In linear algebra, the Singular Value Decomposition (SVD) of a matrix is a factorization of that matrix into three matrices. It has some interesting algebraic properties and conveys important geometrical and theoretical insights about linear transformations. It also has some important applications in data science.

To understand SVD we need to first understand the *Eigenvalue Decomposition* of a matrix. We can think of a matrix **A** as a transformation that acts on a vector **x** by multiplication to produce a new vector **Ax**. We use [**A**]ij or *aij* to denote the element of matrix **A** at row *i* and column *j*. If **A** is an *m*×*p* matrix and **B** is a *p*×*n* matrix, the matrix product **C**=**AB** (which is an *m*×*n matrix*) is defined as:

$$[\mathbf{C}]_{ij} = c_{ij} = \sum_{k=1}^{p} a_{ik} b_{kj}$$

Technical introduction

Singular value decomposition is a method of decomposing a matrix into three other matrices:

$$A = USV^T$$

Where:

- *A* is an *m* × *n* matrix
- *U* is an *m* × *n orthogonal* matrix
- *S* is an *n* × *n diagonal matrix*
- *V* is an *n* × *n* orthogonal matrix

The reason why the last matrix is transposed will become clear later on in the exposition. Also, the term, “orthogonal,” will be defined (in case your algebra has become a little rusty) and the reason why the two outside matrices have this property made clear.