

## Lecture 5: More on the SVD

**Exercise 1.** In Example 3.1, we considered the matrix (3.7) and asserted, among other things, that its 2-norm is approximately 2.9208. Using the SVD, work out (on paper) the exact values of  $\sigma_{\min}(A)$  and  $\sigma_{\max}(A)$ .

**Solution:** The matrix in question is

$$A = \begin{bmatrix} 1 & 2 \\ 0 & 2 \end{bmatrix}$$

By Theorem 5.4, the nonzero singular values of  $A$  are the square roots of the eigenvalues of  $A^*A$  and  $AA^*$  (these matrices have the same eigenvalues). Thus we proceed to find eigenvalues of  $A^*A$

$$A^*A = \begin{bmatrix} 1 & 0 \\ 2 & 2 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 0 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 2 \\ 2 & 8 \end{bmatrix}$$

Now we find its eigenvalues which will be the values  $\lambda$  such that  $A^*A - \lambda I$  is singular. That is, we want  $(A^*A - \lambda I)v = 0$  for nonzero  $v \in \mathbb{C}^2$ :

$$0 = (A^*A - \lambda I)v = \begin{bmatrix} 1 - \lambda & 2 \\ 2 & 8 - \lambda \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

This is equivalent to the system:

$$\begin{aligned} 0 &= (1 - \lambda)x + 2y \\ 0 &= 2x + (8 - \lambda)y \end{aligned}$$

We can multiply the second equation by  $-\frac{1-\lambda}{2}$  and add it to the first to get:

$$\begin{aligned} 0 &= 0x + \left(2 - \frac{1}{2}(1 - \lambda)(8 - \lambda)\right)y \\ 0 &= 2x + (8 - \lambda)y \end{aligned}$$

This will have nonzero solutions if  $2 - \frac{1}{2}(1 - \lambda)(8 - \lambda) = 0$ , which is equivalent to the quadratic equation  $\lambda^2 - 9\lambda + 4 = 0$ . The solutions can be obtained using the quadratic formula, and they are

$$\lambda_{\pm} = \frac{9 \pm \sqrt{65}}{2}$$

Both are positive, as expected because  $A^*A$  is invertible so it has nonzero eigenvalues, and it is also a positive semidefinite operator, so its eigenvalues must be nonnegative. Now

$$\sigma_{\min} = \sqrt{\frac{9 - \sqrt{65}}{2}}, \quad \sigma_{\max} = \sqrt{\frac{9 + \sqrt{65}}{2}} \approx 2.9208$$

**Exercise 5.2.** Using the SVD prove that any matrix in  $\mathbb{C}^{m \times n}$  is the limit of a sequence of matrices of full rank. In other words, prove that the set of full-rank matrices is a dense subset of  $\mathbb{C}^{m \times n}$ . Using the 2-norm for your proof. (The norm doesn't matter, since all norms on a finite-dimensional space are equivalent).

**Solution:**

*Proof.* Let  $A \in \mathbb{C}^{m \times n}$ . □

**Exercise 5.3.** Consider the matrix

$$A = \begin{bmatrix} -2 & 11 \\ -10 & 5 \end{bmatrix}$$

1. Determine, on paper, a real SVD of  $A$  in the form  $A = U\Sigma V^T$ . The SVD is not unique, so find one that has the minimal number of minus signs in  $U$  and  $V$ .
2. List the singular values, left singular vectors, and right singular vectors of  $A$ . Draw a careful, labeled picture of the unit ball in  $\mathbb{R}^2$  and its image under  $A$ , together with the singular vectors, with the coordinates of their vertices marked.
3. What are the 1-, 2-,  $\infty$ - and Frobenius norms of  $A$ ?
4. Find  $A^{-1}$  not directly, but via the SVD.
5. Find the eigenvalues  $\lambda_1, \lambda_2$  of  $A$ .
6. Verify that  $\det A = \lambda_1 \lambda_2$  and  $|\det A| = \sigma_1 \sigma_2$ .
7. What is the area of the ellipsoid into which  $A$  maps the unit ball of  $\mathbb{R}^2$ ?

