### Chapter 3 Vector Spaces

Section 3.6 Row Space and Column Space (Extra)

#### Theorem Let A be an $m \times n$ matrix.

- 1.  $\operatorname{rank}(A) + \dim N(A) = n$ .
- 2.  $rank(A) = rank(A^T)$  [The dimension of column space is the rank].
- 3.  $0 \leq \operatorname{rank}(A) \leq \min(n, m)$ .
- 4. rank(A) = 0 if and only if A = O.

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We are going to show

Theorem Let A be an  $m \times n$  matrix.

- 5.  $\operatorname{rank}(A) = \operatorname{rank}(A^T A) = \operatorname{rank}(AA^T)$ .
- 6. If P is  $m \times m$ , Q is  $n \times n$ , and both P and Q are nonsingular, then rank(PAQ)=rank(A).
- 7. For any  $m \times n$  matrix B,  $rank(A + B) \le rank(A) + rank(B)$ .
- 8. For any  $n \times r$  matrix B,  $rank(AB) \leq min\{rank(A), rank(B)\}$ .

Theorem (5) Let A be an  $m \times n$  matrix. rank $(A) = \text{rank}(A^T A) = \text{rank}(AA^T)$ .

Let 
$$A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$
.

Then 
$$A^T = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix}$$
,  $A^T A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$ ,  $AA^T = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$ .

 $\operatorname{rank}(A) = 2$ ,  $\operatorname{rank}(A^T A) = 2$ ,  $\operatorname{rank}(AA^T) = 2$ .

Theorem (6) Let A be an  $m \times n$  matrix. If P is  $m \times m$ , Q is  $n \times n$ , and both P and Q are nonsingular, then  $\operatorname{rank}(PAQ) = \operatorname{rank}(A)$ .

Example Let 
$$A = \begin{pmatrix} 3 & 0 & 0 \\ 0 & 5 & 0 \end{pmatrix}$$
,  $P = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$ ,  $Q = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$ ,

$$R = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}.$$

Note that P, Q are nonsingular because det(P) = -1 = det(Q). But R is singular because det(R) = 0.

Then 
$$PAI = \begin{pmatrix} 5 & 0 & 0 \\ 0 & 3 & 0 \end{pmatrix}$$
,  $IAQ = \begin{pmatrix} 5 & 0 & 0 \\ 0 & 3 & 0 \end{pmatrix}$ ,  $IAR = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 5 & 0 \end{pmatrix}$ .

rank(A) = 2, rank(PAI) = rank(A) = 2, rank(IAQ) = rank(A) = 2,  $rank(IAR) = 1 \neq rank(A)$ .

Theorem (5) Let A be a matrix.  $rank(A) = rank(A^T A) = rank(AA^T)$ .

## Proof of $rank(A) = rank(A^T A)$

Let  $\mathbf{x} \in N(A)$ . Then  $A\mathbf{x} = \mathbf{0}$  and  $(A^TA)\mathbf{x} = A^T(A\mathbf{x}) = A^T\mathbf{0} = \mathbf{0}$ . So  $\mathbf{x} \in N(A^TA)$ . Hence N(A) is a subspace in  $N(A^TA)$ . Let  $\mathbf{y} \in N(A^TA)$  and  $\mathbf{z} = A\mathbf{y}$ . Then  $(A^TA)\mathbf{y} = \mathbf{0}$  and

$$\mathbf{z}^T\mathbf{z} = (A\mathbf{y})^T(A\mathbf{y}) = (\mathbf{y}^TA^T)A\mathbf{y} = \mathbf{y}^T(A^TA\mathbf{y}) = \mathbf{y}^T\mathbf{0} = \mathbf{0}.$$

Note the  $\mathbf{y}^T \mathbf{0}$  is the  $1 \times 1$  matrix  $\mathbf{0}$ . Since  $\mathbf{z}$  is a column vector such that  $\mathbf{z}^T \mathbf{z} = \mathbf{0}$ , we have  $A\mathbf{y} = \mathbf{z} = \mathbf{0}$  (why?). So  $\mathbf{y} \in N(A)$ , and  $N(A^T A)$  is a subspace of N(A).

