

## Factor Analysis (FA)

FA is a multivariate method used for data reduction purposes. The basic idea is to represent a set of variables by a smaller number of variables. & these variables are called known as factors.

### Technical Definition.

FA is a method for modelling observed variables & their covariance structure, in terms of a smaller number of underlying unobservable (latent) "factors".

What is the aim or purpose of FA in simple words.

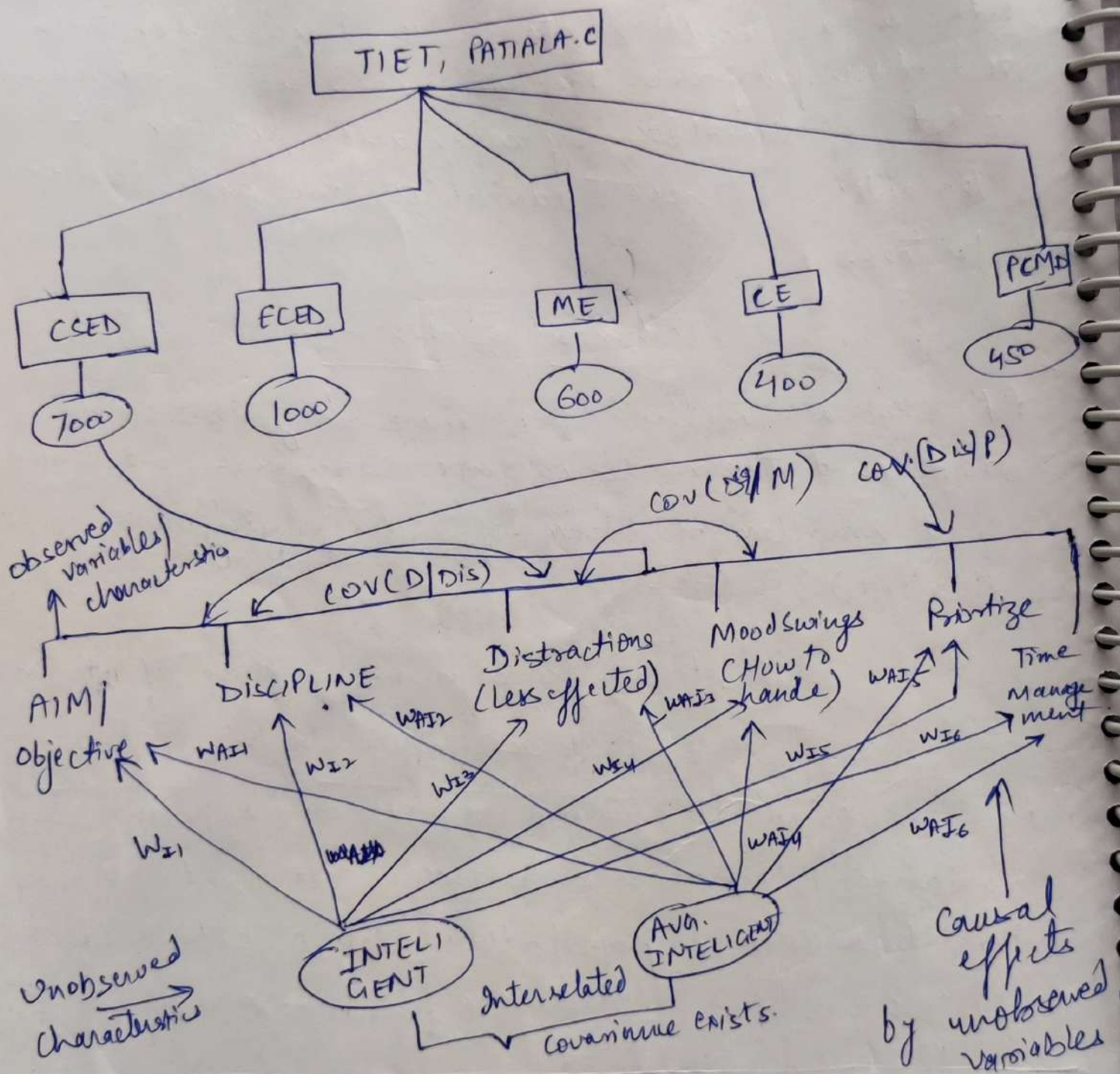
i.e. To estimate a model which explains variance / covariance between a set of observed variables (in a population) by a set of (fewer or less no. of) unobserved factors & weightings.

### Some of the Examples.

- 1) A welfare officer is interested to measure the quality of work life in factories.
- 2) A psychologist is interested to measure mental ability of a person.



