

Experimental Study on Round-off Error in Matrix Inversion

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1 *A priori* Error Estimate

We consider the effect of the rounding errors in the computed inverses. Because the j th column of the inverse of A is the solution of $Ax = e_j$, we consider first the bounds for the errors made in the solution of the equations

$$(1) \quad Ax = b.$$

The method we discuss in this paper depends on the successive transformation of the original matrix $A^{(1)}$ into matrices $A^{(2)}, A^{(3)}, \dots, A^{(n)}$ such that each $A^{(k)}$ is equivalent to $A^{(1)}$ and the final $A^{(n)}$ is triangular. The error bounds are most conveniently expressed in terms of vector and matrix norms, throughout we shall use the maximum norms.

Suppose that the data A in (1) are perturbed by the quantity δA . Then if the perturbation in the solution x of (1) is δx we have

$$(2) \quad (A + \delta A)(x + \delta x) = b.$$

An estimate of the relative change in the solution can be given in terms of the relative changes in A as follows:

Let A be non-singular and the perturbation δA be so small that

$$\|\delta A\| < 1/\|A^{-1}\|.$$

Then if x and δx satisfy (1) and (2), we have

$$(3) \quad \frac{\delta x}{x} \leq \frac{\mu}{1 - \mu} \frac{\|\delta A\|}{\|A\|} \frac{\|A\|}{\|A\|}$$

where the condition number μ is defined as

$$\mu = \mu(A) = \|A\| \cdot \|A^{-1}\|.$$

The basic problem now is to determine the magnitude of the perturbations δA .

It is clear that δA depends upon the round-off errors and method of computation.

We consider the reduction to triangular form by Gaussian elimination using a partial pivoting for size. This strategy nearly determines a re-ordering of the row of A , we can assume that, without any loss of generality, the system has been ordered so that the natural order of pivots is used.

We denote the computed elements of the k th matrix $A^{(k)}$ by $a_{ij}^{(k)}$ and the computed multipliers by m_{ij} . Then we have

$$(4) \quad \sum_{k=1}^{\min(i,j)} m_{ik} a_{kj}^{(k)} = a_{ij}^{(1)} + \sum_{k=2}^{\min(i,j+1)} \epsilon_{ij}^{(k)}$$

Experimental Study on Round-off Error in Matrix Inversion

where $\epsilon_{ij}^{(k)}$ is the error made in computing $a_{ij}^{(k)}$ and m_{ij} . The element $a_{ij}^{(i)}$ is an element of the i th pivotal row and undergoing no further change.

Writing L for lower triangular matrix formed by the m_{ij} augmented by a unit diagonal, and U for the upper triangular matrix formed by the pivotal row, (4) gives

$$(5) \quad LU = A^{(1)} + E^{(2)} + \dots + E^{(n)} = A + E$$

where $E^{(k)}$ is the matrix formed by $\epsilon_{ij}^{(k)}$. Note that this has null rows 1 to $k-1$ and null columns 1 to $k-2$.

The solution of the equations $Ax = b$ is now obtained by solving

$$LUx = b$$

which is performed in the two steps

$$Ly = b, \quad Ux = y.$$

The vectors actually obtained are the exact solutions of, say,

$$(6) \quad (L + \delta L) y = b$$

$$(7) \quad (U + \delta U) x = y.$$

The perturbations δL and δU arise from the finite precision arithmetic performed in solving the triangular systems with the coefficients L and U . Upon multiplying (7) by $L + \delta L$ and using

(6) we have

$$(A + \delta A) = (L + \delta L) (U + \delta U)$$

From (5), it follows that

$$\delta A = E + L(\delta U) + (\delta L)U + (\delta L)(\delta U).$$

Since L and U are explicitly determined by the computations, their norms can also, in principle, be obtained, we must estimate E , δU and δL . We shall assume that floating-point arithmetic operations are performed with a t -digit mantissa, and let $\rho = \max_{i,j,k} |a_{ij}^{(k)}|$. If A is non-singular and t sufficiently large, then we have

$$E = (e_{ij}), \quad |e_{ij}| \leq \begin{cases} 2(i-1)\rho u & (i \leq j) \\ (2j-1)\rho u & (i > j) \end{cases}$$

where $u = \beta^{1-t}$.

