

# The Four Subspaces

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## 1 Preliminaries

Let  $A \in \mathbb{R}^{m \times n}$ .

**Def:** The Null Space of  $A$  (also called the kernel of  $A$ ), denoted  $N(A)$ , is the set  $\{x : Ax = 0\}$ .

**Def:** The Image of  $A$  (also called the column space of  $A$ )<sup>1</sup>, denoted  $Im(A)$ , is the set  $\{Ax : x \in \mathbb{R}^n\}$ .

**Def:** The dimension of a vector space is the number of elements in any basis of the vector space.

**Def:** The Nullity of  $A$ , denoted  $\mathcal{N}(A)$ , is the dimension of  $N(A)$ .

**Def:** The Rank of  $A$ , denoted  $rank(A)$  is the dimension of  $Im(A)$ .

**Def:** A subset of a vector space that is itself a vector space is called a subspace.

**Def:** The sum of two vector spaces  $V, W$ , denoted  $V + W$ , is the set  $\{v + w : v \in V, w \in W\}$ .

**Def:** A vector space  $V$  is called the direct sum of two vector spaces  $W_1, W_2$ , denoted by  $V = W_1 \oplus W_2$ , if  $W_1, W_2$  are subspaces of  $V$  such that  $W_1 \cap W_2 = \{0\}$  and  $W_1 + W_2 = V$ .

**Def:** The inner product of  $x, y$  is denoted by  $\langle x, y \rangle$ .

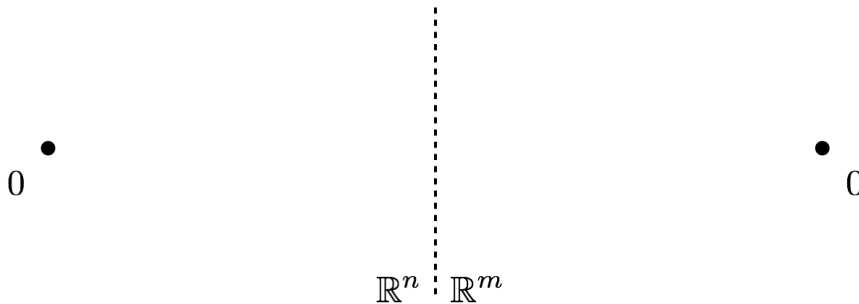
**Def:** Two vectors  $x, y$  are orthogonal means  $\langle x, y \rangle = 0$ .

**Def:** The dot product of two vectors  $x, y \in \mathbb{R}^n$  is  $x \cdot y = x^T y = x_1 y_1 + x_2 y_2 + \dots + x_n y_n$ .

**Def:** The orthogonal complement of a vector space  $V$ , denoted  $V^\perp$ , is the set  $\{w : \langle v, w \rangle = 0 \forall v \in V\}$ .

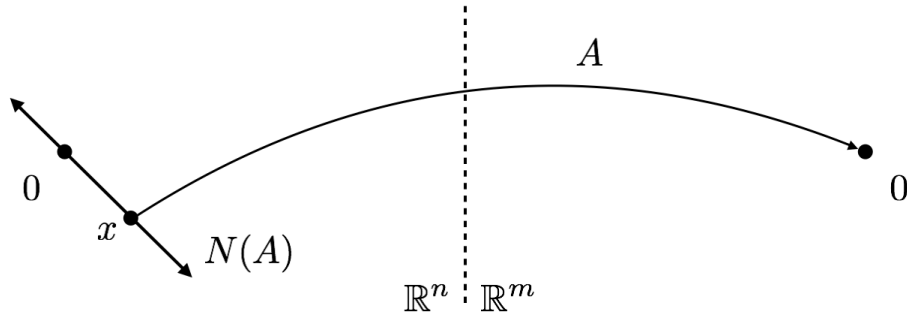
## 2 Euclidean Vector Spaces

We will consider a matrix  $A \in \mathbb{R}^{m \times n}$ . Under multiplication,  $A : \mathbb{R}^n \rightarrow \mathbb{R}^m$ . To aid us in our understanding of the four subspaces, we will draw both the domain and range of  $A$  side by side. The dots in the picture are the origins, denoted by 0.

