ΓΡΑΜΜΙΚΗ ΑΛΓΕΒΡΑ

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How a Matrix is Represented in Space

A matrix represents a **linear transformation** of the plane. To visualize it, we observe its action on the **basis vectors**:

$$\vec{e}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \qquad \vec{e}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

For a matrix

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix},$$

we have:

$$A\vec{e}_1 = \begin{bmatrix} a \\ c \end{bmatrix}, \qquad A\vec{e}_2 = \begin{bmatrix} b \\ d \end{bmatrix}.$$

These two transformed vectors become the **new axes** of the plane. Every other vector is transformed as a combination of these.

Example: Transforming the Grid

Consider

$$A = \begin{bmatrix} 2 & 1 \\ 0 & 1 \end{bmatrix}.$$

Its action on the basis vectors:

$$A\vec{e}_1 = \begin{bmatrix} 2 \\ 0 \end{bmatrix} \quad \Rightarrow \quad \text{stretches the x-axis}$$

$$A\vec{e}_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \Rightarrow \quad \text{tilts the y-axis}$$

Geometric effect:

- Horizontal lines are stretched.
- Vertical lines tilt to the right.
- The whole grid is deformed accordingly.

This deformed grid visually represents the matrix in space.

Matrices as Linear Transformations

A matrix represents a **linear transformation** of vectors. It can:

- **Change direction** of a vector
- **Stretch or shrink** it
- (Sometimes) **reflect** or **rotate** it

$$A = \begin{bmatrix} 2 & 1 \\ 0 & 1 \end{bmatrix} \qquad \text{acts on} \qquad \vec{v} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

The product $A\vec{v}$ shows how the transformation moves the vector.

Example: Direction Change and Stretching

Compute the transformation:

$$A\vec{v} = \begin{bmatrix} 2 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \end{bmatrix}$$

- The original vector $\vec{v} = (1, 1)$ points diagonally.
- After the transformation, $A\vec{v} = (3, 1)$ points in a new direction.
- Horizontal component is **stretched** (from 1 to 3).

This illustrates how a matrix modifies both the **direction** and the **magnitude** of vectors.

Positive Definite Matrices

A symmetric matrix $A \in \mathbb{R}^{n \times n}$ is **positive definite** if

$$x^T A x > 0 \quad \text{for all } x \neq 0.$$

Equivalent characterizations:

- All eigenvalues of A are **positive**.
- The quadratic form $x^T A x$ is always strictly positive.
- A admits a **Cholesky factorization** $A = C^T C$.
- All leading principal minors of A are positive.

This makes positive definite matrices the matrix analogue of a **positive number**.

Geometric Meaning

For any non-zero vector x, the quantity $x^T Ax$ measures how the matrix A stretches and aligns the direction x.

A positive definite matrix:

- stretches every direction,
- never flips, collapses, or sends any non-zero vector to zero,
- transforms the unit sphere into a full ellipsoid with no flat directions.

Example:

$$A = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix}$$

has eigenvalues 4 and 2, both positive, hence A is **positive definite**.

$$x^T Ax = 3x_1^2 + 2x_1x_2 + 3x_2^2 > 0 \quad \text{for all } x \neq 0.$$

Motivation for LU Decomposition

- Direct methods for solving systems of linear equations often rely on matrix factorizations.
- The LU decomposition provides a systematic way to break down a matrix A into simpler building blocks.
- It enables efficient solutions to $Ax = b$ for multiple right-hand sides.

Definition of LU Decomposition

LU Decomposition

For a given $n \times n$ matrix A, an **LU decomposition** (or factorization) is a representation:

$$A = LU$$

where:

- L is a lower-triangular matrix with ones on the diagonal.
- U is an upper-triangular matrix.

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Key Question: Under what conditions does A admit an LU decomposition?

