

# MATH 327 Assignment 4

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## Question 1

First we deduce

$$\|A\|_F^2 = \sum_{i,j} |A_{ij}|^2 = \sum_i \left( \sum_j A_{ij}^T A_{ji} \right) = \sum_i (A^T A)_{ii} = \text{tr}(A^T A) = \text{tr}(A A^T).$$

So then,

$$\begin{aligned} \|A\|_F^2 &= \sum_i \sum_j |a_{ij}|^2 = \text{tr}(A A^T) \\ &= \text{tr}((U \Sigma V^T)(U \Sigma V^T)) \\ &= \text{tr}((U \Sigma V^T)(\Sigma V^T)^T U^T) \\ &= \text{tr}((U \Sigma V^T) V \Sigma^T U^T) \\ &= \text{tr}(\Sigma \Sigma^T) = \sum_i (\sigma_i)^2 \end{aligned}$$

Thus indeed,

$$\|A\|_F = \sqrt{\sum_i (\sigma_i)^2}.$$

## Question 2

(a)

For each row multiplication, there are  $n - 1$  additions and  $n$  multiplications, so for  $m$  rows in total that is  $(n - 1)m + nm = m(2n - 1)$  operations in total.

(b)

For  $v_i^T x$ , we have  $2n - 1$  operations. Multiplying by  $u_i$  from the left that is a total of  $(2n - 1) + m$  operations. And finally, multiplying by the constant  $\sigma_i$  we conclude there are a total of  $(2n - 1) + 2m$  operations.

(c)

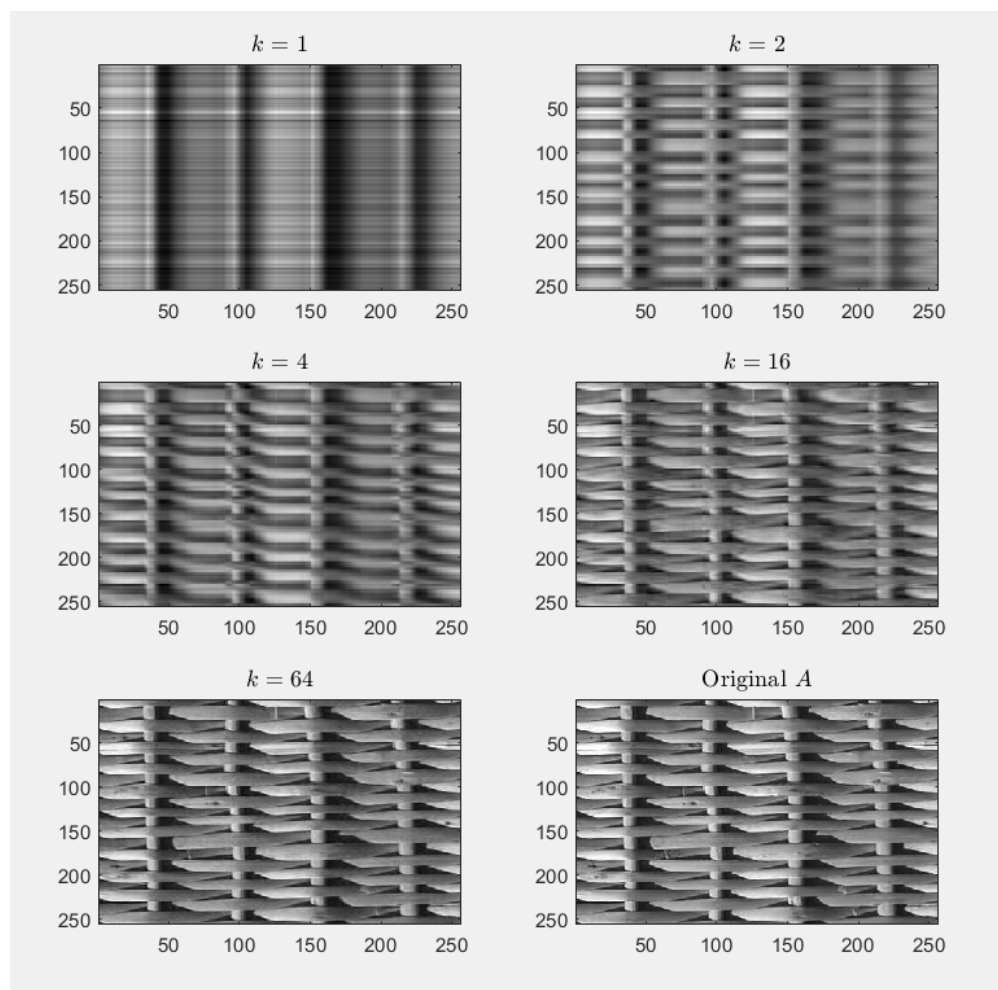
We start by  $\sigma_i u_i$  which encompasses  $m$  operations. Then,  $(\sigma_i u_i) v_i^T$  is an outer product and represents  $m + mn$  operations. Summing over  $k$  we get  $(m + mn)(k - 1)$  operations with an additional  $(k - 1)mn$  operations for summing up the matrices. Finally, from (a) we know that  $Ax$  requires  $m(2n - 1)$  operations so we conclude that

