

Chapter 3: Vector Space

3.1 Def: let V be a set of elements, on which the operations of addition + and scalar multiplication \cdot are defined that satisfy the two closure properties and eight axioms below

(1) For each $x, y \in V$, $x+y \in V$

(2) For each $\alpha \in \mathbb{R}$, and $y \in V$, $\alpha y \in V$

A1 $x+y = y+x$, for any $x, y \in V$

A2 $x+(y+z) = (x+y)+z$, for all $x, y, z \in V$

A3 There exists a zero element $0 \in V$ such that $x+0=x$ for all $x \in V$

A4 for each $x \in V$, there exists an additive $y \in V$, such that

$$x+y=0$$

A5 $\alpha(x+y) = \alpha x + \alpha y$, for $x, y \in V, \alpha \in \mathbb{R}$

A6 $(\alpha+\beta)x = \alpha x + \beta x$, for $x \in V, \alpha, \beta \in \mathbb{R}$

A7 $(\alpha\beta)x = \alpha(\beta x)$, for all $x \in V, \alpha, \beta \in \mathbb{R}$

A8 $1x = x$, for all $x \in V$

Then the set V with two operations forms a vector space.

② Example:

$\mathbb{R}^n, \mathbb{R}^{mn}$

$$P_n = \{a_0 + a_1 x + \dots + a_n x^n \mid a_i \in \mathbb{R}\} \quad \{\text{set } +, \cdot\}$$

$$\text{Ex: } V = \left\{ \begin{pmatrix} x \\ y \end{pmatrix} \mid x, y \in \mathbb{R} \right\}$$

$$\text{Define } \left\{ \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \right\} + \left\{ \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \right\} = \left\{ \begin{pmatrix} x_1 + y_1 \\ x_2 + y_2 \end{pmatrix} \right\}$$

$$\alpha \in \mathbb{R}, \alpha \left\{ \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \right\} = \left\{ \begin{pmatrix} \alpha x_1 \\ 0 \end{pmatrix} \right\}$$

Q: Is $\{V, +, \cdot\}$ a vector space?

Ans: If $\alpha = 1$, $1 \left\{ \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \right\} = \left\{ \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \right\} \neq \left\{ \begin{pmatrix} x_1 \\ 0 \end{pmatrix} \right\}$ doesn't satisfy

V isn't an vector space

③ Theorem

Theorem 3.1.1 If V is a vector space and \mathbf{x} is any element of V , then

- (i) $0\mathbf{x} = \mathbf{0}$.
- (ii) $\mathbf{x} + \mathbf{y} = \mathbf{0}$ implies that $\mathbf{y} = -\mathbf{x}$ (i.e., the additive inverse of \mathbf{x} is unique).
- (iii) $(-1)\mathbf{x} = -\mathbf{x}$.

(i) Proof: $0 = -x + x = -x + (1+0)x = -x + x + 0x = 0 + 0x = 0x$

So. $0x = 0$

\downarrow \downarrow
scalar element

3.2 Subspace

① Def.

If S is a nonempty subset of a vector space V , and S satisfies the conditions

- (i) $\alpha\mathbf{x} \in S$ whenever $\mathbf{x} \in S$ for any scalar α
- (ii) $\mathbf{x} + \mathbf{y} \in S$ whenever $\mathbf{x} \in S$ and $\mathbf{y} \in S$

then S is said to be a **subspace** of V .

