Singular Value Decomposition (SVD) is a matrix factorization technique that represents a given matrix A as a product of three matrices: U, E, and V^T, such that $A = UEV^T$. The U and V matrices are orthogonal matrices, while the E matrix is a diagonal matrix with non-negative elements called singular values.

SVD has a variety of applications in

Data analysis,

Signal processing,

Image compression, and

Machine learning.

One of the most important applications of SVD is its ability to reduce the dimensionality of a dataset while preserving most of its important features.

The process of computing SVD involves the following steps:

1. Start with a matrix A of dimensions m x n.
2. Compute the matrix $A^T A$ and its eigenvectors and eigenvalues. The eigenvectors form the columns of V, and the eigenvalues are the squares of the singular values in E.

SVD can be computed using various numerical methods such as

power iteration,

Jacobi method, or

QR decomposition.

The method used depends on the properties of the matrix being decomposed and the desired computational efficiency.

$$A = \begin{bmatrix} 2 & 2 & -2 \\ 2 & 2 & -2 \\ -2 & -2 & 6 \end{bmatrix}$$