

计算机视觉

§ 0 预备知识

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几何变换

平面点

- $\mathbf{x} = (x \ y)^T \in \mathcal{R}^2$, \mathcal{R}^2 : 2D欧氏平面
- 用齐次坐标(homogeneous coordinates)表示 $\mathbf{x} = (x \ y)^T$:
 - $\tilde{\mathbf{x}} = (\tilde{x} \ \tilde{y} \ \tilde{w})^T \in \mathcal{P}^2$
 - $x = \frac{\tilde{x}}{\tilde{w}}, y = \frac{\tilde{y}}{\tilde{w}}, (\tilde{w} \neq 0)$
 - $\mathcal{P}^2 = \mathcal{R}^3 - (0 \ 0 \ 0)^T$: 2D投影平面(2D Projective Space)
 - $\bar{\mathbf{x}} = (x \ y \ 1)^T$: \mathbf{x} 的增广向量
- 无穷远点(理想点):
 - $\tilde{\mathbf{x}} = (\tilde{x} \ \tilde{y} \ 0)^T$
- 例:
 - $\mathbf{x} = (2 \ 3)^T \rightarrow \bar{\mathbf{x}} = (2 \ 3 \ 1)^T, \tilde{\mathbf{x}} = (4 \ 6 \ 2)^T, \dots \tilde{\mathbf{x}} = \alpha(2 \ 3 \ 1)^T, \alpha \neq 0$
 - $\tilde{\mathbf{x}} = (3 \ 4.5 \ 1.5)^T \rightarrow \mathbf{x} = (2 \ 3)^T$

平面直线

- 直线方程: $l: ax + by + c = 0$

- 齐次坐标表示: $ax_1 + bx_2 + cx_3 = 0 \Leftrightarrow (a \ b \ c) \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = 0$

- 直线的齐次坐标表示: $l = (a, b, c)^T$

- $\forall \mathbf{x} = (x, y)^T \in l \Leftrightarrow l^T \tilde{\mathbf{x}} = \tilde{\mathbf{x}}^T l = 0$

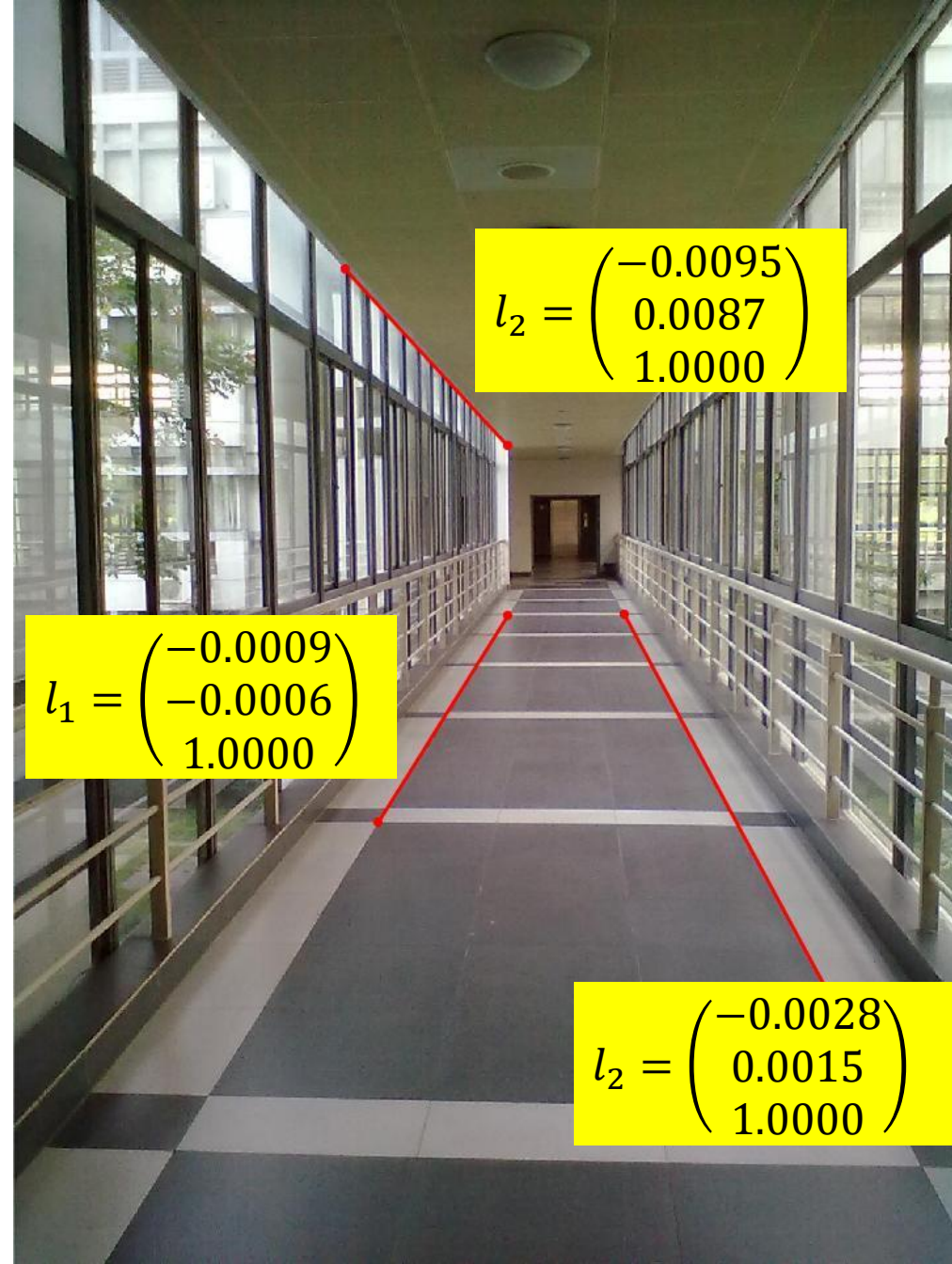
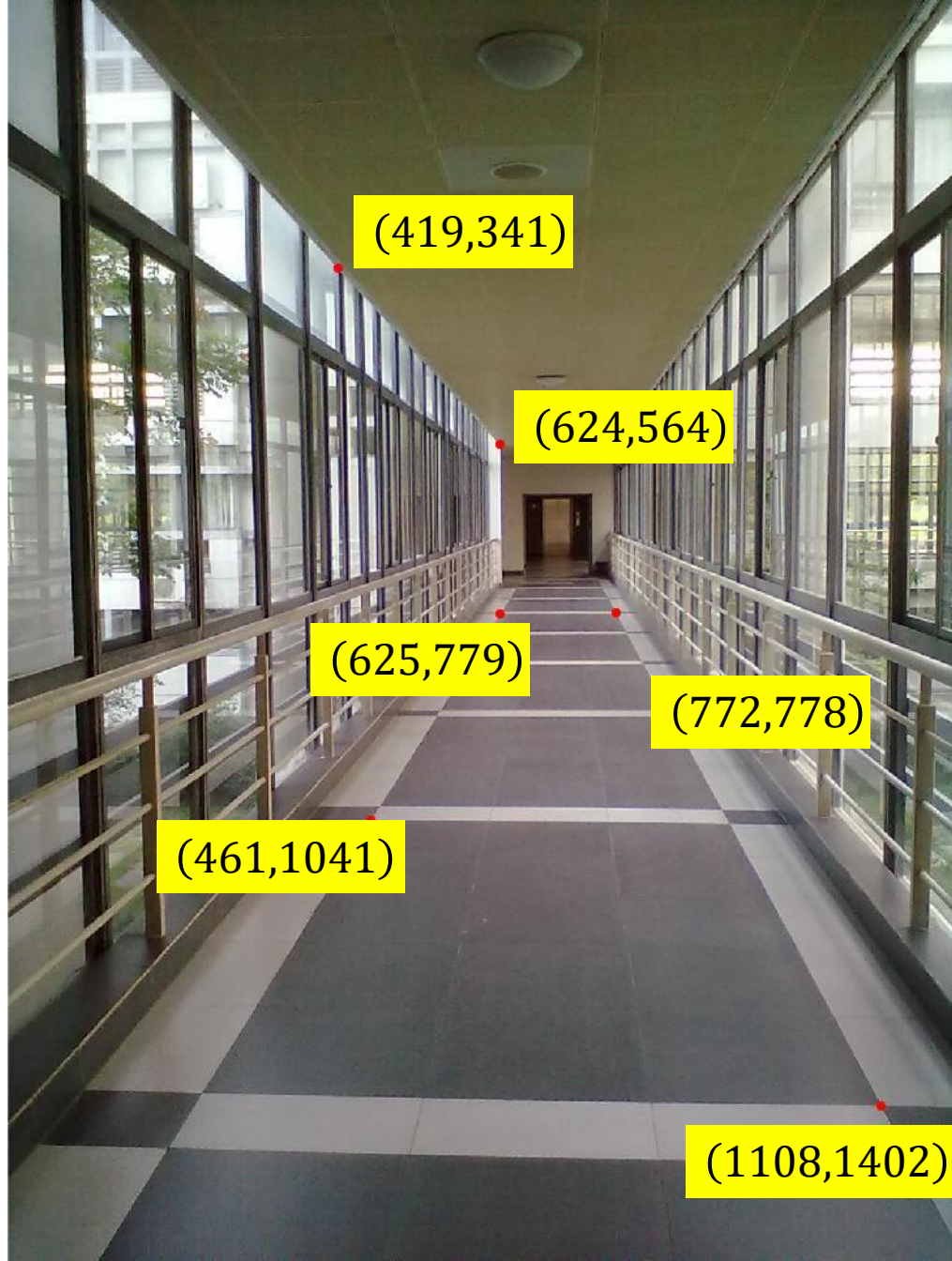
- 两点 $p_1 = (x_1, y_1)^T, p_2 = (x_2, y_2)^T$ 确定一条直线 $l = \begin{vmatrix} i & j & k \\ x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \end{vmatrix} = \begin{vmatrix} y_1 & 1 \\ y_2 & 1 \end{vmatrix} i - \begin{vmatrix} x_1 & 1 \\ x_2 & 1 \end{vmatrix} j + \begin{vmatrix} x_1 & y_1 \\ x_2 & y_2 \end{vmatrix} k$

- $l = \tilde{p}_1 \times \tilde{p}_2 = \left(\begin{vmatrix} y_1 & 1 \\ y_2 & 1 \end{vmatrix}, -\begin{vmatrix} x_1 & 1 \\ x_2 & 1 \end{vmatrix}, \begin{vmatrix} x_1 & y_1 \\ x_2 & y_2 \end{vmatrix} \right) = (y_1 - y_2, x_2 - x_1, x_1 y_2 - x_2 y_1)$

- 两条直线 $l_1 = (a_1, b_1, c_1)^T, l_2 = (a_2, b_2, c_2)^T$ 的交点 X :

- $X = l_1 \times l_2 = \left(\begin{vmatrix} b_1 & c_1 \\ b_2 & c_2 \end{vmatrix}, -\begin{vmatrix} a_1 & c_1 \\ a_2 & c_2 \end{vmatrix}, \begin{vmatrix} a_1 & b_1 \\ a_2 & b_2 \end{vmatrix} \right) = (b_1 c_2 - b_2 c_1, a_2 c_1 - a_1 c_2, a_1 b_2 - a_2 b_1)$