Theorem:

A subspace of a vector space is a vector space

Ex: Is $S = \left\{ \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \mid x_1 + x_2 + x_3 = 1 \right\}$ a subspace

$$\text{let } x_1 + x_2 + x_3 = 1, y_1 + y_2 + y_3 = 1$$

$$z_1 = x_1 + y_1$$

$$z_1 + z_2 + z_3 = 2 \notin S$$

So S isn't a subspace

Two trivial subspace

① Zero subspace $\{0\}$

② V is a subspace of itself

③ the Null space

Let A be a $m \times n$ matrix

The null space of A : $N(A) = \{ \mathbf{x} \in \mathbb{R}^n \mid A\mathbf{x} = \mathbf{0} \} \subset \mathbb{R}^n$

Theorem: The null space of $A_{m \times n}$ is a subspace of \mathbb{R}^n

Proof: (i) $0 \in N(A)$ (ii) For any $u, v \in N(A)$, $Au = 0$, $Av = 0$

$Au + Av = A(u+v) = 0$, which shows $u+v$ is a null space

(iii) for every $u \in N(A)$ $Au = 0$, the $A(\alpha u) = 0$, so $\alpha u \in N(A)$

Thus we can prove $N(A)$ is a subspace

③ Spanning Space (Subspace)

Def.

Let $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$ be vectors in a vector space V . A sum of the form $\alpha_1\mathbf{v}_1 + \alpha_2\mathbf{v}_2 + \dots + \alpha_n\mathbf{v}_n$, where $\alpha_1, \dots, \alpha_n$ are scalars, is called a **linear combination** of $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$. The set of all linear combinations of $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$ is called the **span** of $\mathbf{v}_1, \dots, \mathbf{v}_n$. The span of $\mathbf{v}_1, \dots, \mathbf{v}_n$ will be denoted by $\text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_n)$.

Ex: $A_{m \times n} = \{a_1, a_2, a_3, \dots, a_n\}$

$$\text{Span}\{a_1, a_2, \dots, a_n\} \subset \mathbb{R}^n$$

For any vector $v \in \text{Span}\{a_1, a_2, \dots, a_n\}$

$$v = \alpha_1 a_1 + \alpha_2 a_2 + \dots + \alpha_n a_n$$

$$= A \begin{Bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{Bmatrix}$$

$Ax = b$ has a sol. if and only if $b \in \text{Span}\{a_1, a_2, \dots, a_n\}$

Ex: let $A = \begin{pmatrix} 1 & -2 & 1 & 1 & 2 \\ -1 & 3 & 0 & 2 & -2 \\ 0 & 1 & 1 & 3 & 4 \\ 1 & 2 & 5 & 13 & 5 \end{pmatrix}$ let $Ax = 0$

$$U = \begin{pmatrix} 1 & 0 & 3 & 0 & 7 \\ 0 & 1 & 1 & 3 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$
$$x = \begin{Bmatrix} -3\alpha - 7\beta \\ -\alpha - 3\beta \\ \alpha \\ \beta \\ 0 \end{Bmatrix} = \alpha \begin{Bmatrix} -3 \\ -1 \\ 1 \\ 0 \\ 0 \end{Bmatrix} + \beta \begin{Bmatrix} -7 \\ -3 \\ 0 \\ 1 \\ 0 \end{Bmatrix}$$
$$\downarrow v_1 \quad \downarrow v_2$$

$\rightarrow \in \text{Span}\{v_1, v_2\}$

④ Spanning Set

The set $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ is a **spanning set** for V if and only if every vector in V can be written as a linear combination of $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$.

Ex: $\mathbb{R}^2 = \text{Span} \left\{ \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix} \right\}$

$$\left\{ \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \mid x_i \neq 0 \right\}$$

for any $x \in \mathbb{R}^2$, $x = x_1 e_1 + x_2 e_2$

(e_1, e_2) is a spanning set of \mathbb{R}^2

Ex: let $P_3(x)$ be a polynomial set of degree no less than 3

Is $\{x^2, x+x^2, -x-x^2\}$ a spanning set of P_3

let $P_3(x) = \{a_0 + a_1 x + a_2 x^2\}$

$$a_0 + a_1 x + a_2 x^2 = \alpha_1 x^2 + \alpha_2 (x+x^2) + \alpha_3 (-x-x^2)$$

$$= (\alpha_1 + \alpha_2 - \alpha_3) x^2 + (\alpha_2 - \alpha_3) x$$

$$1 \notin (\alpha_1 + \alpha_2 - \alpha_3) x^2 + (\alpha_2 - \alpha_3) x$$

① linear system

$$Ax = b$$

Theorem

Theorem 3.2.2 If the linear system $Ax = b$ is consistent and x_0 is a particular solution, then a vector y will also be a solution if and only if $y = x_0 + z$ where $z \in N(A)$.

