

$\tilde{X} = \begin{bmatrix} \tilde{x}_1 \\ \vdots \\ \tilde{x}_p \end{bmatrix}_{p \times 1}$  random vector.

for one variable var  $\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$ .

$\tilde{x}, \tilde{y}$  cov( $\tilde{x}, \tilde{y}$ ) =  $E[(x - \bar{x})(y - \bar{y})]$ .

2. r.v.s.

$\tilde{Z} = \begin{pmatrix} \tilde{x} \\ \tilde{y} \end{pmatrix}$

$\sim$  denotes random var or vector.

post experimentation cov( $x_i, x_j$ ).

$s_{ij} = \frac{1}{n} \sum_{i=1}^n (x_{ni} - \bar{x}_i)(x_{nj} - \bar{x}_j)$ .

$s_{ii} = \text{Var}(x_i)$   
 = cov( $x_i, x_i$ ).

$S = [s_{ij}]_{p \times p}$ .  
 Variance - covariance <sup>sample</sup> matrix.

after experimentation, we have the realisations of the variables - deterministic.

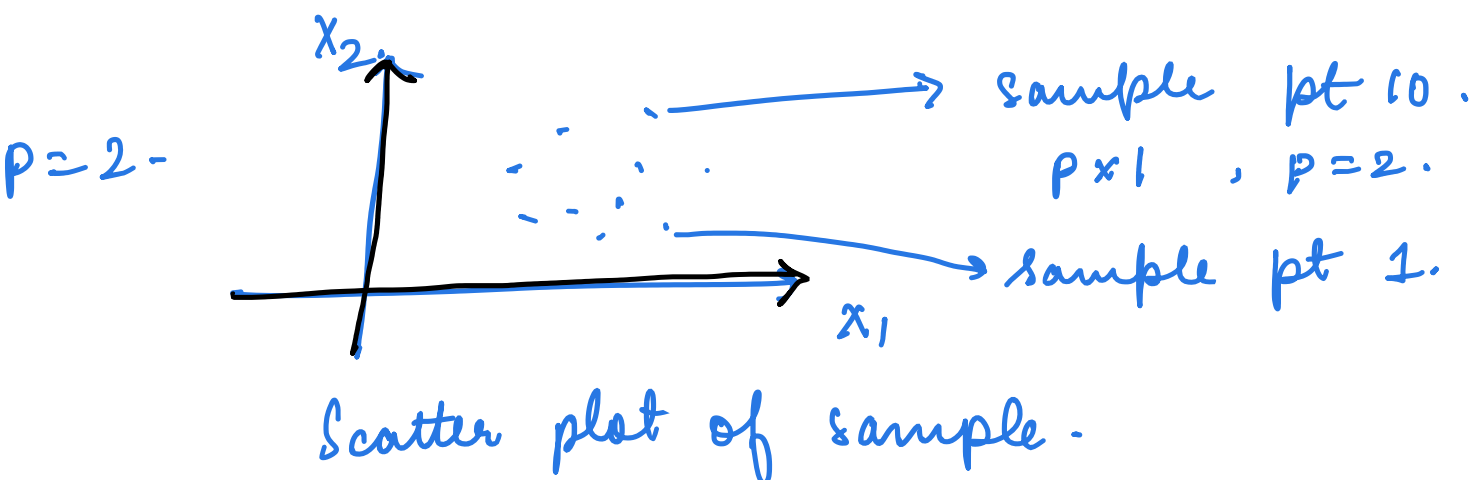
Population from which sample is drawn

$\mu_{p \times 1}$ ,  $\Sigma_{p \times p}$

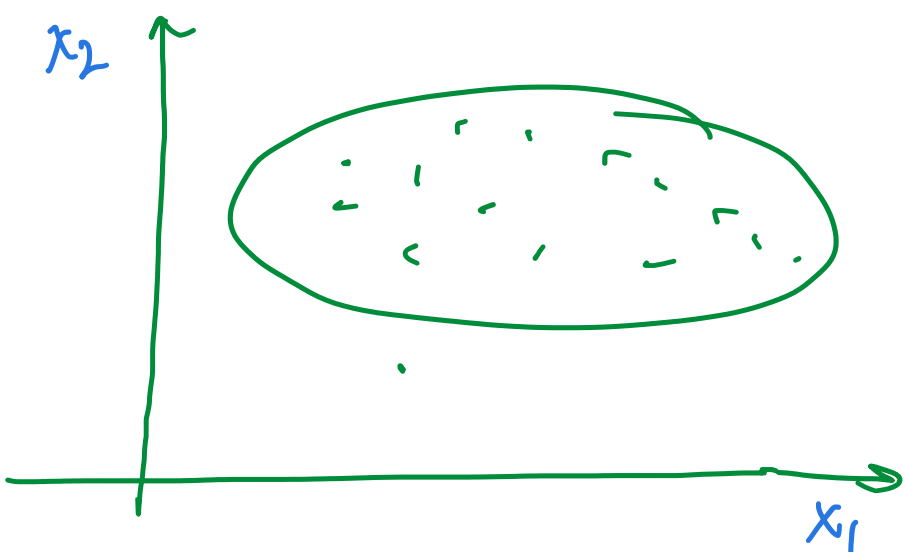
let look at the sample data from  $p$ -dim perspective.  