- $l_1 \parallel l_2 \Rightarrow \frac{a_1}{b_1} = \frac{a_2}{b_2} \Rightarrow X = l_1 \times l_2 = (b_1 c_2 - b_2 c_1, a_2 c_1 - a_1 c_2, 0) \leftarrow$ 无穷远点



$$P_1 = l_1 \times l_2 := \begin{pmatrix} 704.3122 \\ 652.2940 \\ 1.0000 \end{pmatrix}$$

$$P_2 = l_1 \times l_3 := \begin{pmatrix} 704.6585 \\ 651.7407 \\ 1.0000 \end{pmatrix}$$

$$P_3 = l_2 \times l_3 := \begin{pmatrix} 703.1033 \\ 650.0489 \\ 1.0000 \end{pmatrix}$$

$$P_1 = P_2 = P_3?$$



空间点

- $\mathbf{x} = (x \ y \ z)^T \in \mathcal{R}^3$, \mathcal{R}^3 : 3D欧氏空间
- 用齐次坐标(homogeneous coordinates)表示 $\mathbf{x} = (x \ y \ z)^T$:
 - $\tilde{\mathbf{x}} = (\tilde{x} \ \tilde{y} \ \tilde{z} \ \tilde{w})^T \in \mathcal{P}^3$
 - $x = \frac{\tilde{x}}{\tilde{w}}, y = \frac{\tilde{y}}{\tilde{w}}, z = \frac{\tilde{z}}{\tilde{w}}, (\tilde{w} \neq 0)$
 - $\mathcal{P}^3 = \mathcal{R}^4 - (0 \ 0 \ 0 \ 0)^T$: 3D投影空间(3D Projective Space)
 - $\bar{\mathbf{x}} = (x \ y \ z \ 1)^T$: \mathbf{x} 的增广向量
- 无穷远点 (理想点) :
 - $\tilde{\mathbf{x}} = (\tilde{x} \ \tilde{y} \ \tilde{z} \ 0)^T$
- 例:
 - $\mathbf{x} = (1 \ 2 \ 3)^T \rightarrow \bar{\mathbf{x}} = (1, 2, 3, 1)^T, \tilde{\mathbf{x}} = (2, 4, 6, 2)^T, \dots \tilde{\mathbf{x}} = \alpha(2, 4, 6, 2)^T, \alpha \neq 0$
 - $\tilde{\mathbf{x}} = (3 \ 4.5 \ 1.5 \ 3)^T \rightarrow \mathbf{x} = (1, 1.5, 0.5)^T$

平面几何变换

- 平移:

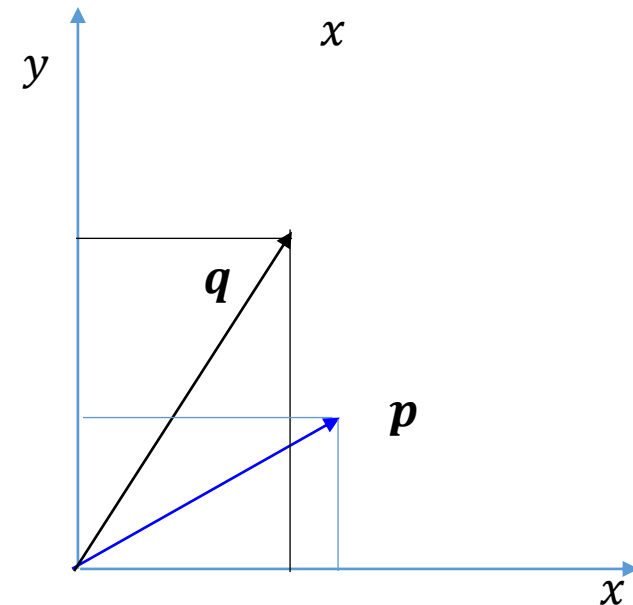
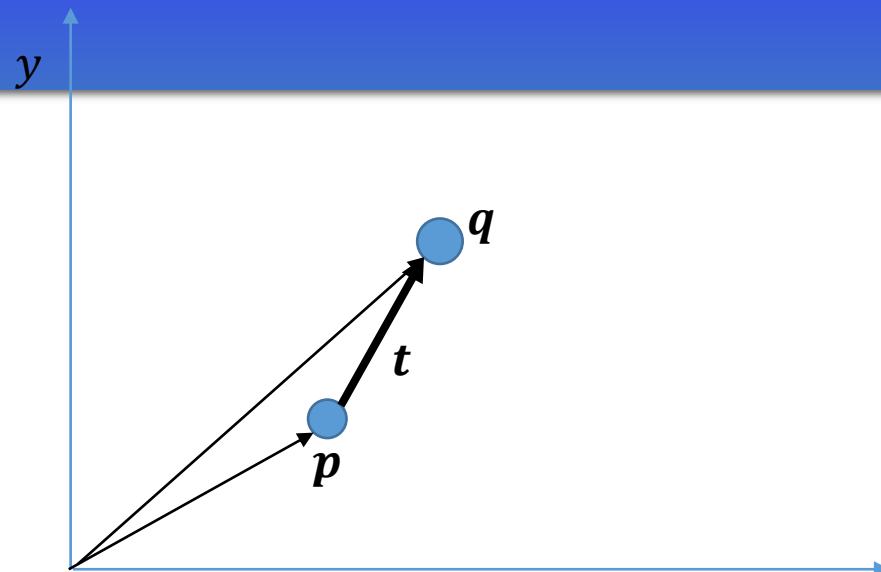
- 平移向量 $\mathbf{t} = \begin{pmatrix} t_x \\ t_y \end{pmatrix}$

- $\mathbf{q} = \mathbf{p} + \mathbf{t}$

- 缩放:

- $\begin{cases} q_x = s_x p_x \\ q_y = s_y p_y \end{cases}$

- $\mathbf{q} = S\mathbf{p}, S = \begin{pmatrix} s_x & 0 \\ 0 & s_y \end{pmatrix}$ 2D缩放矩阵



平面几何变换

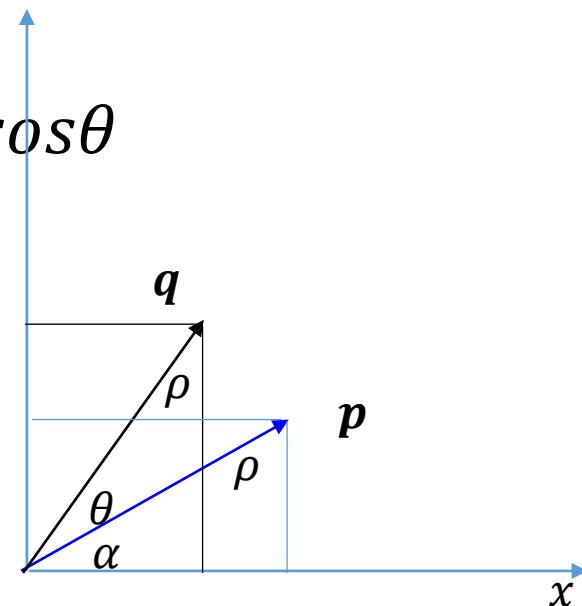
- 旋转:

- $$\begin{cases} p_x = \rho \cdot \cos\alpha \\ p_y = \rho \cdot \sin\alpha \end{cases}$$

- $$\begin{cases} q_x = \rho \cdot \cos(\alpha + \theta) = \rho \cdot \cos\alpha \cdot \cos\theta - \rho \cdot \sin\alpha \cdot \sin\theta \\ \quad = p_x \cdot \cos\theta - p_y \cdot \sin\theta = (\cos\theta \quad -\sin\theta) \mathbf{p}_y \\ q_y = \rho \cdot \sin(\alpha + \theta) = \rho \cdot \cos\alpha \cdot \sin\theta + \rho \cdot \sin\alpha \cdot \cos\theta \\ \quad = p_x \cdot \sin\theta + p_y \cdot \cos\theta = (\sin\theta \quad \cos\theta) \mathbf{p} \end{cases}$$

- $\mathbf{q} = R\mathbf{p}, R = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}$ 2D旋转矩阵

- $R^T R = I_{2 \times 2} \Rightarrow$ 旋转阵R是正交规范阵



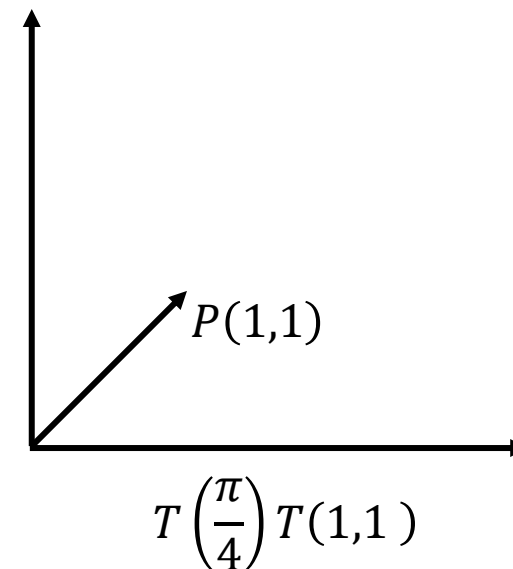
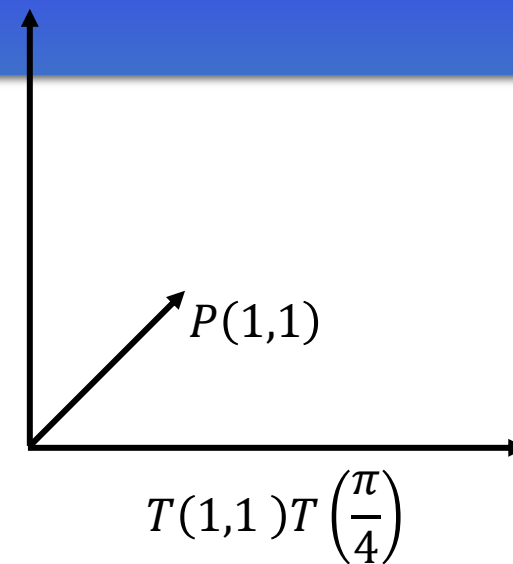
用矩阵表示平面几何变换

- 增广向量: $\mathbf{p} = (p_x \ p_y)^T \rightarrow \bar{\mathbf{p}} = (p_x \ p_y \ 1)^T$
- $\bar{\mathbf{q}} = T\bar{\mathbf{p}}$
- 平移变换: $T(t_x, t_y) = \begin{pmatrix} I_{2 \times 2} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{pmatrix}$
- 缩放变换: $T(s_x, s_y) = \begin{pmatrix} S & \mathbf{0} \\ \mathbf{0}^T & 1 \end{pmatrix} = \begin{pmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{pmatrix}$
 - $s_x = s_y = s: T(s)$:等比例缩放
- 旋转变换: $T(\theta) = \begin{pmatrix} R & \mathbf{0} \\ \mathbf{0}^T & 1 \end{pmatrix} = \begin{pmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix}$

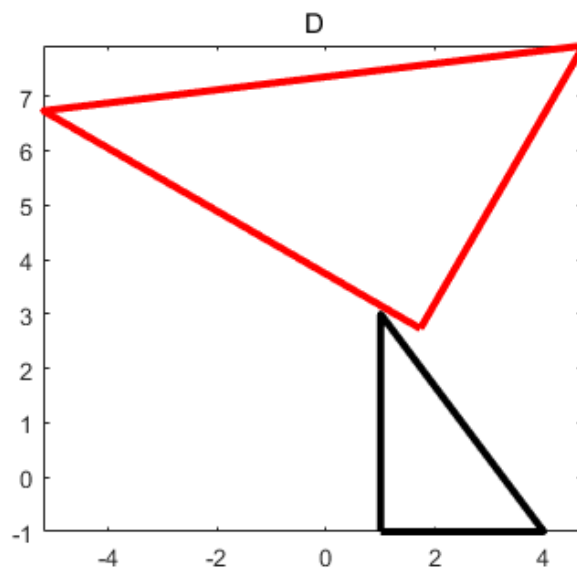
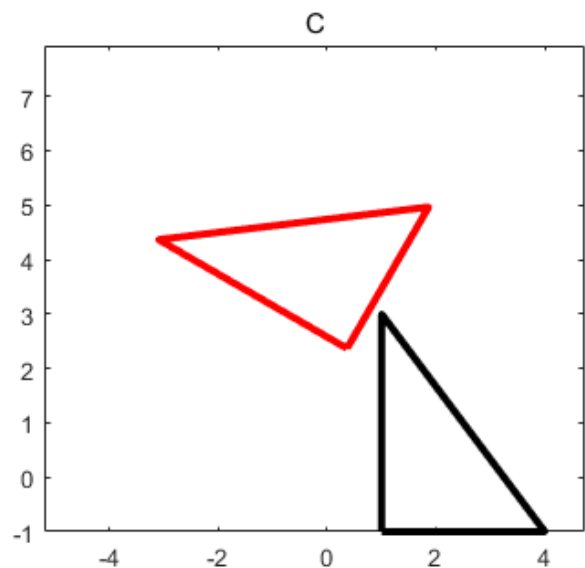
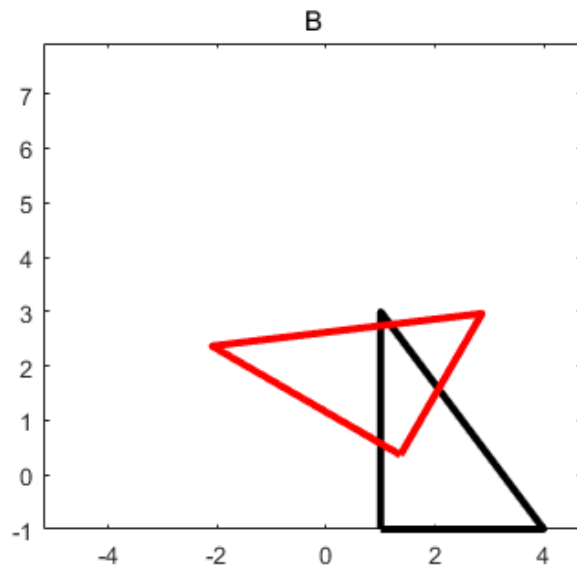
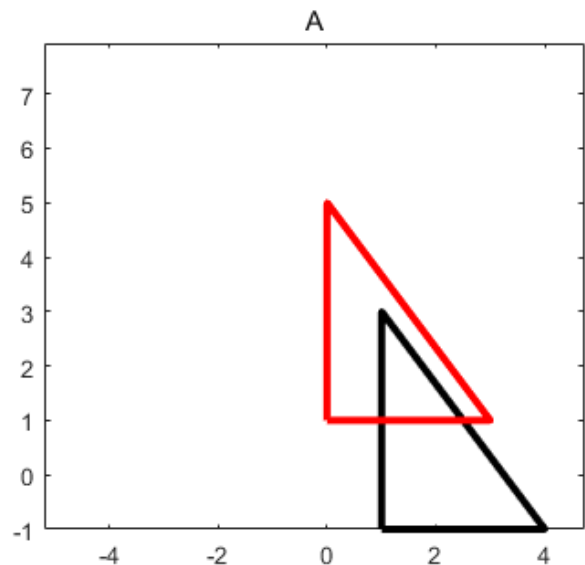
用矩阵表示平面几何变换