Conditions for A to admit an LU decomposition

1. **Square Matrix:**
   - A must be a square matrix ($n \times n$). For non-square matrices, variations of LU decomposition (e.g., $PA = LU$) might be considered.
2. **No Zero Leading Principal Minors:**
   - All leading principal minors (determinants of the upper-left $k \times k$ submatrices of A, where $k = 1, 2, \ldots, n$) must be nonzero. This ensures that the Gaussian elimination process used to compute the LU decomposition does not encounter a zero pivot.
3. **Pivoting or Permutation (if necessary):**
   - If A does not satisfy the condition on leading principal minors, LU decomposition may still exist if row interchanges are allowed. This leads to a *partial pivoting version* of the decomposition, where $PA = LU$, with P being a permutation matrix.
4. **Stability of Numerical Algorithms:**
   - In numerical computation, stability considerations often require pivoting (row swaps), even if A theoretically satisfies the condition for LU decomposition without pivoting. This ensures numerical accuracy.

Constructing the LU Factorization

To find L and U:

1. Perform Gaussian elimination on A without row interchanges.
2. The multipliers used to eliminate entries below the pivots fill in L.
3. The resulting echelon form is U.

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If at any step a pivot is zero, we may need to reorder the equations (pivoting), leading to a $PA = LU$ factorization.

Step-by-Step Procedure for LU Decomposition

Given Matrix:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nn} \end{bmatrix}$$

Step 1: Eliminate entries below a_{11} (first column):
For each $i = 2, 3, \ldots, n$, compute the multiplier:

$$l_{i1} = \frac{a_{i1}}{a_{11}}.$$

Update the entries of row i as:

$$a_{ij} \leftarrow a_{ij} - l_{i1} \cdot a_{1j}, \quad \text{for } j = 1, 2, \ldots, n.$$

Result after Step 1:

$$A^{(1)} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ 0 & a_{22}^{(1)} & a_{23}^{(1)} & \cdots & a_{2n}^{(1)} \\ 0 & a_{32}^{(1)} & a_{33}^{(1)} & \cdots & a_{3n}^{(1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & a_{n2}^{(1)} & a_{n3}^{(1)} & \cdots & a_{nn}^{(1)} \end{bmatrix}.$$

Step 2: Eliminate entries below $a_{22}^{(1)}$ (second column):
For each $i = 3, 4, \ldots, n$, compute the multiplier:

$$l_{i2} = \frac{a_{i2}^{(1)}}{a_{22}^{(1)}}.$$

Update the entries of row i as:

$$a_{ij}^{(1)} \leftarrow a_{ij}^{(1)} - l_{i2} \cdot a_{2j}^{(1)}, \quad \text{for } j = 2, 3, \ldots, n.$$

Result after Step 2:

$$A^{(2)} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ 0 & a_{22}^{(1)} & a_{23}^{(1)} & \cdots & a_{2n}^{(1)} \\ 0 & 0 & a_{33}^{(2)} & \cdots & a_{3n}^{(2)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & a_{n3}^{(2)} & \cdots & a_{nn}^{(2)} \end{bmatrix}.$$

Step k: Eliminate entries below $a_{kk}^{(k-1)}$ (k-th column):
For each $i = k+1, k+2, \ldots, n$, compute the multiplier:

$$l_{ik} = \frac{a_{ik}^{(k-1)}}{a_{kk}^{(k-1)}}.$$

Update the entries of row i as:

$$a_{ij}^{(k-1)} \leftarrow a_{ij}^{(k-1)} - l_{ik} \cdot a_{kj}^{(k-1)}, \quad \text{for } j = k, k+1, \ldots, n.$$

Final Result: After $n-1$ steps, A is transformed into the upper triangular matrix U, and the multipliers l_{ik} form the entries of the lower triangular matrix L.

$$A = LU, \quad \text{where}$$

$$L = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ l_{21} & 1 & 0 & \cdots & 0 \\ l_{31} & l_{32} & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ l_{n1} & l_{n2} & l_{n3} & \cdots & 1 \end{bmatrix}, \quad U = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ 0 & a_{22}^{(1)} & a_{23}^{(1)} & \cdots & a_{2n}^{(1)} \\ 0 & 0 & a_{33}^{(2)} & \cdots & a_{3n}^{(2)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & a_{nn}^{(n-1)} \end{bmatrix}.$$

Example of an LU Decomposition

Consider the matrix

$$A = \begin{pmatrix} 2 & 4 & 2 \\ 4 & 9 & 6 \\ 2 & 6 & 9 \end{pmatrix}.$$

One possible LU decomposition is:

$$L = \begin{pmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 1 & 2 & 1 \end{pmatrix}, \quad U = \begin{pmatrix} 2 & 4 & 2 \\ 0 & 1 & 2 \\ 0 & 0 & 3 \end{pmatrix}.$$

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Note how L captures the elimination steps and U stores the multipliers and final reduced form.

