

## Section 1.1 & 1.2

$V$  is a vectorspace if it is closed under addition & scalar multiplication  
 $x, y \in V \rightarrow \alpha x + y \in V$

$$0 \in V$$

$$(1) \alpha = 0$$

$$\alpha \cdot x = 0 \cdot x = 0$$

$$\alpha x \in V, 0 \in V$$

$$(2) \alpha = -1$$

$$\alpha \cdot x = -x \in V$$

$$-x + x = 0 \in V$$

If  $0 \notin S$ ,  $S$  is not a vectorspace

$$\text{Unit vectors } (e_i)_j = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases} \quad x = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = x_1 e_1 + x_2 e_2 + x_3 e_3$$

$$A = B \text{ if } A, B \in \mathbb{R}^{m \times n}$$

$$a_{ij} = b_{ij} \quad \forall i = 1 \dots m \\ j = 1 \dots n$$

$$(A^T)^T = A$$

$$(A + B)^T = A^T + B^T$$

$$(\alpha A)^T = \alpha A^T$$

$$\text{Diagonal matrix } D = \begin{bmatrix} \lambda_1 & 0 & 0 & 0 \\ 0 & \lambda_2 & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \lambda_n \end{bmatrix}$$

Symmetric

$$A^T = A$$

skew-symmetric

$$A^T = -A \rightarrow a_{ij} = -a_{ji}$$

$$a_{ii} = -a_{ii} \quad (i=j) \rightarrow a_{ii} = 0$$

## Section 1.3

Subspace  $S \subseteq V$   $\begin{cases} \text{trivial subspaces } \{0\}, V \\ \text{non-trivial subspaces line, planes} \end{cases}$

$$\text{Affine space } A = p + X = \{v \in V \mid v = p + x, x \in X\}$$

Linearly dependent if one of them can be written as linear combination  
if  $\exists x \neq 0 \ni Ax = 0$

Linearly independent  $\sum \alpha_i v_i = 0 \rightarrow \alpha_i = 0 \forall i$

$$A = [v_1 \ v_2 \ \dots \ v_n]$$
$$Ax = 0 \rightarrow x = 0$$

## Section 1.4 & 1.5

Norm  $\|x\| = \left( \sum_{i=1}^n x_i^2 \right)^{1/2} = \sqrt{x^T x}$

$$\begin{aligned} \|\alpha x\| &= \sqrt{\langle \alpha x, \alpha x \rangle} \\ &= \sqrt{\alpha^2 \langle x, x \rangle} \\ &= |\alpha| \sqrt{\langle x, x \rangle} \\ &= |\alpha| \|x\| \end{aligned}$$

(1)  $\|x\| \geq 0$

(2)  $\|x\| = 0 \rightarrow x = 0$

(3)  $\|\alpha x\| = |\alpha| \|x\|$

(4)  $\|x+y\| \leq \|x\| + \|y\|$  ( $\Delta$  inequality)

Inner product  $\langle x, y \rangle = \sum_{i=1}^n x_i y_i = \text{trace}(x^T y)$

(1) Bilinear  $\langle \alpha x + y, v \rangle = \alpha \langle x, v \rangle + \langle y, v \rangle$   $\langle \alpha u, \alpha v \rangle = \alpha^2 \langle u, v \rangle$   
 $\langle x, v + \beta w \rangle = \langle x, v \rangle + \beta \langle x, w \rangle$

(2)  $\langle x, x \rangle \geq 0$

$$\langle x, x \rangle = 0 \rightarrow x = 0$$

$$\langle x, y \rangle = 0 \rightarrow x \perp y$$

(3) Symmetric  $\langle x, y \rangle = \langle y, x \rangle$

1-norm  $\|x\|_1 = |x_1| + |x_2| + \dots + |x_n|$   
 $\|x+y\|_1 \leq \|x\|_1 + \|y\|_1$

Proof

$$\begin{aligned} \|x+y\|_1 &= |x_1+y_1| + |x_2+y_2| + \dots + |x_n+y_n| \\ &\leq |x_1| + |y_1| + |x_2| + |y_2| + \dots + |x_n| + |y_n| \\ &= \|x\|_1 + \|y\|_1 \end{aligned}$$

$\infty$ -norm  $\|x\|_\infty = \max_{i=1}^n |x_i|$

General  $\|x\|_p = \left( \sum |x_i|^p \right)^{1/p} \quad (1 \leq p \leq 2)$

CBS Inequality  $|\langle x, y \rangle| \leq \|x\| \|y\|$

Proof

If  $x = 0$ ,  $\|x\| = 0 \rightarrow \langle x, y \rangle = 0 \rightarrow$  inequality holds

