

# Assignment 4: Singular Value Decomposition

## Math 327/397 Winter 2023

Due: Tuesday, March 28, 2023

### Instructions

Submit a copy on myCourses by midnight on the due date or on paper in class. Include a printout of your Matlab m-files as well as output. Questions 1 – 5 are for everyone. Question 6 is for Math 397, and this time also gives +5 points bonus for Math 327.

### Question 1: Geometry of the SVD

- (a)(3pts) Let  $\Sigma = \text{diag}(3, 2, 0) \in \mathbb{R}^{3 \times 3}$ , and let the unit ball in the domain be described by  $\{x \in \mathbb{R}^3 : \|x\|_2 \leq 1\}$ . Using set notation as well as in words, describe the image of this unit ball under action by  $\Sigma$ . Which subset of the surface of the unit ball maps to the surface of the image object?
- (a)(7pts) Here we generalize part (a). A  $k$ -dimensional ellipse, surface and interior, with axes along the standard coordinates is algebraically defined as the set of points  $z = (z_1, z_2, \dots, z_k)^T$  satisfying  $\left(\frac{z_1}{\alpha_1}\right)^2 + \dots + \left(\frac{z_k}{\alpha_k}\right)^2 \leq 1$ . Note that we can have a  $k$ -dimensional ellipse embedded inside  $\mathbb{R}^n$  even in the case  $n > k$  by allowing some of the  $z_j$  to be identically zero. Using these definitions, show that the matrix  $\Sigma = \text{diag}(\sigma_1, \dots, \sigma_{\min(m,n)}) \in \mathbb{R}^{m \times n}$ , where  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_{\min(m,n)} \geq 0$ , maps the unit sphere  $\{x \in \mathbb{R}^n : \|x\|_2 \leq 1\}$ , surface and interior, to an ellipse embedded in  $\mathbb{R}^m$ . Under what conditions is the surface of the unit sphere mapped to the surface of the ellipse? (Suggestion: it may be handy to consider the cases  $m \geq n$  and  $n > m$  separately. Also, some of the axes of the ellipse may be zero, so it may be convenient to introduce  $r \leq \min(m, n)$  such that  $\sigma_1 \geq \dots \geq \sigma_r > 0$ .) In case the surface of the unit ball in the domain doesn't fully map to the surface of the image ellipse, write down into a partition of two sets, the parts of the unit ball which do map to the surface of the ellipse in the image, versus the parts which map to the interior.

## Question 2: Geometry of the SVD with Matlab

Write a matlab function `plotMatrixImage(A,N,n)` which does the following:

- partitions the unit 2-D unit circle into  $N$  equally spaced angles, computes the  $x$  and  $y$  values for these and plots the circle.
- plots the image of that circle under multiplication by the 2-by-2 matrix  $A$ .
- generates  $n$  random points drawn from the normal distribution using `randn(2,n)`, plots them and also plots their image under multiplication by  $A$ .

Show the output for `plotMatrixImage(A,20,100)`, `plotMatrixImage(A,20,1000)`, and `plotMatrixImage(A,20,10000)` for the matrix  $A = \begin{bmatrix} 1 & 2 \\ 2 & 3 \end{bmatrix}$ . This should give you three different figures where each time the function is run you plot all elements on a single figure, using the same scaling for the  $x$  and  $y$  axes.

## Question 3: SVD as an Analytic Tool

Consider  $A \in \mathbb{R}^{m \times n}$  and its (full) SVD  $A = U\Sigma V^T$ . Justifying your answers and using this SVD answer the following questions:

- (4pts) Express  $\text{Null}(A)$ ,  $\text{Range}(A)$ ,  $\text{Range}(A)^\perp$ . What is the dimension of each of these spaces? Here  $\text{Range}(A)^\perp$  is the subspace of  $\mathbb{R}^m$  orthogonal to the column space of  $A$ .
- (2pts) show that  $\dim \text{colspace } A = \dim \text{rowspan } A$ , i.e. the column and row ranks are the same. This justifies the single notion of *rank* for  $A$ .
- (2pts) What are the 2 and Frobenius norms of  $A$ ?
- (2pts) What are the eigenvalues of  $A^T A$ ? What about  $AA^T$ ?

## Question 4: SVD as a Computational Tool

Let  $A \in \mathbb{R}^{5 \times 4}$  have full SVD

$$A = U\Sigma V^T = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ \frac{1}{\sqrt{3}} & 0 & \frac{-1}{\sqrt{2}} & 0 & \frac{-1}{\sqrt{6}} \\ \frac{-1}{\sqrt{3}} & 0 & \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{6}} \\ \frac{1}{\sqrt{3}} & 0 & 0 & 0 & \frac{2}{\sqrt{6}} \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 4 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

- (2pts) What are  $\|A\|_2$ ,  $\|A\|_F$ ,  $\|U\|_2$  and  $\text{rank}(A)$ ?

- (b)(2pts) State the dimension and a basis (if nontrivial) for each of  $\text{range}(A)$  and  $\text{null}(A)$ .
- (c)(2pts) State the reduced SVD of  $A$ .
- (d)(2pts) State  $A^T A$  as a product of three  $4 \times 4$  matrices. What are the eigenvalues and singular values of  $A^T A$ ?
- (e)(2pts) Let  $A_2$  be the best rank-2 approximation to  $A$  in the 2-norm. What is  $\|A - A_2\|_2$ ? State  $A_2$ . You do not need to compute the matrix, either state it as a sum of appropriate terms that you define or as a product of matrices.

## Question 5: Compression with SVD - Application

Download the  $256 \times 256$  image matrix  $A.mat$  from MyCourses, and read it into Matlab using `load A`. To see that it is an image execute (on the same line) `imagesc(A); colormap(gray)`; We'll use the SVD to compute low rank approximations to  $A$ .

- (a)(3pts) Using Matlab's command  $[U, S, V] = \text{svd}(A)$ , find the SVD of  $A$  and then compute the best (in the 2-norm) rank  $k$  approximations  $A_k$  to  $A$  for  $k = 1, 2, 4, 16, 64$ . Plot them and compare visually with the original image.
- (b)(3pts) Using Matlab's command `norm` compute the error of  $A_k$  relative to  $A$ , i.e,  $E_k := \|A - A_k\|_2 / \|A\|_2$ , and plot a graph of  $E_k$  against  $k$ . Also plot the ratio  $\sigma_i / \sigma_1$  of  $A$  against  $i$  for  $i = 1, \dots, 256$ . Comment on the two graphs. How large should  $k$  be to ensure that  $E_k = \|A_k - A\|_2 / \|A\|_2 \leq 0.05$ ?
- (c)(4pts) Let  $A = \sum_{j=1}^{\min(m,n)} \sigma_j u_j v_j^T \in \mathbb{R}^{m \times n}$  represent the sum-of-rank-one matrices SVD of  $A$ , where the  $u_j$  are the left singular vectors,  $v_j$  are the right singular vectors and  $\sigma_j$  are ranked in decreasing order. Assuming that  $\text{rank}(A) \geq k$ , show that the best rank  $k$  approximation of  $A$  in the matrix 2-norm is given by  $A_k = \sum_{j=1}^k \sigma_j u_j v_j^T$ .

## Question 6 (Math 397), +5 bonus (Math 327): Least Squares for Non-Full Column Rank Matrices

If  $A \in \mathbb{R}^{m \times n}$  is non-full column rank and  $y \in \mathbb{R}^m$ , using the SVD describe the solution set to  $\min_{x \in \mathbb{R}^n} \|y - Ax\|_2$ ? Justify.