- 欧氏变换(刚体变换,Rigid):

- $T(\theta, t_x, t_y) = \begin{pmatrix} R & \mathbf{t} \\ \mathbf{0}^T & 1 \end{pmatrix} = \begin{pmatrix} \cos\theta & -\sin\theta & t_x \\ \sin\theta & \cos\theta & t_y \\ 0 & 0 & 1 \end{pmatrix}$
- 仅有旋转和平移变换: $T(\theta, t_x, t_y) = T(t_x, t_y)T(\theta)$
- 注意: $T(t_x, t_y)T(\theta) \neq T(\theta)T(t_x, t_y)$
- 不改变长度、面积、垂直与平行关系



A,B,C,D所示的由黑色图形到红色图形的变换分别对应右边哪一个矩阵？哪些是欧氏变换？



$$T_1 = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & -1 \end{pmatrix}$$

$$T_2 = \begin{pmatrix} 1 & 0 & -1 \\ 0 & 1 & 2 \end{pmatrix}$$

$$T_3 = \begin{pmatrix} 2 & 0 & -1 \\ 0 & 3 & 2 \end{pmatrix}$$

$$T_4 = \begin{pmatrix} \cos\left(\frac{\pi}{3}\right) & -\sin\left(\frac{\pi}{3}\right) & 0 \\ \sin\left(\frac{\pi}{3}\right) & \cos\left(\frac{\pi}{3}\right) & 0 \end{pmatrix}$$


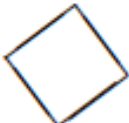



$$T_5 = \begin{pmatrix} \cos\left(\frac{\pi}{3}\right) & -\sin\left(\frac{\pi}{3}\right) & -1 \\ \sin\left(\frac{\pi}{3}\right) & \cos\left(\frac{\pi}{3}\right) & 2 \end{pmatrix}$$

$$T_6 = \begin{pmatrix} 2 \cdot \cos\left(\frac{\pi}{3}\right) & -\sin\left(\frac{\pi}{3}\right) & -1 \\ \sin\left(\frac{\pi}{3}\right) & 2 \cdot \cos\left(\frac{\pi}{3}\right) & 2 \end{pmatrix}$$

用矩阵表示平面几何变换

- 相似变换(Similarity): $T(s, \theta, t_x, t_y) = \begin{pmatrix} sR & \mathbf{t} \\ \mathbf{0}^T & 1 \end{pmatrix} = \begin{pmatrix} s \cdot \cos\theta & -s \cdot \sin\theta & t_x \\ s \cdot \sin\theta & s \cdot \cos\theta & t_y \\ 0 & 0 & 1 \end{pmatrix}$
 - 旋转、平移、等比例缩放、反射
 - 变换前后的图形是相似形
 - 保持角度不变
- 仿射(Affine)变换: $q = Ap, A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{pmatrix}$ 任意2*3矩阵
- 投影(Projective)变换: $\tilde{q} = H\tilde{p}$
 - $H = \begin{pmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{pmatrix}, \begin{cases} q_x = \frac{h_{11}p_x + h_{12}p_y + h_{13}}{h_{31}p_x + h_{32}p_y + h_{33}} \\ q_y = \frac{h_{21}p_x + h_{22}p_y + h_{23}}{h_{31}p_x + h_{32}p_y + h_{33}} \end{cases}$

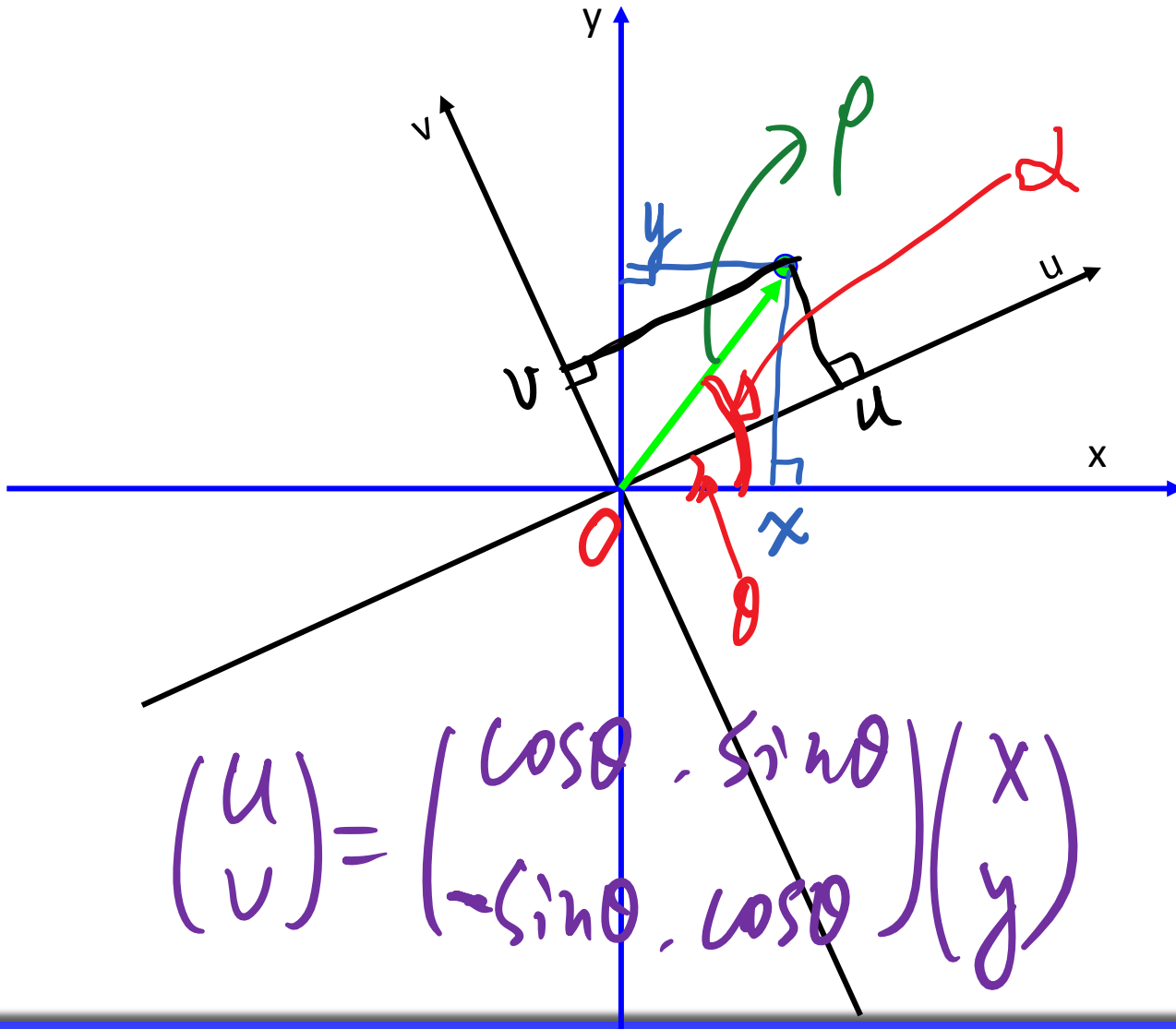
平面几何变换

Transformation	Matrix	# DoF	Preserves	Icon
translation	$\left[\begin{array}{c c} \mathbf{I} & \mathbf{t} \end{array} \right]_{2 \times 3}$	2	orientation	
rigid (Euclidean)	$\left[\begin{array}{c c} \mathbf{R} & \mathbf{t} \end{array} \right]_{2 \times 3}$	3	lengths	
similarity	$\left[\begin{array}{c c} s\mathbf{R} & \mathbf{t} \end{array} \right]_{2 \times 3}$	4	angles	
affine	$\left[\begin{array}{c} \mathbf{A} \end{array} \right]_{2 \times 3}$	6	parallelism	
projective	$\left[\begin{array}{c} \tilde{\mathbf{H}} \end{array} \right]_{3 \times 3}$	8	straight lines	

同一个目标在不同坐标系中的坐标之间的变换



同一个目标在不同坐标系中的坐标之间的变换



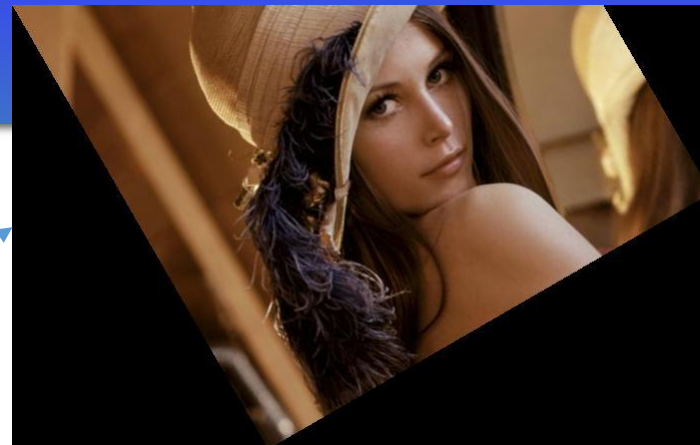
$$\begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

$$\begin{aligned} x &= \rho \cos\alpha, y = \rho \sin\alpha \\ u &= \rho \cos(\alpha - \theta) \\ &= \rho \cos\alpha \cos\theta + \rho \sin\alpha \sin\theta \\ &= \underline{x \cos\theta + y \sin\theta} \\ v &= \rho \sin(\alpha - \theta) \\ &= \rho \sin\alpha \cos\theta - \rho \cos\alpha \sin\theta \\ &= \underline{y \cos\theta - x \sin\theta} \end{aligned}$$

