

$$\frac{1}{S-1} \sum_{s=1}^S \underbrace{(\theta^{(s)} - \bar{\theta})^2}_{\text{not iid}} = \frac{1}{S-1} \sum_{s=1}^S [\theta^{(s)}]^2 - \underbrace{\frac{S}{S-1} \bar{\theta}^2}_{\rightarrow 1}$$

By LLN,

$$\frac{1}{S-1} \sum_{s=1}^S [\theta^{(s)}]^2 \xrightarrow{1} \frac{S}{S-1} \cdot \frac{1}{S} \sum_{s=1}^S [\theta^{(s)}]^2 \rightarrow E(\theta^2|Y)$$

$$\bar{\theta}^2 \rightarrow [E(\theta|Y)]^2$$

$$\frac{1}{S-1} \sum_{s=1}^S (\theta^{(s)} - \bar{\theta})^2 \rightarrow E(\theta^2|Y) - [E(\theta|Y)]^2 = \text{Var}(\theta|Y)$$

LLN $X_1, \dots, X_n \stackrel{iid}{\sim} F$, mean of F is μ
 Var of F is $\sigma^2 < \infty$

$$\frac{1}{n} \sum_{i=1}^n X_i \rightarrow \mu$$

$$\text{CLT: } \sqrt{n} \left(\frac{1}{n} \sum_{i=1}^n X_i - \mu \right) \rightarrow N(0, \sigma^2)$$

$$\text{or roughly speaking, } \bar{X} = \frac{1}{n} \sum_{i=1}^n X_i \stackrel{\text{approx.}}{\sim} N\left(\mu, \frac{\sigma^2}{n}\right)$$

If $\theta^{(1)}, \dots, \theta^{(S)} \stackrel{iid}{\sim} p(\theta|Y)$,

$$\text{LLN } \frac{1}{S} \sum_{s=1}^S \theta^{(s)} \rightarrow E(\theta|Y)$$

$$\text{CLT } \sqrt{S} \left(\underbrace{\frac{1}{S} \sum_{s=1}^S \theta^{(s)}}_{(\mu)} - \underbrace{E(\theta|Y)}_{(\mu)} \right) \rightarrow N(0, \underbrace{\text{Var}(\theta|Y)}_{(\sigma^2) < \infty})$$

$$\frac{1}{S} \sum_{s=1}^S \theta^{(s)} \stackrel{\text{approx.}}{\sim} N\left(E(\theta|Y), \frac{1}{S} \cdot \text{Var}(\theta|Y)\right)$$

Monte Carlo method

$$\frac{1}{S} \sum_{s=1}^S \theta^{(s)} \rightarrow E(\theta|Y)$$

posterior of $\theta|Y$

$$\frac{1}{S} \sum_{s=1}^S g(\theta^{(s)}) \rightarrow E(g(\theta)|Y) = \int g(\theta) \underbrace{p(\theta|Y)}_{\text{posterior of } \theta|Y} d\theta$$

predictive distribution

$$p(\tilde{y}|Y) = \int \underbrace{p(\tilde{y}|\theta)}_{\rightarrow g(\theta)} \cdot p(\theta|Y) d\theta$$

$$= E_{\theta} [p(\tilde{y}|\theta) | Y] \quad \theta^{(1)}, \dots, \theta^{(S)}$$

$$= E_{\theta|Y} [p(\tilde{y}|\theta)] \approx \frac{1}{S} \sum_{s=1}^S p(\tilde{y}|\theta^{(s)})$$

$$p(\tilde{y}|Y) = \int \underbrace{p(\tilde{y}|\theta)}_{\text{data}} p(\theta|Y) d\theta$$

\tilde{y}, Y independent

$$= \int p(\tilde{y}, \theta | Y) d\theta$$

given θ

$$\Rightarrow p(\tilde{y}|\theta, Y)$$

$$= p(\tilde{y}|\theta)$$

$$Y_{\text{data}} \rightarrow \theta \sim p(\theta|Y) \rightarrow \tilde{y} \sim p(\tilde{y}|\theta)$$

This is equivalent to draw from $p(\tilde{y}, \theta|Y)$

$$(\theta^{(1)}, \tilde{y}^{(1)}), \dots, (\theta^{(S)}, \tilde{y}^{(S)})$$