

Question 4

$$\begin{aligned}
 1. \quad E(X) &= \int_0^1 x f(x) dx = \int_0^1 x \beta (1-x)^{\beta-1} dx = \int_0^1 x d(-(1-x)^\beta) \\
 &= -x(1-x)^\beta \Big|_0^1 - \int_0^1 -(1-x)^\beta dx \\
 &= -\int_0^1 d \frac{(1-x)^{\beta+1}}{\beta+1} \\
 \hat{\beta}_M &= \frac{1}{E(X)} - 1 \\
 &= -\frac{1}{\beta+1} \int_0^1 d(1-x)^{\beta+1} = \frac{1}{\beta+1}
 \end{aligned}$$

$$2. \quad E(X^2) = \int_0^1 x^2 f(x) dx = \int_0^1 x^2 \beta (1-x)^{\beta-1} dx = \frac{2}{\beta+1} - \frac{1}{\beta+2}$$

$$\text{Var}(X) = E(X^2) - E(X)^2 = \frac{2}{\beta+1} - \frac{1}{\beta+2} - \frac{1}{(\beta+1)^2}$$

according to CLT

$$\bar{X} - E(X) \rightarrow N\left(0, \frac{\text{Var}(X)}{n}\right) \Rightarrow \sqrt{n}(\bar{X} - E(X)) \rightarrow N(0, \text{Var}(X))$$

$$\left(\frac{1}{\bar{X}} - 1\right) - \left(\frac{1}{E(X)} - 1\right) \rightarrow N\left(0, \frac{\text{Var}(X)}{n} \times \left(E(X)^{-1}\right)^2\right) \quad \text{Delta method}$$

$$\Rightarrow N\left(0, \frac{\text{Var}(X)}{n} \times E(X)^{-4}\right)$$

$$\sqrt{n}(\hat{\beta}_M - \beta) \rightarrow N\left(0, \frac{\text{Var}(X)}{E(X)^4}\right) \quad \text{according to delta method}$$

$$\Rightarrow N\left(0, \frac{\frac{2}{\hat{\beta}_M+1} - \frac{1}{\hat{\beta}_M+2} - \frac{1}{(\hat{\beta}_M+1)^2}}{\left(\frac{1}{\hat{\beta}_M+1}\right)^4}\right)$$

3. MLE estimator of β

$$\begin{aligned}
 L &= \prod_{i=1}^n f_{\beta}(X_i) \quad \ell = \log L = \sum_{i=1}^n \log \beta (1-X_i)^{\beta-1} = \sum_{i=1}^n \log \beta + (\beta-1) \log(1-X_i) \\
 &= n \log \beta + (\beta-1) \sum_{i=1}^n \log(1-X_i)
 \end{aligned}$$

$$\frac{\partial \ell}{\partial \beta} = \frac{n}{\beta} + \sum_{i=1}^n \log(1-X_i) = 0 \quad \hat{\beta}_{MLE} = \frac{-n}{\sum_{i=1}^n \log(1-X_i)}$$

$$4. \text{Var}(\hat{\beta}_{MLE}) \approx \frac{I(\beta)^{-1}}{n}$$

$$I(\beta) = \text{Var}\left(\frac{\partial L}{\partial \beta}\right) = -E\left(\frac{\partial^2 L}{\partial \beta^2}\right) = -E(-n\beta^{-2}) = nE(\beta^{-2}) = \frac{n}{\beta^2}$$

$$\hat{\beta}_{MLE} \xrightarrow{n \rightarrow \infty} N\left(\beta, \frac{\beta^2}{n}\right)$$

$$\text{Var}(\hat{\beta}_{MLE}) \approx \frac{\beta^2}{n}$$

5.

$$\frac{\text{MSE}(\hat{\beta}_{MLE})}{\text{MSE}(\hat{\beta}_M)} \approx \frac{\text{Var}(\hat{\beta}_{MLE})}{\text{Var}(\hat{\beta}_M)} = \frac{\frac{\beta^2}{n}}{2(\beta+1)^3 - \frac{(\beta+1)^4}{\beta+2} - (\beta+1)^2}$$

among all unbiased estimators, MLE estimator have the lowest

Variance. $\text{Var}(\hat{\beta}_M)$ is $O(\beta)$ which will be large when β is

large. However, if β is very small, $\text{Var} \hat{\beta}_M$ can be small as

$\hat{\beta}_{MLE}$ as well

$$6. f_{\eta}(x) = \begin{cases} \frac{1}{\eta} (1-x)^{\frac{1}{\eta}-1} & 0 < x < 1 \\ 0 & \text{others} \end{cases}$$

$$L = \prod_{i=1}^n f_{\eta}(x_i) = \prod_{i=1}^n \frac{1}{\eta} (1-x_i)^{\frac{1}{\eta}-1}$$

$$l = \sum_{i=1}^n -\log \eta + \left(\frac{1}{\eta}-1\right) \log (1-x_i)$$

$$\frac{\partial L}{\partial \eta} = -\frac{n}{\eta} + \left(\sum_{i=1}^n \log (1-x_i)\right) \times \frac{1}{\eta} \times (-\eta^{-2}) = 0$$

$$\frac{\partial L}{\partial \eta} = 0 \quad \hat{\eta}_{MLE} = \sqrt{\frac{-\sum_{i=1}^n \log (1-x_i)}{n}}$$

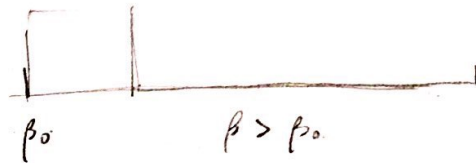
7. $H_0: \beta = \beta_0$
 $H_1: \beta > \beta_0$

$$\beta^{\wedge} \sim (\beta, \text{var}(\beta^{\wedge}))$$

test statistics Z test

$$\frac{\beta^{\wedge} - \beta_0}{\text{var}(\beta^{\wedge})}$$

8. $\frac{\beta^{\wedge} - \beta_0}{\text{var}(\beta^{\wedge})} > Z_{\alpha}$



$$\beta^{\wedge} > Z_{\alpha} \text{var}(\beta^{\wedge}) + \beta_0$$

critical value $Z_{\alpha} \text{var}(\beta^{\wedge}) + \beta_0$

9. $\beta_{MLE}^{\wedge} \sim N(\beta, \frac{\hat{\beta}_2}{n})$

$$\frac{\beta_{MLE}^{\wedge} - \beta}{\sqrt{\frac{\hat{\beta}_2}{n}}} \sim N(0, 1)$$

$$\beta \in \left(\beta^{\wedge} - 1.96 \times \frac{\hat{\beta}_2}{\sqrt{n}}, \beta^{\wedge} + 1.96 \times \frac{\hat{\beta}_2}{\sqrt{n}} \right)$$

with 95% confidence