Step 1: Initialize L and U

Start with L as the identity matrix and U as A:

$$L = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, \quad U = \begin{pmatrix} 2 & 4 & 2 \\ 4 & 9 & 6 \\ 2 & 6 & 9 \end{pmatrix}.$$

Step 2: Eliminate a_{21} and a_{31} (First Column)

Compute the multipliers:

$$l_{21} = \frac{U_{21}}{U_{11}} = \frac{4}{2} = 2, \quad l_{31} = \frac{U_{31}}{U_{11}} = \frac{2}{2} = 1.$$

Update L with these multipliers:

$$L = \begin{pmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix}.$$

Perform row operations on U:

$$R_2 \leftarrow R_2 - l_{21} \cdot R_1, \quad R_3 \leftarrow R_3 - l_{31} \cdot R_1.$$

The updated U becomes:

$$U = \begin{pmatrix} 2 & 4 & 2 \\ 0 & 1 & 2 \\ 0 & 2 & 7 \end{pmatrix}.$$

Step 3: Eliminate a_{32} (Second Column)

Compute the multiplier:

$$l_{32} = \frac{U_{32}}{U_{22}} = \frac{2}{1} = 2.$$

Update L with this multiplier:

$$L = \begin{pmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 1 & 2 & 1 \end{pmatrix}.$$

Perform the row operation on U:

$$R_3 \leftarrow R_3 - l_{32} \cdot R_2.$$

The updated U becomes:

$$U = \begin{pmatrix} 2 & 4 & 2 \\ 0 & 1 & 2 \\ 0 & 0 & 3 \end{pmatrix}.$$

Final L and U

After completing the elimination steps, we have:

$$L = \begin{pmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 1 & 2 & 1 \end{pmatrix}, \quad U = \begin{pmatrix} 2 & 4 & 2 \\ 0 & 1 & 2 \\ 0 & 0 & 3 \end{pmatrix}.$$

Verification

Verify that $A = LU$:

$$LU = \begin{pmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 1 & 2 & 1 \end{pmatrix} \begin{pmatrix} 2 & 4 & 2 \\ 0 & 1 & 2 \\ 0 & 0 & 3 \end{pmatrix}.$$

Compute the product:

$$LU = \begin{pmatrix} 2 & 4 & 2 \\ 4 & 9 & 6 \\ 2 & 6 & 9 \end{pmatrix}.$$

This matches the original matrix A, confirming that the decomposition is correct.

Pivoting and $PA = LU$ Factorization

- Sometimes A does not admit an LU decomposition directly (e.g., if a pivot is zero).
- Introducing a permutation matrix P allows row exchanges, resulting in:
$$PA = LU.$$
- P is obtained from the identity matrix by permuting rows.

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This ensures numerical stability and existence of the factorization in a broader set of cases.

Applications of LU Decomposition

- **Solving Systems:** Once we have $A = LU$, solving $Ax = b$ involves:

  $$LUx = b.$$

  Set $y = Ux$, then solve $Ly = b$ and then $Ux = y$.
- **Inverse and Determinants:** - If A is invertible, A^{-1} can be computed from L and U. - The determinant of A is the product of the diagonal entries of U (up to the sign adjustments from P if pivoting is used).

Summary

- The LU decomposition is a fundamental tool for factorizing a matrix into a product of simpler lower and upper-triangular factors.
- It streamlines the solution of linear systems and the computation of determinants and inverses.
- When direct LU factorization is not possible, consider the $PA = LU$ variant.

Singular Value Decomposition

Unit Disc and Matrix Action

In $\mathbb{R}^2$, the **unit disc** is:

$$D = \{(x, y) \in \mathbb{R}^2 : x^2 + y^2 \leq 1\},$$

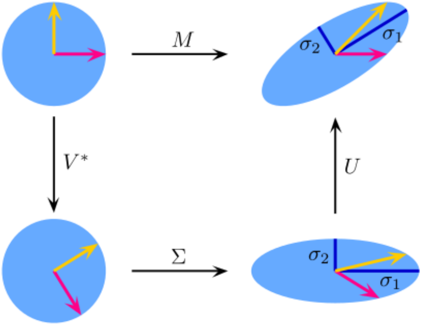
a filled circle of radius 1 centered at the origin.
A matrix $M \in \mathbb{R}^{2\times 2}$ acts on:

- the unit disc D, which is transformed into some shape (typically an ellipse),
- the canonical unit vectors

$$e_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad e_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

By looking at the image of D, e_1, e_2, we can **visualize** how M changes directions and lengths in the plane.

