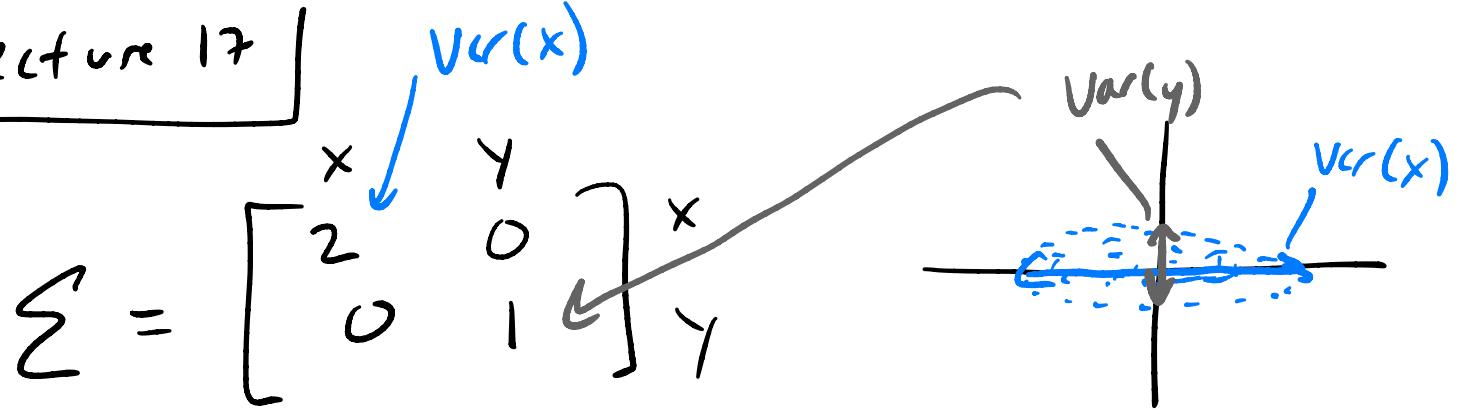


Lecture 17

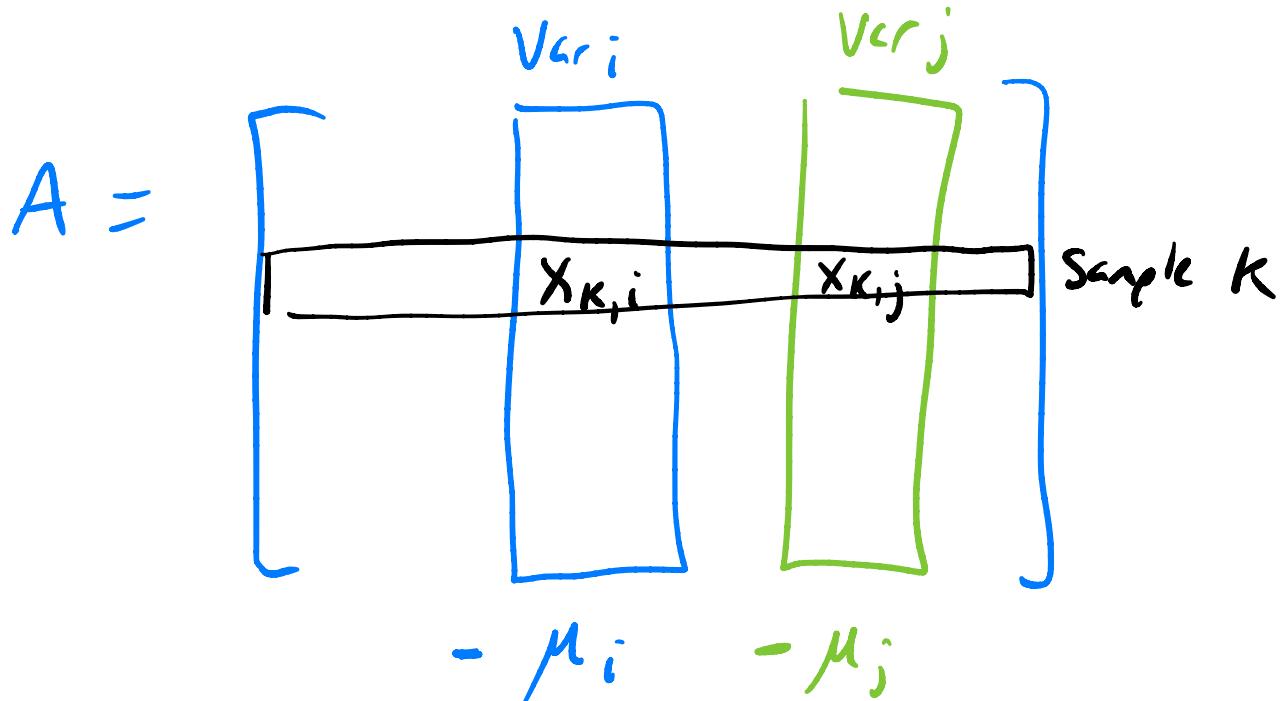


$$\Sigma = \begin{bmatrix} x & y \\ 2 & 0 \\ 0 & 1 \end{bmatrix}$$

Scalar equation

Sum up over all samples \rightarrow

$$\Sigma(i, j) = \sum_{k=1}^N \frac{(x_{ki} - \mu_i) \cdot (x_{kj} - \mu_j)}{N-1}$$



$$\begin{aligned}
 \Sigma(i, i) &= \sum_{k=1}^N \frac{(X_{ki} - \mu_i)(X_{ki} - \mu_i)}{N-1} \\
 &= \sum_{k=1}^N \frac{(X_{ki} - \mu_i)^2}{N-1} \\
 &= \frac{1}{N-1} \sum_{k=1}^N (X_{ki} - \mu_i)^2 \\
 &= \frac{1}{N-1} \sum_{i=1}^N (x_i - \mu)^2
 \end{aligned}$$

ordinary
variance

$$\Sigma = \begin{bmatrix} \text{Var}(x) & \text{Cov}(x, y) \\ \text{Cov}(y, x) & \text{Var}(y) \end{bmatrix}$$

$i=0, j=1 : \Sigma(i, j)$
