

Exercises

Exercise 5.1 Suppose the complex $m \times n$ matrix A is perturbed to the matrix $A + E$.

(a) Show that

$$|\sigma_{max}(A + E) - \sigma_{max}(A)| \leq \sigma_{max}(E)$$

Also find an E that results in the inequality being achieved with equality.

(Hint: To show the inequality, write $(A + E) = A + E$ and $A = (A + E) - E$, take the 2-norm on both sides of each equation, and use the triangle inequality.)

It turns out that the result in (a) actually applies to *all* the singular values of A and $A + E$, not just the largest one. Part (b) below is one version of the result for the smallest singular value.

(b) Suppose A has *less than* full column rank, i.e. has $\text{rank} < n$, but $A + E$ has full column rank. Show (following a procedure similar to part (a) — but looking at $\min \|(A + E)x\|_2$ rather than the norm of $A + E$, etc.) that

$$\sigma_{min}(A + E) \leq \sigma_{max}(E)$$

Again find an E that results in the inequality being achieved with equality.

[The result in (b), and some extensions of it, give rise to the following sound (and widely used) procedure for estimating the rank of some underlying matrix A , given only the matrix $A + E$ and knowledge of $\|E\|_2$: Compute the SVD of $A + E$, then declare the “numerical rank” of A to be the number of singular values of $A + E$ that are larger than the threshold $\|E\|_2$. The given information is consistent with having an A of this rank.]

(c) Verify the above results using your own examples in MATLAB. You might also find it interesting to verify numerically that for large m, n , the norm of the matrix $E = s * \text{randn}(m, n)$ — which is a matrix whose entries are independent, zero-mean, Gaussian, with standard deviation s — is close to $s * (\sqrt{m} + \sqrt{n})$. So if A is perturbed by such a matrix, then a reasonable value to use as a threshold when determining the numerical rank of A is this number.

Exercise 5.2 Let A and E be $m \times n$ matrices. Show that

$$\min_{\text{rank } E \leq r} \|A - E\|_2 = \sigma_{r+1}(A).$$

To prove this, notice that the rank constraint on E can be interpreted as follows: If v_1, \dots, v_{r+1} are linearly independent vectors, then there exists a nonzero vector z , expressed as a linear combination of such vectors, that belongs to the nullspace of E . Proceed as follows:

1. Select the v_i 's from the SVD of A .
2. Select a candidate element z with $\|z\|_2 = 1$.
3. Show that $\|(A - E)z\|_2 \geq \sigma_{r+1}$. This implies that $\|A - E\|_2 \geq \sigma_{r+1}$.
4. Construct an E that achieves the above bound.

Exercise 5.8 Prove or disprove (through a counter example) the following singular values inequalities.

1. $\sigma_{\min}(A + B) \leq \sigma_{\min}(A) + \sigma_{\min}(B)$ for any A and B .
2. $\sigma_{\min}(A + E) \leq \sigma_{\max}(E)$ whenever A does not have column rank, and E is any matrix.
3. If $\sigma_{\max}(A) < 1$, then

$$\sigma_{\max}(I - A)^{-1} \leq \frac{1}{1 - \sigma_{\max}(A)}$$

4. $\sigma_i(I + A) \leq \sigma_i(A) + 1$.