Singular Value Decomposition
(matrix factorization)

Singular Value Decomposition

The SVD is a factorization of a $m \times n$ matrix into

$$\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}$$

where $\boldsymbol{U}$ is a $m \times m$ orthogonal matrix, $\boldsymbol{V}^{\boldsymbol{T}}$ is a $n \times n$ orthogonal matrix and $\boldsymbol{\Sigma}$ is a $m \times n$ diagonal matrix.

For a square matrix ($\boldsymbol{m} = \boldsymbol{n}$):

$$\sigma_1 \geq \sigma_2 \geq \sigma_3 \ldots$$

$$\boldsymbol{A} = \begin{pmatrix} \vdots & \ldots & \vdots \\ \boldsymbol{u}_1 & \ldots & \boldsymbol{u}_n \\ \vdots & \ldots & \vdots \end{pmatrix} \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{pmatrix} \begin{pmatrix} \ldots & \mathbf{v}_1^T & \ldots \\ \vdots & \vdots & \vdots \\ \ldots & \mathbf{v}_n^T & \ldots \end{pmatrix}$$

$$\boldsymbol{A} = \begin{pmatrix} \vdots & \ldots & \vdots \\ \boldsymbol{u}_1 & \ldots & \boldsymbol{u}_n \\ \vdots & \ldots & \vdots \end{pmatrix} \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{pmatrix} \begin{pmatrix} \vdots & \ldots & \vdots \\ \boldsymbol{v}_1 & \ldots & \boldsymbol{v}_n \\ \vdots & \ldots & \vdots \end{pmatrix}^T$$

Reduced SVD

What happens when $\boldsymbol{A}$ is not a square matrix?

1) $\boldsymbol{m > n}$

$$\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^T = \begin{pmatrix} \vdots & \dots & \vdots & \dots & \vdots \\ \boldsymbol{u}_1 & \dots & \boldsymbol{u}_n & \dots & \boldsymbol{u}_m \\ \vdots & \dots & \vdots & \dots & \vdots \end{pmatrix} \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \\ & & 0 \\ & & \vdots \\ & & 0 \end{pmatrix} \begin{pmatrix} \dots & \mathbf{v}_1^T & \dots \\ \vdots & \vdots & \vdots \\ \dots & \mathbf{v}_n^T & \dots \end{pmatrix}$$

$m \times m$ $\quad$ $m \times n$ $\quad$ $n \times n$

We can instead re-write the above as:

$$\boldsymbol{A} = \boldsymbol{U}_{\boldsymbol{R}}\,\boldsymbol{\Sigma}_{\boldsymbol{R}}\boldsymbol{V}^{\boldsymbol{T}}$$

Where $\boldsymbol{U}_{\boldsymbol{R}}$ is a $m \times n$ matrix and $\boldsymbol{\Sigma}_{\boldsymbol{R}}$ is a $n \times n$ matrix

Reduced SVD

2) $\boldsymbol{n > m}$

$$\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{T} = \begin{pmatrix} \vdots & \cdots & \vdots \\ \boldsymbol{u}_1 & \cdots & \boldsymbol{u}_m \\ \vdots & \cdots & \vdots \end{pmatrix} \begin{pmatrix} \sigma_1 & & & 0 & & \\ & \ddots & & & \ddots & \\ & & \sigma_m & & & 0 \end{pmatrix} \begin{pmatrix} \cdots & \mathbf{v}_1^T & \cdots \\ \vdots & \vdots & \vdots \\ \cdots & \mathbf{v}_m^T & \cdots \\ \vdots & \vdots & \vdots \\ \cdots & \mathbf{v}_n^T & \cdots \end{pmatrix}$$

$m \times m$ $\quad$ $m \times n$ $\quad$ $n \times n$

We can instead re-write the above as:

$$\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}_{\boldsymbol{R}}\boldsymbol{V}_{\boldsymbol{R}}{}^{\boldsymbol{T}}$$

where $\boldsymbol{V}_{\boldsymbol{R}}$ is a $n \times m$ matrix and $\boldsymbol{\Sigma}_{\boldsymbol{R}}$ is a $m \times m$ matrix

In general:

$$\boldsymbol{A} = \boldsymbol{U}_{\boldsymbol{R}}\boldsymbol{\Sigma}_{\boldsymbol{R}}\boldsymbol{V}_{\boldsymbol{R}}{}^{\boldsymbol{T}}$$