 $= \Sigma(0, 1)$

Vectorized Equation:

$$\Sigma = \frac{1}{N-1} \sum_{k=1}^N \left[(\vec{x}_k - \vec{\mu}) \cdot \vec{T} \right] \cdot \left[(\vec{x}_k - \vec{\mu}) \cdot \vec{T} \right]^T$$

means of all cols

Shape: $(1, M)$

Shape: $(M, 1)$

result shape: (M, M)

$$A = \begin{bmatrix} 1 & 2 & 3 \\ \{ & \{ & \{ \\ \} & \} & \} \end{bmatrix}$$

$$- [\mu_1, \mu_2, \mu_3]$$

Ver1 Ver2 Ver3

$$\begin{bmatrix} 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 9 \end{bmatrix}$$

Sample K

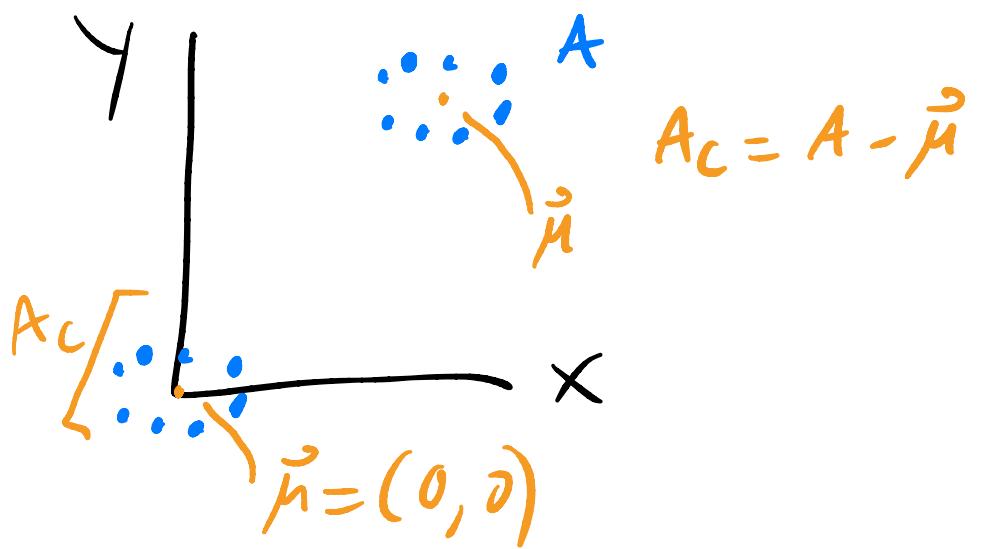
\vec{x}_k

$$- [2, 5, 8]$$

$$A_C = \begin{bmatrix} \{ & \{ & \{ \\ \} & \} & \} \end{bmatrix}$$

$$\begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ +1 & +1 & +1 \end{bmatrix}$$