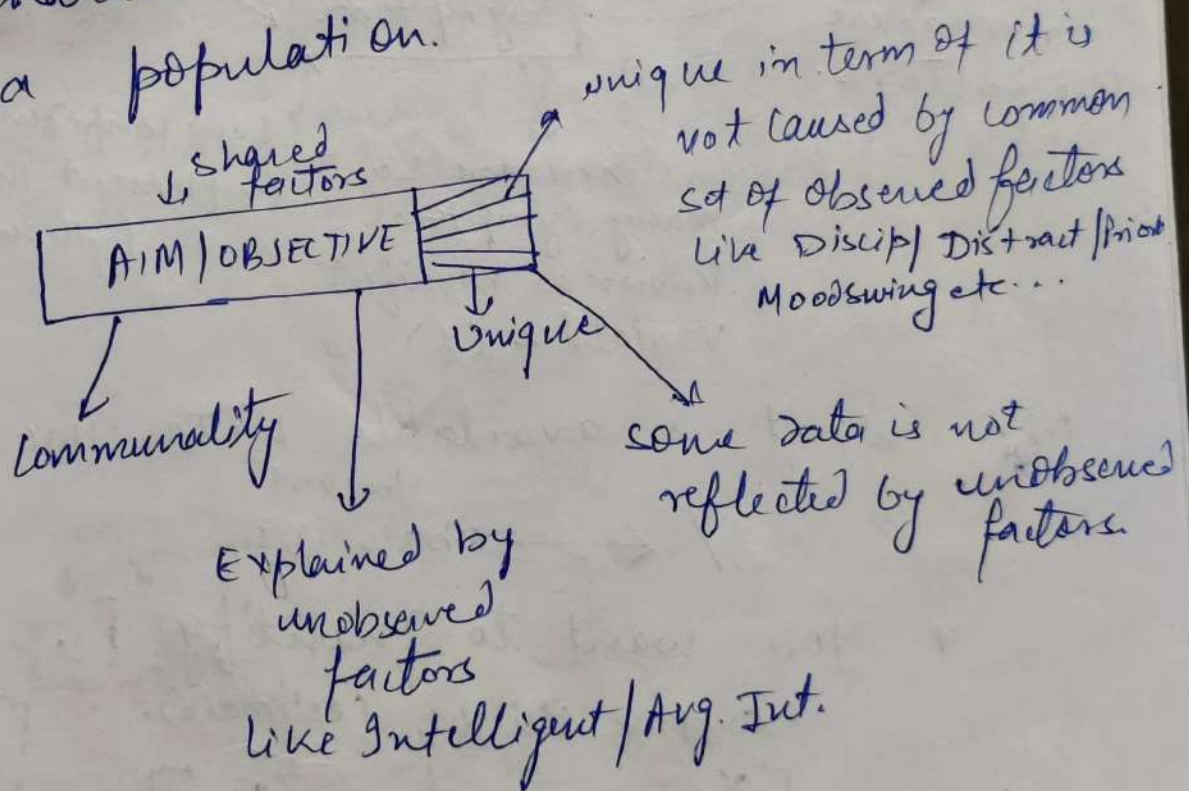
# Raw Example



what we conclude from above Example.

Our Model will explain whether 3<sup>rd</sup> variance)  
Covariance exist b/w observed variables/  
characteristics.

for we have to check about the variance  
of characteristics as an example AIM/OBJECTIVE  
in a population.



AIM  
Discipline  
Distractions  
Moodswings  
Prioritize  
Time Manag.



unobservable  
concepts  
constructs

# Technical Analysis of Factor Analysis

overthinking  
rabbit

some one rabbit  
is too to overthink  
rather than do  
a practical work

constructs/factors  
(F)

causing these  
manifest

मनोविज्ञान, पूछा, मयमर जवाब, मार

Symptoms

Low confidence in  
implement the concepts  
in R, Python or Matlab.

There are so  
many symptoms  
known as manifest  
variables (X)

from these symptoms  
we can judge  
or measure  
the factors.

Now, what is available with you??