$\boldsymbol{U}_{\boldsymbol{R}}$ is a $m \times k$ matrix
$\boldsymbol{\Sigma}_{\boldsymbol{R}}$ is a $k \times k$ matrix
$\boldsymbol{V}_{\boldsymbol{R}}$ is a $n \times k$ matrix

$$k = \min(m, n)$$

Let's take a look at the product $\mathbf{\Sigma}^T\mathbf{\Sigma}$, where $\mathbf{\Sigma}$ has the singular values of a $\boldsymbol{A}$, a $m \times n$ matrix.

$$\mathbf{\Sigma}^T\mathbf{\Sigma} = \underbrace{\begin{pmatrix} \sigma_1 & & & 0 & & \\ & \ddots & & & \ddots & \\ & & \sigma_n & & & 0 \end{pmatrix}}_{n\times m} \underbrace{\begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \\ & & 0 \\ & & \vdots \\ & & 0 \end{pmatrix}}_{m\times n} = \underbrace{\begin{pmatrix} {\sigma_1}^2 & & \\ & \ddots & \\ & & {\sigma_n}^2 \end{pmatrix}}_{n\times n}$$

$m > n$

$$\mathbf{\Sigma}^T\mathbf{\Sigma} = \underbrace{\begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_m \\ & & 0 \\ & & \vdots \\ & & 0 \end{pmatrix}}_{n\times m} \underbrace{\begin{pmatrix} \sigma_1 & & & 0 & & \\ & \ddots & & & \ddots & \\ & & \sigma_m & & & 0 \end{pmatrix}}_{m\times n} = \underbrace{\begin{pmatrix} {\sigma_1}^2 & & & 0 & & \\ & \ddots & & & \ddots & \\ & & {\sigma_m}^2 & & & 0 \\ 0 & & 0 & & & \\ & \ddots & & & \ddots & \\ & & 0 & & & 0 \end{pmatrix}}_{n\times n}$$

$n > m$

Assume $\boldsymbol{A}$ with the singular value decomposition $\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}$. Let's take a look at the eigenpairs corresponding to $\boldsymbol{A}^{\boldsymbol{T}}\boldsymbol{A}$:

$$\boldsymbol{A}^{\boldsymbol{T}}\boldsymbol{A} = \left(\boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}\right)^{\boldsymbol{T}}\left(\boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}\right)$$

$$\left(\boldsymbol{V}^{\boldsymbol{T}}\right)^{\boldsymbol{T}}(\,\boldsymbol{\Sigma}\,)^{\boldsymbol{T}}\boldsymbol{U}^{\boldsymbol{T}}\left(\boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}\right) = \boldsymbol{V}\boldsymbol{\Sigma}^{\boldsymbol{T}}\boldsymbol{U}^{\boldsymbol{T}}\,\boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}} = \boldsymbol{V}\,\boldsymbol{\Sigma}^{\boldsymbol{T}}\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}$$

Hence $\boldsymbol{A}^{\boldsymbol{T}}\boldsymbol{A} = \boldsymbol{V}\,\boldsymbol{\Sigma}^{\boldsymbol{2}}\,\boldsymbol{V}^{\boldsymbol{T}}$

Recall that columns of $\boldsymbol{V}$ are all linear independent (orthogonal matrix), then from diagonalization ($\boldsymbol{B} = \boldsymbol{X}\boldsymbol{D}\boldsymbol{X}^{-\boldsymbol{1}}$), we get:

- the columns of $\boldsymbol{V}$ are the eigenvectors of the matrix $\boldsymbol{A}^{\boldsymbol{T}}\boldsymbol{A}$
- The diagonal entries of $\boldsymbol{\Sigma}^{\boldsymbol{2}}$ are the eigenvalues of $\boldsymbol{A}^{\boldsymbol{T}}\boldsymbol{A}$

Let's call λ the eigenvalues of $\boldsymbol{A}^{\boldsymbol{T}}\boldsymbol{A}$, then ${\sigma_i}^2 = \lambda_i$

In a similar way,

$$\boldsymbol{AA^T} = \left(\boldsymbol{U\,\Sigma\,V^T}\right)\left(\boldsymbol{U\,\Sigma\,V^T}\right)^{\boldsymbol{T}}$$

$$\left(\boldsymbol{U\,\Sigma\,V^T}\right)\left(\boldsymbol{V^T}\right)^{\boldsymbol{T}}(\,\boldsymbol{\Sigma}\,)^{\boldsymbol{T}}\boldsymbol{U^T} = \boldsymbol{U\,\Sigma\,}{\color{red}\boldsymbol{V^TV}}\boldsymbol{\Sigma^TU^T} = \boldsymbol{U\Sigma\,\Sigma^TU^T}$$

Hence $\boldsymbol{AA^T = U\,\Sigma^2\,U^T}$

Recall that columns of $\boldsymbol{U}$ are all linear independent (orthogonal matrices), then from diagonalization ($\boldsymbol{B = XDX^{-1}}$), we get:

- The columns of $\boldsymbol{U}$ are the eigenvectors of the matrix $\boldsymbol{AA^T}$

How can we compute an SVD of a matrix A ?

