

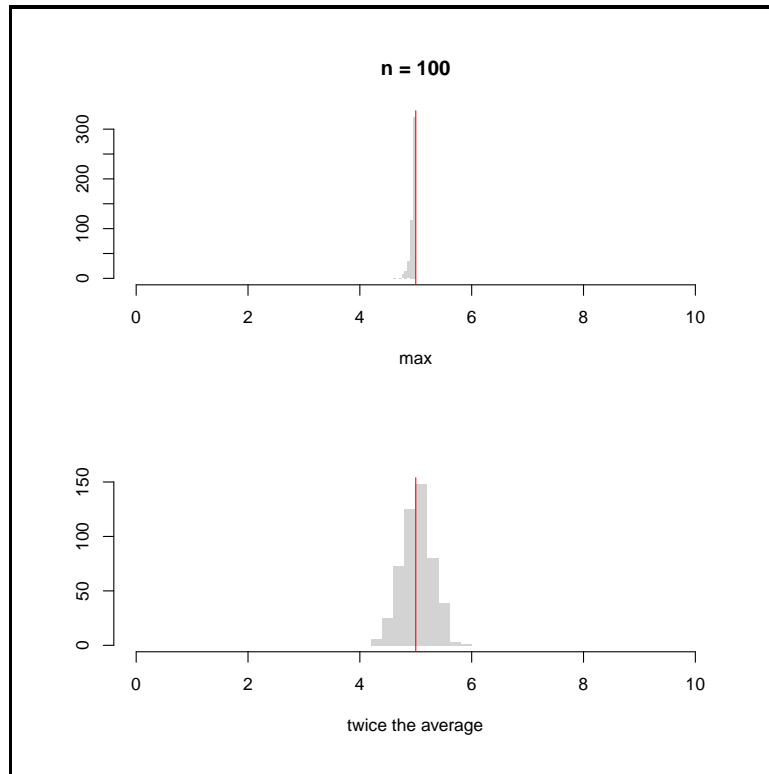
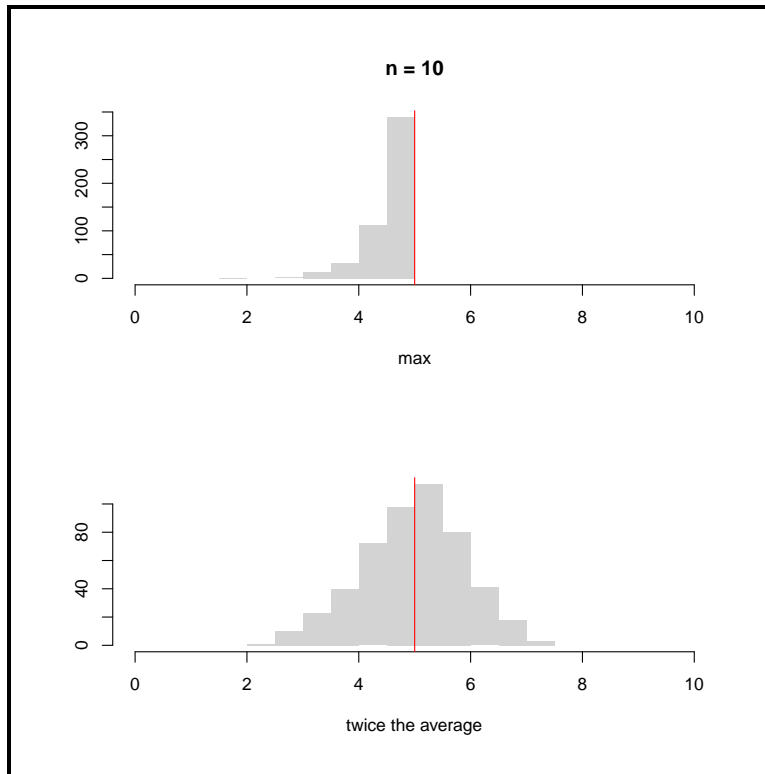
Review

$$f(x_1, \dots, x_n; \theta) \rightarrow \left\{ \begin{array}{l} \{x_1^{(1)}, \dots, x_n^{(1)}\} \rightarrow \hat{\theta}^{(1)} \\ \{x_1^{(2)}, \dots, x_n^{(2)}\} \rightarrow \hat{\theta}^{(2)} \\ \{x_1^{(3)}, \dots, x_n^{(3)}\} \rightarrow \hat{\theta}^{(3)} \\ \vdots \\ \{x_1^{(B)}, \dots, x_n^{(B)}\} \rightarrow \hat{\theta}^{(B)} \end{array} \right\} \text{distribution of } \hat{\theta}$$

imagine **many** data sets from the **same** data-generating process

Review: Uniform(0, θ)

$$\hat{\theta}_{mle} = \max\{X_1, \dots, X_n\} \text{ versus } \hat{\theta}_{mom} = 2\bar{X}$$



```
> source("https://www.math.uwaterloo.ca/~m3zhu/teaching/stat845/f23dp6lec05code.R")  
> do.it(n=10)  
> do.it(n=100)
```

Example: Uniform(0, θ)

MOM $\hat{\theta} = 2\bar{X}$. $\mathbb{E}(X_i) = \theta/2$, $\text{Var}(X_i) = \theta^2/12$.

