Assignment 1

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(a)

$X_T = \overline{Y}_T - \mu_0$ is of order $T^{-\frac{1}{2}}$ in probability. $T^{-\frac{1}{2}}$ is a deterministic sequence of T that converges to 0 as $T \to \infty$.

Proof:

By definition of $O_p(.)$,

if for every $\varepsilon > 0$, there exists a constant M_ε, such that:

$$\underset{T}{sup} Pr(|\frac{X_T}{R_T}| > M_\varepsilon) < \varepsilon$$

then we can write:

$$X_T = O_p(R_T)$$

We know

$$\sqrt{T}(\overline{Y}_T - \mu_0) = O_p(1)$$

$\Longrightarrow$

$$\underset{T}{sup} Pr(|\frac{\sqrt{T}(\overline{Y}_T - \mu_0)}{1}| > M_\varepsilon) < \varepsilon$$

$$\underset{T}{sup} Pr(|\frac{(\overline{Y}_T - \mu_0)}{\frac{1}{\sqrt{T}}}| > M_\varepsilon) < \varepsilon$$

$$\underset{T}{sup} Pr(|\frac{(\overline{Y}_T - \mu_0)}{T^{-\frac{1}{2}}}| > M_\varepsilon) < \varepsilon$$

$$(\overline{Y}_T - \mu_0) = X_T = O_p(T^{-\frac{1}{2}})$$

(b)

$X_T = \overline{Y}_T - \mu_0$ is of smaller order in probability than $T^{-\frac{1}{4}}$

Proof:

By definition of $o_p(.)$,

if for every $\varepsilon > 0$,

$$\underset{T\to\infty}{lim} Pr(|\frac{X_T}{R_T} - 0| > \varepsilon) = 0$$

then we can write:

$$X_T = o_p(R_T)$$

$$\begin{aligned}\frac{\overline{Y}_T - \mu_0}{T^{-\frac{1}{4}}} &= T^{\frac{1}{4}}(\overline{Y}_T - \mu_0)\\ &= T^{-\frac{1}{4}}\sqrt{T}(\overline{Y}_T - \mu_0)\\ &\approx T^{-\frac{1}{4}} \times N(0, \sigma_0^2)\\ &= N(0, T^{-\frac{1}{2}}\sigma_0^2)\end{aligned}$$

since $T^{-\frac{1}{2}} \to 0$ as $T \to \infty$, $N(0, T^{-\frac{1}{2}}\sigma_0^2)$ will become a degenerate distribution concentrate onto 0. In other words, $\frac{\overline{Y}_T-\mu_0}{T^{-\frac{1}{4}}} = \frac{X_T}{T^{-\frac{1}{4}}} = o_p(1)$ and X_T is of smaller order in probability than $T^{-\frac{1}{4}}$.

(c)

(d)

Given the conditions provided in the question 1 and by the central limit theorem,

$$\frac{\sqrt{T}(\overline{Y}_T - \mu_0)}{\sigma_0} \xrightarrow{d} N(0,1)$$

Now $\hat{\sigma}$ is any consistent estimator of $\hat{\sigma}_0$, which means

$$\hat{\sigma}_0 \xrightarrow{p} \hat{\sigma}$$

By the continuous mapping theorem, if $X_T \xrightarrow{d} X$ and $C_T \xrightarrow{p} C$, then $X_T/C_T \xrightarrow{d} X/C$. Thus,

$$\frac{\sqrt{T}(\overline{Y}_T - \mu_0)}{\hat{\sigma}} \xrightarrow{d} N(0,1)$$

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(a)

$$lnL_T(\boldsymbol{\theta}) = \frac{1}{T} lnf(\mathbf{Y}|\boldsymbol{\theta})$$

independence

$$= \frac{1}{T} ln \prod_{t=1}^{T} f(y_t|\boldsymbol{\theta})$$

identically distributed

$$= \frac{1}{T} ln \prod_{t=1}^{T} (2\pi)^{-1/2} (\sigma^2)^{-1/2} exp\{-\frac{1}{2\sigma^2}(y_t - \mu)^2\}$$

$$= \frac{1}{T} ln[(2\pi)^{-T/2} (\sigma^2)^{-T/2} \prod_{t=1}^{T} exp\{-\frac{1}{2\sigma^2}(y_t - \mu)^2\}]$$

$$= \frac{1}{T} ln[(2\pi)^{-T/2} (\sigma^2)^{-T/2} exp\{\sum_{t=1}^{T} -\frac{1}{2\sigma^2}(y_t - \mu)^2\}]$$