$$\text{Shape}(A_C) = \text{Shape}(A)$$



Taking data A , Subtracting column means $\vec{\mu}, \vec{\mu}$
 gives us A_C — **centered data** \leftarrow mean is $\vec{0} = (0, 0, \dots)$

if we have A_C [precomputed]

$$\sum = \frac{1}{N-1} A_C \cdot \top @ A_C$$

column means

where $A_C = A - \vec{\mu}$

Example: Calculate Σ , but 1st A_C

$$A = \begin{bmatrix} \text{Var1} & \text{Var2} & \text{Var3} \\ 1 & 2 & -1 \\ 10 & 2 & 1 \\ 3 & 4 & 5 \\ 3 & 2 & 1 \end{bmatrix} \quad \vec{\mu} = \left(\frac{1}{4}(1+10+3+3), \right. \\ \left. \frac{1}{4}(2+2+4+2), \right. \\ \left. \frac{1}{4}(-1+1+5+1) \right)$$

- $[4.25, 2.5, 1.5] \quad \vec{\mu} = (4.25, 2.5, 1.5)$

$$A_C = A - \vec{\mu}$$

$$A_C = \begin{bmatrix} -3.25 & -1/2 & -2.5 \\ 5.75 & -1/2 & -1/2 \\ -1.25 & 1.5 & 3.5 \\ -1.25 & -1/2 & -1/2 \end{bmatrix}$$