X ← observing  
you are

\* you want to quantify "F".  
(estimate).

suppose this X have

This is known  
about the  
population

$$X_{p \times 1} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix}_{p \times 1}$$

$$\mu_{p \times 1} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_p \end{bmatrix}_{p \times 1}$$

values  
may  
or  
may not  
be known

$$\text{Cov}(X) = \Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \dots & \sigma_{1p} \\ \sigma_{21} & \sigma_{22} & \dots & \sigma_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{p1} & \sigma_{p2} & \dots & \sigma_{pp} \end{bmatrix}$$

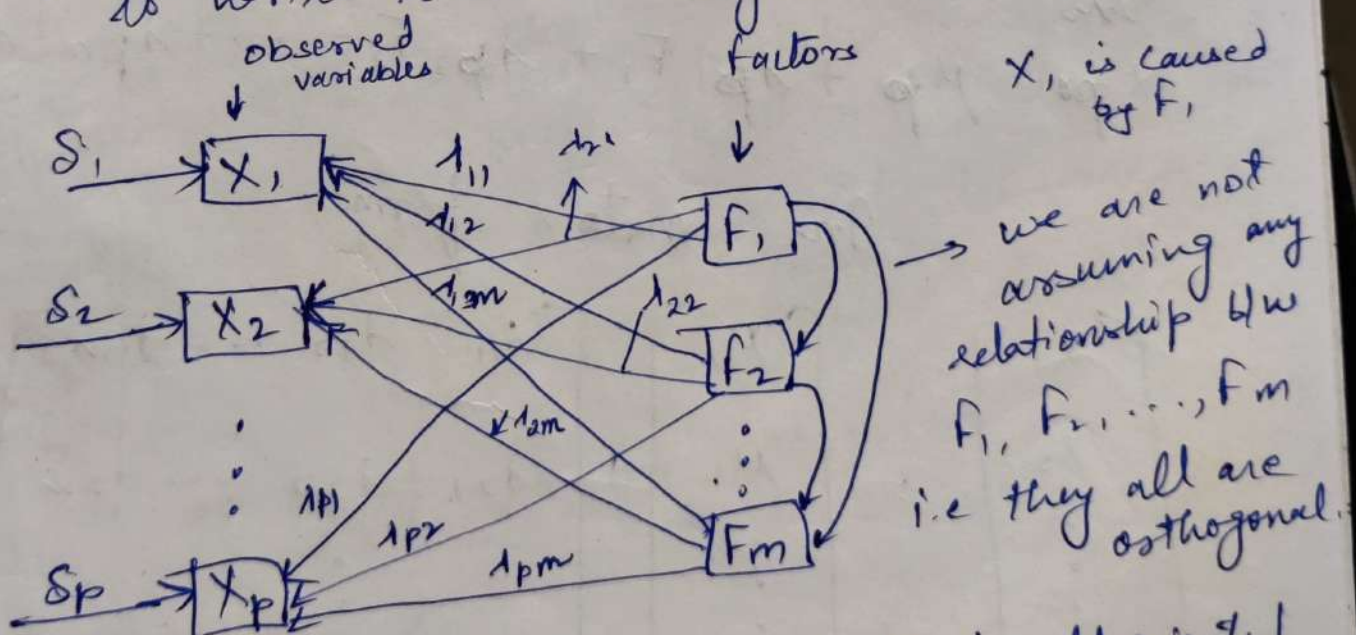
Consider 'm' factors, then

$$F_{m \times 1} = \begin{bmatrix} F_1 \\ F_2 \\ F_3 \\ \vdots \\ F_m \end{bmatrix}$$

"F" is causing X {Symptoms}

So; What you observe in X, it is just because of causal factors i.e  $F_{m \times 1}$ ,

from that conclusion, we are able to write the linear regression kind of eqn. But first see this diagram, which helps to write linear regression Eqn.



These  $\lambda_{pm}$  are influencing factors / coefficients / weighting coefficients.



Now, these factors ( $F_1, F_2, \dots, F_m$ ) are not able to explain each & every thing about  $X_1$  and so on. Thus,  $\exists$  an error term associated with each  $X_1, X_2, \dots, X_p$  variables.

$$X_1 = \mu_1 + \lambda_{11} F_1 + \lambda_{12} F_2 + \dots + \lambda_{1m} F_m + \delta_1$$

$$\text{Similarly } X_2 = \mu_2 + \lambda_{21} F_1 + \lambda_{22} F_2 + \dots + \lambda_{2m} F_m + \delta_2$$

$$\vdots$$

$$X_j = \mu_j + \lambda_{j1} F_1 + \lambda_{j2} F_2 + \dots + \lambda_{jm} F_m + \delta_j$$

$$\vdots$$

$$X_p = \mu_p + \lambda_{p1} F_1 + \lambda_{p2} F_2 + \dots + \lambda_{pm} F_m + \delta_p$$

In matrix form.