**Solution:**

- (a) The matrix  $A$  is nonsingular and thus its singular values are all nonzero. By Theorem 5.4, the nonzero singular values of  $A$  are the square roots of the nonzero eigenvalues of  $A^*A$  or  $AA^*$ . Moreover, suppose that  $A = U\Sigma V^*$ , so that  $A^*A = V\Sigma^2 V^*$ . Then the eigenvectors of  $A^*A$  are the right singular vectors of  $A$ . Similarly, the eigenvectors of  $AA^*$  are the left singular vectors of  $A$ . Thus we begin by finding the eigenvalues of  $A^*A$ :

$$A^*A = \begin{bmatrix} -2 & -10 \\ 11 & 5 \end{bmatrix} \begin{bmatrix} -2 & 11 \\ -10 & 5 \end{bmatrix} = \begin{bmatrix} 104 & -72 \\ -72 & 146 \end{bmatrix}$$

If  $\lambda$  is an eigenvalue of  $A^*A$ , then  $A^*A - \lambda I$  is singular, which means that  $(A^*A - \lambda I)v = 0$  has a nonzero solution  $v \in \mathbb{C}^2$ :

$$0 = (A^*v - \lambda I)v = \begin{bmatrix} 104 - \lambda & -72 \\ -72 & 146 - \lambda \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Hence we have the system

$$\begin{aligned} 0 &= (104 - \lambda)x - 72y \\ 0 &= -72x + (146 - \lambda)y \end{aligned}$$

We can multiply the second equation by  $\frac{1}{72}(104 - \lambda)$  and add it to the first to get

$$\begin{aligned} 0 &= 0x + \left( \frac{1}{72}(104 - \lambda)(146 - \lambda) - 72 \right) y \\ 0 &= -72x + (146 - \lambda)y \end{aligned}$$

This equation will have nonzero solutions if

$$\frac{1}{72}(104 - \lambda)(146 - \lambda) - 72 = 0$$

which simplifies to

$$\lambda^2 - 250\lambda + 10000 = 0$$

The solutions are

$$\sigma_1^2 = 200, \quad \sigma_2^2 = 50$$

Thus  $\sigma_1 = \sqrt{200} = 10\sqrt{2}$ , and  $\sigma_2 = \sqrt{50} = 5\sqrt{2}$ . Now to find the eigenvectors, we substitute  $\sigma_1^2$  and  $\sigma_2^2$  in our equation

$$\begin{aligned} 0 &= 0x + \left( \frac{1}{72}(104 - \lambda)(146 - \lambda) - 72 \right) y \\ 0 &= -72x + (146 - \lambda)y \end{aligned}$$

Since  $\sigma_1^2$  and  $\sigma_2^2$  both make the coefficient of  $y$  in the first equation 0, this implies that  $72x = (146 - \lambda)y$ . If we let  $y = 72$ , then

$$\begin{aligned} \sigma_1^2 = 200 &\rightarrow \begin{bmatrix} -54 \\ 72 \end{bmatrix} \implies v_1 = \frac{1}{90} \begin{bmatrix} -54 \\ 72 \end{bmatrix} = \frac{1}{5} \begin{bmatrix} -3 \\ 4 \end{bmatrix} \\ \sigma_2^2 = 50 &\rightarrow \begin{bmatrix} 96 \\ 72 \end{bmatrix} \implies v_2 = \frac{1}{120} \begin{bmatrix} 96 \\ 72 \end{bmatrix} = \frac{1}{5} \begin{bmatrix} 4 \\ 3 \end{bmatrix} \end{aligned}$$

Here  $v_1, v_2$  is an orthonormal list. Next we find the eigenvectors of  $AA^*$ , using the fact that the eigenvalues are the same as those of  $A^*A$ . We begin by computing  $AA^*$ :

$$AA^* = \begin{bmatrix} -2 & 11 \\ -10 & 5 \end{bmatrix} \begin{bmatrix} -2 & -10 \\ 11 & 5 \end{bmatrix} = \begin{bmatrix} 125 & 75 \\ 75 & 125 \end{bmatrix}$$

