## Stat 641 Fall 2021

## Solutions for Assignment 3

- P1. (10 points) Let Y have a double exponential distribution.
  - (a.) The quantile function

$$Q(u) = \begin{cases} \theta + \beta \log(2u) & \text{for } u \le .5\\ \theta - \beta \log(2(1-u)) & \text{for } u \ge .5 \end{cases}$$

(b.) The survival function is given by

$$S(y) = P(Y > y) = 1 - F(y) \implies S(y) = \begin{cases} 1 - \frac{1}{2}e^{-\left(\frac{\theta - y}{\beta}\right)} & \text{for } y < \theta \\ \frac{1}{2}e^{-\left(\frac{y - \theta}{\beta}\right)} & \text{for } y \ge \theta \end{cases}$$

(c.) The hazard function is given by

$$h(y) = \frac{f(y)}{S(y)} \implies h(y) = \begin{cases} \frac{\frac{1}{\beta}e^{\left(\frac{y-\theta}{\beta}\right)}}{2-e^{\left(\frac{y-\theta}{\beta}\right)}} & \text{for } y \le \theta \\ \frac{1}{\beta} & \text{for } y > \theta \end{cases}$$

P2. (10 points)  $n = 44 \Rightarrow \widehat{Q}(u) = Y_{(43u+1)} \Rightarrow$ 

- $\widehat{Q}(.25) = Y_{(11.75)} = .25Y_{(11)} + .75Y_{(12)} = .25(3.24) + .75(3.39) = 3.35$
- $\widehat{Q}(.5) = Y_{(22.5)} = .5Y_{(22)} + .5Y_{(23)} = .5(7.89) + .5(7.97) = 7.93$
- $\widehat{Q}(.75) = Y_{(33.25)} = .75Y_{(33)} + .25Y_{(34)} = .75(16.00) + .25(18.61) = 16.65$
- P3. (24 points) Using the R code:

```
v = c(0.94.
               1.26.
                        1.44.
                                1.49.
                                         1.63.
                                                    1.80.
                                                             2.00.
                                                                       2.00.
                                                                                2.56.
    2.58,
             3.24,
                      3.39,
                               3.53,
                                         3.77,
                                                  4.36,
                                                           4.41,
                                                                     4.60,
                                                                              4.67,
    5.39,
             6.25,
                      7.02,
                               7.89,
                                         7.97,
                                                  8.00,
                                                           8.28,
                                                                     8.83,
                                                                              8.91,
                              12.15 ,
   8.96,
             9.92.
                     11.36,
                                        14.40.
                                                 16.00,
                                                           18.61.
                                                                    18.75,
                                                                             19.05,
                     23.27,
   21.00,
                              24.71,
                                                 28.75,
                                                          30.23,
h=3
n=length(y)
deni <- function(x){</pre>
  (1/sqrt(2*pi))*exp(-((x-y)/h)^2/2)/(n*h)
f3 = sum(sapply(3,deni))
f16 = sum(sapply(16,deni))
f16i = sapply(16,deni)
min = min(f16i)
imin = which(f16i==min)
ymin=y[imin]
max = max(f16i)
imax=which(f16i==max)
vmax=v[imax]
```

- (a.) The value for  $\widehat{f}(3)$  is f3 = 0.059703 and for  $\widehat{f}(16)$  is f16 = 0.01669353
- (b.) Using a relative frequency histogram with a bin width of 5, with  $n_j = \#Y_i$ 's in [0.94 + 5(j-1), 0.94 + 5j), we have  $n_1 = 19$ ,  $n_2 = 10$ ,  $n_3 = 3$ ,  $n_4 = 4$ ,  $n_5 = 5$ ,  $n_6 = 2$ ,  $n_7 = 1$ .