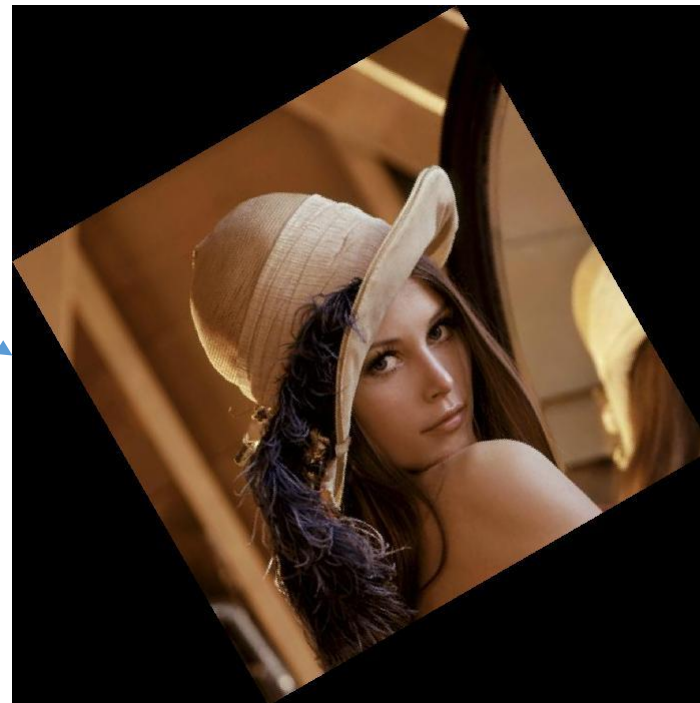
图像旋转



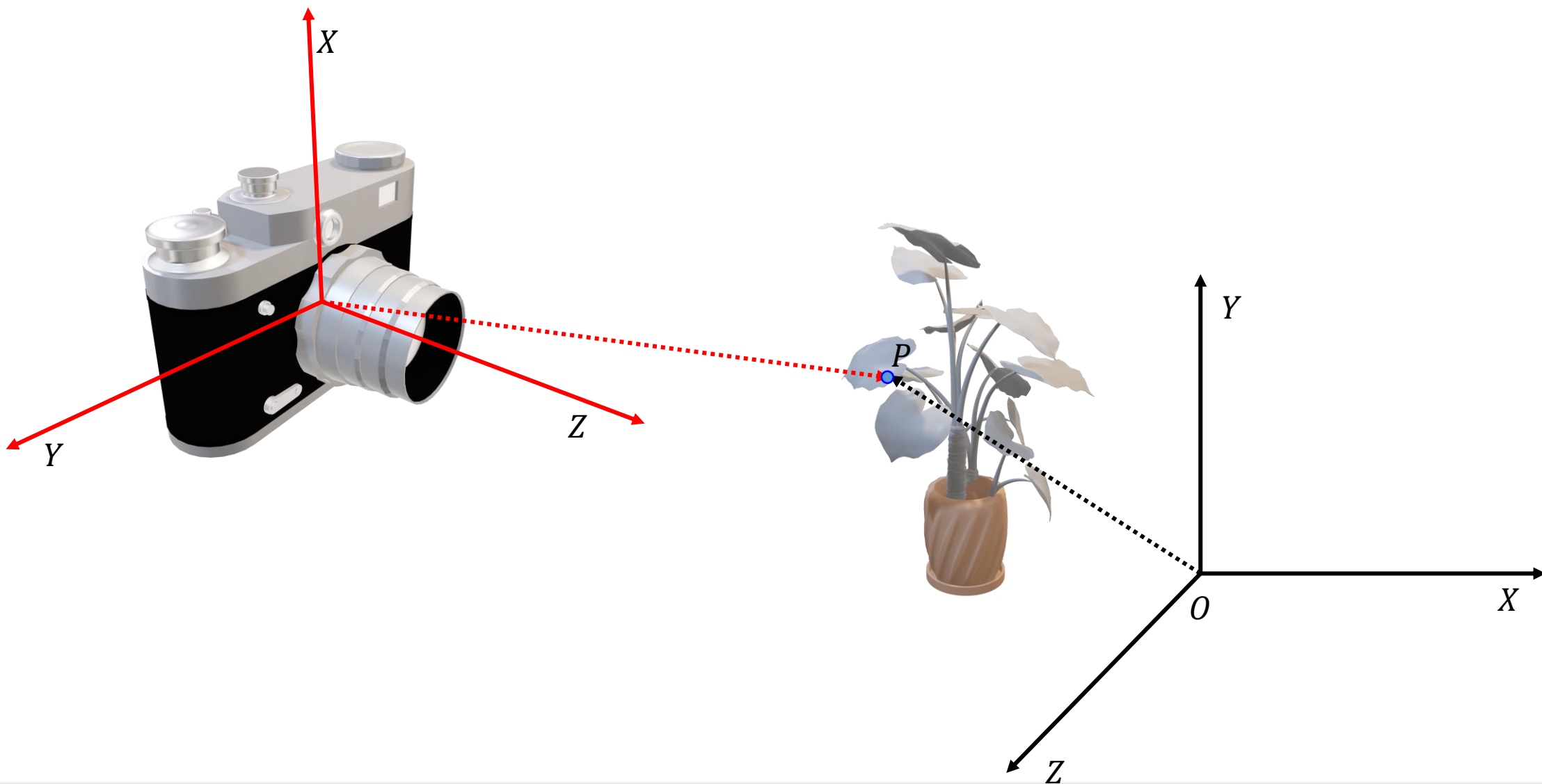
旋转中心：左上角



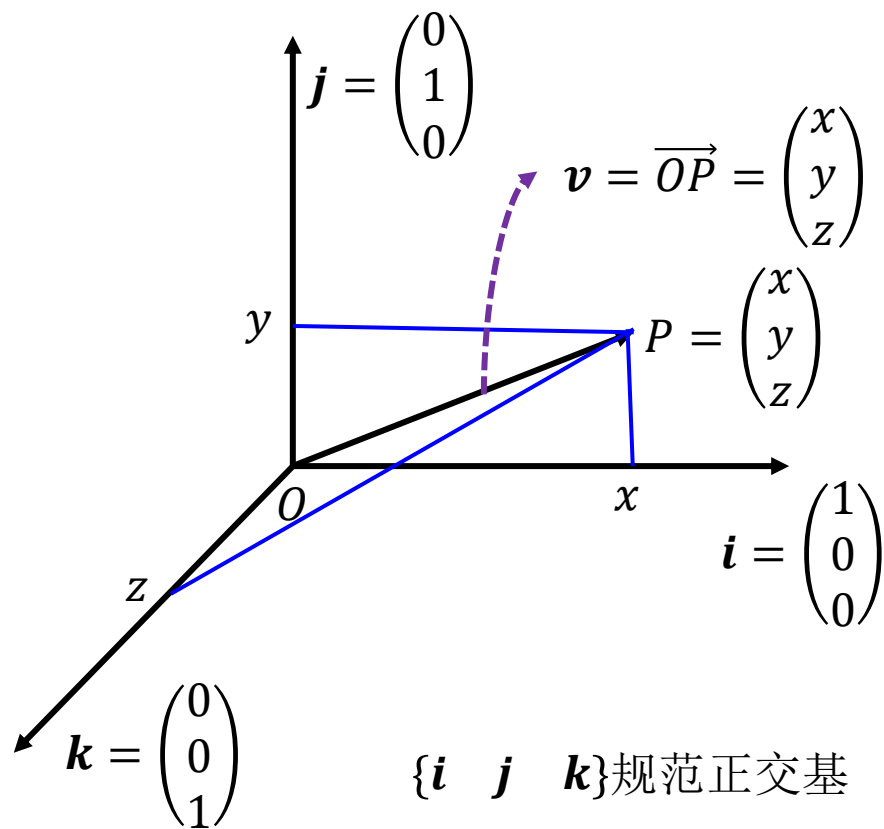
旋转中心：图像中心



空间坐标变换



空间坐标变换

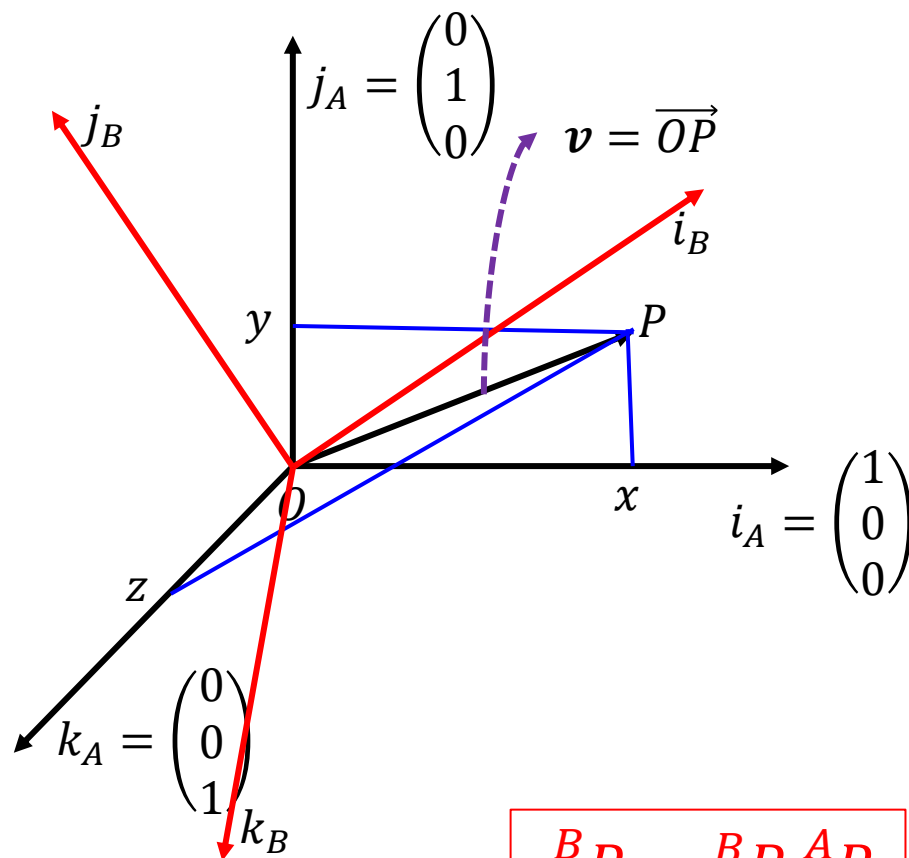


$$\begin{cases} x = v^T i \\ y = v^T j \\ z = v^T k \end{cases}$$

$$P = \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} v^T i \\ v^T j \\ v^T k \end{pmatrix} = (i \ j \ k)^T v = R^T v$$

$$R = (i \ j \ k): \text{旋转矩阵}$$
$$RR^T = R^T R = I_{3 \times 3}$$
$$\det(R) = 1$$

空间坐标变换



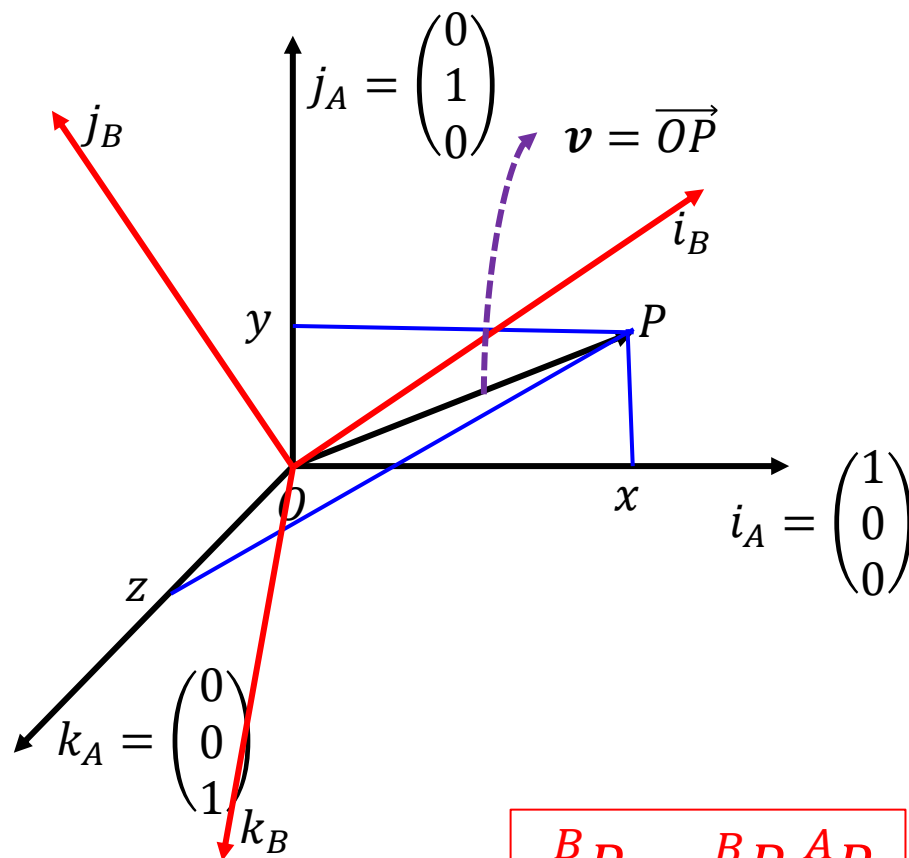
$${}^A P = \begin{pmatrix} x \\ y \\ z \end{pmatrix} \quad {}^B P = f({}^A P)?$$

$$\begin{cases} {}^A P = R_A^T v, R_A = (i_A \ j_A \ k_A) \\ {}^B P = R_B^T v, R_B = (i_B \ j_B \ k_B) \end{cases}$$

$$\begin{aligned} {}^A P = R_A^T v &\Rightarrow v = R_A {}^A P \\ {}^B P = R_B^T v &= R_B^T R_A {}^A P = {}^B_A R {}^A P \end{aligned}$$

$${}^B P = {}^B_A R {}^A P$$

空间坐标变换



$${}^B P = {}^B_A R {}^A P$$

$$\begin{cases} R_A = (i_A & j_A & k_A) \\ R_B = (i_B & j_B & k_B) \end{cases}$$

$${}^B P = {}^B_A R {}^A P$$

$$\begin{aligned} {}^B_A R &= R_B^T R_A = \begin{pmatrix} i_B^T i_A & i_B^T j_A & i_B^T k_A \\ j_B^T i_A & j_B^T j_A & j_B^T k_A \\ k_B^T i_A & k_B^T j_A & k_B^T k_A \end{pmatrix} \\ &= ({}^B i_A \quad {}^B j_A \quad {}^B k_A) = \begin{pmatrix} {}^A i_B^T \\ {}^A j_B^T \\ {}^A k_B^T \end{pmatrix} \end{aligned}$$