Illustration of the singular value decomposition $U\Sigma V^*$



$$M = U \cdot \Sigma \cdot V^*$$

Top: The action of M, indicated by its effect on the unit disc D and the two canonical unit vectors e_1 and e_2.
Left: The action of V^*, a rotation, on D, e_1, and e_2.
Bottom: The action of Σ, a scaling by the singular values σ_1 horizontally and σ_2 vertically.
Right: The action of U, another rotation.

Geometric Meaning

- Consider the transformation defined by $A : \mathbb{R}^n \to \mathbb{R}^m$.
- The matrix V provides an orthonormal basis for the input space. In this basis, A stretches or shrinks along the coordinate axes defined by V.
- The singular values σ_i describe how much A stretches these basis vectors.
- The matrix U gives an orthonormal basis of the output space aligned with these stretched directions.

$$Av_i = \sigma_i u_i.$$

Singular Value Decomposition Example

We are given the matrix:

$$A = \begin{pmatrix} 3 & 1 \\ 1 & 3 \end{pmatrix}.$$

The goal is to compute the Singular Value Decomposition (SVD) of A in the form:

$$A = U\Sigma V^\top,$$

where:

- U is an orthogonal matrix,
- Σ is a diagonal matrix with non-negative singular values,
- V is an orthogonal matrix.

Step 1: Compute $A^\top A$

First, compute $A^\top A$:

$$A^\top A = \begin{pmatrix} 3 & 1 \\ 1 & 3 \end{pmatrix}^\top \begin{pmatrix} 3 & 1 \\ 1 & 3 \end{pmatrix} = \begin{pmatrix} 10 & 6 \\ 6 & 10 \end{pmatrix}.$$

Step 2: Eigenvalues and Eigenvectors of $A^\top A$

Solve $\det(A^\top A - \lambda I) = 0$ to find the eigenvalues:

$$\det\left(\begin{pmatrix}10 & 6\\ 6 & 10\end{pmatrix} - \lambda\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix}\right) = \det\begin{pmatrix}10-\lambda & 6\\ 6 & 10-\lambda\end{pmatrix}.$$

$$\det = (10-\lambda)^2 - 36 = \lambda^2 - 20\lambda + 64.$$

Solve $\lambda^2 - 20\lambda + 64 = 0$:

$$\lambda = 16, \quad \lambda = 4.$$

The eigenvalues of $A^\top A$ are $\lambda_1 = 16$ and $\lambda_2 = 4$.
The singular values of A are:

$$\sigma_1 = \sqrt{\lambda_1} = 4, \quad \sigma_2 = \sqrt{\lambda_2} = 2 \quad \Sigma = \begin{bmatrix}4 & 0\\ 0 & 2\end{bmatrix}$$

Step 3: Compute V

Find the eigenvectors of $A^\top A$ corresponding to $\lambda_1 = 16$ and $\lambda_2 = 4$.
For $\lambda_1 = 16$:

$$(A^T A - 16I)x = 0 \Rightarrow \begin{bmatrix} -6 & 6 \\ 6 & -6 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = 0 \Rightarrow x_1 = x_2.$$

All eigenvectors lie on the line

$$x = t \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

Take eigenvector $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$, and For SVD we use unit vectors, so compute its length to normalize: **1. Compute its length (norm):**

$$\|w\| = \sqrt{1^2 + 1^2} = \sqrt{2}.$$

2. Divide by the norm to obtain a unit vector:

$$v_1 = \frac{1}{\|w\|} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

The eigenvector is:

$$v_1 = \begin{pmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}.$$

For $\lambda_2 = 4$:

$$\begin{pmatrix} 10-4 & 6 \\ 6 & 10-4 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}.$$