 (new wise).

each sample in  $\mathbb{R}^p$  &  $n$  samples.

plot these samples - we get a scatter plot in  $p$ -dim.



These pts. are independent



It takes almost an elliptical shape  
 there might be some outliers.

$S_{2 \times 2}$ .  $\begin{bmatrix} \alpha & 0 \\ 0 & \beta \end{bmatrix}$ .  $\alpha, \beta$  ratio not very large.  
 $\alpha \approx \beta$ .

Another ex.

variation along 1 feature is much more as compared to along the other feature.

Feedback example.

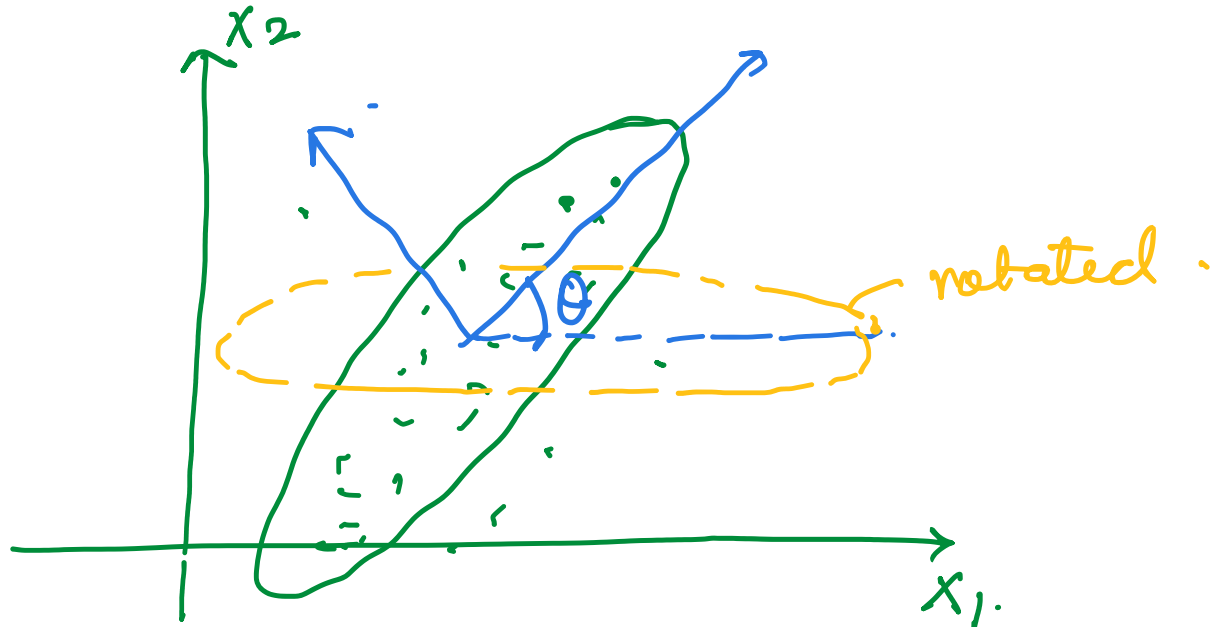
independent so covariance zero

$S_{2 \times 2}$ .  $\begin{bmatrix} \gamma & 0 \\ 0 & \delta \end{bmatrix}$ .

$\gamma \gg \delta$ .

Since diagonal matrix, these values are the eigen values  $\alpha, \beta$ .

# Dependent •  $p=2$ .



rotate  $\theta$  angle to make it standard ellipse.  
 Similarly for the next.

Can also shift entire data to origin so that centroid of the datapoints = 0.

