

Math 218D-1: Homework #14

due Wednesday, April 26, at 11:59pm

1. For each matrix A of HW13#6:

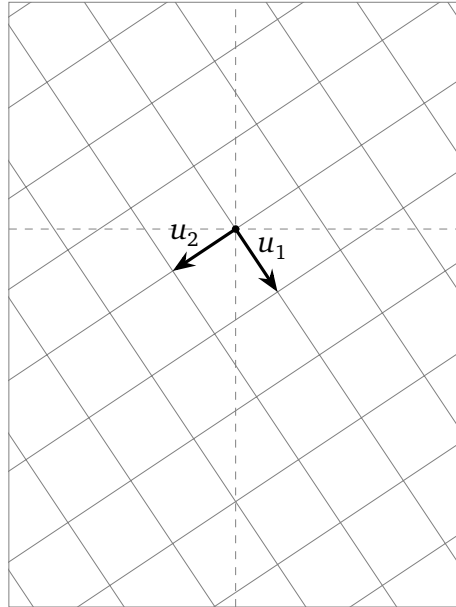
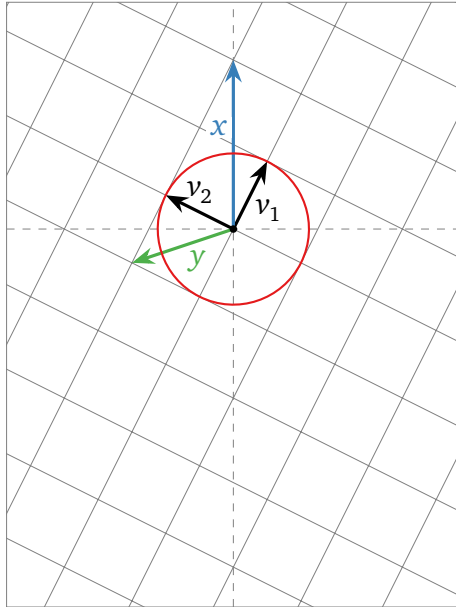
$$\begin{array}{lll} \text{a)} \begin{pmatrix} 8 & 4 \\ 1 & 13 \end{pmatrix} & \text{b)} \begin{pmatrix} 1 & 3 \\ 2 & 6 \end{pmatrix} & \text{c)} \begin{pmatrix} -3 & 11 \\ 10 & -2 \\ 1 & 5 \\ -4 & 6 \end{pmatrix} \\ \text{d)} \begin{pmatrix} 9 & 7 & 10 & 8 \\ -13 & 1 & 5 & -6 \end{pmatrix} & \text{e)}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

find the singular value decomposition in the matrix form

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

2. 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 1.)
3. 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 $|\det(A)|$. What is $\det(A^T A)$?]
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 HW13#6 works.]
4. Let S be a symmetric matrix with eigenvalues $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$. Let $S = QDQ^T$ be an orthogonal diagonalization of S , where D has diagonal entries $\lambda_1, \dots, \lambda_n$. Show that $S = QDQ^T$ is a singular value decomposition if and only if S is positive-semidefinite. [See HW13#9.]
5. 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: What is A^+ ?]
b) Let λ be an eigenvalue of A . Use HW13#12(b) and a) to show that $\sigma_n \leq |\lambda|$. It follows that the absolute values of all eigenvalues of A are contained in the interval $[\sigma_n, \sigma_1]$. Compare Problem 3.

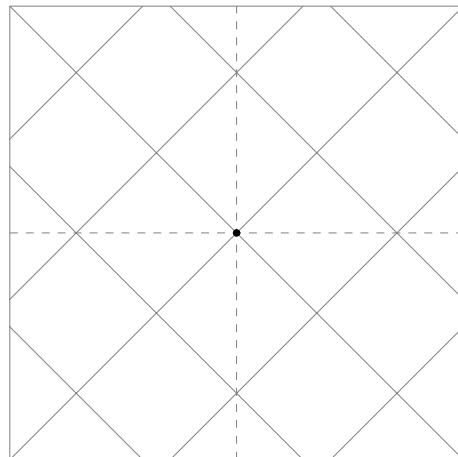
6. A certain 2×2 matrix A has singular values $\sigma_1 = 2$ and $\sigma_2 = 1.5$. The right-singular vectors v_1, v_2 and the left-singular vectors u_1, u_2 are shown in the pictures below.
- Draw Ax and Ay in the picture on the right.
 - Draw $\{Ax : \|x\| = 1\}$ (what you get by multiplying all vectors on the unit circle by A) in the picture on the right.



7. Consider the following 3×2 matrix A and its SVD:

$$A = \begin{pmatrix} 1 & 1 & 0 \\ 0 & -1 & -1 \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix} \begin{pmatrix} \sqrt{3} & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} 1/\sqrt{6} & 1/\sqrt{2} & 1/\sqrt{3} \\ 2/\sqrt{6} & 0 & -1/\sqrt{3} \\ 1/\sqrt{6} & -1/\sqrt{2} & 1/\sqrt{3} \end{pmatrix}^T.$$

Draw $\{Ax : \|x\| = 1\}$ (what you get by multiplying all vectors on the unit sphere by A) in the picture on the right.



8. Compute the pseudoinverse of each matrix of Problem 1.

9. a) Find a *left inverse* of the matrix

$$A = \begin{pmatrix} -3 & 11 \\ 10 & -2 \\ 1 & 5 \\ -4 & 6 \end{pmatrix}$$

from Problem 1(c). (This is a matrix B such that BA is the identity.)

b) Find a *right inverse* of the matrix

$$A = \begin{pmatrix} 9 & 7 & 10 & 8 \\ -13 & 1 & 5 & -6 \end{pmatrix}$$

from Problem 1(d). (This is a matrix B such that AB is the identity.)

c) Explain why the matrix

$$A = \begin{pmatrix} 1 & 3 \\ 2 & 6 \end{pmatrix}$$

from Problem 1(b) does not admit a left inverse or a right inverse.

