

7 ESTIMATORS OF RANDOM VECTORS

Let a random vector $X \equiv \begin{bmatrix} X_{n,1} \\ \vdots \\ X_{n,m} \end{bmatrix} \in \mathbb{R}^m$ with PDF $f(x)$ that has $\mu \equiv E[X] \in \mathbb{R}^m$ and $\Sigma \equiv \text{var}[X] \in \mathbb{R}^{m \times m}$.
To estimate the true μ , Σ or even the true multivariate distribution of $X \{f(x)\}$, take:

a sample $\{X_1, \dots, X_n\}$ where $X_i \in \mathbb{R}^m$ and are i.i.d. and define the analog estimators:

$$\hat{\mu} \equiv \bar{X}_n \equiv \frac{1}{n} \sum_{k=1}^n X_k = \begin{pmatrix} \bar{X}_{n,1} \\ \bar{X}_{n,2} \\ \vdots \\ \bar{X}_{n,m} \end{pmatrix}, \quad \hat{\Sigma} \equiv \frac{1}{n-1} \sum_{k=1}^n (X_k - \bar{X}_n)(X_k - \bar{X}_n)^T, \quad \text{In particular:}$$

$$\mu_i \equiv E[X_{n,i}] \rightarrow \hat{\mu}_i \equiv \bar{X}_{n,i}, \quad \text{var}_i^2 \equiv \text{var}[X_{n,i}] \equiv \Sigma_{ii} \rightarrow \hat{\sigma}_i^2 \equiv \hat{\Sigma}_{ii}, \quad \sigma_{ij}^2 \equiv \text{cov}[X_{n,i}, X_{n,j}] \equiv \Sigma_{ij} \rightarrow \hat{\sigma}_{ij}^2 \equiv \hat{\Sigma}_{ij}$$

$\text{mse}[\bar{X}_n] = \frac{\Sigma}{n}$

- $E[\bar{X}_n] = \mu$ $\{ \bar{X}_n: \text{unbiased} \}$, also $E[\bar{X}_{n,i}] = \mu_i$ $\{ \bar{X}_{n,i}: \text{unbiased} \}$
- $E[\hat{\Sigma}] = \Sigma$ $\{ \hat{\Sigma}: \text{unbiased} \}$, thus $E[\hat{\Sigma}_{ij}] = \Sigma_{ij} \equiv \sigma_{ij}^2$ $\{ \hat{\Sigma}_{ij}: \text{unbiased} \}$
- $\text{var}[\bar{X}_n] \equiv E[(\bar{X}_n - E[\bar{X}_n])(\bar{X}_n - E[\bar{X}_n])^T] = \Sigma/n$

Also the MSE-matrix of \bar{X}_n , $\text{mse}[\bar{X}_n] \equiv E[(\bar{X}_n - \mu)(\bar{X}_n - \mu)^T] = \Sigma/n$
and we can prove that \bar{X}_n : best linear unbiased estimator of μ

If $X \in \mathbb{R}^m \sim N(\mu, \Sigma) \implies \bar{X}_n \sim N(\mu, \Sigma/n)$ and $\hat{\Sigma} \sim \text{Wishart} \left\{ \begin{smallmatrix} \text{multivariate} \\ \text{generalization of } \chi^2_{n-1} \end{smallmatrix} \right\}$