

Homework #12

due **Thursday**, November 12, at 11:59pm

Note on the first two problems: I'm sorry these are so tedious. I made an effort to create the nicest SVD problems that I could while still exhibiting all of the intricacies of these computations, but I'm afraid these things are inherently messy. So don't be surprised if your answers have a $\sqrt{78}$ and a $\sqrt{165}$ in them. I recommend verifying your answers numerically, with [linalg.js](#) or otherwise.

1. For each matrix A , find the singular value decomposition in the outer product form

$$A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \cdots + \sigma_r u_r v_r^T.$$

$$\begin{array}{lll} \text{a) } \begin{pmatrix} 8 & 4 \\ 1 & 13 \end{pmatrix} & \text{b) } \begin{pmatrix} 1 & 3 \\ 2 & 6 \end{pmatrix} & \text{c) } \begin{pmatrix} -3 & 11 \\ 10 & -2 \\ 1 & 5 \\ -4 & 6 \end{pmatrix} \\ \text{d) } \begin{pmatrix} 9 & 7 & 10 & 8 \\ -13 & 1 & 5 & -6 \end{pmatrix} & \text{e) } \begin{pmatrix} 3 & 7 & 1 & 5 \\ 3 & 1 & 7 & 5 \\ 6 & 2 & 2 & -2 \end{pmatrix} \end{array}$$

[**Hint:** one of the singular values in **e)** is 12.]

2. For each matrix A of Problem 1, find the singular value decomposition in the matrix form

$$A = U\Sigma V^T.$$

3. For each matrix A of Problem 1, write down orthonormal bases for all four fundamental subspaces. (This can be read off from your answers to Problem 2.)
4. Consider the matrix

$$A = \begin{pmatrix} 8 & 4 \\ 1 & 13 \end{pmatrix}$$

of Problem 1(a). Let σ_1, σ_2 be the singular values of A .

a) Find *all* singular value decompositions $A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T$.

b) Find an orthonormal eigenbasis $\{v_1, v_2\}$ of $A^T A$ such that $A^T A v_i = \sigma_i^2 v_i$ and an orthonormal eigenbasis $\{u_1, u_2\}$ of $A A^T$ such that $A A^T u_i = \sigma_i^2 u_i$, such that A is *not* equal to $\sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T$.

[**Hint:** The condition $A v_i = \sigma_i u_i$ is not automatic!]

5. Find the matrix A satisfying

$$A \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \\ 2 \end{pmatrix} \quad \text{and} \quad A \begin{pmatrix} 2 \\ -2 \end{pmatrix} = \begin{pmatrix} 2 \\ 1 \\ -2 \end{pmatrix},$$

and write the SVD of A in vector form.

[**Hint:** Start by finding the SVD.]

6. Let A be a matrix with nonzero orthogonal columns w_1, \dots, w_n of lengths $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n$, respectively. Find the SVD of A in vector form.
7.
 - a) Let A be an invertible $n \times n$ matrix. Show that the product of the singular values of A equals the absolute value of the product of the (real and complex) eigenvalues of A (counted with algebraic multiplicity).
[**Hint:** Both equal $|\det(A)|$.]
 - b) Find an example of a 2×2 matrix A with distinct positive eigenvalues that are not equal to any of the singular values of A .
[**Hint:** One of the matrices in Problem 1 works.]
8. Let S be a symmetric matrix with eigenvalues $\lambda_1, \dots, \lambda_n$ (counted with multiplicity). Order the eigenvalues so that $|\lambda_1| \geq |\lambda_2| \geq \dots \geq |\lambda_r| > 0 = \lambda_{r+1} = \dots = \lambda_n$.
 - a) Show that the singular values of S are $|\lambda_1|, \dots, |\lambda_r|$. In particular, $\text{rank}(S) = r$.
 - b) Suppose that $S = QDQ^T$, where Q is orthogonal and D is the diagonal matrix with diagonal entries $\lambda_1, \dots, \lambda_n$. Show that S has a singular value decomposition of the form $U\Sigma Q^T$ (i.e., $V = Q$). How is Σ related to D ? How is U related to Q ?
 - c) Show that $S = QDQ^T$ is a singular value decomposition if and only if S is positive-semidefinite.
9.
 - a) Let A be an $m \times n$ matrix, let Q_1 be an $m \times m$ orthogonal matrix, and let Q_2 be an $n \times n$ orthogonal matrix. Show that A has the *same singular values* as Q_1AQ_2 .
[**Hint:** Use Problem 11 on Homework 9.]
Remark: This fact is heavily exploited when numerically computing the SVD: a complicated matrix is simplified by multiplying on the left and right by simple orthogonal matrices.
 - b) Show that all singular values of an orthogonal matrix are equal to 1.
10. Let A be a matrix of full column rank and let $A = QR$ be the QR decomposition of A .
 - a) Show that A and R have the same singular values $\sigma_1, \dots, \sigma_r$ and the same right singular vectors v_1, \dots, v_r .
 - b) What is the relationship between the left singular vectors of A and R ?
11. Let A be a matrix with first singular value σ_1 and first right singular vector v_1 .
 - a) Show that the maximum value of $\|Ax\|$ subject to $\|x\| = 1$ is the same as the maximum value of $\|Ax\|/\|x\|$ subject to $x \neq 0$.
 - b) Show that $\|Ax\|/\|x\|$ is maximized at $x = v_1$, with maximum value σ_1 .

[**Hint:** How do you maximize $\|Ax\|^2 = x^T(A^T A)x$ for $\|x\| = 1$?]

- c) Suppose now that A is square and λ is an eigenvalue of A . Show that $|\lambda| \leq \sigma_1$. (You may assume λ is real, although it is also true for complex eigenvalues.)

This shows that *the largest singular value is at least as big as the largest eigenvalue*.

Remark: The maximum value of $\|Ax\|/\|x\|$ for $x \neq 0$ is called the *norm* of A and is denoted $\|A\|$.

12. Let A be a square, invertible matrix with singular values $\sigma_1, \dots, \sigma_n$.

- a) Show that A^{-1} has the same singular vectors as A^T , with singular values $\sigma_n^{-1} \geq \dots \geq \sigma_1^{-1}$.

[**Hint:** Invert $A = U\Sigma V^T$.]

- b) Let λ be an eigenvalue of A . Use Problem 11(c) and a) to show that $\sigma_n \leq |\lambda|$.

13. a) Find the eigenvalues and singular values of

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{pmatrix}.$$

- b) Find the (real and complex) eigenvalues and singular values of

$$A' = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0.0001 & 0 & 0 & 0 \end{pmatrix}.$$

- c) Note that A is very close to A' numerically. Were the eigenvalues of A close to the eigenvalues of A' ? What about the singular values?

This problem is meant to illustrate the fact that *eigenvalues are numerically unstable* but *singular values are not*. This is another advantage of the SVD.

14. Decide if each statement is true or false, and explain why.

- a) The left singular vectors of A are eigenvectors of $A^T A$ and the right singular vectors are eigenvectors of AA^T .
- b) For any matrix A , the matrices AA^T and $A^T A$ have the same nonzero eigenvalues.
- c) If S is symmetric, then the nonzero eigenvalues of S are its singular values.
- d) If A does not have full column rank, then 0 is a singular value of A .
- e) Suppose that A is invertible with singular values $\sigma_1, \dots, \sigma_n$. Then for $c \geq 0$, the singular values of $A + cI_n$ are $\sigma_1 + c, \dots, \sigma_n + c$.
- f) The right singular vectors of A are orthogonal to $\text{Nul}(A)$.