1. Let **A** be an  $m \times n$  matrix, set  $p = \min(m, n)$ , and suppose that the singular value decomposition of **A** takes the form

$$\mathbf{A} = \mathbf{U} \quad \mathbf{D} \quad \mathbf{V}^*$$
$$m \times n \qquad m \times p \quad p \times p \quad p \times n.$$
(1)

Let k be an integer such that  $1 \leq k < p$  and let  $\mathbf{A}_k$  denote the truncation of the SVD to the first k terms:

$$\mathbf{A}_k = \mathbf{U}(:, 1:k)\mathbf{D}(1:k, 1:k)\mathbf{V}(:, 1:k)^*$$

Prove directly from the definition of the spectral and Frobenius norms that

$$\|\mathbf{A} - \mathbf{A}_k\| = \sigma_{k+1} \tag{2}$$

and that

$$\|\mathbf{A} - \mathbf{A}_k\|_F = \left(\sum_{j=k+1}^p \sigma_j^2\right)^{1/2}.$$
 (3)

Solution: First, partition the factorization  $UDV^*$  as

$$m \begin{bmatrix} \mathbf{U}_1 & \mathbf{U}_2 \\ k & p-k \end{bmatrix} p-k \begin{bmatrix} \mathbf{D}_1 & 0 \\ 0 & \mathbf{D}_2 \\ k & p-k \end{bmatrix} p-k \begin{bmatrix} \mathbf{V}_1^* \\ \mathbf{V}_2^* \\ n \end{bmatrix}.$$

Then observe that  $\mathbf{U}_1 = \mathbf{U}(:, 1:k)$ ,  $\mathbf{D}_1 = D(1:k, 1:k)$ , and  $\mathbf{V}_1^* = V(:, 1:k)^*$ , so that  $\mathbf{A}_k = \mathbf{U}_1 \mathbf{D}_1 \mathbf{V}_1^*$ . By carrying out block multiplication on the partitioned factorization, we see that

$$\mathbf{A} = \mathbf{U}_1 \mathbf{D}_1 \mathbf{V}_1^* + \mathbf{U}_2 \mathbf{D}_2 \mathbf{V}_2^* = \mathbf{A}_k + \mathbf{U}_2 \mathbf{D}_2 \mathbf{V}_2^*,$$

 $\mathbf{SO}$ 

$$\mathbf{A} - \mathbf{A}_k = \mathbf{U}_2 \mathbf{D}_2 \mathbf{V}_2^*. \tag{4}$$

(a) First we'll show that  $\|\mathbf{A} - \mathbf{A}_k\| = \sigma_{k+1}$ . Let  $\mathbf{x} \in \mathbb{R}^n$  be any vector such that  $\|\mathbf{x}\| = 1$ . We will show that  $\|(\mathbf{A} - \mathbf{A}_k)\mathbf{x}\| \leq \sigma_{k+1}$ . We establish the notation that  $\mathbf{v}_i$  and  $\mathbf{u}_i$  are the columns of  $\mathbf{V}$  and  $\mathbf{U}$ , respectively. Since the columns of  $\mathbf{V}$  are orthonormal we can construct an orthonormal basis of  $\mathbb{R}^n$ :  $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_p, \mathbf{v}_{p+1}, \dots, \mathbf{v}_n\}$  (note that vectors  $\mathbf{v}_{p+1}$  through  $\mathbf{v}_n$ 

are not actually columns of  ${\bf V}$  but are simply used to construct the basis), and thus

$$\mathbf{x} = \sum_{i=1}^{n} c_i \mathbf{v}_n$$

for some  $c_i, i = 1, \ldots, n$ . Now, we have that

$$(\mathbf{A} - \mathbf{A}_k)\mathbf{x} = \mathbf{U}_2\mathbf{D}_2\mathbf{V}_2^*\mathbf{x}$$