3.3 Linear independence

① Def,

Definition

The vectors v_1, v_2, \dots, v_n in a vector space V are said to be **linearly independent** if

$$c_1 v_1 + c_2 v_2 + \dots + c_n v_n = \mathbf{0}$$

implies that all the scalars c_1, \dots, c_n must equal 0.

② In \mathbb{R}^m

let $v_1 = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$ $v_2 = \begin{pmatrix} 2 \\ 1 \end{pmatrix}$ $v_3 = \begin{pmatrix} 4 \\ 1 \end{pmatrix}$

Is $\{v_1, v_2, v_3\}$ linear independence

Given $v_1, v_2, \dots, v_k \in \mathbb{R}^m$

The system $c_1v_1 + c_2v_2 + \dots + c_kv_k = 0$

is equivalent to

$$\begin{bmatrix} v_1 & v_2 & \cdots & v_k \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_k \end{bmatrix} = 0$$
$$Ac = 0$$

③ Theorem

Theorem 3.3.1 Let x_1, x_2, \dots, x_n be n vectors in \mathbb{R}^n and let $X = (x_1, \dots, x_n)$. The vectors x_1, x_2, \dots, x_n will be linearly dependent if and only if X is singular.

Lemma: Given v_1, v_2, \dots, v_n , one is linear dependent if and only if one is linear combination of others.

Proof: If $v_1 = \alpha_2v_2 + \alpha_3v_3 + \dots + \alpha_nv_n$,

$$\text{then } (-1)v_1 + \alpha_2v_2 + \dots + \alpha_nv_n = 0$$

$$\begin{Bmatrix} -1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{Bmatrix} \neq 0 \text{ is a solution}$$

So $\{v_1, v_2, \dots, v_n\}$ is linear dependent.

\Rightarrow If (v_1, v_2, \dots, v_n) are linear dependent

the System $c_1v_1 + c_2v_2 + \dots + c_nv_n = 0$

has a nonzero sol.

* let $\{v_1, v_2, \dots, v_k\}$ be linearly independent

$\{v_1, v_2, \dots, v_{k-1}\}$ is still linearly independent

Proof: the system $\alpha_1 v_1 + \dots + \alpha_k v_k = 0$ has only zero sol.

If $\{v_1, v_2, \dots, v_{k-1}\}$ is linearly dependent

there exist $\{\beta_1, \beta_2, \dots, \beta_{k-1}\}$, not all zero

such that $\beta_1 v_1 + \beta_2 v_2 + \dots + \beta_{k-1} v_{k-1} + 0 \cdot v_k = 0$

which shows that $\{v_1, v_2, \dots, v_k\}$ is linearly dependent

and contradicts with the assumption

Theorem 3.3.2 Let v_1, \dots, v_n be vectors in a vector space V . A vector $v \in \text{Span}(v_1, \dots, v_n)$ can be written uniquely as a linear combination of v_1, \dots, v_n if and only if v_1, \dots, v_n are linearly independent.

$$v = \alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_n v_n, \text{ Uniquely } \alpha_1, \alpha_2, \dots, \alpha_n$$

Proof: Assume that $\{v_1, v_2, \dots, v_k\}$ is linear independent

If for $u \in \text{Span}\{v_1, v_2, \dots, v_k\}$

and $\begin{cases} u = \alpha_1 v_1 + \dots + \alpha_k v_k \\ u = \beta_1 v_1 + \dots + \beta_k v_k \end{cases}$

$$0 = (\alpha_1 - \beta_1) v_1 + \dots + (\alpha_k - \beta_k) v_k$$

Since $\{v_1, \dots, v_k\}$ is linear independent

$$\alpha_1 - \beta_1 = 0 \quad \dots \quad \alpha_k - \beta_k = 0$$

So we prove that's uniquely combined

3.4 Basis and dimension

① Def

The vectors v_1, v_2, \dots, v_n form a **basis** for a vector space V if and only if