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix}_{p \times 1} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_p \end{bmatrix}_{p \times 1} + \begin{bmatrix} \lambda_{11} & \lambda_{12} & \dots & \lambda_{1m} \\ \lambda_{21} & \lambda_{22} & \dots & \lambda_{2m} \\ \vdots & \vdots & & \vdots \\ \lambda_{p1} & \lambda_{p2} & \dots & \lambda_{pm} \end{bmatrix}_{p \times m} \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_m \end{bmatrix}_{m \times 1} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_p \end{bmatrix}_{p \times 1}$$



$$X_{(p \times 1)} = \mu_{(p \times 1)} + 1_{(p \times m)} F_{(m \times 1)} + S_{(p \times 1)}$$

$$\Rightarrow X - \mu = 1F + S \quad \text{--- (1)}$$

Eg<sup>n</sup>. known as Factor Model.

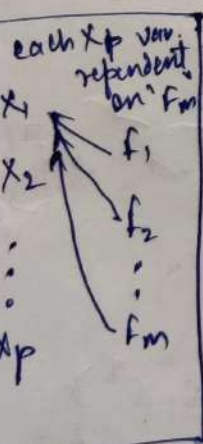
One important assumption is there  
i.e.  $F_1, F_2, \dots, F_m$

"No" relationship i.e. orthogonal  
 $\text{cov}(F_i) = 0$  ( $\text{cov}(F) = \Psi$ )

Serial Assum<sup>t</sup>  
 $E(X) = \mu$   
 $\text{cov}(X) = \Sigma$   
 $E(F) = 0$   
 $E(S) = 0$   
 $\text{cov}(F) = E(F F^T) = I$

But, if  $F_1, F_2, \dots, F_m$   
 & if these all assumptions are hold  
 true, then FA is called  
 up to orthogonal when there is correlation  
 exist b/w them

Diagonal  
matrices  
 $\begin{bmatrix} \psi_{11} & 0 & \dots & 0 \\ 0 & \psi_{22} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \psi_{mm} \end{bmatrix}$



then above factor model becomes  
 "Oblique" factor model.

Types of factor Model

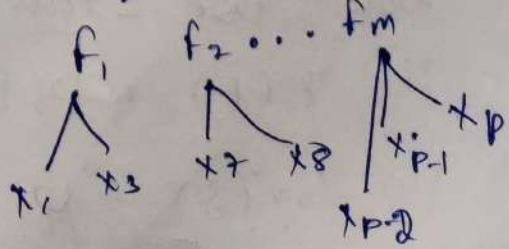
Exploratory

You are exploring  
the possibilities  
of hidden factors  
"F".

$$X - \mu = 1F + S$$

↑ not clearly  
that's why each &  
every thing connected.

Confirmatory (You know clearly)





From above discussion it is cleared that purpose of factor analysis is to describe, if possible, the covariance relationships among many variables in terms of a few underlying but unobservable, random quantities called factors.

i.e.  $\text{Cov}(X) = \sum_{p \times p}$

we know that assumptions.

Now  $X - \mu = \Lambda F + S$  ← factor model.

I want to know that what kind of variability you are able to explain by above model.

$$\begin{aligned} \Sigma = \text{Cov}(X) &= E\{(X - \mu)(X - \mu)^T\} \\ &= E\{(\Lambda F + S)(\Lambda F + S)^T\} \\ &= E\{\Lambda F \cdot F^T \Lambda^T + \Lambda F S^T + S \cdot F^T \Lambda^T + S S^T\} \\ &= \Lambda E(F \cdot F^T) \Lambda^T + \Lambda E(F S^T) + E(S \cdot F^T) \Lambda^T + E(S \cdot S^T) \end{aligned}$$

Now, Use standard assumption, Proof by yourself.

(1)  $E(F) = 0$  (2)  $E(S) = 0$ , (3)  $\text{Cov}(F) = E(F F^T) = I$

(4)  $\text{Cov}(S) = \Psi$  (5)  $\text{Cov}(FS) = 0$   
 or  $E(S S^T) = \Psi$



$$= 11^T + 1 \cdot 0 + 0 \cdot 1^T + \psi$$

$$\Sigma = 11^T + \psi = \text{cov}(X) \quad \text{--- (2)}$$

↑ what is benefit of that??

i.e. If I know  $1, \psi$  then, I can easily compute variability  $\Sigma / \text{cov}(X)$ .

$$1 = \begin{bmatrix} \boxed{1_{11} \quad 1_{12} \quad \dots \quad 1_{1m}} \\ 1_{21} \quad 1_{22} \quad \dots \quad 1_{2m} \\ \vdots \\ 1_{p1} \quad 1_{p2} \quad \dots \quad 1_{pm} \end{bmatrix} \quad p \times m$$

