

Chapter 4: Orthogonality

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Abstract

This chapter focuses on the orthogonality of the four subspaces, projections, and least squares approximations.

1 Orthogonality of the Four Subspaces

Two vectors are orthogonal when their dot product is zero $\mathbf{v} \cdot \mathbf{w} = \mathbf{v}^T \mathbf{w} = 0$. This chapter will revolve around orthogonal subspaces, orthogonal bases, and orthogonal matrices.

Definition 1.1. Orthogonal vectors have the following properties:

- i. $\mathbf{v}^T \mathbf{w} = 0$
- ii. $\|\mathbf{v}\|^2 + \|\mathbf{w}\|^2 = \|\mathbf{v} + \mathbf{w}\|^2 \rightarrow \mathbf{v}^T \mathbf{v} + \mathbf{w}^T \mathbf{w} = (\mathbf{v} + \mathbf{w})^T (\mathbf{v} + \mathbf{w})$

Remark. *The zero vector is orthogonal to any vector.*

Remark. *The subspaces have orthogonal properties.*

1. **The row space $C(A^T)$ is perpendicular to the nullspace $N(A)$.** Every row of A is perpendicular to the solution of $A\mathbf{x} = \mathbf{0}$.
2. **The column space $C(A)$ is perpendicular to the left nullspaces $N(A^T)$.** When \mathbf{b} is outside of the column space when we're trying to solve for $A\mathbf{x} = \mathbf{b}$, then this nullspace of A^T comes into its own. It contains the error $\mathbf{e} = \mathbf{b} - A\mathbf{x}$ in the least-squares solution.

Definition 1.2. Two subspaces \mathbf{V} and \mathbf{W} of a vector space are orthogonal if every vector \mathbf{v} in \mathbf{V} is perpendicular to every vector \mathbf{w} in \mathbf{W} .

$$\mathbf{v}^T \mathbf{w} = 0 \text{ for all } \mathbf{v} \text{ in } \mathbf{V} \text{ and all } \mathbf{w} \text{ in } \mathbf{W}.$$

Theorem 1. Every vector \mathbf{x} in the nullspace is perpendicular to every row of A , because $A\mathbf{x} = \mathbf{0}$. The nullspace $N(A)$ and the row space $C(A^T)$ are orthogonal subspaces of \mathbb{R}^n .

$$A\mathbf{x} = \begin{bmatrix} \text{row 1} \\ \vdots \\ \text{row } m \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$C_1(\text{row}_1^T) = 0$$

$$C_2(\text{row}_2^T) = 0$$

$$\vdots$$

$$C_m(\text{row}_m^T) = 0$$

(row 1) $\cdot \mathbf{x}$ is zero and (row m) $\cdot \mathbf{x}$ is also zero. Every row has a zero dot product with \mathbf{x} . Then \mathbf{x} is perpendicular to every combination of the rows. **The whole row space $C(A^T)$ is orthogonal to $N(A)$.**

Proof. The vectors in the row space are combinations of $A^T \mathbf{y}$ of the rows. We take the dot product of $A^T \mathbf{y}$ with any \mathbf{x} in the nullspace.

$$\mathbf{x} \cdot (A^T \mathbf{y}) = \mathbf{x}^T (A^T \mathbf{y}) = (A\mathbf{x})^T \mathbf{y} = \mathbf{0}^T \mathbf{y} = 0$$

□

Example 1. The rows of A are perpendicular to $\mathbf{x} = (1, 1, -1)$ in the nullspace:

$$A\mathbf{x} = \begin{bmatrix} 1 & 3 & 4 \\ 5 & 2 & 7 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 + 3 - 4 \\ 5 + 2 - 7 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

In this example, the column space is all of \mathbb{R}^2 . The nullspace of A^T is the zero vector. The column space of A and the nullspace of A^T are always orthogonal subspaces.

Theorem 2. Every vector \mathbf{y} in the nullspace of A^T is perpendicular to every column of A . The left nullspace $N(A^T)$ and the column space $C(A)$ are orthogonal in \mathbb{R}^m .

Proof. The nullspace of A^T is orthogonal to the row space of A^T , which is the column space of A .

$$A^T \mathbf{y} = \begin{bmatrix} (\text{column 1})^T \\ \vdots \\ (\text{column } n)^T \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

□

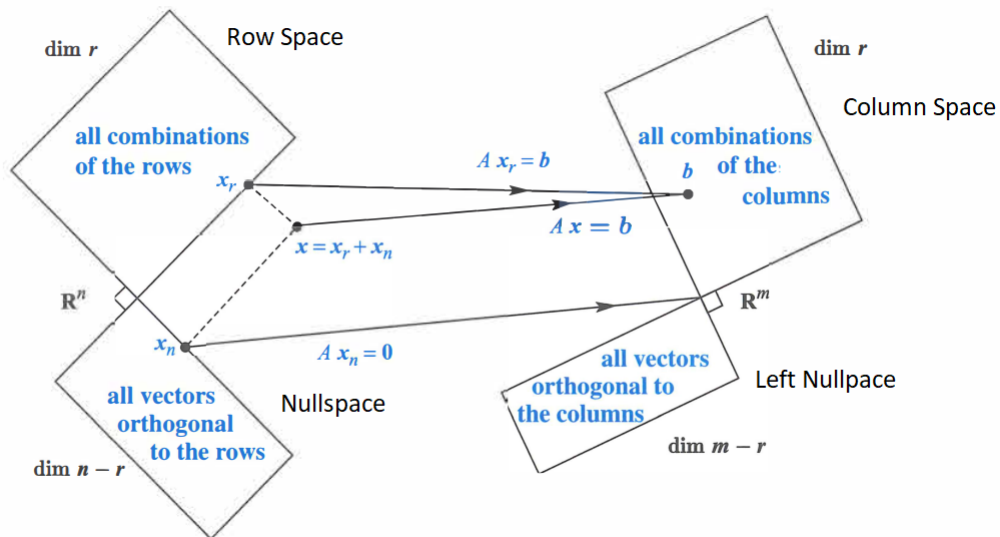


Figure 1: The Four Subspaces. There are two pairs of orthogonal subspaces.

Theorem 3. If a vector \mathbf{v} is orthogonal to itself, then \mathbf{v} is the zero vector.

Theorem 4. Fundamental Theorem of Linear Algebra, Part 2:

$N(A)$ is the orthogonal complement of the row space $C(A^T)$ in \mathbb{R}^n .

$N(A^T)$ is the orthogonal complement of the column space $C(A)$ in \mathbb{R}^m .

Things to note from Figure 1

1. When A multiplies to $\mathbf{x} = \mathbf{x}_r + \mathbf{x}_n$, it goes to \mathbf{b} which is in the column space.
2. When A multiplies to \mathbf{x}_r , it goes to \mathbf{b} which is also in the column space.
3. When A multiplies to \mathbf{x}_n , the nullspace component goes to $\mathbf{0}$.

1.1 Combining Bases from Subspaces

Theorem 5. Any independent vectors in \mathbb{R}^n must span \mathbb{R}^n . So they are a basis.

Any n vectors that span \mathbb{R}^n must be independent. So they are a basis

Theorem 6. If the n columns of A are independent, they span \mathbb{R}^n . So $A\mathbf{x} = \mathbf{b}$ is solvable. If the n columns span \mathbb{R}^n , they are independent. So $A\mathbf{x} = \mathbf{b}$ has only one solution.

2 Problems

Problem 1.1. asd

Solution. soln

□