- (i) v_1, \dots, v_n are linearly independent.
- (ii) v_1, \dots, v_n span V .

what about $N(A)$?

$$\text{Ex: let } A = \begin{pmatrix} 1 & -2 & 11 & 2 \\ -1 & 3 & 0 & 2 \\ 0 & 1 & 1 & 3 \\ 1 & 2 & 5 & 13 \end{pmatrix} \quad N(A) = \{x \mid Ax=0\}$$

$$A \rightarrow \begin{pmatrix} 1 & 0 & 3 & 7 & 0 \\ 0 & 1 & 1 & 3 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \Rightarrow x = \begin{Bmatrix} -3\alpha - 7\beta \\ -\alpha - 3\beta \\ \alpha \\ 0 \end{Bmatrix} = \alpha \begin{Bmatrix} -3 \\ -1 \\ 1 \\ 0 \end{Bmatrix} + \beta \begin{Bmatrix} -7 \\ 0 \\ 0 \\ 1 \end{Bmatrix} = \text{span}(v_1, v_2) = N(A)$$

v_1 v_2

And v_1, v_2 are linear independent, so they are basis of $N(A)$

② Theorem

If $\{v_1, v_2, \dots, v_n\}$ is a spanning set for a vector space V , then any collection of m vectors in V , where $m \geq n$, is linearly dependent.

Proof: Let $u_1, u_2, \dots, u_m \in V$

Consider $C_1u_1 + C_2u_2 + \dots + C_mu_m = 0$, $u_i \in V$, so $u_i = \alpha_{i1}v_1 + \alpha_{i2}v_2 + \dots + \alpha_{in}v_n$

$$u_i = \sum_{j=1}^n \alpha_{ij}v_j$$

$$\sum_{i=1}^m C_i u_i = \sum_{i=1}^m C_i \sum_{j=1}^n \alpha_{ij} v_j = 0$$

$$\sum_{j=1}^n v_j \left| \sum_{i=1}^m \alpha_{ij} C_i \right| = 0 \quad \text{enforced to be } 0, \text{ possible?}$$

$$\text{Let } \sum_{i=1}^m \alpha_{ij} C_i = 0 \quad A = (a_{ij}) \quad AC = \sum \alpha_{ij} C_i$$

$$A^T C = 0, \quad A^T = nxm, m > n, \quad \left| \begin{array}{|c|c|} \hline \square & \square \\ \hline \end{array} \right| = 0, \text{ so this system has non zero } C$$

Since $m > n$, there exists $C \neq 0$, so $\{u_1, u_2, \dots, u_m\}$ is linear dependent

Corollary 3.4.2 If both $\{v_1, \dots, v_n\}$ and $\{u_1, \dots, u_m\}$ are bases for a vector space V , then $n = m$.

③ Dimension

If (v_1, v_2, \dots, v_n) is a basis of V , then the dimension

of V is $\dim(V) = n$

Theorem 3.4.3 If V is a vector space of dimension $n > 0$, then

- (I) any set of n linearly independent vectors spans V .
- (II) any n vectors that span V are linearly independent.

proof = (i) let $v_1, v_2 \dots v_n$ be linearly independent $\Rightarrow V = \text{Span}\{v_1, v_2 \dots v_n\}$

For any $x \in V$. $\{v_1, v_2 \dots v_n, x\}$ must be linearly dependent

(otherwise, $\dim(V) = n+1$)

$c_1v_1 + c_2v_2 + \dots + c_{n+1}x = 0$, c_j are not always equal to 0

which shows $c_{n+1} \neq 0$. Since $\{v_1, v_2 \dots v_n\}$ are linearly independent

$$\text{So } x = -\frac{c_1}{c_{n+1}}v_1 - \frac{c_2}{c_{n+1}}v_2 - \dots - \frac{c_n}{c_{n+1}}v_n \in \text{Span}\{v_1, v_2 \dots v_n\}$$