1. Evaluate the n eigenvectors $\mathbf{v}_i$ and eigenvalues λ_i of $\boldsymbol{A}^T\boldsymbol{A}$
2. Make a matrix $\boldsymbol{V}$ from the normalized vectors $\mathbf{v}_i$. The columns are called "right singular vectors".

$$\boldsymbol{V} = \begin{pmatrix} \vdots & \cdots & \vdots \\ \mathbf{v}_1 & \cdots & \mathbf{v}_n \\ \vdots & \cdots & \vdots \end{pmatrix}$$

3. Make a diagonal matrix from the square roots of the eigenvalues.

$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{pmatrix} \quad \sigma_i = \sqrt{\lambda_i} \quad \text{and} \quad \sigma_1 \geq \sigma_2 \geq \sigma_3 \ldots$$

4. Find $\boldsymbol{U}$: $\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^T \Longrightarrow \boldsymbol{U}\,\boldsymbol{\Sigma} = \boldsymbol{A}\,\boldsymbol{V} \Longrightarrow \boldsymbol{U} = \boldsymbol{A}\,\boldsymbol{V}\,\boldsymbol{\Sigma}^{-1}$. The columns are called the "left singular vectors".

True or False?

$\boldsymbol{A}$ has the singular value decomposition $\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}$.

- The matrices $\boldsymbol{U}$ and $\boldsymbol{V}$ are not singular
- The matrix $\boldsymbol{\Sigma}$ can have zero diagonal entries
- $\|\boldsymbol{U}\|_2 = 1$
- The SVD exists when the matrix $\boldsymbol{A}$ is singular
- The algorithm to evaluate SVD will fail when taking the square root of a negative eigenvalue

Singular values are always non-negative

Singular values cannot be negative since $\boldsymbol{A^T A}$ **is a positive semi-definite matrix** (for real matrices $\boldsymbol{A}$)

- A matrix is positive definite if $\boldsymbol{x^T B x > 0}$ for $\forall \boldsymbol{x \neq 0}$
- A matrix is positive semi-definite if $\boldsymbol{x^T B x \geq 0}$ for $\forall \boldsymbol{x \neq 0}$

- What do we know about the matrix $\boldsymbol{A^T A}$?

