Homework I: DATA130048

Biostatistics

Due Thursday, March 26th, 2020

1 Problem 1: MLE & MME

Suppose that X is a discrete random variable with the following probability mass function, where $0 \le \theta \le 1$ is a parameter. The following 10 independent observations were taken from such a distribution: $(3,0) \ 2,1) \ 3,2,1) \ 0 \ 2,1)$

X	0	1	2	3
P(X)	$\frac{2\theta}{3}$	$\frac{\theta}{3}$	$\frac{2(1-\theta)}{3}$	$\frac{1-\theta}{3}$

Derive the MLE (maximum likelihood estimator) and MME (method of moments estimator) of θ .

V2: 1 The probability density function of X is:

$$P(X=x) = \left[\left(\frac{2\theta}{3} \right)^{\frac{1}{6}(1-x)} \cdot \left(\frac{\theta}{3} \right)^{\frac{1}{3}x} \right]^{(2-x)(3-x)} * \left[\left(\frac{2}{3}(1-\theta) \right)^{-\frac{1}{3}(3-x)} \cdot \left(\frac{1-\theta}{3} \right)^{\frac{1}{6}(2-x)} \right]^{x(1-x)}$$

$$\Rightarrow \quad L(\theta) = \sum_{i=1}^{h} \left[\frac{1}{6} (1-x_i) \ln(\theta) + \frac{x_i}{2} \ln(\theta) \right]_{\frac{1}{4}(2-x_i)(3-x_i)} + \left[-\frac{1}{2} (3-x_i) \ln(1-\theta) + \frac{1}{6} (2-x_i) \ln(1-\theta) \right]_{\frac{1}{4}(1-x_i)} + Const.$$

$$\Rightarrow \frac{\partial L(\theta)}{\partial \theta} = \frac{1}{\theta} \sum_{i=1}^{h} \left(\frac{1}{\theta} + \frac{\alpha_i}{3} \right) (2 - \alpha_i) (3 - \alpha_i) - \frac{1}{1 - \theta} \sum_{i=1}^{h} \left(-\frac{7}{\theta} + \frac{\alpha_i}{3} \right) \alpha_i (1 - \alpha_i) = 0 \Rightarrow \frac{\partial L(\theta)}{\partial \theta} = \frac{7}{\theta} - \frac{7}{1 - \theta} \Rightarrow \hat{\theta} = 0.5$$

2) Sample mean
$$\overline{\chi} = \frac{1}{10} \sum_{i=1}^{10} \chi_i = 1.5$$
 where the first moment $E[\chi] = \frac{9}{3} + \frac{1}{3} (1-9) + (1-9) = \frac{7}{3} - 39$
 \Rightarrow The NME: $\hat{\theta} = \frac{5}{12} = 0.4167$.

2 Problem 2: MLE & MME

Suppose $X_1, X_2, ..., X_n$ are iid random variables with density function

$$f(x \mid \sigma) = \frac{1}{2\sigma} \exp(-\frac{|x|}{\sigma})$$

Find the MLE and MME of σ .

$$\widehat{\mathbb{W}}: \quad \widehat{\mathbb{W}} = \mathbb{E} \left[\mathbb{E} \left[\frac{|\chi_i|}{6} - \log(2\delta) \right] \Rightarrow \stackrel{\stackrel{\leftarrow}{\leftarrow}}{\leftarrow} \frac{\partial L(\vec{\chi}; \delta)}{\partial \delta} = \sum_{i=1}^{h} \left[|\chi_i| + \frac{1}{6^{\nu}} - \frac{1}{6} \right] \Rightarrow \hat{\delta} = \frac{1}{h} \sum_{i=1}^{h} |\chi_i|$$

2) The NME:
$$\mathbb{E}[X] = \int_{-\infty}^{\infty} x \cdot \frac{1}{26} \exp\left\{-\frac{|x|}{6}\right\} dx = 0$$

$$\mathbb{E}[X^{2}] = \int_{-\infty}^{\infty} x^{2} \cdot \frac{1}{26} \exp\left\{-\frac{|x|}{6}\right\} dx = 26^{2}$$

$$\Rightarrow \hat{G} = \sqrt{\frac{1}{2\ln} \sum_{i=1}^{h} \chi_{i}^{2}}$$

3 Problem 3: MLE & MME

Suppose that $X_1, ..., X_n$ form a random sample from a <u>uniform distribution</u> on the interval $(0, \theta)$, where parameter $\theta > 0$ is unknown. Find the MME and MLE of θ .

VD: ① MLE:
$$f(x) = \frac{1}{\theta}$$
, $0 \le x \le \theta$ \Rightarrow $L(\vec{x}; \theta) = \left(\frac{1}{\theta}\right)^n$ 由于 $\hat{\theta} = argmax \ L(\vec{x}; \theta)$,则它间($0, \theta$) 应尽可能包括更多 data points \Rightarrow $\hat{\theta} = max\{x_i, i=1,...,n\}$
② NME: $E[X] = \frac{1}{\theta} \Rightarrow \tilde{\theta} = 2\bar{X} = \frac{1}{n}\sum_{i=1}^{n} x_i$

4 Problem 4: Central Limit Theorem & Delta Method

Suppose $X_n \sim Binomial(n,p)$, with $p \neq \frac{1}{2}$. Because $\frac{X_n}{n}$ is the maximum likelihood estimator for p, the maximum likelihood estimator for p(1-p) is $\delta_n = \frac{X_n(n-X_n)}{n^2}$. Use Central Limit Theorem to show the limiting distribution for $\frac{X_n}{n}$, and use Delta Method to derive the limiting distribution for δ_n .