Therefore $V = \text{Span}\{v_1, v_2 \dots v_n\}$ (a basis)

(ii) let $V = \text{Span}\{u_1, u_2 \dots u_n\}$

If $u_1, u_2 \dots u_n$ are not linearly independent

$$c_1u_1 + c_2u_2 + \dots + c_nu_n = 0 \quad \text{for } c_j \text{ not all 0}$$

Assume that $c_n \neq 0$, then u_n is the linear combination of others

$$u_n = -\frac{c_1}{c_n}u_1 - \frac{c_2}{c_n}u_2 - \dots - \frac{c_{n-1}}{c_n}u_{n-1}$$

Thus $V = \text{Span}\{u_1, u_2 \dots u_{n-1}\}$

If $u_1, u_2 \dots u_{n-1}$ are linearly independent

then $u_1, u_2 \dots u_n$ is a basis, which contradicts with $\dim(V) = n$

Theorem 3.4.4 If V is a vector space of dimension $n > 0$, then

- (i) no set of fewer than n vectors can span V .
- (ii) any subset of fewer than n linearly independent vectors can be extended to form a basis for V .
- (iii) any spanning set containing more than n vectors can be pared down to form a basis for V .

3.5 change of Basis

① Def Let V be a vector space, $\dim(V) = n$

$\{v_1, v_2, \dots, v_n\}$ is a basis of V

for any $x \in V = \text{span}\{v_1, v_2, \dots, v_n\}$

there exists unique $\alpha_1, \alpha_2, \dots, \alpha_n$ such that

$$x = \alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_n v_n$$

Suppose that $\beta = \{v_1, v_2, \dots, v_n\}$ is a ordered basis for V

and $v \in V$

then $[v]_{\beta} = \begin{Bmatrix} c_1 \\ \vdots \\ c_n \end{Bmatrix}$ is called coordinate vector of v with respect to β

Ex: for a polynomial $P(x) = x(x-1)(x-2) = x^3 - 3x^2 + 2x$

$$P_4(x) = \text{span}\{1, x, x^2, x^3\}$$

$$[P]_{\beta} = \begin{Bmatrix} 1 \\ -3 \\ 2 \end{Bmatrix}$$

② Transition matrix

let $\beta = \{u_1, u_2, \dots, u_n\}$ and $\gamma = \{w_1, w_2, \dots, w_n\}$

let two Bases form a vector space V

The $n \times n$ matrix

$L = \{(w_1)_{\beta}, (w_2)_{\beta}, \dots, (w_n)_{\beta}\}$ is called the transition matrix

from β to γ

for $u \in V$

$$u = \alpha_1 w_1 + \alpha_2 w_2 + \dots + \alpha_n w_n$$

$$[u]_{\beta} = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}$$

$$\forall v \in V, v = u_1 \beta_1 + \dots + u_n \beta_n$$

$$[v]_{\beta} = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_n \end{bmatrix}$$

$$v = w_1 \gamma_1 + \dots + w_n \gamma_n$$

$$[v]_{\gamma} = \begin{bmatrix} \gamma_1 \\ \vdots \\ \gamma_n \end{bmatrix}$$

Theorem , $\beta = [u_1, u_2, \dots, u_n]$, $\gamma = [w_1, \dots, w_n]$ = bases of V

