



Contact during exam

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## EXAM IN NUMERICAL LINEAR ALGEBRA (TMA4205)

Thursday December 9, 2010

Time: 09:00–13:00

Aids: Code C,. The following printed/ hand written aids are allowed.

- Y. Saad, Iterative Methods for Sparse Linear Systems, 2nd ed.
- Trefethen and Bau, Numerical linear algebra *or* Notes from the same book found on the course home page
- Golub and Van Loan, Matrix Computations *or* Note from the same book found on the course home page
- Own lecture notes from the course

**Problem 1** A matrix  $A \in \mathbb{Z}^{4 \times 4}$  is being QR-factorized. After one Householder transformation using the matrix  $Q_1$  generated by  $v$ , one has found

$$A_2 = Q_1 A = 7 \cdot \begin{bmatrix} 1 & -1 & 1 & -1 \\ 0 & 0 & 1 & -1 \\ 0 & -\frac{3}{5} & \frac{3}{5} & \frac{1}{5} \\ 0 & -\frac{4}{5} & \frac{4}{5} & -\frac{7}{5} \end{bmatrix}, \quad v = \frac{w}{\|w\|_2}, \quad w = \begin{bmatrix} -10 \\ 0 \\ -2 \\ -6 \end{bmatrix}$$

- a) Determine the original matrix  $A$ . You can use that  $2\frac{w^T A_2}{w^T w} = [-1, \frac{8}{5}, -\frac{8}{5}, \frac{9}{5}]$ .

*Hint to check the answer:*  $A$  has only integer elements.

**Answer:** Use the fact that Householder transformations are their own inverse, so  $A = Q_1^{-1} A_2 = Q_1 A_2$ . We need to find  $(I - 2vv^T)A_2$

$$= A_2 - 2w \frac{w^T A_2}{w^T w} = 7 \cdot \begin{bmatrix} 1 & -1 & 1 & -1 \\ 0 & 0 & 1 & -1 \\ 0 & -\frac{3}{5} & \frac{3}{5} & \frac{1}{5} \\ 0 & -\frac{4}{5} & \frac{4}{5} & -\frac{7}{5} \end{bmatrix} - \begin{bmatrix} -10 \\ 0 \\ -2 \\ -6 \end{bmatrix} \cdot [-1, \frac{8}{5}, -\frac{8}{5}, \frac{9}{5}] = \begin{bmatrix} -3 & 9 & -9 & 11 \\ 0 & 0 & 7 & -7 \\ -2 & -1 & 1 & 5 \\ -6 & 4 & -4 & 1 \end{bmatrix}$$

- b) Determine the upper triangular matrix  $R$  such that  $A = QR$ , use Householder transformations and give also the vectors  $v_2$  and  $v_3$  which generate  $Q_2$  and  $Q_3$ . You are not to compute  $Q$ .

*Hint to check the answer:* All the elements in  $R$  are integers divisible by 7.

**Answer:** We begin by setting  $x = A_2(2:4, 2) = 7 \cdot [0, -3/5, -4/5]^T$  and use the formula  $v = w/\|w\|_2$  where  $w = x + \text{sign}(x_1)\|x\|$ . Since  $\|x\|_2 = 7$  we get  $w = 7 \cdot [1, -3/5, -4/5]^T := 7 \cdot \tilde{w}$ , such that  $\tilde{w}^T \tilde{w} = 2$ . Let  $\tilde{A}_2 = A_2(2:4, 2:4)$ , we just change this part of  $A_2$  to find  $A_3$ . One has  $\tilde{Q}_2 \tilde{A}_2 = (I - 2vv^T) \tilde{A}_2$

$$\tilde{A}_3 = \tilde{A}_2 - 2\frac{ww^T}{w^T w} \tilde{A}_2 = \tilde{A}_2 - 2\tilde{w} \frac{\tilde{w}^T \tilde{A}_2}{\tilde{w}^T \tilde{w}} = \tilde{A}_2 - \tilde{w} \tilde{w}^T \tilde{A}_2 = \tilde{A}_2 - 7\tilde{w} \cdot [1, 0, 0]$$

