^{(i)}\right)\left[-\mathbf{z}^{(i)}+\left(I+A^{-1} \delta A^{(i)}\right)^{-1} \mathbf{z}^{(i)}\right. \\
&\left.\quad \quad \quad+\left(I+A^{-1} \delta A^{(i)}\right)^{-1}\left(A^{-1} E^{(i)} A\right) \mathbf{z}^{(i)}\right]+F^{(i)} \mathbf{x} \\
&=\left(I+F^{(i)}\right)\left(I+A^{-1} \delta A^{(i)}\right)^{-1}\left(A^{-1} \delta A^{(i)} \mathbf{z}^{(i)}+A^{-1} E^{(i)} A \mathbf{z}^{(i)}\right)+F^{(i)} \mathbf{x}
\end{aligned}
$$

which we rewrite as

$$
\mathbf{z}^{(i+1)}=K^{(i)} \mathbf{z}^{(i)}+\mathbf{c}^{(i)}
$$

Taking norms yields

$$
\left\|\mathbf{z}^{(i+1)}\right\| \leq\left\|K^{(i)}\right\|\left\|\mathbf{z}^{(i)}\right\|+\left\|\mathbf{c}^{(i)}\right\| .
$$

Under the assumptions

$$
\left\|K^{(i)}\right\| \leq \tau, \quad\left\|\mathbf{c}^{(i)}\right\| \leq \sigma\|\mathbf{x}\|
$$

we obtain

$$
\begin{aligned}
\left\|\mathbf{z}^{(i+1)}\right\| & \leq \tau\left\|\mathbf{z}^{(i)}\right\|+\sigma\|\mathbf{x}\| \\
& \leq \tau^{i+1}\left\|\mathbf{z}^{(0)}\right\|+\sigma\left(1+\tau+\cdots+\tau^{i}\right)\|\mathbf{x}\| \\
& \leq \tau^{i+1}\left\|\mathbf{z}^{(0)}\right\|+\sigma \frac{1-\tau^{(i+1)}}{1-\tau}\|\mathbf{x}\|
\end{aligned}
$$

Assuming $\left\|A^{-1}\right\|\left\|\delta A^{(i)}\right\| \leq \alpha$ and $\left\|E^{(i)}\right\| \leq \omega$,

$$
\tau=\frac{(1+\epsilon)(\alpha+\kappa(A) \omega)}{1-\alpha}
$$

where $\left\|F^{(i)}\right\| \leq \epsilon$. For sufficiently large $i$, we have

$$
\frac{\left\|\mathbf{z}^{(i)}\right\|}{\|\mathbf{x}\|} \leq \frac{\epsilon}{1-\tau}+O\left(\epsilon^{2}\right)
$$

From

$$
1-\tau=\frac{(1-\alpha)-(1+\epsilon)(\alpha+\kappa(A) \omega)}{1-\alpha}
$$

we obtain

$$
\frac{1}{1-\tau}=\frac{1-\alpha}{(1-\alpha)-(1+\epsilon)(\alpha+\kappa(A) \omega)} \approx \frac{1-\alpha}{1-2 \alpha-\kappa(A) \omega} .
$$

Therefore, $1 /(1-\tau) \leq 2$ whenever

$$
\alpha \leq \frac{1}{3}-\frac{2}{3} \kappa(A) \omega,
$$

approximately.
It can be shown that if the vector $\mathbf{r}^{(k)}$ is computed using double or extended precision that $\mathbf{x}^{(k)}$ converges to a solution where almost all digits are correct when $\kappa(A) \mathrm{u} \leq 1$.

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