図:
$$\mathbb{E}\left[\frac{X_{h}}{n}\right] = p$$
; $Var\left[\frac{X_{h}}{n}\right] = \frac{p}{h}(i-p)$
由中の根限定理,有: $\frac{\frac{X_{h}}{n} - p}{\sqrt{p(i-p)/n}} \xrightarrow{D} N(0.1)$ as $n \to \infty$ 用 $\frac{X_{h}}{n} \xrightarrow{D} N(p, \frac{p(i-p)}{n})$ as $n \to \infty$
持于 $\delta_{n} = \frac{X_{h}}{n} - \left(\frac{X_{h}}{n}\right)^{2}$. 由 Delta Method 可知:
$$\left[q\left(\frac{X_{h}}{n}\right) - q(p)\right] \xrightarrow{D} N\left(0, \frac{p(i-p)}{n} * \left[q'(p)\right]^{2}\right) \text{ as } n \to \infty$$
中 $\delta_{n} = q\left(\frac{X_{h}}{n}\right) \xrightarrow{D} N(p(i-p), \frac{1}{n}, p(i-p)(i-2p)^{2})$ as $n \to \infty$

5 Problem 5: Central Limit Theorem & Delta Method

Suppose $X_1, X_2, ...$ are iid with mean μ and finite variance σ^2 , and $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$. What is the limiting distribution of \bar{X}_n^2 ?

Therefore
$$\overline{X}_n := \frac{1}{n} \sum_{i=1}^{n} X_i$$
 has $\overline{E}[\overline{X}] = \mu$, $Var(\overline{X}) = \frac{\sigma^n}{n}$

By the CLT we have $\frac{\overline{X}_n - \mu}{\sqrt{\sigma^n/n}} \xrightarrow{D} N(0,1)$ as $n \to \infty$

• $q(x) = x^2$, $q'(x) = 2x$, $q''(x) = 2$.

① If $q'(\mu) = 2\mu \neq 0$, then by the first order delta method:

$$\overline{In} \left[q(\overline{X}_n) - q(\mu) \right] \longrightarrow N\left(0, \sigma^2 q'(\mu)^2\right) \Rightarrow \overline{X}_n^2 \xrightarrow{D} N(\mu^2, \frac{4\sigma^2 \mu^2}{n})$$
 as $n \to \infty$
② If $q'(\mu) = 2\mu = 0$, then by the second order delta method:

$$n \left[q(\overline{X}_n) - q(\mu) \right] \longrightarrow \frac{\sigma^2}{2} q''(\mu) \cdot X_1^2 \Rightarrow \overline{X}_n^2 - \mu^2 \xrightarrow{D} \frac{\sigma^2}{n} X_1^2$$
 as $n \to \infty$

6 Problem 6: Confidence intervals

Suppose that a clinical trial was conducted to estimate the response rate p of an experimental drug. We observed 13 responses among 65 subjects treated by this drug. Based on the binomial distribution, the estimated response rate is $\hat{p}=0.2$. Construct the 95% confidence interval for p using the asymptotic normal approximation.

Vg: Suppose
$$X_1, ..., X_n \stackrel{\text{iid}}{\sim} \text{ Bernoulli}(p)$$

Then $f(X_i = x_i) = p^{x_i} (1-p)^{1-x_i}$ Thus $L(\tilde{x}; p) = \sum_{i=1}^n x_i \log p + (1-x_i) \log (1-p)$
 $\Rightarrow \hat{p} = \frac{1}{n} \sum_{i=1}^n X_i \Rightarrow \text{ In this case, } \hat{p} = \frac{13}{65} = 0.2$

By the asymptotic normal approximation, 95% confidence interval is $p \in \left[\hat{p} \pm \mathbb{E}_{M/2} \sqrt{\frac{1}{n} \hat{p}(1-\hat{p})}\right] \Rightarrow p \in \left[0.1028, 0.2972\right]$

>> Rcodes

```
# Read in Data
1.
setwd("./Desktop/MyRcodes")
    data <- read.table("./gamma-arrivals.txt")</pre>
3.
    #data <- as.numeric(data)</pre>
4.
5.
    # Make a histogram of arrival time
    hist(data[,], main = "histogram of number of gamma-
    arrivals", prob=TRUE, right=FALSE, xlim=c(0, 800), ylim = c(0, 0.012))
8.
9. # Compute the MME of data
10. sample_mean = mean(data[,])
11. sample_variance = var(data[,])
12. mme_a = sample_mean**2 / sample_variance
13. mme_b = sample_mean / sample_variance
14.
15. # compute the MLE of data
16. X <- data[,]
17. n <- length(X)</pre>
18. negloglike <- function(param){</pre>
       param[2]*sum(X) + n*log(gamma(param[1])) - n*param[1]*log(param[2]) - (param[1]-
    1)*sum(log(X))
20. }
21. out <- nlm(negloglike, p = c(0.5, 0.5), hessian = TRUE)
22. mle_a <- out$estimate[1]</pre>
23. mle_b <- out$estimate[2]</pre>
24.
25. # plot gamma(alpha=shape, beta=rate) distribution
26. x <- seq(0, 800, 0.1)
27. lines(x, dgamma(x, shape=mme_a, rate = mme_b), lty = 2, col = "blue") # MME.dist
28. lines(x, dgamma(x, shape=mle_a, rate=mle_b), lty = 4, col = "red") # MLE.dist
```

histogram of number of gamma-arrivals