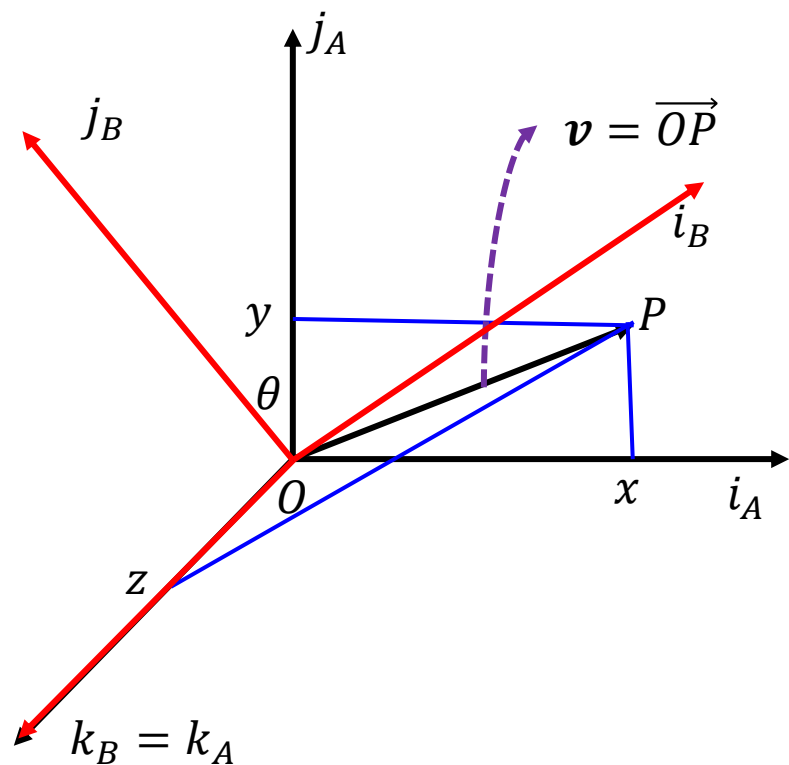
$${}^B_A R^{-1} = (R_B^T R_A)^{-1} = R_A^{-1} R_B^{-T} = R_A^T R_B = {}^B_A R^T$$

$${}^B_A R {}^B_A R^T = {}^B_A R^T {}^B_A R = I_{3 \times 3}$$

$$\det({}^B_A R) = \det(R_B^T) \det(R_A) = 1$$

空间坐标变换

例：绕z轴旋转 θ



$${}^A P = \begin{pmatrix} x \\ y \\ z \end{pmatrix} \quad {}^B P = \begin{pmatrix} x' \\ y' \\ z' \end{pmatrix}, z' = z$$

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

$${}^B P = \begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{pmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = {}^B_A R {}^A P$$

$${}^B_A R = R_z(\theta) = \begin{pmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

空间坐标变换

$$R_x(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta & -\sin \theta \\ 0 & \sin \theta & \cos \theta \end{bmatrix}$$

$$R_y(\theta) = \begin{bmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{bmatrix}$$

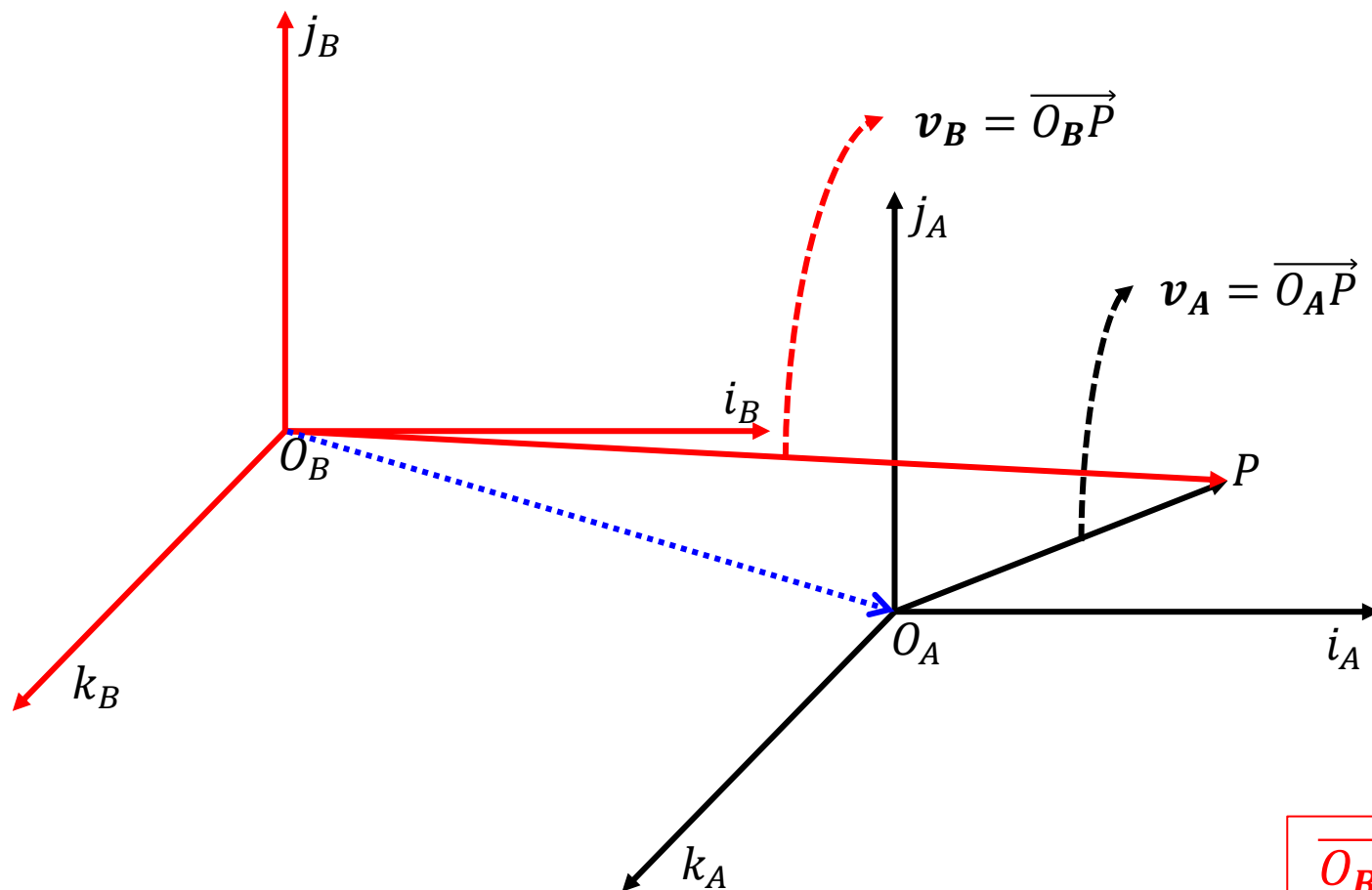
$$R_z(\theta) = \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R = R_z(\gamma) R_y(\beta) R_x(\alpha)$$

三维旋转的三个自由度:

α, β, γ : 欧拉角(Euler Angles)

空间坐标变换



$$\overrightarrow{O_B P} = \overrightarrow{O_A P} + \overrightarrow{O_B O_A} \Rightarrow {}^B P = {}^A P + {}^B O_A$$

空间坐标变换

- 平移:

- 3×1 平移向量 $\mathbf{t} = \begin{pmatrix} t_x \\ t_y \\ t_z \end{pmatrix}$

- $\mathbf{q} = \mathbf{p} + \mathbf{t}$

- 旋转:


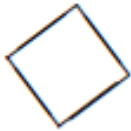
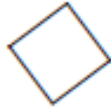


- 3×3 旋转矩阵 \mathbf{R} (规范正交阵)

- $\mathbf{q} = \mathbf{R}\mathbf{p}$

空间坐标变换

- 欧氏变换(刚体变换):
 - 3×1 平移向量 $\mathbf{t} = \begin{pmatrix} t_x \\ t_y \\ t_z \end{pmatrix}$
 - 3×3 旋转矩阵 \mathbf{R} (规范正交阵)
 - $\mathbf{q} = \mathbf{R}\mathbf{p} + \mathbf{t}$
- 用齐次坐标表示欧氏变换:
 - $\bar{\mathbf{q}} = \begin{pmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{pmatrix} \bar{\mathbf{p}}$

空间几何变换

Transformation	Matrix	# DoF	Preserves	Icon
translation	$\begin{bmatrix} \mathbf{I} & \mathbf{t} \end{bmatrix}_{3 \times 4}$	3	orientation	
rigid (Euclidean)	$\begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix}_{3 \times 4}$	6	lengths	
similarity	$\begin{bmatrix} s\mathbf{R} & \mathbf{t} \end{bmatrix}_{3 \times 4}$	7	angles	
affine	$\begin{bmatrix} \mathbf{A} \end{bmatrix}_{3 \times 4}$	12	parallelism	
projective	$\begin{bmatrix} \tilde{\mathbf{H}} \end{bmatrix}_{4 \times 4}$	15	straight lines	

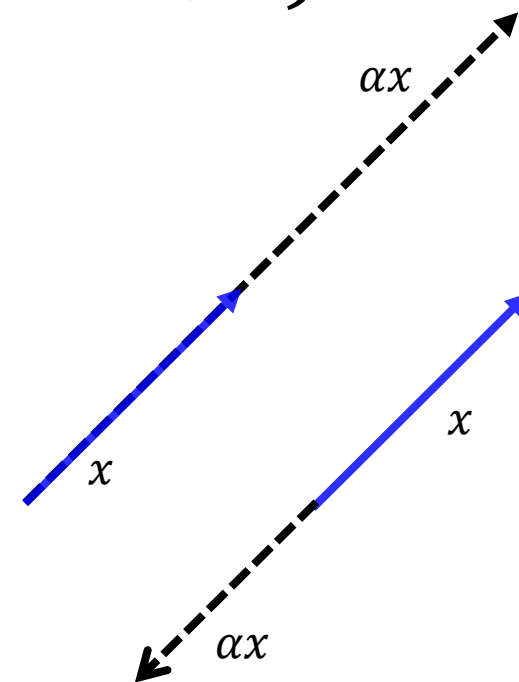
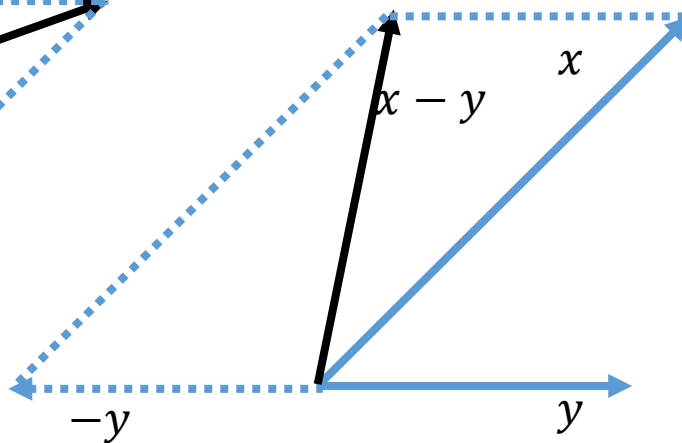
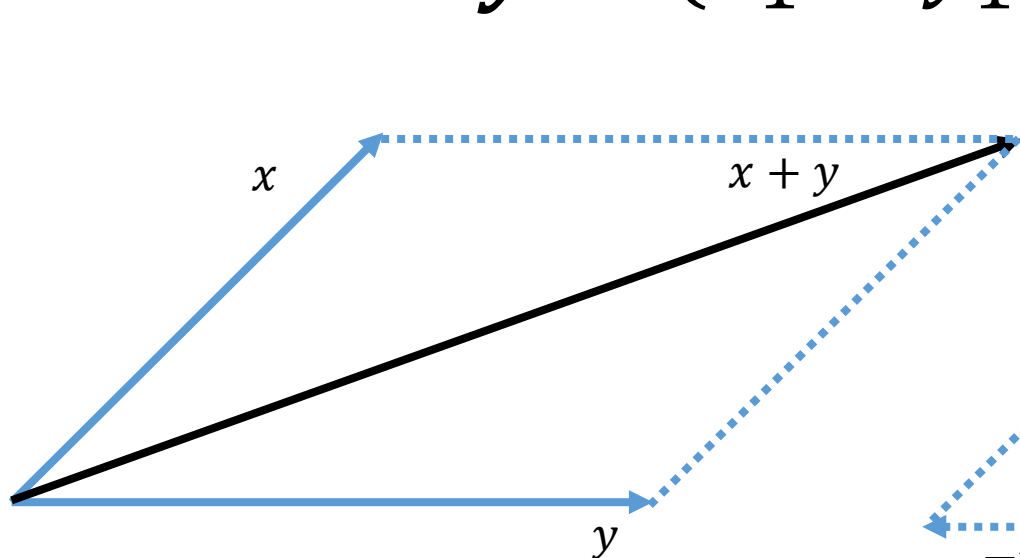
线性代数