$$= \frac{1}{T} ln[(2\pi)^{-T/2} (\sigma^2)^{-T/2} exp\{-\frac{1}{2\sigma^2} \sum_{t=1}^{T}(y_t - \mu)^2\}]$$

$$= \frac{1}{T}[ln((2\pi)^{-T/2}) + ln((\sigma^2)^{-T/2}) + ln(exp\{-\frac{1}{2\sigma^2} \sum_{t=1}^{T}(y_t - \mu)^2\})]$$

$$= \frac{1}{T}[ln((2\pi)^{-T/2}) + ln((\sigma^2)^{-T/2}) - \frac{1}{2\sigma^2} \sum_{t=1}^{T}(y_t - \mu)^2]$$

$$= \frac{1}{T}[\frac{-T}{2} ln(2\pi) + \frac{-T}{2} ln(\sigma^2) - \frac{1}{2\sigma^2} \sum_{t=1}^{T}(y_t - \mu)^2]$$

$$= -\frac{1}{2} ln(2\pi) - \frac{1}{2} ln(\sigma^2) - \frac{1}{2\sigma^2} \frac{1}{T} \sum_{t=1}^{T}(y_t - \mu)^2$$

(b)

$$
\begin{aligned}
G_T(\boldsymbol{\theta}) &= \frac{1}{T}\sum_{t=1}^{T} g_t(\boldsymbol{\theta}) \\
&= \frac{1}{T}\sum_{t=1}^{T} \frac{\partial lnf(y_t|\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \\
&= \frac{1}{T}\sum_{t=1}^{T} \frac{\partial ln((2\pi)^{-1/2}(\sigma^2)^{-1/2}exp\{-\frac{1}{2\sigma^2}(y_t-\mu)^2\})}{\partial \boldsymbol{\theta}} \\
&= \frac{1}{T}\sum_{t=1}^{T} \frac{\partial ln((2\pi)^{-1/2}) + ln((\sigma^2)^{-1/2}) - \frac{1}{2\sigma^2}(y_t-\mu)^2}{\partial \boldsymbol{\theta}} \\
&= \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} \frac{\partial ln((2\pi)^{-1/2})+ln((\sigma^2)^{-1/2})-\frac{1}{2\sigma^2}(y_t-\mu)^2}{\partial \boldsymbol{\mu}} \\ \frac{\partial ln((2\pi)^{-1/2})+ln((\sigma^2)^{-1/2})-\frac{1}{2\sigma^2}(y_t-\mu)^2}{\partial \boldsymbol{\sigma}} \end{bmatrix} \\
&= \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} \frac{1}{\sigma^2}(y_t-\mu) \\ -\frac{1}{\sigma} + (y_t-\mu)^2\sigma^{-3} \end{bmatrix}
\end{aligned}
$$

(c)

$$
\begin{aligned}
H_T(\boldsymbol{\theta}) &= \frac{1}{T}\sum_{t=1}^{T} h_t(\boldsymbol{\theta}) \\
&= \frac{1}{T}\sum_{t=1}^{T} \frac{\partial^2 lnf(y_t|\boldsymbol{\theta})}{\partial \boldsymbol{\theta}\partial \boldsymbol{\theta}'} \\
&= \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} \frac{\partial^2 lnf(y_t|\boldsymbol{\theta})}{\partial \mu^2} & \frac{\partial^2 lnf(y_t|\boldsymbol{\theta})}{\partial \mu \partial \sigma} \\ \frac{\partial^2 lnf(y_t|\boldsymbol{\theta})}{\partial \sigma \partial \mu} & \frac{\partial^2 lnf(y_t|\boldsymbol{\theta})}{\partial \sigma^2} \end{bmatrix} \\
&= \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} -\frac{1}{\sigma^2} & -2(y_t-\mu)\sigma^{-3} \\ -2(y_t-\mu)\sigma^{-3} & \frac{1}{\sigma^2} - 3(y_t-\mu)^2\sigma^{-4} \end{bmatrix}
\end{aligned}
$$

(d)

