

## 18.05 Problem Set 6, Spring 2022 Solutions

### Problem 1. (10 pts.) Continuous MLE

Suppose we have a distribution with the following pdf (called a gamma distribution)

$$f(x|a) = \frac{a^5}{(4)!} x^4 e^{-ax}.$$

Suppose we have independent data  $x_1, x_2, \dots, x_m$  drawn from this distribution. Find the maximum likelihood estimate (MLE) for  $a$ .

**Suggestion:** The likelihood can be compactly written in terms of the sum  $S$  and the product  $P$  of the data.

**Solution:** The likelihood for  $x_i$  is  $f(x_i|a) = \frac{a^5}{4!} x_i^4 e^{-ax_i}$ . So, the likelihood of the data is

$$f(\text{data}|a) = \prod_{i=1}^m f(x_i|a) = \frac{a^{5m}}{(4!)^m} P^4 e^{-aS},$$

where  $P = \prod x_i$  (product of data) and  $S = \sum x_i$  (sum of data).

So, the log likelihood is

$$l(a) = 5m \ln(a) + 4 \ln(P) - aS - m \ln(4!).$$

Taking the derivative and setting it to 0, we get

$$l'(a) = \frac{5m}{a} - S = 0 \Rightarrow \boxed{\text{The MLE } \hat{a} = \frac{5m}{S}}.$$

Note: It turns out, the distribution mean is  $5/a$  and  $\hat{a} = 5/(S/m) = 5/\bar{x}$ , where  $\bar{x}$  is the data mean.

### Problem 2. (25: 5,10,10 pts.) Least squares

In this problem we will use maximum likelihood estimates to develop Gauss' method of least squares for fitting lines to data.

Bivariate data means data of the form

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n).$$

For bivariate data the simple linear regression model assumes that, for some values of the parameters  $a$  and  $b$ , we have

$$y_i = ax_i + b + \text{random measurement error}.$$

The model assumes the measurement errors are independent and identically distributed and follow a  $N(0, \sigma^2)$  distribution. (The values  $x_i$  may or may not be random.)

In general terms, we can say that the value of  $x$  'explains' the value of  $y$  except for some random noise. Graphically, the model says to make a scatter plot and find the line that best fits the data. This is called a simple linear regression model.

It turns out that, under some assumptions about random variation of measurement error, one way to find a “best” line is by solving a maximum likelihood problem.

The goal is to find the values of the model parameters  $a$  and  $b$  that give the MLE for this model. To guide you, we note that the model says that

$$y_i \sim N(ax_i + b, \sigma^2).$$

Also remember that you know the density function for this distribution.

(a) For a general datum  $(x_1, y_1)$  give the likelihood and log likelihood functions (these will be functions of  $y_1, x_1, a, b,$  and  $\sigma$ .)

**Solution:** Since  $y_i \sim N(ax_i + b, \sigma^2)$  the likelihood with data  $(x_1, y_1)$  is

$$f(x_1, y_1 | a, b, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(y_1 - ax_1 - b)^2 / (2\sigma^2)}.$$

The log likelihood is

$$\ln(f(x_1, y_1 | a, b, \sigma)) = -\ln(\sqrt{2\pi}\sigma) - \frac{(y_1 - ax_1 - b)^2}{2\sigma^2}.$$

(b) Consider the data  $(1, 8), (3, 2), (5, 1)$ . Assume that  $\sigma = 3$  is a known constant and find the maximum likelihood estimate for  $a$  and  $b$ .

**Note:** since there are two variables  $a$  and  $b$ , in order to find a critical point you will have to take partial derivatives and set them equal to 0. This part of the problem takes a fair amount of tedious algebra –sorry.

**Note:** We gave you a specific value of  $\sigma$ , to avoid the distraction of one more symbol. If you look at your calculations, you should see that the value of  $\sigma$  plays no role in finding the MLE for  $a$  and  $b$ . We get the same answer no matter what the value.