If  $x \neq 0$ ,  $\alpha = \frac{\langle x, y \rangle}{\|x\|^2}$   $v = \alpha x - y$

$$\langle x, v \rangle = \langle x, \alpha x - y \rangle = \alpha \langle x, x \rangle - \langle x, y \rangle = \frac{\langle x, y \rangle}{\|x\|^2} \|x\|^2 - \langle x, y \rangle = 0$$

$$\begin{aligned} 0 \leq \|v\|^2 &= \langle v, v \rangle = \langle \alpha x - y, \alpha x - y \rangle \\ &= \alpha \langle x, \alpha x - y \rangle - \langle y, \alpha x - y \rangle \\ &= \alpha(0) - \alpha \langle y, x \rangle + \langle y, y \rangle \\ &= \|y\|^2 - \frac{\langle x, y \rangle}{\|x\|^2} \langle x, y \rangle \\ &= \frac{\|y\|^2 \|x\|^2 - \langle x, y \rangle^2}{\|x\|^2} \end{aligned}$$

$$\therefore \|x\|^2 \|y\|^2 \geq \langle x, y \rangle^2 \quad \therefore |\langle x, y \rangle| \leq \|x\| \|y\|$$

Proof  $\Delta$   
inequality

$$\begin{aligned} \|x+y\|^2 &= \langle x+y, x+y \rangle = \langle x, x \rangle + \langle x, y \rangle + \langle y, x \rangle + \langle y, y \rangle \\ &= \|x\|^2 + 2\langle x, y \rangle + \|y\|^2 \\ &\leq \|x\|^2 + 2|\langle x, y \rangle| + \|y\|^2 \quad a \leq |a| \\ &= (\|x\| + \|y\|)^2 \end{aligned}$$

$$\therefore \|x+y\| \leq \|x\| + \|y\|$$

Backward  $\Delta$  inequality  $|\|x\| - \|y\|| \leq \|x-y\|$

Proof

$$\begin{aligned} \|x\| &= \|x-y+y\| \leq \|x-y\| + \|y\| \quad \therefore \|x\| - \|y\| \leq \|x-y\| \\ \|y\| &= \|y-x+x\| \leq \|y-x\| + \|x\| = \|x-y\| + \|x\| \quad \therefore \|y-x\| \leq \|x-y\| \\ \therefore |\|x\| - \|y\|| &\leq \|x-y\| \end{aligned}$$

## Section 1.6

Orthogonality  $\langle x, y \rangle = 0 \rightarrow \|x\|^2 + \|y\|^2 = \|x-y\|^2$

Angle  $\cos \theta = \frac{\langle x, y \rangle}{\|x\| \|y\|}$

Orthogonal set  $\{u_1, u_2, \dots, u_n\}$   
 $\langle u_i, u_j \rangle = 0 \quad (i \neq j)$   
 $\rightarrow$  linearly independent

Orthonormal  $\langle u_i, u_j \rangle = \begin{cases} 0, & i \neq j \\ 1, & i = j \end{cases}$   
 $\|u_i\| = 1$   
 $\rightarrow$  orthogonal matrix  
 (use  $\frac{u}{\|u\|}$ )

## Section 1.7

Linear transformation  $f(\alpha x + y) = \alpha f(x) + f(y)$

If  $y$  fixed:  $f_y(x) = \langle x, y \rangle$

$$f_y(x+u) = \langle x+u, y \rangle = \langle x, y \rangle + \langle u, y \rangle$$

If  $x$  fixed:  $f_x(u+v) = \langle u+v, y \rangle = \langle u, y \rangle + \langle v, y \rangle = f_x(u) + f_x(v)$

Matrix times vector

$$\begin{matrix} \text{1st coeff } x & \text{1st col} \end{matrix} \begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix} \begin{vmatrix} y_1 \\ y_2 \\ y_3 \end{vmatrix} = y_1 x_1 + y_2 x_2 + y_3 x_3$$

Nullspace kernel  $\mathcal{N}(f) = \{x \in V \mid f(x) = 0\}$

$$f(0) = 0$$

Range

$$R(f) = \{y \in \mathbb{R} \mid \exists x \in \mathcal{D}, f(x) = y\}$$

$$0 \in R(f)$$

Composition of linear maps is a linear map

Proof  $\rightarrow$









$$\begin{aligned} (f \circ g)(\alpha x + y) &= f(g(\alpha x + y)) = f(\alpha g(x) + g(y)) && \text{linear } g \\ &\quad \uparrow && \\ &\quad \text{composition} && \\ &= \alpha f(g(x)) + f(g(y)) && \text{linear } f \\ &= \alpha (f \circ g)(x) + (f \circ g)(y) \end{aligned}$$

Matrix times matrix

$$c_{ij} = \sum_{k=1}^{n_2} a_{ik} b_{kj}$$

$$\text{matrix } \times \text{ each col } \begin{bmatrix} 1 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 3 \end{bmatrix} \begin{vmatrix} 1 \\ 1 \end{vmatrix} \& \begin{bmatrix} 1 & 0 \\ 0 & 3 \end{bmatrix} \begin{vmatrix} 1 \\ -1 \end{vmatrix}$$

$Ax = b$  consistent if  $\exists$  at least 1 soln ( $b$  is linear combination of  $A$ 's cols)

Triangular  $\rightarrow$  lower  $a_{ij} = 0 \ (i < j)$    $\therefore$    $\cdot$    $=$    
upper  $a_{ij} = 0 \ (i > j)$    $\therefore$    $\cdot$    $=$  

