



Introduction to Linear Algebra

Vector Spaces, Linear Transformations, Eigenvalues/Eigenvectors, SVD, & PCA
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Motivation & Application

- High-dimensional data (images, sounds, etc.) is hard to analyze.
- Principal Component Analysis (PCA) uses eigenvectors of the data covariance matrix to identify key directions (“principal components”).
- Why? Reduce dimensionality while preserving maximal variance-enables compression, denoising, and visualization.



Vector Spaces

Definition: A vector space V over a field F is a set with two operations (addition and scalar multiplication), such that:

- For all $u, v \in V$, $u+v \in V$
- For all $a \in F$, $av \in V$
- The zero vector exists; addition is commutative and associative; distribution, identity, and inverse laws hold

Examples:

- \mathbb{R}^n : vectors of n real numbers
- Polynomials of degree ≤ 3 : $a_0 + a_1 \cdot x + a_2 \cdot x^2 + a_3 \cdot x^3$



Linear Transformation

Definition: A function $T : V \rightarrow W$ is a linear transformation if:

$T(\mathbf{u} + \mathbf{v}) = T(\mathbf{u}) + T(\mathbf{v})$ and $T(a\mathbf{v}) = a \cdot T(\mathbf{v})$ for all $a \in F$.

Examples:

- Rotation of vectors in \mathbb{R}^2
- Scaling: $T(\mathbf{v}) = 2 \cdot \mathbf{v}$
- Matrix multiplication: $T_A(\mathbf{x}) = A \cdot \mathbf{x}$

Matrix Representation:

Every linear transformation can be represented by a matrix



Eigenvalues & Eigenvectors

Definition: For a square matrix A , $v \neq 0$ is an eigenvector if $A.v = \lambda.v$
Here, λ is the eigenvalue.

Key Theorem:

An $n \times m$ matrix has $\leq n$ eigenvalues (some may be complex/repeated).

Geometric Meaning:

Eigenvectors are invariant directions under transformation A ; eigenvalues scale them.

Example: For $A = \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix}$

The standard basis vectors are eigenvectors with eigenvalues 2 and 3.



Singular Value Decomposition (SVD)

Theorem(SVD):

Every real $m \times n$ matrix A can be decomposed:

$$A = U\Sigma V^T$$

where U and V are orthogonal, and Σ is diagonal (with non-negative numbers “singular values”).

Interpretation:

- Columns of U : output directions
- Columns of V : input directions
- Σ : scaling factors

Application: Used in PCA, image compression, latent semantic analysis (LSA).



Worked Problem

Problem: Find the eigenvalues and vectors of

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

Solution:

1. **Characteristic equation:**

$$\det(A - \lambda I) = 0$$

$$\Rightarrow \begin{vmatrix} 2 - \lambda & 1 \\ 1 & 2 - \lambda \end{vmatrix}$$

$$= 0$$

$$(2 - \lambda)^2 - 1 = 0 \Rightarrow (2 - \lambda)^2 = 1 \Rightarrow 2 - \lambda = \pm 1$$

$$\text{Thus, } \lambda_1 = 1, \lambda_2 = 3$$



2. Eigenvectors:

For $\lambda_1 = 1$: $(A - I)v = 0 \Rightarrow v_1 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$

For $\lambda_2 = 3$: $(A - 3I)v = 0 \Rightarrow v_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$



Summary

- Core concepts: vector spaces, linear transformations, eigenvalue & eigenvector, SVD
- Eigenvectors key to engineering use cases (PCA, stability analysis)
- SVD as a powerful generalization to all matrices