This simplifies to:

$$\begin{pmatrix} 6 & 6 \\ 6 & 6 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}.$$

The eigenvector is:

$$v_2 = \begin{pmatrix} -1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}.$$

Thus, V is:

$$V = \begin{pmatrix} 1/\sqrt{2} & -1/\sqrt{2} \\ 1/\sqrt{2} & 1/\sqrt{2} \end{pmatrix}.$$

Step 4: Compute U

Compute U using $U = AV\Sigma^{-1}$, where:

$$\Sigma = \begin{pmatrix} 4 & 0 \\ 0 & 2 \end{pmatrix}.$$

Left Singular Vectors and Final Form

Left singular vectors:

$$u_i = \frac{1}{\sigma_i} A v_i.$$

For u_1:

$$Av_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 3 \cdot 1 + 1 \cdot 1 \\ 1 \cdot 1 + 3 \cdot 1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 4 \\ 4 \end{bmatrix}, \quad u_1 = \frac{1}{4} Av_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

For u_2:

$$Av_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 3 \cdot 1 + 1 \cdot (-1) \\ 1 \cdot 1 + 3 \cdot (-1) \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 2 \\ -2 \end{bmatrix}, \quad u_2 = \frac{1}{2} Av_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}.$$

Hence

$$U = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}, \quad A = U \Sigma V^T.$$

We obtained the SVD using the general procedure:

$$A^T A \ \Rightarrow \ V, \ \Sigma; \quad AV \ \Rightarrow \ U.$$

Final Result

The Singular Value Decomposition of A is:

$$A = U\Sigma V^\top,$$

where:

$$U = \begin{pmatrix} \cdots & \cdots \\ \cdots & \cdots \end{pmatrix}, \quad \Sigma = \begin{pmatrix} 4 & 0 \\ 0 & 2 \end{pmatrix}, \quad V^\top = \begin{pmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ -1/\sqrt{2} & 1/\sqrt{2} \end{pmatrix}.$$

Special cases

SVD of $A = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix}$. We compute the SVD $A = U\Sigma V^T$. Since A is symmetric and positive definite, its SVD coincides with its eigen-decomposition.

1. Eigenvalues = Singular values

$$\det(A - \lambda I) = (3-\lambda)^2 - 1 = 0$$

$$(3-\lambda)^2 = 1 \quad \Rightarrow \quad \lambda_1 = 4,\ \lambda_2 = 2.$$

Thus

$$\Sigma = \begin{bmatrix} 4 & 0 \\ 0 & 2 \end{bmatrix}.$$

Eigenvectors

2. Eigenvectors = Columns of U and V

$$\lambda_1 = 4: \quad x_1 = x_2 \Rightarrow u_1 = v_1 = \frac{1}{\sqrt{2}}\begin{bmatrix}1\\1\end{bmatrix}$$

$$\lambda_2 = 2: \quad x_1 = -x_2 \Rightarrow u_2 = v_2 = \frac{1}{\sqrt{2}}\begin{bmatrix}1\\-1\end{bmatrix}$$

$$U = V = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\1 & -1\end{bmatrix}.$$

Low-Rank Approximation

- The SVD provides the best low-rank approximation to a given matrix.
- Truncate the SVD after k terms:

$$A \approx U_k \Sigma_k V_k^T$$

where Σ_k contains only the top k singular values.

- This approximation minimizes the Frobenius norm error:

$$\|A - U_k \Sigma_k V_k^T\|_F = \min_{\text{rank}(B) \leq k} \|A - B\|_F.$$

Data Compression

- SVD is used extensively in data compression, image processing, and noise reduction.
- For example, compressing an image by storing only the top singular values and corresponding singular vectors drastically reduces storage while preserving image quality.

Principal Component Analysis (PCA)

- PCA can be derived using the SVD of a data matrix.
- Given data with mean zero:

$$X \in \mathbb{R}^{m \times n}, \quad X = U \Sigma V^T.$$

- The columns of V (eigenvectors of $X^T X$) are the principal directions.
- The singular values determine the importance of each principal component.

Summary

- SVD is a powerful decomposition that applies to any $m \times n$ matrix.
- It reveals the intrinsic structure of the linear transformation defined by the matrix.
- SVD is critical for dimensionality reduction, noise filtering, and data analysis techniques like PCA.