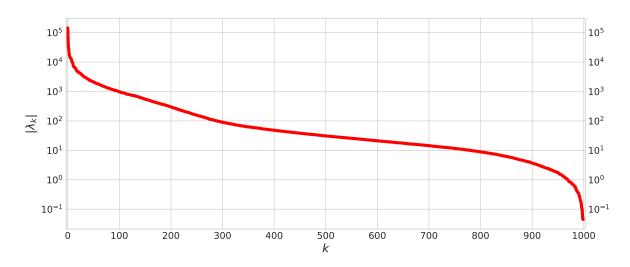
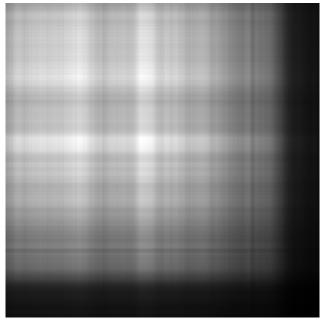
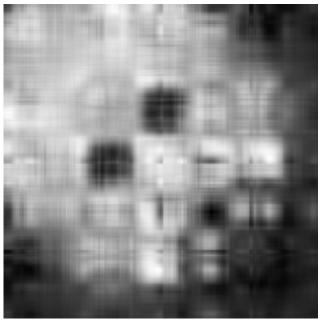
## Eigenvalues of the matrix A

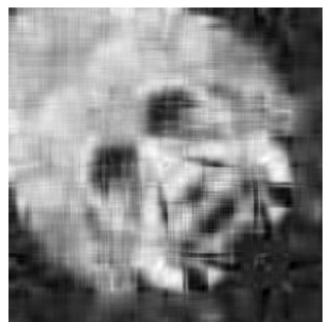




matrix B<sub>1</sub> 1001 bytes compression 1000:1



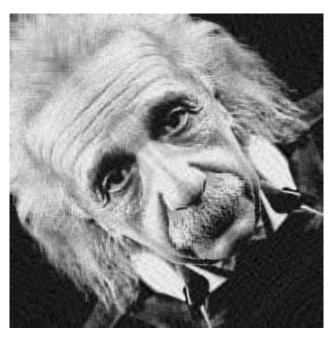
matrix B<sub>5</sub> 5005 bytes compression 200:1



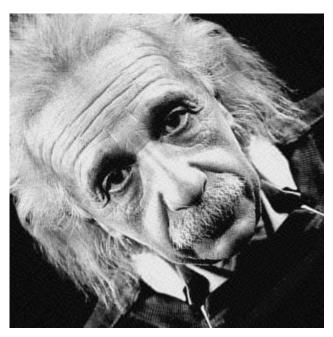
matrix B<sub>10</sub> 10,010 bytes compression 100:1



 $\begin{array}{l} \textbf{matrix} \ B_{20} \\ 20,020 \ bytes \\ \textbf{compression} \ 50:1 \end{array}$ 



 $\begin{array}{l} \textbf{matrix} \ B_{50} \\ 50,\!050 \ bytes \\ \textbf{compression} \ 20:1 \end{array}$ 



 $\begin{array}{l} \textbf{matrix} \ B_{100} \\ 100,100 \ bytes \\ \textbf{compression} \ 10:1 \end{array}$ 

## 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:

$$\begin{bmatrix} \sigma_{1} & 0 & \cdots & 0 \\ 0 & \sigma_{2} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & \sigma_{n} \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & \vdots & \vdots & \ddots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & \sigma_{m} & 0 & \cdots & 0 \end{bmatrix}$$

$$(\text{if } n \leq m)$$

$$(\text{if } n \geq m)$$

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  $\Sigma$  is uniquely determined, but U and V depend on some choices.