**Solution:** The likelihood for all the data is the product of the individual likelihoods. So,

$$f((1, 8), (3, 2), (5, 1) | a, b, \sigma) = \left( \frac{1}{\sqrt{2\pi}\sigma} \right)^3 e^{-((8-a-b)^2 + (2-3a-b)^2 + (1-5a-b)^2) / (2\sigma^2)}$$

Taking the natural log (and replacing the list of data by the word ‘data’) we get

$$\ln(f(\text{data} | a, b, \sigma)) = -3\ln(\sqrt{2\pi}\sigma) - \frac{(8-a-b)^2 + (2-3a-b)^2 + (1-5a-b)^2}{2\sigma^2}$$

Since we want to find  $a$  and  $b$  that maximize the likelihood we take the partial derivatives and set them to 0.

$$\begin{aligned} \frac{\partial \ln(f(\text{data}) | a, b, \sigma)}{\partial a} &= \frac{2}{2\sigma^2} ((8-a-b) + 3(2-3a-b) + 5(1-5a-b)) = 0 \\ \frac{\partial \ln(f(\text{data}) | a, b, \sigma)}{\partial b} &= \frac{2}{2\sigma^2} ((8-a-b) + (2-3a-b) + (1-5a-b)) = 0 \end{aligned}$$

These are two equations in the unknowns  $a$  and  $b$ . We simplify and solve:

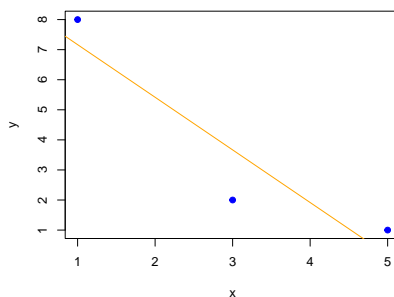
$$\begin{aligned} 35a + 9b &= 19 \\ 9a + 3b &= 11 \end{aligned} \quad \text{which gives} \quad a = -7/4 = -1.75; \quad b = 107/12 \approx 8.917.$$

The linear regression fit of a line to the data is  $y = ax + b = -7x/4 + 107/12$ .

(c) Use R to plot the data and the regression line you found in part (ii) The commands `plot(x,y, pch=19)` and `abline()` will come in handy. For `abline` be careful: the parameter `a` is the intercept and `b` is the slope – exactly the opposite of our usage. Print the plot and turn it in.

**Solution:** Here is the code for this plot:

```
x = c(1,3,5)
y = c(8,2,1)
a = -7/4
b = 107/12
plot(x, y, pch=19, col='blue')
#Perversely, in abline a is the intercept and b is the slope.
abline(a=b, b=a, col='orange', lwd=2)
```



**Problem 3.** (15: 10,5 pts.) **Estimating uniform parameters**

(a) Suppose we have data 1.2, 2.1, 1.3, 10.5, 5 which we know is drawn independently from a uniform( $a, b$ ) distribution. Give the maximum likelihood estimate for the parameters  $a$  and  $b$ .

Hint: in this case you should not try to find the MLE by differentiating the likelihood function.

**Solution:** The pdf for uniform( $a, b$ ) distribution takes two values

$$f(x | a, b) = \begin{cases} 1/(b - a) & \text{if } x \text{ is in } [a, b] \\ 0 & \text{otherwise} \end{cases}$$

Since the likelihood is the product of the likelihoods of each data point, the likelihood function is

$$f(\text{data} | a, b) = \begin{cases} 1/(b - a)^5 & \text{if all data is in } [a, b] \\ 0 & \text{if not} \end{cases}$$

This is maximized when  $(b - a)$  is as small as possible. Since all the data has to be in the interval  $[a, b]$  we minimize  $(b - a)$  by taking  $a =$  minimum of data and  $b =$  maximum of data.

Answer:  $a = 1.2, b = 10.5$ .

(b) Suppose we have data  $x_1, x_2, \dots, x_n$  which we know is drawn independently from a  $\text{uniform}(a, b)$  distribution. Give the maximum likelihood estimate for the parameters  $a$  and  $b$ .

**Solution:** The same logic as in part (a) shows  $a = \min(x_1, \dots, x_n)$  and  $b = \max(x_1, \dots, x_n)$ .

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18.05 Introduction to Probability and Statistics

Spring 2022

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