# Recall:

1) If A is  $n \times n$  symmetric matrix then A can be written as a product

$$A = QDQ^T$$

where:

- $Q = [\mathbf{u}_1 \ \mathbf{u}_2 \ \dots \ \mathbf{u}_n]$  is an orthogonal matrix.
- *D* is diagonal matrix:

$$D = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \dots & \lambda_n \end{bmatrix}$$

2) Spectral decomposition of a symmetric matrix:

$$A = \lambda_1(\mathbf{u}_1\mathbf{u}_1^T) + \lambda_2(\mathbf{u}_2\mathbf{u}_2^T) + \ldots + \lambda_n(\mathbf{u}_n\mathbf{u}_n^T)$$

where  $|\lambda_1| \ge |\lambda_2| \ge \ldots \ge |\lambda_n|$ .

#### Theorem

Any A an  $m \times n$  matrix can be written as a product

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

where:

- $U = [ \mathbf{u}_1 \dots \mathbf{u}_m ]$  is an  $m \times m$  orthogonal matrix.
- $V = [v_1 \dots v_n]$  is an  $n \times n$  orthogonal matrix.
- $\Sigma$  is an  $m \times n$  matrix of the following form:

$$\begin{bmatrix} \sigma_{1} & 0 & \cdots & 0 \\ 0 & \sigma_{2} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & \sigma_{n} \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & \vdots & \vdots & \ddots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & \sigma_{m} & 0 & \cdots & 0 \end{bmatrix}$$
(if  $n \leq m$ )
$$(\text{if } n \geq m)$$

where  $\sigma_1 \geq \sigma_2 \geq \ldots \geq 0$ .

#### Note.

- The numbers  $\sigma_1, \sigma_2, \ldots$  are called *singular values* of A.
- The vectors  $\mathbf{u}_1, \dots, \mathbf{u}_m$  are called *left singular vectors* of A.
- Then the vectors  $v_1, \ldots, v_n$  are called *right singular vectors* of A.
- The formula  $A = U \Sigma V^T$  is called a *singular value decomposition (SVD)* of A.
- ullet The matrix  $oldsymbol{\Sigma}$  is uniquely determined, but U and V depend on some choices.

### **Theorem**

Let A be a matrix with a singular value decomposition

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

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$$U = [\mathbf{u}_1 \dots \mathbf{u}_m] \qquad V = [\mathbf{v}_1 \dots \mathbf{v}_n]$$

and  $\sigma_1, \ldots, \sigma_r$  are singular values of A then then

$$A = \sigma_1(\mathbf{u}_1\mathbf{v}_1^T) + \sigma_2(\mathbf{u}_2\mathbf{v}_2^T) + \ldots + \sigma_r(\mathbf{u}_r\mathbf{v}_r^T)$$

# Example:

$$A = U \cdot \Sigma \cdot V^{T} = [u_{1} \ u_{2} \ u_{3}] \cdot \begin{bmatrix} \sigma_{1} & O \\ O & \sigma_{2} \\ O & O \end{bmatrix} \cdot \begin{bmatrix} v_{1}^{T} \\ v_{2}^{T} \end{bmatrix}$$

$$= [\sigma_{1} \ u_{1} \ \sigma_{2} u_{2}] \cdot \begin{bmatrix} v_{1}^{T} \\ v_{2}^{T} \end{bmatrix}$$

$$= \sigma_{1}(u_{1} v_{1}^{T}) + \sigma_{2}(u_{2} v_{2}^{T})$$

# Application: Image compression



- $\bullet$  The size of this image is  $800 \times 700$  pixels.
- The color of each pixel is represented by an integer between 0 (black) and 255 (white).
- The whole image is described by a matrix A consisting of  $800 \times 700 = 560,000$  numbers.
- Each number is stored in 1 byte, so the image file size is 560,000 bytes ( $\approx 0.53$  MB).

## How to make the image file smaller:

**1)** Compute SVD of the matrix *A*:

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

where

$$U = [\mathbf{u}_1 \dots \mathbf{u}_m] \qquad V = [\mathbf{v}_1 \dots \mathbf{v}_n]$$

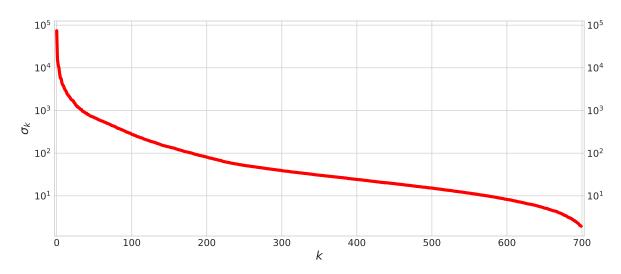
and  $\sigma_1, \ldots, \sigma_r$  are singular values of A.

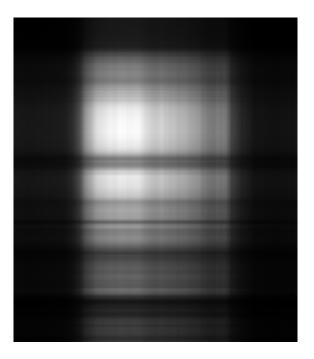
2) Replace A by the matrix

$$B_k = \sigma_1(\mathbf{u}_1\mathbf{v}_1^T) + \ldots + \sigma_k(\mathbf{u}_k\mathbf{v}_k^T)$$

for some  $1 \le k \le 700$ . This matrix can be stored using  $k \cdot (800 + 700 + 1)$  numbers.

# Singular values of the matrix A





matrix B<sub>1</sub> 1501 bytes compression 374:1



matrix B<sub>5</sub> 7905 bytes compression 75:1



matrix  $B_{10}$ 15,010 bytes compression 37:1



 $\begin{array}{l} \textbf{matrix} \ B_{20} \\ 30,020 \ bytes \\ \textbf{compression} \ 18:1 \end{array}$ 



matrix B<sub>50</sub> 75,050 bytes compression 7:1



matrix B<sub>100</sub> 150,100 bytes compression 4:1