$(3,3)$ $(3,4)$ $(4,3)$

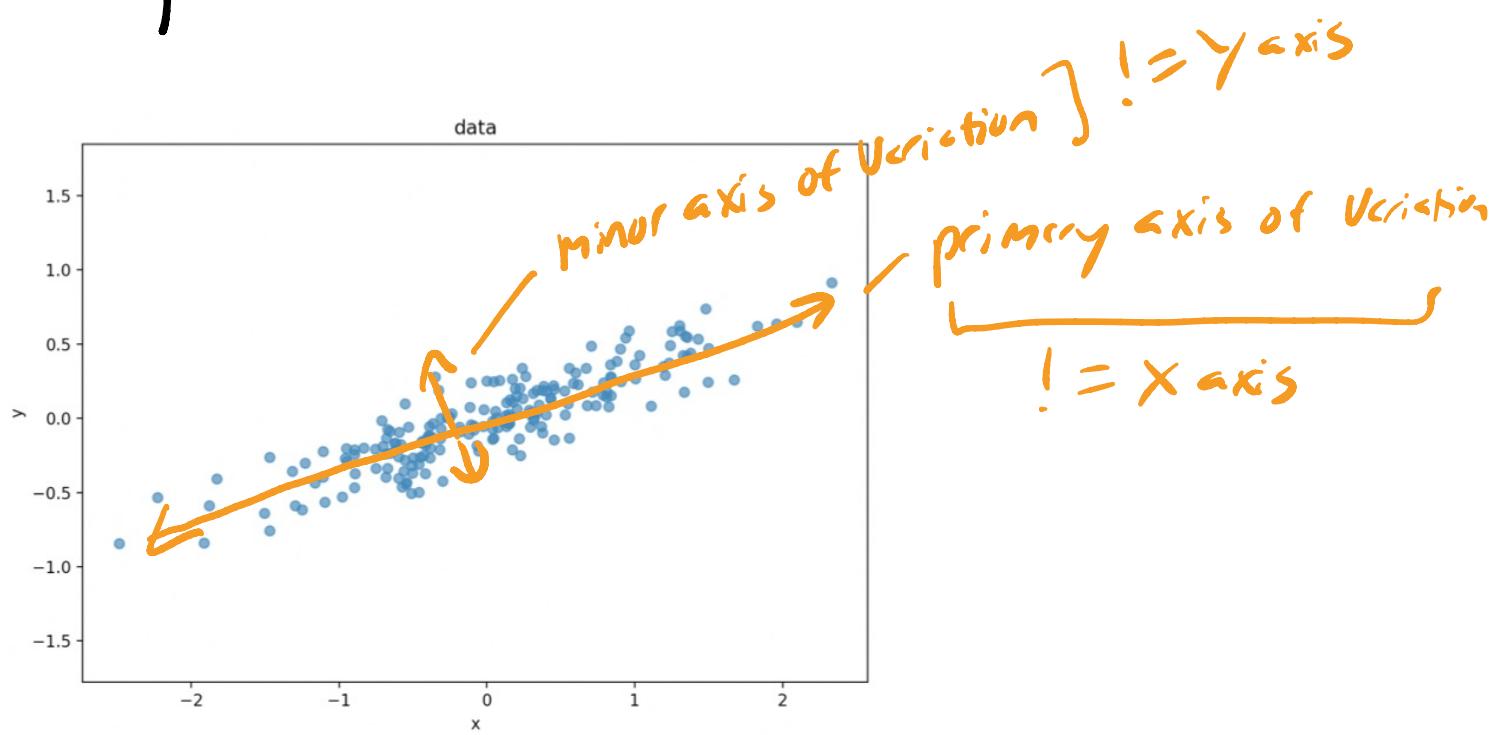
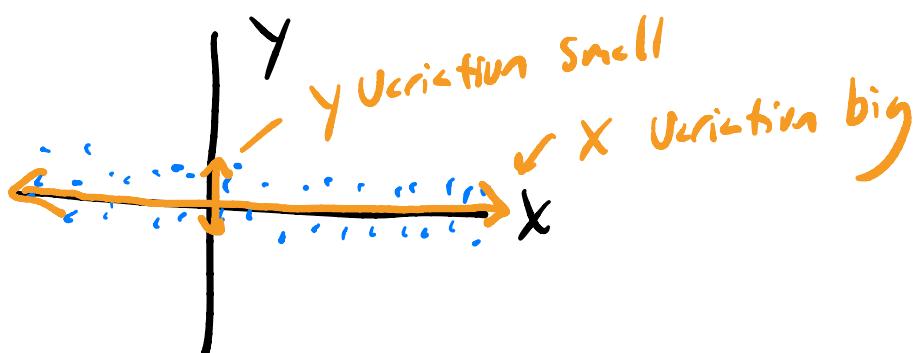
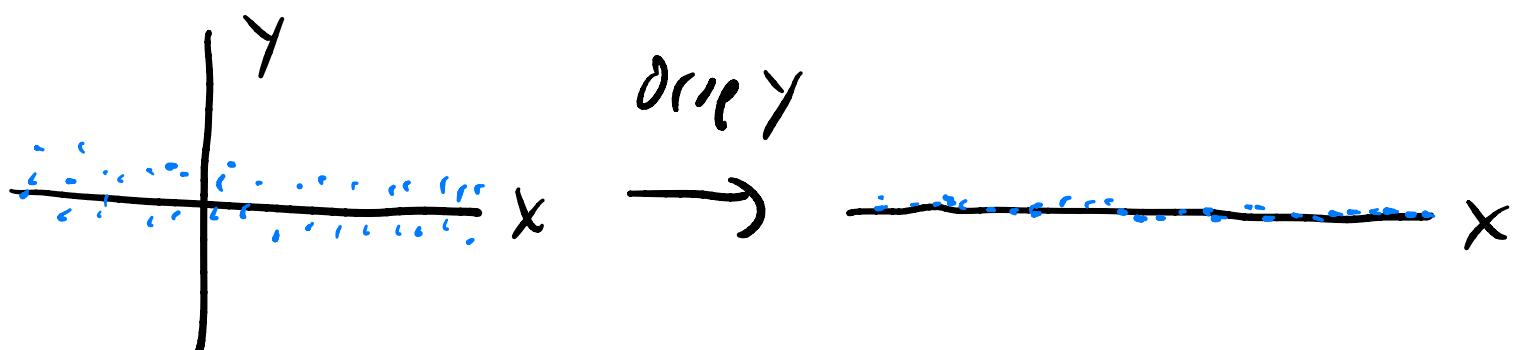
$$\Sigma = \frac{1}{N-1} A_C \cdot T @ A_C$$