To derive the MLE, we set the first order derivative of $lnL_T(\boldsymbol{\theta})$ to $\mathbf{0}$

$$
\begin{aligned}
G_T(\boldsymbol{\theta}) = \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} \frac{1}{\sigma^2}(y_t-\mu) \\ -\frac{1}{\sigma} + (y_t-\mu)^2\sigma^{-3} \end{bmatrix} &= \mathbf{0} \\
\begin{bmatrix} \frac{1}{T}\sum_{t=1}^{T} \frac{1}{\sigma^2}(y_t-\mu) \\ \frac{1}{T}\sum_{t=1}^{T} -\frac{1}{\sigma} + (y_t-\mu)^2\sigma^{-3} \end{bmatrix} &= \mathbf{0} \\
\hat{\mu}_{MLE} &= \overline{y} \\
\hat{\sigma}_{MLE} &= \frac{1}{T}\sum_{t=1}^{T}(y_t-\overline{y})^2 \\
\hat{\boldsymbol{\theta}}_{MLE} &= (\hat{\mu}_{MLE}, \hat{\sigma}_{MLE})'
\end{aligned}
$$

We define a non-zero column vector $\boldsymbol{z}$ with real entries a and b

$$
\begin{aligned}
\boldsymbol{z}' H_T(\boldsymbol{\theta})\boldsymbol{z} &= \begin{bmatrix} a & b \end{bmatrix} (\frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} -\frac{1}{\sigma^2} & -2(y_t-\mu)\sigma^{-3} \\ -2(y_t-\mu)\sigma^{-3} & \frac{1}{\sigma^2} - 3(y_t-\mu)^2\sigma^{-4} \end{bmatrix}) \begin{bmatrix} a \\ b \end{bmatrix} \\
&= \begin{bmatrix} a\frac{1}{T}\sum_{t=1}^{T} -\frac{1}{\sigma^2} + b\frac{1}{T}\sum_{t=1}^{T} -2(y_t-\mu)\sigma^{-3} & a\frac{1}{T}\sum_{t=1}^{T} -2(y_t-\mu)\sigma^{-3} + b\frac{1}{T}\sum_{t=1}^{T} \frac{1}{\sigma^2} - 3(y_t-\mu)^2\sigma^{-4} \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} \\
&= a^2\frac{1}{T}\sum_{t=1}^{T} -\frac{1}{\sigma^2} + ab\frac{1}{T}\sum_{t=1}^{T} -2(y_t-\mu)\sigma^{-3} + ab\frac{1}{T}\sum_{t=1}^{T} -2(y_t-\mu)\sigma^{-3} + b^2\frac{1}{T}\sum_{t=1}^{T} \frac{1}{\sigma^2} - 3(y_t-\mu)^2\sigma^{-4} \\
&= a^2\frac{1}{T}\sum_{t=1}^{T} -\frac{1}{\sigma^2} + 2ab\frac{1}{T}\sum_{t=1}^{T} -2(y_t-\mu)\sigma^{-3} + b^2\frac{1}{T}\sum_{t=1}^{T} \frac{1}{\sigma^2} - 3(y_t-\mu)^2\sigma^{-4} \\
&= -\frac{a^2}{\sigma^2} + \frac{b^2}{\sigma^2} - \frac{b^2}{T}\sum_{t=1}^{T} 3(y_t-\mu)^2\sigma^{-4} - \frac{2ab}{T}\sum_{t=1}^{T} 2(y_t-\mu)\sigma^{-3} \\
&= \frac{b^2-a^2}{\sigma^2} - 3\frac{b^2}{T}\sigma^{-4}\sum_{t=1}^{T}(y_t-\mu)^2 - \frac{4ab}{T}\sigma^{-3}\sum_{t=1}^{T}(y_t-\mu)
\end{aligned}
$$

$$
\begin{aligned}
\boldsymbol{z}' H_T(\hat{\boldsymbol{\theta}}_{MLE})\boldsymbol{z} &= \frac{b^2-a^2}{\hat{\sigma}^2_{MLE}} - 3\frac{b^2}{T}\hat{\sigma}^{-4}_{MLE}\sum_{t=1}^{T}(y_t-\hat{\mu}_{MLE})^2 - \frac{4ab}{T}\hat{\sigma}^{-3}_{MLE}\sum_{t=1}^{T}(y_t-\hat{\mu}_{MLE}) \\
&= \frac{b^2-a^2}{\hat{\sigma}^2_{MLE}} - 3\frac{b^2}{T}\hat{\sigma}^{-4}_{MLE}T\hat{\sigma}^2_{MLE} - 0 \\
&= \frac{-2b^2-a^2}{\hat{\sigma}^2_{MLE}}
\end{aligned}
$$

Given $-2b^2 - a^2 \leq 0$ and $\hat{\sigma}^2_{MLE} > 0$,

$$\frac{-2b^2-a^2}{\hat{\sigma}^2_{MLE}} \leq 0$$

$H_T(\boldsymbol{\theta})$ is a negative semi-definite matrix. The second-order condition for a maximum holds.