

ASYMPTOTIC DISTRIBUTION OF LIKELIHOOD RATIO - STATISTICS

Theorem (Thm. 12.2.3 in Lehmann / Romano (2005)):

Let $(P_\theta)_{\theta \in \Theta}$ be differentiable in quadratic mean at θ_0 , where Θ is an open subset of $\mathbb{R}^2$. Suppose that $I(\theta_0)$ is positive definite.

Define, for an iid. sample $X = (X_1, \dots, X_n)^T$ and $\theta \in \mathbb{R}^2$ fixed θ

$$L_n, \theta = \frac{\ell(\theta_0 + R_{n^{-1/2}}, X)}{\ell(\theta_0, X)}$$

$$= \prod_{i=1}^n \frac{\ell(\theta_0 + R_{n^{-1/2}}, X_i)}{\ell(\theta_0, X_i)}$$

Then it holds:

(i) As $n \rightarrow \infty$,

$$\log(L_n, \theta) - \left[\langle R, \dot{\ell}(\theta_0) \rangle - \frac{1}{2} \langle R, I(\theta_0) R \rangle \right] = o_{P_{\theta_0}}^x(1), \text{ where}$$

$$R_n \equiv Z_n, \theta_0 = n^{-1/2} \sum_{i=1}^n \dot{\ell}(X_i, \theta_0).$$

(ii) Under θ_0 , $Z_n \xrightarrow{D} N(0, I(\theta_0))$ and, hence,

$$\log(L_n, \theta) \xrightarrow{D} N\left(-\frac{1}{2} \langle R, I(\theta_0) R \rangle, \langle R, I(\theta_0) R \rangle\right).$$

Proof:

Let $Y_{n,1}, \dots, Y_{n,m}$ be defined by

$$Y_{n,i} = \frac{\sqrt{\ell(\vartheta_0 + h n^{-1/2}, X_i)}}{\sqrt{\ell(\vartheta_0, X_i)}} - 1.$$

Then it holds $\forall n \forall 1 \leq i \leq n$: $\mathbb{E}_{\vartheta_0} [Y_{n,i}^2] < \infty$ and, moreover,

$$\log(L_n, h) = 2 \sum_{i=1}^m \log(1 + Y_{n,i}).$$

Taylor expansion of $\log(\cdot)$:

$$\log(1+y) = y - \frac{1}{2} y^2 + y^2 r(y), \text{ where } r(y) \xrightarrow{y \rightarrow 0} 0.$$

$$\Rightarrow \log(L_n, h) = 2 \sum_{i=1}^m Y_{n,i} - \sum_{i=1}^m Y_{n,i}^2 + 2 \sum_{i=1}^m Y_{n,i}^2 r(Y_{n,i}).$$

We will now show four convergence results: (n $\rightarrow \infty$)

$$[R1] \quad \sum_{i=1}^m \mathbb{E}_{\vartheta_0} [Y_{n,i}] \rightarrow -\frac{1}{8} < h, I(\vartheta_0) h >$$

$$[R2] \quad \sum_{i=1}^m \{Y_{n,i} - \mathbb{E}_{\vartheta_0} [Y_{n,i}]\} = \frac{1}{2} < h, z_n > \xrightarrow{P_{\vartheta_0}^n} 0$$

$$[R3] \quad \sum_{i=1}^m Y_{n,i}^2 \xrightarrow{P_{\vartheta_0}^n} \frac{1}{4} < h, I(\vartheta_0) h >$$

$$[R4] \quad \sum_{i=1}^m Y_{n,i}^2 r(Y_{n,i}) \xrightarrow{P_{\vartheta_0}^n} 0$$

②

Proof of [R1]:

$$\begin{aligned} \sum_{i=1}^n E_{\theta_0} [Y_{ni}] &= n \int_{\Omega} \left\{ \frac{-\ell(\theta_0 + h n^{-1/2}, x)}{-\ell(\theta_0, x)} - 1 \right\} d\mu(x) \\ &= -\frac{n}{2} \int_{\Omega} \left[\ell(\theta_0 + h n^{-1/2}, x) - \ell(\theta_0, x) \right]^2 d\mu(x) \end{aligned}$$

$$\rightarrow -\frac{1}{2} \int_{\Omega} \left| \frac{\partial}{\partial \theta} \ell(\theta, x) \right|_{\theta=\theta_0}^2 d\mu(x), h > 0$$

That the latter expression equals $-\frac{1}{8} \langle h, I(\theta_0) h \rangle$ is left as an exercise.

Proof of [R2]:

$$\text{We write } Y_{ni} = \frac{1}{2} n^{-1/2} \langle h, \dot{\ell}(x_i, \theta_0) \rangle +$$

$$n^{-1/2} \frac{R_n(x_i)}{\sqrt{\ell(\theta_0, x_i)}}, \quad [****]$$

where the remainder term R_n satisfies

$$\int_{\Omega} R_n^2(x) d\mu(x) \rightarrow 0 \quad \text{due to differentiability in quadratic mean.}$$

$$\text{Notice: } \dot{\ell}(x_i, \theta_0) = \frac{2 \partial/\partial \theta \sqrt{\ell(\theta, x_i)}|_{\theta=\theta_0}}{\sqrt{\ell(\theta_0, x_i)}}.$$