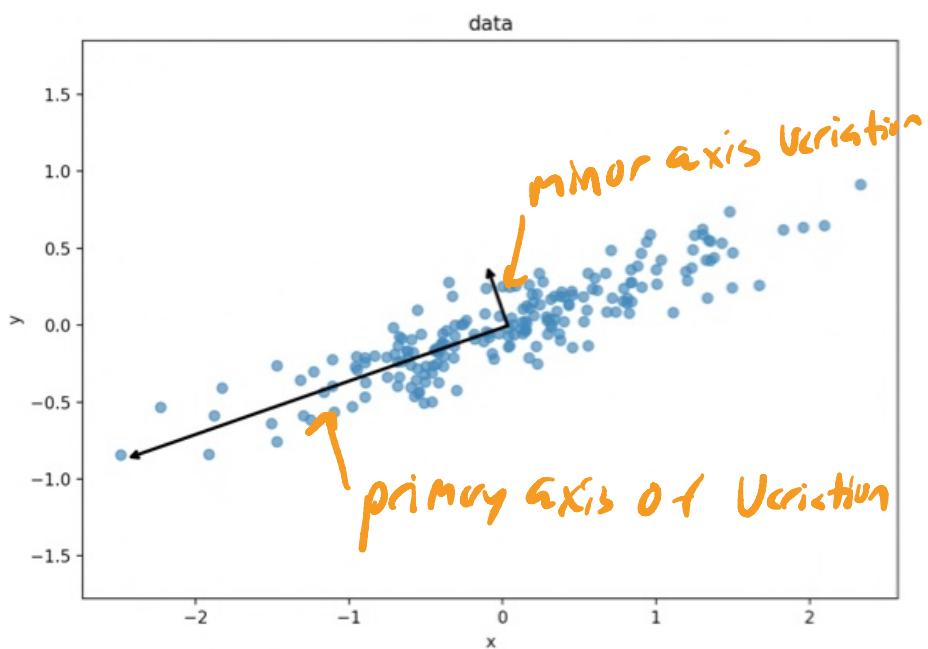
$$\sum = \frac{1}{3} \begin{bmatrix} -3.25 & 5.75 & -1.25 & -1.25 \\ -1/2 & -1/2 & 1.5 & -1/2 \\ -2.5 & -1/2 & 3.5 & -1/2 \end{bmatrix} \begin{bmatrix} -3.25 & -1/2 & -2.5 \\ 5.75 & -1/2 & -1/2 \\ -1.25 & 1.5 & 3.5 \\ -1.25 & -1/2 & -1/2 \end{bmatrix}$$

$\underbrace{\qquad\qquad\qquad}_{A_c \cdot T}$ $\underbrace{\qquad\qquad\qquad}_{A_c}$

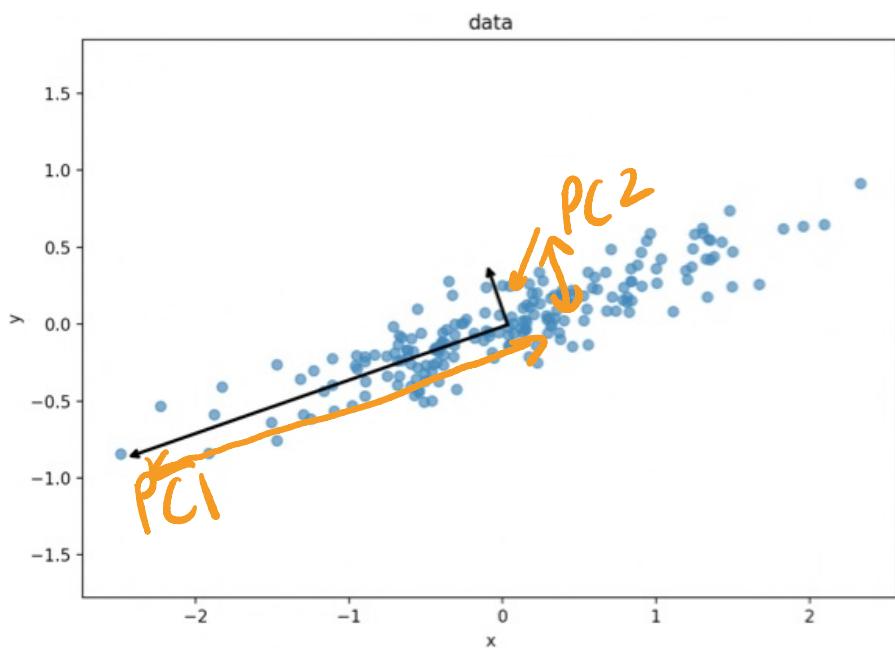
$$= \begin{bmatrix} x & y & z \\ 15.8 & -0.83 & 0.5 \\ -0.83 & 1.0 & 2.3 \\ 0.5 & 2.3 & 6.3 \end{bmatrix} \begin{matrix} x \\ y \\ z \end{matrix}$$

Principal component analysis (PCA)





Principal Components (PCs): intrinsic axes of Variation in data



Smaller the PC number
bigger the axis
of Variation.

Goal of PCA

We want to drop PCs intrinsic axes of Variation that are insignificant / small

\Rightarrow Do not want to drop data Variables