A triangular  $\rightarrow A^{-1}$  also triangular  $\text{diag}(A^{-1}) = \text{diag}(\frac{1}{a_{ii}})$

$\text{diag}(AB) = \text{diag}(A) \cdot \text{diag}(B)$

$$(AB)_{ii} = A_{ii} \cdot B_{ii}$$

## Section 1.8

Diagonal matrix  $ij = \begin{cases} 1 & (i=j) \\ 0 & (i \neq j) \end{cases}$   $IA = A$   
 $AI = A$

$A^0 = I$   $(AB)^T = B^T A^T$   $(ABC)^{-1} = C^{-1} B^{-1} A^{-1}$   
 $A^x \cdot A^y = A^{x+y}$   $(A^T A)^T = A^T (A^T)^T = A^T A$   
 $(A^x)^y = A^{x \cdot y}$  always symmetric

Inverse  $A \cdot B = I \rightarrow B = A^{-1}$   
 $\rightarrow$  exists if cols of  $A$  are linearly independent

$\text{trace}(AB) = \text{trace}(BA)$

Proof  
 $\text{trace}(AB) = \sum_{i=1}^n (AB)_{ii} = \sum_{i=1}^n A_{i*} B_{*i} = \sum_{i=1}^n \sum_{k=1}^m a_{ik} b_{ki}$   
 $= \sum_{i=1}^n \sum_{k=1}^m b_{ki} a_{ik} = \sum_{k=1}^m \sum_{i=1}^n b_{ki} a_{ik} = \sum_{k=1}^m B_{k*} A_{*k} = \sum_{k=1}^m (BA)_{kk}$   
 $= \text{trace}(BA)$

$\text{trace}(ABC) = \text{trace}(CAB) = \text{trace}(BCA)$

Nonsingular (linearly independent)  $Ax = 0 \rightarrow x = 0$   
 $Ax = b$  has unique soln  
 $AX = I \rightarrow XA = I$

## Section 1.9 & 1.10

Matrix norm  $\|AB\| \leq \|A\| \cdot \|B\|$

$\|A\| = \sup_{x \neq 0} \frac{\|Ax\|}{\|x\|} = \sup_{\|x\|=1} \|Ax\|$

Orthogonal matrix  $U$

(1) maintain length

$\|Ux\|^2 = \langle Ux, Ux \rangle = (Ux)^T Ux$   
 $= x^T U^T Ux = x^T I x$   
 $= x^T x = \|x\|^2$  ✓

(2) maintain angle

$\cos(Ux, Uy) = \frac{\langle Ux, Uy \rangle}{\|Ux\| \|Uy\|}$   
 $= \frac{(Ux)^T Uy}{\|x\| \|y\|} = \frac{x^T y}{\|x\| \|y\|} = \frac{\langle x, y \rangle}{\|x\| \|y\|} = \cos \theta$  ✓

A, B orthogonal  $\rightarrow$  show  $A^T A = I$

$$\|A^{-1}\| = \max_{x \neq 0} \frac{\|A^{-1}x\|}{\|x\|} = \max_{y \neq 0} \frac{\|y\|}{\|Ay\|} = \frac{1}{\min_{y \neq 0} \frac{\|Ay\|}{\|y\|}}$$

$$\rightarrow \min_{\|x\| \neq 0} \|Ax\| = \frac{1}{\|A^{-1}\|}$$

Reflections  $R = I - \frac{2uu^T}{u^T u} \xrightarrow{\substack{u^T u = 1 \\ \|u\| = 1}} R = I - uu^T$

(1)  $R^T = R$

Proof  $\rightarrow$

$$R^T = I^T - 2(uu^T)^T = I - 2(uu^T) = R$$

(2)  $RR = I$

Proof  $\rightarrow$

$$RR = (I - 2uu^T)(I - 2uu^T) = I - 2uu^T - 2uu^T + 4\underbrace{uu^T uu^T}_{= I} = I - 4uu^T + 4uu^T = I$$

(3)  $Ru = -u$

Proof  $\rightarrow$

$$Ru = (I - 2uu^T)u = u - 2\underbrace{uu^T u}_u = u - 2u = -u$$

if  $u^T w = 0 \rightarrow (I - 2uu^T)w = w - 2\underbrace{uu^T w}_0 = w$

(4)  $\therefore R w = w$

Orthogonal projection  $P = I - uu^T$

(1)  $P^2 = P$  (general projection)

Proof  $\rightarrow$

$$P^2 = (I - uu^T)^2 = I - 2uu^T + \underbrace{uu^T uu^T}_{= uu^T} = I - 2uu^T + uu^T = I - uu^T = P$$

(2)  $P^T = P$  (orthogonal projection)

Proof  $\rightarrow$

$$P^T = I - (uu^T)^T = I - uu^T = P$$

(3) if  $w \perp u$   $Pw = w$

Proof  $\rightarrow$

$$P(u+w) = Pu + Pw = 0 + w = w$$