$$\boldsymbol{x^T\, A^T A\, x = (Ax)^T Ax = \|Ax\|_2^2} \geq 0$$

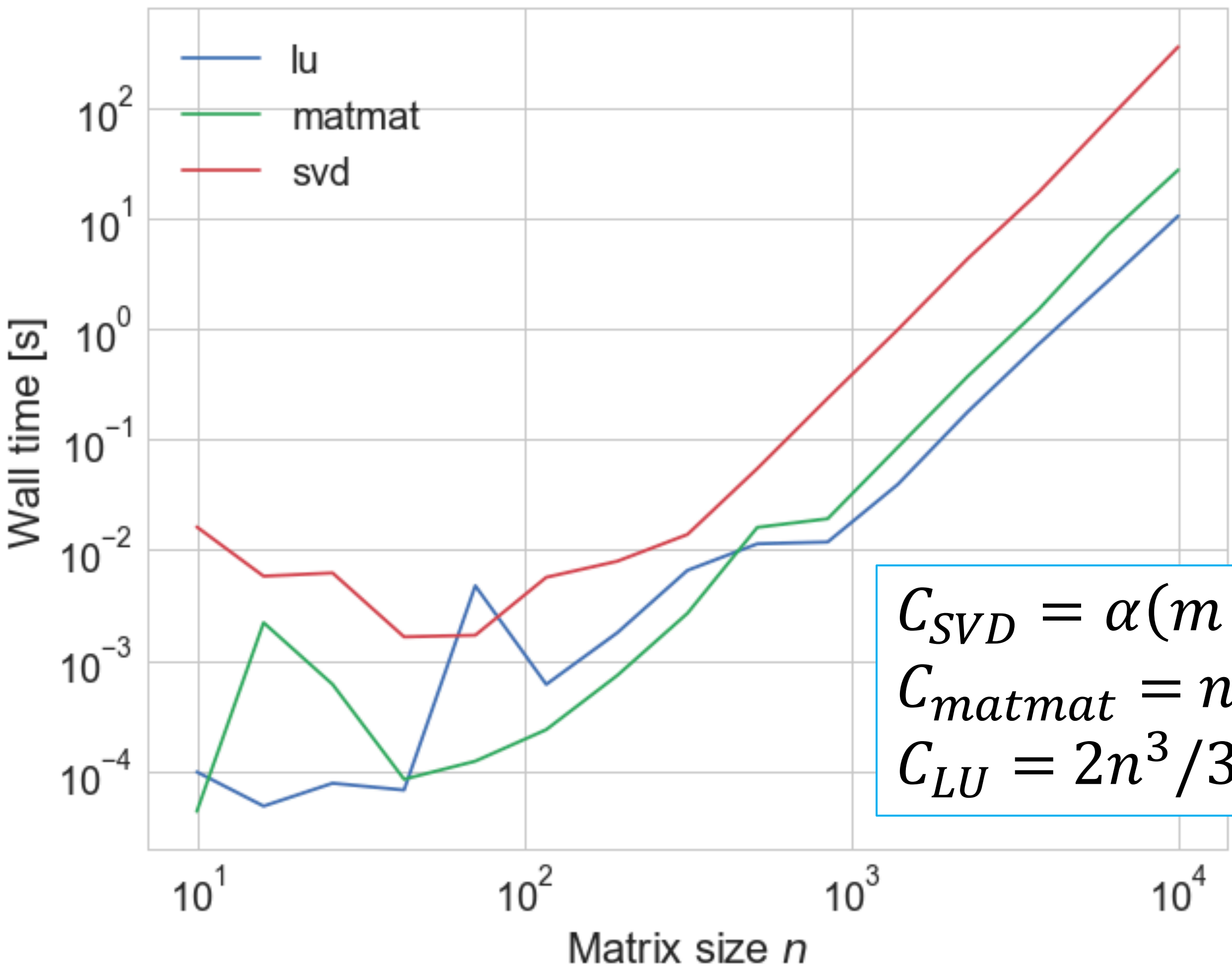
- Hence we know that $\boldsymbol{A^T A}$ is a positive semi-definite matrix

- A positive semi-definite matrix has non-negative eigenvalues

$$\boldsymbol{Bx} = \lambda \boldsymbol{x} \Longrightarrow \boldsymbol{x^T B x} = \boldsymbol{x^T}\, \lambda\, \boldsymbol{x} = \lambda\, \|\boldsymbol{x}\|_2^2 \geq 0 \Longrightarrow \lambda \geq 0$$

Cost of SVD

The cost of an SVD is proportional to $\boldsymbol{m\,n^2 + n^3}$ where the constant of proportionality constant ranging from 4 to 10 (or more) depending on the algorithm.



$$C_{SVD} = \alpha(m\,n^2 + n^3) = O(\,n^3)$$
$$C_{matmat} = n^3 = O(\,n^3)$$
$$C_{LU} = 2n^3/3 = O(\,n^3)$$

SVD summary:

- The SVD is a factorization of a $m \times n$ matrix into $\boldsymbol{A} = \boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}$ where $\boldsymbol{U}$ is a $m \times m$ orthogonal matrix, $\boldsymbol{V}^{\boldsymbol{T}}$ is a $n \times n$ orthogonal matrix and $\boldsymbol{\Sigma}$ is a $m \times n$ diagonal matrix.
- In reduced form: $\boldsymbol{A} = \boldsymbol{U_R \Sigma_R V_R}^{\boldsymbol{T}}$, where $\boldsymbol{U_R}$ is a $m \times k$ matrix, $\boldsymbol{\Sigma_R}$ is a $k \times k$ matrix, and $\boldsymbol{V_R}$ is a $n \times k$ matrix, and $k = \min(m, n)$.
- The columns of $\boldsymbol{V}$ are the eigenvectors of the matrix $\boldsymbol{A^T A}$, denoted the right singular vectors.
- The columns of $\boldsymbol{U}$ are the eigenvectors of the matrix $\boldsymbol{A A^T}$, denoted the left singular vectors.
- The diagonal entries of $\boldsymbol{\Sigma^2}$ are the eigenvalues of $\boldsymbol{A^T A}$. $\sigma_i = \sqrt{\lambda_i}$ are called the singular values.
- The singular values are always non-negative (since $\boldsymbol{A^T A}$ is a positive semi-definite matrix, the eigenvalues are always $\lambda \geq 0$)

Singular Value Decomposition (applications)

