MAT 245 Lab 4

Oct. 16, 2017

Ill-conditioned matrices

The condition number. Recall that the condition number of an $n \times n$ matrix A is defined to be

$$\kappa(A) := \left(\sup_{e \neq 0} \frac{\|A^{-1}e\|_2}{\|e\|_2}\right) \left(\sup_{b \neq 0} \frac{\|b\|_2}{\|A^{-1}b\|_2}\right) = \left\|A^{-1}\right\|_2 \|A\|_2.$$

If we are studying the linear system Ax = b, one can intuitively think of the condition number as measuring the rate of change solution of the solution x as we perturb b. When we working with the Frobenius matrix norm, as above, there is a particularly simple formula for the condition number. If $\sigma_{\max}(A)$ and $\sigma_{\min}(A)$ denote the maximum and minimum singular values of A respectively, then

$$\kappa(A) = \frac{\sigma_{\max}}{\sigma_{\min}}.$$

The Hilbert matrix. The $n \times n$ Hilbert matrix is the matrix H(n) defined by

$$(H(n))_{ij} = \frac{1}{i+j-1}.$$

In other words, it is the matrix whose ij^{th} entry is $\frac{1}{i+j-1}$. For example:

$$H(5) = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \frac{1}{5} \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \frac{1}{6} \\ \frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \frac{1}{6} & \frac{1}{7} \\ \frac{1}{4} & \frac{1}{5} & \frac{1}{6} & \frac{1}{7} & \frac{1}{8} \\ \frac{1}{5} & \frac{1}{6} & \frac{1}{7} & \frac{1}{8} & \frac{1}{9} \end{bmatrix}$$

Goals

- 1. Write a python function that returns the Hilbert matrix H(n) given $n \in \mathbb{N}$.
- 2. Write a python function that takes a numpy 2D-array A and computes the condition number $\kappa(A)$.
- 3. Use your implementation of the condition number function to compute $\kappa(H(n))$ for n = 10, 15, 20, 25. Compare these values with those computed by the University of Kyoto at: http://bit.ly/2x6jIP7. Do they match?
- 4. Plot the graph of the function $n \mapsto \kappa(H(n))$ for $1 \le n \le 10$.
- 5. Define random two vectors $t_0, t_1 \in \mathbb{R}^{20}$ using the numpy.random.rand function. Set

$$b_0 := H(20) \cdot t_0$$
 and $b_1 := H(20) \cdot t_1$

Now compute x_0 and x_1 by

$$x_0 = H(20)^{-1} \cdot b_0$$
 and $x_1 := H(20)^{-1} \cdot b_1$

Clearly $x_i = t_i$ since

$$x_i = H(20)^{-1}H(20)t_i$$
 $i = 0, 1.$

Use numpy.linalg.norm to compute the norm of $||x_i - t_i||_2$ for i = 0, 1. Do you obtain the expected result?

6. Now let's try computing the x_i in a different way. This time use numpy.linalg.solve to solve the linear systems

$$H(20)x_0 = b_0$$
 and $H(20)x_1 = b_1$.

By the definition of b_i , we should again have $x_i = t_i$. Compute $||x_i - t_i||_2$ as above to see whether this is the case.

Computing the variance

Consider the following two formulas for computing the variance of a vector in \mathbb{R}^n :

(a)
$$S^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (x_{i} - \overline{x})^{2}$$

(b)
$$S^{2} = \frac{1}{n-1} \left(\sum_{i=1}^{n} x_{i}^{2} - n\overline{x}^{2} \right).$$

One of these algorithms is numerically unstable.

- 1. Write python implementations of both formulas.
- 2. Can you determine which one is more numerically stable? Use examples to demonstrate the issues with the unstable algorithm. (Hint: Try sample data whose variance is very small relative to the mean and consider the placement of the ²).
- 3. Compare both algorithms to the results obtained from numpy's own variance function numpy.var. If v_1 and v_2 are the results of any two variance computations, try computing $\frac{|v_1-v_2|}{|v_1|}$.

Approximating the exponential function

1. Implement a python function that computes the N^{th} partial sum of $\exp(x)$. In other words, implement the mapping

$$(x,N) \longmapsto \sum_{k=0}^{N} \frac{x^k}{k!}.$$

- 2. Compute approximate values for $\exp(-5.5)$ for N = 5, 10, 15 in three ways:
 - (a) directly with the function you implemented in the first step.
 - (b) with $\exp(-5.5) = 1/\exp(5.5)$, and your implementation for $\exp(5.5)$.
 - (c) with $\exp(-5.5) = (\exp(0.5))^{-11}$, and your implementation for $\exp(0.5)$.

How can the results be interpreted?