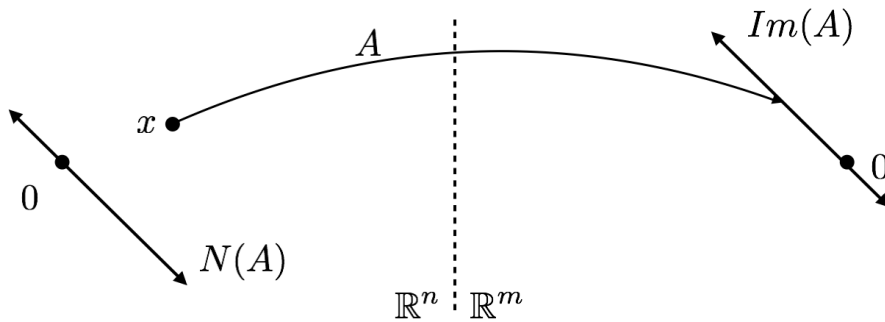


The set  $N(A)$  is a subspace of  $\mathbb{R}^n$ . Any vector  $x \in N(A)$  maps to 0 under matrix multiplication with  $A$ . Here we draw  $N(A)$  as a line through the origin. Recall that any subspace of a vector space must include the origin. Any point  $x \in N(A)$  is mapped to the origin of  $\mathbb{R}^m$  by multiplication with  $A$ .

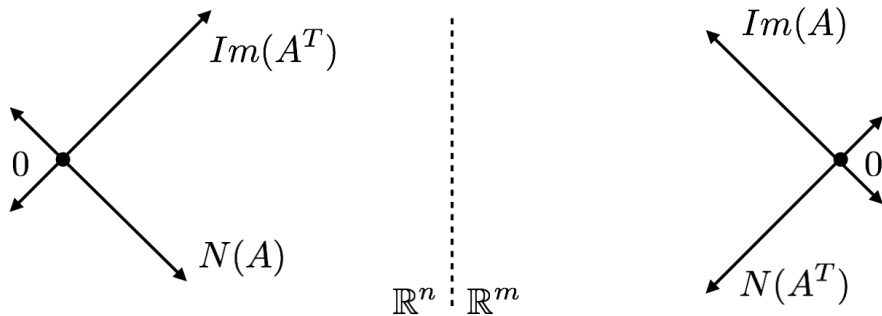
<sup>1</sup>It is also often called the Range of  $A$ , but I find that name confusing since it conflicts with the definition of the range of a function, and I don't recommend it.



The set  $Im(A)$  is a subspace of  $\mathbb{R}^m$ . Any vector  $x \in \mathbb{R}^n$  maps to  $Im(A)$ . Any vector  $x \in \mathbb{R}^n - N(A)$  maps to a nonzero vector in  $Im(A)$ , as shown below.



Let us consider the matrix  $A^T \in \mathbb{R}^{n \times m}$ . Similar to our discussion of  $A$ ,  $N(A^T)$  is a subspace of  $\mathbb{R}^m$  and  $Im(A^T)$  is a subspace of  $\mathbb{R}^n$ .



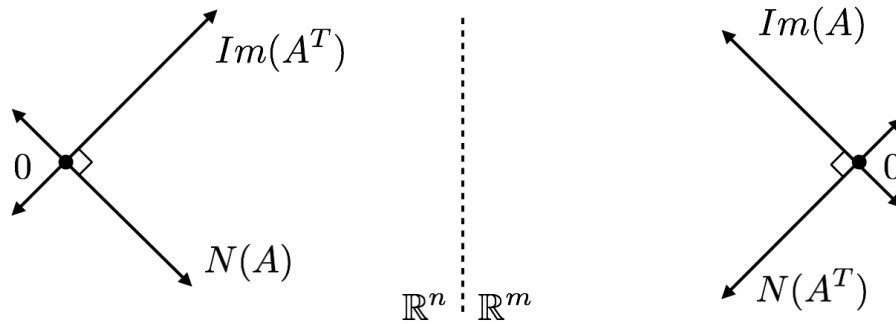
The four sets shown in the figure above,  $Im(A), Im(A^T), N(A), N(A^T)$  are called the four subspaces. Denote the  $i^{\text{th}}$  column of  $A$  by  $a_i$ . Then

$$A = \begin{bmatrix} | & | & \cdots & | \\ a_1 & a_2 & \cdots & a_n \\ | & | & \cdots & | \end{bmatrix} \quad \text{and} \quad A^T = \begin{bmatrix} - & a_1^T & - \\ - & a_2^T & - \\ & \vdots & \\ - & a_n^T & - \end{bmatrix}.$$