Thus

$$\tilde{A}_3 = 7 \cdot \begin{bmatrix} 0 & 1 & -1 \\ -\frac{3}{5} & \frac{3}{5} & \frac{1}{5} \\ -\frac{4}{5} & \frac{4}{5} & -\frac{7}{5} \end{bmatrix} - 7 \cdot \begin{bmatrix} 1 \\ -\frac{3}{5} \\ -\frac{4}{5} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} = 7 \cdot \begin{bmatrix} -1 & 1 & -1 \\ 0 & \frac{3}{5} & \frac{1}{5} \\ 0 & \frac{4}{5} & -\frac{7}{5} \end{bmatrix}.$$

One can use for the Householder transformation,  $v_2 = \sqrt{1/2} [1, -3/5, -4/5]^T$ .

We proceed in the same way and define  $\tilde{\tilde{A}}_3 = \tilde{A}_3(2:3, 2:3)$ . Set  $x = 7 \cdot [3/5, 4/5]^T$ , and find  $\|x\|_2 = 7$ , and thus  $w = 7 \cdot [3/5 + 1, 4/5]^T = 28 \cdot [2/5, 1/5]^T = 28 \cdot \tilde{\tilde{w}}$ , where  $\tilde{\tilde{w}}^T \tilde{\tilde{w}} = 1/5$ . The same type of computation as above yields

$$\tilde{\tilde{A}}_4 = 7 \cdot \begin{bmatrix} -1 & 1 \\ 0 & -1 \end{bmatrix}$$

We substitute the matrices back into each other to obtain

$$R = 7 \cdot \begin{bmatrix} 1 & -1 & 1 & -1 \\ 0 & -1 & 1 & -1 \\ 0 & 0 & -1 & 1 \\ 0 & 0 & 0 & -1 \end{bmatrix}$$

One may define  $v_3 = \sqrt{1/5} \cdot [2, 1]^T$ .

**Problem 2** We shall apply a projection method to approximate the solution of the linear system

$$Ax = b, \quad A \in \mathbb{R}^{n \times n}, \quad b \in \mathbb{R}^n$$

For this purpose, we use a search space  $\mathcal{K}$  and a constraint space  $\mathcal{L}$ , both of dimension  $m \leq n$ . For a given initial value  $x_0$  we seek an approximation  $\tilde{x} \in x_0 + \mathcal{K}$  such that  $\tilde{r} \perp \mathcal{L}$ , i.e.  $\tilde{r} = b - A\tilde{x}$  is orthogonal to all vectors in  $\mathcal{L}$ .

- a) Suppose that we can write  $\mathcal{L} = B\mathcal{K}$  for a nonsingular  $n \times n$  matrix  $B$ . Show that if  $(Ax, Bx) > 0$  for all  $x \in \mathbb{R}^n$ , then this method is well defined, i.e. there exists a unique  $\tilde{x} \in x_0 + \mathcal{K}$  such that  $\tilde{r} \perp \mathcal{L}$ .

**Answer:** We introduce a basis for  $\mathcal{K}$  as the columns of the  $n \times m$  matrix,  $V_m = [v_1 | \dots | v_m] \in \mathbb{R}^{n \times m}$ . The vectors  $w_j = Bv_j, j = 1, \dots, m$  then form a linearly independent set in  $\mathcal{L}$ , which we can take as a basis, we set  $W_m = [w_1 | \dots | w_m] \in \mathbb{R}^{n \times m}$ . Any vector  $\tilde{x}$  in  $x_0 + \mathcal{K}$  can be written in the form  $\tilde{x} = x_0 + V_m y, y \in \mathbb{R}^m$ . We have

$$\tilde{r} = b - A\tilde{x} = b - Ax_0 - AV_m y = r_0 - AV_m y.$$

We require that  $\tilde{r} \perp \mathcal{L}$  which is equivalent to  $w_j \perp \tilde{r}, r = 1, \dots, m$  or  $W_m^T \tilde{r} = 0$ . This yields

$$(BV_m)^T (r_0 - AV_m y) = 0 \quad \Leftrightarrow \quad (V_m^T B^T AV_m) y = V_m^T B^T r_0$$

