

# Lecture 9

## Review

In  $\mathbb{R}^{2 \times 1}$ , two linearly independent vectors generated the entire vector space

Case 1



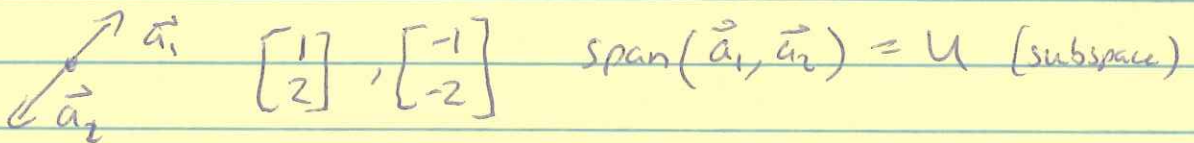
two non-parallel vectors can generate the entire  $\mathbb{R}^2$  space. Therefore a solution to  $A\vec{x} = \vec{b}$  where  $A = [\vec{a}_1, \vec{a}_2]$  always exists for any  $\vec{b} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$ .  $\vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

$$\text{Span}(\vec{a}_1, \vec{a}_2) = W, \text{ where } W = \mathbb{R}^2$$

We can always find  $x_1, x_2$  uniquely that satisfies the system for  $b_1, b_2$

$$\vec{a}_1 x_1 + \vec{a}_2 x_2 = \vec{b}$$

Case 2



$\text{span}(\vec{a}_1, \vec{a}_2) = U$  (subspace)

Let  $U$  consist of all vectors in  $\mathbb{R}^2$  whose entries are s.t.

$$U = \left\{ \begin{bmatrix} a \\ b \end{bmatrix} : b = 2a \right\} \text{ "such that"}$$

therefore, we can only find a solution  $x_1, x_2$  if  $\vec{b} \in U \Rightarrow$  all  $\vec{b}$ 's s.t.

$$A\vec{x} = \vec{b} \qquad b_1 = 2b_2$$

(2)

## Linear spans

Suppose  $\vec{u}_1, \dots, \vec{u}_n$  are any vectors in a vector space  $V$ . The collection of all linear combinations

$a_1\vec{u}_1 + a_2\vec{u}_2 + \dots + a_n\vec{u}_n$  where  $a_i$  are scalars denoted by

$\text{span}(\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n)$  or  $\text{span}(\vec{u}_i)$  is called the linear span of  $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n$

zero vector belongs to the  $\text{span}(\vec{u}_i)$ , since  
 $0 = 0 \cdot \vec{u}_1 + 0 \cdot \vec{u}_2 + \dots + 0 \cdot \vec{u}_n$

Theorem If  $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n \in V$ , then

- (i) the  $\text{span}(\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n)$  is a subspace of  $V$  that contains  $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n$
- (ii) If  $W$  is a subspace of  $V$  containing  $\{\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n\}$  then  
 $\text{span}(\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n) \subseteq W$   
"is a subset"

## Rowspace of a Matrix

Let  $A = [a_{ij}]$  be an arbitrary  $m \times n$  matrix over a field  $\mathbb{R}$ . The rows of  $A$ ,

$$\vec{r}_1 = (a_{11} \ a_{12} \ \dots \ a_{1n})$$

$$\vec{r}_2 = (a_{21} \ a_{22} \ \dots \ a_{2n})$$

$\vdots$

$$\vec{r}_m = (a_{m1} \ a_{m2} \ \dots \ a_{mn})$$

3

may be viewed as vectors in  $\mathbb{R}^n$ . They span a subspace of  $\mathbb{R}^n$  called the row space of  $A$  and denoted by  $\text{rowsp}(A)$ .