The elements in δL and δU can be estimated from a single analysis of the error in solving any triangular system with the same arithmetic. Assuming that scalar products are accumulated in a double precision accumulator, we have

$$\delta L = \text{diag} (-\epsilon_i), \quad |\epsilon_i| < u$$

and

$$\delta U = \text{diag} (-u_{ii}w_i), \quad |w_i| < u.$$

We are now able to obtain estimates of the elements in δA . Let t be so large that $nu < 1$. Then the computed solution x satisfies

$$(A + \delta A) x = b$$

where

$$(8) \quad |\delta a_{ij}| \leq \begin{cases} \rho(2i-1)u & (i < j) \\ 2\rho ju & (i \geq j) \end{cases}$$

From (8) we easily find that

$$(9) \quad \|\delta A\| \leq \rho n(n+1)u$$

and this can be employed in (3) to obtain maximum norm bounds on the relative error.

Above results can be applied to inversion of a matrix A . Since the j th column x_j of the inverse matrix is the solution of the equation

$$LUx = e_j \quad (j=1,2,\dots,n),$$

the each computed x_j satisfies the relation

$$(A + \delta A_j) x_j = e_j.$$

Although the perturbation δA_j depends on e_j , but the bound of $\|\delta A_j\|$ is independent of each j .

Thus, if A is non-singular and $\|A^{-1}\delta A\| < 1$, then $A + \delta A$ is non-singular and we have

$$(10) \quad \frac{\|(A + \delta A)^{-1} - A^{-1}\|}{\|A^{-1}\|} \leq \frac{\|A^{-1}\delta A\|}{1 - \|A^{-1}\delta A\|} \leq \frac{\mu}{1 - \mu} \frac{\|\delta A\|}{\|A\|}$$

where

$$\|\delta A\| \leq n(n+1)\rho u.$$

2 A Posteriori Error Estimate

As shown in the following numerical experiments *a priori* error bound (10) is, in general, a tremendous overestimate for large n . Thus we consider now the *a posteriori* error bounds for computed inverse.

Let A be the matrix to be inverted and let C be the computed inverse. We use a measure of error called the residual matrix

$$R = AC - I.$$

If $\|R\| < 1$, then we have

$$(11) \quad \|C - A^{-1}\| \leq \|C\| \|R\| / (1 - \|R\|).$$

Since A and C are presumed known, we could actually compute $\|C\|$, $\|A\|$ and $\|R\|$ in the estimate (11). This, of course, is what is meant by *a posteriori* estimate.

3 Numerical examples

We consider the numerical inversion of the following symmetric matrices.

$$A_1 = (a_{ij}), \quad a_{ij} = \begin{cases} d = 1.001 & (i = j) \\ 1 & (i \neq j) \end{cases}$$

$$A_2 = (a_{ij}), \quad a_{ij} = n - |i - j|$$

$$A_3 = (a_{ij}), \quad a_{ij} = \left(\frac{2}{n+1}\right)^{1/2} \sin\left(\frac{ij\pi}{n+1}\right)$$

$$A_4 = (a_{ij}), \quad a_{ij} = \begin{cases} -2 & (i = j) \\ 1 & (|i - j| = 1) \\ 0 & (|i - j| \geq 2) \end{cases}$$

Numerical results are given in the following table.

For simplicity, we have denoted say, 4.45×10^{-5} by 4.45 (-5). These numerical experiments were performed with the HITAC 8250 computer. Since for this computer, $\beta = 16$, $t_s = 6$, and $t_d = 14$, so we have used $u = 2^{-20}$ and $u = 2^{-52}$ for single and double precision arithmetic respectively. Moreover, we have evaluated the relative error in the computed inverse by $\|R\|$, assuming that, in (11), $\|C\|$ is

Experimental Study on Round-off Error in Matrix Inversion

A₁ : positive definite

A₂ : positive definite

n	A	A ⁻¹	μ	ρ
	$\frac{ C-A^{-1} }{ A^{-1} }$	nρu A ⁻¹	R	$\frac{ R }{\frac{ C-A^{-1} }{ A^{-1} }}$
5	5.00	1.60(3)	8.00(3)	1.00
	4.45(-5)	7.64(-3)	3.05(-4)	6.86
	2.20(-14)	1.78(-12)	5.68(-13)	25.9
10	10.0	1.80(3)	1.80(4)	1.00
	4.47(-5)	1.72(-2)	2.90(-4)	6.48
	1.46(-14)	4.00(-12)	9.77(-13)	66.9
15	15.0	1.87(3)	2.80(4)	1.00
	4.50(-5)	2.67(-2)	5.04(-4)	11.2
	1.22(-14)	6.22(-12)	1.47(-12)	120.
20	20.0	1.90(3)	3.80(4)	1.00
	8.55(-4)	3.63(-2)	3.97(-4)	0.464
	2.22(-13)	8.45(-12)	2.06(-12)	9.28
25	25.0	1.92(3)	4.80(4)	1.00
	3.88(-4)	4.59(-2)	8.24(-4)	2.13
	1.96(-13)	1.07(-11)	2.48(-12)	12.6