1) Determining the rank of a matrix

Suppose $\boldsymbol{A}$ is a $m \times n$ rectangular matrix where $m > n$:

$$\boldsymbol{A} = \begin{pmatrix} \vdots & \dots & \vdots & \dots & \vdots \\ \boldsymbol{u}_1 & \dots & \boldsymbol{u}_n & \dots & \boldsymbol{u}_m \\ \vdots & \dots & \vdots & \dots & \vdots \end{pmatrix} \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \\ & & 0 \\ & & \vdots \\ & & 0 \end{pmatrix} \begin{pmatrix} \dots & \mathbf{v}_1^T & \dots \\ \vdots & \vdots & \vdots \\ \dots & \mathbf{v}_n^T & \dots \end{pmatrix}$$

$$\boldsymbol{A} = \begin{pmatrix} \vdots & \dots & \vdots \\ \boldsymbol{u}_1 & \dots & \boldsymbol{u}_n \\ \vdots & \dots & \vdots \end{pmatrix} \begin{pmatrix} \dots & \sigma_1 \mathbf{v}_1^T & \dots \\ \vdots & \vdots & \vdots \\ \dots & \sigma_n \mathbf{v}_n^T & \dots \end{pmatrix} = \sigma_1 \boldsymbol{u}_1 \mathbf{v}_1^T + \sigma_2 \boldsymbol{u}_2 \mathbf{v}_2^T + \cdots + \sigma_n \boldsymbol{u}_n \mathbf{v}_n^T$$

$$\boldsymbol{A} = \sum_{i=1}^{n} \sigma_i \boldsymbol{u}_i \mathbf{v}_i^T$$

$\boldsymbol{A}_1 = \sigma_1 \boldsymbol{u}_1 \mathbf{v}_1^T$ what is $\text{rank}(\boldsymbol{A}_1) = ?$

A) 1
B) n
C) depends on the matrix
D) NOTA

In general, $\text{rank}(\boldsymbol{A}_k) = k$

Rank of a matrix

For general rectangular matrix $\boldsymbol{A}$ with dimensions $m \times n$, the reduced SVD is:

$$\boldsymbol{A} = \boldsymbol{U_R \Sigma_R V_R}^{\boldsymbol{T}}$$

$\boldsymbol{A}$: $m \times n$; $\boldsymbol{U_R}$: $m \times k$; $\boldsymbol{\Sigma_R}$: $k \times k$; $\boldsymbol{V_R}^{\boldsymbol{T}}$: $k \times n$

$$k = \min(m, n)$$

$$\boldsymbol{A} = \sum_{i=1}^{k} \sigma_i \boldsymbol{u}_i \mathbf{v}_i^T$$

$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_k \\ 0 & & 0 \\ & \ddots & \vdots \\ & & 0 \end{pmatrix} \qquad \boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1 & & & 0 & & \\ & \ddots & & & \ddots & \\ & & \sigma_k & 0 & \dots & 0 \end{pmatrix}$$

If $\sigma_i \neq 0 \ \forall i$, then $\text{rank}(\boldsymbol{A}) = k$ (Full rank matrix)

In general, $\text{rank}(\boldsymbol{A}) = \boldsymbol{r}$, where $\boldsymbol{r}$ is the number of non-zero singular values σ_i

$r < k$ (Rank deficient)

Rank of a matrix

- The rank of **A** equals the number of non-zero singular values which is the same as the number of non-zero diagonal elements in $\boldsymbol{\Sigma}$.
- Rounding errors may lead to small but non-zero singular values in a rank deficient matrix, hence the rank of a matrix determined by the number of non-zero singular values is sometimes called "effective rank".
- The right-singular vectors (columns of $\boldsymbol{V}$) corresponding to vanishing singular values span the null space of **A**.
- The left-singular vectors (columns of $\boldsymbol{U}$) corresponding to the non-zero singular values of **A** span the range of **A**.

2) Pseudo-inverse

- **Problem:** if **A** is rank-deficient, $\boldsymbol{\Sigma}$ is not be invertible
- **How to fix it:** Define the Pseudo Inverse
- **Pseudo-Inverse of a diagonal matrix**:

$$(\boldsymbol{\Sigma}^{+})_i = \begin{cases} \frac{1}{\sigma_i}, & \text{if } \sigma_i \neq 0 \\ 0, & \text{if } \sigma_i = 0 \end{cases}$$