L : transition matrix , for any $v \in V$

$$(i) [v]_{\gamma} = L [v]_{\beta} \quad (ii) L \text{ nonsingular}$$

Since $u_j \in V$

$$u_j = a_{1j} w_1 + a_{2j} w_2 + \dots + a_{nj} w_n$$

for any $v \in V$

$$v = c_1 u_1 + c_2 u_2 + \dots + c_n u_n = \sum c_j u_j = \sum_{j=1}^n c_j \sum_{i=1}^n a_{ij} w_i$$

$$= \sum_{i=1}^n w_i \underbrace{\left[\sum_{j=1}^n a_{ij} c_j \right]}_{b_i}$$

$$= \sum_{i=1}^n w_i b_i$$

$$= w_1 b_1 + w_2 b_2 + \dots + w_n b_n \Rightarrow [v]_{\gamma} = \begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix}$$

$$[v]_{\gamma} = A [v]_{\beta} = L [v]_{\beta}$$

(iii) If L is singular

there exists $x \neq 0$, $Lx = 0$

$$\text{choose } [v]_{\beta} = x \text{ to get } v = x_1 v_1 + x_2 v_2 + \dots + x_n v_n$$

$$\star v = c_1 u_1 + \dots + c_n u_n$$

uniquely

$$\Rightarrow [v]_{\beta} = 0$$

$$\Rightarrow V=0$$

$$0 = x_1 u_1 + x_2 u_2 + \dots + x_n u_n$$

$$0 = 0 \cdot u_1 + \dots + 0 \cdot u_n$$

$$\Rightarrow x=0$$

Ex: $V=\mathbb{R}^n$

$$[u_1 \dots u_n] = \tilde{U} \quad n \times n \text{ matrix}$$

$$[w_1 \dots w_n] = \tilde{W} \quad n \times n \text{ matrix}$$

For any $v \in \mathbb{R}^n$, $v = \tilde{U}x = x_1 u_1 + x_2 u_2 + \dots + x_n u_n$

$$v = \tilde{W}y = y_1 w_1 + y_2 w_2 + \dots + y_n w_n$$

$$\tilde{U}x = \tilde{W}y$$

$$y = \tilde{W}^{-1} \tilde{U}x \quad \text{transition matrix}$$

$$y = \underline{\tilde{U}x}$$

3.6 Row space and column space ⭐

① Def

If A is an $m \times n$ matrix, the subspace of $\mathbb{R}^{1 \times n}$ spanned by the row vectors of A is called the **row space** of A . The subspace of \mathbb{R}^m spanned by the column vectors of A is called the **column space** of A .

$A_{\text{max}} = (a_1 \dots a_n)$, $\text{Span}(a_1, \dots, a_n) = \text{Column space of } A$

$A_{\text{max}} = \begin{pmatrix} \tilde{a}_1 \\ \vdots \\ \tilde{a}_n \end{pmatrix}$, $\text{Span}(\tilde{a}_1 \dots \tilde{a}_n) = \text{row space of } A$

② Theorem

Theorem 3.6.1 Two row equivalent matrices have the same row space.

Let $A = \begin{pmatrix} \tilde{a}_1 \\ \vdots \\ \tilde{a}_n \end{pmatrix}$ and $B = \begin{pmatrix} \tilde{b}_1 \\ \vdots \\ \tilde{b}_n \end{pmatrix}$ be two row equivalent matrix

$$A = L B, A^T = B^T L^T$$

$$(a_1^T \dots a_n^T) = (b_1^T \dots b_n^T) L$$

$$a_i^T = u_{i1} b_1^T + u_{i2} b_2^T + \dots + u_{in} b_n^T$$

$$\tilde{a}_i \in \text{Span}(b_1^T \dots b_n^T) = \text{row space of } B$$

row space of $A \subset$ row space of B

$L^{-1} A = B \Rightarrow$ row space of $B \subset$ row space of A

③ Dimension

$$\left\{ \begin{array}{l} \dim(N(A)) = \text{nullity of } A \\ \dim(\text{row space}) = \text{rank}(A) \\ \dim(\text{Column space}) \end{array} \right.$$

$$\dim(N(A^T))$$

④ Base

Given a matrix A

$E_k \dots E_2 E_1 A = U$ echelon form, A and U have same row/null space

$$\begin{matrix} v_1 & \leftarrow & [& 1 & &] \\ v_2 & \leftarrow & [& 1 & - &] \\ v_3 & \leftarrow & [& 0 & - & 0] \end{matrix}$$

base: $\{v_1, v_2, v_3\}$ of row space

Ex: Find a basis of row space of $A = \begin{bmatrix} 1 & -2 & 3 \\ 2 & -5 & 1 \\ 1 & -4 & -4 \end{bmatrix}$