$$A_k(x) \rightarrow (m + mn)(k - 1) + (k - 1)mn + m(2n - 1) \text{ operations.}$$

Evidently it is more efficient to compute  $Ax$  instead of  $A_k x$ . There is an additional  $(k - 1)(m + mn) + (k - 1)m$  operations within the latter case so for  $k, m, n \geq 1$  the  $Ax$  is more efficient.

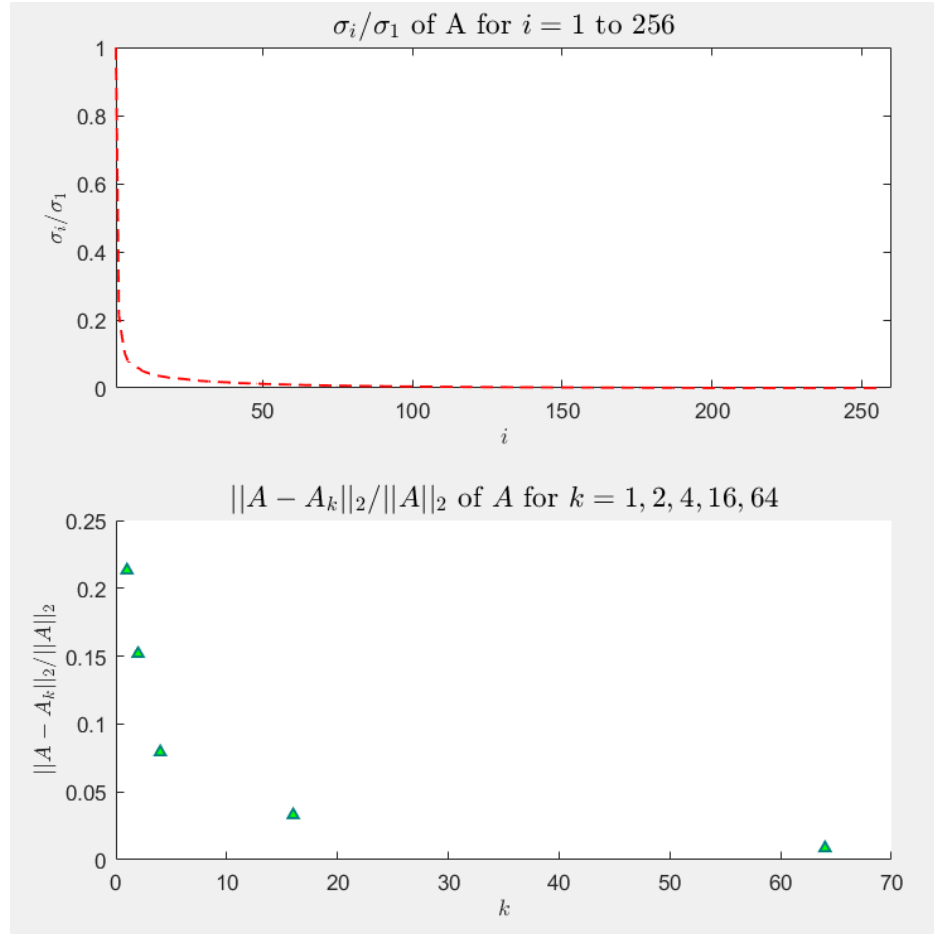
**Question 3**

(a)



**Figure 1:** SVD decomposition for  $k$  approximations of 1, 2, 4, 16, 64, compared to the original picture defined by  $A$ .