- **Pseudo-Inverse of a matrix $\boldsymbol{A}$**:

$$\boldsymbol{A}^{+} = \boldsymbol{V}\boldsymbol{\Sigma}^{+}\boldsymbol{U}^{T}$$

3) Matrix norms

The Euclidean norm of an orthogonal matrix is equal to 1

$$\|\boldsymbol{U}\|_2 = \max_{\|\boldsymbol{x}\|_2=1} \|\boldsymbol{U}\boldsymbol{x}\|_2 = \max_{\|\boldsymbol{x}\|_2=1} \sqrt{(\boldsymbol{U}\boldsymbol{x})^{\boldsymbol{T}}(\boldsymbol{U}\boldsymbol{x})} = \max_{\|\boldsymbol{x}\|_2=1} \sqrt{\boldsymbol{x}^{\boldsymbol{T}}\boldsymbol{x}} = \max_{\|\boldsymbol{x}\|_2=1} \|\boldsymbol{x}\|_2 = 1$$

The Euclidean norm of a matrix is given by the largest singular value

$$\|\boldsymbol{A}\|_2 = \max_{\|\boldsymbol{x}\|_2=1} \|\boldsymbol{A}\boldsymbol{x}\|_2 = \max_{\|\boldsymbol{x}\|_2=1} \left\|\boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}\boldsymbol{x}\right\|_2 = \max_{\|\boldsymbol{x}\|_2=1} \left\|\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}\boldsymbol{x}\right\|_2 =$$

$$= \max_{\left\|\boldsymbol{V}^{\boldsymbol{T}}\boldsymbol{x}\right\|_2=1} \left\|\boldsymbol{\Sigma}\,\boldsymbol{V}^{\boldsymbol{T}}\boldsymbol{x}\right\|_2 = \max_{\|\boldsymbol{y}\|_2=1} \|\boldsymbol{\Sigma}\,\boldsymbol{y}\|_2 = \max(\sigma_i)$$

Where we used the fact that $\|\boldsymbol{U}\|_2 = 1$, $\|\boldsymbol{V}\|_2 = 1$ and $\boldsymbol{\Sigma}$ is diagonal

$$\|\boldsymbol{A}\|_2 = \max(\sigma_i) = \sigma_{max}$$

σ_{max} is the largest singular value

4) Norm for the inverse of a matrix

The Euclidean norm of the inverse of a square-matrix is given by:

Assume here $\boldsymbol{A}$ is full rank, so that $\boldsymbol{A}^{-1}$ exists

$$\|\boldsymbol{A}^{-1}\|_2 = \max_{\|\boldsymbol{x}\|_2=1} \left\|(\boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^T)^{-1}\boldsymbol{x}\right\|_2 = \max_{\|\boldsymbol{x}\|_2=1} \left\|\boldsymbol{V}\,\boldsymbol{\Sigma}^{-1}\boldsymbol{U}^T\boldsymbol{x}\right\|_2$$

Since $\|\boldsymbol{U}\|_2 = 1$, $\|\boldsymbol{V}\|_2 = 1$ and $\boldsymbol{\Sigma}$ is diagonal then

$$\|\boldsymbol{A}^{-1}\|_2 = \frac{1}{\sigma_{min}}$$

σ_{min} is the smallest singular value

5) Norm of the pseudo-inverse matrix

The norm of the pseudo-inverse of a $m \times n$ matrix is:

$$\|\boldsymbol{A}^{+}\|_2 = \frac{1}{\sigma_r}$$

where σ_r is the smallest **non-zero** singular value. This is valid for any matrix, regardless of the shape or rank.

Note that for a full rank square matrix, $\|\boldsymbol{A}^{+}\|_2$ is the same as $\|\boldsymbol{A}^{-1}\|_2$.

Zero matrix: If $\boldsymbol{A}$ is a zero matrix, then $\boldsymbol{A}^{+}$ is also the zero matrix, and $\|\boldsymbol{A}^{+}\|_2 = 0$

6) Condition number of a matrix

The condition number of a matrix is given by

$$cond_2(\boldsymbol{A}) = \|\boldsymbol{A}\|_2 \, \|\boldsymbol{A}^+\|_2$$

If the matrix is full rank: $rank(\boldsymbol{A}) = min(m, n)$

$$cond_2(\boldsymbol{A}) = \frac{\sigma_{max}}{\sigma_{min}}$$

where σ_{max} is the largest singular value and σ_{min} is the smallest singular value

