## **EXERCISE 4**

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- 1. Read the first 4 chapters of Empirical Likelihood by Owen.
- 2. Apply the empirical likelihood method to draw the 50%, 90%, 95%, 99% confidence regions of law dataset in bootstrap package, and compare them with confidence regions of normal distribution. (Use scel.R on http://statweb.stanford.edu/owen/empirical/)

```
# scel.R has two callable functions
# emplik
            does one EL calculation,
             calls emplik on a trajectory from {\tt mu0} to {\tt mu1} in N+1 steps
# tracelr
# However, one can only copy the part without tracelr in this problem
# We omit the copying part here
# Start from the drawing part
library(plotrix) # to draw ellipses
m <- colMeans(law)</pre>
s <- cov(law)
values <- eigen(s)$values</pre>
vectors <- eigen(s)$vectors</pre>
n <- nrow(law)</pre>
p <- 2
# EL confidence regions : all in red
ilabel \leftarrow seq(m[1] - 30, m[1] + 50, 1)
jlabel \leftarrow seq(m[2] - .3, m[2] + .3, 0.01)
test <- matrix(rep(1: 81 * 61), 81, 61)
for (i in 1 : 81) {
  for (j in 1 : 61) {
    test[i,j] <- emplik(law, c(ilabel[i], jlabel[j]))$logelr</pre>
  }
}
plot(c(560, 640), c(2.8, 3.4))
contour(ilabel, jlabel, exp(test), levels = c(0.5, 0.1, 0.05, 0.01), col = 'red', add = TRUI
# Normal confidence regions : all in blue
c \leftarrow (n-1) * p / (n-p) * qf(0.5, p, n-p)
```

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```
a <- sqrt(values[1] * c / n)
b <- sqrt(values[2] * c / n)
angle <- atan(vectors[2] / vectors[1])</pre>
draw.ellipse(m[1], m[2], a, b, angle, deg = FALSE, border = 'blue') # 50% CR
c \leftarrow (n-1) * p / (n-p) * qf(0.9, p, n-p)
a <- sqrt(values[1] * c / n)
b <- sqrt(values[2] * c / n)
angle <- atan(vectors[2] / vectors[1])</pre>
draw.ellipse(m[1], m[2], a, b, angle, deg = FALSE, border = 'blue') # 90% CR
c \leftarrow (n - 1) * p / (n - p) * qf(0.95, p, n - p)
a <- sqrt(values[1] * c / n)
b <- sqrt(values[2] * c / n)</pre>
angle <- atan(vectors[2] / vectors[1])</pre>
draw.ellipse(m[1], m[2], a, b, angle, deg = FALSE, border = 'blue') # 95% CR
c \leftarrow (n - 1) * p / (n - p) * qf(0.99, p, n - p)
a <- sqrt(values[1] * c / n)
b <- sqrt(values[2] * c / n)</pre>
angle <- atan(vectors[2] / vectors[1])</pre>
draw.ellipse(m[1], m[2], a, b, angle, deg = FALSE, border = 'blue') # 99% CR
```

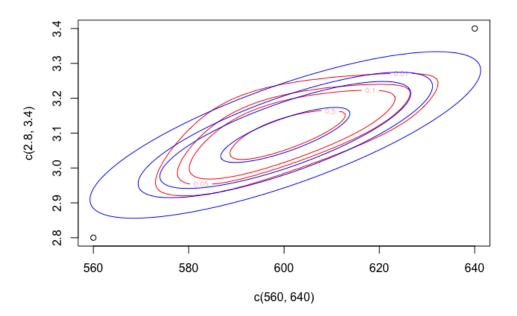


FIGURE 1. Red: EL confidence regions. Blue: normal confidence regions. Larger percentages lead to wider regions, respectively.

**Remark 1.** According to Owen, one can also use F calibration to make the confidence regions narrower.

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3. Suppose i.i.d. samples  $(X_i,Y_i), i=1,\ldots,n$  from the population (X,Y). We are interested in the parameter  $\tau=\sigma_X^2/\sigma_Y^2$ , where  $\sigma_X^2$  and  $\sigma_Y^2$  are variances of X and Y, respectively. Denote  $\theta=(\tau,\eta')'$ , where  $\eta$  is a nuisance parameter. Solve estimate equations of an estimator for  $\theta$ , and then give the empirical likelihood confidence interval of  $\tau$ .

Solve. Let  $\eta = (\sigma_Y^2, \mu_X, \mu_Y)$ , then the parameters are determined by

$$\begin{cases} E(X_1 - \mu_X) = 0 \\ E(Y_1 - \mu_Y) = 0 \\ E[(Y_1 - \mu_Y)^2 - \sigma_Y^2] = 0 \\ E[(X_1 - \mu_X)^2 - \sigma_Y^2\tau] = 0 \end{cases}$$

which gives the estimate equations

$$\begin{cases} \hat{\mu_X} = \frac{1}{n} \sum_i X_i \\ \hat{\mu_Y} = \frac{1}{n} \sum_i Y_i \\ \hat{\sigma_Y^2} = \frac{1}{n} \sum_i (Y_i - \hat{\mu_Y})^2 \\ \hat{\tau} = \frac{\frac{1}{n} \sum_i (X_i - \hat{\mu_X})^2}{\hat{\sigma_Y^2}} = \frac{\sum_i (X_i - \hat{\mu_X})^2}{\sum_i (Y_i - \hat{\mu_Y})^2} \end{cases}$$

In the slides, we only know how to compute EL confidence set of  $\theta$ , but for  $\tau$ , we estimate the other elements of  $\theta$  first, and then give the  $(1-\alpha)$ - EL confidence interval as

$$\{\tau: \log L(\tau) + n\log n > -0.5\xi_{1,1-\alpha}^2\},$$

$$\{ \tau : \log L(\tau) + n \log n > -0.5\xi_{1,1-\alpha}^2 \},$$
 where  $\log L(\tau) = \max \left\{ \sum_i \log p_i : p_i \ge 0, \sum_i p_i = 1, \tau = \frac{\sum_i p_i (X_i - \hat{\mu_X})^2}{\sum_i p_i (Y_i - \hat{\mu_Y})^2} \right\}, \ \hat{\mu_X} = \sum_i p_i X_i,$  
$$\hat{\mu_Y} = \sum_i p_i Y_i.$$