$$\frac{\bar{X} - \theta/2}{\theta/\sqrt{12n}} \sim N(0, 1) \Rightarrow \bar{X} \sim N\left(\frac{\theta}{2}, \frac{\theta^2}{12n}\right) \text{ approximately}$$

$$\Rightarrow \hat{\theta} = 2\bar{X} \sim N\left(\theta, \frac{\theta^2}{3n}\right) \text{ approximately}$$

MLE $\hat{\theta} = \max\{X_1, X_2, \dots, X_n\} \equiv Y$. $f_X(x) = 1/\theta$, $F_X(x) = x/\theta$.

$$\hat{\theta} \equiv Y \sim f(y) = n[F_X(y)]^{n-1} f_X(y) = n \left[\frac{y}{\theta}\right]^{n-1} \left[\frac{1}{\theta}\right] = \frac{ny^{n-1}}{\theta^n}$$

Bias

Definition An estimator $\hat{\theta}$ is **unbiased** if $\mathbb{E}(\hat{\theta}) = \theta$.

$$\text{Bias}(\hat{\theta}) = \mathbb{E}(\hat{\theta}) - \theta.$$

Exercise 5.7 (p. 78) For $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$, the MLE,

$$\hat{\sigma}_{(mle)}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2.$$

is **biased**, whereas the so-called “**sample variance**”,

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2,$$

is **unbiased**. [*Remark: But the actual distribution of S^2 is much harder to find.*]

Efficiency

Definition If both $\hat{\theta}_1$ and $\hat{\theta}_2$ are unbiased, then $\hat{\theta}_1$ is more efficient than $\hat{\theta}_2$ if $\text{Var}(\hat{\theta}_1) \leq \text{Var}(\hat{\theta}_2)$.

Example Given two independent observations X, Y from the same distribution with mean/expectation θ , which one,

$$\frac{2X + 8Y}{10} \quad \text{or} \quad \frac{3X + 7Y}{10}$$

is a more efficient way of estimating the unknown parameter θ ?

[Think: Can you find an even more efficient way?]

Mean-Squared Error

Definition The mean-squared error of $\hat{\theta}$ is

$$\text{MSE}(\hat{\theta}) = \mathbb{E}[(\hat{\theta} - \theta)^2].$$

Theorem

$$\begin{aligned}\text{MSE}(\hat{\theta}) &\equiv \mathbb{E}[(\hat{\theta} - \theta)^2] = \mathbb{E}\{[\hat{\theta} - \mathbb{E}(\hat{\theta}) + \mathbb{E}(\hat{\theta}) - \theta]^2\} \\ &= \mathbb{E}\{[\hat{\theta} - \mathbb{E}(\hat{\theta})]^2\} + [\mathbb{E}(\hat{\theta}) - \theta]^2 + \underbrace{2\mathbb{E}\{[\hat{\theta} - \mathbb{E}(\hat{\theta})][\mathbb{E}(\hat{\theta}) - \theta]\}}_{=0} \\ &= \text{Var}(\hat{\theta}) + [\text{Bias}(\hat{\theta})]^2\end{aligned}$$

Exercise Show that $\mathbb{E}\{[\hat{\theta} - \mathbb{E}(\hat{\theta})][\mathbb{E}(\hat{\theta}) - \theta]\} = 0$.

Exercise 5.8d (pp. 78–79): Uniform(0, θ)

MOM

$$\hat{\theta}_{mom} = 2\bar{X} \sim N\left(\theta, \frac{\theta^2}{3n}\right) \text{ approximately}$$

$$\mathbb{E}(\hat{\theta}_{mom}) = \dots, \quad \text{Var}(\hat{\theta}_{mom}) = \dots, \quad \text{MSE}(\hat{\theta}_{mom}) = \dots$$

MLE

$$\hat{\theta}_{mle} = \max\{X_1, X_2, \dots, X_n\} \equiv Y \sim f(y) = \frac{ny^{n-1}}{\theta^n}$$

$$\mathbb{E}(\hat{\theta}_{mle}) = \dots, \quad \text{Var}(\hat{\theta}_{mle}) = \dots, \quad \text{MSE}(\hat{\theta}_{mle}) = \dots$$

Recall Example 5.2 (pp. 72–73)

X_1, X_2, \dots, X_n independent, each $\sim \text{Poisson}(\theta v_i)$

e.g., X_i = number of disasters,

v_i = number of activities

$$L(\theta) = \prod_{i=1}^n \frac{e^{-\theta v_i} (\theta v_i)^{x_i}}{x_i!} \quad \Rightarrow \quad \ell(\theta) = \sum_{i=1}^n -\theta v_i + x_i \log(\theta v_i) + C$$

$$\ell'(\theta) = 0 \quad \Rightarrow \quad \hat{\theta}_{mle} = \frac{\sum_{i=1}^n X_i}{\sum_{i=1}^n v_i} = \frac{\#\{\text{disasters over } n \text{ teams}\}}{\#\{\text{activities over } n \text{ teams}\}}$$

Continuation: Example 5.4 (pp. 76–78)

- take slightly different point of view
- n separate “data sets”, each of size one
- on each “data set”, the same “disaster-to-activity” estimator would be equal to X_i/v_i , for $i = 1, 2, \dots, n$
- can then average these n “individual MLEs” to obtain an overall estimator,

$$\hat{\theta}_{alt} = \frac{1}{n} \sum_{i=1}^n \frac{X_i}{v_i}$$

Question Which estimator has smaller MSE, $\hat{\theta}_{alt}$ or $\hat{\theta}_{mle}$?