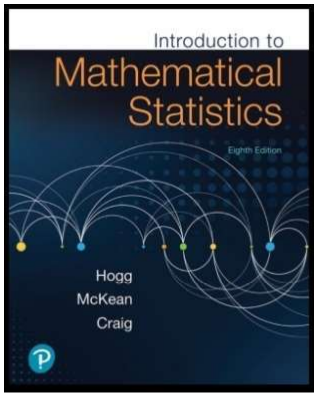
Mathematical Statistics 1

Chapter 5. Consistency and Limiting Distributions

5.4. Extensions to Multivariate Distributions—Proofs of Theorems



Lemma 5.4.1

Lemma 5.4.1. Let $\mathbf{v}' = (v_1, v_2, \ldots, v_p) \in \mathbb{R}^p$. Then $|v_j| \le \|\mathbf{v}\| \le \sum_{i=1}^p |v_i|$ for all $j = 1, 2, \ldots, p$.

Proof. For all $j = 1, 2, \ldots, p$ we have $v_j \le \sum_{i=1}^p v_i^2 = \|\mathbf{v}\|^2$ and so (taking square roots) $|v_j| \le \|\mathbf{v}\|$. Next, by the Triangle Inequality,

$$\|\mathbf{v}\| = \left\{ \sum_{i=1}^p v_i \mathbf{e}_i \right\| \le \sum_{i=1}^p \|v_i \mathbf{e}_i\| = \sum_{i=1}^p |v_i|$$

(since $\|\mathbf{e}_i\| = 1$ for each i). Therefore, $|v_j| \le \|\mathbf{v}\| \le \sum_{i=1}^p |v_i|$, as claimed. □

Theorem 5.4.1

Theorem 5.4.1. Let $\{\mathbf{X}_n\}$ be a sequence of p-dimensional vectors and let $\mathbf{X}$ be a random vector, all defined on the same sample space. Then

$$\mathbf{X}_n \xrightarrow{P} \mathbf{X} \text{ if and only if } X_{nj} \xrightarrow{P} X_j \text{ for all } j = 1, 2, \ldots, p.$$

Proof. Let $\varepsilon > 0$.

Suppose $\mathbf{X}_n \xrightarrow{P} \mathbf{X}$. For any $j = 1, 2, \ldots, p$, if we have $\varepsilon \le |X_{nj} - X_j|$ then

$$\varepsilon \le |X_{nj} = X_j| \le \|\mathbf{X}_n - \mathbf{X}\| \text{ by Lemma 5.4.1.}$$

Hence $\overline{\lim}_{n\to\infty} P(|X_{nj} - X_j| \ge \varepsilon) \le \overline{\lim}_{n\to\infty} P(\|\mathbf{X}_n = \mathbf{X}\| \ge \varepsilon) = 0$ since $\mathbf{X}_n \xrightarrow{P} \mathbf{X}$. Since $P(|X_{nj} - X_j| \ge \varepsilon) \ge 0$ for all $n \in \mathbb{N}$, then $\lim_{n\to\infty} P(|X_{nj} - X_j| \ge \varepsilon) = 0$ and hence $X_{nj} \xrightarrow{P} X_j$ for all $j = 1, 2, \ldots, p$, as claimed.

Theorem 5.4.1 (continued)

Proof (continued). Conversely, suppose $X_{nj} \xrightarrow{P} X_j$ for all $j = 1, 2, \ldots, p$. If we have $\varepsilon \le \|\mathbf{X}_n - \mathbf{X}\|$ then

$$\varepsilon \le \|\mathbf{X}_n - \mathbf{X}\| \le \sum_{i=1}^p |X_{nj} - X_j| \text{ by Lemma 5.4.1.}$$

Hence

$$\begin{aligned}
\overline{\lim}_{n\to\infty} P(\|\mathbf{X}_n - \mathbf{X}\| \ge \varepsilon) &\le \overline{\lim}_{n\to\infty} P\left(\sum_{j=1}^p |X_{nj} - X_j| \ge \varepsilon \right) \\
&\le \sum_{j=1}^p \overline{\lim}_{n\to\infty} P(|X_{nj} - X_j| \ge \varepsilon/p) \\
&= 0 \text{ since } X_{nj} \xrightarrow{P} X_j \text{ for } j = 1, 2, \ldots, p \\
&\quad \text{by hypothesis.}
\end{aligned}$$

Since $P(\|\mathbf{X}_n - \mathbf{X}\| \ge \varepsilon) \ge 0$ then $\lim_{n\to\infty} P(\|\mathbf{X}_n - \mathbf{X}\| \ge \varepsilon) = 0$ and hence $\mathbf{X}_n \xrightarrow{P} \mathbf{X}$, as claimed. □