向量

- 列向量 $\mathbf{v} \in \mathcal{R}^{n \times 1}$: $\mathbf{v} = \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{pmatrix}$
- 行向量 $\mathbf{v}^T \in \mathcal{R}^{1 \times n}$: $\mathbf{v}^T = (v_1 \quad v_2 \quad \cdots \quad v_n)$
- 零向量 $\mathbf{0} = (0 \quad 0 \quad \cdots \quad 0)^T$
- 本课程用向量表示:
 - 几何元素（点、直线、平面、方向）： $\mathbf{p} = (x \quad y)^T, \mathbf{q} = (x \quad y \quad z)^T$
 - 数据（图像、特征描述、直方图.....）（不完全符合向量的数学定义）

向量的运算

- $\mathbf{x} = (x_1 \ x_2 \ \cdots \ x_n)^T, \mathbf{y} = (y_1 \ y_2 \ \cdots \ y_n)^T$
- $\alpha \mathbf{x} = (\alpha x_1 \ \alpha x_2 \ \cdots \ \alpha x_n)^T, \alpha \in \mathcal{R}$
- $\mathbf{z} = \mathbf{x} + \mathbf{y} = (x_1 + y_1 \ x_2 + y_2 \ \cdots \ x_n + y_n)^T$



向量的运算

- 向量内积:

- $\mathbf{x} = (x_1 \ x_2 \ \cdots \ x_n)^T, \mathbf{y} = (y_1 \ y_2 \ \cdots \ y_n)^T$

- $\mathbf{x}^T \mathbf{y} = \mathbf{y}^T \mathbf{x} = \sum_{i=1}^n x_i y_i$

- 向量模长(2-范数, Norm)

- $\|\mathbf{x}\|_2 = \sqrt{\mathbf{x}^T \mathbf{x}} = \sqrt{\sum_{i=1}^n x_i^2}$

- $\|\mathbf{x}\|_2 \geq 0$

- $\|\mathbf{x}\|_2 = 0 \Leftrightarrow \mathbf{x} = \mathbf{0}$

- $\|\alpha \mathbf{x}\|_2 = |\alpha| \|\mathbf{x}\|_2, \alpha \in \mathcal{R}$

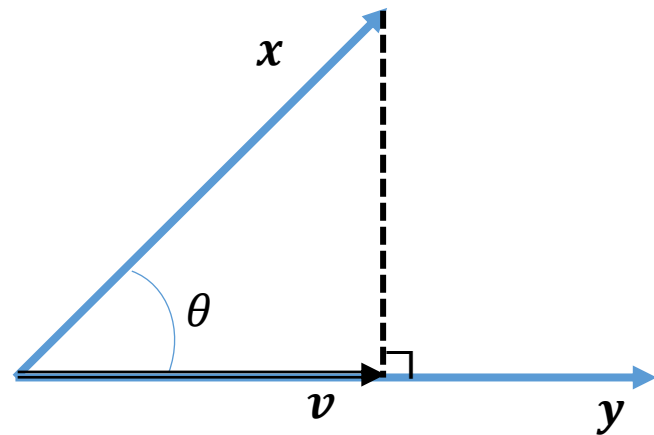
- $\|\mathbf{x} + \mathbf{y}\|_2 \leq \|\mathbf{x}\|_2 + \|\mathbf{y}\|_2$

- \mathbf{x} 与 \mathbf{y} 之间的欧氏距离 $d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|_2 = \sqrt{(\mathbf{x} - \mathbf{y})^T (\mathbf{x} - \mathbf{y})} = \sqrt{\mathbf{x}^T \mathbf{x} + \mathbf{y}^T \mathbf{y} - 2\mathbf{x}^T \mathbf{y}}$

- 单位向量: $\mathbf{x}: \|\mathbf{x}\|_2 = 1$

向量的运算

- 两个向量的夹角
 - $\mathbf{x}^T \mathbf{y} = \|\mathbf{x}\|_2 \|\mathbf{y}\|_2 \cos \theta$
 - $\theta = 0: \mathbf{x} \parallel \mathbf{y}, \mathbf{x}^T \mathbf{y} = \|\mathbf{x}\|_2 \|\mathbf{y}\|_2$
 - $\theta = \pm \frac{\pi}{2}: \mathbf{x} \perp \mathbf{y}, \mathbf{x}^T \mathbf{y} = 0$
 - $0 \leq \mathbf{x}^T \mathbf{y} \leq \|\mathbf{x}\|_2 \|\mathbf{y}\|_2$
- \mathbf{x} 在 \mathbf{y} 上的投影向量 \mathbf{v} :
 - $\mathbf{v} = \mathbf{x}^T \mathbf{y} \frac{\mathbf{y}}{\|\mathbf{y}\|_2}$
 - $\mathbf{v} \parallel \mathbf{y}$
 - $\|\mathbf{v}\|_2 = \mathbf{x}^T \mathbf{y}$
 - $\mathbf{x} \perp \mathbf{y} \Rightarrow \mathbf{v} = \mathbf{0}$



矩阵

- $A = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{bmatrix} \in \mathcal{R}^{m \times n}, A = [a_{i,j}]_{i=1,j=1}^{m,n}$

- $A = \begin{bmatrix} - & \mathbf{a}_1^T & - \\ - & \mathbf{a}_2^T & - \\ & \vdots & \\ - & \mathbf{a}_m^T & - \end{bmatrix} = \begin{bmatrix} | & | & & | \\ \tilde{\mathbf{a}}_1 & \tilde{\mathbf{a}}_2 & \cdots & \tilde{\mathbf{a}}_n \\ | & | & & | \end{bmatrix}$

- $\mathbf{a}_i^T = (a_{i,1} \ a_{i,2} \ \cdots \ a_{i,n}), i = 1 \cdots m, \tilde{\mathbf{a}}_j^T = (a_{1,j} \ a_{2,j} \ \cdots \ a_{m,j}), j = 1 \cdots n$

- 单位阵 $I_{n \times n} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \in \mathcal{R}^{n \times n}$, 对角阵 $A_{n \times n} = \begin{bmatrix} a_{1,1} & 0 & \cdots & 0 \\ 0 & a_{2,2} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & a_{n,n} \end{bmatrix} \in \mathcal{R}^{n \times n}$

矩阵的运算

- $A = [a_{i,j}]_{i=1,j=1}^{m,n}, B = [b_{i,j}]_{i=1,j=1}^{m,n} \Rightarrow C = A + B = [a_{i,j} + b_{i,j}]_{i=1,j=1}^{m,n}$

- $\alpha A = [\alpha a_{i,j}]_{i=1,j=1}^{m,n}, \alpha \in \mathcal{R}$

- $A^T = [a_{j,i}]_{i=1,j=1}^{m,n} = \begin{bmatrix} a_{1,1} & a_{2,1} & \cdots & a_{n,1} \\ a_{1,2} & a_{2,2} & \cdots & a_{n,2} \\ \vdots & \vdots & \vdots & \vdots \\ a_{1,m} & a_{2,m} & \cdots & a_{n,m} \end{bmatrix}$

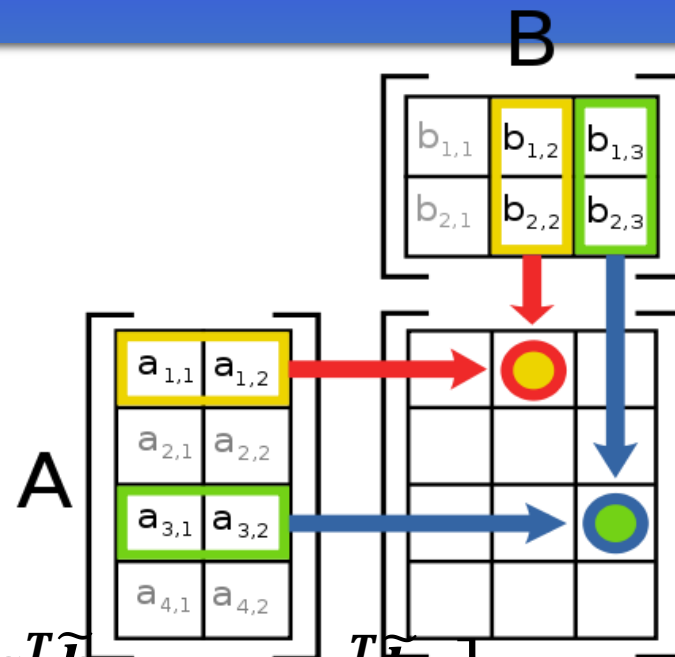
- 对称阵: $A^T = A$

矩阵的运算

- $A \in \mathcal{R}^{m \times p}, B \in \mathcal{R}^{p \times n} \Rightarrow C = AB \in \mathcal{R}^{m \times n}$

- $c_{i,j} = \sum_{k=1}^p a_{i,k} b_{k,j}$

- $$C = AB = \begin{bmatrix} - & a_1^T & - \\ - & a_2^T & - \\ & \vdots & \\ - & a_m^T & - \end{bmatrix} \begin{bmatrix} | & | & & | \\ \tilde{b}_1 & \tilde{b}_2 & \dots & \tilde{b}_n \\ | & | & & | \end{bmatrix} = \begin{bmatrix} a_1^T \tilde{b}_1 & a_1^T \tilde{b}_2 & \dots & a_1^T \tilde{b}_n \\ a_2^T \tilde{b}_1 & a_2^T \tilde{b}_2 & \dots & a_2^T \tilde{b}_n \\ \vdots & \vdots & \ddots & \vdots \\ a_m^T \tilde{b}_1 & a_m^T \tilde{b}_2 & \dots & a_m^T \tilde{b}_n \end{bmatrix}$$



矩阵的运算

$$\bullet \quad A = \begin{bmatrix} - & \mathbf{a}_1^T & - \\ - & \mathbf{a}_2^T & - \\ & \vdots & \\ - & \mathbf{a}_m^T & - \end{bmatrix} = \begin{bmatrix} | & | & & | \\ \tilde{\mathbf{a}}_1 & \tilde{\mathbf{a}}_2 & \cdots & \tilde{\mathbf{a}}_n \\ | & | & & | \end{bmatrix} \in \mathcal{R}^{m \times n}$$

$$\bullet \quad I_{m \times m} A = A I_{n \times n} = A$$

$$\bullet \quad B_{n \times n} = \begin{bmatrix} b_1 & 0 & \cdots & 0 \\ 0 & b_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & b_n \end{bmatrix} \rightarrow AB_{n \times n} = \begin{bmatrix} | & | & & | \\ b_1 \tilde{\mathbf{a}}_1 & b_2 \tilde{\mathbf{a}}_2 & \cdots & b_n \tilde{\mathbf{a}}_n \\ | & | & & | \end{bmatrix}$$