If the matrix is rank deficient: $rank(\boldsymbol{A}) < min(m, n)$

$$cond_2(\boldsymbol{A}) = \infty$$

7) Low-Rank Approximation

Another way to write the SVD (assuming for now $m > n$ for simplicity)

$$\boldsymbol{A} = \begin{pmatrix} \vdots & \cdots & \vdots \\ \boldsymbol{u}_1 & \cdots & \boldsymbol{u}_m \\ \vdots & \cdots & \vdots \end{pmatrix} \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \\ & & 0 \\ & & \vdots \\ & & 0 \end{pmatrix} \begin{pmatrix} \cdots & \mathbf{v}_1^T & \cdots \\ \vdots & \vdots & \vdots \\ \cdots & \mathbf{v}_n^T & \cdots \end{pmatrix}$$

$$= \begin{pmatrix} \vdots & \cdots & \vdots \\ \boldsymbol{u}_1 & \cdots & \boldsymbol{u}_n \\ \vdots & \cdots & \vdots \end{pmatrix} \begin{pmatrix} \cdots & \sigma_1\, \mathbf{v}_1^T & \cdots \\ \vdots & \vdots & \vdots \\ \cdots & \sigma_n\, \mathbf{v}_n^T & \cdots \end{pmatrix}$$

$$= \sigma_1 \boldsymbol{u}_1 \mathbf{v}_1^T + \sigma_2 \boldsymbol{u}_2 \mathbf{v}_2^T + \cdots + \sigma_n \boldsymbol{u}_n \mathbf{v}_n^T$$

The SVD writes the matrix A as a sum of outer products (of left and right singular vectors).

7) Low-Rank Approximation (cont.)

The best **rank-*k*** approximation for a $m \times n$ matrix $\boldsymbol{A}$, (where $k \leq min(m,n)$) is the one that minimizes the following problem:

$$\min_{A_k} \|A - A_k\| \quad \text{such that} \quad \operatorname{rank}(A_k) \leq k.$$

When using the induced 2-norm, the best **rank-*k*** approximation is given by:

$$\boldsymbol{A}_k = \sigma_1 \boldsymbol{u}_1 \mathbf{v}_1^T + \sigma_2 \boldsymbol{u}_2 \mathbf{v}_2^T + \cdots + \sigma_k \boldsymbol{u}_k \mathbf{v}_k^T$$

$$\sigma_1 \geq \sigma_2 \geq \sigma_3 \ldots \geq 0$$

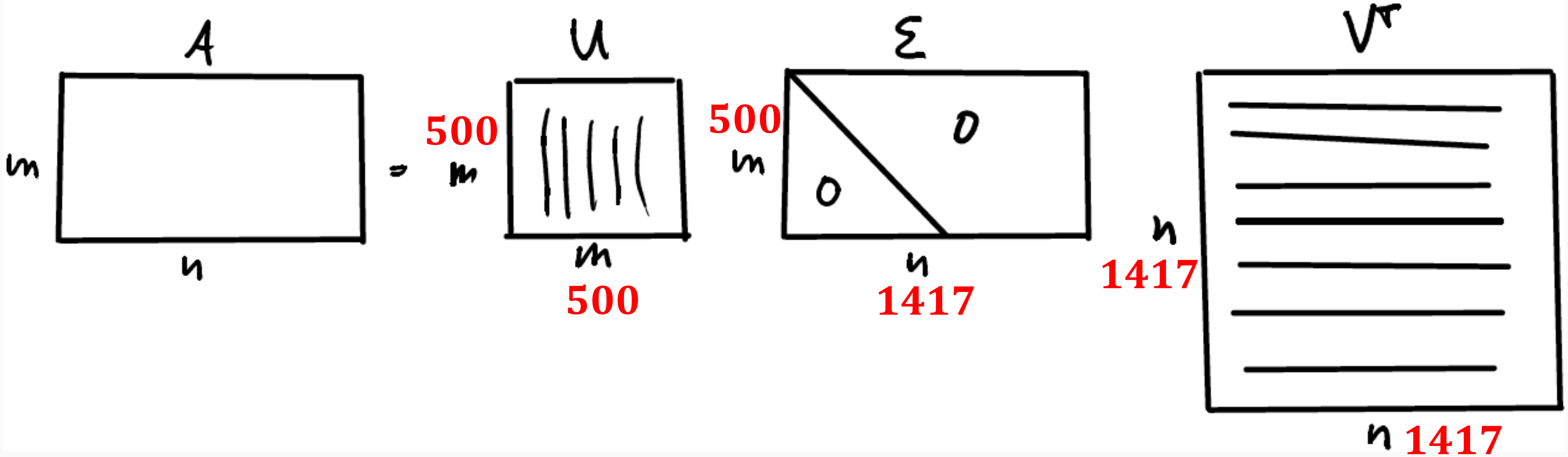
Note that $rank(\boldsymbol{A}) = n$ and $rank(\boldsymbol{A}_k) = k$ and the norm of the difference between the matrix and its approximation is

$$\|\boldsymbol{A} - \boldsymbol{A}_k\|_2 = \left\|\sigma_{k+1} \boldsymbol{u}_{k+1} \mathbf{v}_{k+1}^T + \sigma_{k+2} \boldsymbol{u}_{k+2} \mathbf{v}_{k+2}^T + \cdots + \sigma_n \boldsymbol{u}_n \mathbf{v}_n^T\right\|_2 = \sigma_{k+1}$$