$$\text{rowsp}(A) = \text{span}(\vec{r}_1, \vec{r}_2, \dots, \vec{r}_m)$$

This is analogous to when we viewed the columns of  $A$  as vectors in  $\mathbb{R}^m$ , called the column space of  $A$

$$\text{colsp}(A) = \text{span}(\vec{a}_1, \vec{a}_2, \dots, \vec{a}_n)$$

Note that  $\text{colsp}(A) = \text{rowsp}(A^T)$

Example

If  $A = \begin{bmatrix} 1 & 0 & 3 \\ 4 & -1 & 0 \end{bmatrix}$  then the transpose

of  $A$ , denoted  $A^T$  is such that the  $i$ -th column becomes the  $i$ -th row

$$\Rightarrow A^T = \begin{bmatrix} 1 & 4 \\ 0 & -1 \\ 3 & 0 \end{bmatrix}$$

$$\text{colsp}(A) = \text{span}\left(\begin{bmatrix} 1 \\ 4 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 3 \\ 0 \end{bmatrix}\right)$$

$$\text{rowsp}(A^T) = \text{span}\left((1, 4), (0, -1), (3, 0)\right)$$



(4)

Theorem Row equivalent matrices have  
the same row space

Example

pivot points  
circled

$$A = \begin{bmatrix} 1 & 2 & -1 & 3 \\ 2 & 4 & 1 & -2 \\ 3 & 6 & 3 & -7 \end{bmatrix} \xrightarrow{\text{row Canonical Form}} \begin{bmatrix} \textcircled{1} & 2 & 0 & 1/3 \\ 0 & 0 & \textcircled{1} & -8/3 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\text{Span}\{(1, 2, -1, 3), (2, 4, 1, -2), (3, 6, 3, -7)\} = \text{Span}\{(1, 2, 0, 1/3), (0, 0, 1, -8/3)\}$$

Suppose we have another system w/ the same  
row canonical form

$$B = \begin{bmatrix} 1 & 2 & -4 & 11 \\ 2 & 4 & -5 & 14 \end{bmatrix} \xrightarrow{\text{row Canonical Form}} \begin{bmatrix} 1 & 2 & 0 & 1/3 \\ 0 & 0 & 1 & -8/3 \end{bmatrix}$$

$$\text{rowsp}(A) = \text{rowsp}(B)$$

Theorem The non-zero rows of a matrix in  
echelon form are linearly independent

(5)

## Basis and Dimension

Two equivalent definitions of a basis

Def A: A set  $S = \{ \vec{u}_1, \vec{u}_2, \dots, \vec{u}_n \}$  of vectors is a basis of  $V$  if it has the following two properties:

(1)  $S$  is linearly independent

(2)  $S$  spans  $V$

Def B: A set  $S = \{ \vec{u}_1, \vec{u}_2, \dots, \vec{u}_n \}$  of vectors is a basis of  $V$  if every  $\vec{v} \in V$  can be written uniquely as a linear combination of the basis vectors

Example

Basis for  $\mathbb{R}^2$   $\left\{ \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix} \right\}$

or  $\left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} -1 \\ 1 \end{bmatrix} \right\}$

\* A vector space  $V$  is said to be  $n$ -dimensional, written  $\dim V = n$  if  $V$  has a basis with  $n$  elements

→ The vector space  $\{0\}$  is defined to have dimension 0

Lemma: Suppose  $\{\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n\}$  spans  $V$ , then a set of  $n+1$  or more vectors in  $V$  are linearly dependent

If  $\dim V = n$ , then the entire vector space can be generated by  $n$  linearly independent vectors. If any additional vector  $\vec{w}$  is added that is in  $V$ , then by definition  $\vec{w}$  can be written as a linear combination of the set

$$\vec{w} = k_1 \vec{v}_1 + k_2 \vec{v}_2 + \dots + k_n \vec{v}_n$$

So that

$\{\vec{w}, \vec{v}_1, \vec{v}_2, \dots, \vec{v}_n\}$  is linearly dependent set

A Any basis of  $\mathbb{R}^n$  has  $n$  elements

$\mathbb{R}^2$  has a basis of two vectors

$\mathbb{R}^3$  has a basis of three vectors

Example:  $\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$  ← standard basis

$\mathbb{R}^4$  has a basis of four vectors

$$\dim(\mathbb{R}^n) = n$$

Definition: The rank of a matrix  $A$ , written  $\text{rank}(A)$  is equal to the maximum number of linearly independent rows of  $A$ , or equivalently, the dimension of the row space of  $A$ .

Theorem The maximum number of linearly independent rows of any matrix  $A$  is equal to ~~the~~ the maximum number of linearly independent columns of  $A$ , thus the dimension of the row space of  $A$  is equal to the dimension of the column space of  $A$ .