↓  
loading matrix

In General case:

$$X_j = 1_{j1} F_1 + 1_{j2} F_2 + \dots + \boxed{1_{jk}} F_k + \dots + 1_{jm} F_m + \epsilon_j$$

$1_{jk}$  = loading of  $k^{\text{th}}$  factor on  $j^{\text{th}}$   $X$

loading ~~on~~  
 $j = 1, 2, \dots, p$   
 $k = 1, 2, \dots, m$

$$\text{then } 1 \cdot 1^T = 1_{p \times m} \cdot 1_{m \times p}^T$$

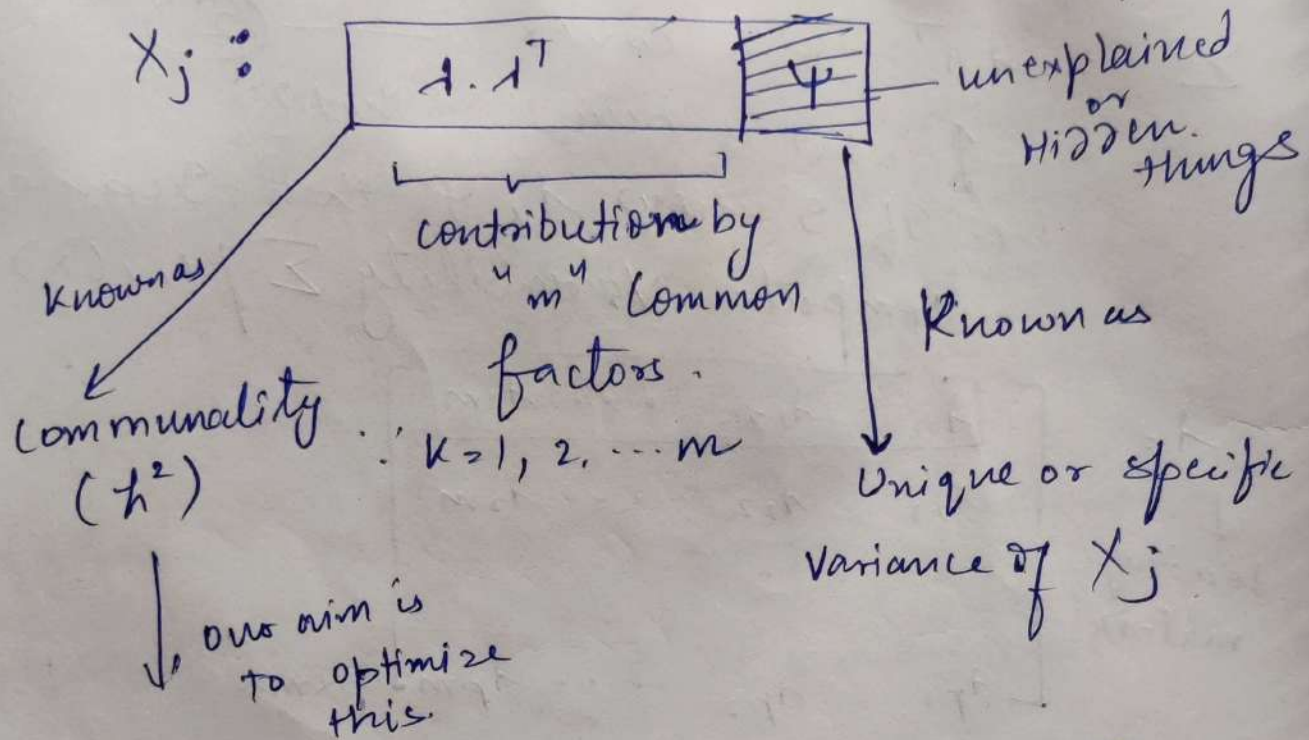
✓  
Symmetric matrix.

$$= \begin{bmatrix} \sum_{k=1}^m 1_{1k}^2 & \sum_{k=1}^m 1_{1k} 1_{2k} & \dots & \sum_{k=1}^m 1_{1k} 1_{pk} \\ \sum_{k=1}^m 1_{1k} 1_{2k} & \sum_{k=1}^m 1_{2k}^2 & \dots & \sum_{k=1}^m 1_{2k} 1_{pk} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{k=1}^m 1_{1k} 1_{pk} & \sum_{k=1}^m 1_{2k} 1_{pk} & \dots & \sum_{k=1}^m 1_{pk}^2 \end{bmatrix}$$

Cov.  
↑  
var.  $p \times p$



so, our data is partitioned into two parts



Next topic is to estimate (11)