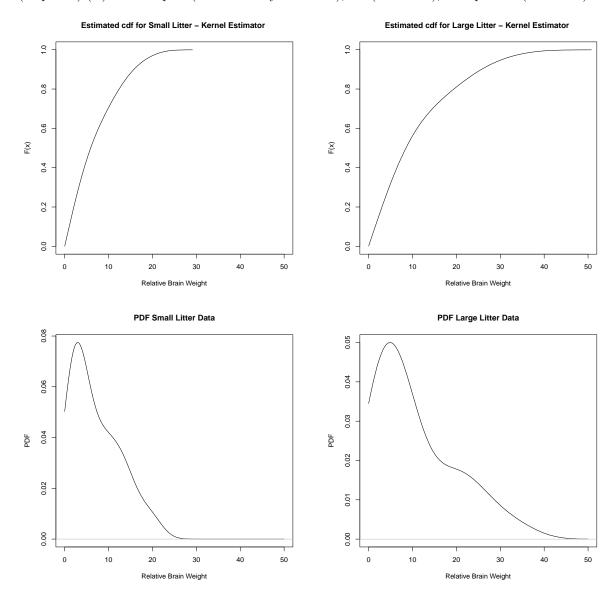
- Therefore, the estimates are  $\widehat{f}(3) = 19/(44 \times 5) = 0.08636364$  and for  $\widehat{f}(16) = 4/(44 \times 5) = 0.01818182$ . A fairly close agreement between the estimates obtained by the two methods.
- (c.) The data value provides the smallest contribution to the estimator at y=16,  $\hat{f}(16)$  is the data value furthest from 16, which is y = 35.45 with a contribution of 2.253479e-12 to  $\hat{f}(16)$ =0.01669353. This is obtained by computing by hand:

$$\frac{1}{nh}K\left(\frac{y-Y_i}{h}\right) = \frac{1}{44*3}K\left(\frac{16-35.45}{3}\right) = \left(\frac{1}{132}\right)\left(\frac{1}{2*\pi}\right)e^{-\left(\frac{16-35.45}{3}\right)^2/2} = 2.253479e^{-12}$$

(d.) The data value provides the largest contribution to the estimator at y=16,  $\hat{f}(16)$  is the data value closest to 16, which is y = 16 with a contribution of 0.00302229 to  $\hat{f}(16)$ =0.01669353. This is obtained by computing by hand:

$$\frac{1}{nh}K\left(\frac{y-Y_i}{h}\right) = \frac{1}{44*3}K\left(\frac{16-16}{3}\right) = \left(\frac{1}{132}\right)\left(\frac{1}{2*\pi}\right)e^{-\left(\frac{16-16}{3}\right)^2/2} = .00302229$$

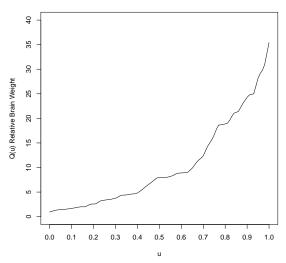
P4. (28 points) (a.) Plots of pdfs (kernel density estimator), edf (smoothed), and quantile (smoothed):





## 4 35 30 Q(u) Relative Brain Weight 32 20 12 9 2 0.0 0.1 0.2 0.3 0.7 8.0 0.9 1.0 0.6

## Quantile Large Litter Data



(a)

See code at end of document.

(b.) Small Litter: Relative brain weights are somewhat right skewed which indicates that a few species of mammals with small average litters have large brains relative to their body weights.

Large Litter: Relative brain weights are highly right skewed which indicates that sizeable proportion of the species of mammals with large average litters have large brains relative to their body weights.

