Instructions: You must show all your work to receive full credit. Partial answers will only receive partial credit. Please choose 3 of the 4 problems to solve. Please indicate which 3 problems you would like graded.

- 1. (a) Show that for any induced matrix norm,  $\kappa(A) \geq 1$ .
  - (b) If Ax = b and  $(A + \delta A)(x + \delta x) = b$ , prove the inequality

$$\frac{||\delta x||}{||x + \delta x||} \le \kappa(A) \frac{||\delta A||}{||A||}$$

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

- (c) Is the inequality in Part b above what we need to estimate the impact of perturbations in the matrix on perturbations in the solution? Why or why not?
- (d) Verify the inequality for the system

$$\begin{pmatrix} 1 & 1/2 & 1/3 \\ 1/2 & 1/3 & 1/4 \\ 1/3 & 1/4 & 1/5 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

using \*

$$\Delta A = \begin{pmatrix} 0 & 0 & 0.00003 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}.$$

- (e) Is the determinant of a matrix a good measure of the condition of a matrix? Give an example to help justify your answer.
- 2. Solving  $Ax = \lambda x$  is equivalent for certain matrices to finding stationary points of the Rayleigh quotient.

- (a) For which type of matrices is the above statement true?
- (b) Write out the Rayleigh quotient R for the matrix

$$A = \begin{bmatrix} 1 & 5 \\ 5 & 1 \end{bmatrix}.$$

- (c) For the matrix A above, calculate  $\partial R/\partial x_1$  and  $\partial R/\partial x_2$ .
- (d) Which vectors x minimize and maximize this Rayleigh quotient?
- (e) What subspace results from this gradient direction?
- (f) The conjugate gradient method is also an optimal way to minimize and maximize R. What trick does the conjugate gradient algorithm use to achieve a better rate of convergence than steepest descent? Explain your answer in both algebraic and geometric terms. (Hint: explain why the conjugate gradient method is able to converge to a solution of the linear system Ax = b in n iterations if  $A \in \mathbb{R}^{n \times n}$ .)
- 3. Prove that the vector norms  $\|\cdot\|_1$  and  $\|\cdot\|_2$  are equivalent in  $\mathbb{R}^n$ , that is, show that

$$c_1 \|x\|_2 \le \|x\|_1 \le c_2 \|x\|_2$$
 for all  $x \in \mathbb{R}^n$ .

with  $c_1 = 1$  and  $c_2 = \sqrt{n}$ . Demonstrate that the inequalities are sharp, that is, specify example vectors  $x^{(\ell)}$  and  $x^{(r)}$  such that the left and right inequality, respectively, becomes an equality.

- 4. Let  $u \in \mathbb{R}^m$  and  $v \in \mathbb{R}^n$  be non-zero, and define the rank-one matrix  $A = uv^T \in M_{m \times n}$ .
  - (i) Compute a singular value decomposition of A, and determine  $||A||_2$ . (Hint: define  $u_1 = u/\|u\|_2$ ,  $v_1 = v/\|v\|_2$  and complete each of  $u_1, v_1$  to an orthonormal basis in their spaces.)
  - (ii) Compute the pseudoinverse A<sup>+</sup> of A.
  - (iii) Briefly explain the relevance of  $A^+$  to the question of finding the least-norm solution of the least-squares problem

$$\min_{x \in \mathbb{R}^n} ||Ax - b||_2 ,$$

for a general matrix  $A \in M_{m \times n}$  and  $b \in \mathbb{R}^m$ . Given  $b = [1, ..., 1]^T \in \mathbb{R}^m$  and A as in (a), find (in terms of the vectors u, v) the least-norm solution of the least-squares problem

$$\min_{x \in \mathbb{R}^n} ||Ax - b||_2.$$