Now we find eigenvectors by finding the nonzero solutions to:

$$\begin{aligned} 0 &= (AA^* - \sigma_1^2 I)v = \begin{bmatrix} -75 & 75 \\ 75 & -75 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \\ 0 &= (AA^* - \sigma_2^2 I)v = \begin{bmatrix} 75 & 75 \\ 75 & 75 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \end{aligned}$$

The first system has the nontrivial solution  $x = y = 1$ , and the second system has the nontrivial solution  $x = 1$  and  $y = -1$ . Thus

$$u_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad u_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

is an orthonormal list of eigenvectors of  $AA^*$ . Now we let  $U$  be the matrix whose columns are  $u_1$  and  $u_2$ , let  $V$  be the matrix whose columns are  $v_1$  and  $v_2$ , and let  $\Sigma$  be the matrix whose diagonal entries are  $\sigma_1 = \sqrt{200}$  and  $\sigma_2 = \sqrt{50}$ , then  $U\Sigma V^*$  is an SVD of  $A$ . To see this, we can multiply them

$$\begin{aligned} U\Sigma V^* &= \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} \sqrt{200} & 0 \\ 0 & \sqrt{50} \end{bmatrix} \cdot \frac{1}{5} \begin{bmatrix} -3 & 4 \\ 4 & 3 \end{bmatrix} \\ &= \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} -3 & 4 \\ 4 & 3 \end{bmatrix} \\ &= A \end{aligned}$$

(b) The singular value of  $A$  are

$$\sigma_1 = \sqrt{200}, \quad \sigma_2 = \sqrt{50}$$

The left singular vectors are

$$u_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad u_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

The right singular vectors are

$$v_1 = \frac{1}{5} \begin{bmatrix} -3 \\ 4 \end{bmatrix} \quad v_2 = \frac{1}{5} \begin{bmatrix} 4 \\ 3 \end{bmatrix}$$

(c) The 1-norm of  $A$  is the largest 1-norm among its columns, by Example 3.3 (Equation 3.9). Since  $\|a_1\|_1 = |-2| + |-10| = 12$  and  $\|a_2\|_1 = 11 + 5 = 17$ , we see that  $\|A\|_1 = 17$ . By Example 3.4, the infinity norm of  $A$  is the largest 1-norm of its rows, which is the largest of  $|-10| + 5$  and  $|-2| + 11$ , and hence  $\|A\|_\infty = 15$ . By Theorem 5.3,  $\|A\|_2 = \sigma_1 = \sqrt{200}$ , the largest singular value of  $A$ . By the same Theorem,  $\|A\|_F = \sqrt{\sigma_1^2 + \sigma_2^2} = \sqrt{200 + 50} = \sqrt{250}$ .

- (d) To find  $A^{-1}$  we note that  $U$  and  $V^T$  are unitary and  $\Sigma$  is diagonal, so  $A^{-1} = (V^*)^{-1}\Sigma^{-1}U^{-1}$ , and hence  $A^{-1} = V\Sigma^{-1}U^T$

$$\begin{aligned} A^{-1} &= \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{200}} & 0 \\ 0 & \frac{1}{\sqrt{50}} \end{bmatrix} \frac{1}{5} \begin{bmatrix} -3 & 4 \\ 4 & 3 \end{bmatrix} \\ &= \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} \frac{1}{100} & 0 \\ 0 & \frac{1}{50} \end{bmatrix} \begin{bmatrix} -3 & 4 \\ 4 & 3 \end{bmatrix} \\ &= \frac{1}{100} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} -3 & 4 \\ 4 & 3 \end{bmatrix} \\ &= \frac{1}{100} \begin{bmatrix} 5 & -11 \\ 10 & -2 \end{bmatrix} \end{aligned}$$

- (e) The eigenvalues of  $A$  are the values that make  $A - \lambda I$  a singular matrix. We want nonzero solutions to

$$(A - \lambda I)v = \begin{bmatrix} -2 - \lambda & 11 \\ -10 & 5 - \lambda \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

We have the equations

$$\begin{aligned} 0 &= (-2 - \lambda)x + 11y \\ 0 &= -10x + (5 - \lambda)y \end{aligned}$$