A unique solution exists if and only if  $P = V_m^T B^T AV_m \in \mathbb{R}^{m \times m}$  is nonsingular. A sufficient condition for this is that  $P$  is positive definite, i.e.  $z^T P z > 0 \forall z \in \mathbb{R}^m$ . We show that it is exactly that under the assumption  $(Ax, Bx) > 0$ . We have

$$z^T P z = z^T V_m^T B^T AV_m z = (Bx)^T (Ax) = (Ax, Bx) > 0, \quad x = V_m z.$$

- b) Assume now that  $B$  is chosen such that  $C := BA^{-1}$  is symmetric positive definite. Show that the result  $\tilde{x}$  will satisfy

$$\|b - A\tilde{x}\|_C = \min_{y \in x_0 + \mathcal{K}} \|b - Ay\|_C$$

where  $\|\cdot\|_C$  is the vector norm on  $\mathbb{R}^n$  defined as  $\|v\|_C = \sqrt{v^T C v}$ .

**Answer:** First a minor comment. That such a  $B$  exists we can see for instance by taking the candidates  $B = I$  or  $B = A$  where we have assumed that  $A$  is nonsingular. Let us perturb the given candidate, by setting  $y = \tilde{x} + \delta, \delta \in \mathcal{K}$  and then study  $\|b - Ay\|_C$

$$\|b - Ay\|_C^2 = \|b - A\tilde{x} - A\delta\|_C^2 = (\tilde{r} - A\delta)^T C (\tilde{r} - A\delta) = \|\tilde{r}\|_C^2 + \|A\delta\|_C^2 - 2\tilde{r}^T BA^{-1} A\delta.$$

We notice that the last term vanishes because  $\tilde{r} \perp B\delta$  siden  $B\delta \in \mathcal{L}$ . Therefore

$$\|b - Ay\|_C \geq \|\tilde{r}\|_C$$

and equality requires  $A\delta = 0$  which again calls for  $\delta = 0$  i.e.  $y = \tilde{x}$ , the minimum is unique.

- c) Let us now assume that  $A$  is symmetric so that the eigenvalues are real. Let  $\lambda_{\min}$  and  $\lambda_{\max}$  be the smallest and largest eigenvalue of  $A$  respectively. We also set  $B = (1 - \mu)I + \mu A$ . Show that the assumptions of the previous question are satisfied such that  $C = BA^{-1}$  is SPD if and only if

$$\mu < \frac{1}{1 - \lambda_{\min}} \quad \text{if } \lambda_{\min} < 1 \quad \text{and} \quad \mu > \frac{1}{1 - \lambda_{\max}} \quad \text{if } \lambda_{\max} > 1.$$

By this we mean that the first inequality can be ignored if  $\lambda_{\min} \geq 1$ , and the second inequality can be ignored if  $\lambda_{\max} \leq 1$ .

**Answer:** We now find that

$$C = BA^{-1} = ((1 - \mu)I + \mu A)A^{-1} = (1 - \mu)A^{-1} + \mu I$$

$C$  is obviously symmetric if  $A$  is symmetric. Considering the eigenvalues of  $C$  we have

$$\lambda(C) = \frac{1 - \mu}{\lambda(A)} + \mu$$

and we need only demand that they are positive. For those eigenvalues of  $A$  which are larger than 1, it is the biggest of them, namely  $\lambda_{\max}$  which determines the most restrictive condition. For those less than 1, it is  $\lambda_{\min}$  which determines the condition.

**Problem 3** In this problem, we shall study in some detail the properties of splitting methods as preconditioners.

- a) Let  $A$  be a nonsingular square matrix. We begin by assuming that we want to approximate the solution to the equation  $Ae = r$  by using  $k$  iterations with a splitting method, and that we set the initial value to zero, i.e.  $e^{(0)} = 0$ . Assume first a general splitting  $A = D - N$ ,  $D$  invertible, and an iteration of the form

$$e^{(k+1)} = Ge^{(k)} + \bar{r}, \quad G = D^{-1}N, \quad \bar{r} = D^{-1}r$$

Show that one has  $e^{(k)} = (I - G)^{-1}(I - G^k)\bar{r}$ , and if the corresponding preconditioned system is  $\tilde{A}x = M^{-1}Ax = M^{-1}b$  then one has