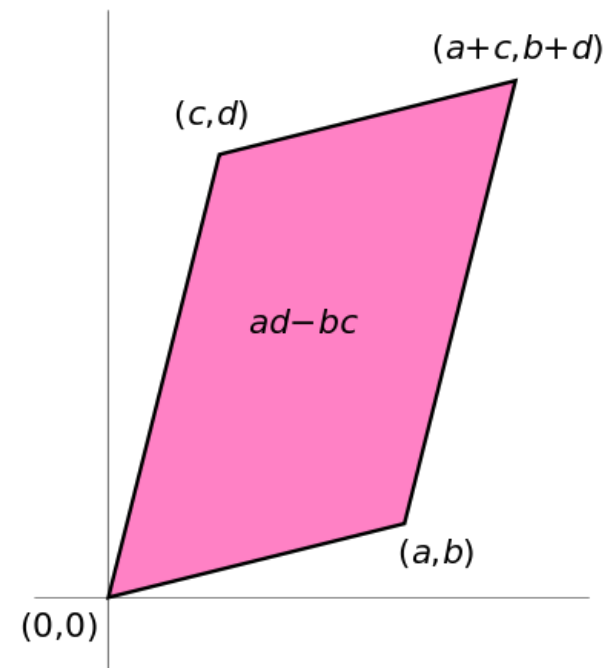
$$\bullet \quad C_{m \times m} = \begin{bmatrix} c_1 & 0 & \cdots & 0 \\ 0 & c_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & c_m \end{bmatrix} \rightarrow C_{m \times m} A = \begin{bmatrix} - & c_1 \mathbf{a}_1^T & - \\ - & c_2 \mathbf{a}_2^T & - \\ & \vdots & \\ - & c_m \mathbf{a}_m^T & - \end{bmatrix}$$

矩阵的运算

- 矩阵乘法满足结合律:
 - $A(BC) = (AB)C$
- 矩阵乘法对加法的分布律
 - $A(B + C) = AB + AC$
- 矩阵乘法不满足交换律
 - 一般情况: $AB \neq BA$
- $(AB)^T = B^T A^T$
- 矩阵的逆 A^{-1} : $A^{-1}A = AA^{-1} = I$
 - 如果 A^{-1} 存在, A 称为可逆阵, 或非奇异阵(non-singular), 否则 A 是奇异阵
 - $(AB)^{-1} = B^{-1}A^{-1}, A^{-T} \triangleq (A^T)^{-1} = (A^{-1})^T$
- $IA = AI = A$

矩阵的运算

- 矩阵的行列式
 - $\det(A) \in \mathcal{R}$
 - $\det(A) = 0 \Leftrightarrow A$ 是奇异阵
 - $\det(AB) = \det(BA)$
 - $\det(A^{-1}) = \frac{1}{\det(A)}$
 - $\det(A^T) = \det(A)$
- 矩阵的迹(trace)
 - $\text{tr}(A) = \sum_{i=1}^n a_{i,i}$
 - $\text{tr}(AB) = \text{tr}(BA)$
 - $\text{tr}(A + B) = \text{tr}(B) + \text{tr}(A)$
 - $\text{tr}(\alpha A) = \alpha \text{tr}(A), \alpha \in R$



$$A = \begin{pmatrix} a & b \\ c & d \end{pmatrix} : \det(A) = ad - bc$$

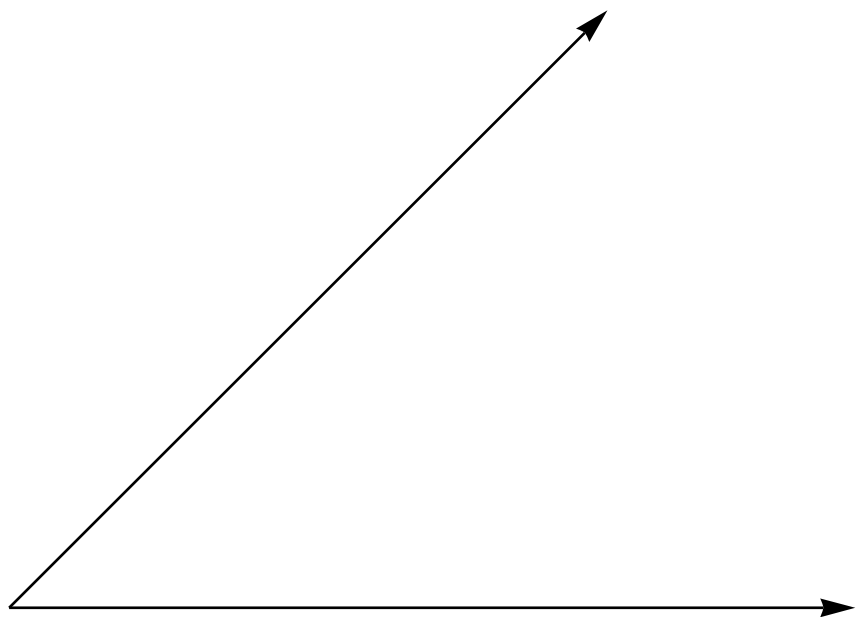
矩阵的运算

- $A = \begin{bmatrix} - & a_1^T & - \\ - & a_2^T & - \\ & \vdots & \\ - & a_m^T & - \end{bmatrix} = \begin{bmatrix} | & | & & | \\ \tilde{a}_1 & \tilde{a}_2 & \cdots & \tilde{a}_n \\ | & | & & | \end{bmatrix} \in \mathcal{R}^{m \times n}$
- $\mathbf{x} = (x_1 \ x_2 \ \cdots \ x_n)^T, \mathbf{y} = (y_1 \ y_2 \ \cdots \ y_m)^T$
- $\mathbf{u} = A\mathbf{x} = \sum_{j=1}^n x_j \tilde{a}_j \in \mathcal{R}^{m \times 1} \leftarrow A$ 的各列的线性组合
- $\mathbf{u} = A\mathbf{x} = (a_1^T \mathbf{x} \ a_2^T \mathbf{x} \ \cdots \ a_m^T \mathbf{x})^T \in \mathcal{R}^{m \times 1}$
 - u_i : \mathbf{x} 在向量 a_i 上的投影
- $\mathbf{v} = \mathbf{y}^T A = \sum_{i=1}^m y_i a_i^T \in \mathcal{R}^{1 \times n} \leftarrow A$ 的各行的线性组合
- $\mathbf{v} = \mathbf{y}^T A = (y^T \tilde{a}_1 \ y^T \tilde{a}_2 \ \cdots \ y^T \tilde{a}_n)^T \in \mathcal{R}^{1 \times n}$
 - v_j : \mathbf{y} 在向量 \tilde{a}_j 上的投影

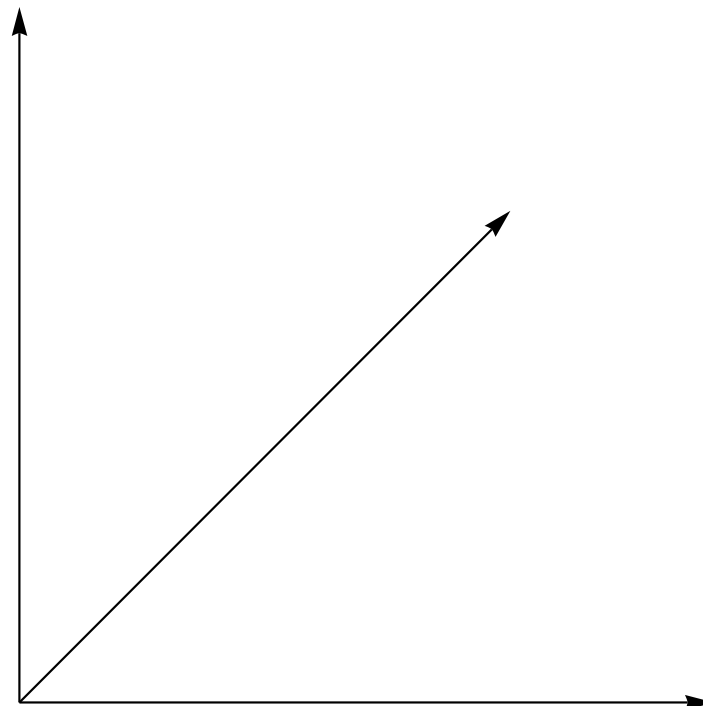
线性无关(Linear Independence)

- $V = \{\mathbf{v}_1 \quad \mathbf{v}_2 \quad \mathbf{v}_n\}$
- \mathbf{v}_1 可以由 $\{\mathbf{v}_2 \quad \mathbf{v}_3 \quad \mathbf{v}_n\}$ 线性表示
 - $\mathbf{v}_1 = \alpha_{1,2}\mathbf{v}_2 + \alpha_{1,3}\mathbf{v}_3 + \cdots \alpha_{1,n}\mathbf{v}_n, \quad \alpha_{1,j} \in \mathcal{R}$
 - $\mathbf{v}_1 - \alpha_{1,2}\mathbf{v}_2 - \alpha_{1,3}\mathbf{v}_3 - \cdots - \alpha_{1,n}\mathbf{v}_n = \mathbf{0}$
- $\{\mathbf{v}_1 \quad \mathbf{v}_2 \quad \mathbf{v}_n\}$ 线性相关
 - $\alpha_1\mathbf{v}_1 + \alpha_2\mathbf{v}_2 + \alpha_3\mathbf{v}_3 + \cdots \alpha_n\mathbf{v}_n = \mathbf{0}, \quad \exists \alpha_j \in \mathcal{R}, \alpha_j \text{不全为} 0$
- $\{\mathbf{v}_1 \quad \mathbf{v}_2 \quad \mathbf{v}_n\}$ 线性无关
 - $\alpha_1\mathbf{v}_1 + \alpha_2\mathbf{v}_2 + \alpha_3\mathbf{v}_3 + \cdots \alpha_n\mathbf{v}_n = \mathbf{0} \rightarrow \alpha_j = 0, \forall j$
- $V\alpha = \mathbf{0}, V = (\mathbf{v}_1 \quad \mathbf{v}_2 \quad \mathbf{v}_n), \alpha = (\alpha_1 \quad \alpha_2 \quad \alpha_n)^T$
 - 有非零解: 线性相关
 - 只有零解: 线性无关

线性无关(Linear Independence)



线性无关



线性相关

线性无关(Linear Independence)

$$\left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \right\}$$

线性无关

$$\left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 2 \\ 3 \\ 4 \end{pmatrix} \right\}$$

$$\begin{pmatrix} 2 \\ 3 \\ 4 \end{pmatrix} = 4 \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} - \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

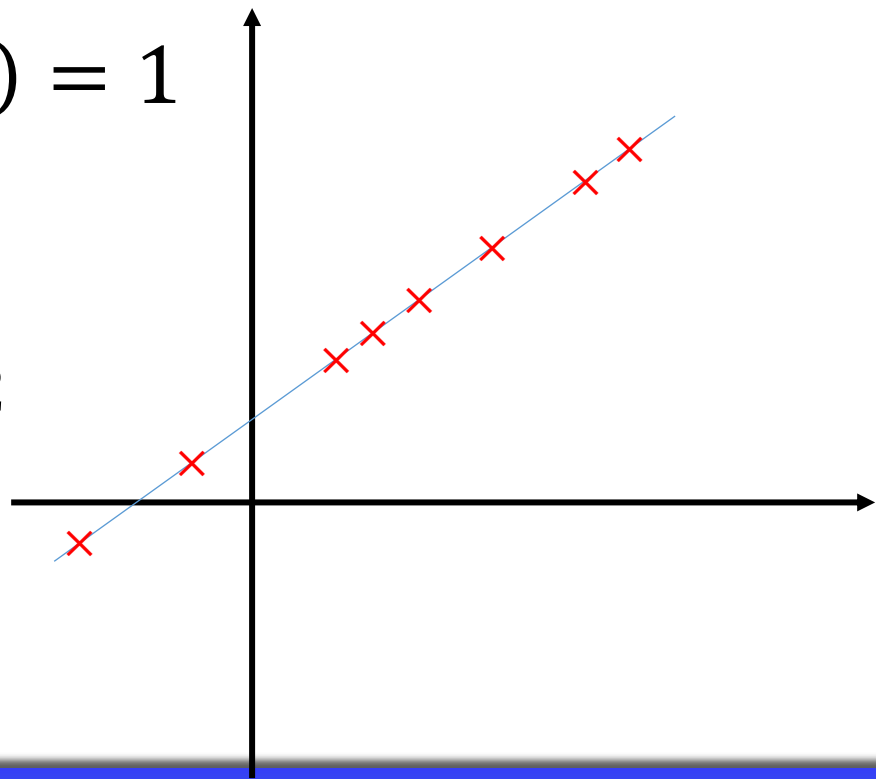
线性相关

矩阵的秩

- 列秩：矩阵 A 的线性无关的列向量的极大数目
- 行秩：矩阵 A 的线性无关的行向量的极大数目
- 行秩=列秩： $\text{rank}(A)$
- $A \in \mathcal{R}^{m \times n}$:
 - $\text{rank}(A) \leq \min(m, n)$
 - $\text{rank}(AA^T) = \text{rank}(A^T A) = \text{rank}(A) = \text{rank}(A^T)$
- $A \in \mathcal{R}^{n \times n}$:
 - $\text{rank}(A) < n \rightarrow \det(A) = 0, A$ 是奇异阵、不可逆
 - $\text{rank}(A) = n \rightarrow \det(A) \neq 0, A$ 是奇异阵、可逆