So  $N(A^TA) = N(A)$ . By the Rank-Nullity Theorem,  $rank(A^TA) = n - dim(N(A^TA)) = n - dim(N(A)) = rank(A)$ .

Theorem (Half of 6) Let A be an  $m \times n$  matrix, P be  $m \times m$  nonsingular matrix. Then rank(PA) = rank(A).

#### **Proof**

Let  $\mathbf{x} \in \mathcal{N}(A)$ . Then  $PA\mathbf{x} = P\mathbf{0} = \mathbf{0}$  and hence  $\mathbf{x} \in \mathcal{N}(PA)$ . Thus  $\mathcal{N}(A)$  is a subspace of  $\mathcal{N}(PA)$ .

On the other hand, if  $\mathbf{y} \in N(PA)$ , then  $P(Ay) = PA\mathbf{y} = \mathbf{0}$  and hence  $A\mathbf{y} \in N(P)$ . But  $N(P) = \{\mathbf{0}\}$  since P is nonsingular. Therefore  $A\mathbf{y} = \mathbf{0}$  and hence  $\mathbf{y} \in N(A)$ . Thus N(PA) is a subspace of N(A).

Now, N(PA) = N(A). It follows from the Rank-Nullity Theorem that rank(A) = n - dimN(A) = n - dimN(PA) = rank(PA).

Theorem (7) Let A be an  $m \times n$  matrix. Let B be an  $n \times r$  matrix. Then  $rank(AB) < min\{rank(A), rank(B)\}$ .

Example Let 
$$A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$
 and  $B = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{pmatrix}$ .  $AB = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$  rank $(A) = 2$ , rank $(B) = 2$ , rank $(AB) = 1$ .

Example Let 
$$A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$
 and  $B = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix}$ .  $AB = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$  rank $(A) = 1$ , rank $(B) = 2$ , rank $(AB) = 1$ .

Example Let 
$$A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$
 and  $B = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix}$ .  $AB = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix}$  rank $(A) = 2$ , rank $(B) = 2$ , rank $(AB) = 2$ .

Theorem (8) Let A, B be  $m \times n$  matrices. Then  $rank(A + B) \le rank(A) + rank(B)$ .

Example Let 
$$A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$
 and  $B = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix}$ .  $A + B = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$  rank $(A) = 2$ , rank $(B) = 2$ , rank $(A + B) = 2$ .

Example Let 
$$A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$
 and  $B = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$ .  $A + B = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$  rank $(A) = 2$ , rank $(B) = 1$ , rank $(A + B) = 3$ .

Theorem (7) Let A be an  $m \times n$  matrix. Let B be an  $n \times r$  matrix. Then  $rank(AB) \le min\{rank(A), rank(B)\}$ .

Proof

Let Col(A), Col(AB) be the column space of A and AB respectively.

Let  $\mathbf{d} \in Col(AB)$ . By Theorem (\*),  $\mathbf{d} = AB\mathbf{x}$  for some  $\mathbf{x} \in \mathbf{R}^r$ . Let  $\mathbf{y} = B\mathbf{x}$ . Since  $\mathbf{d} = A\mathbf{y}$ , it follows that  $\mathbf{d}$  is in Col(A) by Theorem (\*). Hence Col(AB) is a subspace of Col(A). Hence  $Col(AB) = \dim(Col(AB)) < \dim(Col(AB)) = \operatorname{rank}(A)$ .

$$\operatorname{rank}(AB) = \operatorname{rank}((AB)^T)$$
 dim. of col. sp.=rank
$$= \operatorname{rank}(B^TA^T)$$

$$\leq \operatorname{rank}(B^T)$$
 we have just shown  $\operatorname{rank}(CD) \leq \operatorname{rank}(C)$ 

$$= \operatorname{rank}(B)$$
 dim. of col. sp.=rank

Theorem (81) Let A, B be  $m \times n$  matrices. Then  $rank(A + B) \le rank(A) + rank(B)$ .