n	A	A ⁻¹	μ	ρ
	$\frac{ C-A^{-1} }{ A^{-1} }$	nρu A ⁻¹	R	$\frac{ R }{\frac{ C-A^{-1} }{ A^{-1} }}$
5	19.0	2.00	38.0	5.00
	1.81(-6)	4.77(-5)	3.44(-6)	1.90
	2.83(-16)	1.11(-14)	1.39(-15)	4.94
10	75.0	2.00	150.	10.0
	3.32(-6)	1.91(-4)	1.44(-5)	4.33
	7.42(-16)	4.44(-14)	3.35(-15)	4.52
15	169.	2.00	338.	15.0
	7.10(-6)	4.29(-4)	2.77(-5)	3.90
	1.81(-15)	9.99(-14)	7.23(-15)	4.00
20	300.	2.00	600.	20.0
	4.07(-5)	7.63(-4)	9.02(-5)	2.21
	1.05(-14)	1.78(-13)	2.18(-14)	2.08
25	469.	2.00	938.	25.0
	1.52(-4)	1.19(-3)	2.13(-4)	1.40
	1.84(-14)	2.78(-13)	4.42(-14)	2.40

A₃ : orthogonal

A₄ : negative definite

5	2.15	2.15	4.64	2.00
	1.88(-6)	2.05(-5)	2.00(-6)	1.06
	9.92(-16)	4.78(-15)	1.10(-15)	1.11
10	2.97	2.97	8.80	3.10
	1.09(-5)	8.78(-5)	4.57(-6)	0.489
	2.39(-15)	2.04(-14)	1.43(-15)	0.599
15	3.59	3.59	12.9	2.88
	8.78(-6)	1.48(-4)	8.26(-6)	0.941
	2.11(-15)	3.45(-14)	2.49(-15)	1.18
20	4.12	4.12	17.0	3.48
	1.22(-5)	2.73(-4)	1.14(-5)	0.935
	3.28(-15)	6.37(-14)	3.41(-15)	1.04
25	4.59	4.59	21.0	4.82
	2.38(-5)	5.27(-4)	1.65(-5)	0.694
	4.21(-15)	1.23(-13)	4.28(-15)	1.02

5	4.00	4.50	18.0	2.00
	1.21(-6)	4.29(-5)	3.22(-6)	2.67
	2.31(-16)	9.99(-15)	8.47(-16)	3.66
10	4.00	15.0	60.0	2.00
	6.76(-6)	2.86(-4)	9.95(-6)	1.47
	9.76(-16)	6.66(-14)	2.51(-15)	2.57
15	4.00	32.0	128.	2.00
	1.38(-5)	9.16(-4)	2.45(-5)	1.77
	1.45(-15)	2.13(-13)	4.95(-15)	3.42
20	4.00	55.0	220.	2.00
	1.99(-5)	2.10(-3)	4.18(-5)	2.11
	2.01(-15)	4.88(-13)	1.00(-14)	4.99
25	4.00	84.5	338.	2.00
	2.68(-5)	4.03(-3)	6.10(-5)	2.28
	3.03(-15)	9.38(-13)	1.49(-14)	4.91

Takashi Yoshimura

approximately equal to $\|A\|$, and $\|R\|$ is far smaller than unity.

From above results, we see that the accuracy of the computed inverse with double precision arithmetic has been improved by 9 or 10 decimal places than with single precision arithmetic. For symmetric and positive definite matrix A it can be shown that

$$\rho \leq \max_{ij} |a_{ij}| \cdot$$

For any real matrix, however, from our experience, it might be expected that

$$\rho = \rho(n) \leq n.$$

References

- 1) J.H.Wilkinson: Rounding Error in Algebraic Processes. Her Britannic Majesty's Stationery Office (1963) .
- 2) E.Issacson and H.B.Keller: Analysis of Numerical Methods. John Wiley & Sons, Inc. (1966) .
- 3) J.R.Westlake: A Handbook of Numerical Matrix Inversion and Solution of Linear Equations. John Wiley & Sons, Inc. (1968) .