矩阵的秩

- 例：假设平面上有 n 个点： $\left\{p_i = \begin{pmatrix} x_i \\ y_i \end{pmatrix}, i = 1..n, n \geq 3\right\}$ ，如果这 n 个点共线： $l: ax + by + c = 0, a \neq 0, b \neq 0$ ，那么矩阵 $A = (p_1 \ p_2 \ \cdots \ p_n)$
- 如果 $c = 0$ ，那么 $y = \alpha x$ ， A 的秩 $\text{rank}(A) = 1$
 - A 的第二行可以由第一行线性表示
- 如果 $c \neq 0$ ，那么 $y = \alpha x + \beta, \beta \neq 0$
 - A 的第二行无法由第一行线性表示, $\text{rank}(A) = 2$



特征值与特征向量

- $A\mathbf{v} = \lambda\mathbf{v}, \mathbf{v} \neq \mathbf{0}$
- 矩阵 A 作用于 \mathbf{v} , 等价于对 \mathbf{v} 做了一个缩放操作: $\lambda\mathbf{v}$
- $tr(A) = \sum_{i=1}^n \lambda_i, det(A) = \prod_{i=1}^n \lambda_i$
- 不同特征值对应的特征向量是线性无关的
- $AV = VD$

$$\bullet V = (\mathbf{v}_1 \quad \mathbf{v}_2 \quad \cdots \quad \mathbf{v}_n), D = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix} =$$
$$diag(\lambda_1, \lambda_2, \dots, \lambda_n)$$

- 如果 $\mathbf{v}_1 \quad \mathbf{v}_2 \quad \cdots \quad \mathbf{v}_n$ 线性无关 $\Rightarrow V$ 可逆 $\Rightarrow A = VDV^{-1}, V^{-1}AV = D$

实对称阵

- $A = A^T \in \mathcal{R}^{n \times n}$
- 实对称阵的特征值都是实数
- 不同特征值对应的特征向量是正交的
- $A = VDV^{-1} = A^T = V^{-T}DV^T \Rightarrow V^{-1} = V^T$
- $V^{-1} = V^T \Rightarrow V^T V = I_{n \times n} \Rightarrow \boldsymbol{v}_i^T \boldsymbol{v}_j = \begin{cases} 0 & i \neq j \\ 1 & i = j \end{cases}$
- $V^T V = I_{n \times n}$: V 是规范正交阵

奇异值分解(Singular Value Decomposition, SVD)

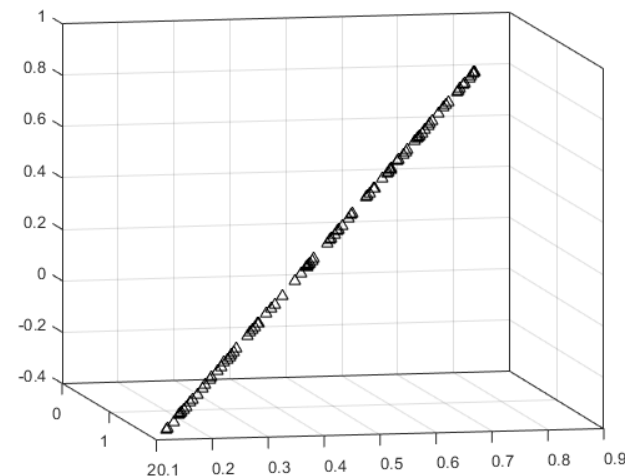
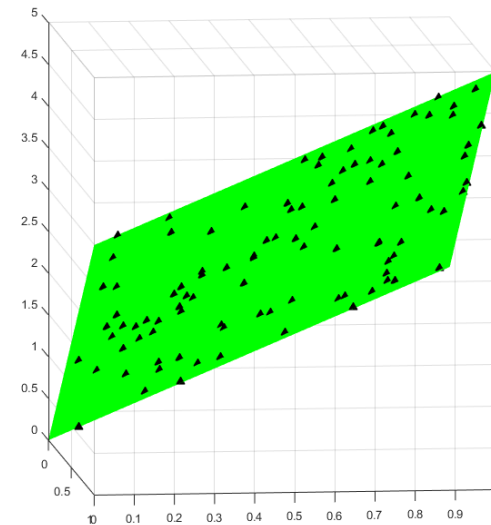
- 任何一个 $m \times n$ 的矩阵 $A \in \mathcal{R}^{m \times n}$ 都可以分解为 $A = U\Sigma V^T$
 - $U \in \mathcal{R}^{m \times m}$, U 的每一列 \mathbf{u}_i 是 AA^T 的 1 个特征向量, $U^T U = I_{m \times m}$
 - $V \in \mathcal{R}^{n \times n}$, V 的每一列 \mathbf{v}_i 是 $A^T A$ 的 1 个特征向量, $V^T V = I_{n \times n}$
 - $\Sigma \in \mathcal{R}^{m \times n}$, 是一个对角阵, 包含 r 个奇异值, $\{\sigma_1 \ \sigma_2 \ \cdots \ \sigma_r\}$, 奇异值 σ_i 是 AA^T 与 $A^T A$ 的非零特征值的平方根, $r = \text{rank}(A)$
 - $A = \sum_{i=1}^r \sigma_i \mathbf{u}_i \mathbf{v}_i^T$
- 实对称阵 $AA^T = U\Sigma V^T V\Sigma U^T = U\Sigma^2 U^T$, 对 AA^T 做特征分解得到: $AA^T = \Phi D \Phi^T$
 - $\Phi = U$: U 是 AA^T 的特征向量构成的矩阵, AA^T 的特征值 $\lambda_i = \sigma_i^2$
- 实对称阵 $A^T A = V\Sigma U^T U\Sigma V^T = V\Sigma^2 V^T$, 对 $A^T A$ 做特征分解得到: $A^T A = \Psi D \Psi^T$
 - $\Psi = V$: V 是 $A^T A$ 的特征向量构成的矩阵, $A^T A$ 的特征值 $\lambda_i = \sigma_i^2$

注意特征值与奇异值的区别

为什么 AA^T 与 $A^T A$ 的特征值相同?

示例：3D空间的平面与直线

- 例：假设空间中有 n 个点 $\left\{ p_i = \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix}, i = 1..n, n \geq 3 \right\}$,
 - 如果矩阵 $A = (p_1 \ p_2 \ \cdots \ p_n)$ 的秩 $\text{rank}(A) = 2$ ，那么这些点共面或者共线。如果 $\text{rank}(A) = 1$ ，那么这些点一定共线，为什么？
- 如何判断任意 n 个点共面或共线？
 - 对 A 做奇异值分解，检查三个奇异值中最小的是否接近0
 - 对实对称阵 AA^T 做特征值分解，检查三个特征值中最小的是否接近0
- 如果这 n 个点共面，平面点只需要两个坐标就可以表示，如何得到这个 n 个3D点在平面上的2D平面坐标？



用SVD压缩图像



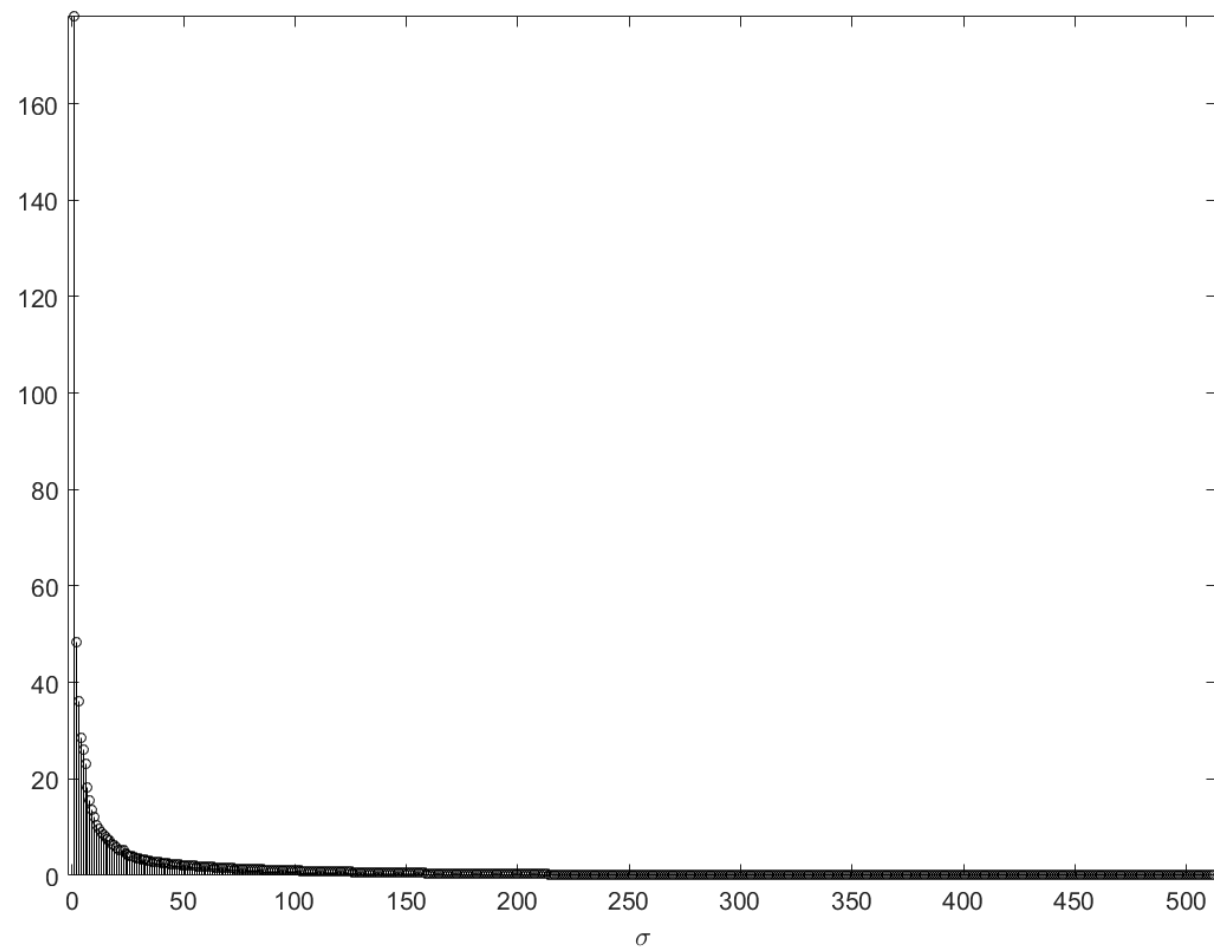
$A \in \mathcal{R}^{512 \times 512}$ 2^{18} 个值

$$A = U\Sigma V^T = \sum_{i=1}^{512} \sigma_i \mathbf{u}_i \mathbf{v}_i^T$$

用SVD压缩图像



$A \in \mathcal{R}^{512 \times 512}$ 2^{18} 个值



用SVD压缩图像



$A \in \mathcal{R}^{512 \times 512}$ 2^{18} 个值

$$A \approx \sum_{i=1}^k \sigma_i \mathbf{u}_i \mathbf{v}_i^T$$

$$\{\sigma_i \quad \mathbf{u}_i \quad \mathbf{v}_i\}_{i=1}^k$$

$1025 \times k \approx 2^{10} \times k$ 个值

用SVD压缩图像



$A \in \mathcal{R}^{512 \times 512}$ 2^{18} 个值



$k = 32$

用SVD压缩图像



$A \in \mathcal{R}^{512 \times 512}$ 2^{18} 个值



$k = 64$

用SVD压缩图像



$A \in \mathcal{R}^{512 \times 512}$ 2^{18} 个值



$k = 128$