Consider a vector  $x \in N(A^T)$ . This means that  $A^T x = 0$ . Written out more explicitly,

$$\begin{bmatrix} - & a_1^T & - \\ - & a_2^T & - \\ & \vdots & \\ - & a_n^T & - \end{bmatrix} x = \begin{bmatrix} a_1^T x \\ a_2^T x \\ \vdots \\ a_n^T x \end{bmatrix} = 0.$$

This shows that  $x$  is orthogonal to all the columns of  $A$ . Since  $Im(A)$  equals the span of the columns of  $A$ ,  $x$  is orthogonal to  $Im(A)$ . And since  $x$  was any vector in  $N(A^T)$ ,  $N(A^T) \perp Im(A)$ . Similarly,  $N(A) \perp Im(A^T)$ .



From the above, we see that  $N(A) \oplus \text{Im}(A^T) = \mathbb{R}^n$  and  $N(A^T) \oplus \text{Im}(A) = \mathbb{R}^m$ .

The above picture summarizes some very powerful knowledge in Linear Algebra. As an example of this power, we'll now use our new understanding to prove two very famous theorems.

**The Rank-Nullity Theorem:**  $\text{rank}(A) + \mathcal{N}(A) = n$ .

**Proof:** Let  $\alpha$  be a basis for  $N(A)$  with dimension  $a$  where  $a \leq n$ . We can find a basis  $\beta$  for  $\text{Im}(A^T)$  of dimension  $n - a$ .  $\dim(A(\beta)) = \dim(\beta)$ , and  $\dim(A(\beta)) = \dim(\text{Im}(A)) = \text{rank}(A)$ . Therefore,  $\text{rank}(A) = \dim(\beta) = n - \mathcal{N}(A)$ . ■

**Theorem:**  $\text{rank}(A) = \text{rank}(A^T)$ .

**Proof:** Since  $\text{Im}(A^T) \oplus N(A) = \mathbb{R}^n$ ,  $\text{rank}(A^T) + \mathcal{N}(A) = n$ . From the last theorem, we know  $\text{rank}(A) + \mathcal{N}(A) = n$ . Subtracting one equation from the other yields  $\text{rank}(A) - \text{rank}(A^T) = 0$ . ■

The previous theorem shows us that  $A$  (when viewed as a mapping) is one-to-one when restricted to  $\text{Im}(A^T)$ . It's like  $\text{Im}(A^T)$  is the "true" domain of  $A$ , and the vectors in  $N(A)$  are just a distraction.

### 3 Inner Product Spaces

So far we've been working in Euclidean vector spaces. Now we'll work in the more general inner product spaces. We'll start by presenting more relevant definitions.

**Def:** A function  $f$  is linear means  $f(x + y) = f(x) + f(y)$  and  $f(kx) = kf(x)$  for any scalar  $k$ .

**Def:** A function  $T$  is a linear transformation means  $T$  is a linear function and it maps one vector space onto another.

**Def:** The adjoint of a linear transformation  $T : V \rightarrow W$ , denoted  $T^*$ , is the linear transformation that satisfies  $\langle Tx, y \rangle = \langle x, T^*y \rangle$  for all  $x \in V, y \in W$ .

**Def:** A function  $T$  is a linear operator means  $T$  is a linear transformation that maps a vector space onto itself.

**Def:** The null space of  $T : V \rightarrow W$ , denoted  $N(T)$ , is the set  $x \in V : T(x) = 0$ .

**Def:** The image of  $T : V \rightarrow W$ , denoted  $\text{Im}(T)$ , is the set  $\{T(x) : x \in V\}$ .

**Def:** An inner product space is a vector space together with an inner product.

Let  $T : V \rightarrow W$  such that  $T$  is a linear transformation and  $V, W$  are finite dimensional inner product spaces.

**Theorem:**  $\text{Im}(T) \perp N(T^*)$ .

**Proof:** Let  $y \in N(T^*)$ . Then  $T^*(y) = 0$ , which implies  $\langle x, T^*y \rangle = 0$  for any  $x \in V$ . But  $\langle x, T^*(y) \rangle = \langle T(x), y \rangle$ , so  $\langle T(x), y \rangle = 0$ . This shows that  $y$  is perpendicular to  $\text{Im}(T)$ . And, since  $y$  was any vector in  $N(T^*)$ , the proof is complete. ■

From here, we gain an understanding like before that is summarized in the figure below.