Sol:

$$A \xrightarrow{\text{row operation}} \begin{bmatrix} 1 & -2 & 3 \\ 0 & -1 & -5 \\ 0 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -2 & 3 \\ 0 & 1 & 5 \\ 0 & 0 & 0 \end{bmatrix} = U$$

So $\{(1, -2, 3), (0, 1, 5)\}$ is a basis of row space

and Rank is 2

Question?

For Given $v_1, v_2, \dots, v_k \in \mathbb{R}^n$, find a basis of $\text{Span}\{v_1, v_2, \dots, v_k\}$

$\text{Span}\{v_1, \dots, v_k\}$ is the column space of a matrix $(v_1 \dots v_k)$

Find $\dim(\text{Span}(v_1, \dots, v_k)) = \text{rank}(B)$

Let $v \in \text{Span}(v_1, \dots, v_k)$, $v = x_1 v_1 + \dots + x_k v_k$, $v = Ax$

where $A = (v_1, v_2, \dots, v_k)$

$$\text{Ex: } A = \begin{bmatrix} 1 & -2 & 1 & 1 & 2 \\ -1 & 3 & 0 & 2 & -2 \\ 0 & 1 & 1 & 3 & 4 \\ 1 & 2 & 5 & 13 & 5 \end{bmatrix}$$

Find a basis for

(i) row space (ii) column space

$$A \rightarrow \begin{bmatrix} 1 & -2 & 1 & 1 & 2 \\ 0 & 1 & 1 & 3 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

(iii) $N(A)$ (iv) $\text{Rank}(A)$

Theorem 3.6.5 The Rank–Nullity Theorem

If A is an $m \times n$ matrix, then the rank of A plus the nullity of A equals n .

Proof Let U be the reduced row echelon form of A . The system $Ax = \mathbf{0}$ is equivalent to the system $Ux = \mathbf{0}$. If A has rank r , then U will have r nonzero rows, and consequently the system $Ux = \mathbf{0}$ will involve r lead variables and $n - r$ free variables. The dimension of $N(A)$ will equal the number of free variables. ■

Theorem 3.6.6 If A is an $m \times n$ matrix, the dimension of the row space of A equals the dimension of the column space of A .

③ linear system

Theorem = (consistency theorem for linear system)

A linear system $Ax=b$ is consist if and only if b is in the column space of A

$$A = (a_1, a_2, \dots, a_m) \quad Ax=b \Leftrightarrow x_1a_1 + x_2a_2 + \dots + x_ma_m = b$$

Theorem 3.6.2 (i) The system $Ax=b$ is constant for any $b \in \mathbb{R}^m$ if and only if

if the column vectors of A spans \mathbb{R}^m (column space of A is \mathbb{R}^m)

proof: (ii) $Ax=b$ has at most one solution for every $b \in \mathbb{R}^m$

If and only if the column vectors of A are linearly independent.

proof: let x_1, x_2 be two solution

$$\begin{cases} Ax_1 = b \\ Ax_2 = b \end{cases} \Rightarrow A(x_1 - x_2) = 0$$

if the column vectors of A is linearly independent

then $Ax=0$ has only zero sol so $x_1=x_2$. $Ax=b$ has only one solution.