Since the *i*-th entry of  $\mathbf{V}_2^* \mathbf{x}$  is  $\langle \mathbf{v}_i, \mathbf{x} \rangle$ , and since  $\mathbf{x}$  is a linear combination of the orthonormal basis  $\{\mathbf{v}_i\}_{i=1}^n$ ,

$$\mathbf{V}_2^* \mathbf{x} = \begin{bmatrix} c_{k+1} \\ c_{k+2} \\ \vdots \\ c_p \end{bmatrix},$$

and so

$$\mathbf{U}_2 \mathbf{D}_2 \mathbf{V}_2^* \mathbf{x} = \sum_{i=k+1}^p c_i \sigma_i \mathbf{u}_i$$

which implies

$$\|\mathbf{U}_2\mathbf{D}_2\mathbf{V}_2^*\mathbf{x}\| \le \sigma_{k+1}\|\sum_{i=k+1}^p c_i\mathbf{u}_i\|.$$

Finally, by the orthonormality of  $\{\mathbf{u}_i\}_{i=1}^p$ ,

$$\|\sum_{i=k+1}^{p} c_i \mathbf{u}_i\|^2 = \sum_{i=k+1}^{p} c_i^2,$$

and by the orthonormality of  $\{\mathbf{v}_i\}_{i=1}^n$ ,

$$1 = \|\mathbf{x}\|^2 = \|\sum_{i=1}^n c_i \mathbf{v}_n\|^2 = \sum_{i=1}^n c_i^2 \implies \sum_{i=k+1}^p c_i^2 \le 1,$$

and therefore

$$\|(\mathbf{A} - \mathbf{A}_k)\mathbf{x}\| \le \sigma_{k+1} \|\sum_{i=k+1}^p c_i \mathbf{u}_i\| \le \sigma_{k+1}$$

Thus, we have shown that  $\|\mathbf{A} - \mathbf{A}_k\| \leq \sigma_{k+1}$ . Next, we observe that for  $\mathbf{x} = \mathbf{v}_{k+1}$ ,

$$\|(\mathbf{A} - \mathbf{A}_k)\mathbf{x}\| = \|\sigma_{k+1}\mathbf{u}_{k+1}\| = \sigma_{k+1}\|\mathbf{u}_{k+1}\| = \sigma_{k+1},$$

so since  $\|\mathbf{v}_{k+1}\| = 1$ ,  $\|\mathbf{A} - \mathbf{A}_k\| \ge \sigma_{k+1}$ . Therefore,

$$\|\mathbf{A} - \mathbf{A}_k\| = \sigma_{k+1}.$$

(b) Next, we'll prove (3). We have that  $\|\mathbf{A} - \mathbf{A}_k\|_F = \|\mathbf{U}_2\mathbf{D}_2\mathbf{V}_2^*\|_F$ , and we claim that  $\|\mathbf{U}_2\mathbf{D}_2\mathbf{V}_2^*\|_F = \|\mathbf{D}_2\|_F$ . Let  $\mathbf{y}_i, i = 1, 2, \ldots, n$  be the columns of  $\mathbf{D}_2\mathbf{V}_2^*$ . Then we have

$$\|\mathbf{U}_{2}\mathbf{D}_{2}\mathbf{V}_{2}^{*}\|_{F}^{2} = \sum_{i=1}^{n} \|\mathbf{U}_{2}\mathbf{y}_{i}\|_{2}^{2} = \sum_{i=1}^{n} \langle \mathbf{U}_{2}\mathbf{y}_{i}, \mathbf{U}_{2}\mathbf{y}_{i} \rangle = \sum_{i=1}^{n} \|\mathbf{y}_{i}\|_{2}^{2} = \|\mathbf{D}_{2}\mathbf{V}_{2}^{*}\|_{F}^{2}$$

by the orthonormality of  $\mathbf{U}_2$ , which implies

$$\|\mathbf{U}_2\mathbf{D}_2\mathbf{V}_2^*\|_F = \|\mathbf{D}_2\mathbf{V}_2^*\|_F.$$

Similarly, since the columns of  $\mathbf{V}_2$  are orthonormal, we have

$$\|\mathbf{D}_{2}\mathbf{V}_{2}^{*}\|_{F} = \|(\mathbf{D}_{2}\mathbf{V}_{2}^{*})^{*}\|_{F} = \|\mathbf{V}_{2}\mathbf{D}_{2}\|_{F} = \|\mathbf{D}_{2}\|_{F}.$$

Then we can compute  $\|\mathbf{D}_2\|_F$  directly to obtain

$$\|\mathbf{A} - \mathbf{A}_k\|_F = \|\mathbf{D}_2\|_F = \left(\sum_{j=k+1}^p \sigma_j^2\right)^{1/2}.$$