$$\begin{aligned}
 \dot{\ell}(x, y_0) &= \frac{\partial}{\partial y} \log(\ell(x, y_0)) \Big|_{y=y_0} \\
 &= 2 \frac{\partial}{\partial y} \log(-\sqrt{\ell(x)}) \Big|_{y=y_0} \\
 &= 2 \frac{\frac{\partial}{\partial y} (-\sqrt{\ell(x)})}{-\sqrt{\ell(x)}} \Big|_{y=y_0}
 \end{aligned}$$

$$Y_{n,i} = \frac{-\sqrt{\ell(y_0 + h_n^{-1/2} x_i)}}{-\sqrt{\ell(y_0, x_i)}} = -\sqrt{\frac{\ell(x_i, y_0)}{\ell(y_0, x_i)}}$$

$$= \frac{h_n^{-1/2}}{-\sqrt{\ell(y_0, x_i)}} \sqrt{\ell(y_0 + h_n^{-1/2} x_i)} = -\sqrt{\frac{\ell(x_i, y_0)}{\ell(y_0, x_i)}}$$

$$\approx_{(n \rightarrow \infty)} \frac{h_n^{-1/2}}{-\sqrt{\ell(y_0, x_i)}} \sqrt{\ell(y_0)} \Big|_{y=y_0}$$

$$= \frac{h_n^{-1/2}}{-\sqrt{\ell(y_0, x_i)}} \left[\dot{\ell}(x_i, y_0) - \sqrt{\ell(y_0, x_i)} \right] \Big|_2$$

$$= \frac{h_n^{-1/2}}{2} \langle h_i, \dot{\ell}(x_i, y_0) \rangle$$

$$\Rightarrow \sum_{i=1}^n \{Y_{ni} - E_{\mathcal{D}_0}[Y_{ni}]\} = \frac{1}{2} \langle h, Z_n \rangle + m^{-1/2} \sum_{i=1}^n \left\{ \frac{P_n(x_i)}{\ell(\mathcal{D}_0, x_i)} - E_{\mathcal{D}_0} \left[\frac{P_n(x_i)}{\sqrt{\ell(\mathcal{D}_0, x_i)}} \right] \right\}$$

Every Summand in the latter sum is centered and the variance is bounded by

$$E_{\mathcal{D}_0} \left[\frac{P_n^2(x_i)}{\ell(\mathcal{D}_0, x_i)} \right] = \int_{\Omega} P_n^2(x) d\mu(x) \rightarrow 0,$$

so [RZ] follows.

Proof of [R3]:

By the law of large numbers,

$$\frac{1}{n} \sum_{i=1}^n [\langle h, \dot{\ell}(x_i, \mathcal{D}_0) \rangle]^2 \xrightarrow{P_{\mathcal{D}_0}}$$

$$E_{\mathcal{D}_0} [\langle \langle h, \dot{\ell}(x_i, \mathcal{D}_0) \rangle \rangle^2] = \langle h, I(\mathcal{D}_0) h \rangle.$$

Using [****], we get

$$\begin{aligned} \sum_{i=1}^n Y_{ni}^2 &= \frac{1}{4n} \sum_{i=1}^n (\langle h, \dot{\ell}(x_i, \mathcal{D}_0) \rangle)^2 \\ &+ \frac{1}{n} \sum_{i=1}^n (\langle h, \dot{\ell}(x_i, \mathcal{D}_0) \rangle) \sum_{j=1}^n \frac{P_n(x_j)}{\sqrt{\ell(\mathcal{D}_0, x_j)}} \\ &+ \frac{1}{n} \sum_{i=1}^n \frac{P_n^2(x_i)}{\ell(\mathcal{D}_0, x_i)}. \end{aligned}$$

(4)

The first summand converges under $\mathcal{V}_0$ in probability to $\frac{1}{4} \langle R, I(\mathcal{V}_0) R \rangle$. The third summand is non-negative and has expectation under $\mathcal{V}_0$ equal to $\int_{\mathbb{R}} P_n^2(x) \mu(dx) \rightarrow 0$. Hence,

Markov's inequality yields that it tends to 0 in probability under $\mathcal{V}_0$. To see that the second summand tends to zero in probability under $\mathcal{V}_0$, apply the Cauchy-Schwarz inequality.

Proof of [R4]:

$$\begin{aligned} \text{We note that } & \left| \sum_{i=1}^n Y_{ni}^2 - \tau(Y_{ni}) \right| \\ & \leq \max_{1 \leq i \leq n} |\tau(Y_{ni})| \sum_{i=1}^n Y_{ni}^2. \end{aligned}$$

Therefore, it suffices to show that

$$\max_{1 \leq i \leq n} |\tau(Y_{ni})| \rightarrow 0 \text{ in probability under } \mathcal{V}_0,$$

which is in turn implied by $\max_{1 \leq i \leq n} |Y_{ni}| \xrightarrow{P_{\mathcal{V}_0}} 0$.

Since $\sum_{i=1}^n \{Y_{ni} - E_{\mathcal{V}_0}[Y_{ni}]\}$ is asymptotically

normal by [R2], we can argue that

$\max_{1 \leq i \leq n} |Y_{ni}| \xrightarrow{P_{\mathcal{V}_0}} 0$ by making use of Lindeberg's condition and

the fact that $E_{\mathcal{V}_0}[Y_{ni}] \rightarrow 0$, $n \rightarrow \infty$. $\square$ (5)