Example: Image compression

500

1417



Example: Image compression

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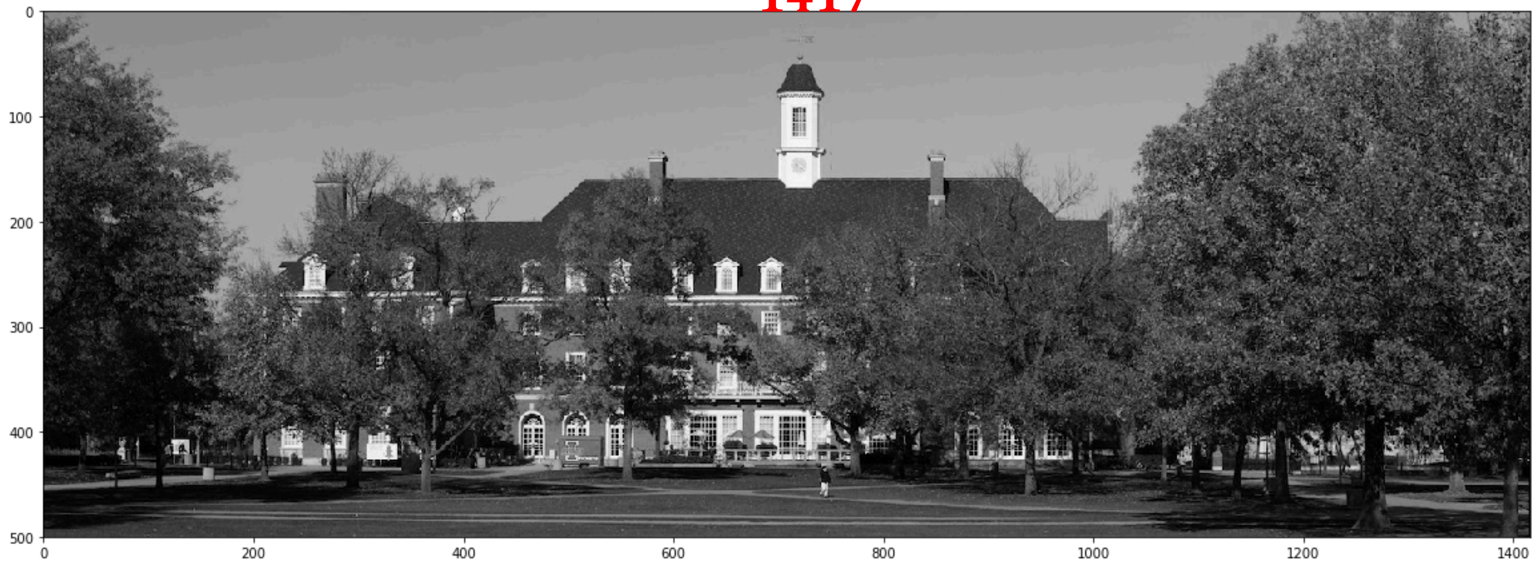

Image using rank-50 approximation

8) Using SVD to solve square system of linear equations

If $\boldsymbol{A}$ is a $n \times n$ square matrix and we want to solve $\boldsymbol{A}\,\boldsymbol{x} = \boldsymbol{b}$, we can use the SVD for $\boldsymbol{A}$ such that

$$\boldsymbol{U}\,\boldsymbol{\Sigma}\,\boldsymbol{V}^T\boldsymbol{x} = \boldsymbol{b}$$
$$\boldsymbol{\Sigma}\,\boldsymbol{V}^T\boldsymbol{x} = \boldsymbol{U}^T\boldsymbol{b}$$

Solve: $\boldsymbol{\Sigma}\,\boldsymbol{y} = \boldsymbol{U}^T\boldsymbol{b}$ (diagonal matrix, easy to solve!)

Evaluate: $\boldsymbol{x} = \boldsymbol{V}\,\boldsymbol{y}$

Cost of solve: $O(n^2)$

Cost of decomposition $O(n^3)$ (recall that SVD and LU have the same cost asymptotic behavior, however the number of operations - constant factor before n^3 - for the SVD is larger than LU)