# linear algebra in CS

你们觉得你们现在学的东西没有用,并不是因为它真的没有用,只是你们还没有遇到要用到那门课的时候

- 一个CS的学生, 在大学期间其实会多次重新学习线性代数
- 学习过的内容不需要你牢牢记住, 但是需要你知道它的存在, 以及它的用途, 以及清楚的知道你需要的时候去哪里找



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「大学招生简直诡计多端…某个uc数学系的博士生说,现在愿意修线性代数的美国本科生越来越少了,后来他们改了个名字大概叫Math Foundationsof MachineLearning,爆满,学生给教授写邮件要去上这门课,其实还是线性代数。」

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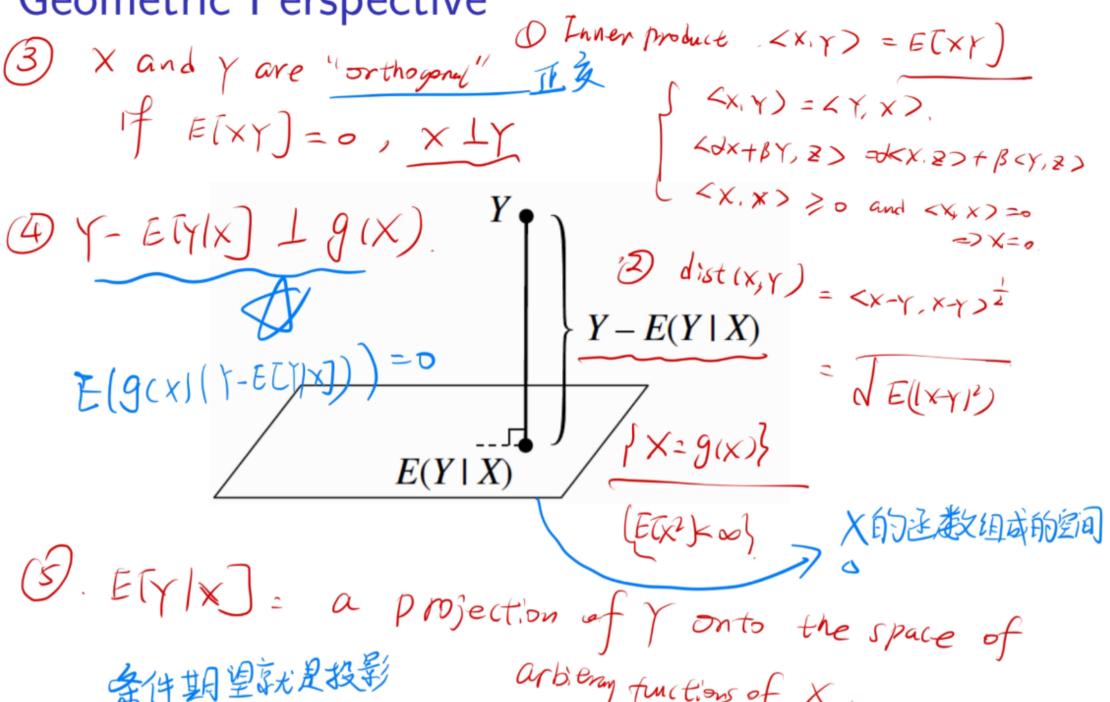




• for algorithm and data structure / information theory e.g. the Laplacian matrix of a graph

$$L_{ij} = \left\{ egin{array}{ll} D_{ii} & ext{if } i = j \\ -1 & ext{if } i 
eq j ext{ and } v_i ext{ is adjacent to } v_j \\ 0 & ext{otherwise} \end{array} 
ight.$$

Geometric Perspective



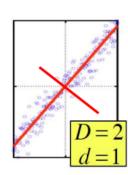
for machine learning(ML)

## Principal Component Analysis (PCA)

 $(X X^T)v = \lambda v$ , so v (the first PC) is the eigenvector of sample correlation/covariance matrix  $X X^T$ 

Sample variance of projection  $\mathbf{v}^T X X^T \mathbf{v} = \lambda \mathbf{v}^T \mathbf{v} = \lambda$ 

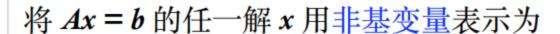
Thus, the eigenvalue  $\lambda$  denotes the amount of variability captured along that dimension (aka amount of energy along that dimension).



Eigenvalues  $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \cdots$ 

- The 1<sup>st</sup> PC  $v_1$  is the the eigenvector of the sample covariance matrix  $XX^T$  associated with the largest eigenvalue
- The 2nd PC  $v_2$  is the the eigenvector of the sample covariance matrix  $X X^T$  associated with the second largest eigenvalue
- And so on ...