Multiplying the second equation by  $\frac{1}{10}(-2 - \lambda)$  and adding it to the first equation, we get

$$\begin{aligned} 0 &= 0x + \left( \frac{1}{10}(-2 - \lambda)(5 - \lambda) + 11 \right) y \\ 0 &= -10x + (5 - \lambda)y \end{aligned}$$

The system will admit nontrivial solutions if

$$\begin{aligned} \frac{1}{10}(-2 - \lambda)(5 - \lambda) + 11 &= 0 \\ (-2 - \lambda)(5 - \lambda) + 110 &= 0 \\ -10 - 3\lambda + \lambda^2 + 110 &= 0 \\ \lambda^2 - 3\lambda + 100 &= 0 \end{aligned}$$

which has solutions

$$\lambda_1 = \frac{3 + i\sqrt{391}}{2}, \quad \lambda_2 = \frac{3 - i\sqrt{391}}{2}$$

Hence the eigenvalues are  $\lambda_1 = 15$  and  $\lambda_2 = -8$ .

(f)  $\det A = a_{11} \cdot a_{22} - a_{21} \cdot a_{12} = -2 \cdot 5 - (-10) \cdot 11 = -10 + 110 = 100$  This also equals  $\lambda_1 \cdot \lambda_2$  and  $\sigma_1 \cdot \sigma_2$ .

(g) The area of an ellipse is  $A = \pi ab$ , where  $a$  and  $b$  are the lengths of the ellipse axes. Thus  $A = \pi \cdot \sigma_1 \cdot \sigma_2 = \pi \cdot \sqrt{200} \cdot \sqrt{50} = 100\pi$ .

**Exercise 5.4.** Suppose  $A \in \mathbb{C}^{m \times m}$  has an SVD  $A = U\Sigma V^*$ . Find an eigenvalue decomposition of the  $2m \times 2m$  hermitian matrix

$$\begin{bmatrix} 0 & A^* \\ A & 0 \end{bmatrix}$$

**Solution:** Let  $x, y \in \mathbb{C}^m$  and set

$$B = \begin{bmatrix} 0 & A^* \\ A & 0 \end{bmatrix} \quad z = \begin{bmatrix} x \\ y \end{bmatrix}$$

That is,  $z$  is the vector in  $\mathbb{C}^{2m}$  with  $x$  stacked on top of  $y$ . If  $\lambda$  is an eigenvalue of  $B$ , then

$$\begin{aligned} Bz &= \lambda z \\ \begin{bmatrix} 0 & A^* \\ A & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} &= \lambda \begin{bmatrix} x \\ y \end{bmatrix} \\ \begin{bmatrix} A^*y \\ Ax \end{bmatrix} &= \lambda \begin{bmatrix} x \\ y \end{bmatrix} \end{aligned}$$

The equations  $A^*y = \lambda x$  and  $Ax = \lambda y$  reduce to  $A^*Ax = \lambda^2 x$  and  $AA^*y = \lambda^2 y$ . In other words, every eigenvalue of  $A^*A$  is the square of an eigenvalue of  $B$ . Thus the eigenvalues are  $\sigma_1, -\sigma_1, \dots, \sigma_n, -\sigma_n$ . In particular, the eigenvectors of  $B$  are the left and right singular vectors stacked on top of each other, of the form

$$\begin{bmatrix} v_j \\ u_j \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} v_j \\ -u_j \end{bmatrix}$$

where  $j \in \{1, \dots, m\}$ . In particular,

$$\begin{aligned} \begin{bmatrix} 0 & A^* \\ A & 0 \end{bmatrix} \begin{bmatrix} v_j \\ u_j \end{bmatrix} &= \begin{bmatrix} A^*u_j \\ Av_j \end{bmatrix} = \sigma_1 \begin{bmatrix} v_j \\ u_j \end{bmatrix} \\ \begin{bmatrix} 0 & A^* \\ A & 0 \end{bmatrix} \begin{bmatrix} v_j \\ -u_j \end{bmatrix} &= \begin{bmatrix} -A^*u_j \\ Av_j \end{bmatrix} = -\sigma_1 \begin{bmatrix} v_j \\ -u_j \end{bmatrix} \end{aligned}$$