**Singular Value Decomposition (SVD):**

SVD is a widely used matrix factorization technique that decomposes a matrix A into three matrices: U, Σ (sigma), and V.

Mathematically, for an m x n matrix A:

A = UΣV^T

Where:

* U is an m x m orthogonal matrix (left singular vectors).
* Σ (sigma) is an m x n diagonal matrix with non-negative real numbers on the diagonal (singular values).
* V^T is an n x n orthogonal matrix (transpose of right singular vectors).

Let's use a numerical example to illustrate this:

Suppose we have a 3 x 3 matrix A:

A = | 1 2 3 |

| 4 5 6 |

| 7 8 9 |

We can perform SVD to factorize it:

1. Calculate U, Σ, and V^T:

U = | -0.214 -0.887 -0.408 |

| -0.520 -0.249 0.817 |

| -0.826 0.387 -0.408 |

Σ = | 16.849 0 0 |

| 0 1.171 0 |

| 0 0 0.074 |

V^T = | -0.479 -0.572 -0.669 |

**To approximate A, we can select a rank k (e.g., k = 2) and truncate Σ to keep only the top k singular values and corresponding columns of U and V:**

**U\_k = | -0.214 -0.408 |**

**| -0.520 0.817 |**

**| -0.826 -0.408 |**

**Σ\_k = | 16.849 0 |**

**| 0 1.171 |**

**(V^T)\_k = | -0.479 -0.572 -0.669 |**

**Now, you can approximate A as:**

**A\_k ≈ U\_kΣ\_k(V^T)\_k**

YU : https://youtu.be/V7BtsK6WKE4?si=RYO-DSzmFMv0LBo4