• for optimization

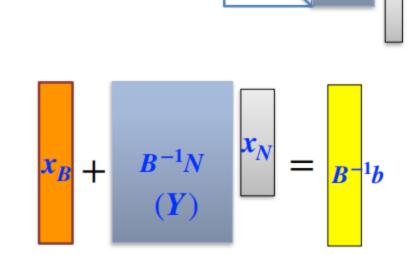


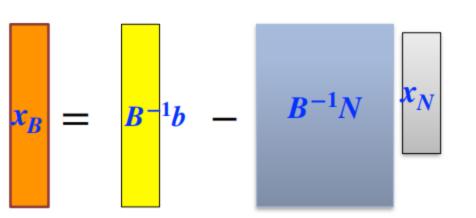
$$x_1 = \bar{b}_1 - \sum_{j=m+1}^n y_{1j} x_j$$

$$x_2 = \bar{b}_2 - \sum_{j=m+1}^n y_{2j} x_j$$

$$\vdots$$

$$x_m = \bar{b}_m - \sum_{j=m+1}^n y_{mj} x_j$$

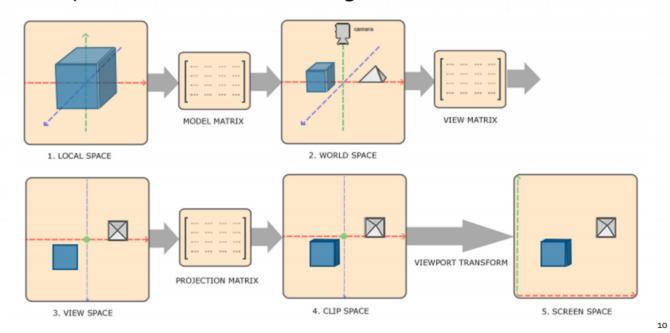




• for computer graphics(CG)

## **Coordinate spaces**

- The global picture
  - Space transformations using matrices



for computer vision(CV)

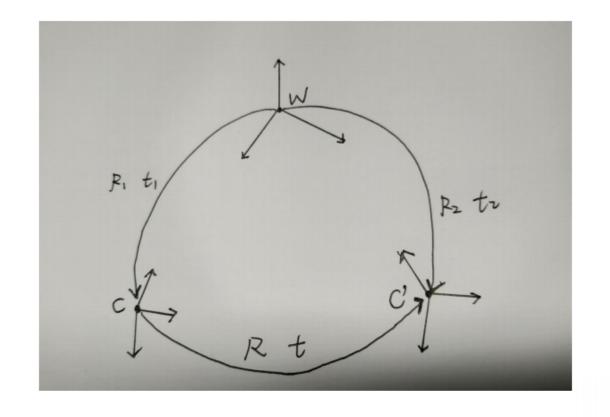
### homography projective transformation(单应性变换)

• 想要任意变换(正方形变为任意四边形)



$$H = K_2 R_2 (I - rac{1}{d} (-R_1^{-1} t_1 + R_2^{-1} t_2) n^T R_1) R_1^T K_1^{-1}$$

for computer vision(CV)



$$\begin{bmatrix} R_2 & t_2 \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix}^{-1} \begin{bmatrix} R & t \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix} \begin{bmatrix} R_1 & t_1 \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix} P = P$$

$$\begin{bmatrix} R & t \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix} = \begin{bmatrix} R_2 R_1^{-1} & -R_2 R_1^{-1} t_1 + t_2 \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix}$$

$$R = R_2 R_1^{-1}$$

$$t = -R_2 R_1^{-1} t_1 + t_2$$

$$H = K_2 (R - t \frac{n^T}{d}) K_1^{-1}$$

$$H = K_2 (R_2 R_1^{-1} - (-R_2 R_1^{-1} t_1 + t_2) \frac{n^T}{d}) K_1^{-1}$$

$$H = K_2 R_2 (I - rac{1}{d} (-R_1^{-1} t_1 + R_2^{-1} t_2) n^T R_1) R_1^T K_1^{-1}$$

for computer vision(CV)

## Camera calibration: Linear method

$$\begin{bmatrix} 0^T & \mathbf{X}_1^T & -y_1 \mathbf{X}_1^T \\ \mathbf{X}_1^T & 0^T & -x_1 \mathbf{X}_1^T \\ \dots & \dots & \dots \\ 0^T & \mathbf{X}_n^T & -y_n \mathbf{X}_n^T \\ \mathbf{X}_n^T & 0^T & -x_n \mathbf{X}_n^T \end{bmatrix} \begin{pmatrix} \mathbf{P}_1 \\ \mathbf{P}_2 \\ \mathbf{P}_3 \end{pmatrix} = 0 \qquad \mathbf{A}\mathbf{p} = \mathbf{0}$$

- P has 11 degrees of freedom
- One 2D/3D correspondence gives us two linearly independent equations
  - 6 correspondences needed for a minimal solution
- Homogeneous least squares: find  $\mathbf{p}$  minimizing  $||\mathbf{A}\mathbf{p}||^2$ 
  - Solution given by eigenvector of A<sup>T</sup>A with smallest eigenvalue

- for natural language processing(NLP)
- for robotics
- for data mining
- for data science

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