

Lesson 3.4: Vectors & Inner Products

Mathematical Intuition · Module 3 — Numbers Spaces

Node 3.4

Overview

Understanding vectors as directions with magnitude and inner products as measures of alignment and projection.

Learning Objectives

- See vectors as arrows in space with direction and magnitude
- Understand inner products as measuring alignment
- Build geometric intuition for orthogonality and projection
- Recognize vector spaces and their properties

Core Concepts

What Are Vectors?

Geometric View

- **Arrow in space:** direction + magnitude
- **Position vector:** from origin to point
- **Displacement vector:** from one point to another

Algebraic View

- **Column of numbers:** $\mathbf{v} = [v_1, v_2, \dots, v_n]^T$
- **Linear combination:** $\mathbf{v} = v_1\mathbf{e}_1 + v_2\mathbf{e}_2 + \dots + v_n\mathbf{e}_n$
- **Basis vectors:** $\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n$ (standard basis)

Vector Operations

Addition

- $\mathbf{u} + \mathbf{v}$: tip-to-tail (parallelogram rule)
- Component-wise: $[u_1 + v_1, u_2 + v_2, \dots]^T$
- Commutative: $\mathbf{u} + \mathbf{v} = \mathbf{v} + \mathbf{u}$

Scalar Multiplication

- $\alpha \cdot \mathbf{v}$: scales magnitude by $|\alpha|$, flips direction if $\alpha < 0$
- Component-wise: $[\alpha \cdot v_1, \alpha \cdot v_2, \dots]^T$

Linear Combinations

- $\mathbf{w} = \alpha \cdot \mathbf{u} + \beta \cdot \mathbf{v}$: span of $\mathbf{u}$ and $\mathbf{v}$
- Span: all possible linear combinations

Inner Products

Dot Product (Euclidean)

- $\mathbf{u} \cdot \mathbf{v} = \mathbf{u}_1\mathbf{v}_1 + \mathbf{u}_2\mathbf{v}_2 + \dots + \mathbf{u}_n\mathbf{v}_n$: sum of component products
- $\mathbf{u} \cdot \mathbf{v} = \|\mathbf{u}\| \cdot \|\mathbf{v}\| \cdot \cos(\theta)$: geometric interpretation
- Measures alignment: positive if acute angle, negative if obtuse

Properties

- **Symmetric:** $\mathbf{u} \cdot \mathbf{v} = \mathbf{v} \cdot \mathbf{u}$
- **Linear:** $(\alpha\mathbf{u} + \beta\mathbf{v}) \cdot \mathbf{w} = \alpha(\mathbf{u} \cdot \mathbf{w}) + \beta(\mathbf{v} \cdot \mathbf{w})$
- **Positive definite:** $\mathbf{v} \cdot \mathbf{v} \geq 0$, with equality iff $\mathbf{v} = \mathbf{0}$

Orthogonality

- $\mathbf{u} \perp \mathbf{v}$: “u and v are orthogonal” (perpendicular)
- $\mathbf{u} \cdot \mathbf{v} = \mathbf{0}$: inner product is zero
- Orthogonal vectors are independent

Norms and Distance

Euclidean Norm

- $\|\mathbf{v}\|_2 = \sqrt{\mathbf{v} \cdot \mathbf{v}} = \sqrt{\mathbf{v}_1^2 + \mathbf{v}_2^2 + \dots + \mathbf{v}_n^2}$: length of vector
- $\|\mathbf{v}\| = \mathbf{0}$ iff $\mathbf{v} = \mathbf{0}$

Unit Vectors

- $\mathbf{v} / \|\mathbf{v}\|$: unit vector in direction of $\mathbf{v}$
- $\|\mathbf{v}\| = 1$: normalized

Distance

- $d(\mathbf{u}, \mathbf{v}) = \|\mathbf{u} - \mathbf{v}\|$: distance between u and v
- Metric: satisfies triangle inequality

Projections

Projection onto Vector

- $\text{proj}_{\mathbf{u}}(\mathbf{v}) = (\mathbf{v} \cdot \mathbf{u} / \mathbf{u} \cdot \mathbf{u}) \cdot \mathbf{u}$: component of v in direction of u
- $\mathbf{v} = \text{proj}_{\mathbf{u}}(\mathbf{v}) + \text{perp}_{\mathbf{u}}(\mathbf{v})$: orthogonal decomposition

Projection onto Subspace

- $\text{proj}_W(\mathbf{v})$: closest point in subspace W to v
- Minimizes $\|\mathbf{v} - \mathbf{w}\|$ over all $\mathbf{w} \in W$

Examples in Context

Physics

- **Force vectors:** $\mathbf{F} = F_x\hat{i} + F_y\hat{j} + F_z\hat{k}$
- **Work:** $W = \mathbf{F} \cdot \mathbf{d}$ (force dot displacement)
- **Torque:** $\boldsymbol{\tau} = \mathbf{r} \times \mathbf{F}$ (cross product)

Machine Learning

- **Feature vectors:** $\mathbf{x} = [x_1, x_2, \dots, x_n]^T$
- **Cosine similarity:** $\cos(\theta) = (\mathbf{u} \cdot \mathbf{v}) / (||\mathbf{u}|| \cdot ||\mathbf{v}||)$
- **Projection:** least squares regression

Quantum Mechanics

- **State vectors:** $|\psi\rangle$ in Hilbert space
- **Inner product:** $\langle\varphi|\psi\rangle$ (overlap of states)
- **Orthonormal basis:** $\langle\mathbf{e}_i|\mathbf{e}_j\rangle = \delta_{ij}$

Computer Graphics

- **3D coordinates:** position vectors
- **Normal vectors:** perpendicular to surfaces
- **Lighting:** dot product for diffuse shading

Vector Spaces

Definition

- Set V with addition and scalar multiplication
- Satisfies axioms: closure, associativity, commutativity, identity, inverses

Examples

- $\mathbb{R}^n$: n -dimensional real vectors
- $\mathbb{C}^n$: n -dimensional complex vectors
- **Polynomials:** $p(x) = a_0 + a_1x + \dots + a_nx^n$
- **Functions:** $f: \mathbb{R} \rightarrow \mathbb{R}$

Subspaces

- $\mathbf{W} \subseteq \mathbf{V}$: closed under addition and scalar multiplication
- Examples: lines through origin, planes through origin

Practice Problems

1. If $\mathbf{u} \cdot \mathbf{v} = 0$ and $\mathbf{u} \cdot \mathbf{w} = 0$, what can you say about $\mathbf{u}$ and $\text{span}\{\mathbf{v}, \mathbf{w}\}$?
2. Find the projection of $\mathbf{v} = [3, 4]$ onto $\mathbf{u} = [1, 0]$.
3. Why is the inner product crucial in quantum mechanics?

Key Takeaways

- Vectors have direction and magnitude
- Inner products measure alignment and enable geometry
- Orthogonal vectors are independent (perpendicular)
- Projections find closest points in subspaces
- Vector spaces generalize the concept beyond $\mathbb{R}^n$

Next Steps

Next, we'll explore Hilbert spaces—infinite-dimensional vector spaces where quantum mechanics lives.

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Concepts: vector-space, inner-product, orthogonality, dimensionality

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