$$\tilde{A} = M^{-1}A = (I - G)^{-1}(I - G^k)(I - G).$$

**Answer:** We can prove this by induction. The  $e^{(1)} = \bar{r}$  can be seen directly from the iteration formula with  $k = 0$ , since  $e^{(0)} = 0$ . If the formula is correct up to  $k - 1$  we can find  $e^{(k)}$  by

$$e^{(k)} = Ge^{(k-1)} + \bar{r} = (I + G(I - G)^{-1}(I - G^{k-1}))\bar{r} = (I - G)^{-1}(I - G + G(I - G^{k-1}))\bar{r} = (I - G)^{-1}(I - G^k)\bar{r}$$

To find the expression for  $\tilde{A}$  we need to substitute  $\bar{r} = D^{-1}r$  and use that  $A = D(I - G)$ .

$$\tilde{A} = M^{-1} \cdot A = (I - G)^{-1}(I - G^k)D^{-1} \cdot (D - N) = (I - G)^{-1}(I - G^k)(I - G)$$

- b) Assume in the rest of this problem that  $A$  is symmetric positive definite (SPD) of the form  $A = \alpha I - N$ ,  $N^T = N$ ,  $\alpha > \frac{1}{2}\lambda_{\max}$ , where  $\lambda_{\max} = \rho(A)$  is the largest eigenvalue of  $A$ . Let  $D = \alpha I$ . Show that the preconditioner  $M$  from the question above then will also be SPD

**Answer:** We have  $M^{-1} = (I - G)^{-1}(I - G^k)D^{-1} = \frac{1}{\alpha}(I - G)^{-1}(I - G^k)$  where  $G = \frac{1}{\alpha}N$  is symmetric. Therefore both  $(I - G)^{-1}$  and  $I - G^k$  are symmetric and we have  $M^{-T} = (I - G^k)(I - G)^{-1} = (I - G)^{-1}(I - G^k) = M^{-1}$ , so  $M^{-1}$  (and thus  $M$ ) is symmetric.

Now  $\lambda(G) = 1 - \frac{\lambda(A)}{\alpha}$  such that

$$\lambda(M^{-1}) = \frac{1}{\alpha}(1 - \lambda(G))^{-1}(1 - \lambda(G)^k) = \frac{1}{\alpha} \frac{\alpha}{\lambda(A)} \left( 1 - \left( 1 - \frac{\lambda(A)}{\alpha} \right)^k \right)$$

So  $\lambda(M^{-1}) > 0$  if  $1 - \left( 1 - \frac{\lambda(A)}{\alpha} \right)^k > 0$ . Since  $\alpha > \frac{1}{2}\lambda_{\max}$  we must have  $-1 < 1 - \frac{\lambda(A)}{\alpha} < 1$  for all eigenvalues of  $A$ , and therefore  $-1 < \left( 1 - \frac{\lambda(A)}{\alpha} \right)^k < 1$ . It follows that  $1 - \left( 1 - \frac{\lambda(A)}{\alpha} \right)^k > 0$  and therefore  $\lambda(M^{-1}) > 0$ , so  $M^{-1}$  (and thus  $M$ ) is SPD.

- c) Suppose as before that  $A$  is SPD, and that the smallest and largest eigenvalue of  $A$  are  $\lambda_{\min}$  and  $\lambda_{\max}$  respectively. We choose the splitting parameter  $\alpha = \frac{1}{2}(\lambda_{\min} + \lambda_{\max})$  such that the preconditioner is SPD. Suppose that we use  $k$  iterations of the splitting method where  $k$  is an odd integer. Show that under these circumstances one has

$$\kappa_2(\tilde{A}) = \frac{1 + \left( \frac{\kappa-1}{\kappa+1} \right)^k}{1 - \left( \frac{\kappa-1}{\kappa+1} \right)^k}$$

where  $\kappa = \kappa_2(A)$  is the condition number of  $A$ .

Comment on the result.

