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Chap. 3: Numerical Linear Algebra

## §3.1 Introduction to solving linear systems

MA385 – Numerical Analysis 1

November 2019

Homework: Exers 2.7, 2.14, 3.12, 3.15.

Deadline: <sup>Thu</sup> 21 Nov 2019.

This section of the course is concerned with solving systems of linear equations (“simultaneous equations”). All problems are of the form: *find the set of real numbers  $x_1, x_2, \dots, x_n$  such that*

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ \vdots & & & \\ & & a_{nn} & \end{pmatrix} \begin{aligned} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n &= b_1 \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n &= b_2 \\ &\vdots \\ a_{n1}x_1 + a_{n2}x_2 + \cdots + a_{nn}x_n &= b_n \end{aligned}$$

where the  $a_{ij}$  and  $b_i$  are real numbers.

It is natural to rephrase this using the language of linear algebra:

*Find  $\mathbf{x} = (x_1, x_2, \dots, x_n)^T \in \mathbb{R}^n$  such that*

$$A\mathbf{x} = \mathbf{b}, \quad \text{where } A \in \mathbb{R}^{n \times n}, \text{ and } \mathbf{b} \in \mathbb{R}^n. \quad (1)$$

In this section, we'll try to find a clever way to solving this system. In particular,

1. we'll argue that its unnecessary and (more importantly) expensive to try to compute  $A^{-1}$ ;
2. we'll have a look at *Gaussian Elimination*, but will study it in the context of *LU*-factorisation;
3. after a detour to talk about *matrix norms*, we calculate the *condition number* of a matrix;
4. this last task will require us to be able to estimate the eigenvalues of matrices, so we will finish the module by studying how to do that.

- A vector  $\mathbf{x} \in \mathbb{R}^n$ , is an ordered  $n$ -tuple of real numbers,  $\mathbf{x} = (x_1, x_2, \dots, x_n)^T$ .
- A matrix  $A \in \mathbb{R}^{m \times n}$  is a rectangular array of  $n$  columns of  $m$  real numbers. (But we will only deal with **square** matrices, i.e., ones where  $m = n$ ).
- You already know how to multiply a matrix by a vector, and a ~~matrix by a matrix (right??)~~.
- You can write the **scalar** product as  $(\mathbf{x}, \mathbf{y}) = \mathbf{x}^T \mathbf{y} = \sum_{i=1}^n x_i y_i$ . `=sum(x.*y)` in MATLAB
- Recall that  $(A\mathbf{x})^T = \mathbf{x}^T A^T$ , so  $(\mathbf{x}, A\mathbf{y}) = \mathbf{x}^T A\mathbf{y} = (A^T \mathbf{x})^T \mathbf{y} = (A^T \mathbf{x}, \mathbf{y})$ .
- Letting  $I$  be the identity matrix, if there is a matrix  $B$  such that  $AB = BA = I$ , when we call  $B$  the **inverse** of  $A$  and write  $B = A^{-1}$ . If there is no such matrix, we say that  $A$  is **singular**.

**Theorem 3.1**

The following statements are equivalent. *Finished here wq.1*

1. For **any**  $b$ ,  $Ax = b$  has a solution.
2. If there is a solution to  $Ax = b$ , it is unique. *(mon 4/11/19.)*
3. If  $Ax = 0$  then  $x = 0$ .
4. The columns (or rows) of  $A$  are linearly independent.
5. There exists a matrix  $A^{-1} \in \mathbb{R}^{n \times n}$  such that  
 $AA^{-1} = I = A^{-1}A$ .
6.  $\det(A) \neq 0$ .
7.  $A$  has rank  $n$ .

8. If  $\lambda$  is an eigenvalue of  $A$   
then  $\lambda \neq 0$ .

Item 5 of the above lists suggests that we could solve  $Ax = b$  as follows: find  $A^{-1}$  and then compute  $x = A^{-1}b$ . However this is not the best way to proceed. We only need  $x$  and computing  $A^{-1}$  requires quite a bit a work.

In introductory linear algebra courses, you might compute

$$A^{-1} = \frac{1}{\det(A)} A^*$$

where  $A^*$  is the adjoint matrix. But it turns out that computing  $\det(A)$  directly can be **very** time-consuming.

Let  $d_n$  be the number of multiplications required to compute the determinant of an  $n \times n$  matrix using the **Method of Minors** (also called “the Laplacian determinant expansion”). We know that if

$$A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$$

then  $\det(A) = ad - bc$ . So  $d_2 = 2$ .

If

$$A = \begin{pmatrix} a & b & c \\ d & e & f \\ g & h & j \end{pmatrix}$$

then

$$\det(A) = \begin{vmatrix} a & b & c \\ d & e & f \\ g & h & j \end{vmatrix} = a \begin{vmatrix} e & f \\ h & j \end{vmatrix} - b \begin{vmatrix} d & f \\ g & j \end{vmatrix} + c \begin{vmatrix} d & e \\ g & h \end{vmatrix},$$

so  $d_3 \geq 3d_2$ .

(See notes from class)

In general we find that it takes  $(n)(n-1) \cdots (4)(3)(2)(1) = n!$  operations to compute the determinant this way. And that is a lot of operations.

### Exercise 3.1

Suppose you had a computer that computer perform 2 billion operations per second. Give a lower bound for the amount of time required to compute the determinant of a 10-by-10, 20-by-20, and 30-by-30, matrix using the method of minors.

### Exercise 3.2

The Cauchy-Binet formula for determinants tells us that, if  $A$  and  $B$  are square matrices of the same size, then  $\det(AB) = \det(A) \det(B)$ . Using it, or otherwise, show that  $\det(\sigma A) = \sigma^n \det(A)$  for any  $A \in \mathbb{R}^{n \times n}$  and any scalar  $\sigma \in \mathbb{R}$ .

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*Note: this exercise gives us another reason to avoid trying to calculate the determinant of the coefficient matrix in order to find the inverse, and thus the solution to the problem. For example  $A \in \mathbb{R}^{16 \times 16}$  and the system is rescaled by  $\sigma = 0.1$ , then  $\det(A)$  is rescaled by  $10^{-16}$ . On standard computing platforms, like MATLAB, it would be indistinguishable from a singular matrix!*