

Problem 7.2. Let X_1, \dots, X_n be a random sample from a $\text{gamma}(\alpha, \beta)$ population.

(a) Find the MLE of β , assuming α is known.

We begin by finding

$$\begin{aligned} L(\beta|\vec{x}) &= \prod_{i=1}^n \frac{1}{\Gamma(\alpha)\beta^\alpha} x_i^{\alpha-1} e^{-x_i/\beta} = \frac{1}{\Gamma(\alpha)^n \beta^{n\alpha}} \left(\prod_{i=1}^n x_i^{\alpha-1} \right) \left(\prod_{i=1}^n \exp(-x_i/\beta) \right) \\ &= \frac{1}{\Gamma(\alpha)^n \beta^{n\alpha}} \left(\prod_{i=1}^n x_i^{\alpha-1} \right) \left(\exp \left(-\sum_{i=1}^n x_i/\beta \right) \right) \end{aligned}$$

Then

$$\begin{aligned} \log(L(\beta|\vec{x})) &= \log \left(\frac{1}{\Gamma(\alpha)^n \beta^{n\alpha}} \left(\prod_{i=1}^n x_i^{\alpha-1} \right) \left(\exp \left(-\sum_{i=1}^n x_i/\beta \right) \right) \right) \\ &= \log \left(\frac{1}{\Gamma(\alpha)^n \beta^{n\alpha}} \right) + \log \left(\prod_{i=1}^n x_i^{\alpha-1} \right) + \log \left(\exp \left(-\sum_{i=1}^n x_i/\beta \right) \right) \\ &= -\log(\Gamma(\alpha)^n \beta^{n\alpha}) + (\alpha-1) \log \left(\prod_{i=1}^n x_i \right) + \left(-\sum_{i=1}^n x_i/\beta \right) \\ &= -\log(\Gamma(\alpha)^n) - \log(\beta^{n\alpha}) + (\alpha-1) \log \left(\prod_{i=1}^n x_i \right) + \left(-\sum_{i=1}^n x_i/\beta \right) \\ &= -n \log(\Gamma(\alpha)) - (n\alpha) \log(\beta) + (\alpha-1) \log \left(\prod_{i=1}^n x_i \right) + \left(-\sum_{i=1}^n x_i/\beta \right) \\ &= -n \log(\Gamma(\alpha)) - (n\alpha) \log(\beta) + (\alpha-1) \sum_{i=1}^n \log(x_i) + \left(-\sum_{i=1}^n x_i/\beta \right) \end{aligned}$$

Next, we find the derivative with respect to β and set this equal to zero.

$$\frac{d}{d\beta} \log(L(\beta|\vec{x})) = \frac{d}{d\beta} (-n\alpha) \log(\beta) + \frac{d}{d\beta} \left(-\sum_{i=1}^n x_i/\beta \right) = \frac{-n\alpha}{\beta} - \sum_{i=1}^n x_i \frac{-1}{\beta^2}$$

Setting this equal to zero and solving for β , we get

$$\begin{aligned} \frac{-n\alpha}{\beta} + \frac{\sum_{i=1}^n x_i}{\beta^2} &= 0 \implies \frac{\sum_{i=1}^n x_i}{\beta^2} = \frac{n\alpha}{\beta} \\ \implies \sum_{i=1}^n x_i &= n\alpha\beta \implies \hat{\beta} = \frac{\sum_{i=1}^n x_i}{n\alpha} = \frac{\bar{x}}{\alpha} \end{aligned}$$

To show that this is the MLE, we should take the second derivative.

$$\begin{aligned} \frac{d^2}{d\beta^2} \log(L(\beta|\vec{x})) &= \frac{d}{d\beta} \frac{-n\alpha}{\beta} + \sum_{i=1}^n x_i \frac{1}{\beta^2} = \frac{n\alpha}{\beta^2} - \sum_{i=1}^n x_i \frac{2}{\beta^3} = \frac{n\alpha}{\left(\frac{\sum_{i=1}^n x_i}{n\alpha} \right)^2} - \sum_{i=1}^n x_i \frac{2}{\left(\frac{\sum_{i=1}^n x_i}{n\alpha} \right)^3} \\ &= \frac{(n\alpha)^3}{(\sum_{i=1}^n x_i)^2} - \frac{2 \sum_{i=1}^n x_i (n\alpha)^3}{(\sum_{i=1}^n x_i)^3} = \frac{(n\alpha)^3}{(\sum_{i=1}^n x_i)^2} - \frac{2(n\alpha)^3}{(\sum_{i=1}^n x_i)^2} = -\frac{(n\alpha)^3}{(\sum_{i=1}^n x_i)^2} < 0 \end{aligned}$$

Which is what we wanted to show.

- (b) If α and β are both unknown, there is no explicit formula for the MLEs of α and β , but the maximum can be found numerically. The result on part (a) can be used to reduce the problem to the maximization of a univariate function. Find the MLEs for α and β for the data in Exercise 7.10(c).

Then plugging in $\hat{\beta}$, we need to find the values that maximize

$$\begin{aligned}\log(L(\alpha|\vec{x})) &= -n \log(\Gamma(\alpha)) - (n\alpha) \log\left(\frac{\bar{x}}{\alpha}\right) + (\alpha - 1) \sum_{i=1}^n \log(x_i) + \left(-\sum_{i=1}^n x_i/(\bar{x}/\alpha)\right) \\ &= -n \log(\Gamma(\alpha)) - (n\alpha) \log\left(\frac{\bar{x}}{\alpha}\right) + (\alpha - 1) \sum_{i=1}^n \log(x_i) - \left(\frac{\alpha}{\bar{x}} \sum_{i=1}^n x_i\right)\end{aligned}$$

Then

$$\frac{dL}{d\alpha} = n \log(\alpha) - n \log(\bar{x}) - n\psi(\alpha) + \sum_{i=1}^n \log(x_i)$$

and

$$\frac{d^2L}{d\alpha^2} = \frac{n}{\alpha} - n\psi'(\alpha)$$

I will use R and the Newton-Raphson method for estimating mle.

```
data <- c(22.0, 23.9, 20.9, 23.8, 25.0, 24.0, 21.7,
          23.8, 22.8, 23.1, 23.1, 23.5, 23.0, 23.0)

sum.ln <- function(x){
  n <- length(x)
  sum = 0
  for (i in 1:n) {
    sum = sum + log(x[i])
  }
  sum
}
c <- sum.ln(data)
d <- n*log(mean(data))
# find first derivative
f.prime <- function(alpha) n*log(alpha) - d - n*digamma(alpha) + c
# find second derivative
f.double <- function(alpha) (n/alpha) - n*trigamma(alpha)

newton.raphson.gamma <- function(x1 = 1, tol = 1e-8){
  x0 = x1 + 1
  while (abs(x1 - x0) > tol) {
    x0 <- x1
    x1 <- x0 - f.prime(x0)/f.double(x0)
  }
  alpha.hat = x1
}

# Newton-Raphson for estimating gamma mle
mle.alpha <- newton.raphson.gamma()
mle.alpha

mle.beta <- mean(data)/mle.alpha
mle.beta

Output:
> mle.alpha
[1] 514.3354
> mle.beta
[1] 0.0449401
```