Proof Let  $Col(A) + Col(B) = \{ \mathbf{x} + \mathbf{y} | \mathbf{x} \in Col(A), \mathbf{y} \in Col(B) \}.$ Let  $\mathbf{d} \in Col(A+B)$ . Then  $(A+B)\mathbf{x} = \mathbf{d}$  for some  $\mathbf{x}$ . Then  $\mathbf{d} = A\mathbf{x} + B\mathbf{x}$ . Since  $A\mathbf{x}$  is in Col(A) and  $B\mathbf{x}$  is in Col(B), we have  $\mathbf{d} \in Col(A) + Col(B)$ . So Col(A + B) is a subspace of Col(A) + Col(B). Hence. rank(A+B) $= \dim(Col(A+B))$  $< \dim(Col(A) + Col(B))$  $= \dim(Col(A)) + \dim(Col(B)) - \dim(Col(A) \cap Col(B))$ by the dimension theorem at the end of the slides  $< \dim(Col(A)) + \dim(Col(B))$ =rank(A) + rank(B)

Theorem (8) Let A, B be  $m \times n$  matrices. Then  $rank(A + B) \le rank(A) + rank(B)$ .

Proof 2 Let  $Q = \begin{pmatrix} A & O \\ \hline O & B \end{pmatrix}$ . Then rank(Q) = rank(A) + rank(B). (You can see this by converting Q into row-echelon form).

Since Q and 
$$Q' = \begin{pmatrix} A & O \\ \hline A & B \end{pmatrix}$$
 are row equivalent,  $rank(Q) = rank(Q')$ .

Since 
$$Q'^T = \begin{pmatrix} A^T & A^T \\ \hline O & B^T \end{pmatrix}$$
 and  $Q'' = \begin{pmatrix} A^T & A^T \\ \hline A^T & A^T + B^T \end{pmatrix}$  are row equivalent,  $\operatorname{rank}(Q'^T) = \operatorname{rank}(Q'')$ .

Since dimension of the column space of a matrix equals the rank,  $rank(Q) = rank(Q') = rank(Q'^T) = rank(Q''^T)$ .

Note that  $Q''^T$  has a submatrix A + B. Since the rank of a submatrix cannot exceed the rank of the whole matrix (why?),  $\operatorname{rank}(A + B) < \operatorname{rank}(Q) = \operatorname{rank}(A) + \operatorname{rank}(B)$ .

Dimension Theorem Let U, V be subspaces of a vector space W. Let  $U+V=\{\mathbf{u}+\mathbf{v}|\mathbf{u}\in U,\mathbf{v}\in V\}$ . Then  $\dim(U)+\dim(V)=\dim(U+V)+\dim(U\cap V)$ . Example  $U=\{(x,y,0)^T|x,y\in\mathbf{R}\}$   $V=\{(0,0,z)^T|z\in\mathbf{R}\}$   $U\cap V=\{\mathbf{0}\},$   $U+V=\mathbf{R}^3$   $\dim U=2$ 

 $\dim V = 1$ 

 $\dim(U \cap V) = 0$  $\dim(U + V) = 3$ 

Dimension Theorem Let U, V be subspaces of a vector space W. Let  $U+V=\{\mathbf{u}+\mathbf{v}|\mathbf{u}\in U,\mathbf{v}\in V\}$ . Then

## Example

$$U = \{(0, y, 0)^T | y \in \mathbf{R}\}\$$

$$V = \{(0, 0, z)^T | z \in \mathbf{R}\}\$$

$$U \cap V = \{\mathbf{0}\}, \qquad U + V = \{(0, y, z)^T | y, z \in \mathbf{R}\}\$$

$$\dim U = 1, \dim V = 1$$

$$\dim(U \cap V) = 0, \dim(U + V) = 2$$

 $\dim(U) + \dim(V) = \dim(U + V) + \dim(U \cap V).$ 

Dimension Theorem Let U, V be subspaces of a vector space W.