Theorem 5.4.4

Theorem 5.4.4. Multivariate Central Limit Theorem.
Let $(\mathbf{X}_n)$ be a sequence of independent and identically distributed ("iid") random vectors with common mean vector μ and variance-covariance matrix $\mathbf{\Sigma}$ which is positive definite. Assume that the common moment generating function $M(\mathbf{t})$ exists in an open neighborhood of $\mathbf{0}$. Let

$$\mathbf{Y}_n = \frac{1}{\sqrt{n}}\sum_{i=1}^{n}(\mathbf{X}_i - \mu) = \sqrt{n}(\sqrt{\mathbf{X}} - \mu).$$

Then $\mathbf{Y}_n$ converges in distribution to a $N_p(\mathbf{0}, \mathbf{\Sigma})$ distribution.

Proof. Let $\mathbf{t} \in \mathbb{R}^p$ be in the neighborhood of $\mathbf{0}$ on which $M(\mathbf{t})$ exists. The moment generating function of $\mathbf{Y}_n$ is

$$M_n(\mathbf{t}) = E\left[\exp\left(\mathbf{t}'\frac{1}{\sqrt{n}}\sum_{i=1}^{n}(\mathbf{X}_i - \boldsymbol{\mu})\right)\right]\ldots$$

Theorem 5.4.4 (continued 1)

Proof (continued). ...

$$M_n(\mathbf{t}) = E\left[\exp\left(\frac{1}{\sqrt{n}}\sum_{i=1}^{n}\mathbf{t}'(\mathbf{X}_i - \boldsymbol{\mu})\right)\right] = E\left[\exp\left(\frac{1}{\sqrt{n}}\sum_{i=1}^{n}\mathbf{W}_i\right)\right]$$

where $\mathbf{W}_i = \mathbf{t}'(\mathbf{X}_i = \boldsymbol{\mu})$. Note that $\mathbf{W} - 1, \mathbf{W}_2, \ldots, \mathbf{W}_n$ are iid (since $\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_n$ are) with mean $\mathbf{0}$ and variance

$$\mathrm{Var}(W_i) = (W_i - 0)^2 = \mathbf{t}'(\mathbf{X}_i - \boldsymbol{\mu})(\mathbf{t}'(\mathbf{X}_i - \boldsymbol{\mu}))'$$

$$= \mathbf{t}'(\mathbf{X}_i - \boldsymbol{\mu})(\mathbf{X}_i' - \boldsymbol{\mu}')\mathbf{t} = \mathbf{t}'\mathbf{\Sigma}\mathbf{t}.$$

So by the Central Limit Theorem (Theorem 5.3.1) and Note 5.3.A,

$$\frac{1}{\sqrt{n}}\sum_{i=1}^{n}W_i \xrightarrow{D} N(0, \mathbf{t}'\mathbf{\Sigma}\mathbf{t}). \qquad (*)$$

Theorem 5.4.4 (continued 2)

Proof (continued). Since the moment generating function of $\mathbf{Y}_n$ is

$$M_n(\mathbf{t}) = E\left[\exp\left(\frac{1}{\sqrt{n}}\sum_{i=1}^{n}W_i\right)\right],$$

we see that this is the moment generating function of $(1/\sqrt{n})\sum_{i=1}^{n}W_i$ evaluated at $t = 1$. So

$$M_n(\mathbf{t}) = E\left[\exp\left((1)\frac{1}{\sqrt{n}}\sum_{i=1}^{n}W_i\right)\right] \to e^{(1)^2\mathbf{t}'\mathbf{\Sigma}\mathbf{t}/2} = e^{\mathbf{t}'\mathbf{\Sigma}\mathbf{t}/2}$$

by Theorem 5.4.3 and $(*)$, since the moment generating function of $N(0, \mathbf{t}'\mathbf{\Sigma}\mathbf{t})$ is $e^{t^2\mathbf{t}'\mathbf{\Sigma}\mathbf{t}/2}$ by Note 3.4.B. But $e^{\mathbf{t}'\mathbf{\Sigma}\mathbf{t}/2}$ is the moment generating function of a $N_p(\mathbf{0}, \mathbf{\Sigma})$ by Note 3.5.E, so by the uniqueness of the moment generating function (by Theorem 1.9.2) we have that $\mathbf{Y}_n \xrightarrow{D} N(\mathbf{0}, \mathbf{\Sigma})$, as claimed. □