

$\therefore X_i \sim \text{Binomial}(40, \theta)$ and IID

$$\therefore P_{X_i}(\theta) = \binom{40}{x_i} \theta^{x_i} (1-\theta)^{40-x_i}$$

$$P_X(\theta) = (40!)^8 (\prod x_i! (40-x_i)!)^{-1} (1-\theta)^{320} \left(\frac{\theta}{1-\theta}\right)^{\sum x_i}$$

we can find

$T(X) = \sum \theta x_i$ is sufficient statistic for θ

assume $\hat{\theta} = \frac{X}{n}$

then $E[\hat{\theta}] = E\left[\frac{X}{n}\right] = \theta$ unbiased

$$\text{Var}[\hat{\theta}] = \frac{\theta(1-\theta)}{n}$$

$$\frac{\partial}{\partial \theta} \log L(\theta; X) = \frac{\partial}{\partial \theta} \log P_X(X; \theta)$$

$$= \frac{\sum x_i}{\theta} - \frac{\sum (40-x_i)}{1-\theta}$$

Fisher Information

$$I(X) = -E\left[\frac{\partial^2 \log L}{\partial \theta^2}\right] = -E\left[\frac{\sum x_i}{\theta^2} - \frac{\sum (40-x_i)}{(1-\theta)^2}\right]$$

$$= \frac{320}{\theta(1-\theta)}$$

\therefore Cramer-Rao Lower Bound

$$\therefore E[(\hat{\theta} - \theta)^2] \geq \frac{1}{I(X)} = \frac{\theta(1-\theta)}{320} = \text{Var}(\hat{\theta})$$

$\therefore \hat{\theta} = \frac{X}{n}$ is the estimator which minimizes MSE