Theorem (Equivalent Conditions)

- (i) A is nonsingular (ii) $Ax=0$ has only zero sol.
- (iii) A is row equivalent to I (iv) $Ax=b$ has exactly one sol.
- (v) $\det(A) \neq 0$ (vi) Column vectors of A forms a basis for \mathbb{R}^n
- (vii) Row vector of A forms a basis for $\mathbb{R}^{1 \times n}$
- (viii) the nullity of A is 0 $\Leftrightarrow \dim(\text{N}(A)) = 0$

④ Remarks

Given $(v_1, v_2, \dots, v_n) \in \mathbb{R}^n$, $\text{span}(v_1, \dots, v_n)$, Find the basis

(i) $A_{m \times n}$

Column space of $A = \text{Span}(a_1, \dots, a_n) = \{y' = Ax \mid X \in \mathbb{R}^n\}$

For any $z \in$ Column space of A

the z is a linear combination of A , or there exist a $\alpha \in \mathbb{R}^n$

such that $\mathbf{z} = A\mathbf{x}$

$N(A^T) = \{y | A^T y = 0\}$, then $A^T y = 0$

Question: what's the relation between \mathbf{z} and \mathbf{y} ?

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

⑤ Review

linear combination, span space

linear independent/dependent

concept basis

dimension

Rank

- $v_1 - v_k$ are linearly dependent, then one can be written as the linear combination of others
- $v_1 - v_k$ are linearly independent the subset is linearly independent
- $v_1 - v_k \in V$ are linearly independent, for any $v \in V$
 $v_1 - v_k, v$ are linearly dependent
- $\{v_1 - v_k\}$ is a basis for V , for any $y \in V$

y can be written as the linear combination of $v_1 - v_k$ uniquely

- $\dim(V) = n$, then any n linearly independent vectors forms a basis
- $L \subset V$, $\dim(L) \leq \dim(V)$
- let $v_1 - v_k \in \mathbb{R}^n$ be linearly independent

and A is a $n \times n$ nonsingular matrix

Then $\{Av_1, \dots, Av_k\}$ are also linearly independent

Ex: Let v_1, \dots, v_m be linearly dependent

with $v_1 \neq 0$, Then there exist v_k for index k such that

v_k is a linear combination of $\{v_1, \dots, v_{k-1}\}$

⑥ Rank

Theorem: let A be a $m \times n$ matrix

$$(i) \text{Rank}(A) + \dim(N(A)) = n$$

$$(ii) \text{Rank}(A) = \text{Rank}(A^T)$$

$$(iii) 0 \leq \text{rank}(A) \leq \min(n, m)$$

$$(iv) \text{rank} = 0 \text{ if and only if } A = 0$$

$$(v) \text{Rank}(A) = \text{Rank}(A^T A) = \text{Rank}(AA^T)$$

(vi) if P is $m \times n$ and Q is $n \times m$. And both are nonsingular

$$\text{the rank}(PAQ) = \text{rank}(A)$$

$$(vii) \text{Rank}(A+B) \leq \text{Rank}(A) + \text{Rank}(B)$$

$$(viii) \text{Rank}(AB) \leq \min\{\text{Rank}(A), \text{Rank}(B)\}$$

$$(ix) \text{Rank}(A, B) \leq \text{Rank}(A) + \text{Rank}(B)$$

Proof of (v): $N(A) = N(A^T A)$

$$\text{since } \text{Rank}(A) + \dim(N(A)) = n$$

$$\text{Rank}(A^T A) + \dim(N(A^T A)) = n$$

$$\text{so } \text{Rank}(A) = \text{Rank}(A^T A)$$

Proof of (vi): Let $B = A\mathbf{Q}$

so B and A have the same column space

$$\dim(\text{Column space of } B) = \dim(\text{Column space of } A)$$

$$\text{So } \text{Rank}(B) = \text{Rank}(A)$$

$$\text{Rank}(A\mathbf{Q}) = \text{Rank}(A)$$

$$\text{Rank}(P A \mathbf{Q}) = \text{Rank}(P A \mathbf{Q})^T = \text{Rank}(\mathbf{Q}^T A^T P^T)$$

$$= \text{Rank}(\mathbf{Q}^T A^T) = \text{Rank}(A^T \mathbf{Q}) = \text{Rank}(A)$$