**Answer:** The condition number of  $A$  is given as  $\kappa = \kappa_2(A) = \frac{\lambda_{\max}}{\lambda_{\min}}$ . Let  $\tilde{\lambda} \in \sigma(\tilde{A})$ . Since  $\tilde{A} = (I - G)^{-1}(I - G^k)(I - G)$  then  $\tilde{\lambda} \in \sigma(I - G^k)$ . Because  $\alpha = \frac{1}{2}(\lambda_{\min} + \lambda_{\max})$  we have

$$\tilde{\lambda} = 1 - \left( 1 - \frac{2\lambda}{\lambda_{\min} + \lambda_{\max}} \right)^k, \quad \lambda \in \sigma(A).$$

One can see that this expression is monotonically increasing in  $\lambda$  for instance by differentiating

$$\frac{d}{d\lambda} \tilde{\lambda} = \frac{2k}{\lambda_{\min} + \lambda_{\max}} \left( 1 - \frac{2\lambda}{\lambda_{\min} + \lambda_{\max}} \right)^{k-1}$$

Since  $k$  is odd,  $k - 1$  is even, and the expression is non-negative. Therefore the minimum is attained at  $\lambda = \lambda_{\min}$  and the maximum at  $\lambda = \lambda_{\max}$ . We compute

$$\kappa_2(\tilde{A}) = \frac{\tilde{\lambda}_{\max}}{\tilde{\lambda}_{\min}} = \frac{1 - \left( 1 - \frac{2\lambda_{\max}}{\lambda_{\min} + \lambda_{\max}} \right)^k}{1 - \left( 1 - \frac{2\lambda_{\min}}{\lambda_{\min} + \lambda_{\max}} \right)^k} = \frac{1 + \left( \frac{\kappa-1}{\kappa+1} \right)^k}{1 - \left( \frac{\kappa-1}{\kappa+1} \right)^k}$$

**Problem 4**

- a) Show that the Frobenius norm of an  $n \times n$  matrix can be written as

$$\|A\|_F = \sqrt{\sigma_1^2 + \sigma_2^2 + \cdots + \sigma_n^2},$$

where  $\sigma_1, \dots, \sigma_n$  are the singular values of  $A$ .

**Answer:** The Frobenius norm of  $A$  can be written in the form

$$\|A\|_F = \left( \sum_{i,j=1}^n a_{ij}^2 \right)^{1/2} = \sqrt{\text{Tr}(A^T A)}$$

Then one may just use the given information that the trace of a matrix equals the sum of its eigenvalues and that the square of the singular values of  $A$  are the eigenvalues of  $A^T A$ , the result then follows.

- b) Suppose that  $A$  is a  $202 \times 202$  matrix with  $\|A\|_2 = 100$  and  $\|A\|_F = 101$ . Find from this the largest possible lower bound for  $\kappa_2(A) = \|A\|_2 \|A^{-1}\|_2$ .

**Answer:** Here we use the answer from the previous question. Note that  $\|A\|_2 = \sigma_1$  i.e. the largest singular value, whereas  $\|A^{-1}\|_2 = 1/\sigma_n$  i.e. the inverse of the smallest singular value, here  $n = 202$ . One finds

$$201 = 101^2 - 100^2 = \|A\|_F^2 - \|A\|_2^2 = \sum_{k=2}^{202} \sigma_k^2 \geq 201 \cdot \sigma_{202}^2$$

such that  $\sigma_{202} \leq 1$ . Therefore

$$\kappa_2(A) = \frac{\sigma_1}{\sigma_{202}} \geq \frac{100}{1} = 100.$$

**Appendix.** Some useful formulas

1. For all  $n \times n$  matrices  $C$  with elements  $c_{ij}$  and eigenvalues  $\lambda_i$  one has

$$\text{Tr}(C) = \sum_{i=1}^n c_{ii} = \sum_{i=1}^n \lambda_i$$

2. The condition number of a matrix  $A$  is given by the formula  $\kappa(A) = \|A\| \|A^{-1}\|$ . In particular, using the  $p$ -norm, one writes  $\kappa_p(A) = \|A\|_p \|A^{-1}\|_p$