

Section 4.5-~~4.6~~ Dimension and ~~rank of~~ vector spaces

& 4.6 rank of a matrix

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Dimension of a vector space

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$$v \rightarrow [v]_B \in \mathbb{R}^n$$

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Thm9 If a vector space V has a basis $B = \{b_1, b_2, \dots, b_n\}$, then any set in V containing more than n vectors must be linearly dependent.

(i.e., a basis cannot have more than n vectors)

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- So there exist scalars c_1, c_2, \dots, c_p , not all zero, such that

$$c_1[u_1]_B + c_2[u_2]_B + \dots + c_p[u_p]_B = 0$$

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- By linearity, we have

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- Since c_i are not all zero, $\{u_1, \dots, u_p\}$ is linearly dependent.

- Theorem 10: If a vector space V has a basis of n vectors, then every basis of V must consist of exactly n vectors.

B_1 — n vectors

B_2 — m vectors

$$\left. \begin{array}{l} m \leq n \\ n \leq m \end{array} \right\} \Rightarrow m = n$$

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- Thus B_2 consists of exactly n vectors.

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- ▶ 0-dimension: zero subspace
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- ▶ 3-dimension: the \mathbf{R}^3 .

Example

Ex. Find the dimension of the subspace

$$H = \left\{ \begin{bmatrix} a - 3b + 6c \\ 5a + 4d \\ b - 2c - d \\ 5d + 1 \end{bmatrix} : a, b, c, d \in \mathbf{R} \right\}.$$

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So $H = \text{Span}\{v_1, v_2, v_3, v_4\}$.

$$= \dim(A)$$

$$A = \begin{bmatrix} v_1 & v_2 & v_3 & v_4 \end{bmatrix}$$

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So $\dim H = 3$.

Subspaces of a finite-dimensional space

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Pf. Let $S = \{v_1, v_2, \dots, v_k\}$ be a linearly independent set in H .

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- $\dim H \leq \dim V$ follows as a corollary.

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- Any linearly independent set of exactly p elements in V is automatically a basis for V .

Handwritten blue ink showing three vectors in \mathbb{R}^3 :

$$\left\{ \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} * \\ 2 \\ 0 \end{bmatrix}, \begin{bmatrix} * \\ * \\ 1 \end{bmatrix} \right\} \in \mathbb{R}^3$$

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- Now suppose S has p elements and span V . Then by the Spanning Set Theorem, S contains a basis. But a basis contains p elements, so S must be a basis.

Dimension of $Nul A$ and $Col A$

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To see the dimension of $Nul A$, we suppose that $Ax = 0$ has k free variables. Then each solution to $Ax = 0$ can be expression a linear combination of k independent vectors, one for each free variable. So the k vectors form a basis for $Nul A$.

Example

Ex. Find the dimension of the null space and column space of

$$A = \begin{bmatrix} -3 & 6 & -1 & 1 & -7 \\ 1 & -2 & 2 & 3 & -1 \\ 2 & -4 & 5 & 8 & -4 \end{bmatrix}$$

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$$\dim(\text{col}(A)) = 2$$

$$\dim(\text{Nul}(A)) = 3$$

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There are two pivot columns, so $\dim \text{Col } A = 2$.

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- It is indeed true....

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- One way to study $Row A$ is to study $Col A^T$. But there are more directed ways to do it!

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On the other hand, the row operations are reversible, so the same argument shows that the row space of A is contained in the row space of B . So the two row spaces are the same.

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Example

Ex. Find bases for the row space, column space, and the null space of the matrix

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Blue arrows indicate pivot positions: up arrows under the first, second, and fourth columns of A ; left arrows under the first, second, and third rows of B .

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- By the theorem, the basis for row space of A is the first three rows of B : $\{(1, 3, -5, 1, 5), (0, 1, -2, 2, -7), (0, 0, 0, -4, 20)\}$.

- The pivot columns of B (thus A) are the first, second and fourth columns. So a basis for column space of A is the first, second, and fourth columns of A :
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- Therefore a basis for $Nul A$ is $\{(-1, 2, 1, 0, 0)^T, (-1, -3, 0, 5, 1)^T\}$.

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- The second part follows from $\text{rank } A = \dim \text{Row } A = \dim \text{Col } A$ and $\text{rank } A + \dim \text{Nul } A = n$.

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Sol. (a) the rank of A is $9 - 2 = 7$.

(b) A 6×9 matrix cannot have a two-dimensional null space, for otherwise, the rank of A is $9 - 2 = 7$, which equals the dimension of column space, but the column space is a subspace of \mathbf{R}^6 .

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