- (c.) Based on the graphs, I would conclude that there is a positive relation ship between average litter size and relative brain weights. However, it would be more informative to have the actual litter sizes associated with each species to draw a more concrete conclusion.
- P5. (28 points) Multiple Choice Questions:
  - 1. E Given any one of the four functions then you can derive the other three from the given function
  - 2. D See page 24 in Handout 4
  - 3. B See page 24 in Handout 4
  - 4. D See pages 30 & 32 in Handout 4
  - 5. **B** See page 50 in Handout 4
  - 6. **B** See page 37 in Handout 4
  - 7. **D** See pages 16 & 17 in Handout 5
  - 8. **C** or **D** See page 13 & 14 in Handout 5
  - 9. C See page 23 in Handout 5
  - 10. A or D See page 27 in Handout 5
  - 11. **E** See page 14 in Handout 5
  - 12. E See pages 25-27 in Handout 5

A. is false because  $\sigma$  does not exist for Cauchy which is symmetric whereas both SIQR and MAD exist and are equal

- B. is false because MAD is nearly always preferred to SIQR
- C. is false because for a normal distribution MAD=SIQR  $\,$
- 13. **B** See page 33 in Handout 5:

$$\theta = 22.3, \ \rho = .6, \ \sigma_e^2 = 2.8 \ \Rightarrow \mu_X = \frac{\theta}{1-\rho} = \frac{22.3}{1-.6} = 55.75$$

$$\sigma_X^2 = \frac{\sigma_e^2}{1-\rho^2} = \frac{2.8}{1-.36} = 4.375$$

```
##
## (2)
##
dta <- read.csv("Assign3_BrainSize.csv")</pre>
y <- dta[, 2]
y <- y[!is.na(y)]</pre>
n <- length(y)</pre>
y_s <- sort(y)</pre>
## 0.25: (n - 1) * 0.25 + 1 = 11.75
(n - 1) * 0.25 + 1
y_s[11] + 0.75 * (y_s[12] - y_s[11])
## 0.5: (n - 1) * 0.5 + 1 = 22.5
(n - 1) * 0.5 + 1
y_s[22] + 0.5 * (y_s[23] - y_s[22])
## 0.75: (n - 1) * 0.5 + 1 = 33.25
(n - 1) * 0.75 + 1
y_s[33] + 0.25 * (y_s[34] - y_s[33])
##
## (3)
dd <- density(y_s)</pre>
plot(dd, type = "1")
h <- 3
## (a)
K_u <- function(u) {</pre>
 return(dnorm(u))
}
## f(3)
sum(K_u((3 - y_s) / h)) / (n * h)
## f(16)
sum(K_u((16 - y_s) / h)) / (n * h)
## (b)
brks \leftarrow y_s[1] + 5 * (0:7)
n_j <- hist(y_s, prob = FALSE, breaks = brks)$counts</pre>
R_j \leftarrow n_j / n
f_hat_j <- R_j / 5
hist(y_s, prob = TRUE, breaks = brks)$density
## (c)
kk \leftarrow K_u((16 - y) / h) / (n * h)
y[which.min(kk)]
## (d)
```

```
y[which.max(kk)]
##
## (4)
##
y_small <- dta[, 1]</pre>
y_large <- dta[, 2]</pre>
y_large <- y_large[!is.na(y_large)]</pre>
## (a)
## PDFs
par(mfrow = c(1, 2))
plot(density(y_small), xlab = "y", ylab = "f", main = "Small Litters", xlim = c(-10, 50),
 cex.axis = 0.75)
plot(density(y_large), xlab = "y", ylab = "f", main = "Large Litters", xlim = c(-10, 50),
  cex.axis = 0.75)
## EDFs
qq_small <- quantile(y_small, probs <- seq(0, 1, by = 0.01))
qq_large <- quantile(y_large, probs)</pre>
plot(qq_small, probs, type = "s", xlab = "y", ylab = "F", main = "Small Litters",
 xlim = c(0, 35), cex.axis = 0.75)
plot(qq_large, probs, type = "s", xlab = "y", ylab = "F", main = "Large Litters",
 xlim = c(0, 35), cex.axis = 0.75)
## Quantile functions
plot(probs, qq_small, type = "s", xlab = "Q(u)", ylab = "u", main = "Small Litters",
 ylim = c(0, 35), cex.axis = 0.75)
plot(probs, qq_large, type = "s", xlab = "Q(u)", ylab = "u", main = "Large Litters",
 ylim = c(0, 35), cex.axis = 0.75)
```