(b)

**Figure 2**

The largest value of  $k$  is 9 and is found using the following code snippet :

```

A_k_list = [];
[U,S,V] = svd(A);
i=1;
for k=1:64
    Ak = U(:,1:k)*S(1:k,1:k)*V(:,1:k)';
    A_k_list{i} = Ak;
    if (norm(A-A_k_list{i},2)/norm(A,2) <=0.05)
        largest_k = k;
        break;
    end
    i=i+1;
end
end

```

**Question 4**

(a)

- $\|A\|_2 = \max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} = \max_i \sigma_i(A) = 4.$
- $\|A\|_F = \sqrt{\sum_i \sigma_i^2} = \sqrt{30}.$
- Since  $\|QA\| = \|A\|$  for  $Q \perp$ . Then  $\|U\|_2 = 1.$
- By inspection of  $\Sigma$ , we deduce that  $\text{rank}(A) = 4.$

(b)

$$\mathcal{R}(A) = \text{Span}\{u_1, \dots, u_r\} \xrightarrow{\text{basis}} \begin{pmatrix} 0 \\ 1/\sqrt{3} \\ -1/\sqrt{3} \\ 1/\sqrt{3} \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ -1/\sqrt{2} \\ -1/\sqrt{2} \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} \quad \dim(\mathcal{R}(A)) = 4$$

$$\mathcal{N}(A) = \text{Span}\{v_{r+1}, \dots, v_n\} \rightarrow \text{no basis since} \quad \dim(\mathcal{N}(A)) = 0.$$

(c)

Let  $U = [U_1 \ U_2]$  and  $\Sigma = [\hat{\Sigma} \ 0]^T$  for  $U_{m \times m}$ ,  $U_{1,m \times n}$ ,  $U_{2,m \times (m-n)}$ ,  $\Sigma_{m \times n}$  and  $\hat{\Sigma}_{n \times n}$ . Then we state ;

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1/\sqrt{3} & 0 & -1/2 & 0 \\ -1/3 & 0 & -1/2 & 0 \\ -1/3 & 0 & -1/2 & 0 \\ 1/3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 4 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

(d)

$$A^T A = (U \Sigma V^T)^T (U \Sigma V^T) = V \Sigma^T U^T U \Sigma V^T = V (\hat{\Sigma})^2 V^T.$$

Here  $\hat{\Sigma}$  is diagonal so  $\sigma_i(A^T A) = \sigma_i^2(\hat{\Sigma}) = \{16, 9, 4, 1\}$ . Moreover, the eigenvalues of  $A^T A$  are the same as the singular values in the present case.

(e)

We use the definition ;

$$\frac{\|A - A_2\|_2}{\|A\|_2} = \frac{1}{\kappa_2(A)} \Rightarrow \frac{\min_{x \neq 0} \|Ax\|_2 / \|x\|_2}{\max_{x \neq 0} \|Ax\|_2 / \|x\|_2} \|A\|_2 = \frac{\sigma_{\min}(A)}{\sigma_{\max}(A)} \sigma_{\max}(A) = \frac{1}{4} 4 = 1.$$

Moreover,

$$A_2 = U(:, 1:2) \Sigma(1:2, 1:2) V(:, 1:2)^T = \begin{pmatrix} 0 & 1 \\ 1/\sqrt{3} & 0 \\ -1/\sqrt{3} & 0 \\ 1/\sqrt{3} & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} 4 & 0 \\ 0 & 3 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & 0 \end{pmatrix}.$$

## Question 5

(a)

$$A = \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix} \sim \begin{pmatrix} 1 & 2 & 3 \\ 0 & 1 & 2 \\ 0 & 1 & 2 \end{pmatrix} \rightarrow \text{Rank}(A) = 2.$$

(b)

It returns  $1 \times 10^{-15}$  which is actually the machine precision. This arises from the  $\text{svd}(A)$  function called. The answer therefore does not contradict that from (a).