Let 
$$U + V = \{\mathbf{u} + \mathbf{v} | \mathbf{u} \in U, \mathbf{v} \in V\}$$
. Then  $\dim(U) + \dim(V) = \dim(U + V) + \dim(U \cap V)$ .

# Example

$$U = \{(0, y, 0)^T | y \in \mathbf{R}\}\$$

$$V = \{(0, 0, z)^T | z \in \mathbf{R}\}\$$

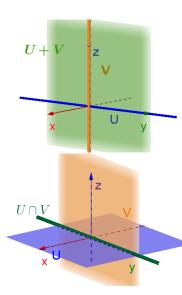
$$U \cap V = \{\mathbf{0}\}, \qquad U + V = \{(0, y, z)^T | y, z \in \mathbf{R}\}\$$

$$\dim U = 1, \dim V = 1$$

$$\dim(U \cap V) = 0, \dim(U + V) = 2$$

## Example

Example 
$$U = \{(x, y, 0)^T | x, y \in \mathbf{R}\}\$$
  $V = \{(0, y, z)^T | y, z \in \mathbf{R}\}\$   $U \cap V = \{(0, y, 0)^T | y, 0 \in \mathbf{R}\},$   $U + V = \mathbf{R}^3$  dim  $U = 2$ , dim  $V = 2$  dim $(U \cap V) = 1$ , dim $(U + V) = 3$ 



Dimension Theorem Let U, V be subspaces of a vector space W. Let  $U + V = \{\mathbf{u} + \mathbf{v} | \mathbf{u} \in U, \mathbf{v} \in V\}$ . Then  $\dim(U) + \dim(V) = \dim(U + V) + \dim(U \cap V)$ .

Idea of a proof Let  $\{\mathbf{x}_1, \dots, \mathbf{x}_k\}$  be a basis for  $U \cap V$ . Then we can extend  $\{\mathbf{x}_1, \dots, \mathbf{x}_k\}$  to a basis  $\{\mathbf{x}_1, \dots, \mathbf{x}_k, \mathbf{y}_1, \dots, \mathbf{y}_\ell\}$  of U and  $\{\mathbf{x}_1, \dots, \mathbf{x}_k, \mathbf{z}_1, \dots, \mathbf{z}_m\}$  of V.

Do some work (next two slides) to argue  $\{\mathbf{x}_1, \dots, \mathbf{x}_k, \mathbf{y}_1, \dots, \mathbf{y}_\ell, \mathbf{z}_1, \dots, \mathbf{z}_m\}$  is a basis of U + V. So

$$\dim(U) + \dim(V) = (k + \ell) + (k + m) = (k + \ell + m) + k$$
  
=  $\dim(U + V) + \dim(U \cap V)$ .

(Span) Let  $\mathbf{w} \in U + V$ . Then  $\mathbf{w} = \mathbf{u} + \mathbf{v}$  for some  $\mathbf{u} \in U$  and  $\mathbf{v} \in V$ . Since  $\mathbf{u} \in U$  and  $\{\mathbf{x}_1, \cdots, \mathbf{x}_k, \mathbf{y}_1, \cdots, \mathbf{y}_\ell\}$  is a basis of U, we have  $\mathbf{u} = a_1\mathbf{x}_1 + \cdots + a_k\mathbf{x}_k + a_{k+1}\mathbf{y}_1 + \cdots + a_{k+\ell}\mathbf{y}_\ell$  for some  $a_i$ 's. Since  $\mathbf{v} \in V$  and  $\{\mathbf{x}_1, \cdots, \mathbf{x}_k, \mathbf{z}_1, \cdots, \mathbf{z}_m\}$  is a basis of V, we have  $\mathbf{v} = b_1\mathbf{x}_1 + \cdots + b_k\mathbf{x}_k + b_{k+1}\mathbf{z}_1 + \cdots + b_{k+m}\mathbf{z}_m$  for some  $b_i$ 's. So,

