

Math 221 Lec 13

3.2 The 4 fundamental subspaces

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October 3, 2023

1 Fundamental subspaces of linear transforms

Remark. There are really two fundamental subspaces of linear transformations

Definition 1 (Kernel and image). Let $f : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation. The **kernel** of f is $\ker(f) = \{\mathbf{v} \in \mathbb{R}^n : f(\mathbf{v}) = \mathbf{0}\}$. $\ker(f) \subset \mathbb{R}^n$. The **image** of f is $\text{Im}(f) = \{f(\mathbf{v}) : \mathbf{v} \in \mathbb{R}^n\}$. $\text{Im}(f) \subset \mathbb{R}^m$.

Theorem 2 (Kernel and image subspaces). Let $f : \mathbb{R}^n \mapsto \mathbb{R}^m$ be a linear transformation.

- (a) $\ker(f)$ is a subspace of \mathbb{R}^n .
- (b) $\text{Im}(f)$ is a subspace of \mathbb{R}^m .

Proof. Normal subspace proof

□

2 Fundamental subspaces of matrices

Definition 3 (column space). The **column space** of a matrix A , $C(A)$, is the span of its columns.

Remark. The column space of A is the image of the linear transformation represented by A , μ_A .

Definition 4 (nullspace). The **nullspace** of A is the set of vectors \mathbf{x} s.t. $A\mathbf{x} = \mathbf{0}$, aka the homogeneous solution of A .

Remark. The null space of A is the kernel of the linear transformation represented by A .

Definition 5 (row space). The row space of A , $R(A)$ is the span of its rows. Note that the book calls this $R(A^\top)$, because it treats every vector as a column.

Definition 6 (left nullspace). The **left nullspace** of A , $N(A^\top)$ consists of row vectors $\{\mathbf{x} \in \mathbb{R}_{row}^m | \mathbf{x}A = \mathbf{0}\}$. A linear combination of the rows of A using components of $\mathbf{x} \in N(A^\top)$ will produce $\mathbf{0}$.

Theorem 7 (relationship between nullspace and row space). $N(A) = R(A)^\perp$

Proof. Let $x \in N(A)$. Let $y_i \in R(A)$. We know that $A\mathbf{x} = \mathbf{0}$ since $x \in N(A)$.

$$A\mathbf{x} = \begin{bmatrix} - & \mathbf{y}_1 & - \\ - & \mathbf{y}_2 & - \\ & \vdots & \\ - & \mathbf{y}_m & - \end{bmatrix} \mathbf{x} = \begin{bmatrix} \mathbf{y}_1 \cdot \mathbf{x} \\ \mathbf{y}_2 \cdot \mathbf{x} \\ \vdots \\ \mathbf{y}_m \cdot \mathbf{x} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$\mathbf{x} \cdot \mathbf{y}_i$ is always 0, so they are orthogonal.

□