10. Consider the matrix

$$A = \begin{pmatrix} 3 & 7 & 1 & 5 \\ 3 & 1 & 7 & 5 \\ 6 & 2 & 2 & -2 \end{pmatrix}$$

of Problem 8(e). Find the matrix P_V for projection onto $V = \text{Row}(A)$ in two ways:

a) Multiply out $P_V = A^+A$.

b) In Problem 2 you found $\text{Nul}(A) = \text{Span}\{v\}$ for $v = (1, -1, -1, 1)$. Compute $P_{V^\perp} = vv^T / v \cdot v$ and $P_V = I_4 - P_{V^\perp}$.

Your answers to a) and b) should be the same, of course!

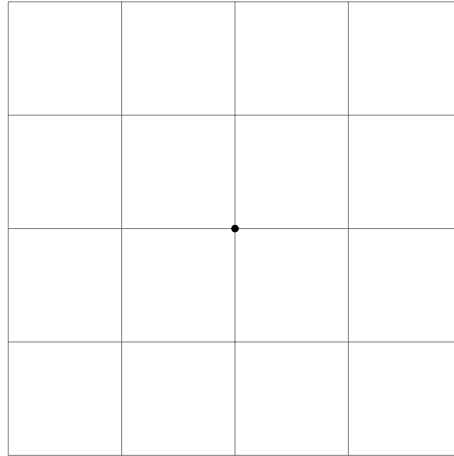
11. Let A be a matrix and let A^+ be its pseudoinverse. Match the subspaces on the left to the subspaces on the right:

$\text{Col}(A)$	$\text{Col}(A^+)$
$\text{Nul}(A)$	$\text{Nul}(A^+)$
$\text{Row}(A)$	$\text{Row}(A^+)$
$\text{Nul}(A^T)$	$\text{Nul}((A^+)^T)$

What is the rank of A^+ ?

12. What is the pseudoinverse of the $m \times n$ zero matrix?

13. Consider the matrix $A = \begin{pmatrix} 1 & 3 \\ 2 & 6 \end{pmatrix}$ of Problem 8(b).
- Find all least-squares solutions of $Ax = \begin{pmatrix} 3 \\ 1 \end{pmatrix}$ in parametric vector form.
 - Find the shortest least-squares solution $\hat{x} = A^+ \begin{pmatrix} 3 \\ 1 \end{pmatrix}$.
 - Draw your answers to **a)** and **b)** on the grid below.



14. Consider the following matrix holding 5 samples of 2 measurements each:

$$A_0 = \begin{pmatrix} 22 & -12 & 24 & -29 & 20 \\ 1 & -11 & 37 & -17 & -35 \end{pmatrix}.$$

- Subtract the means of the rows of A_0 to obtain the centered matrix A .
- Compute the covariance matrix $S = \frac{1}{5-1}AA^T$. What is the total variance? What is the covariance of the first row with the second?
- Compute the variance $s(u)^2$ of your data points in the directions

$$u = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix}.$$
- Find the eigenvalues λ_1, λ_2 and unit eigenvectors u_1, u_2 of S . What direction is the first principal component? What is the variance of A in that direction? (It should be larger than the variances you computed in **c**.)
- Find the orthogonal projections of the columns of A onto the first principal component by computing the first summand $\sigma_1 u_1 v_1^T$ of the SVD of A . (Don't forget to rescale by $\sqrt{5-1}$.)
- Draw the columns of A , the first principal component you found in **d**), and the orthogonal projections you found in **e**) on a grid.

15. Let A be a matrix with singular value decomposition

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

Show that A is a centered data matrix (rows sum to zero) if and only if the entries of each right singular vector v_i sum to zero.

[Hint: Multiply by the ones vector $\mathbf{1} = (1, 1, \dots, 1)$.]

16. Let A be a matrix with singular value decomposition

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

Recall that the maximum value of $\|Ax\|$ subject to $\|x\| = 1$ is σ_1 , and is achieved at $x = v_1$.

- a) Show that the maximum value of $\|Ax\|$ subject to the conditions $\|x\| = 1$ and $x \cdot v_1 = 0$ is equal to σ_2 , and is achieved at $x = v_2$.

[Hint: If $x \cdot v_1 = 0$ then $Ax = A'x$ for $A' = \sigma_2 u_2 v_2^T + \sigma_3 u_3 v_3^T + \cdots + \sigma_r u_r v_r^T$.]

- b) More generally, show that the maximum value of $\|Ax\|$ subject to the conditions $\|x\| = 1$ and $x \cdot v_1 = 0, x \cdot v_2 = 0, \dots, x \cdot v_j = 0$ is equal to σ_{j+1} , and is achieved at $x = v_{j+1}$.

- c) If A has full column rank, show that the *minimum* value of $\|Ax\|$ subject to $\|x\| = 1$ is equal to σ_r , and is achieved at $x = v_r$.

In the language of principal component analysis, this says that v_2 is the direction of *second-largest variance*, etc.

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

- a) If A is a matrix of rank r , then A is a linear combination of r rank-1 matrices.

- b) If A is a matrix of rank 1, then A^+ is a scalar multiple of A^T .

- c) If $A = U\Sigma V^T$ is the SVD of A , then the SVD of A^+ is $A^+ = V\Sigma^+ U^T$.