$$\begin{aligned} \mathbf{w} &= \mathbf{u} + \mathbf{v} \\ &= a_1 \mathbf{x}_1 + \dots + a_k \mathbf{x}_k + a_{k+1} \mathbf{y}_1 + \dots + a_{k+\ell} \mathbf{y}_{\ell} \\ &\quad + b_1 \mathbf{x}_1 + \dots + b_k \mathbf{x}_k + b_{k+1} \mathbf{z}_1 + \dots + b_{k+m} \mathbf{z}_m \\ &= (a_1 + b_1) \mathbf{x}_1 + \dots + (a_k + b_k) \mathbf{x}_k + a_{k+1} \mathbf{y}_1 + \dots + a_{k+\ell} \mathbf{y}_{\ell} \\ &\quad + b_{k+1} \mathbf{z}_1 + \dots + b_{k+m} \mathbf{z}_m \\ &\in \mathsf{Span} \{ \mathbf{x}_1, \dots, \mathbf{x}_k, \mathbf{y}_1, \dots, \mathbf{y}_{\ell}, \mathbf{z}_1, \dots, \mathbf{z}_m \} \end{aligned}$$

(Linear independence) Let 
$$a_1, \dots, a_k, b_1, \dots, b_\ell, c_1, \dots, c_m$$
 such that  $a_1 \mathbf{x}_1 + \dots + a_k \mathbf{x}_k + b_1 \mathbf{y}_1 + \dots + b_\ell \mathbf{y}_\ell + c_1 \mathbf{z}_1 + \dots + c_m \mathbf{z}_m = \mathbf{0}$ .

Then the vector

$$\mathbf{v} = a_1 \mathbf{x}_1 + \dots + a_k \mathbf{x}_k + b_1 \mathbf{y}_1 + \dots + b_\ell \mathbf{y}_\ell \qquad --(1)$$
  
=  $-c_1 \mathbf{z}_1 - \dots - c_m \mathbf{z}_m \qquad --(2)$ 

is in both U (by (1)) and in V (by (2)), and so  $\mathbf{v} \in U \cap V$  and

$$\mathbf{v} = d_1 \mathbf{x}_1 + \dots + d_k \mathbf{x}_k. \text{ So,} 
-c_1 \mathbf{z}_1 - \dots - c_m \mathbf{z}_m = d_1 \mathbf{x}_1 + \dots + d_k \mathbf{x}_k - -(3) 
a_1 \mathbf{x}_1 + \dots + a_k \mathbf{x}_k + b_1 \mathbf{y}_1 + \dots + b_\ell \mathbf{y}_\ell = d_1 \mathbf{x}_1 + \dots + d_k \mathbf{x}_k - -(4)$$

Since  $\{\mathbf{x}_1, \dots, \mathbf{x}_k, \mathbf{z}_1, \dots, \mathbf{z}_m\}$  is a basis, it is a linearly independent set, and so (3) implies  $d_1 = \dots = d_k = -c_1 = \dots = -c_m = 0$ . Since  $\{\mathbf{x}_1, \dots, \mathbf{x}_k, \mathbf{y}_1, \dots, \mathbf{y}_\ell\}$  is a basis, it is a linearly independent set, and

so (4) implies  $d_1 - a_1 = \cdots = d_k - a_k = -b_1 = \cdots = -b_\ell = 0$ .

Since  $d_1 = \cdots = d_k = 0$  and  $d_1 - a_1 = \cdots = d_k - a_k = 0$ , we have  $a_1 = \cdots = a_k = 0$ .