# Generation Of Noisy Vectors – Normally Distributed.

**Aim**: To Generate Noisy D-dimensional Vectors whose Mean is $M$ and Covariance Matrix $\Sigma$.

**Theory**: Suppose we had a vector $X$ whose mean was $M$ and Covariance Matrix was $\Sigma$.

Let $\Phi$ be the eigenvector Matrix of $\Sigma$ and $\Lambda$ the eigenvalue Matrix of $\Sigma$.

$$\Phi = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_D \end{bmatrix} \quad \Lambda = \begin{bmatrix} \lambda_1 & & 0 \\ & \lambda_2 & \\ 0 & & \ddots \ \lambda_D \end{bmatrix},$$

$\phi_i$ is eigenvector of eigenvalue $\lambda_i$.

We showed you that to "Diagonalize" $X$ to have independent vector components we use transformation:

$$Z = \Lambda^{-1/2} \Phi^T X$$

$Z$ now has a covariance Matrix $\begin{bmatrix} 1 & & 0 \\ & 1 & \\ 0 & \ddots & 1 \end{bmatrix}$.

Thus if we generate samples of type $Z$

$\Phi \Lambda^{1/2} Z$ will be of type $X$

i.e. have <u>Covariance Matrix $\Sigma$</u>.

This is because $\Phi^{-1} = \Phi^T$.